

PREDICTION OF SURFACE ROUGHNESS OF ADDITIVELY MANUFACTURED  
AND MACHINED PARTS VIA MACHINE LEARNING

A THESIS SUBMITTED TO  
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES  
OF  
MIDDLE EAST TECHNICAL UNIVERSITY

BY

MUHAMMAD USAMA

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS  
FOR  
THE DEGREE OF MASTER OF SCIENCE  
IN  
MECHANICAL ENGINEERING

AUGUST 2025



Approval of the thesis:

**PREDICTION OF SURFACE ROUGHNESS OF ADDITIVELY  
MANUFACTURED AND MACHINED PARTS VIA MACHINE LEARNING**

submitted by **MUHAMMAD USAMA** in partial fulfillment of the requirements for  
the degree of **Master of Science in Mechanical Engineering Department, Middle  
East Technical University** by,

Prof. Dr. Naci Emre Altun  
Dean, Graduate School of **Natural and Applied Sciences**

\_\_\_\_\_

Prof. Dr. Serkan Dağ  
Head of Department, **Mechanical Engineering**

\_\_\_\_\_

Prof. Dr. Ulaş Yaman  
Supervisor, **Mechanical Engineering, METU**

\_\_\_\_\_

Assoc. Prof. Dr. Elif Sürer  
Co-supervisor, **Graduate School Of Informatics, METU**

\_\_\_\_\_

**Examining Committee Members:**

Prof. Dr. Melik Dölen  
Mechanical Engineering, METU

\_\_\_\_\_

Prof. Dr. Ulaş Yaman  
Mechanical Engineering, METU

\_\_\_\_\_

Prof. Dr. Yusuf Kaynak  
Mechanical Engineering, Marmara University

\_\_\_\_\_

Assist. Prof. Dr. Hakan Çalışkan  
Mechanical Engineering, METU

\_\_\_\_\_

Assist. Prof. Dr. Irmak Sargın  
Metallurgical and Materials Engineering, METU

\_\_\_\_\_

Date:21.08.2025



**I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.**

Name, Surname: Muhammad Usama

Signature :



## ABSTRACT

### **PREDICTION OF SURFACE ROUGHNESS OF ADDITIVELY MANUFACTURED AND MACHINED PARTS VIA MACHINE LEARNING**

Usama, Muhammad

M.S., Department of Mechanical Engineering

Supervisor: Prof. Dr. Ulaş Yaman

Co-Supervisor: Assoc. Prof. Dr. Elif Sürer

August 2025, 195 pages

This study addresses a key research gap in predicting surface roughness (Ra) for Poly-lactic Acid (PLA) components produced via Fused Filament Fabrication (FFF) and hybrid AM–CNC machining at varying inclination angles using supervised regression-based machine learning. Few prior works considered inclination angle or CNC post-processing; this study employs a comprehensive design of 54 parts via Taguchi L54 DOE, covering 10°–80° inclinations. Ten Machine Learning (ML) algorithms were evaluated, with the Explainable Boosting Machine (EBM) achieving the highest predictive accuracy ( $R^2 = 0.983$  for AM,  $R^2 = 0.616$  for hybrid).

For AM, the most influential factors were Inclination Angle, Layer Height, Nozzle Diameter, and Printing Temperature. Optimal surface quality was achieved with 0.10 mm layer height, 0.25 mm nozzle, and 210 °C extrusion temperature. In hybrid machining, AM parameters coupled with depth of cut and infill density further influenced Ra as values decreased by 85–91%; a 0.20 mm depth of cut yielded 1.8  $\mu\text{m}$  averaged across inclinations. Most parts ranged between 1–3.5  $\mu\text{m}$ . Verification tests showed EBM predicted AM Ra within  $\pm 2 \mu\text{m}$  (MAPE 6.62%) and hybrid machining within

$\pm 1 \mu\text{m}$  (MAPE 9.17%).

A preliminary coolant-assisted machining study indicated 15–21% Ra improvement by keeping cutting temperatures below PLA's glass transition and enhancing chip evacuation. These results provide a predictive framework for achieving target surface finishes with reduced trial-and-error, lower costs, and improved surface integrity, supporting the industrial adoption of PLA-based AM and hybrid processes.

**Keywords:** Additive Manufacturing, Surface Roughness, CNC Milling, Machine Learning



## ÖZ

### **EKLEMELİ İMALAT VE TALASLI İMALAT İLE ÜRETİLEN PARCALARIN YÜZEY PURUZLULUGUNUN MAKİNE ÖĞRENMESİ İLE TAHMİN EDİLMESİ**

Usama, Muhammad

Yüksek Lisans, Makina Mühendisliği Bölümü

Tez Yöneticisi: Prof. Dr. Ulaş Yaman

Ortak Tez Yöneticisi: Doç. Dr. Elif Sürer

Ağustos 2025 , 195 sayfa

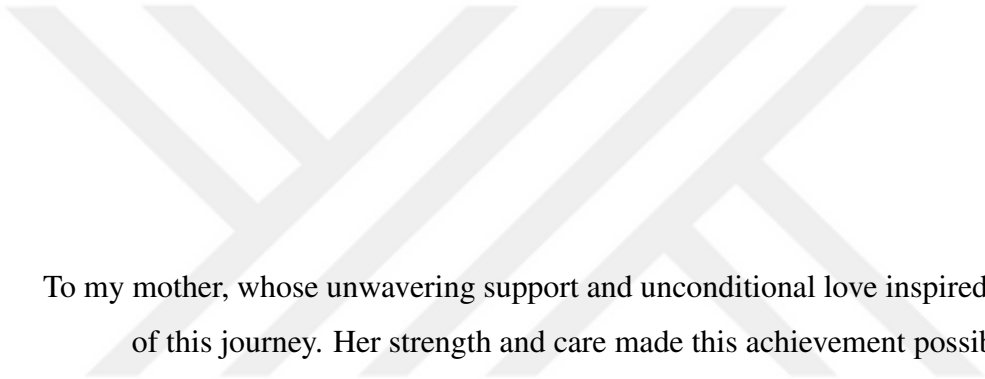
Bu çalışma, Katmanlı İmalatın (AM) Ergiyik Filament İmalatı (FFF) ve hibrit AM–CNC işleme yöntemleriyle üretilen Polilaktik Asit (PLA) parçalarının farklı eğim açılarında yüzey pürüzlülüğü (Ra) değerlerinin denetimli regresyon tabanlı makine öğrenmesi ile tahmin edilmesine yönelik önemli bir araştırma boşluğunu ele almaktadır. Önceki çalışmalar eğim açısı veya CNC son işlemini nadiren dikkate almışken, bu çalışmada Taguchi L54 DOE yöntemiyle tasarlanan 54 parça üzerinden 10°–80° aralığı incelenmiştir. On farklı Makine Öğrenmesi (ML) algoritması değerlendirilmiş, Açıklanabilir Artırma Makinesi (EBM) en yüksek tahmin doğruluğunu sağlamıştır ( $R^2 = 0,983$  AM,  $R^2 = 0,616$  hibrit).

AM için en etkili faktörler Eğim Açısı, Katman Yüksekliği, Nozul Çapı ve Baskı Sıcaklığı olmuştur. En iyi yüzey kalitesi 0,10 mm katman yüksekliği, 0,25 mm nozul ve 210 °C ekstrüzyon sıcaklığı ile elde edilmiştir. Hibrit işlemede ise AM parametreleri, talaş derinliği ve doluluk oranı ile birlikte Ra üzerinde etkili olmuş; Ra değerleri

%85–91 oranında azalmış ve 0,20 mm talaş derinliği tüm açılar için ortalama 1,8 µm sonuç vermiştir. Parçaların çoğu 1–3,5 µm aralığında yer almıştır. Doğrulama testleri, EBM'nin AM Ra'yı  $\pm 2$  µm doğrulukla (MAPE %6,62) ve hibrit işlemede  $\pm 1$  µm doğrulukla (MAPE %9,17) tahmin edebildiğini göstermiştir.

Ön deneme kapsamında yapılan soğutma sıvısı destekli işleme, kesme sıcaklıklarını PLA'nın camsı geçiş sıcaklığının altında tutarak ve talaş tahliyesini iyileştirerek Ra'da %15–21 iyileşme sağlamıştır. Bu sonuçlar, daha az deneme-yanılma ile hedef yüzey kalitesine ulaşmayı, maliyetleri azaltmayı ve yüzey bütünlüğünü geliştirmeyi sağlayan öngörülebilir bir çerçeve sunmakta; PLA tabanlı AM ve hibrit imalat süreçlerinin endüstriyel olarak benimsenmesini desteklemektedir.

Anahtar Kelimeler: Katmanlı İmalat, Yüzey Pürüzlülüğü, CNC Frezeleme, Makine Öğrenmesi



To my mother, whose unwavering support and unconditional love inspired every step of this journey. Her strength and care made this achievement possible.

## ACKNOWLEDGMENTS

I would like to express my sincerest gratitude and appreciation to my supervisor Prof. Dr. Ulaş Yaman whose continued support, counseling, and encouragement shaped my academic carrier and sparked my interest in Additive Manufacturing.

I would like to express my sincere gratitude to my co-supervisor, Assoc. Prof. Dr. Elif Sürer, for her encouragement and guidance. Her valuable insights into the machine-learning process enabled this work to be completed smoothly.

I deeply appreciate the unparalleled support and clever problem solving ideas provided by Dr. Süha Tirkeş to overcome the challenges encountered during the CNC machining stage.

The support and guidance of Orhan Aydın proved to be very critical in understanding the operation of HAAS VF-1 CNC machine effectively.

My appreciation extends to the faculty and staff of the Department of Mechanical Engineering, Middle East Technical University, for providing an excellent academic environment and the resources necessary to conduct my research.

I would also like to express my sincere gratitude to my team leader, Huseyin Ceylan, for kindly permitting me to work from home a couple of days each week, which enabled me to focus on my thesis.

I owe my heartfelt thanks to my family, especially my sister, for their unconditional love, constant encouragement, and unwavering belief in me. Their patience, sacrifices, and moral support have been my greatest source of strength throughout my studies.

Finally, I am profoundly grateful to my soon to be fiance Yeşim Güzel whose unparalleled support, patience and belief in me have been a corner stone in completing this research.

## TABLE OF CONTENTS

|                                                                                                                                   |       |
|-----------------------------------------------------------------------------------------------------------------------------------|-------|
| ABSTRACT . . . . .                                                                                                                | v     |
| ÖZ . . . . .                                                                                                                      | vii   |
| ACKNOWLEDGMENTS . . . . .                                                                                                         | x     |
| TABLE OF CONTENTS . . . . .                                                                                                       | xi    |
| LIST OF TABLES . . . . .                                                                                                          | xiv   |
| LIST OF FIGURES . . . . .                                                                                                         | xviii |
| LIST OF ABBREVIATIONS . . . . .                                                                                                   | xxiv  |
| CHAPTERS                                                                                                                          |       |
| 1 INTRODUCTION . . . . .                                                                                                          | 1     |
| 1.1 Overview . . . . .                                                                                                            | 1     |
| 1.1.1 Synopsis of the Additive Manufacturing Process using Fused<br>Filament Fabrication for Printing Parts Made of PLA . . . . . | 1     |
| 1.1.2 Motivation for Investigating Surface Roughness in AM . . . . .                                                              | 3     |
| 1.1.3 Employment of Machine Learning in Predicting Surface Rough-<br>ness in AM . . . . .                                         | 5     |
| 1.2 Problem Statement . . . . .                                                                                                   | 9     |
| 1.3 Objectives . . . . .                                                                                                          | 11    |
| 1.4 Scope of the Study . . . . .                                                                                                  | 12    |
| 1.5 Limitations of the Study . . . . .                                                                                            | 12    |

|       |                                                                                                          |    |
|-------|----------------------------------------------------------------------------------------------------------|----|
| 2     | LITERATURE REVIEW . . . . .                                                                              | 15 |
| 2.1   | Prediction of Surface Roughness of AM Parts made of PLA With FFF using ML Algorithms . . . . .           | 15 |
| 2.2   | Prediction of Surface Roughness of hybrid AM+CNC Parts using ML Algorithms . . . . .                     | 18 |
| 2.3   | Research Gap . . . . .                                                                                   | 21 |
| 3     | METHODOLOGY FOR SURFACE ROUGHNESS PREDICTION . . . . .                                                   | 23 |
| 3.1   | Development of a 3D CAD Design . . . . .                                                                 | 24 |
| 3.1.1 | Design Iterations . . . . .                                                                              | 24 |
| 3.2   | Determination of the Design of Experiments . . . . .                                                     | 30 |
| 3.2.1 | Selection of the input parameters . . . . .                                                              | 30 |
| 3.2.2 | Design of Experiments Using Taguchi L54 Methodology . . . . .                                            | 36 |
| 3.3   | Additive Manufacturing of the Selected Design Using Taguchi L-54 DOE . . . . .                           | 42 |
| 3.3.1 | FFF - Process and Components . . . . .                                                                   | 43 |
| 3.3.2 | Hardware Specifications, Software Environment and Printing Procedure . . . . .                           | 46 |
| 3.4   | Surface Roughness Measurements . . . . .                                                                 | 55 |
| 3.4.1 | Surface Roughness - Parameters and Characterization . . . . .                                            | 55 |
| 3.4.2 | Surface Roughness Measurements on AM Parts Using Custom Printed Fixtures . . . . .                       | 57 |
| 3.5   | Hybrid-Machining Process . . . . .                                                                       | 63 |
| 3.5.1 | Role of CNC Milling in the Hybrid (Additive-Subtractive) Process and its Cutting Parameters . . . . .    | 64 |
| 3.5.2 | CNC Milling Process on AM Parts, CAM Software, Depth of Cut and Surface Roughness Measurements . . . . . | 66 |
| 3.6   | Machine Learning Algorithms, Types and Implementation . . . . .                                          | 83 |



|       |                                                                                                                                                 |     |
|-------|-------------------------------------------------------------------------------------------------------------------------------------------------|-----|
| 3.6.1 | Machine Learning Basics, Types in Literature, and Evaluation Metrics in terms of Surface Roughness Prediction on FFF and Hybrid Parts . . . . . | 83  |
| 3.6.2 | Machine Learning Implementation . . . . .                                                                                                       | 89  |
| 4     | RESULTS AND DISCUSSION . . . . .                                                                                                                | 95  |
| 4.1   | Surface Roughness Evaluation for AM Parts . . . . .                                                                                             | 96  |
| 4.2   | Surface Roughness Evaluation for Hybrid (AM+CNC) Parts . . . . .                                                                                | 111 |
| 4.3   | Machine Learning Results and Analysis . . . . .                                                                                                 | 128 |
| 4.4   | Verification and Validation . . . . .                                                                                                           | 162 |
| 4.5   | Coolant Assisted Wet Machining . . . . .                                                                                                        | 168 |
| 5     | CONCLUSION AND FUTURE RESEARCH ROADMAP . . . . .                                                                                                | 171 |
| 5.1   | Summary of the Findings . . . . .                                                                                                               | 171 |
| 5.2   | Future Research Roadmap . . . . .                                                                                                               | 175 |
|       | APPENDICES . . . . .                                                                                                                            | 189 |
| A     | Additional Validation Equation, stylus uncertainty, G-codes (AM and CNC), Excel File DOE, and Surface Roughness Data . . . . .                  | 189 |
| B     | Machine Learning Codes . . . . .                                                                                                                | 195 |

## LIST OF TABLES

### TABLES

|           |                                                                                                                                                                                                                                                                                                                                                                         |    |
|-----------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----|
| Table 3.1 | Summary of Studies Based on Part Geometry and Measured Angles                                                                                                                                                                                                                                                                                                           | 26 |
| Table 3.2 | Comparison of Factors between Initial and Final Designs . . . . .                                                                                                                                                                                                                                                                                                       | 28 |
| Table 3.3 | Summary of input parameters used in PLA-based FFF studies (ND = Nozzle Diameter, LH = Layer Height, WT = Wall Thickness, TT = Top Thickness, ID = Infill Density, IP = Infill Pattern, PT = Printing Temp, BPT = Build Plate Temp, PS = Print Speed, FS = Fan Speed, FR = Flow Rate, OWS = Outer Wall Speed) . . . . .                                                  | 31 |
| Table 3.4 | Physical and Mechanical Properties of Ultimaker PLA Black (RAL 9005) . . . . .                                                                                                                                                                                                                                                                                          | 33 |
| Table 3.5 | Additive Input Parameters and Their Levels . . . . .                                                                                                                                                                                                                                                                                                                    | 34 |
| Table 3.6 | Summary of DOE Methodologies Used in Related Studies . . . . .                                                                                                                                                                                                                                                                                                          | 39 |
| Table 3.7 | Taguchi L54 Design of Experiments (DOE): Experiments 1–27 with 0.4 mm Nozzle Diameter. Abbreviations — ND: Nozzle Diameter; LH: Layer Height; WT: Wall Thickness; TT: Top Thickness; ID: Infill Density; IP: Infill Pattern (C: Cubic, G: Grid, T: Triangle); PT: Printing Extrusion Temperature; BPT: Build Plate Temperature; PS: Print Speed; FS: Fan Speed. . . . . | 41 |

|                                                                                                                                                                                                                                                                                                                                                             |     |
|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----|
| Table 3.8 Taguchi L54 DOE: Experiments 28-54 with 0.25 mm Nozzle Diameter. Abbreviations — ND: Nozzle Diameter; LH: Layer Height; WT: Wall Thickness; TT: Top Thickness; ID: Infill Density; IP: Infill Pattern (C: Cubic, G: Grid, T: Triangle); PT: Printing Extrusion Temperature; BPT: Build Plate Temperature; PS: Print Speed; FS: Fan Speed. . . . . | 42  |
| Table 3.9 Technical specifications of the Ultimaker S5 printer [3] . . . . .                                                                                                                                                                                                                                                                                | 47  |
| Table 3.10 Comparative Analysis of Literature Studies Using Various Roughness Parameters, Readings and Apparatuses . . . . .                                                                                                                                                                                                                                | 58  |
| Table 3.11 Surface Roughness Measurements at Three Regions for Part 1 on All Angles . . . . .                                                                                                                                                                                                                                                               | 62  |
| Table 3.12 Summary of CNC Machining Parameters Used in Literature . . . .                                                                                                                                                                                                                                                                                   | 66  |
| Table 3.13 Machining Parameters Used in the Milling Process . . . . .                                                                                                                                                                                                                                                                                       | 68  |
| Table 3.14 Technical Specifications of HAAS VF-1 CNC Milling Machine [69]                                                                                                                                                                                                                                                                                   | 69  |
| Table 3.15 Technical Specifications of End Mill [70] . . . . .                                                                                                                                                                                                                                                                                              | 71  |
| Table 3.16 Classification of Studies Based on Machine Learning Algorithms and Learning Type . . . . .                                                                                                                                                                                                                                                       | 88  |
| Table 4.1 Surface Roughness (Ra) Values for AM Parts at Various Inclination Angles . . . . .                                                                                                                                                                                                                                                                | 96  |
| Table 4.2 Surface Roughness (Ra) Values for AM Parts at Various Inclination Angles . . . . .                                                                                                                                                                                                                                                                | 97  |
| Table 4.3 Surface Roughness Ra for Layer Height of 0.1 mm . . . . .                                                                                                                                                                                                                                                                                         | 101 |
| Table 4.4 Surface Roughness Ra for 0.15 mm Layer Height . . . . .                                                                                                                                                                                                                                                                                           | 101 |
| Table 4.5 Surface Roughness Ra for 0.20 mm Layer Height . . . . .                                                                                                                                                                                                                                                                                           | 102 |
| Table 4.6 0.1 mm Layer Height Best and Worst Parts . . . . .                                                                                                                                                                                                                                                                                                | 104 |
| Table 4.7 0.15 mm Layer Height Best and Worst Parts . . . . .                                                                                                                                                                                                                                                                                               | 106 |

|                                                                                                                        |     |
|------------------------------------------------------------------------------------------------------------------------|-----|
| Table 4.8 0.2 mm Layer Height Best and Worst Parts . . . . .                                                           | 109 |
| Table 4.9 Surface Roughness Measurements for 10°–40° inclinations at Different Depths of Cuts (Parts 1-27) . . . . .   | 112 |
| Table 4.10 Surface Roughness Measurements for 50°–80° inclinations at Different Depths of Cuts (Parts 1-27) . . . . .  | 113 |
| Table 4.11 Surface Roughness Measurements for 10°–40° inclinations at Different Depths of Cuts (Parts 28-54) . . . . . | 114 |
| Table 4.12 Surface Roughness Measurements for 50°–80° inclinations at Different Depths of Cuts (Parts 28-54) . . . . . | 115 |
| Table 4.13 Surface roughness improvement after CNC machining for Part No. 36 at different depths of cut. . . . .       | 117 |
| Table 4.14 Surface roughness improvement after CNC machining for Part No. 29 at different depths of cut. . . . .       | 118 |
| Table 4.15 Surface roughness improvement after CNC machining for Part No. 24 at different depths of cut. . . . .       | 119 |
| Table 4.16 Surface roughness improvement after CNC machining for Part No. 53 at different depths of cut. . . . .       | 120 |
| Table 4.17 Surface roughness improvement after CNC machining for Part No. 12 at different depths of cut. . . . .       | 121 |
| Table 4.18 Surface roughness improvement after CNC machining for Part No. 40 at different depths of cut. . . . .       | 121 |
| Table 4.19 Average Ra for different inclination angles and depths of cut. . . . .                                      | 128 |
| Table 4.20 AM-Training Evaluation Metrics . . . . .                                                                    | 129 |
| Table 4.21 AM-Testing Evaluation Metrics . . . . .                                                                     | 130 |
| Table 4.22 10-fold Cross-Validation (mean $\pm$ SD) for AM — Part I . . . . .                                          | 131 |

|                                                                                                                                              |     |
|----------------------------------------------------------------------------------------------------------------------------------------------|-----|
| Table 4.23 10-fold Cross-Validation (mean $\pm$ SD) for AM — Part II . . . . .                                                               | 132 |
| Table 4.24 Hybrid-Training Evaluation Metrics . . . . .                                                                                      | 140 |
| Table 4.25 Hybrid-Testing Evaluation Metrics . . . . .                                                                                       | 140 |
| Table 4.26 10-fold Cross-Validation for Hybrid (mean $\pm$ SD) — Part I . . . . .                                                            | 141 |
| Table 4.27 10-fold Cross-Validation for Hybrid (mean $\pm$ SD) — Part II . . . . .                                                           | 141 |
| Table 4.28 AM Input Parameters for Verification Parts . . . . .                                                                              | 163 |
| Table 4.29 External validation (EBM): per-sample errors on unseen AM data . .                                                                | 164 |
| Table 4.30 EBM performance comparison across evaluation settings . . . . .                                                                   | 165 |
| Table 4.31 External validation (EBM): hybrid per-sample errors by depth of cut                                                               | 166 |
| Table 4.32 External validation (EBM): hybrid per-sample errors by depth of cut<br>(cont.) . . . . .                                          | 167 |
| Table 4.33 EBM performance comparison across evaluation settings (hybrid data)                                                               | 167 |
| Table 4.34 Comparison of $R_a$ Values and Percentage Improvement for Dry and<br>Coolant-Assisted (Wet) Hybrid CNC Machining Part 4 . . . . . | 169 |
| Table 4.35 Comparison of $R_a$ Values and Percentage Improvement for Dry and<br>Coolant-Assisted (Wet) Hybrid CNC Machining Part 5 . . . . . | 170 |
| Table A.1 Surface Roughness $R_a$ for 0.10 mm Layer Height and 0.4 mm nozzle)                                                                | 190 |
| Table A.2 Input Parameters and Corresponding Values . . . . .                                                                                | 190 |
| Table A.3 Comparison of Experimental and Predicted $R_a$ values using the Hy-<br>brid Model . . . . .                                        | 191 |

## LIST OF FIGURES

### FIGURES

|             |                                                                                       |    |
|-------------|---------------------------------------------------------------------------------------|----|
| Figure 1.1  | Ultimaker S5 [3] . . . . .                                                            | 3  |
| Figure 1.2  | Types of Machine Learning [9] . . . . .                                               | 6  |
| Figure 3.1  | Initial CAD Design Isometric View . . . . .                                           | 26 |
| Figure 3.2  | Final CAD Design Isometric View . . . . .                                             | 27 |
| Figure 3.3  | Left: Initial CAD Design 10° and 80°. Right: Initial CAD Design 20° and 70° . . . . . | 27 |
| Figure 3.4  | Left: Final CAD Design 10° to 40°. Right: Final CAD Design 50° to 80° . . . . .       | 27 |
| Figure 3.5  | Initial Print Time and Material . . . . .                                             | 29 |
| Figure 3.6  | Final Print Time and Material . . . . .                                               | 29 |
| Figure 3.7  | Ultimaker Print Core AA 0.25 mm and AA 0.4 mm [42] . . . . .                          | 34 |
| Figure 3.8  | Infill Patterns: Left - Grid, Middle - Cubic, Right - Triangle . . . . .              | 36 |
| Figure 3.9  | A FFF Schematic overview [54] . . . . .                                               | 43 |
| Figure 3.10 | Ultimaker S5 Core and Extruder Assembly [3] . . . . .                                 | 44 |
| Figure 3.11 | Cooling Fan in Ultimaker S5 . . . . .                                                 | 45 |
| Figure 3.12 | Ultimaker S5 used in this research . . . . .                                          | 46 |
| Figure 3.13 | Guide Rail and Lead Screw . . . . .                                                   | 46 |

|             |                                                                                                                                                                 |    |
|-------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------|----|
| Figure 3.14 | Ultimaker Cura Environment [24] . . . . .                                                                                                                       | 47 |
| Figure 3.15 | Design Imported in Cura . . . . .                                                                                                                               | 48 |
| Figure 3.16 | Core and Material Selection . . . . .                                                                                                                           | 48 |
| Figure 3.17 | Layer Height, Wall Thickness, and Top Thickness, Infill Density,<br>Infill Pattern, Printing Temperature, Build Plate Temperature, and Print<br>Speed . . . . . | 49 |
| Figure 3.18 | Fan Speed, No Supports and Brim Adhesion . . . . .                                                                                                              | 50 |
| Figure 3.19 | Sliced Model with Brim Adhesion - Isometric View . . . . .                                                                                                      | 50 |
| Figure 3.20 | Labelled Angled Surfaces in Cura - Right View . . . . .                                                                                                         | 51 |
| Figure 3.21 | Initial Internal Structure - Top View . . . . .                                                                                                                 | 51 |
| Figure 3.22 | Intermediate Internal Structure - Top View . . . . .                                                                                                            | 51 |
| Figure 3.23 | Final Structure - Top View . . . . .                                                                                                                            | 52 |
| Figure 3.24 | Initial Print Stage . . . . .                                                                                                                                   | 52 |
| Figure 3.25 | Final Print Stage . . . . .                                                                                                                                     | 53 |
| Figure 3.26 | Isometric, Front, Left, and Right Views of AM sample . . . . .                                                                                                  | 53 |
| Figure 3.27 | 0.4 mm Nozzle Parts 1-27 . . . . .                                                                                                                              | 54 |
| Figure 3.28 | 0.25 mm Nozzle Parts 28-54 . . . . .                                                                                                                            | 54 |
| Figure 3.29 | Surface Roughness Parameters . . . . .                                                                                                                          | 57 |
| Figure 3.30 | MasrSurf PS 10 Surface Roughness Profilometer [62] . . . . .                                                                                                    | 59 |
| Figure 3.31 | Fixture and The Part Placed for 10° and 80° . . . . .                                                                                                           | 59 |
| Figure 3.32 | Fixture and The Part Placed for 20° and 70° . . . . .                                                                                                           | 60 |
| Figure 3.33 | Fixture and The Part Placed for 30° and 60° . . . . .                                                                                                           | 60 |
| Figure 3.34 | Fixture and The Part Placed for 40° and 50° . . . . .                                                                                                           | 60 |

|             |                                                                                     |    |
|-------------|-------------------------------------------------------------------------------------|----|
| Figure 3.35 | Complete Setup for Roughness Measurement . . . . .                                  | 61 |
| Figure 3.36 | Surface Roughness Measurement Regions- Right, Middle, and<br>Left . . . . .         | 62 |
| Figure 3.37 | Right, Middle, and Left Readings for 10° Surface of Part 1 . . . .                  | 63 |
| Figure 3.38 | HAAS VF-1 . . . . .                                                                 | 69 |
| Figure 3.39 | 3 Flutes End Mill . . . . .                                                         | 70 |
| Figure 3.40 | Autodesk Fusion CAM . . . . .                                                       | 72 |
| Figure 3.41 | Autodesk Fusion Machine Setup . . . . .                                             | 72 |
| Figure 3.42 | Left: 50°-80° upwards, Right: 10°-40° upwards . . . . .                             | 73 |
| Figure 3.43 | Virtual HAAS VF-1 and Part in Fusion Environment . . . . .                          | 74 |
| Figure 3.44 | Tool, Spindle Speed and Feed Rate Input . . . . .                                   | 74 |
| Figure 3.45 | Stepover and Direction of Milling . . . . .                                         | 75 |
| Figure 3.46 | Tool Paths and Enlarged View . . . . .                                              | 76 |
| Figure 3.47 | CNC Simulation . . . . .                                                            | 76 |
| Figure 3.48 | Flat End Mill Attached to the Spindle . . . . .                                     | 77 |
| Figure 3.49 | Part Secured on the Fixture . . . . .                                               | 77 |
| Figure 3.50 | Initial Phase of Tool Engagement with the Workpiece . . . . .                       | 78 |
| Figure 3.51 | Control Panel Highlighting Spindle Speed, Feed Rate, and Op-<br>tion Stop . . . . . | 79 |
| Figure 3.52 | 50° Surface Showing 0.2, 0.3 and 0.4 mm Depth of Cuts . . . . .                     | 79 |
| Figure 3.53 | CNC Milling Applied as a Post Process on the FFF Part . . . . .                     | 80 |
| Figure 3.54 | Hybrid - CNC Milled Post Processed Parts Dry Conditions . . . .                     | 80 |
| Figure 3.55 | Wet Machining Conditions with Fluid Coolant . . . . .                               | 81 |



|             |                                                                                                       |     |
|-------------|-------------------------------------------------------------------------------------------------------|-----|
| Figure 3.56 | Parts 4 and 5 after Wet CNC Milling Conditions . . . . .                                              | 82  |
| Figure 3.57 | ML Implementation Pipeline . . . . .                                                                  | 91  |
| Figure 4.1  | Average Trend of Ra vs Inclination Angles . . . . .                                                   | 98  |
| Figure 4.2  | Stack and Step Effect on 10 and 80 Degrees . . . . .                                                  | 99  |
| Figure 4.3  | Stack and Step Effect on 10 and 80 Roughness profiles . . . . .                                       | 99  |
| Figure 4.4  | General Trend of Ra vs Inclination Angles based on Layer Heights                                      | 102 |
| Figure 4.5  | 0.1 mm Layer height Worst and Best Parts . . . . .                                                    | 105 |
| Figure 4.6  | 0.15 mm Layer height Worst and Best Parts . . . . .                                                   | 107 |
| Figure 4.7  | 0.15 mm Layer height Worst and Best Parts Surface Roughness<br>Profiles . . . . .                     | 107 |
| Figure 4.8  | 0.2 mm Layer height Worst and Best Parts . . . . .                                                    | 110 |
| Figure 4.9  | 0.2 mm Layer height Worst and Best Parts Surface Roughness<br>Profiles . . . . .                      | 110 |
| Figure 4.10 | Pre and Post Machining Part 54 - Surface Defects . . . . .                                            | 116 |
| Figure 4.11 | Surface Roughness Profiles of Parts 36 and 40 at 0.2 mm depth<br>of cut and 30° inclination . . . . . | 123 |
| Figure 4.12 | Surface Roughness Profiles of Parts 36 and 40 at 0.2 mm depth<br>of cut and 80° inclination . . . . . | 124 |
| Figure 4.13 | Part 36 and Part 40 after CNC Machining . . . . .                                                     | 125 |
| Figure 4.14 | Depth of Cut and Wall thickness . . . . .                                                             | 127 |
| Figure 4.15 | Polynomial Regression Predicted vs Actual Plot . . . . .                                              | 133 |
| Figure 4.16 | Decision Tree Predicted vs Actual Plot . . . . .                                                      | 133 |
| Figure 4.17 | Random Forest Regressor Predicted vs Actual Plot . . . . .                                            | 134 |

|             |                                                                                 |     |
|-------------|---------------------------------------------------------------------------------|-----|
| Figure 4.18 | Gradient Boosting Regressor Predicted vs Actual Plot . . . . .                  | 134 |
| Figure 4.19 | Extreme Gradient Boosting Regressor Predicted vs Actual Plot .                  | 135 |
| Figure 4.20 | Category Boosting Regressor Predicted vs Actual Plot . . . . .                  | 135 |
| Figure 4.21 | Adaptive Boosting Regressor Predicted vs Actual Plot . . . . .                  | 136 |
| Figure 4.22 | Extra Tree Regressor Predicted vs Actual Plot . . . . .                         | 136 |
| Figure 4.23 | Explainable Boosting Machine Predicted vs Actual Plot . . . . .                 | 137 |
| Figure 4.24 | Support Vector Regression Predicted vs Actual Plot . . . . .                    | 137 |
| Figure 4.25 | EBM Predicted vs Actual plot (AM) with residuals . . . . .                      | 139 |
| Figure 4.26 | Hybrid - Polynomial Regression (4 Degree) Predicted vs Actual<br>Plot . . . . . | 143 |
| Figure 4.27 | Hybrid - Decision Tree Predicted vs Actual Plot . . . . .                       | 143 |
| Figure 4.28 | Hybrid - Random Forest Regression Predicted vs Actual Plot . .                  | 144 |
| Figure 4.29 | Hybrid - Gradient Boosting Regression Predicted vs Actual Plot                  | 144 |
| Figure 4.30 | Hybrid - Extreme Gradient Boosting Predicted vs Actual Plot . .                 | 145 |
| Figure 4.31 | Hybrid - Category Boosting Predicted vs Actual Plot . . . . .                   | 145 |
| Figure 4.32 | Hybrid - Adaptive Boosting Predicted vs Actual Plot . . . . .                   | 146 |
| Figure 4.33 | Hybrid - Extra Tree Regressor Predicted vs Actual Plot . . . . .                | 146 |
| Figure 4.34 | Hybrid - Explainable Boosting Predicted vs Actual Plot . . . . .                | 147 |
| Figure 4.35 | Hybrid - Support Vector Regression Predicted vs Actual Plot . .                 | 147 |
| Figure 4.36 | Hybrid - Predicted vs Actual Plot EBM with Residuals . . . . .                  | 149 |
| Figure 4.37 | AM - EBM Top Ten Feature Importances . . . . .                                  | 152 |
| Figure 4.38 | AM - Local Feature Importance Plot Displaying Effect of Angle                   | 153 |

|             |                                                                                               |     |
|-------------|-----------------------------------------------------------------------------------------------|-----|
| Figure 4.39 | AM - Local Feature Importance Plot Displaying Effect of Layer Height . . . . .                | 154 |
| Figure 4.40 | AM - Local Feature Importance Plot Displaying Interaction of Angle and Layer Height . . . . . | 155 |
| Figure 4.41 | AM - SHAP Plot Taken from GBR ML . . . . .                                                    | 156 |
| Figure 4.42 | Hybrid-Top Ten Feature Importances . . . . .                                                  | 158 |
| Figure 4.43 | Hybrid-Local Feature Importance Plot for the Effect of the Depth of Cut . . . . .             | 159 |
| Figure 4.44 | Hybrid - SHAP Plot Taken from GBR ML . . . . .                                                | 160 |
| Figure 4.45 | AM - Verification Parts . . . . .                                                             | 163 |

## LIST OF ABBREVIATIONS

### ABBREVIATIONS

|        |                                               |
|--------|-----------------------------------------------|
| 2D     | 2 Dimensional                                 |
| 3D     | 3 Dimensional                                 |
| ABR    | Adaptive Boosting Regression                  |
| ABS    | Acrylonitrile Butadiene Styrene               |
| AM     | Additive Manufacturing                        |
| ANN    | Artificial Neural Network                     |
| BBD    | Box Behenken Design                           |
| CAD    | Computer Aided Design                         |
| CART   | Classification and Regression Trees           |
| CCD    | Central Composite Design                      |
| CFNN   | Cascade Forward Neural Network                |
| CNC    | Computer Numerically Controlled               |
| DED    | Direct Energy Deposition                      |
| DOE    | Design of Experiments                         |
| DT     | Decision Tree                                 |
| EBM    | Explainable Boosting Machine                  |
| ERTR   | Extremely Randomized Tree Regression          |
| FFNN   | Feed Forward Neural Network                   |
| FFF    | Fused Filament Fabrication                    |
| GA     | Genetic Algorithm                             |
| GBR    | Gradient Boosting Regressor                   |
| GRPROP | Globally Convergent Resilient Backpropagation |
| KNN    | K-Nearest Neighbour                           |

|                |                                                    |
|----------------|----------------------------------------------------|
| LR             | Linear Regression                                  |
| MAE            | Mean Absolute Error                                |
| MAPE           | Mean Absolute Percentage Error                     |
| ML             | Machine Learning                                   |
| MLP            | Multi-Layer Perceptron                             |
| MRA            | Multiple Regression Analysis                       |
| MSE            | Mean Squared Error                                 |
| PA             | Polyamide                                          |
| PC             | Polycarbonate                                      |
| PCA            | Principal Component Analysis                       |
| PE             | Polyethylene                                       |
| PEEK           | Polyether Ether Ketones                            |
| PLA            | Polylactic Acid                                    |
| PP             | Polypropylene                                      |
| PPSF           | Polyphenylsulfonee                                 |
| PSO            | Particle Swarm Optimization                        |
| R <sup>2</sup> | Coefficient of Determination                       |
| RE             | Relative Error                                     |
| RF             | Random Forest                                      |
| RMSE           | Root Mean Squared Error                            |
| RS             | Response Surface Methodology                       |
| RVFL           | Random Vector Functional Link                      |
| RPROP+         | Resilient Backpropagation with Weight Backtracking |
| SOS            | Symbiotic Organism Search                          |
| STL            | Standard Tessellation Language                     |
| SVM            | Support Vector Machines                            |
| SVR            | Support Vector Regression                          |
| XGBoost        | Xtreme Gradient Boosting                           |



## **CHAPTER 1**

### **INTRODUCTION**

The primary objective of this study is to conduct a thorough investigation into the influence of additive manufacturing (AM) input parameters affecting the surface roughness of PLA based 3D printed parts across various build angles. In addition to the additive process, the effect of a key subtractive machining parameter specifically, the depth of cut during CNC milling has also been examined. Surface roughness measurements were obtained from both AM and CNC post-processing steps. The machine learning algorithms were then trained with these values to forecast the results of surface roughness in additive and hybrid manufacturing.

#### **1.1 Overview**

##### **1.1.1 Synopsis of the Additive Manufacturing Process using Fused Filament Fabrication for Printing Parts Made of PLA**

AM technology has attracted considerable attention in recent years, with the potential to tackle the complexities of geometries and expedite product development. Of all the advantages of AM, one is the cost-effectiveness that is realized through minimized material wastage and the absence of the need for tools. These factors render AM an extremely competitive option compared to traditional manufacturing techniques. AM is also helpful in simplifying the assembly procedure and saving on transportation costs by the production of integrated, weight-optimized components. AM can handle an extensive variety of materials, including polymers, metals, ceramics, composites, biomaterials, sand, concrete, and elastomers, as the case may be with respect to the AM technique in use.

These fabrication processes range greatly, from material extrusion (mainly for thermoplastics) to vat photopolymerization (liquid photopolymers and resins), to powder bed fusion, binder jetting, sheet lamination, and directed energy deposition (DED) for metals and ceramics. More applications of biomanufacturing have also been developed, allowing for the printing of living materials like cells, hydrogels, and bioinks.

Fused Filament Fabrication (FFF) has been a well-known and widely employed material extrusion process of AM. The process entails the extrusion of a continuous filament composed of thermoplastic via a heated nozzle, which is deposited layer by layer on the build platform, in the desired shape, where it harden and solidifies. The standard FFF process starts by developing a 3D design within a computer-aided design (CAD) program. The design is then translated to an Stereo Tessellation Language (STL) file, where the surface of the model is approximated by a series of triangular facets. The STL file is then transferred to a Computer Aided Manufacturing (CAM) software, where the layer thickness, infill percentage, and printing speed, among other parameters, are defined, depending on the dimensions of the to-be-produced part.

A G-code file is generated by the slicing software, which contains the set of instructions the 3D printer follows to fabricate the part [1]. During the printing process, the filament is unraveled from a spool and fed into a heated nozzle, where it is melted to a semi-fluid form. The molten substance is laid onto the build surface, where it cools and solidifies, fusing with the layers that were previously added. The build platform is incrementally brought down after each layer is deposited, repeating the process until the part is fully formed [2].

The FFF machine utilized in this study is illustrated in Figure 1.1. It belongs to the company called Ultimaker, and the model version is S5. It can print with approximately 280 plus materials and has an option of easy swappable cores, which makes it the preferred printer to be used in this study [3]. The specifications of this printer is thoroughly discussed in Section 3.3.2.

Materials most often used for FFF include Polylactic Acid (PLA), Acrylonitrile butadiene styrene (ABS), polycarbonate (PC), polyphenylsulfone (PPSF), polypropylene (PP), polyethylene (PE), polyether ether ketones (PEEK), nylon (PA), among many others [2]. PLA is perhaps the most dominant material for AM, particularly FFF, ow-



ing to the countless advantages it has over other thermoplastics. PLA is favored for being easy to use and printable, coupled with being biodegradable and biocompatible, thus being the most suitable for medical applications as well as for environmentally friendly applications. Extracted from renewable sources such as corn starch as well as sugarcane, it also has increased stiffness, along with strength, over the case of materials like ABS, further making it the best for structural, functional components [4]. Due to these traits, this paper focuses on the application of PLA as the primary material for the AM process, highlighting its specific environmental benefits.

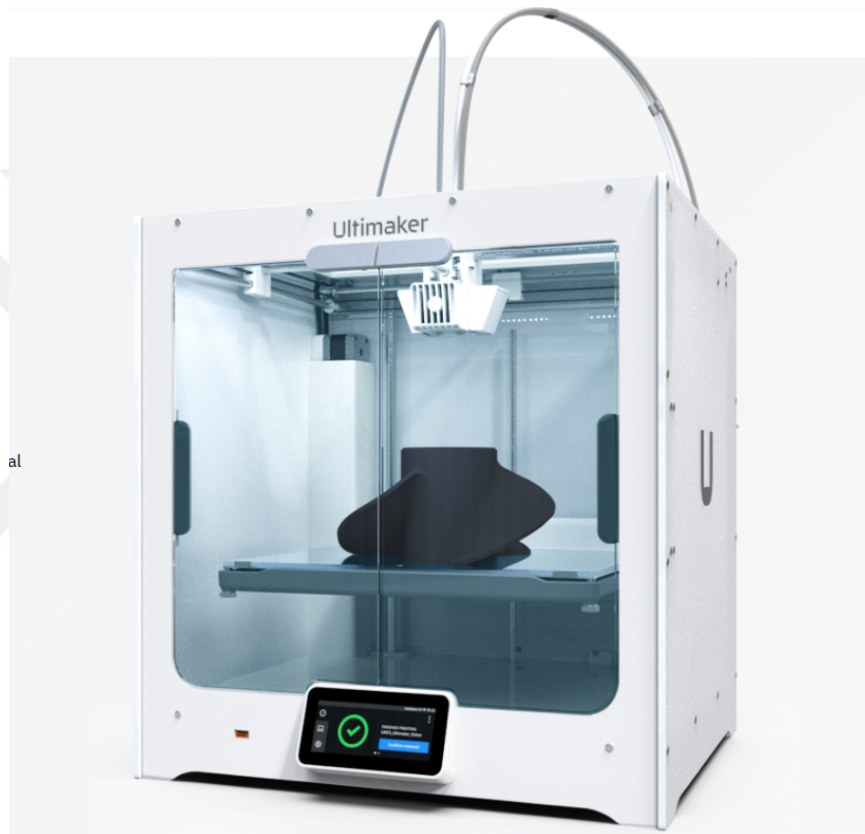


Figure 1.1: Ultimaker S5 [3]

### 1.1.2 Motivation for Investigating Surface Roughness in AM

Although AM has major benefits for shortening lead times and reducing the number of assembly steps, a successful product development process requires the surface quality of the produced parts to be tightly controlled. Surface roughness is an essential parameter influencing not merely the look-and-feel appearance of the component

but also its functionality to interact and interface efficiently with other parts within an assembly. Both the appearance as well as functional performance of the component largely depends on its level of surface finish. Where high precision fits, together with close tolerances, are demanded specifically within the aerospace and mechanical sectors, low-quality surfaces can result in producers, engineers, and designers considering the use of other manufacturing techniques, often with further costs, and increased complexity [5]. This is particularly true for applications involving coupling functions, for instance, bearings, gears, and sliding contact, where small-scale deviations on the surface can be enough to degrade operations.

A characteristic instance is for biomedical medical applications, for instance, prosthetic limbs. For hip prostheses, the inner contact surfaces with the femoral head need to possess extremely high finishes to guarantee functionality, minimum wear, together with the prevention of biological complications [6]. Therefore, rigorous control of surface roughness is essential in both industrial and medical domains.

Surface roughness is defined as the presence of microscopic deviations or irregularities on a part's surface, affecting significantly its functional performance. Higher levels of surface roughness can translate to increased wear, together with increased friction, eventually leading to the degradation of the efficiency, as well as the life of the component. High roughness, additionally, can result in localized heat generation, further reducing the structural integrity of the part with time. More than this, the presence of roughness on the surfaces presents stress concentrations, hence resulting in the initiation of crack, eventually leading to mechanical stress-induced early failure. Hence, the roughness of the surfaces is a significant factor affecting a component's functionality, reliability, together with durability. Improved mechanical functionality, as well as better contaminant-resistant capabilities, arise with an enhanced level of the surface roughness by reducing dirt, together with the build-up of debris. Smoother surfaces, again, are easy to clean, together with being less likely to suffer wear-related degradation. For the case of AM, the process parameters need to be optimized to ensure lowered roughness values on the surfaces to guarantee the correct dimensions, mechanical integrity, as well as long-term functionality of the parts produced [7].

One of the major challenges associated with FFF is the staircase effect, a phenomenon

that significantly contributes to the elevated surface roughness commonly observed in AM parts. This effect arises due to the layer-by-layer nature of FFF, where the slicing of the CAD model introduces discretization that alters the fidelity of the original geometry. As a result, the printed part may deviate from its intended design, leading to surface artifacts and increased roughness [8].

The slicing process, while essential for generating printer instructions, inadvertently contributes to surface degradation by approximating curved or inclined surfaces with stacked layers, particularly at shallow angles. In light of this, considerable research has focused on optimizing process parameters such as layer height, build orientation, and extrusion speed to minimize the impact of the staircase effect and improve surface finish.

Despite the availability of studies on surface roughness optimization in additive manufacturing, a noticeable underexplored area in the literature regarding surface roughness at various angles and hybrid manufacturing strategies has been observed. Few studies have explored the advantage of combining additive and subtractive methods to enhance surface quality at a range of angles. Motivated by this gap, the present study investigates a hybrid manufacturing approach, wherein AM parts produced at various build angles undergo a secondary Computer Numerically Controlled (CNC) milling operation. This strategy aims to assess the extent to which post-processing can mitigate surface roughness and restore geometric accuracy, thereby offering a more reliable solution for functional and precision-critical components.

### **1.1.3 Employment of Machine Learning in Predicting Surface Roughness in AM**

Machine Learning (ML) has emerged as a prominent and rapidly evolving area of research, particularly in the domain of predictive analytics. ML involves developing computational methods and algorithms that learn patterns from data and iteratively improve their performance without manual intervention. ML techniques are broadly divided into two main branches: supervised learning and unsupervised learning.

Supervised learning involves training a model from labeled sets of data with an input

(feature) having a corresponding output (target value). The key idea is to learn a mapping function from input to output so that it can be used to make predictions on new unseen data. Supervised learning is further classified into classification (predicting discrete labels) and regression (predicting continuous values). Common supervised learning algorithms include decision trees (DT), Naïve Bayes, Support Vector Machines (SVM), and neural networks

In contrast, unsupervised learning deals with data that does not have associated output labels. The goal in this case is to identify hidden patterns, structures, or groupings within the input data. Unsupervised learning is typically categorized into clustering (e.g., k-means, hierarchical clustering) and dimensionality reduction (e.g., PCA, t-SNE) techniques, which help reveal underlying relationships without prior labeling [9]. Figure 1.2 provides an overview of the two primary categories of machine learning, along with their respective subtypes.

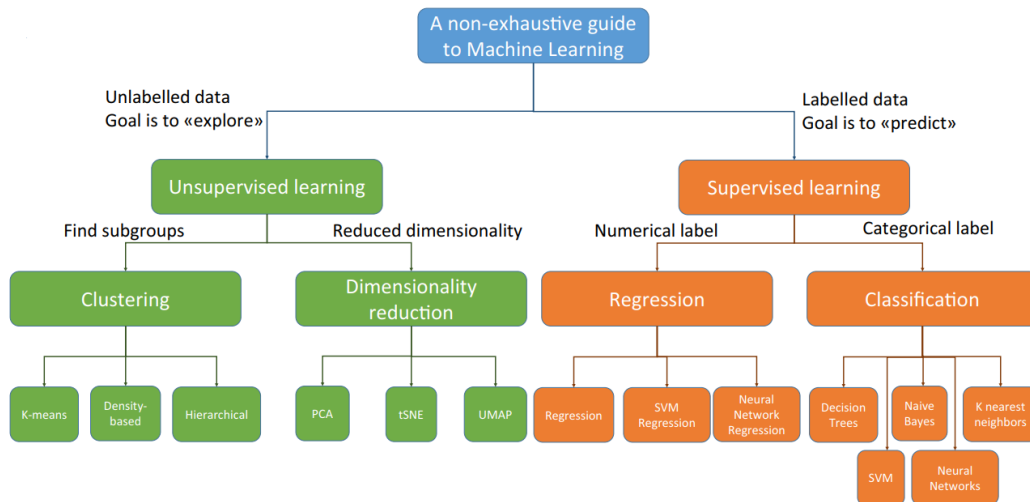


Figure 1.2: Types of Machine Learning [9]

Numerous studies have explored the application of ML techniques for predicting the surface roughness of parts produced via FFF. A variety of algorithms have been employed, ranging from artificial neural networks (ANNs) to support vector machines (SVMs) and ensemble methods.

In one such study, Boschetto et al. [5] proposed a predictive model using a feed-

forward neural network (FFNN) architecture. The network comprises three layers: an input layer, a hidden layer consisting of multiple parallel neurons, and an output layer. Each neuron in the hidden layer performs a weighted summation of the input features, processes the data through an activation function, and transmits the result to subsequent layers. Their findings demonstrated that FFNNs are capable of effectively predicting surface roughness in AM parts, thereby eliminating the need for time-consuming trial-and-error experimentation.

In another significant contribution, Li et al. [10] developed a ML framework specifically aimed at predicting surface roughness in extrusion-based AM processes. The study employed six different base learners, including Random Forest (RF), AdaBoost, Classification and Regression Trees (CART), Support Vector Regression (SVR), Ridge Regression (RR), and the Random Vector Functional Link (RVFL) network. Moreover, the researchers proposed an ensemble learning model that combined the predictive strengths of these individual learners. The ensemble model achieved superior performance, outperforming all individual models based on evaluation metrics such as Root Mean Squared Error (RMSE) and Relative Error, highlighting its robustness and accuracy in surface roughness prediction.

Barrios et al. [11] investigated the use of decision tree-based algorithms—specifically C4.5, RF, and Random Tree (RT) to predict surface roughness in additively manufactured parts. DT are widely utilized in data mining due to their interpretability and effectiveness. In a DT, each node represents a condition based on a specific attribute, while the leaf nodes indicate class outcomes based on the path of conditions satisfied. Their study concluded that the RT model outperformed the others in terms of prediction accuracy and computational efficiency.

In a related study, Cero et al. [12] employed ten base classification algorithms, including Naïve Bayes and RF, to predict surface roughness. To enhance predictive performance, ensemble methods were applied, and it was found that the bagging method combined with a Multi-Layer Perceptron (MLP) yielded the most accurate results among all tested configurations. Kandananond et al. [13] recommended the use of ANNs for surface roughness prediction, highlighting their capability to model complex, non-linear relationships between process parameters and surface quality.

Similarly, Yaseer and Cheng [14] conducted a comparative analysis using RF and MLP models to predict surface roughness. Their findings indicated that the RF algorithm provided superior accuracy compared to MLP, reinforcing its reliability in surface quality prediction tasks within the domain of AM.

Saad et al. [15] investigated the optimization of surface roughness in FFF parts by integrating ANNs with a Symbiotic Organism Search (SOS) algorithm. Their hybrid ANN-SOS model was demonstrated to be effective in minimizing surface roughness, and its application was recommended for obtaining optimal surface quality in FFF components. In a separate study, García-Martínez et al. [16] focused on predicting surface roughness in material extrusion-based AM processes using various machine learning models. The algorithms evaluated included ZeroR (a baseline model using the mean of the dataset), Linear Regression (LR), SMOReg (a support vector machine tailored for regression tasks), Decision Stump (DS) from the DT family, and RF. Their results highlighted that the RF algorithm delivered the highest prediction accuracy, establishing it as the most effective model for surface roughness prediction in extrusion-based AM. Osman et al [17] developed a hybrid approach combining a Cascade Forward Neural Network (CFNN) with a Genetic Algorithm (GA) to both predict and optimize surface roughness in FFF parts. The CFNN-GA model achieved a Mean Absolute Percentage Error (MAPE) of just 3.37%, demonstrating high reliability and accuracy. This hybrid method offers a robust solution for surface quality optimization in FFF, confirming its potential for application in precision manufacturing scenarios.

Mishra et al. [7] investigated the prediction of surface roughness in FFF parts made from PLA using nine different regression-based machine learning (ML) algorithms. These included SVR, RF, XGBoost, AdaBoost, CatBoost, DT, Extra Trees Regressor (ETR), the Explainable Boosting Machine (EBM), and the Gradient Boosting Regressor (GBR). Among these, XGBoost demonstrated superior performance with a high coefficient of determination ( $R^2 = 0.9634$ ). Its ability to efficiently handle large datasets, prevent overfitting, and manage missing values through gradient-based sampling was credited for its high predictive accuracy.

In a separate study, Huang et al. [18] proposed a hybrid predictive model for PLA

based FFF parts by integrating Particle Swarm Optimization (PSO) with the KNearest Neighbor (KNN) algorithm, referred to as APSO-KNN. Their model completed accurate predictions after only two iterations, with a training time of just 14 seconds, outperforming several existing classifiers. The study concluded that APSO-KNN is effective in addressing challenges such as data imbalance and the influence of multiple factors in surface roughness prediction. Saxena et al. [19] explored the use of machine learning techniques to predict the surface roughness of FFF parts fabricated from PLA+. The algorithms evaluated included SVM, LR, and two ensemble learning methods: XGBoost and RFR. Their findings revealed that the RFR achieved the best performance, with an  $R^2$  value of 0.9685 and a mean squared error (MSE) of 0.1255, indicating its strong suitability for accurately predicting the surface quality of FFF-manufactured parts.

## **1.2 Problem Statement**

Surface roughness is a critical quality attribute in AM parts, as it directly influences the mechanical performance, wear resistance, and functional reliability of components. Excessive surface roughness can accelerate material degradation and limit the applicability of printed parts in precision-driven industries [20]. Therefore, the ability to accurately predict and control surface roughness in AM processes is essential for optimizing part quality and ensuring process efficiency.

Numerous studies have been conducted to identify the process parameters that significantly influence surface roughness in AM. For instance, Mishra et al. [21] examined eight process parameters, including layer height, wall thickness, infill density, infill pattern, nozzle temperature, bed temperature, print speed, and fan speed. Their results indicated that layer height had the most substantial impact on surface roughness. However, their experimental setup was limited to standard tensile specimens and did not incorporate angular variation, which is essential for evaluating surface roughness across inclined geometries. Vahabli et al. [22] investigated the influence of layer thickness and build angle on surface roughness in ABS parts, using specimens with surface inclinations ranging from  $0^\circ$  to  $180^\circ$ . While insightful, their work only considered two parameters, build angle and layer thickness, limiting the generalizability

of their findings.

The current study expands on this prior work by evaluating the effects of ten different AM process parameters on surface roughness in PLA parts, printed at build angles ranging from  $10^\circ$  to  $80^\circ$  in  $10^\circ$  increments. The technology employed is FFF, and machine learning algorithms are used to model and predict the surface roughness at each inclined surface. The aim is to predict the surface roughness by providing a set of process parameters for each angle, enabling more precise and generalized surface quality control in AM parts.

Despite process optimization, inherent limitations such as the staircase effect continue to affect surface finish in FFF-printed parts. Therefore, this study also incorporates subtractive post-processing specifically CNC milling to further enhance surface quality. In this context, Djurović et al. [23] explored the use of ANNs to predict surface roughness in PLA parts produced using a hybrid (additive + subtractive) approach. Their experimental setup involved a basic cuboidal geometry with varied AM parameters (print speed and nozzle diameter) and machining parameters (depth of cut, spindle speed, and feed rate). To address the limitations in previous work, the present research adopts a comprehensive approach by combining angled geometries, a broad range of AM process parameters, and hybrid post-processing, using ML to predict and optimize surface roughness in a more robust and generalized manner. In summary, the key contribution of this study is the comprehensive investigation of ten distinct input parameters in AM using the Taguchi L54 design of experiments (DOE) methodology applied for the first time in this context. By significantly expanding the number of experimental runs, the study provides a robust analysis of surface roughness behavior on inclined surfaces ranging from  $10^\circ$  to  $80^\circ$ , with particular emphasis on identifying peak roughness values across the specified angles. Furthermore, the integration of AM with CNC milling has been systematically examined as a post-processing strategy to mitigate surface roughness, under both dry and coolant-assisted cutting conditions. Finally, a wide range of machine learning algorithms have been employed and compared for both manufacturing strategies, and the most effective model has been identified based on multiple evaluation metrics.



### 1.3 Objectives

The primary objective of this study is to predict the surface roughness of parts produced through both AM and subsequent CNC machining, with a specific focus on the influence of varying surface angles. To achieve this, machine learning algorithms are utilized to optimize key process parameters and enhance predictive accuracy. The AM technology employed here is FFF, a widely used material extrusion method. The hybrid approach integrates CNC milling as a secondary subtractive process to refine the surface finish of the additively manufactured parts by exploring the effect of the depth of cut.

To systematically fulfill the research objective, the study is structured into the following phases:

- Designing a part with surface varying from 10 to 80° angles
- Determination of the AM process parameters involving nozzle diameter, layer height, wall thickness, top thickness, infill density, infill pattern, printing extrusion temperature, build plate temperature, print speed, and fan speed.
- Design of Experiments (DOE) using Taguchi L54 array design with total 54 experiments while varying the process parameters at three different levels, excluding nozzle diameter at two levels
- Additively Manufacturing the part using Black PLA and FFF Technology according to the DOE
- Measuring the surface roughness using a profilometer on all the angled surfaces for all 54 trials
- CNC milling the angled surfaces by varying the depth of cut. For each surface, three different depth of cuts are applied
- Measurement of the surface roughness again for the hybrid process
- Applying 10 ML algorithms for both AM and Hybrid processes and selection of the best ML based on evaluation metrics

- Using that ML model and determining the effect of the parameters on the surface roughness
- Prediction of the surface roughness by providing a set of input parameters and angles for the testing and validation stage

#### **1.4 Scope of the Study**

The methodology developed in this study is applicable to PLA parts fabricated using FFF-AM, specifically those featuring surface inclinations ranging from  $10^{\circ}$  to  $80^{\circ}$ . The proposed framework can be utilized to optimize both the AM and hybrid post-processing workflows, enabling the achievement of improved surface finish. As a result, this approach contributes to the enhancement of functional performance, reliability, and overall quality of the manufactured components.

#### **1.5 Limitations of the Study**

The scope of this research is specifically limited to the use of PLA as the material in the FFF process. PLA was selected due to its biodegradable, environmentally sustainable, and widely adopted nature in material extrusion-based additive manufacturing. Consequently, the parameter levels defined in this study are material-specific and cannot be directly generalized to other thermoplastics or composite materials without further experimentation.

The surface roughness values obtained through experimental analysis are intended to be validated against existing literature focused specifically on PLA, ensuring consistency and comparability. Due to time constraints, the study was limited to 54 experimental runs, covering 10 input parameters each varied across three levels. A Taguchi L54 orthogonal array was selected to design the experiments efficiently. However, the experimental framework could be further expanded using a fractional factorial design to increase the robustness, statistical power, and accuracy of the machine learning predictions.

In terms of manufacturing processes, this study is constrained to the use of the Ultimaker S5 [3] 3D printer in combination with Ultimaker Cura software [24] for the slicing and toolpath generation. Although the part was carefully designed to minimize deformation, a degree of warping was still observed in the PLA components during the printing phase. As a result, the CNC machining stage, used as part of the hybrid manufacturing process, was performed with a tolerance of  $\pm 0.1$  mm in the depth of cut to accommodate dimensional inconsistencies. While the methodology developed in this study is potentially transferable to other FFF-compatible materials, the corresponding material properties and process parameters must be carefully redefined in accordance with the specific requirements of the selected material and its intended application. Likewise, the CNC machining parameters, such as spindle speed, cutting feed rate, and depth of cut should be adjusted based on the mechanical characteristics of the workpiece material. It is important to note that this approach is not directly applicable to additive manufacturing technologies beyond FFF, particularly those involving metal-based processes, as they involve entirely different parameter sets, thermal behaviors, and post-processing requirements.



## CHAPTER 2

### LITERATURE REVIEW

This chapter presents a comprehensive literature review on the prediction of surface roughness in both AM and machined parts using ML algorithms. It explores the methodologies employed in the fabrication of PLA-based components via the FFF process, along with the range of ML techniques used for surface roughness prediction. In addition, the chapter outlines the evaluation metrics commonly applied to assess the performance of these predictive models. Special attention is given to recent studies involving hybrid manufacturing approaches, where additive and subtractive processes specifically CNC machining following AM are integrated to enhance surface quality. The review aims to identify research gaps and highlight effective strategies in modeling, prediction, and optimization of surface roughness in advanced manufacturing workflows.

#### **2.1 Prediction of Surface Roughness of AM Parts made of PLA With FFF using ML Algorithms**

Numerous studies have been carried out on predicting and improving surface roughness of AM parts which are produced using the FFF technology. This sub-section solely focuses on the material PLA because of the advantages in terms of sustainability mentioned in Chapter 1.

In this context, Kandananond et al. [13] employed a machine learning-based ANN in combination with the Box–Behnken (BB) response surface methodology to predict the surface roughness of additively manufactured parts. The experimental setup involved fabricating a cylindrical workpiece with a diameter of 40 mm and a height of

10 mm. Surface roughness measurements were collected from both the top and bottom surfaces, with data acquired from five distinct locations on each surface—four positioned at 90° intervals and one at the center. The BB design was used to evaluate the effects of three key process parameters at three levels, bed temperature: 80°C, 85°C, and 90°C; print speed: 40 mm/s, 80 mm/s, and 120 mm/s; layer thickness: 0.1 mm, 0.25 mm, and 0.4 mm. This experimental design resulted in 16 runs per surface (top and bottom), generating a dataset for training and testing the ANN model. The input layer of the ANN consisted of the three process parameters, while the output layer represented the predicted surface roughness. Hidden layers were configured to capture the non-linear interactions between inputs and output. Two training algorithms were employed for MLPs: Globally Convergent Resilient Backpropagation (GRPROP) and Resilient Backpropagation with Weight Backtracking (RPROP+). The results demonstrated that the ANN model offered higher prediction accuracy compared to the BB method, with GRPROP outperforming RPROP+ in terms of consistency and prediction reliability.

Saad et al. [15] proposed a novel optimization framework that integrates ANNs with the SOS algorithm to minimize surface roughness in FFF parts. The study focused on four key input parameters: layer thickness, print speed, nozzle temperature, and outer shell thickness. Experimental design was conducted using the Central Composite Design (CCD) approach under the umbrella of Response Surface Methodology (RSM), with each parameter varied across five levels. A rectangular PLA specimen was fabricated for testing, and surface roughness was measured using a SV-C4500 Mitutoyo Formtracer. The CCD-based RSM design yielded a total of 46 experimental runs, which were then used to train and validate an ANN model. The trained ANN was subsequently optimized using the SOS algorithm, which was configured with an ecosystem size of 30, 50 iterations, and 4 organisms. The optimization process identified the optimal combination of process parameters, yielding a minimum surface roughness value of 2.011  $\mu\text{m}$ . This optimized parameter set was validated using a 4-8-8-1 ANN architecture, which confirmed the prediction by producing the same surface roughness output. Furthermore, the performance of the ANN-SOS hybrid model was benchmarked against traditional RSM, and the results demonstrated that the ANN-SOS model provided superior prediction accuracy and optimization

capability, highlighting its effectiveness over conventional statistical methods.

Mishra et al. [21] proposed a novel hybrid framework for predicting surface roughness by coupling a Genetic Algorithm (GA) with four different ML models: DT, RF, ANN, and GBR. To ensure standardization in specimen geometry, the study adhered to the ASTM E8 standard, with all dimensions scaled down by 50% to reduce print time and material usage. A total of 30 experimental trials were conducted, using a three-level factorial design for the input parameters. The slicing process was carried out using Ultimaker Cura, and the samples were fabricated on a Creality 3D printer. The study varied 8 key input parameters: layer height, wall thickness, infill density, infill pattern, bed temperature, and nozzle temperature, print speed, and fan speed. For data handling and visualization, Python libraries such as Pandas, NumPy, and Seaborn were employed. The Genetic Algorithm was used to optimize both the process parameters (e.g., layer height) and the internal hyperparameters of the ML models (e.g., tree depth, learning rate) to achieve minimal surface roughness. The models were trained using the experimental dataset, and their performance was assessed using standard metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), and  $R^2$  (coefficient of determination). Analysis of a correlation heatmap and feature importance plots revealed that layer height was the most influential factor, while parameters such as wall thickness, bed temperature, and fan speed had negligible impact on surface roughness. Among the hybrid models, the GA-DT approach outperformed all others, achieving an  $R^2$  value of 0.9378 with the lowest MSE and MAE. GA-RF followed closely with an  $R^2$  of 0.8987, while GA-GBR reached  $R^2 = 0.7627$ , albeit with higher error values. Conversely, the GA-ANN model yielded a negative  $R^2$  of -0.2966, indicating poor predictive performance. The study concluded that the GA-DT hybrid model offered the best performance for surface roughness prediction, achieving 92% accuracy during the validation phase and demonstrating clear superiority over the other models tested.

Kumar et al. [25] investigated the prediction of surface roughness and tensile strength using a standard dogbone-shaped tensile specimen. The study considered layer thickness, infill density, and infill structure as input parameters, each varied at three levels. A Taguchi L9 orthogonal array was used as the design of experiments, resulting in nine experimental runs. Surface roughness measurements were taken along both the

x- and y-directions. A multivariate regression model was developed using the scikit-learn library, with surface roughness data used to train the model. The results showed that surface roughness increased with layer thickness, decreased with infill density, and was minimally influenced by infill structure.

Deb et al. [26] explored the use of ensemble machine learning (ML) methods to predict the surface roughness and tensile strength of PLA-printed parts, varying five process parameters: build orientation, infill angle, layer thickness, printing speed, and nozzle temperature, each at three levels. The test specimens conformed to the ASTM D638-14 standard, and 27 experiments were designed using a Taguchi L27 orthogonal array. Surface roughness was measured using the SPI Portable Roughness Tester II. ML models were developed using the scikit-learn library and included GBR, XGBR, Adaptive Boosting Regression (ABR), RFR, and ERTR. The performance of these models was compared with KNN and SVM using evaluation metrics such as RMSE, MAE, and MAPE. Results confirmed that ensemble learning methods consistently outperformed traditional algorithms in prediction accuracy.

## **2.2 Prediction of Surface Roughness of hybrid AM+CNC Parts using ML Algorithms**

In the context of hybrid manufacturing, limited research has specifically addressed the prediction of surface roughness parameters when FFF is used as the primary additive process. The term hybrid refers to the integration of an additional post-processing technique most commonly CNC machining to enhance the surface quality of the additively manufactured part. Among these, milling is the predominant method employed, wherein a cutting tool is used to perform a finishing operation that refines the surface characteristics of the printed component.

Djurović et al. [23] investigated the prediction of surface roughness in hybrid manufacturing by employing both Multiple Regression Analysis (MRA) and ANNs. The study varied CNC milling parameters, including spindle speed, depth of cut, and feed rate, while the AM phase involved printing a PLA cubical specimen with 100% infill density, prepared using Ultimaker Cura. CNC post-processing was carried out using



a Haas VF-3SS vertical milling machine equipped with a 6 mm, 3-flute hard metal (VHM) tool. Surface roughness was measured using a Talysurf-6 profilometer, and two ANN architectures were tested using Tanh and ReLU activation functions. The predictive performance was evaluated using the coefficient of determination ( $R^2$ ). For MRA, both second and third order polynomial equations were developed for comparison. The worst surface roughness measured was 3.435  $\mu\text{m}$ , corresponding to a spindle speed of 5000 rpm, feed rate of 1000 mm/min, and depth of cut of 1 mm. The best result, 1.958  $\mu\text{m}$ , was achieved at 5000 rpm, 400 mm/min feed rate, and 0.6 mm depth of cut. The study concluded that ANN models outperformed MRA, with the ReLU-based ANN yielding more accurate predictions than the Tanh-based model.

Li et al. [27] explored a hybrid manufacturing approach that employed a flat-end milling tool to enhance the surface roughness of FFF-produced parts. Instead of applying machine learning techniques, the study focused on developing a physics-based analytical model to capture the relationship between hybrid manufacturing parameters and surface quality. The surface roughness metric used was the arithmetic average height  $R_a$ , defined by ISO 1997 [28] as the average deviation of the actual surface profile from the mean line over a defined sampling length. Using PLA as the material, specimens were printed with surface angles of 20°, 30°, 40°, 50°, 60°, 70°, and 90°, employing a layer thickness of 0.25 mm. Milling was performed with a four-flute end mill of 1/8-inch diameter, and surface roughness was measured using a Micro-Vu Precision Measurement System with a 1  $\mu\text{m}$  resolution. The AM parameters investigated included stratification angle, layer thickness, and layer error coefficients, while the CNC inputs considered were cutting-edge angle and feed rate. The results showed a decrease in  $R_a$  with increasing stratification angle, and overall improvement in surface finish with the hybrid strategy. The authors concluded that their analytical surface profile model is effective in predicting surface roughness in hybrid-manufactured components.

Uğur et al. [29] investigated hybrid manufacturing to achieve smoother surface finishes using PLA and ABS as base materials. The study emphasized that the surface roughness of thermoplastics is influenced by multiple factors, including material behavior, tool geometry, machining parameters, and machine characteristics. As thermoplastics exhibit glassy and brittle behavior at room temperature, their machinabil-

ity can shift toward a more ductile response depending on cutting conditions. The experimental setup involved fabricating cubic specimens using an Ultimaker S3 and post-processing them on a hybrid milling platform. Unlike studies employing formal design of experiments (DOE), this research used fixed parameters derived from preliminary tests for the AM process, with a layer height of 0.5 mm. On the machining side, CNC parameters varied were cutting speed, feed rate, spindle speed, and depth of cut, while testing three different tool geometries with varying diameters and flute counts. Surface roughness was evaluated using a MarSurf PS10 with a 2  $\mu\text{m}$  stylus, focusing on Ra and Rz values. Results indicated that single-flute tools offered improved milling performance. The study further concluded that the glass transition temperature of PLA is a critical factor in selecting optimal cutting parameters. Recommended conditions include: single-flute tools with high rake angles, feed per tooth between 0.03–0.1 mm, cutting speeds of 40–80 m/min, and depths of cut ranging from 0.1 mm to half the nozzle diameter.

Sergiu et al. [30] conducted a study on process parameter optimization for hybrid manufacturing of PLA parts, with a focus on improving surface roughness. The parameters investigated for the CNC machining stage included spindle speed, cutting depth, and feed rate, while the AM parameters analyzed were layer thickness and nozzle speed. A four-flute, 6 mm diameter HSS tool was used for the milling operations. The design of experiments was conducted at three levels for each parameter: depth of cut (0.1, 0.2, 0.3 mm), spindle speed (500, 5250, 10,000 rpm), and cutting speed (80, 240, 400 mm/min). For the AM side, layer heights of 0.2, 0.26, and 0.32 mm were selected. A total of 16 experiments were conducted using a Taguchi L16 orthogonal array, resulting in 32 combined trials. Cubic specimens were printed, and surface roughness was measured using a Mitutoyo Contractor over a 12 mm measurement length at a speed of 0.3 mm/s. An initial linear regression model was developed to analyze the relationships between the input parameters and surface roughness, but the model showed limited accuracy. Optimized printing parameters were then applied in a second round of testing, leading to a further reduction in MSE. Subsequently, a Neural Network Model (NNM) was implemented, with 80% of the data used for training and 20% for validation, yielding significantly better predictive accuracy. The collected data also supported the development of an integrated hybrid manufacturing

equipment (HME) combining AM and CNC milling. A new specimen design incorporating angled surfaces at 30°, 45°, and 60° was tested to further evaluate surface quality. The study concluded that the proposed hybrid approach, using both AM and CNC parameters, can effectively predict surface roughness, and that NNM significantly outperforms linear regression in predictive capability. These results confirm the viability of PLA in hybrid manufacturing with improved surface quality outcomes.

### **2.3 Research Gap**

The comprehensive review of existing literature reveals a significant gap in the prediction of surface roughness using ML for PLA components manufactured at varying inclination angles using both AM and hybrid AM–CNC machining strategies. Among the reviewed studies, only a limited number, specifically by Huang et al. [18], Li et al. [27], and Pascu et al. [30], incorporated inclination angles into the design of PLA-based parts. Furthermore, the integration of CNC machining as a post-processing technique for enhancing surface quality was observed solely in Li et al. [27] and Pascu et al. [30]. Notably, only the study Pascu et al. [30] employed machine learning, in particular artificial neural networks, to predict the surface roughness of PLA components produced via hybrid manufacturing approaches at inclination angles of 30°, 45°, 60°, and 90°. In contrast to these limited investigations, the present study introduces a more extensive experimental design comprising 54 experimental parts, expands the inclination angle range from 10° to 80°, incorporates CNC machining as a surface roughness improvement method, and applies ten distinct supervised regression-based machine learning algorithms to model and predict surface roughness with improved accuracy and generalizability.



## CHAPTER 3

### METHODOLOGY FOR SURFACE ROUGHNESS PREDICTION

This chapter outlines the step-by-step methodology employed for predicting the surface roughness of both AM and machined parts using ML techniques. The process begins with the development of an optimized design capable of incorporating inclined surfaces ranging from  $10^\circ$  to  $80^\circ$ , in  $10^\circ$  increments. Two design iterations were generated and evaluated based on various criteria, including print duration, material consumption, surface appearance, structural integrity under machining forces, geometric complexity, and suitability for surface roughness measurement. Based on these considerations, a final 3D model was selected. Subsequently, relevant input parameters for the AM process were identified through an extensive review of the literature, focusing on variables known to influence surface roughness. These parameters were finalized through an experimental approach. A structured DOE methodology Taguchi L54 was then applied to ensure comprehensive coverage and statistical representation of each parameter's influence. Using the finalized DOE matrix, samples were fabricated through AM, and surface roughness measurements were performed using a handheld profilometer (details provided in the subsequent sections).

For the machining phase, literature insights specifically from Uğur et al [29] were similarly utilized to determine appropriate process parameters. Depth of cut was selected as the primary input variable, and three levels were defined for experimental investigation. The previously finalized 3D model was imported into a CAM software, where toolpaths and G-code were generated for the milling operations. Machining was conducted on a CNC milling machine, and the resulting hybrid (additive + machined) samples were subsequently measured for surface roughness. The compiled surface roughness data was then input into ten various machine learning models

for training and evaluation. Performance of the models was assessed using standard evaluation metrics, and predictive capability was validated through comparison with additional validation samples.

### **3.1 Development of a 3D CAD Design**

The development of the optimized design was achieved through the evaluation of two different design alternatives, with consideration given to several critical factors, including geometric complexity, printability, material consumption, printing duration, surface quality, structural integrity under machining forces, and accessibility for surface roughness measurement. A key requirement for the design was the inclusion of inclined surfaces at angles ranging from  $10^\circ$  to  $80^\circ$ , enabling a comprehensive assessment of surface roughness across varying orientations. The selected geometry was intended to be as generalized and adaptable as possible to facilitate rapid surface roughness predictions, thereby serving as a practical reference for more complex industrial part designs.

The CAD software used for generating and refining these design iterations was Siemens NX [31]. Siemens NX is a globally recognized, industry-grade software platform offering robust modeling capabilities, an intuitive user interface, and integrated design-to-manufacturing workflows. Additionally, the availability of a free student version makes it both accessible and cost-effective for academic research and iterative design development.

#### **3.1.1 Design Iterations**

The design determination process commenced with an extensive review of the existing literature focused on geometries incorporating inclined surfaces fabricated using AM techniques. The review began with studies of Cerro et al. [12] and Kuo et al. [32], which primarily featured models incorporating three inclined surfaces at  $30^\circ$ ,  $45^\circ$ , and  $75^\circ$  made of polyvinyl butyral. In particular, Huang et al. [18] employed a cubical geometry oriented at these angles; however, due to the design's reliance on support structures, additional post-processing was required for support removal,

which adversely impacted the surface quality.

Other investigations, such as those in Vahabli et al. [22] and Reeves et al. [33], featured a design fabricated in ABS material referred to as the "truncheon" that incorporated inclinations from  $0^\circ$  to  $90^\circ$  in  $5^\circ$  increments. This part was also printed with supports, which were subsequently removed through chemical dissolution.

Similarly, Li et al. [27] examined a geometry with inclined surfaces at  $20^\circ$ ,  $30^\circ$ ,  $40^\circ$ ,  $50^\circ$ ,  $60^\circ$ ,  $70^\circ$ , and  $90^\circ$ . Furthermore, Kugunavar et al. [34] included designs with angles of 25, 50, and 70. The designs proposed in studies by Li et al. [27] and Kugunavar et al. [34] were identified as the most relevant to the scope of the present work. Consequently, these designs were adopted as reference models for the development of the current study. The results obtained herein are systematically compared with those reported in the aforementioned studies.

Table 3.1 provides a summary of earlier studies that highlight the part geometries and the angles at which surface roughness was measured for parts manufactured using PLA material. The table features various components, including cuboids, tensile specimens, engine intake flanges, cylinders, and sloped specimens. The studies reported angles from  $0^\circ$  to  $90^\circ$ , with many focusing on the two extreme orientations: horizontal ( $0^\circ$ ) and vertical ( $90^\circ$ ). These angles are important for evaluating surface features that are parallel and perpendicular to the build plate. After reviewing the existing literature, it became clear that researchers have studied these extreme angles in various geometries and contexts. To avoid repeating past work and to add new insights, this study deliberately leaves out  $0^\circ$  and  $90^\circ$  orientations. Instead, it focuses on intermediate angles, specifically those between  $10^\circ$  and  $80^\circ$ . These angles have not received much attention but are important for understanding surface roughness on sloped features or inclined planes in functional parts. This focused approach allows for a detailed exploration of how surface roughness evolves with gradual changes in inclination.

The comparison between the initial design Figure 3.1 and final design Figure 3.2 is illustrated, accompanied by table 3.2, which outlines the key factors considered during the design evaluation process.

Table 3.1: Summary of Studies Based on Part Geometry and Measured Angles

| Study | Part Geometry        | Angles (°)                 |
|-------|----------------------|----------------------------|
| [6]   | Cuboid               | 90                         |
| [7]   | Tensile Specimens    | 0                          |
| [10]  | Engine Intake Flange | 0                          |
| [13]  | Cylinder             | 0                          |
| [15]  | Cuboid               | 0                          |
| [16]  | Cylinder             | 90                         |
| [18]  | Cuboid with Supports | 30, 45, 75                 |
| [19]  | Cuboid               | 0                          |
| [20]  | Engine Intake Flange | 0                          |
| [21]  | Tensile Specimens    | 90                         |
| [23]  | Cuboid               | 90                         |
| [25]  | Tensile Specimens    | 0 & 90                     |
| [27]  | Sloped Specimens     | 20, 30, 40, 50, 60, 70, 90 |
| [29]  | Cuboid               | 90                         |
| [30]  | Cuboid and Sloped    | 30, 45, 60, 90             |
| [34]  | Sloped Specimens     | 25, 50, 70                 |
| [35]  | Cylinder             | 0                          |

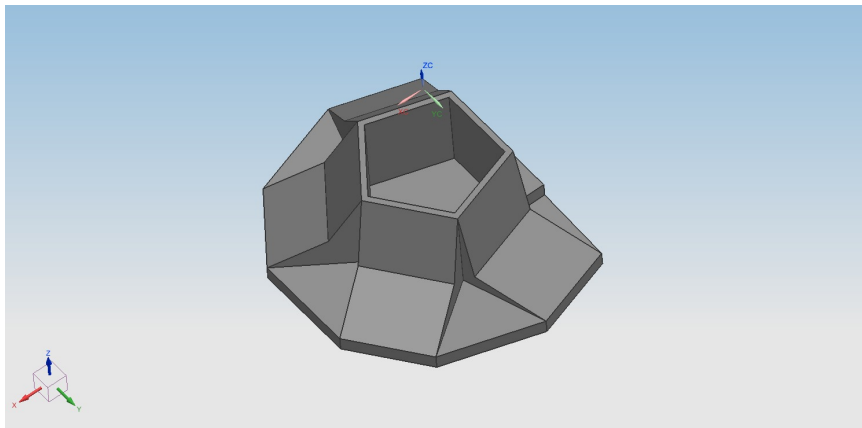


Figure 3.1: Initial CAD Design Isometric View

The surface angles can be observed in Figures 3.3, 3.4 below. To avoid visual clutter,



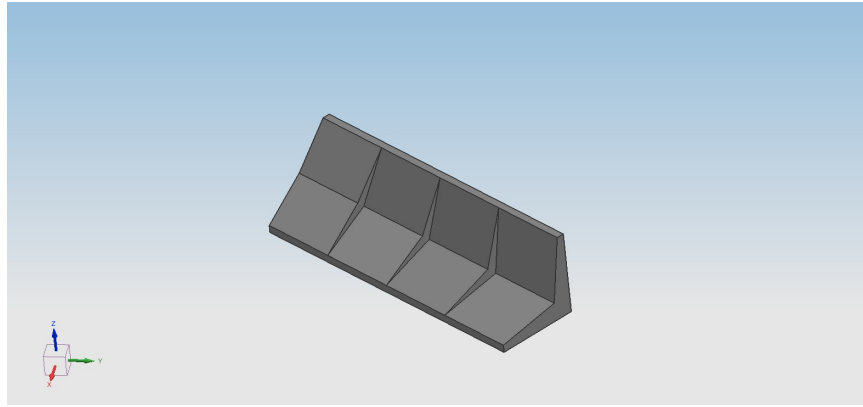


Figure 3.2: Final CAD Design Isometric View

only the  $10^\circ$ ,  $20^\circ$ ,  $70^\circ$ , and  $80^\circ$  angles are labeled in the initial design, while all angles are clearly indicated in the final design for comprehensive reference.

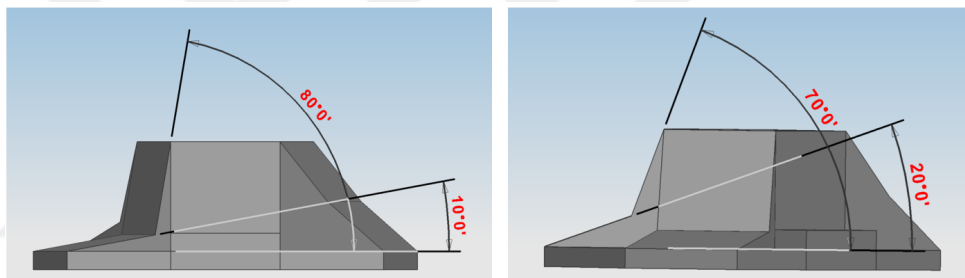


Figure 3.3: Left: Initial CAD Design  $10^\circ$  and  $80^\circ$ . Right: Initial CAD Design  $20^\circ$  and  $70^\circ$

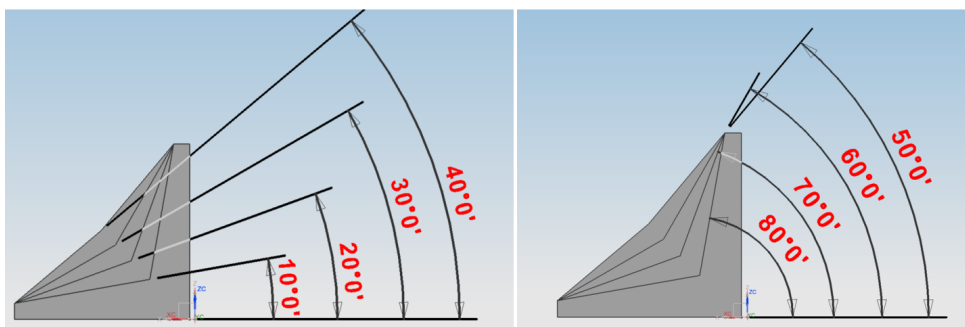


Figure 3.4: Left: Final CAD Design  $10^\circ$  to  $40^\circ$ . Right: Final CAD Design  $50^\circ$  to  $80^\circ$

The following Table 3.2 shows the factors that were considered in selecting the final

design:

Table 3.2: Comparison of Factors between Initial and Final Designs

| Factors                 | Initial Design                   | Final Design            |
|-------------------------|----------------------------------|-------------------------|
| Design Complexity       | High                             | Low                     |
| Angles                  | 0–90°                            | 10–80°                  |
| Volume                  | 78611.7 mm <sup>3</sup>          | 56136.9 mm <sup>3</sup> |
| Supports                | No                               | No                      |
| Print Time              | 17 hrs 49 mins                   | 11 hrs 3 mins           |
| Material                | 87 grams                         | 62 grams                |
| CNC Fixture             | Required                         | Not Required            |
| Resist Machining Forces | Can resist with specific fixture | Can resist              |
| Roughness Measurement   | Difficult to Measure             | Easier to Measure       |
| Symmetry                | No                               | Yes                     |

Table 3.2 shows the evaluation that led to rejecting the initial design in favor of the final version. One major factor was the significant difference in print time, which was about six hours. This difference strongly favored the final design. This reduction not only improves overall production efficiency but also lowers energy use and increases machine availability for the next print jobs. Additionally, even though both designs used the same input parameters in the 3D printing process, the final design used about 25 grams less material on average. This improvement is important for saving costs and promoting sustainability, as it helps conserve resources. Another critical drawback of the initial design was its reliance on a custom CNC fixture for post-processing operations. The need for specialized fixture added unnecessary complexity and increased setup time, thereby extending the production cycle and introducing potential sources of error during alignment and finishing. In contrast, the final design was optimized to be compatible with standard fixture, making it easier to machine. Moreover, the geometric characteristics of the initial design, specifically its asymmetry and higher complexity, posed significant challenges during surface roughness measurement. Using a handheld profilometer under these conditions resulted in inconsistent and unreliable readings. This limited the precision and repeatability of the surface

characterization process. In contrast, the improved symmetry and simplified geometry of the final version allowed for more accurate and consistent measurements.

Figure 3.5 and Figure 3.6 visually demonstrate the differences in print time and material usage as shown in the Ultimaker Cura environment [24].

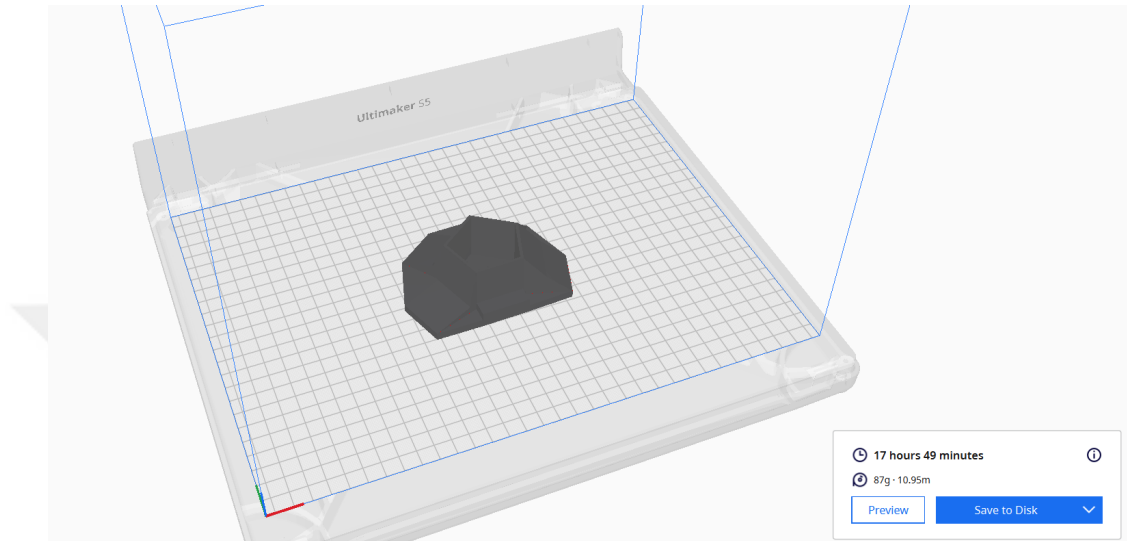


Figure 3.5: Initial Print Time and Material

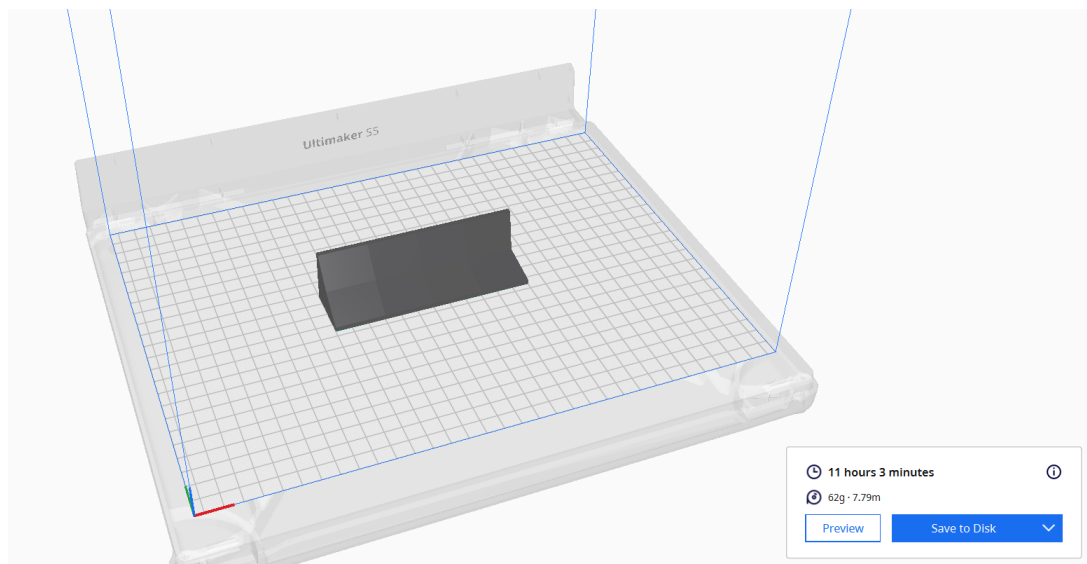


Figure 3.6: Final Print Time and Material

## 3.2 Determination of the Design of Experiments

This section details the selection of input parameters based on both a comprehensive review of the relevant literature and the author's assessment of factors likely to influence surface roughness. Once the parameters were finalized, a systematic strategy was developed to construct a DOE using the Taguchi L54 orthogonal array. Most parameters were varied across three levels, with the exception of nozzle diameter, which was evaluated at two levels due to experimental constraints and availability of the equipment.

### 3.2.1 Selection of the input parameters

Table 3.3 below presents a summary of the literature review focused on AM parameters varied to check the influence of surface roughness. It highlights the input parameters selected in each study and the no of levels each parameter is varied, to facilitate surface roughness prediction. The studies included in this table were specifically chosen based on their use of PLA filament, ensuring relevance and consistency with the material used in the present research.

Table 3.3 highlights the key input parameters identified in various studies as significantly influencing the surface roughness of 3D printed parts. Among them, the nozzle diameter refers to the width of the orifice through which the molten filament is extruded. It plays a critical role in governing the pressure drop during extrusion, and selecting an optimal nozzle diameter ensures consistent flow. Generally, larger nozzle diameters reduce printing time but may compromise surface detail [36]. Another crucial parameter is the layer height, defined as the vertical distance between two successive layers. This value is typically less than the nozzle diameter to ensure adequate bonding and surface finish [6]. The wall thickness, often configured in slicing software like Cura [24], determines the combined width of the walls of the part. The top thickness refers to the height of the fully solid (100% infill) top layers. Adequate top thickness is essential for achieving a smooth, sealed upper surface without visible infill lines. Infill density controls the percentage of material deposited within the internal volume of the part. While higher infill densities improve strength and stiffness,

Table 3.3: Summary of input parameters used in PLA-based FFF studies (ND = Nozzle Diameter, LH = Layer Height, WT = Wall Thickness, TT = Top Thickness, ID = Infill Density, IP = Infill Pattern, PT = Printing Temp, BPT = Build Plate Temp, PS = Print Speed, FS = Fan Speed, FR = Flow Rate, OWS = Outer Wall Speed)

| Authors         | ND | LH | WT | TT | ID % | IP | PT | BPT | PS | FS | FR | OWS | No of Levels |
|-----------------|----|----|----|----|------|----|----|-----|----|----|----|-----|--------------|
| [6]             | -  | ✓  | -  | -  | -    | -  | ✓  | -   | ✓  | -  | ✓  | -   | 2            |
| [7], [21]       | -  | ✓  | ✓  | -  | ✓    | ✓  | ✓  | ✓   | ✓  | ✓  | -  | -   | 3            |
| [10]            | -  | ✓  | -  | -  | -    | -  | ✓  | -   | ✓  | -  | -  | -   | 3            |
| [13]            | -  | ✓  | -  | -  | -    | -  | -  | ✓   | ✓  | -  | -  | -   | 3            |
| [15]            | -  | ✓  | -  | -  | -    | -  | ✓  | -   | ✓  | -  | -  | ✓   | 5            |
| [16]            | -  | ✓  | ✓  | -  | -    | -  | ✓  | -   | ✓  | -  | -  | -   | 3            |
| [18]            | ✓  | ✓  | -  | -  | -    | -  | ✓  | -   | ✓  | -  | ✓  | -   | 3            |
| [19]            | -  | ✓  | -  | -  | ✓    | -  | ✓  | -   | ✓  | -  | -  | -   | 5            |
| [20]            | -  | ✓  | -  | -  | -    | -  | ✓  | -   | ✓  | -  | -  | -   | 3            |
| [25]            | -  | ✓  | -  | -  | ✓    | ✓  | -  | -   | -  | -  | -  | -   | 3            |
| [30]            | -  | ✓  | -  | -  | -    | -  | -  | -   | ✓  | -  | ✓  | -   | 3            |
| [34]            | -  | ✓  | -  | -  | -    | -  | ✓  | -   | ✓  | -  | -  | -   | 3            |
| [35]            | -  | ✓  | ✓  | -  | -    | ✓  | ✓  | -   | ✓  | -  | -  | -   | Variable     |
| <b>Our Work</b> | ✓  | ✓  | ✓  | ✓  | ✓    | ✓  | ✓  | ✓   | ✓  | ✓  | -  | -   | 3            |

they also increase print time and material consumption [37].

Infill pattern defines the geometric structure used to fill the part's interior [38]. Cura offers several patterns, such as grid, lines, cubic, and octet, and triangle etc, each influencing strength, weight, and material usage differently. The extrusion temperature is the nozzle's temperature, and the viscosity and flow behavior of the molten filament are associated with it. It must be optimized to ensure smooth extrusion without clogging or degradation [39]. The build plate temperature heats the print bed, helping the initial layers adhere properly and preventing warping or delamination. An appropriate bed temperature is crucial for first-layer success and overall dimensional accuracy. Print speed refers to the velocity of the extruder head as it deposits material. While increasing print speed can shorten build time, it may introduce vibrations, layer misalignment, or incomplete extrusion if not carefully balanced [40]. Fan speed, expressed as a percentage, regulates the cooling rate of the extruded filament. Proper cooling promotes layer solidification and bridging. The flow rate measures the actual volume of material extruded compared to the theoretical value. Correct flow calibration ensures accurate geometry and prevents over- or under-extrusion [6]. Finally, the

outer wall speed defines the specific print speed used for the outermost perimeters of the part.

The selection of input parameters in this thesis was carried out through a comprehensive evaluation of the comparative table discussed above. Nozzle diameter was included as a variable due to the limited research available on its influence on surface roughness; only one relevant study by Huang et al. [18] addressed its effect. The availability of two distinct nozzle diameters in our research allowed this parameter to be examined at two different levels. The layer height was an unquestionable choice, as it was consistently reported across all reviewed studies to significantly impact surface roughness. Wall thickness was also considered an important factor, supported by its inclusion in studies by Mishra et al. [7], [21], Garcia-Martinez et al. [16], and Perez et al. [35]. In Cura [24], wall thickness is defined by the following relationship:

$$\text{Wall Thickness} = \text{Wall Line Count} \times \text{Line Width} \quad (3.1)$$

By manually setting the wall thickness, Cura automatically calculates the appropriate wall line count. Another critical parameter included in this study is top thickness, which has been largely overlooked in previous literature. Given its potential influence on surface finish, it was deemed important to investigate. In Cura [24], top thickness is determined using the relation:

$$\text{Top Thickness} = \text{Top Layers} \times \text{Layer Height} \quad (3.2)$$

With the layer height specified, Cura automatically calculates the corresponding number of top layers based on the defined top thickness. Infill density was also selected due to its demonstrated significance in studies by Mishra et al. [7], [21], Saxena et al. [19], and Kumar et al. [25], directly influencing the internal structure and mechanical behavior of the printed part. In conjunction with it, the infill pattern was included to assess how different internal geometries influence surface finish. Printing temperature was another parameter incorporated into the study, owing to its widespread reporting in the literature as a key determinant of surface quality. Although build plate temperature was reported less frequently (notably in studies by Mishra et al. [7], [21], and

Kandananond et al. [13]), it was included due to its role in first-layer adhesion and warping prevention.

Additional parameters such as printing speed and fan speed were also selected for investigation, given their potential to influence thermal gradients, layer bonding, and cooling behavior. In total, 10 additive manufacturing input parameters were selected, along with build angle as an eleventh parameter, to comprehensively assess their impact on the surface roughness of 3D printed parts.

In order to systematically vary the input parameters, the selection of the number of levels for each input parameter was a critical step in assessing their influence on the surface roughness of the additively manufactured parts. To support this selection, Table 3.3 was revisited and carefully analyzed. Based on the review, the number of levels for each parameter was set to three, with the exception of nozzle diameter, which was varied at two levels due to material and equipment constraints.

Table 3.4 gives the physical and mechanical properties of the Ultimaker PLA Black material, as provided by Ultimaker [41], which guided the selection of printing conditions in this study.

Table 3.4: Physical and Mechanical Properties of Ultimaker PLA Black (RAL 9005)

| Property                       | Value                |
|--------------------------------|----------------------|
| Material                       | PLA Black (RAL 9005) |
| Diameter (mm)                  | $2.85 \pm 0.10$      |
| Mass of the Filament Spool (g) | 750                  |
| Young's Modulus (MPa)          | $3250 \pm 119$       |
| Tensile Yield Stress (MPa)     | $52.5 \pm 0.9$       |
| Melting Temperature (°C)       | 151.8                |
| Printing Temperature (°C)      | 190–210              |
| Bed Temperature (°C)           | 50–60                |

The values for the input parameters were meticulously selected based on a comprehensive review of the relevant literature and are summarized in Table 3.5

The availability of two different nozzles enabled the variation of this parameter at two

Table 3.5: Additive Input Parameters and Their Levels

| Input Parameters             | Level 1 | Level 2 | Level 3  |
|------------------------------|---------|---------|----------|
| Nozzle Diameter (mm)         | 0.25    | 0.4     | –        |
| Layer Height (mm)            | 0.1     | 0.15    | 0.2      |
| Wall Thickness (mm)          | 0.75    | 1       | 2        |
| Top Thickness (mm)           | 1.2     | 1.4     | 1.6      |
| Infill Density (%)           | 20      | 50      | 80       |
| Infill Pattern               | Grid    | Cubic   | Triangle |
| Printing Extrusion Temp (°C) | 190     | 200     | 210      |
| Build Plate Temp (°C)        | 50      | 55      | 60       |
| Print Speed (mm/s)           | 40      | 60      | 80       |
| Fan Speed (%)                | 50      | 75      | 100      |

distinct levels. The nozzle diameter values were selected on the recommendation of the sizes officially provided by the manufacturer, Ultimaker, which offers print cores with nozzle diameters of 0.25 mm, 0.4 mm, 0.6mm, and 0.8 mm [42].

Due to equipment constraints and the need to limit material consumption, only the 0.25 mm and 0.4 mm nozzles were utilized in this study. Images of the corresponding print cores are presented in Figure 3.7 for reference.

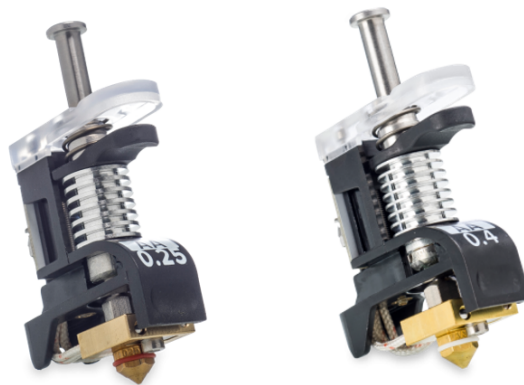


Figure 3.7: Ultimaker Print Core AA 0.25 mm and AA 0.4 mm [42]



Notably, the three nozzle sizes were also employed in the study conducted by [43], where no dominant effect on surface roughness was reported, likely due to a smaller number of experiments. Therefore, in this research, the inclusion of two nozzle diameters was aimed at more comprehensively capturing the influence of nozzle size on surface roughness, supported by a significantly increased number of experimental samples compared to the study of Martin et al. [43].

The values for the second factor, layer height, were carefully selected by considering the requirements for both nozzle diameters. According to the manufacturer's guidelines, the minimum recommended layer height is 0.06 mm for the 0.25 mm nozzle and 0.1 mm for the 0.4 mm nozzle. Consequently, a layer height of 0.1 mm was chosen to ensure compatibility with both nozzle sizes. Regarding the maximum limit, it is widely accepted that the layer height should not exceed 80% of the nozzle diameter [6]. Based on this criterion, a maximum layer height of 0.2 mm was selected, ensuring it remains within the safe operational range for both the 0.25 mm and 0.4 mm nozzles.

The wall thickness values were also chosen with careful consideration of the nozzle diameters used in this study. Values of 0.75 mm, 1.0 mm, and 2.0 mm were selected to ensure printability and consistency across both the 0.25 mm and 0.4 mm nozzles. In addition, these values were chosen considering the depth of cut values mentioned in the subsequent chapters to see the effect of machining beyond the initial shells on the surface roughness. Similarly, the top thickness values were set at three levels 1.2 mm, 1.4 mm, and 1.6 mm based on their dependence on the layer height, as described in Equation 3.2. The infill density levels were chosen to explore the influence of internal material volume on surface roughness: 20% (low infill), 50% (medium/half infill), and 80% (high infill) were chosen to cover a wider range of mechanical behavior. Regarding the infill pattern, selections were based on criteria of common usage, mechanical strength, and the need for stiffness to effectively withstand the forces experienced during the subsequent machining process.

The grid structure was selected due to its widespread application in standard prints, while cubic and triangular structures were included for their well-documented ability to provide mechanical strength and rigidity in all directions [44]. The infill patterns

utilized in this study are illustrated in Figure 3.8. Both the printing extrusion temperature and build plate temperature values were selected in accordance with the recommended ranges provided by the manufacturer for PLA material as given in Table 3.4.



Figure 3.8: Infill Patterns: Left - Grid, Middle - Cubic, Right - Triangle

The print speed values were chosen to span a broad range from low to high, ensuring that the entire operational spectrum was investigated. Lower print speeds are known to reduce vibration and enhance surface smoothness [6]; however, to comprehensively assess the effect of print speed on surface roughness, it was essential to explore a wide range of values. Similarly, the fan speed settings were selected based on the manufacturer's guidelines, varying from 50% to 100%, to evaluate their effect on the cooling behavior and final surface quality of the printed parts.

### 3.2.2 Design of Experiments Using Taguchi L54 Methodology

After the selection of the input parameters and their respective levels, as outlined in the preceding section, several experimental design methodologies were evaluated to determine the required number of experiments. The initial approach considered was the full factorial design, which comprehensively examines the effects of all factors, as well as their interactions, on the output response [45]. Here, the factors refer to the input parameters such as layer height, nozzle diameter, etc, and the response refers to the surface roughness. The general expression for calculating the number of experiments in a full factorial design is given by Equation 3.3:

$$\text{Total Experiments} = (\text{Number of Levels})^{\text{Number of Factors}} \quad (3.3)$$

In this study, the experimental setup involved 10 input parameters, with 9 parameters at three levels and 1 parameter at two levels. Applying the full factorial formula yields Equation 3.4:

$$\text{Total Experiments} = 3^9 \times 2^1 = 39366 \quad (3.4)$$

Conducting 39,366 experiments was deemed impractical due to limitations in material availability and the considerable time required for printing, with each part taking approximately seven hours to manufacture on average. Consequently, the full factorial design approach was found to be unmanageable for this study and would have resulted in a highly complex and resource-intensive model, thereby necessitating the consideration of alternative design methodologies.

Following the impracticality of the full factorial design, focus was shifted towards the fractional factorial design. This method is employed as a practical alternative to the full factorial design, offering many of the same advantages, such as the ability to study the main effects of factors, while requiring significantly fewer experiments. A fractional factorial design is formally defined as a subset or fraction of the complete factorial design set [46]. By using only a selected fraction of all possible combinations, the resulting experimental model becomes less complex and more manageable. However, a notable drawback arises from the reduction in the number of experiments: certain interaction effects between factors may become confounded and therefore more difficult to distinguish [47]. The total number of experiments required using a fractional factorial design can be calculated by the Equation 3.5:

$$\text{Total Experiments} = (\text{No of levels})^{k-p} \quad (3.5)$$

where  $k$  represents how many factors there are and  $p$  represents the degree of fractionation (i.e., the number of factors confounded to reduce the design size). For the present study, using a fraction size of  $1/2$  would still result in 19,683 experiments,

while even with a fraction as small as 1/32, the required number of experiments would be approximately 1,230. Consequently, this approach was also deemed unmanageable given the resource constraints of the thesis.

Further investigation was conducted to evaluate the employment of the Central Composite Design (CCD) strategy in estimating the number of experiments. CCD is widely employed to generate a response surface, which represents the correlation between the response variable and the levels of the input factors. This surface corresponds to a mathematical function and can be visualized in two or three dimensions, fitted to the experimental data [48]. CCD primarily aims to construct a quadratic (second-order) model for the output variable, effectively capturing both linear interaction effects as well as curvature. It requires fewer experimental runs compared to a full factorial design and is specifically intended for continuous input variables [47]. The total number of experiments required in CCD can be calculated using the Equation 3.6:

$$N = k^2 + 2k + C_p \quad (3.6)$$

where  $k$  represents the number of factors and  $C_p$  refers to the number of replicates at the centre point. However, one of the input parameters in this study—infill pattern—was a categorical variable with three levels. Since CCD is designed exclusively for continuous factors, it was deemed unsuitable for this experimental setup.

The Box-Behnken Design (BBD) is another experimental design method that adapts a quadratic (second-order) model for analyzing the response surface. However, it is specifically applicable only when all factors have three or more levels [49]. The number of experiments required for a Box-Behnken Design can be calculated using Equation 3.7:

$$N = 2k(k - 1) + C_p \quad (3.7)$$

In the current study, one of the input parameters nozzle diameter was varied at only two levels. Since BBD requires all factors to have at least three levels, this methodology was deemed unsuitable for the experimental design.

A comprehensive review of the literature was conducted to identify the types of DOE methodologies employed in related studies. The methodologies utilized across these studies are summarized in Table 3.6.

Table 3.6: Summary of DOE Methodologies Used in Related Studies

| Studies   | Type of DOE                      | Number of Experiments |
|-----------|----------------------------------|-----------------------|
| [6]       | Two Level Full Factorial         | 19                    |
| [7], [21] | Response Surface Method          | 30                    |
| [10]      | Three Level Full Factorial       | 27                    |
| [13]      | Box Behnken Design               | 32                    |
| [15]      | Central Composite Design         | 46                    |
| [16]      | Taguchi L16                      | 16                    |
| [18]      | Taguchi L27                      | 27                    |
| [19]      | Taguchi L25                      | 25                    |
| [20]      | Taguchi L27                      | 27                    |
| [25]      | Taguchi L9                       | 9                     |
| [30]      | Taguchi L16                      | 16                    |
| [34]      | Taguchi L27                      | 27                    |
| [35]      | Two Level Fractionated Factorial | 23                    |

According to Table 3.6, a significant number of studies such as [16], [18], [19], [20], [25], [30], and [34] employed the Taguchi method within their DOE. In light of these precedents, the Taguchi approach was selected for this study. Developed by Dr. Genichi Taguchi in the 1950s, this method is designed to investigate the influence of input parameters varied across two, three, or more levels. Unlike classical DOE approaches that typically begin with full factorial designs and are followed by sequential designs such as Central Composite Design (CCD) or Box-Behnken Design (BBD), the Taguchi method offers a non-sequential alternative. It allows for the systematic exploration of main effects and critical interactions with a significantly reduced number of experimental trials [50].

The foundation of the Taguchi method lies in its use of orthogonal arrays (OAs), which enable balanced and statistically efficient experimental setups. Each column

of an OA corresponds to a specific factor with designated levels, while each row represents a unique combination of input settings for a single experimental run [51]. A critical aspect of implementing the Taguchi method involves correctly assigning input factors to the appropriate columns within the OA to preserve orthogonality and interpretability.

Taguchi orthogonal arrays are denoted using the format  $L_N(S^m)$ , where  $N$  is the number of experiments,  $S$  is the number of levels, and  $m$  is the number of factors. For instance,  $L_9(3^4)$  refers to an array comprising 9 experiments for 4 factors each varied at 3 levels [52]. This structured approach makes it possible to efficiently study the effects of multiple factors without the need for exhaustive experimental runs.

According to Table 3.5, which outlines the selected input factors and their respective levels, the choice of a suitable Taguchi orthogonal array was important to accommodate the experimental design requirements. Specifically, the design needed to balance one input factor at two levels (nozzle diameter) with nine input factors at three levels. To satisfy this mixed-level requirement, the Taguchi L54 orthogonal array was selected. Although the L54 array is less commonly employed, it is particularly suited for such configurations, as it supports one two-level factor and up to twenty-five three-level factors, making it highly efficient for complex experimental designs [53].

This configuration represents a mixed-level design strategy, ideal for systematically studying the influence of multiple parameters with different levels, eliminating the necessity for a full factorial design, which would be computationally and practically intensive. Given a total of ten input factors in this study, the L54 array was deemed appropriate. The resulting design of experiments (DOE) structure, incorporating the specified factor levels, is presented in the following tables created with the help of the Minitab software. For improved clarity and readability, the full design matrix has been divided into two separate tables, corresponding to combinations involving 0.4 mm and 0.25 mm nozzle diameters, respectively.

The configurations presented in Tables 3.7 and 3.8 illustrate the DOE adopted in this research. By leveraging the Taguchi L54 mixed-level orthogonal array, a total of 54 unique experimental trials were systematically generated. This represents the most extensive experimental setup among the reviewed studies on this topic, enabling

a comprehensive investigation of the parameter effects across varying levels. Each row refers to a unique combination of input parameters used in an individual experiment, designed to assess the influence of the input parameters on the resulting surface roughness values.

Table 3.7: Taguchi L54 Design of Experiments (DOE): Experiments 1–27 with 0.4 mm Nozzle Diameter. Abbreviations — ND: Nozzle Diameter; LH: Layer Height; WT: Wall Thickness; TT: Top Thickness; ID: Infill Density; IP: Infill Pattern (C: Cubic, G: Grid, T: Triangle); PT: Printing Extrusion Temperature; BPT: Build Plate Temperature; PS: Print Speed; FS: Fan Speed.

| No | ND (mm) | LH (mm) | WT (mm) | TT (mm) | ID (%) | IP | PT (°C) | BPT (°C) | PS (mm/s) | FS (%) |
|----|---------|---------|---------|---------|--------|----|---------|----------|-----------|--------|
| 1  | 0.4     | 0.1     | 0.75    | 1.6     | 80     | C  | 200     | 50       | 40        | 100    |
| 2  | 0.4     | 0.1     | 0.75    | 1.6     | 80     | C  | 200     | 50       | 60        | 50     |
| 3  | 0.4     | 0.1     | 0.75    | 1.6     | 80     | C  | 200     | 50       | 80        | 75     |
| 4  | 0.4     | 0.1     | 1       | 1.2     | 20     | T  | 210     | 60       | 40        | 100    |
| 5  | 0.4     | 0.1     | 1       | 1.2     | 20     | T  | 210     | 60       | 60        | 50     |
| 6  | 0.4     | 0.1     | 1       | 1.2     | 20     | T  | 210     | 60       | 80        | 75     |
| 7  | 0.4     | 0.1     | 2       | 1.4     | 50     | G  | 190     | 55       | 40        | 100    |
| 8  | 0.4     | 0.1     | 2       | 1.4     | 50     | G  | 190     | 55       | 60        | 50     |
| 9  | 0.4     | 0.1     | 2       | 1.4     | 50     | G  | 190     | 55       | 80        | 75     |
| 10 | 0.4     | 0.2     | 0.75    | 1.4     | 80     | G  | 210     | 60       | 40        | 75     |
| 11 | 0.4     | 0.2     | 0.75    | 1.4     | 80     | G  | 210     | 60       | 60        | 100    |
| 12 | 0.4     | 0.2     | 0.75    | 1.4     | 80     | G  | 210     | 60       | 80        | 50     |
| 13 | 0.4     | 0.2     | 1       | 1.6     | 20     | C  | 190     | 55       | 40        | 75     |
| 14 | 0.4     | 0.2     | 1       | 1.6     | 20     | C  | 190     | 55       | 60        | 100    |
| 15 | 0.4     | 0.2     | 1       | 1.6     | 20     | C  | 190     | 55       | 80        | 50     |
| 16 | 0.4     | 0.2     | 2       | 1.2     | 50     | T  | 200     | 50       | 40        | 75     |
| 17 | 0.4     | 0.2     | 2       | 1.2     | 50     | T  | 200     | 50       | 60        | 100    |
| 18 | 0.4     | 0.2     | 2       | 1.2     | 50     | T  | 200     | 50       | 80        | 50     |
| 19 | 0.4     | 0.15    | 0.75    | 1.6     | 50     | T  | 190     | 60       | 40        | 100    |
| 20 | 0.4     | 0.15    | 0.75    | 1.6     | 50     | T  | 190     | 60       | 60        | 50     |
| 21 | 0.4     | 0.15    | 0.75    | 1.6     | 50     | T  | 190     | 60       | 80        | 75     |
| 22 | 0.4     | 0.15    | 1       | 1.2     | 80     | G  | 200     | 55       | 40        | 100    |
| 23 | 0.4     | 0.15    | 1       | 1.2     | 80     | G  | 200     | 55       | 60        | 50     |
| 24 | 0.4     | 0.15    | 1       | 1.2     | 80     | G  | 200     | 55       | 80        | 75     |
| 25 | 0.4     | 0.15    | 2       | 1.4     | 20     | C  | 210     | 50       | 40        | 100    |
| 26 | 0.4     | 0.15    | 2       | 1.4     | 20     | C  | 210     | 50       | 60        | 50     |
| 27 | 0.4     | 0.15    | 2       | 1.4     | 20     | C  | 210     | 50       | 80        | 75     |

Table 3.8: Taguchi L54 DOE: Experiments 28-54 with 0.25 mm Nozzle Diameter. Abbreviations — ND: Nozzle Diameter; LH: Layer Height; WT: Wall Thickness; TT: Top Thickness; ID: Infill Density; IP: Infill Pattern (C: Cubic, G: Grid, T: Triangle); PT: Printing Extrusion Temperature; BPT: Build Plate Temperature; PS: Print Speed; FS: Fan Speed.

| No | ND (mm) | LH (mm) | WT (mm) | TT (mm) | ID (%) | IP | PT (°C) | BPT (°C) | PS (mm/s) | FS (%) |
|----|---------|---------|---------|---------|--------|----|---------|----------|-----------|--------|
| 28 | 0.25    | 0.1     | 0.75    | 1.2     | 20     | G  | 190     | 50       | 40        | 50     |
| 29 | 0.25    | 0.1     | 0.75    | 1.2     | 20     | G  | 190     | 50       | 60        | 75     |
| 30 | 0.25    | 0.1     | 0.75    | 1.2     | 20     | G  | 190     | 50       | 80        | 100    |
| 31 | 0.25    | 0.1     | 1       | 1.4     | 50     | C  | 200     | 60       | 40        | 50     |
| 32 | 0.25    | 0.1     | 1       | 1.4     | 50     | C  | 200     | 60       | 60        | 75     |
| 33 | 0.25    | 0.1     | 1       | 1.4     | 50     | C  | 200     | 60       | 80        | 100    |
| 34 | 0.25    | 0.1     | 2       | 1.6     | 80     | T  | 210     | 55       | 40        | 50     |
| 35 | 0.25    | 0.1     | 2       | 1.6     | 80     | T  | 210     | 55       | 60        | 75     |
| 36 | 0.25    | 0.1     | 2       | 1.6     | 80     | T  | 210     | 55       | 80        | 100    |
| 37 | 0.25    | 0.2     | 0.75    | 1.2     | 50     | C  | 210     | 55       | 40        | 50     |
| 38 | 0.25    | 0.2     | 0.75    | 1.2     | 50     | C  | 210     | 55       | 60        | 75     |
| 39 | 0.25    | 0.2     | 0.75    | 1.2     | 50     | C  | 210     | 55       | 80        | 100    |
| 40 | 0.25    | 0.2     | 1       | 1.4     | 80     | T  | 190     | 50       | 40        | 50     |
| 41 | 0.25    | 0.2     | 1       | 1.4     | 80     | T  | 190     | 50       | 60        | 75     |
| 42 | 0.25    | 0.2     | 1       | 1.4     | 80     | T  | 190     | 50       | 80        | 100    |
| 43 | 0.25    | 0.2     | 2       | 1.6     | 20     | G  | 200     | 60       | 40        | 50     |
| 44 | 0.25    | 0.2     | 2       | 1.6     | 20     | G  | 200     | 60       | 60        | 75     |
| 45 | 0.25    | 0.2     | 2       | 1.6     | 20     | G  | 200     | 60       | 80        | 100    |
| 46 | 0.25    | 0.15    | 0.75    | 1.4     | 20     | T  | 200     | 55       | 40        | 75     |
| 47 | 0.25    | 0.15    | 0.75    | 1.4     | 20     | T  | 200     | 55       | 60        | 100    |
| 48 | 0.25    | 0.15    | 0.75    | 1.4     | 20     | T  | 200     | 55       | 80        | 50     |
| 49 | 0.25    | 0.15    | 1       | 1.6     | 50     | G  | 210     | 50       | 40        | 75     |
| 50 | 0.25    | 0.15    | 1       | 1.6     | 50     | G  | 210     | 50       | 60        | 100    |
| 51 | 0.25    | 0.15    | 1       | 1.6     | 50     | G  | 210     | 50       | 80        | 50     |
| 52 | 0.25    | 0.15    | 2       | 1.2     | 80     | C  | 190     | 60       | 40        | 75     |
| 53 | 0.25    | 0.15    | 2       | 1.2     | 80     | C  | 190     | 60       | 60        | 100    |
| 54 | 0.25    | 0.15    | 2       | 1.2     | 80     | C  | 190     | 60       | 80        | 50     |

### 3.3 Additive Manufacturing of the Selected Design Using Taguchi L-54 DOE

This section describes the 3D printing procedure carried out based on the aforementioned DOE strategy involving a total of 54 experimental tests. The final part design shown in Figure 3.2 was printed through the use of FFF-AM. A concise overview of



the FFF process is given, including its major principles, components, and operating characteristics. The Ultimaker S5 printer [3], the one employed in this research for the fabrication of all samples, is also presented. The visual documentation of all 54 experimentally printed samples is provided to aid in experimental arrangement and sample identification.

### 3.3.1 FFF - Process and Components

Fabrication of the part in this work was achieved through FFF, a commonly embraced additive manufacturing method based on its cost competitiveness and design versatility [54]. With FFF, the part is constructed in response to a G-code file that defines toolpath instructions for each deposited layer. The process starts with a thermoplastic-based filament available in reel or spool form and fed into an extruder at a regulated rate. The material is melted as it is moved through a heated nozzle and deposited onto the build platform according to G-code instructions. The material cools and solidifies while being extruded and simultaneously bonds with previously deposited layers. The layer-by-layer deposition continues as the build platform slowly descends until it finally constructs a complete 3D part [2]. A basic outline of the mechanism of FFF extrusion is given in Figure 3.9.

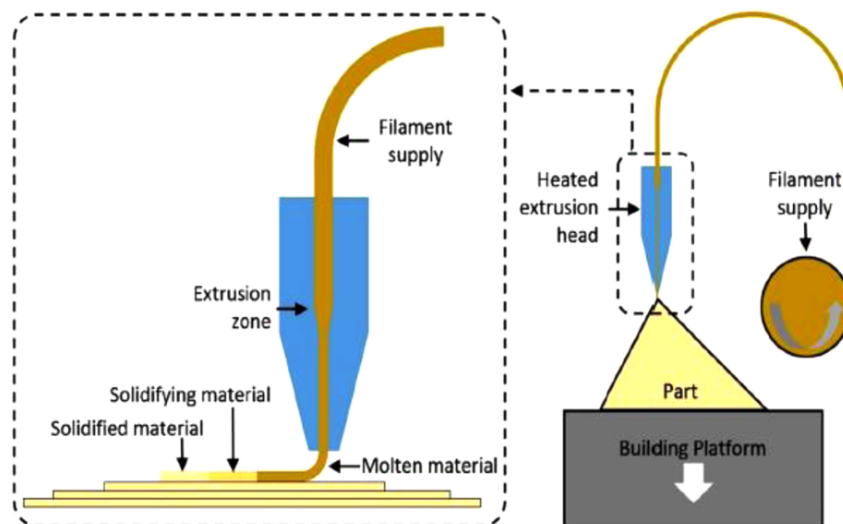


Figure 3.9: A FFF Schematic overview [54]

At the core of the FFF process is the extruder, which has four main sub-components: nozzle, hot end, cold end, and extrusion drive. The nozzle at the tip of the extruder has a precisely defined diameter that controls the volumetric flow rate of extruded filament. The nozzle is firmly attached to the hot end, normally through a threaded connection. The hot end deals with melting the filament through a cartridge heater and holding the extrusion temperature within its set operating range. On top of it sits the cold end equipped with dedicated cooling fans preventing heat creep through limiting thermal conduction upwards through the extruder assembly [55]. The thermal break between the hot and cold zones is normally through a metal barrel. A thermal break between the hot and cold zones ensures thermal isolation of the pre-heated and molten parts of the filament. The extrusion drive contains a stepper motor accompanied by a drive gear that grips and pushes the filament into the extruder with an appropriate amount of pressure. The drive structure guarantees persistent feeding of material from the cold end into the hot zone for continuous extrusion [56]. A diagram representation of the core and the extruder assembly can be seen in Figure 3.10.

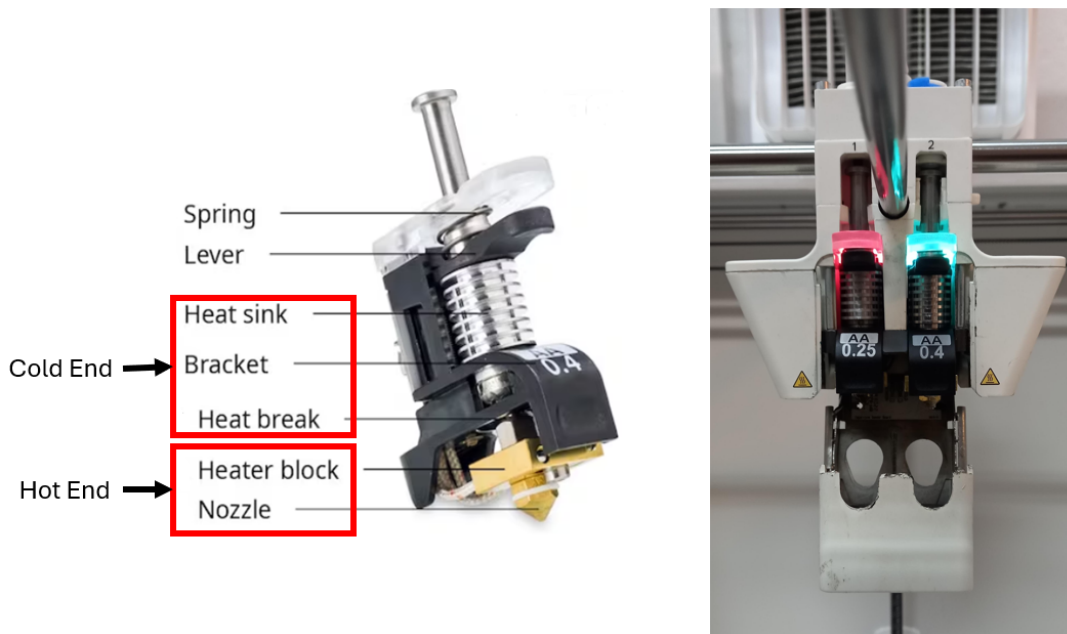


Figure 3.10: Ultimaker S5 Core and Extruder Assembly [3]

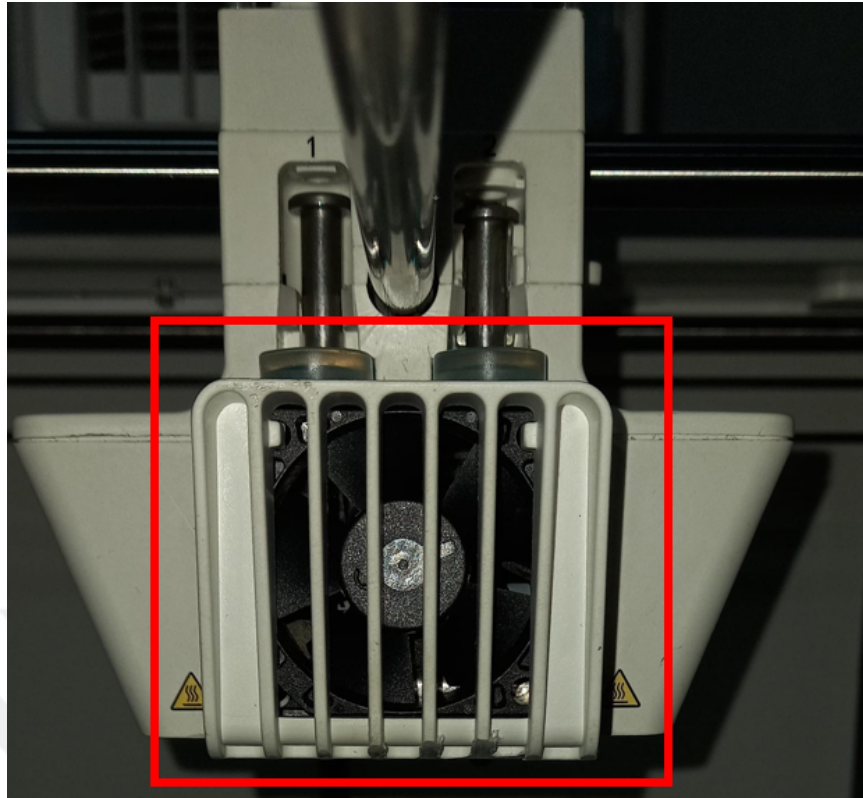


Figure 3.11: Cooling Fan in Ultimaker S5

Another integral part of the FFF system, apart from the extruder, is the heated print bed. The main role of the heated bed is to aid in having an optimum sticking of the first-printed layer. The heated bed provides uniform thermal conditions during printing in its formative stages, minimizing thermal gradients that are the principal causes of warping and deformation of individual layers in thermoplastic materials [57]. The printer's mainboard controls temperature regulation, motion coordination, and sensor feedback. An LCD-based user interface enables interaction with the system, allowing users to insert a memory card and load the corresponding G-code file for execution. The structural frame supports the mechanical components, while the enclosure helps maintain a stable internal environment by reducing thermal fluctuations [58]. A precision rail mechanism facilitates controlled movement of the extruder assembly and build platform across the X, Y, and Z axes. Integrated sensors provide critical functions such as automatic bed leveling, filament runout detection, and thermal monitoring to ensure consistent and reliable operation. Figures 3.12 and 3.13 show the Ultimaker S5 with the components labelled.

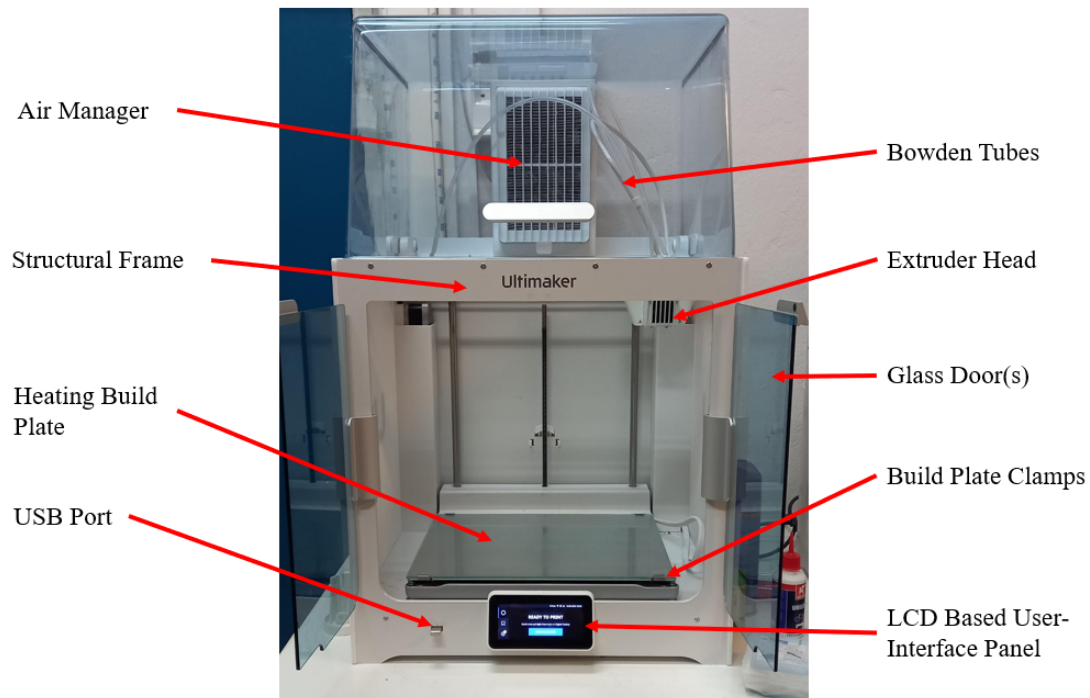


Figure 3.12: Ultimaker S5 used in this research

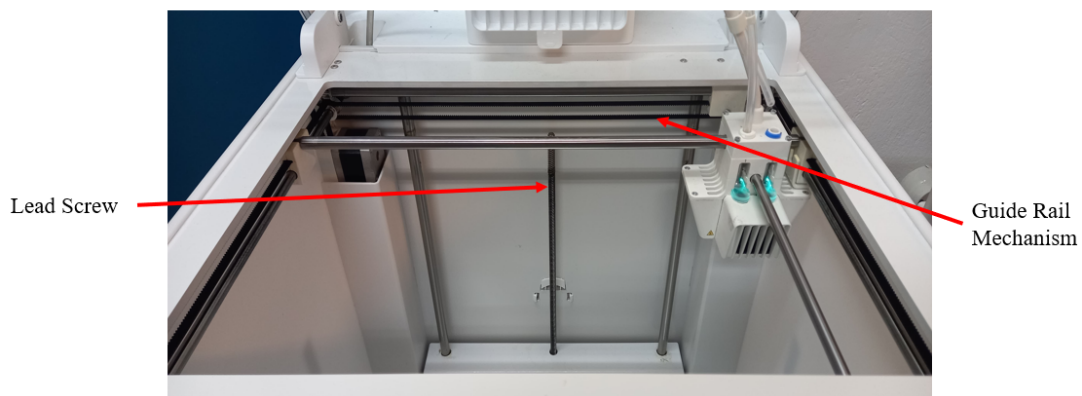


Figure 3.13: Guide Rail and Lead Screw

### 3.3.2 Hardware Specifications, Software Environment and Printing Procedure

Figures 3.12 and 3.13 mentioned above shows the hardware, i.e Ultimaker S5 [3], used in this study in detail, with the components labelled. Table 3.9 shows the Ultimaker S5 specifications:

Table 3.9: Technical specifications of the Ultimaker S5 printer [3]

| Parameters            | Values                                 |
|-----------------------|----------------------------------------|
| Technology            | Fused Filament Fabrication             |
| Print Head            | Dual Extrusion Print Head              |
| Build Volume          | 330 × 240 × 300 mm                     |
| Build Volumetric Rate | 24 mm <sup>3</sup> /s                  |
| Build Plate           | Heated Glass Build Plate (20 – 140 °C) |
| Nozzle Diameter       | 0.25, 0.4, 0.6 and 0.8 mm              |
| Physical Dimensions   | 495 × 457 × 520 mm                     |
| Weight                | 20.6 kg                                |
| Power                 | Max 500 W                              |

The specifications in Table 3.9 are present in the user manual of Ultimaker S5 given at the Ultimaker website. The software used for setting the input parameters was Ultimaker Cura version 5.5.0 [24]. Figure 3.14 shows the Ultimaker Cura environment.

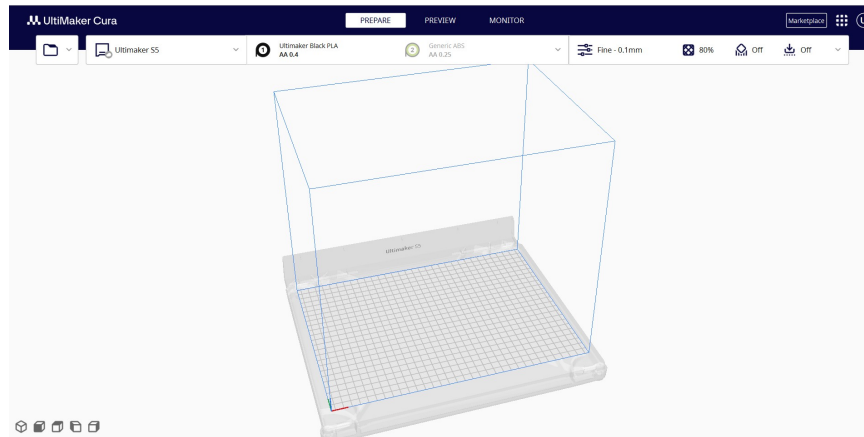


Figure 3.14: Ultimaker Cura Environment [24]

Figure 3.15 shows the import of the design in the Cura environment. The model was reoriented so that it can sit flat on the printer surface.

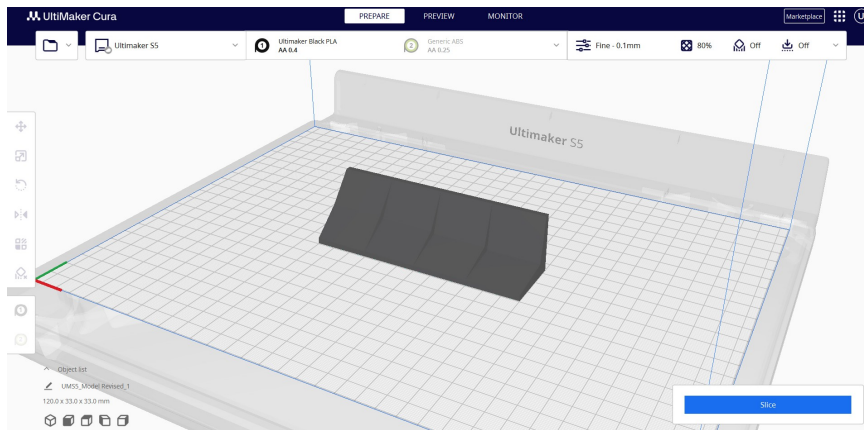


Figure 3.15: Design Imported in Cura

After the design was imported in Cura, the input parameter selection was carried out one by one, starting from the core selection and material as shown in the Figure 3.16.

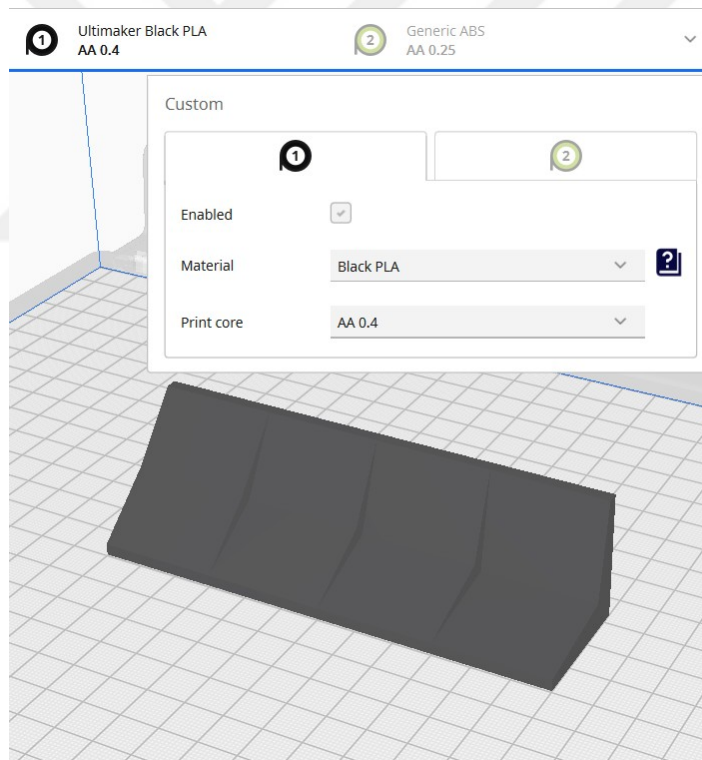


Figure 3.16: Core and Material Selection

Following the selection of the core and material, the remaining process parameters, including layer height, wall thickness, top thickness, infill density, infill pattern, Ex-



trusion temperature, build plate temperature, print speed, and fan speed, were assigned based on the Taguchi L54 design of experiments (DOE). The accompanying Figure 3.17 illustrate the parameter settings applied for the first sample as a representative example.

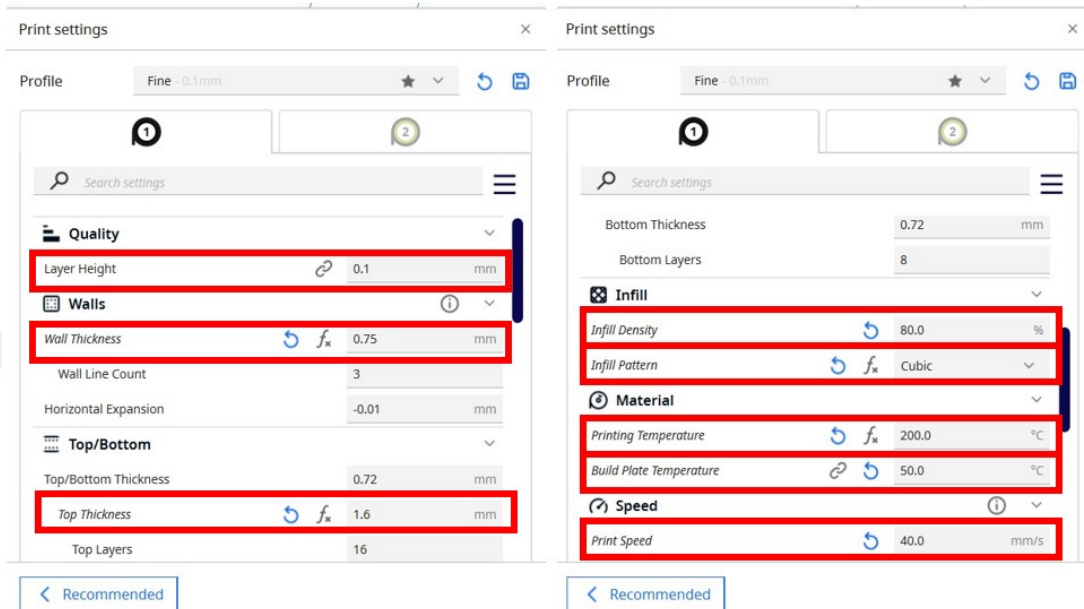


Figure 3.17: Layer Height, Wall Thickness, and Top Thickness, Infill Density, Infill Pattern, Printing Temperature, Build Plate Temperature, and Print Speed

In addition to the selected fan speed values, no support structures were used during the printing process. This decision was intentional, as the part geometry was specifically designed to consist of generally inclined surfaces, thereby eliminating the need for support material. The presence of supports can significantly influence the measured surface roughness due to contact marks and residual artifacts, and their removal introduces an additional post-processing step that can affect consistency and accuracy in surface evaluation. Furthermore, brim was chosen as the build plate adhesion type to ensure strong attachment of the initial layers to the build plate. This helps to prevent warping or detachment during printing, especially for the bottom layers, thereby ensuring dimensional stability and repeatability across all experimental samples. Figure 3.18 represents the selection of these settings.

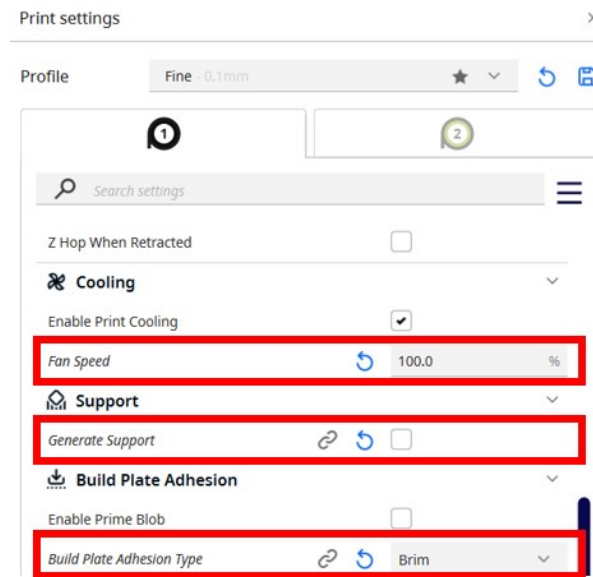


Figure 3.18: Fan Speed, No Supports and Brim Adhesion

Once all input parameters were configured within the Cura slicing environment, the slicing process was performed to generate the corresponding G-code for 3D printing. Figure 3.19 illustrates a visual representation of the sliced model.

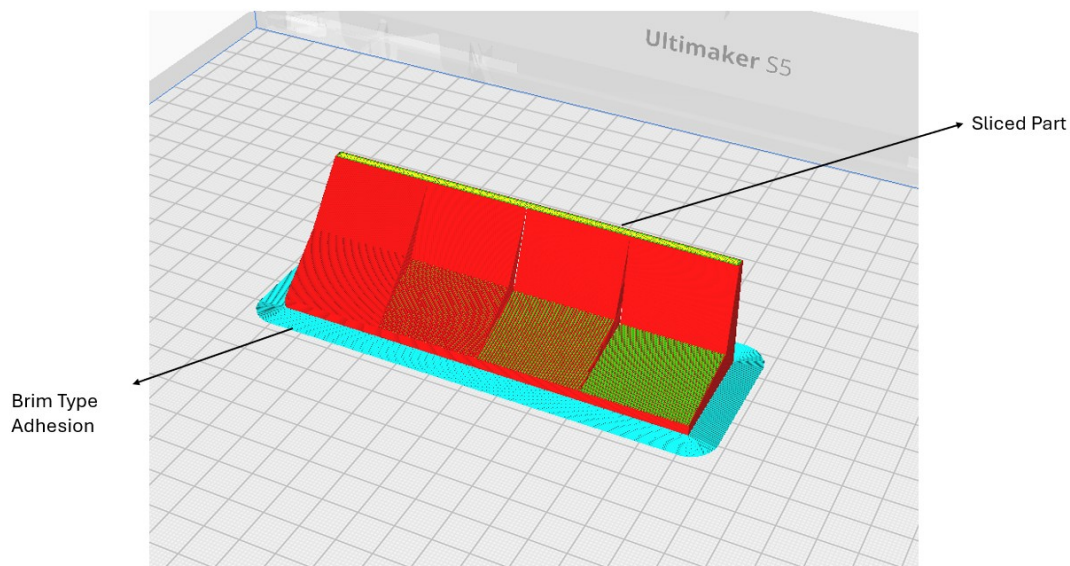


Figure 3.19: Sliced Model with Brim Adhesion - Isometric View

Figure 3.20 illustrates the inclined surfaces incorporated into the sliced model.



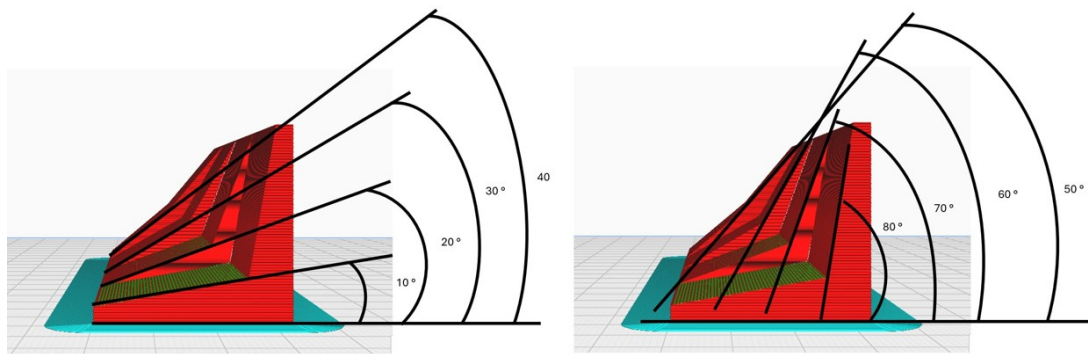


Figure 3.20: Labelled Angled Surfaces in Cura - Right View

Figures 3.21, 3.22, and 3.23 show the top view of the internal structures of the model in the Cura environment.

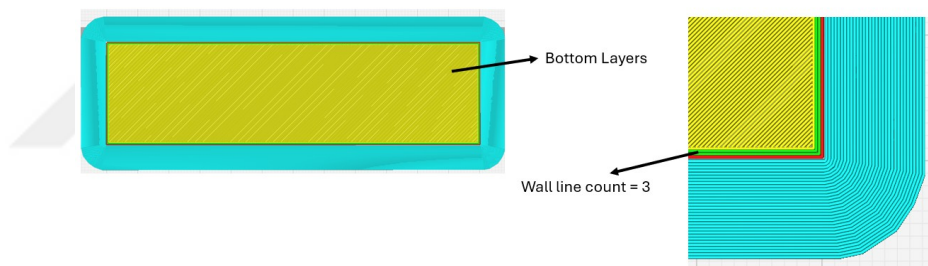


Figure 3.21: Initial Internal Structure - Top View

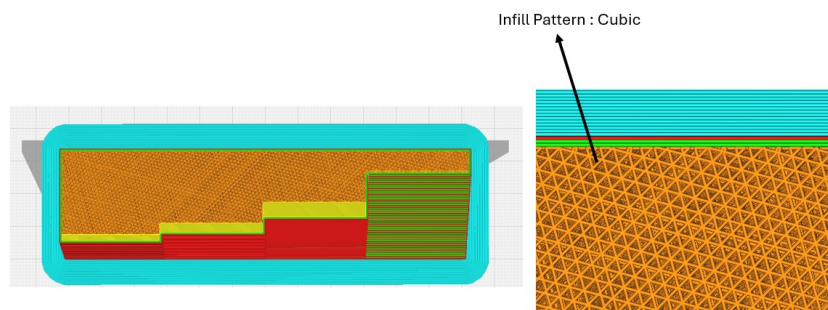


Figure 3.22: Intermediate Internal Structure - Top View

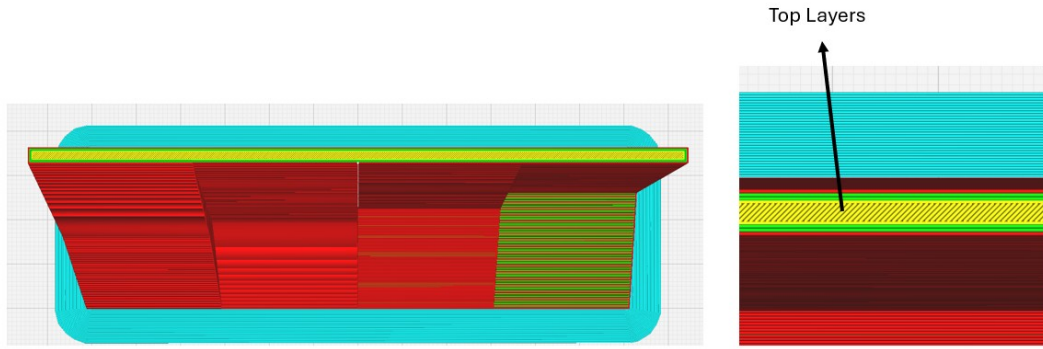


Figure 3.23: Final Structure - Top View

After slicing, the created G-code file was uploaded into the Ultimaker S5 for execution of the print operation. Careful monitoring was conducted throughout the first few stages for a right first-time adhesion of the bottom layers onto the build plate, since successful print quality and accurate dimensions are especially important at this point. Figures 3.24 and 3.25 presented herein record the printing process at the initial and final stages, demonstrating the sample being created.

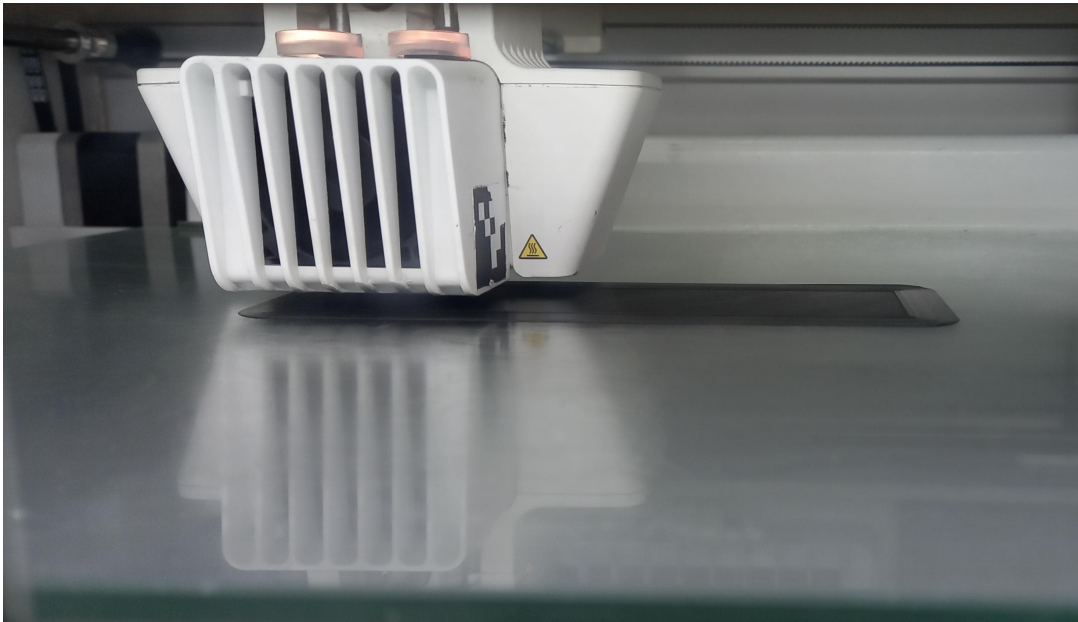


Figure 3.24: Initial Print Stage

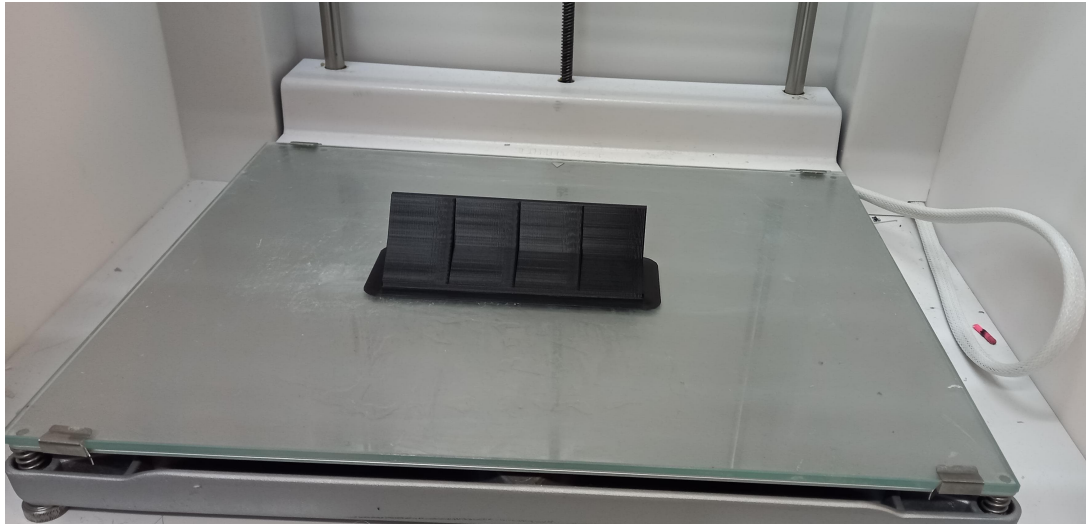
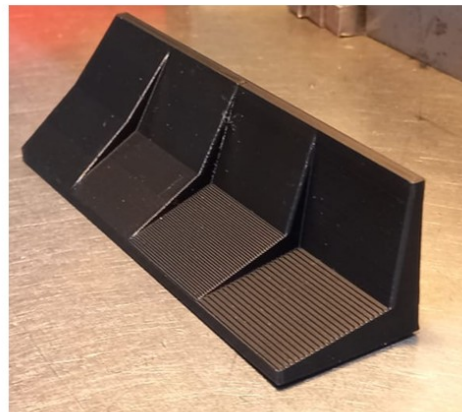


Figure 3.25: Final Print Stage

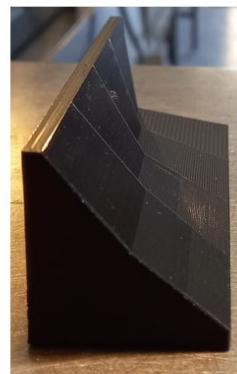
The isometric view, front view, left view, and right view of the part printed are shown in Figure 3.26.



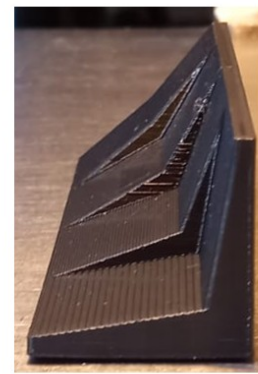
Isometric View



Front View



Left View



Right View

Figure 3.26: Isometric, Front, Left, and Right Views of AM sample

All 54 samples were fabricated using the same standardized methodology to ensure consistency across the experimental process. The images of the completed samples



are provided in Figures 3.27 and 3.28. They have been categorized based on the nozzle diameter used during printing: 27 samples were produced with a 0.4 mm nozzle, and the remaining 27 samples with a 0.25 mm nozzle. This large-scale production was carried out specifically to generate a diverse and comprehensive set of data aimed at creating dependable machine learning models to predict the surface roughness of both additively manufactured and machined components. By incorporating a large number of parameter combinations, the aim was to ensure that the resulting data reflected the complex interactions and effects of the many process variables on surface quality.

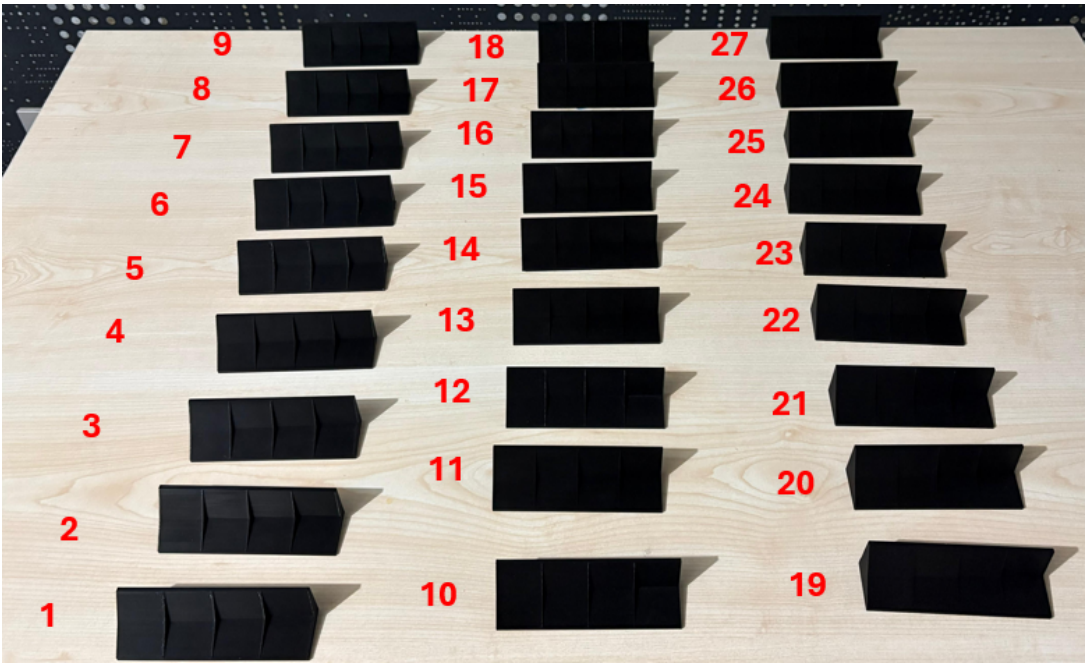


Figure 3.27: 0.4 mm Nozzle Parts 1-27

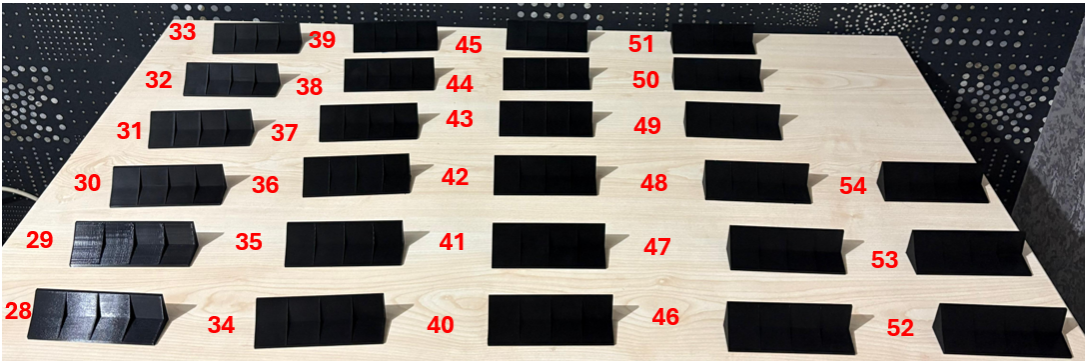


Figure 3.28: 0.25 mm Nozzle Parts 28-54

### **3.4 Surface Roughness Measurements**

This section provides a detailed explanation of surface roughness parameters, with a particular focus on the parameter arithmetic average height selected for quantifying surface roughness in accordance with the existing literature. It offers a concise overview of the various surface texture parameters and their significance. Furthermore, the section outlines the methodology employed for surface roughness measurements on the additively manufactured components and presents the technical specifications of the equipment used in the experimental analysis.

#### **3.4.1 Surface Roughness - Parameters and Characterization**

As discussed in preceding chapters, surface roughness is a significant quality parameter, of particular significance for FFF process parts. FFF parts have comparatively high surface finish primarily because of the staircase effect, due to layer-by-layer additions of material to the build plate. Surface finish is formally defined as the repeating or varied deviation of an ideal, extremely smooth surface, of the three-dimensional part topology [59]. It encompasses various forms of surface irregularity, which are also an indicator of the quality of the process related to manufacturing and have a direct effect on the functional and aesthetic performance of the final component. The basic evaluation of the surface roughness is carried out by analyzing the fine-scale irregularities of a profile which is a section of the real surface. This profile is analyzed on specific segments, called the sampling length [60]. According to ISO 4287-1997, a sampling length is defined as the nominal length which is related to the wavelength of the roughness filter. In other words a single roughness measurement is carried out on a sampling length. These sampling lengths together make up the evaluation length which is composed of five consecutive sampling lengths [28]. To quantitatively assess surface roughness, a variety of parameters are employed, among which amplitude parameters hold particular importance, as they describe the vertical deviations of the surface profile. The most widely recognized and universally applied amplitude parameter is the arithmetical mean roughness, denoted as  $R_a$ . Also referred to as the center line average (CLA),  $R_a$  is defined as the average of the absolute deviations of the surface irregularities from the mean line over a single sampling

length. Its simplicity and effectiveness make it a standard reference in both industrial and academic contexts for characterizing surface roughness [61]. The mathematical formula for calculating Ra is given in Equation 3.8.

$$\mathbf{Ra} = \frac{1}{l} \int_0^l |y(x)| dx \quad (3.8)$$

This equation represents the continuous form of the equation where  $l$  represents the evaluation length and  $y(x)$  represents the profile height function relative to the mean line. The discrete form of Ra is given in Equation 3.9.

$$\mathbf{Ra} = \frac{1}{n} \sum_{i=1}^n |y_i| \quad (3.9)$$

where  $n$  represents the number of specified points in the sampling length.

Another significant surface roughness parameter is the Root Mean Square roughness, denoted as Rq. It is defined as the standard deviation of the surface height distribution relative to the mean line, providing a measure of the spread of surface deviations. Compared to the mean roughness of arithmetic Ra, the Rq parameter is more sensitive to larger deviations due to the squaring of height values, which makes it extremely important for detecting peaks and valleys. The mathematical formulations for both the continuous and discrete representations are presented in Equations 3.10 and 3.11:

$$\mathbf{Rq} = \sqrt{\frac{1}{l} \int_0^l \{y(x)\}^2 dx} \quad (3.10)$$

$$\mathbf{Rq} = \sqrt{\frac{1}{n} \sum_{i=1}^n y_i^2} \quad (3.11)$$

Ten-point height Rz is defined as the difference of the average of the five highest peaks and the five lowest valleys along the assessment length. It is the most sensitive parameter to sudden vertical deviations compared to other roughness parameters. The mathematical formula used for discrete points is given in Equation 3.12.

$$R_z = \frac{1}{n} \left( \sum_{i=1}^n p_i - \sum_{i=1}^n v_i \right) \quad (3.12)$$

Figure 3.29 has been taken as an example from one of the readings carried out on a surface in this study. It illustrates the parameters mentioned above as well as the sampling length, and the evaluation length. The peaks are given above the mean line corresponding to the zero value on the y-axis, and the valleys are below the mean line.

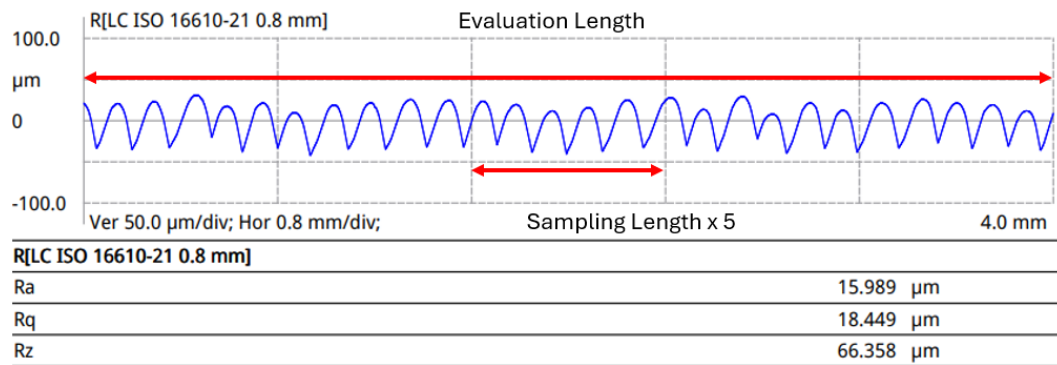


Figure 3.29: Surface Roughness Parameters

### 3.4.2 Surface Roughness Measurements on AM Parts Using Custom Printed Fixtures

A comprehensive literature survey was conducted to examine the methodologies employed for surface roughness measurement, with a particular focus on the parameters used to quantify surface texture and the measurement instruments applied in the context of AM and hybrid components. The aim was to identify prevailing practices, evaluate parameter selection, and assess the types of apparatuses utilized across various studies. A summary and comparative analysis of the measurements are presented in the following table. Table 3.10 is structured into four columns, presenting the types of surface roughness parameters examined, the number of readings obtained per part during the measurements, and the specific apparatuses employed for surface roughness evaluation.

Table 3.10: Comparative Analysis of Literature Studies Using Various Roughness Parameters, Readings and Apparatuses

| Studies | Roughness Parameter | Readings | Apparatuses                                   |
|---------|---------------------|----------|-----------------------------------------------|
| [5]     | Ra, Rq, Rt          | -        | Taylor Hobson Talysurf Plus Profilometer      |
| [6]     | Ra                  | 1        | Taylor Hobson Talysurf 2 contact meter        |
| [7]     | Ra                  | 4        | Mitutoyo SJ-10, surface roughness tester      |
| [10]    | Ra                  | 3        | Profilometer                                  |
| [11]    | Ra                  | 5        | Mitutoyo perthometer model SJ-201             |
| [12]    | Ra                  | 5        | Mitutoyo perthometer model SJ-201             |
| [13]    | Ra                  | 5        | Surface Roughness Tester                      |
| [15]    | Ra                  | -        | SV-C4500 Mitutoyo Formtracer                  |
| [16]    | Ra                  | 8        | Taylor Hobson profilometer                    |
| [17]    | Ra                  | 2        | Mitutoyo Surftest SJ-210                      |
| [18]    | Ra                  | 5        | g OLS40-SU laser confocal microscope          |
| [19]    | Ra                  | 3        | Taylor Hobson surface roughness tester        |
| [20]    | Ra                  | 3        | Contact Profilometer                          |
| [21]    | Ra                  | -        | -                                             |
| [22]    | Ra                  | 2        | MahrSurf MFW250 surface scanner               |
| [23]    | Ra                  | 1        | TALYSURF-6 measuring system                   |
| [25]    | Ra                  | -        | Mitutoyo Surftest SJ-210                      |
| [26]    | Ra                  | -        | SPI Portable Roughness Tester                 |
| [27]    | Ra                  | -        | Bruker-Nano Contour GT-K Optical Profilometer |
| [29]    | Ra, Rz              | -        | MarSurf PS 10 surface profilometer            |
| [30]    | Ra                  | 1        | Mitutoyo Contracer CP—200/400                 |
| [34]    | Ra                  | -        | SJ-410                                        |
| [35]    | Ra                  | 6        | Mitutoyo Surftest SJ-210                      |
| [43]    | Ra                  | 5        | Mitutoyo Surftest SJ-210                      |

As evidenced by Table 3.10, the arithmetic mean roughness, Ra, is the most frequently reported parameter in the surveyed literature. To ensure consistency with prior work and facilitate meaningful comparisons, Ra is therefore adopted as the principal surface-roughness metric in the present study. The apparatus which was used during this research is a MarSurf PS 10 Surface Profilometer equipped with a stylus of 2 $\mu$ m, which was seen to be used in the research carried out in [29]. The sampling



length was set to be 0.8 mm, and the total evaluation length was 4mm. Figure 3.30 displays the apparatus used for surface roughness measurement.



Figure 3.30: MasrSurf PS 10 Surface Roughness Profilometer [62]

Due to the inclination angles present in the manufactured part, custom fixtures needed to be designed and manufactured in order to take readings in the direction perpendicular to the extrusion path as mentioned in the studies by Cerro et al. [12] and Martin et al [43]. Four unique custom fixtures were designed and built to accommodate surface inclination angle sets between  $10^\circ$  and  $80^\circ$ ,  $20^\circ$  and  $70^\circ$ ,  $30^\circ$  and  $60^\circ$ , and  $40^\circ$  and  $50^\circ$ . Utilization of the fixtures made sure that any inclined surface was oriented horizontally for measurement with the profilometer stylus traversing perpendicular to the extrusion path. Figures 3.31, 3.32, 3.33, and 3.34 represent the fixtures and the parts placed on them.



Figure 3.31: Fixture and The Part Placed for  $10^\circ$  and  $80^\circ$



Figure 3.32: Fixture and The Part Placed for 20° and 70°

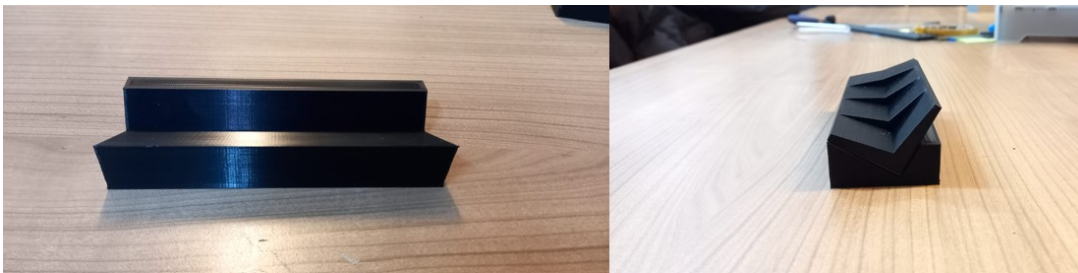


Figure 3.33: Fixture and The Part Placed for 30° and 60°

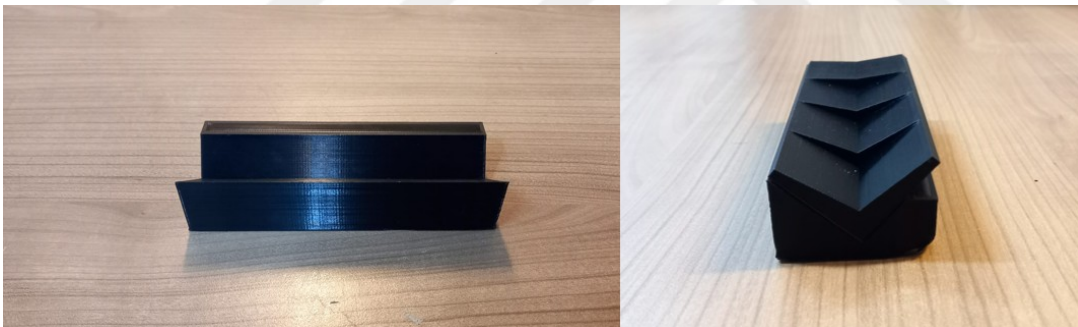


Figure 3.34: Fixture and The Part Placed for 40° and 50°

As illustrated in the figures above, the placement of the parts onto the specifically designed fixtures effectively ensured that the inclined surfaces were positioned in a horizontal orientation during measurement.

Following the alignment of the parts onto the specially designed fixtures, the leveling of the inclined surfaces was required for the elimination of any potential sources of measurement errors. A metal cube was used at the rear end of each fixture for the purpose, serving as a mechanical restraint for the avoidance of movement or shift

upon the functioning of the profilometer. This ensured a fixed alignment of the surfaces throughout the measurement process. This complete experimental setup with the fixture, metal block, and the profilometer is depicted in Figure 3.35.

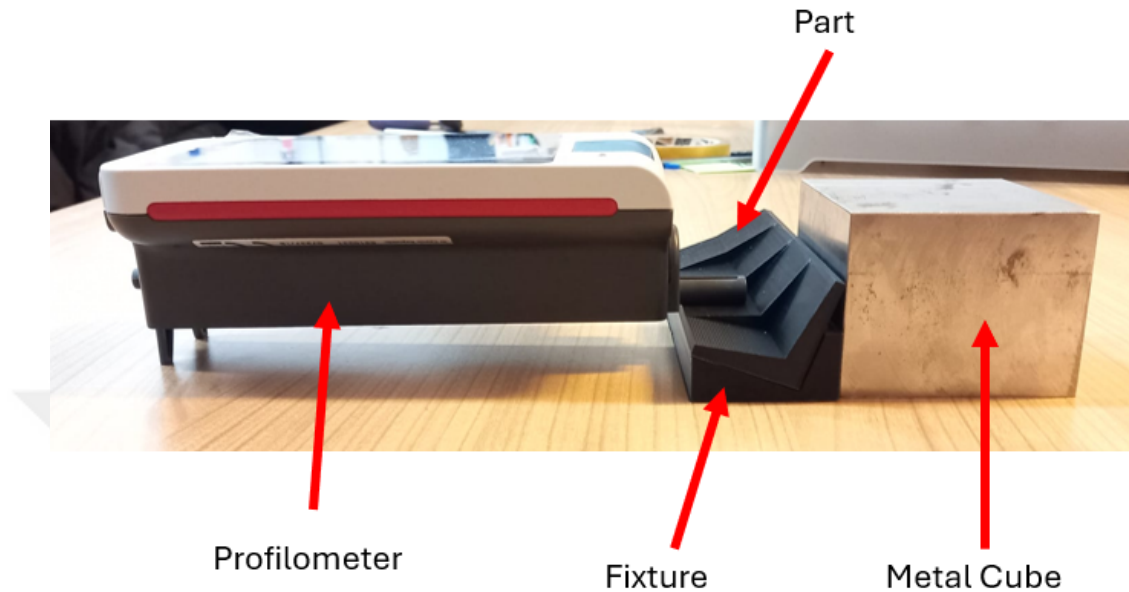


Figure 3.35: Complete Setup for Roughness Measurement

For each inclined surface, a set of three surface roughness measurements was obtained, one from the left edge, one from the center, and one from the right edge. The arithmetic average of these three readings was then calculated to determine the representative  $R_a$  value for that surface. The purpose of taking three readings was to make sure that the manufacturing errors were minimally reflected during the measurements. Although Table 3.10 indicates that some studies employed five measurements per surface for averaging, in this research, three representative readings were deemed sufficient. This decision was made to balance measurement reliability with experimental efficiency, particularly given the extensive number of samples involved. Figure 3.36 indicate the respective areas for measurement for surface roughness for the surface inclined at  $10^\circ$ . This figure depicts the right, middle, and left regions for measurements. The same procedure was applied to all the inclined surfaces and expanded to all 54 parts. The surface roughness data can be accessed for all 54 parts by following the link in Appendix A.



Figure 3.36: Surface Roughness Measurement Regions- Right, Middle, and Left

A sample measurement Table 3.11 is given for the part numbered as one, showing all three Ra their averages, and the standard deviation computed for all the inclined surfaces. The standard deviation did not exceed  $0.51 \mu\text{m}$  corresponding to less than 3% of the Ra values showcasing high degree of consistency and reliability in the measurements.

Table 3.11: Surface Roughness Measurements at Three Regions for Part 1 on All Angles

| Angle ( $^{\circ}$ ) | Ra Right ( $\mu\text{m}$ ) | Ra Middle ( $\mu\text{m}$ ) | Ra Left ( $\mu\text{m}$ ) | Ra Average ( $\mu\text{m}$ ) | Std Dev ( $\mu\text{m}$ ) |
|----------------------|----------------------------|-----------------------------|---------------------------|------------------------------|---------------------------|
| 10                   | 15.252                     | 15.955                      | 16.242                    | 15.816                       | 0.5094                    |
| 20                   | 18.425                     | 18.573                      | 19.367                    | 18.788                       | 0.5066                    |
| 30                   | 17.657                     | 17.324                      | 17.570                    | 17.517                       | 0.1727                    |
| 40                   | 15.989                     | 15.362                      | 16.178                    | 15.843                       | 0.4271                    |
| 50                   | 12.844                     | 12.775                      | 12.668                    | 12.762                       | 0.0887                    |
| 60                   | 11.511                     | 11.538                      | 11.399                    | 11.483                       | 0.0719                    |
| 70                   | 10.132                     | 9.794                       | 9.909                     | 9.945                        | 0.0587                    |
| 80                   | 9.445                      | 9.506                       | 9.783                     | 9.578                        | 0.1800                    |

In addition to the data presented in Table 3.11, Figure 3.37 provide a visual representation of the surface roughness measurements obtained at a  $10^{\circ}$  inclination angle from three distinct regions—namely, the left, center, and right areas of the surface.

MarSurf PS 10 surface profilometer, not only outputs the arithmetic average roughness (Ra) values but also provide PDF reports. Each report includes a corresponding surface profile graph generated as the stylus traverses the measured surface.



Figure 3.37: Right, Middle, and Left Readings for 10° Surface of Part 1

### 3.5 Hybrid-Machining Process

This section presents the experimental procedures undertaken to improve the surface quality of AM parts through post-processing via CNC machining. The primary objective was to reduce surface roughness by introducing a supplementary finishing operation using the milling process. A detailed description of the CNC milling procedure is provided, including an overview of the machining parameters considered, informed by a thorough review of relevant literature. The methodology employed to execute the machining trials is systematically outlined, with a particular focus on varying the depth of cut to evaluate its influence on surface roughness. Furthermore, this section addresses the role of cutting fluids specifically, coolant application as an auxiliary process aimed at improving the effectiveness and quality of the machining

operation.

### **3.5.1 Role of CNC Milling in the Hybrid (Additive-Subtractive) Process and its Cutting Parameters**

Earlier chapters also emphasized the high surface roughness characteristic of additively manufactured (AM) parts by virtue of the layer-on-layer addition typical of AM technologies. Besides, the quantitative findings tabulated in Table 3.11 clearly indicate the high values of roughness assessed on inclined surfaces between 10° and 80° for part 1. These outcomes also indicate the requirement for an effective post-processing technique capable of removing surface anomalies. Any such procedure must prove time-efficient, cost-efficient, as well as scalable for volume-industrial applications. In such a context, CNC milling does prove to be a highly viable choice in terms of offering accuracy, scalability, and AM-material compatibility [63].

CNC milling is a subtractive manufacturing technique operating by using G-code—a machine language specifying the exact movement of the tool as well as operations for creating a part. Such G-code is input into the machine controller and serves as a series of instructions controlling the cutting instrument by predefined paths to mimic the part's intended geometry. To realize this, there are various Computer-Aided Manufacturing (CAM) software tools through which the users can design as well as verify the milling procedure. On the software, the users input the part geometry, fixtures, as well as areas to be machined. The CAM software then automatically creates the G-code, significantly reducing the programming effort required.

For the specific case of hybrid additive-subtractive manufacturing, where post-processing is performed by machining on additive-built parts, some specific parameters must be entered into the CAM software. These are the depth of cut, feed rate, and spindle speed. These are by far more commonly emphasized in the literature. These are critical for specifying post-process operation surface finish quality, dimensional accuracy, as well as overall efficiency. With optimal selection and adjustment of these variables, the addition of CNC milling into additive processes becomes not only viable but also highly effective for improved surface quality as well as ultimate functional properties. The usage of the milling tool also carries high significance and should be determined



according to the material of the part [23].

Spindle speed is defined as the speed of rotation of the spindle, determining how fast the cutting tool rotates during machining. The formula for the spindle speed is given in Equation 3.13.

$$N = \frac{1000 \times V_c}{\pi \times D} \quad (3.13)$$

Here,  $N$  represents the spindle speed in rpm,  $V_c$  represents the cutting speed in m/min and  $D$  represents the tool diameter in mm [64].

Depth of cut  $a_p$  is defined as the amount of material removed when the tool completes a single pass. It is measured perpendicular to the machining surface. The cutting feed rate  $V_f$  is defined as the rate at which the tool advances into the workpiece and is a combination of spindle speed, feed per tooth and number of tool teeth (flutes). Equation 3.14 for the cutting feed rate is given below.

$$V_f = N \times Z \times f_z \quad (3.14)$$

Here,  $N$  represents the spindle speed,  $Z$  represents the number of flutes, and  $f_z$  represents the feed per tooth [65].

From a comprehensive literature search on relevant journal articles, ranges for principal machining variables notably spindle speed, depth of cut, and feed rate of cut, diameter of the tool, and no of flutes were inferred. They are tabulated accordingly in the Table 3.12 as follows. The parameter value choice for this work was dictated by data reported by work previously carried out, so as to achieve experimental conditions consistent with existing practice and within substantiated ranges of operation.

Table 3.12: Summary of CNC Machining Parameters Used in Literature

| Studies | N (rpm)       | ap (mm)       | V <sub>f</sub> (mm/min) | D (mm)   | Flutes  | CNC Machine    |
|---------|---------------|---------------|-------------------------|----------|---------|----------------|
| [23]    | 3000 - 6000   | 0.3, 0.6, 1   | 400 - 1000              | 6        | 3       | HAAS VF 3SS    |
| [29]    | 1000 - 6500   | 0.05 - 0.4    | 240 - 1080              | 6, 8, 12 | 1, 3, 4 | Custom Machine |
| [30]    | 500 - 10000   | 0.1, 0.2, 0.3 | 80 - 400                | 6        | 4       | —              |
| [66]    | 3500          | 3, 6          | 280 - 420               | 6, 12    | 2       | DMC 635V       |
| [67]    | 10000 - 21000 | 0.1 – 0.7     | 200 - 600               | —        | —       | Custom Machine |

As can be seen from the table above, there are not a lot of studies focusing on improving the surface roughness in the hybrid context specifically for the PLA parts. Hence, this research aimed to fill this gap by providing large-scale experimentation on this topic.

### 3.5.2 CNC Milling Process on AM Parts, CAM Software, Depth of Cut and Surface Roughness Measurements

In this study, 54 specimens were additively manufactured based on the Taguchi L54 design of experiments (DOE), incorporating a diverse range of input parameters. Since the final objective is to study the joint effect of AM parameters alongside those for CNC milling on final surface roughness, values for milling process parameters were selected by referring to pertinent literature tabulated in Table 3.12. Although the original plan was to experiment with three significant milling parameters—the spindle speed, feed rate, and depth of cut—with three varying levels for each another during experimentation, such a scheme proved to be impractical given the time- and resource-conscious nature it would bear. More specifically, it would translate into subdivision of each of the inclined surfaces into 27 individual regions to accommodate all possible parameter combinations, significantly increasing experimental complexity as well as time resources.

To ensure a focused and manageable experimental framework, the most practical strategy adopted in this study was to hold two of the machining parameters constant spindle speed and cutting feed rate while systematically investigating the third pa-



parameter, namely depth of cut, which remains relatively underexplored in the existing literature concerning PLA parts fabricated via fused filament fabrication (FFF).

With respect to spindle speed, other works also provided recommendations on optimal ranges. Djurovic et al. [23] stated that a spindle speed of 3000 rpm delivered superior surface roughness values over wider rotational speeds. Uğur et al. [29] cautioned against high spindle speeds since materials melted and adhered to the tool, such that it could lead to processing errors with respect to dimensions as well as tool wear. Accordingly, they recommended the range 1000–6500 rpm for spindle speed. Similarly, Pamarac et al. [66] stated that 3500 rpm was an optimum value for processing PLA parts, where improved surface finish outcomes were recorded at this setting. Grguras et al. [67] also confirmed the fact that over-speeds lead to an entanglement/welding of the material on the tool with resultant processing errors and low part quality. Due to such observations in this case work, a stable spindle speed setting of 4000 rpm was selected so as to fit nicely into the proposed safe operating range by Uğur et al. [29], remain near the optimum value by Pamarac et al. [66], as 3500 rpm, while avoiding the detrimental thermal effects during high-speed processing.

Together, the feed rate during cutting was also decided using observations compiled from the literature. It was seen by Djurovic et al. [23] that minimum surface roughness was achieved when the feed rate was 400 mm/min. Uğur et al. [29] also suggested an operating range between 240–1080 mm/min, which is within a safe zone for efficient cutting with minimal distortion in the materials. In yet one more contribution, Pamarac et al. [66] utilized feed rates of 280 mm/min as well as 420 mm/min, both of which achieved reasonable results for PLA. There must be a trade-off between higher and lower feed rates as higher feed rates can cause excessive wear on the FFF parts due to inappropriate layer bonding while the lower feed rates can result in localized heat accumulation [68]. Keeping in consideration all this background, for the purpose of this study, a feed rate level of 360 mm/min was selected as a balance compromise compliant with values suggested by various authoritative publications.

The selection of the cutting tool is critical in determining the surface quality of machined parts, particularly in additive manufacturing applications. As highlighted by Uğur et al. [29], the number of flutes (or teeth) on a milling tool has a direct in-

fluence on the resulting surface roughness, with fewer flutes generally contributing to smoother surface finishes. In this study, a three-flute tool was utilized. Based on the selected spindle speed of 4000 rpm and a feed rate of 360 mm/min, the feed per tooth, calculated using Equation 3.14, is approximately 0.03 mm/tooth well within the acceptable range for machining PLA materials.

From the significant factors, the depth of cut was varied in this work to observe its influence on surface finish. Each inclination surface was also subdivided into three zones to accommodate the three depths of cut values: 0.2 mm, 0.3 mm, and 0.4 mm. The low value of 0.2 mm was intentionally chosen, taking into consideration deposited layer height settings (0.1 mm, 0.15 mm, and 0.2 mm) so as to ensure the milling cutter engaged with at least one original deposited layer, thus acquiring valid and meaningful surface finish data. Conversely, the highest value of depth of cut, 0.4 mm, was chosen so as to exceed the part's printed first perimeter wall. The 0.4 mm depth of cut goes beyond the first layer into the second layer as highlighted by the number of layers given by the total wall thicknesses of 0.75 mm, 1 mm, and 2 mm pertaining to the number of walls, 2, 4, and 8, respectively.

Table 3.13 gives the CNC milling parameters and tool characteristics used in this research.

Table 3.13: Machining Parameters Used in the Milling Process

| <b>N (rpm)</b> | <b><math>V_f</math> (mm/min)</b> | <b><math>a_p</math> (mm)</b> | <b>D (mm)</b> | <b>Flutes</b> |
|----------------|----------------------------------|------------------------------|---------------|---------------|
| 4000           | 360                              | 0.2, 0.3, 0.4                | 4             | 3             |

The CNC milling machine used to carry out the post-processing of the FFF parts in this study was the HAAS VF-1, given in Figure 3.38, a widely recognized and reliable 3-axis vertical machining center. Known for its versatility and ease of operation, the HAAS VF-1 provided a stable and precise platform for performing finishing operations on the 3D printed parts. Table 3.14 gives a brief overview of the technical specifications of the CNC machine, stating the max spindle speed, max tool diameter, spindle power, movements, etc.

Table 3.14: Technical Specifications of HAAS VF-1 CNC Milling Machine [69]

| Feature               | Specification                            |
|-----------------------|------------------------------------------|
| X-axis travel         | 508 mm (20 in)                           |
| Y-axis travel         | 406 mm (16 in)                           |
| Z-axis travel         | 508 mm (20 in)                           |
| Spindle Power         | 22.4 kW (30 hp)                          |
| Spindle Speed         | 8100 rpm (max)                           |
| Spindle Torque        | 122 Nm @ 2000 rpm                        |
| Table Size            | 660 mm × 356 mm (26 × 14 in)             |
| Cutting Feedrate      | 16.5 m/min (650 in/min)                  |
| Tool Changer Capacity | 20 tools (carousel type)                 |
| Max Tool Diameter     | 89 mm (3.5 in)                           |
| Tool Change Time      | Tool-to-tool: 4.2 s; Chip-to-chip: 4.5 s |
| Coolant Tank Capacity | 208 L (55 gal)                           |
| Machine Weight        | 3539 kg (7800 lb)                        |



Figure 3.38: HAAS VF-1

The machine features a large working area of  $660 \times 356$  mm, which allows the ease of holding the printed samples during the milling process. The three-axis system of the machine includes X (left-right), Y (front-back), and Z (up-down), providing complete tool path and part positioning control. The axis travel capacity of 508 mm (X), 406 mm (Y), and 508 mm (Z) allows flexible and precise machining on both flat and inclined surfaces. The spindle system of the VF-1 reaches high speeds of up to 8000 rpm through its 22.4 kW (30 hp) vector drive motor. The automatic tool changer on the VF-1 enables 20 tools to be stored, thus allowing tool switches to happen without operator involvement. This research utilized the HAAS VF-1 to create a dependable, high-precision machining environment that can work well for combining subtractive manufacturing with additive manufacturing processes.

The flat end mill given in Figure 3.39 is made of solid carbide and has a cutting diameter of 4 mm with three flutes. The overall length of the tool is 55 mm, whereas the maximum depth of cut in the feed direction is 10 mm. Table 3.15 gives the technical specifications of the end mill.



Figure 3.39: 3 Flutes End Mill

Table 3.15: Technical Specifications of End Mill [70]

| Feature               | Specification                   |
|-----------------------|---------------------------------|
| Cutting Diameter      | 4.0 mm                          |
| Number of Flutes      | 3 (Peripheral and face cutting) |
| Helix Angle           | 48°                             |
| Corner Chamfer Radius | 0.045 mm                        |
| Cutting Length        | 10.0 mm                         |
| Overall Length        | 55.0 mm                         |
| Shank Diameter        | 6.0 mm                          |
| Neck Diameter         | 4.0 mm                          |
| Material              | Solid tungsten carbide          |

Autodesk Fusion provides an integrated platform for computer-aided design (CAD), computer-aided manufacturing (CAM), and computer-aided engineering (CAE). For finishing operations in CNC milling, Fusion 360 offers robust CAM tools that allow users to define toolpaths, select cutting tools, configure machining strategies, and generate G-code suitable for 3-axis, 3+2, and even 5-axis CNC machines [71]. The free student license up to one year allows Autodesk Fusion to be accessed with the academic institution's credentials. In this research, Fusion 360 was employed for defining the tool paths and generating the G-code.

The geometry designed in Siemens NX was imported into the Autodesk Fusion environment for tool path generation. A custom fixture, modeled as a cuboidal structure, was created within the CAM setup to replicate the physical fixture already mounted on the CNC machine. Figure 3.40 given below represents the Fusion environment along with the part and the fixture design.

After the design stage was finished, Autodesk Fusion 360's "Manufacture" workspace was used to move into the manufacturing phase. A full range of CAM (Computer-Aided Manufacturing) tools is available in this environment to create tool paths and simulate machining processes. In order to ensure compatibility between the virtual setup and the real machining environment, the HAAS VF-1 CNC milling machine

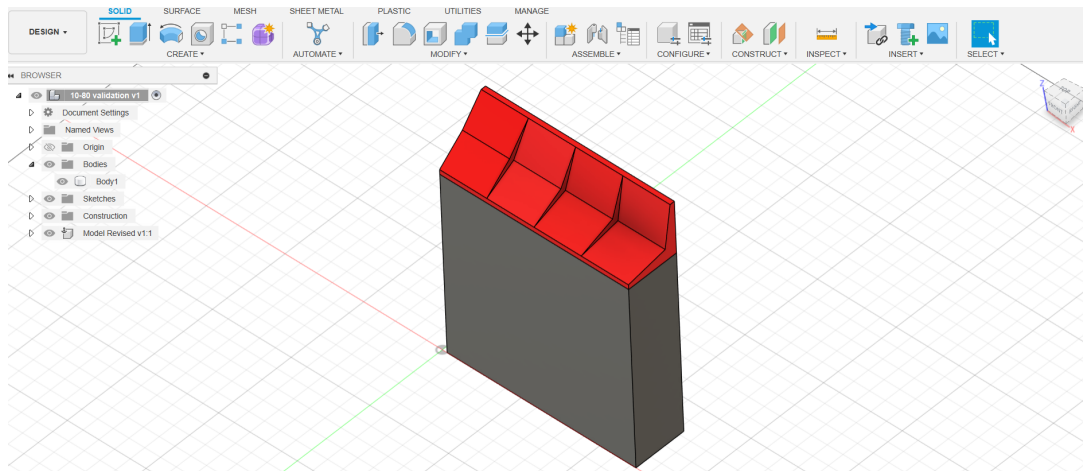


Figure 3.40: Autodesk Fusion CAM

was chosen from the software's integrated machine library. The operation type was specified as milling, aligning with the subtractive manufacturing process planned for the workpieces. A machine coordinate system (WCS) was established to define the orientation and origin of the part relative to the machine setup. The workpiece and custom fixture were appropriately assigned. This comprehensive setup allowed for precise tool path planning while minimizing the risk of tool interference or fixturing errors, as visually represented in Figure 3.41.

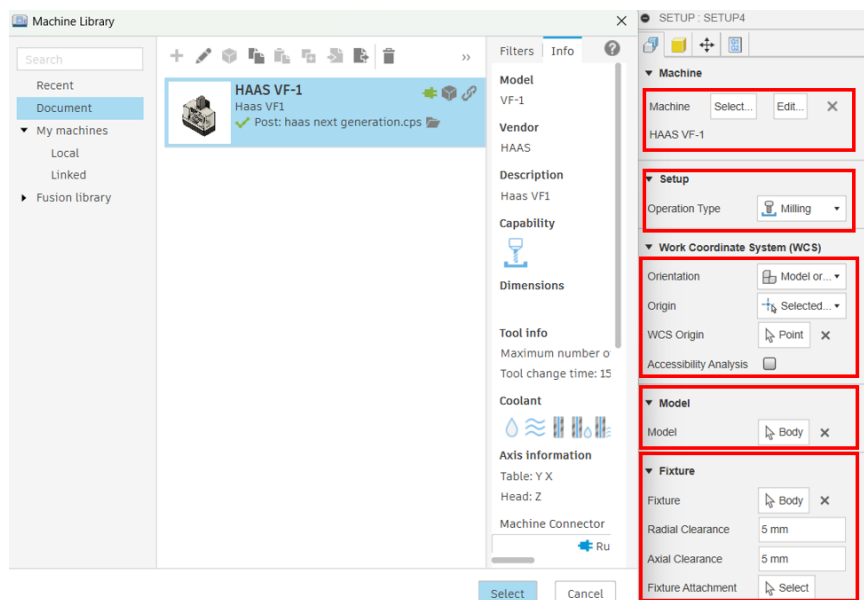


Figure 3.41: Autodesk Fusion Machine Setup

To examine the impact of different cut depths at three predetermined levels, each inclined surface was divided into three separate regions. Furthermore, the maximum effective length of the section where the tool performs the cut limits the segmentation. This factor prevented possible collisions between the tool, spindle, and workpiece during the machining process by guaranteeing that the tool path stayed within safe operating bounds. Two different machining programs with different tool paths had to be created because of the part's geometry. These programs matched two distinct workpiece orientations: in the first setup, the 50° to 80° surfaces faced upward, while the 10° to 40° surfaces were oriented downward; in the second setup, the opposite was true. This method guaranteed the best possible tool accessibility and efficient material removal on all sloping surfaces. Figure 3.42 represent both cases.

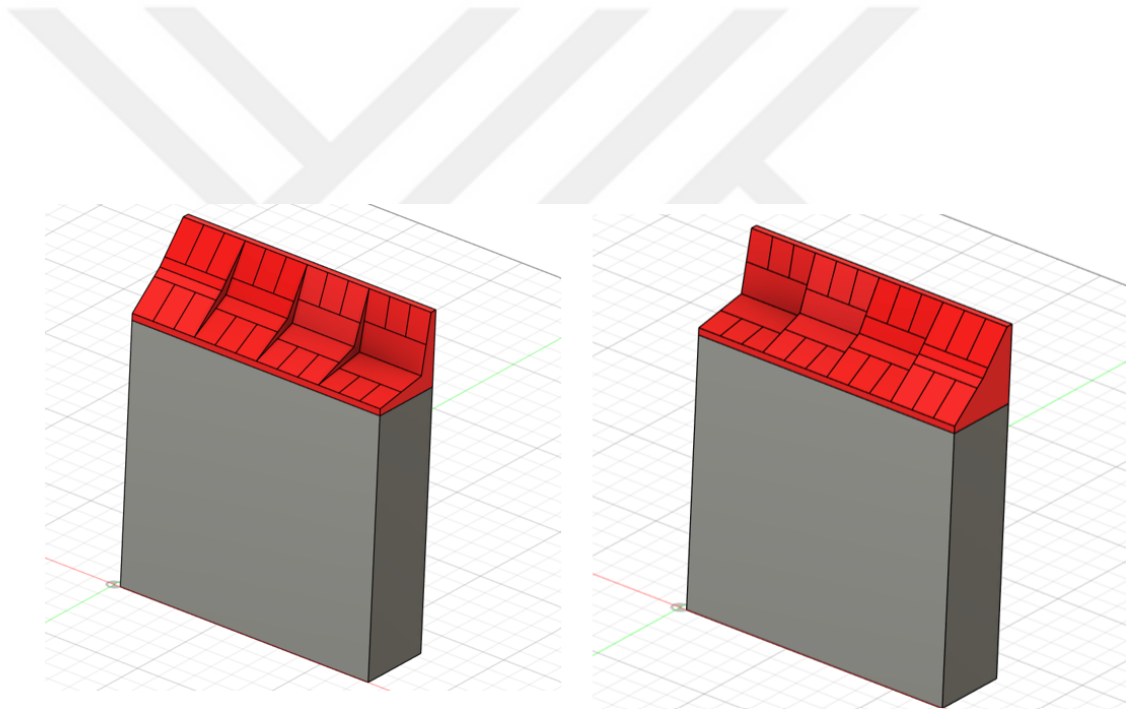


Figure 3.42: Left: 50°-80° upwards, Right: 10°-40° upwards

Figure 3.43 represents the virtual HAAS VF-1 in the Fusion environment, along with the part and the fixture placed on the work table.



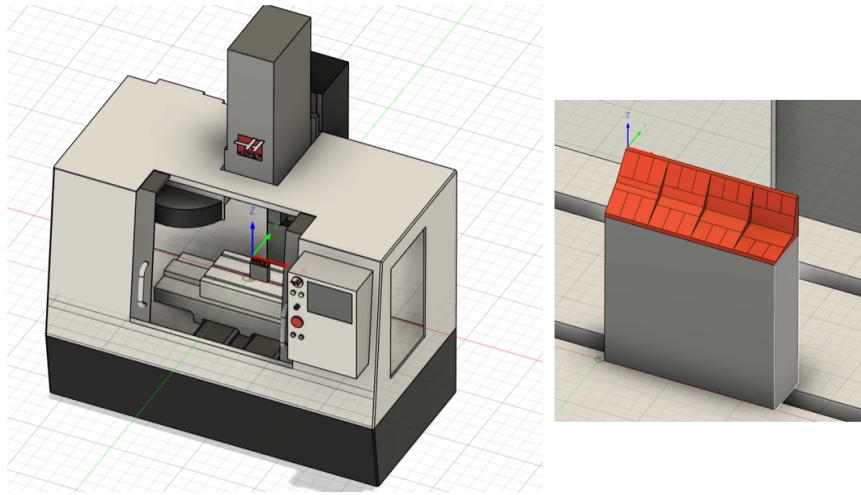


Figure 3.43: Virtual HAAS VF-1 and Part in Fusion Environment

In the manufacturing tab and under the milling 3D segment, the parallel strategy was chosen to be applied on the inclined surfaces ranging from 50-80°. The diameter of the flat end mill was chosen to be 4 mm, similar to the actual tool; the spindle speed was set to 4000 rpm, and the cutting feed rate was set to be at 360 mm/min. Dry cutting conditions were selected. These inputs are shown in Figure 3.44 below.

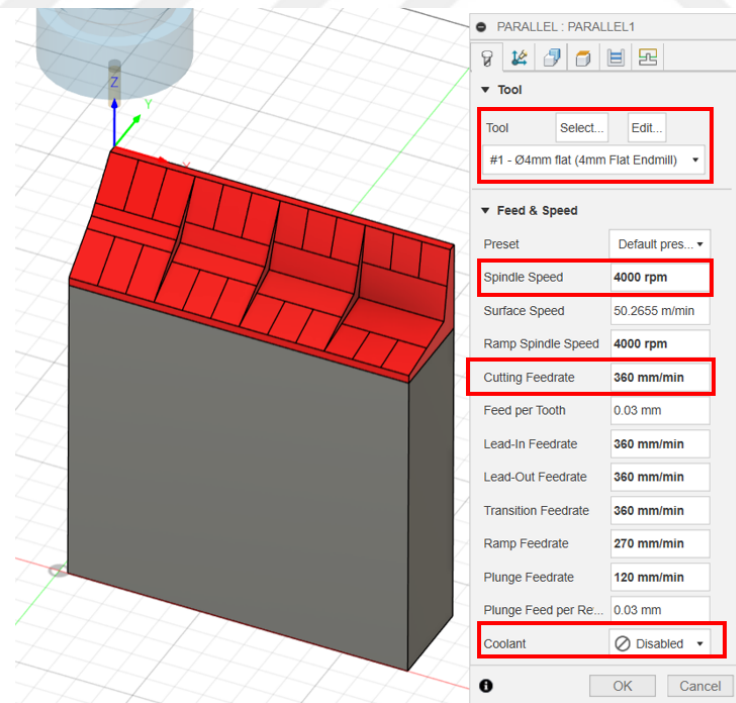


Figure 3.44: Tool, Spindle Speed and Feed Rate Input



The stepover parameter, which governs the horizontal distance between successive tool passes, was set to 0.2 mm for the finishing operation. Selecting a smaller stepover value is known to enhance surface quality by reducing scallop height and producing a finer surface texture, particularly on inclined or curved geometries. Although smaller stepover values increase machining time due to the greater number of tool passes required, this trade-off is justified in applications where surface integrity and finish are of high importance. The direction of milling was selected to be both ways, meaning in both upwards and downwards directions. These settings are shown in Figure 3.45 below.

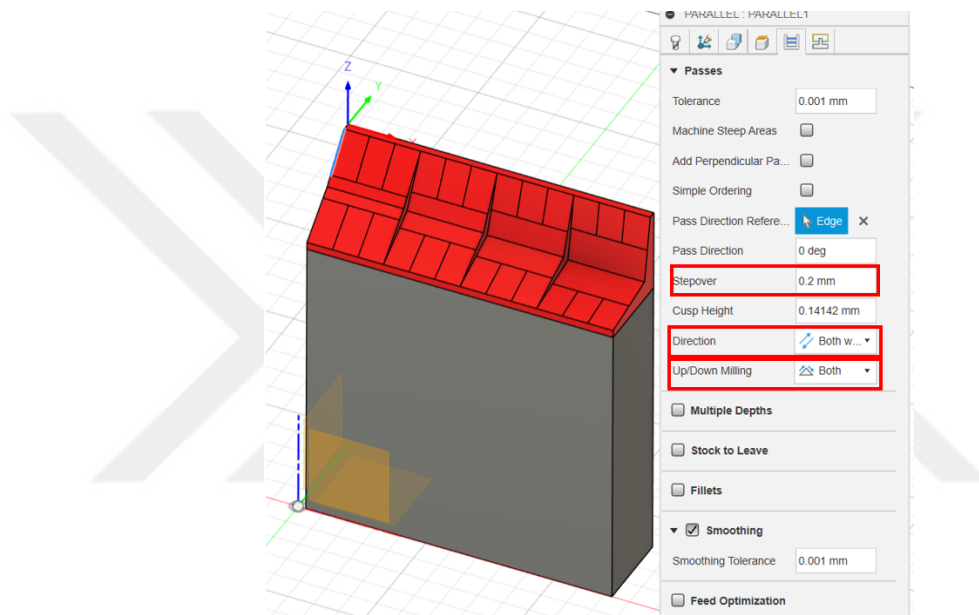


Figure 3.45: Stepover and Direction of Milling

The depth of cut is not directly controlled by the parallel finishing strategy in Autodesk Fusion 360's parameter settings. Therefore, in order to achieve the desired depth increments during machining, a manual approach had to be used. This was accomplished by adding the M1 command, an optional stop, at the end of each tool path block that corresponded to a distinct inclined surface. This was done as a custom modification to the generated G-code. The M1 command made it possible for the machining process to halt at predetermined points so that the machined surface could be visually inspected before moving on to the next surface pertaining to another depth of cut. The CNC table position was manually adjusted to resume the machining process.

To increase the depth of cut for the next pass, the table was moved forward by 0.1 mm at a time. This iterative procedure helped to achieve the necessary surface finish on all inclined surfaces and guaranteed exact control over material removal. Figure 3.46 represents the tool paths for the surfaces inclined at  $50^\circ - 80^\circ$ . The same case has been implemented for the surfaces inclined at  $10^\circ - 40^\circ$ .

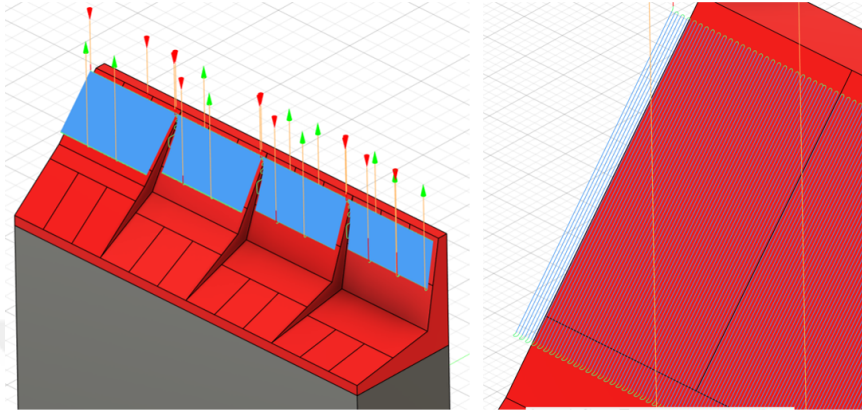


Figure 3.46: Tool Paths and Enlarged View

Figure 3.47 illustrates the simulation of the virtual flat end mill executing a tool path over the surface, based on the specified machining parameters and tool settings.

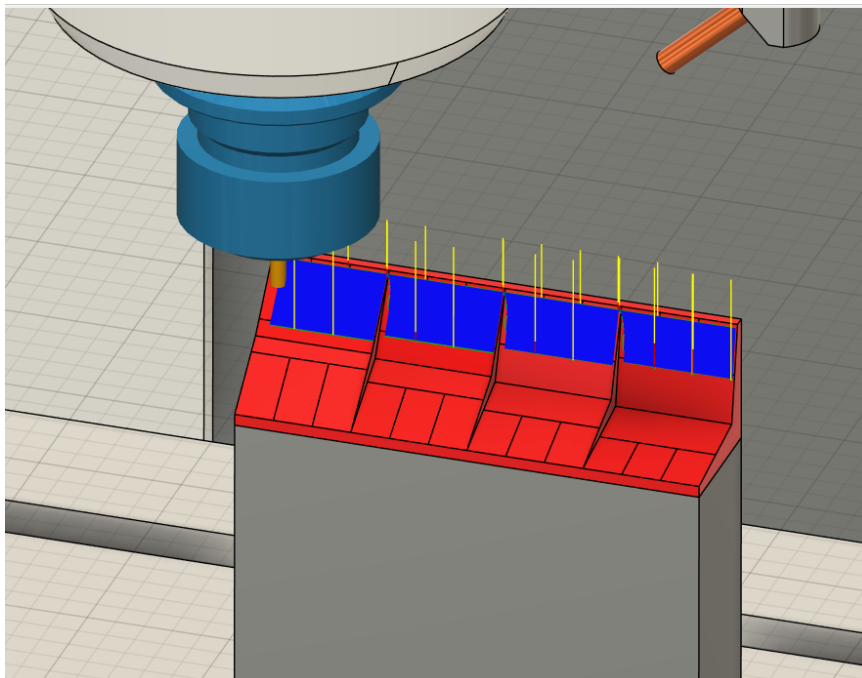


Figure 3.47: CNC Simulation

This simulation provides a visual representation of the cutter engagement and material removal process, thereby enabling verification of tool accessibility, surface coverage, and overall strategy effectiveness prior to physical machining.

With the two G-codes created for both orientations provided in Appendix A, the flat end mill was fixed on the spindle, and Figure 3.48 represents the end mill attached to the spindle.



Figure 3.48: Flat End Mill Attached to the Spindle

The part was placed onto the existing fixture and clamped securely as shown in Figure 3.49.

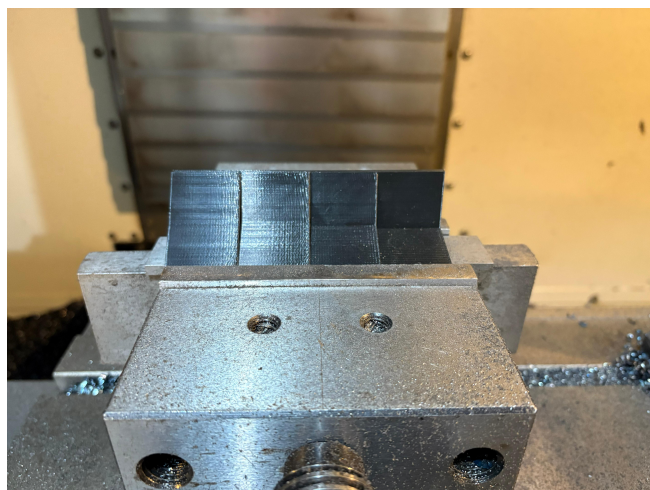


Figure 3.49: Part Secured on the Fixture

The optional stop function was activated when the CNC program was started, enabling the machine to pause automatically after each specified operation. Initially, the machining process started with a 0.2 mm depth of cut region on the 50° inclined surface. After this operation, the optional stop was activated, allowing for increasing the depth of cut from 0.2 mm to 0.3 mm and subsequently from 0.3 mm to 0.4 mm. In this way, all the inclined surfaces in both orientations were machined, each having a depth of cut varying from 0.2 to 0.4 mm. The first steps of the CNC milling process are shown in Figure 3.50, emphasizing the tool's engagement with the workpiece.

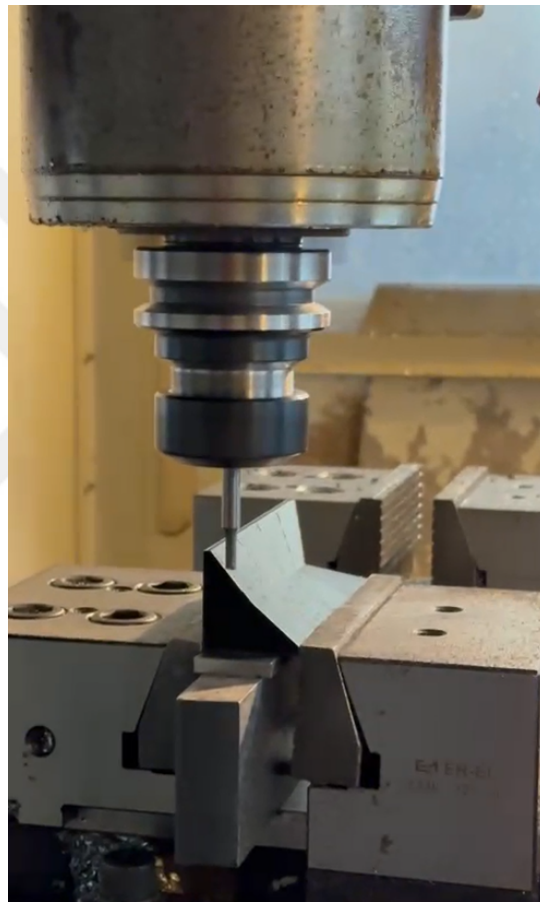


Figure 3.50: Initial Phase of Tool Engagement with the Workpiece

Figure 3.51 represents the cutting parameters displayed on the control panel of HAAS VF-1, ensuring that the process is operating according to the G-code instructions. In addition to the spindle speed of 4000 rpm, feed rate of 360 mm/min, it also shows the symbol indicating that the option stop is active and the machine will pause after the execution of each code block.



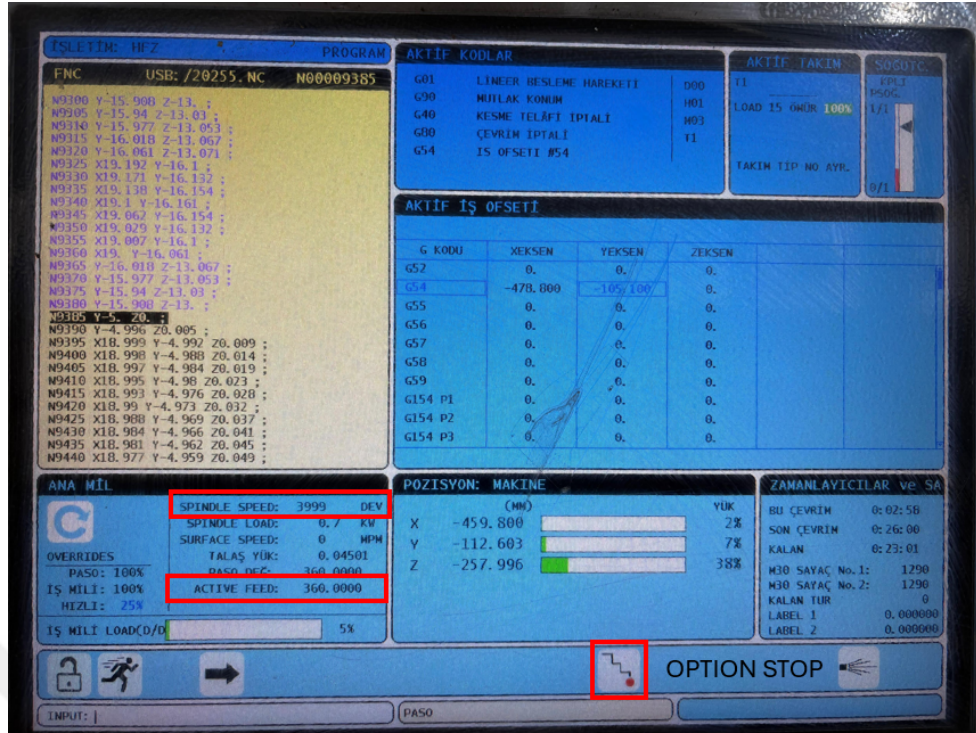


Figure 3.51: Control Panel Highlighting Spindle Speed, Feed Rate, and Option Stop

Figure 3.52 illustrates the 50° inclined surface after the completion of all three machining passes, each corresponding to a depth of cut of 0.2, 0.3, and 0.4 mm.

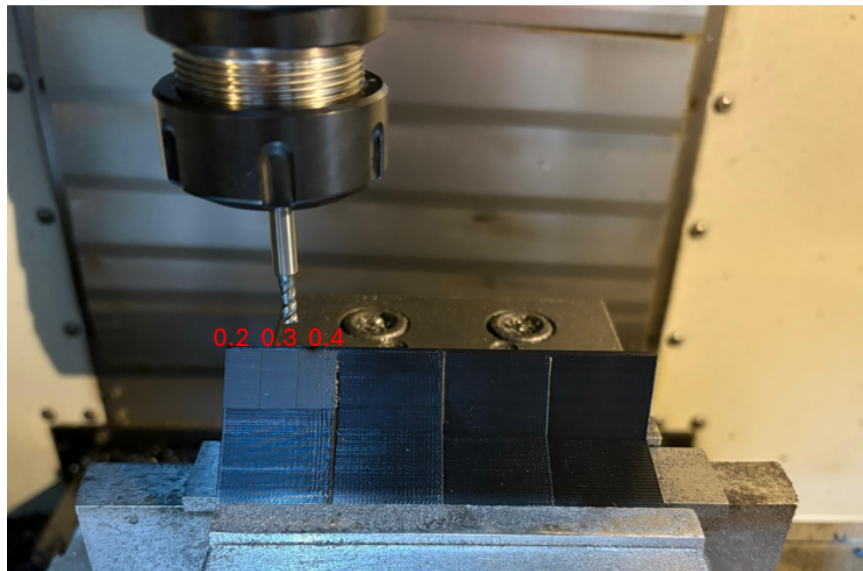


Figure 3.52: 50° Surface Showing 0.2, 0.3 and 0.4 mm Depth of Cuts

The same methodology described above was systematically applied to all inclined surfaces on each test specimen. Figure 3.53 presents the machined part, showcasing varying depth of cut levels specifically 0.2 mm, 0.3 mm, and 0.4 mm across the inclined regions. These variations demonstrate the controlled implementation of the hybrid manufacturing approach, which integrates additive and subtractive processes.

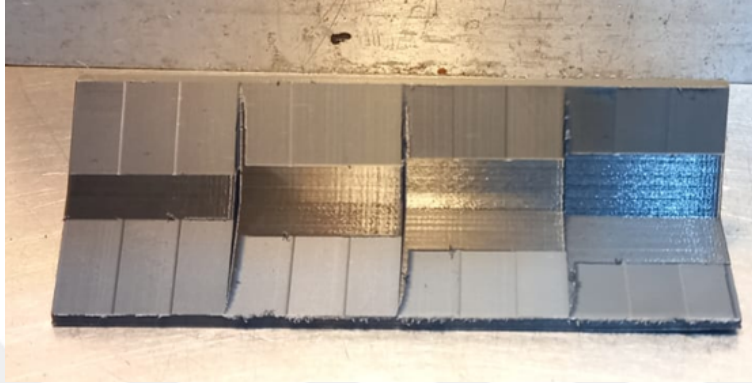


Figure 3.53: CNC Milling Applied as a Post Process on the FFF Part

The post-processing operation involving CNC machining was conducted on a total of 52 parts, with the exception of parts numbered 41 and 42, the details of which will be discussed in the subsequent chapter. The machining process was applied in accordance with the methodology outlined previously, ensuring consistency in tool path strategy and depth of cut variation. Figure 3.54 illustrates the set of parts that underwent CNC machining as part of the hybrid manufacturing workflow.

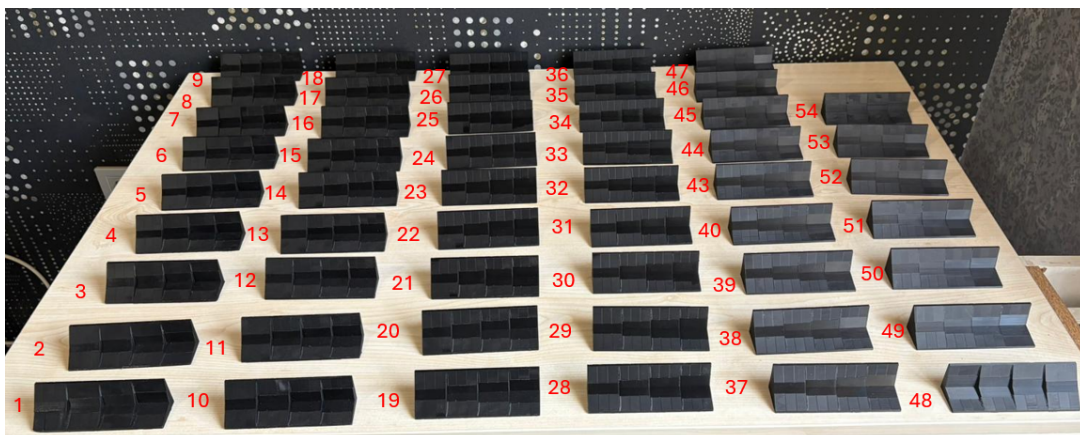


Figure 3.54: Hybrid - CNC Milled Post Processed Parts Dry Conditions

In addition to the specimens machined under dry conditions, two additional parts, specifically those numbered 4 and 5, were subjected to machining with the application of a water soluble fluid coolant. Parts 4 and 5 were 3D printed again with the same AM settings, and then they were CNC machined with wet cutting conditions. This was undertaken to evaluate the potential influence of coolant-assisted machining on surface quality. Figure 3.55 illustrates the continuous application of coolant throughout the machining of each inclined surface, highlighting the implementation of wet machining conditions in selected trials of parts 4 and 5.



Figure 3.55: Wet Machining Conditions with Fluid Coolant

Figure 3.56 presents parts 4 and 5, which were machined under wet conditions utilizing fluid coolant. This approach differed from the dry machining method applied to the other specimens, thereby providing an alternative processing route under controlled conditions. The figure clearly illustrates the surfaces of the parts post-machining, highlighting the implementation of fluid-assisted milling. The compari-



son of the surface roughness for parts 4 and 5 in both dry and wet conditions is given in the subsequent chapter.

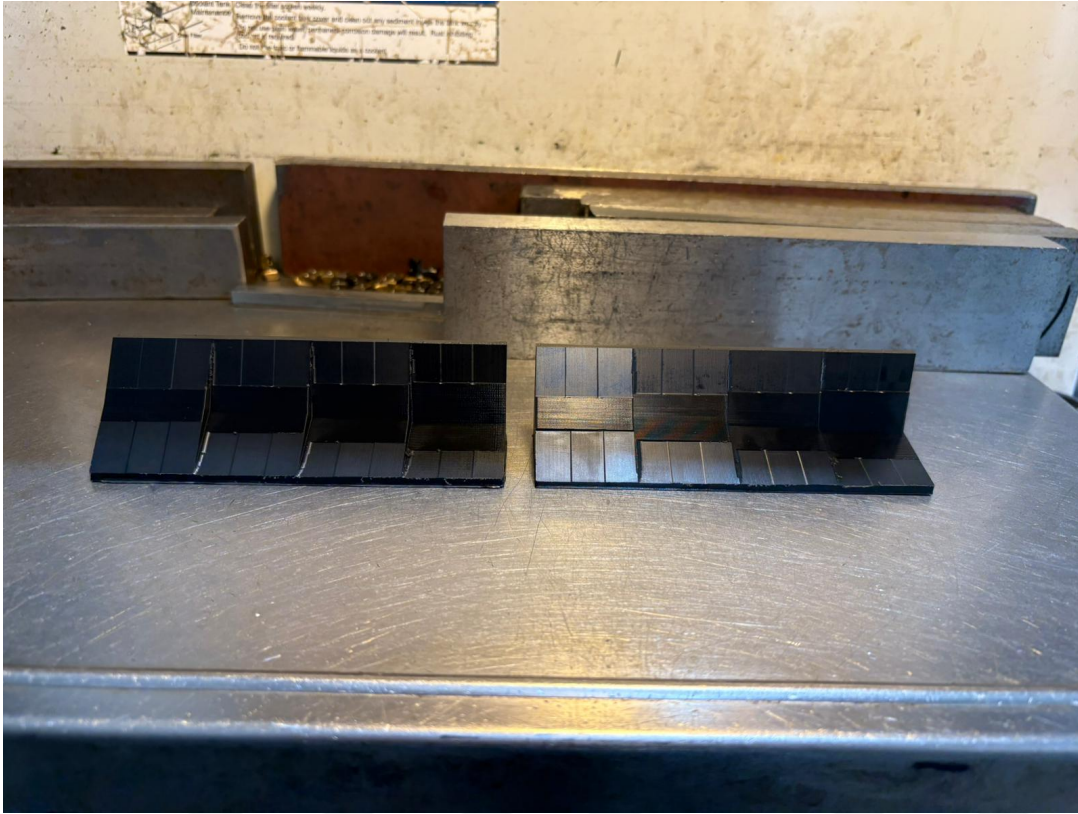


Figure 3.56: Parts 4 and 5 after Wet CNC Milling Conditions

Following CNC milling, each part's surface roughness was assessed using the standardized process described in 3.4.2. To guarantee the validity and comparability of the results, this methodology was consistently applied to all machined specimens. After being processed with three different depths of cut levels, three distinct measurements were made within each of these regions using the same profilometer. This approach resulted in a total of nine measurements per inclined surface, thereby enhancing the statistical robustness of the surface roughness data hence, emphasizing the systematic and repeatable methodology employed to characterize the post-machining surface quality across all experimental conditions. The Ra measurement reports obtained for both AM and Hybrid stages using the profilometer are provided in Appendix A for all 54 parts. In addition, the stylus measurement uncertainty equation has been derived and presented in Appendix A.



### **3.6 Machine Learning Algorithms, Types and Implementation**

This section provides a comprehensive overview of the machine learning (ML) algorithms commonly employed in the literature for the prediction of surface roughness in both additive manufacturing (AM) and hybrid manufacturing processes. It further elaborates on the key evaluation metrics utilized in how each ML algorithm is performing and predicting. In addition to the literature review, this section outlines the specific ML strategies adopted in the present study, detailing the number and types of algorithms applied for both fused filament fabrication (FFF) and hybrid-manufactured parts. The discussion highlights the rationale behind the selection of particular models, as well as their role in capturing the complicated relationships between process parameters and the resulting surface quality.

#### **3.6.1 Machine Learning Basics, Types in Literature, and Evaluation Metrics in terms of Surface Roughness Prediction on FFF and Hybrid Parts**

The concept of machine learning came from the human mind to understand and identify patterns in data with the help of computers. The two main types of machine learning fall under the categories of supervised and unsupervised methods. In the supervised method, the goal is to identify relationships between the labeled data points, called a training dataset, and to predict outcomes based on a model. Unsupervised learning tends to identify patterns in data without any prior knowledge or a training dataset. The prediction of surface roughness is one such problem in which we provide a set of training data to the computer to learn relationships and predict the outcome; therefore, this problem falls under the domain of supervised machine learning. A dataset consists of data points that represent an entity, which we need to analyze [9]. In our case, the entity is surface roughness. These data points are described by properties called features. The features of this research are the input parameters that affect surface roughness, as listed in Table 3.5 for AM and Table 3.13 for hybrid processes. A dimension of feature space is marked by the feature, and the data point lies in a place according to that space. A set of features results in creating a feature vector, which increases the dimensionality of the feature space.

Issues like high dimensionality, underfitting, and overfitting can affect machine learning (ML) techniques. When an algorithm learns the training data including noise and outliers too well, it is said to be overfitting. This leads to great performance on the training dataset but poor generalization to testing data that hasn't been seen yet. Underfitting occurs when the selected model is too basic to adequately represent the underlying relationships in the data. For instance, poor performance on both training and testing datasets is frequently the result of using a model that maps the relationships linearly instead of representing a non-linear relationship [72]. Furthermore, because of the sparse distribution of data in high-dimensional spaces, the model may have trouble learning significant patterns when the feature space outputs high dimensionality. Known as the "curse of dimensionality," this phenomenon can seriously reduce the predictive accuracy of the model [73]. To produce accurate and broadly applicable predictions, it is crucial to maintain a suitable balance between underfitting and overfitting.

The two main categories of supervised learning include regression and classification. Both differ in terms of their outputs. The former outputs numeric predictions, whereas the latter outputs categorical values. Since surface roughness is a numerical value therefore this study is focused on numeric predictions using regression-based MLs. The performance of regression-based models is assessed using different methods, and the goal is to reach minimization on the distance between the model and the data numerically. This distance is also called the loss function or cost function. Two key concepts that a balanced model should follow are that the model should predict values close to the training data set; otherwise, underfitting occurs, termed as high bias, and the model should also generalize well. Failure to do this results in overfitting, also termed as high variance. To select a good model that provides a tradeoff between high bias and high variance, a general principle is to separate the data into training, testing, and validation. The training set is implemented on different models, and they are tested using the testing set. The model displaying the best performance on the testing set is then selected. The validation set is used to assess the model's performance on unseen data and check the generalization error.

Model performance can be checked by using cross-validation, where the dataset is divided into two parts, training and testing. The ratios of training and testing vary;

however, common agreement is on 80% - 20% respectively. In addition, k-fold cross-validation can also be applied, picking k subsets from the training data and k-1 subsets for checking performance. The repetition of this process is carried out k times, resulting in averaging the performance scores of each subset [74].

The performance scores are judged using evaluation metrics, and especially for regression based ML following performance measures are utilized in this study. The most important evaluation measure is the mean squared error MSE which provides the difference between the actual values and the predicted values squared. In other words, MSE tells us how close the points are to the line of best fit. A value closer to zero or a smaller MSE is considered to be good. Equation 3.15 used to calculate MSE is given below.

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (3.15)$$

where n is the number of data points,  $y_i$  are the actual values and  $\hat{y}_i$  are the predicted values [72].

Similarly, Root Mean Squared Error RMSE takes the square root of the MSE and can be referred to as the standard deviation of the errors. Equation 3.16 gives us RMSE.

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (3.16)$$

The performance measure, which takes the absolute difference between the observed and predicted values, is called mean absolute error MAE. Equation 3.17 gives us MAE.

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (3.17)$$

This evaluation can be assessed in percentage terms, and the performance measure is called Mean Absolute Percentage Error MAPE. Equation 3.18 is as follows.

$$\text{MAPE} = \frac{100\%}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (3.18)$$

The coefficient of determination, also known as  $R^2$ , is the most commonly used performance metric for assessing regression models. It indicates the wellness of the data fitting the model. It measures how much of the variance in the dependent variable can be predicted based on the independent variables.  $R^2$  has a value between 0 and 1, with a value nearer 1 denoting a more accurate model and a stronger correlation between the observed and predicted values. Below is a mathematical formulation represented by Equation 3.19.

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (3.19)$$

The performance metrics mentioned above are used as quantitative tools to compare the efficacy of various models and are mainly utilized in regression-based supervised machine learning algorithms. These metrics give important information about each algorithm's capacity for generalization and prediction accuracy. These evaluation criteria should serve as a guide for choosing models, giving preference to those that produce the lowest error values (such as MAE, MSE, RMSE, and MAPE) and the highest coefficient of determination  $R^2$ , which denotes superior predictive performance.

There are various regression-based supervised machine learning methods; however, the methods applied in this research are mostly based on decision trees, random forests, and gradient boosting. Decision trees can be considered a significant building block of several ML algorithms. The concept behind decision trees is very straightforward, and their main advantage is the ability to model non-linear relationships. Recursively dividing the dataset into subsets according to feature values that minimize impurity (e.g., mean squared error for regression) is how a decision tree works. In other words, a decision tree starts by asking a series of yes or no questions, and a tree-like model is produced as a result of this process, with internal nodes standing in for decision rules, branches for outcomes, and leaf nodes for anticipated outputs [75]. The decision tree keeps on splitting the data so that the variance of the target variable is minimized in each group. In our study, the surface roughness is the target variable,

and the features include layer height, nozzle diameter, etc. The decision tree checks all the features and tries to split the data in every possible way. It tries to find the best split that divides the data into groups with similar roughness values by minimizing the MSE. Once the best feature is found, the data splits into further branches and repeats itself recursively, building deeper and deeper branches until the variance between a node is very low or the max depth has been reached.

Decision trees can sometimes become too complex and fit the training data too closely, which leads to poor performance on the new data. To overcome this problem, advanced models like Random Forest and Gradient Boosting were developed. These models build many decision trees and combine their results to make better and more reliable predictions. During training, the Random Forest ensemble learning algorithm builds a large number of decision trees and outputs the combined prediction of each tree, by averaging for regression tasks. The algorithm uses random feature selection and bootstrap aggregation (bagging) to minimize overfitting and lower variance, which enhances generalization performance. A random subset of features is taken into consideration at each split to determine the best division, and each tree in the forest is trained on a random subset of the data with replacement. This approach yields reliable estimates even when noise and non-linear feature interactions are present, and it works especially well with high-dimensional datasets.

Gradient Boosting is an ensemble learning machine learning method that develops a strong predictive model through a sequential addition of multiple weak learners, usually decision trees, in a stage-wise fashion. Gradient Boosting does not randomly sample instances from the dataset like Random Forest, but it attempts to correct the residual error from the previous portion of the sequence. Each iteration of Gradient Boosting produces an entirely new tree that learns from, and minimizes a specified loss function, commonly mean squared error for regression problems, with gradient descent as the optimization that the model is using to perform this correction. After the model has successfully trained using this incremental approach, we effectively have a model that is capable of distributing the influence of multiple factors and learning complex patterns in the data by correcting the prediction errors of the previous trees added to increase the predictive model's accuracy. Gradient Boosting has seen a massive increase in popularity and use through its high prediction accuracy

and flexibility. Some of the common Gradient boosting algorithms are GBR, XGBR, CATBoost, and EBM. These will be mentioned in the subsequent section.

The studies summarized in Table 3.16 below have been categorized based on the specific types of machine learning algorithms implemented, as well as the nature of the supervised learning approach employed (i.e., regression or classification).

Table 3.16: Classification of Studies Based on Machine Learning Algorithms and Learning Type

| Study | Types of ML Used                                                                           | Classification or Regression |
|-------|--------------------------------------------------------------------------------------------|------------------------------|
| [7]   | SVR, DT, RF, XGBoost, CatBoost, AdaBoost, ETR, GBR, EBM                                    | Regression                   |
| [10]  | RF, AdaBoost, CART, SVR, Ridge Regression, RVFL                                            | Regression                   |
| [11]  | J48 (C4.5), RF, RT                                                                         | Classification               |
| [12]  | MLP, Bayes Net, Naïve Bayes, IBK, K Star, J48, LMT, RF, Bagging, Boosting, Random Subspace | Classification               |
| [13]  | ANNs                                                                                       | Regression                   |
| [15]  | ANN-SOS                                                                                    | Regression                   |
| [16]  | ZeroR, Linear Regression, SMOreg, Decision Stump, RF                                       | Regression                   |
| [17]  | Cascade Forward Neural Network with GA                                                     | Regression                   |
| [18]  | APMSO-KNN                                                                                  | Classification               |
| [19]  | Linear Regression, SVR, RFR, GBR                                                           | Regression                   |
| [20]  | RF, SVR, Ridge Regression, LASSO                                                           | Regression                   |
| [21]  | GA-GBR, GA-DT, GA-RFR, GA-ANN                                                              | Regression                   |
| [22]  | RBFNN-ICA                                                                                  | Regression                   |
| [23]  | MLR, ANNs - ReLU and Tanh                                                                  | Regression                   |
| [26]  | GBR, XGBoost, AdaBoost, RFR, ETR                                                           | Regression                   |
| [30]  | ANNs                                                                                       | Regression                   |

As we can see from Table 3.16, most of the studies have used ML for predicting surface roughness as a continuous numeric value, hence making use of regression-based algorithms. Studies carried out by Barrios et al. [11], Cerro et al. [12], and Huang et al. [18] divide the surface roughness values into classes and use classification-based MLs to predict the surface roughness class.

Furthermore, a cross-comparison of Table 3.1, Table 3.12 and Table 3.16 reveals a notable gap in the literature: only study conducted by Pascu et al. [30] specifically addresses the prediction of surface roughness for intermediate inclination angles of 30°, 45°, 60° and 90° in PLA AM-hybrid parts using machine learning. However, even in this case, the authors employed a neural network framework for predicting surface roughness values. The present study aims to bridge this gap by employing regression-based machine learning models for the prediction of surface roughness of the range 10 - 80° inclinations. This approach enables a more precise and quantitative evaluation of surface quality, offering a valuable contribution to the body of knowledge in the subject of surface roughness of PLA AM-hybrid parts.

### **3.6.2 Machine Learning Implementation**

The surface roughness measurements obtained from both additive and hybrid processed parts were input into an Excel file given in Appendix A, which contains the DOE and results, and Google Colaboratory (Colab) was used for the execution of the ML algorithms. The reason for using Google Colab is that it is free and web-based, enabling users to write code using Python in a web browser. It saves the coded files to the Google Drive for later access. Due to its interactive development environment, it is well-suited for machine learning tasks, making use of resources such as GPUs and TPUs directly. It also provides wide support for ML libraries like scikit-learn, TensorFlow, PyTorch, etc [76].

Some significant libraries were imported into the Colabs environment, which include pandas, numpy, matplotlib, seaborn, and scikit-learn. Pandas library is a very useful library, and it is used in ML to preprocess the data by restructuring, transforming, filtering, cleaning, and merging. Pandas library was used to load the Excel file containing measurements into the algorithm. It was used to convert the categorical variable

infill pattern into binary indicators, it was used to create a data frame for a feature importance plot, and to read the Excel file for validation prediction with manual inputs of the features. The Numpy library is also another useful tool that allows for rapid mathematical calculations, statistical analysis using vectorized operations. The Numpy library was employed in this research for the evaluation metrics calculation of each ML algorithm. Matplotlib, as the name suggests, is a very common library that allows the user to visualize data by means of interactive plots using high-quality graphical tools. In this research, matplotlib library was used for plotting a bar chart using feature importance and an actual vs. predicted surface roughness plot in all the ML algorithms. Seaborn library is used for statistical data visualization, highlighting residuals for feature importances, making it ideal for data exploration and analysis. It is also used along with matplotlib to create a feature importance plot with labels and feature names. Lastly, the core library used for ML implementation is called scikit-learn. All the machine learning algorithms used in this study, including decision trees, random forest, and gradient boosting algorithms like GBR, XGBR, EBM, etc, were implemented using this library. Moreover, it was used to split the data into training and testing, preventing overfitting and underfitting. It was also used to carry out the employment of evaluation metrics to assess the model's performance.

Figure 3.57 provides a pipeline of the ML algorithms implementation. By following the pipeline mentioned in Figure 3.57, the machine learning algorithms were employed systematically, one after another. A total of ten ML algorithms were used, including Polynomial Regression of 4 degrees, Decision Tree, Random Forest Regression, Gradient Boosting Regression, CAT Boost Regression, Extreme Boosting Regression, Adaptive Boosting Regression, Extra Tree Regression, Explainable Boosting Machine Regression, and Support Vector Regression. The codes of these algorithms are provided in Appendix B.

Polynomial regression is a very straightforward regression-based algorithm where an n-degree polynomial is used to model relationships between the features and the targets and captures the curved trends in the data. Mathematically, it is written by Equation 3.20 below.



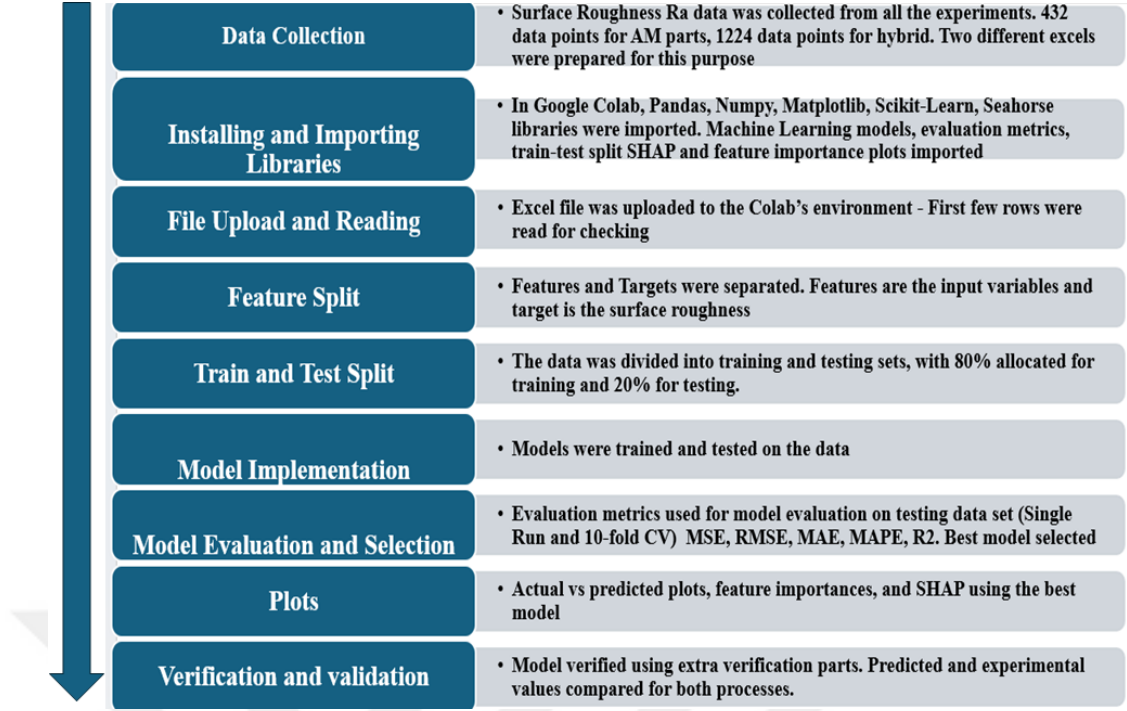


Figure 3.57: ML Implementation Pipeline

$$y(\mathbf{x}) = \beta_0 + \beta_1 \mathbf{x} + \beta_2 \mathbf{x}^2 + \cdots + \beta_n \mathbf{x}^n + \varepsilon \quad (3.20)$$

where,  $y$  is the target variable,  $x$  is the independent variable or the vector containing input variables,  $\beta_0, \beta_1, \dots, \beta_n$  are the model coefficients, and  $\varepsilon$  is the error term (residual). The  $n$  represents the degree of the polynomial. The degrees of the polynomial regression were increased systematically by checking the evaluation metrics, and a 4-degree polynomial regression was chosen to predict the surface roughness values.

Details of the Decision Tree and Random Forest algorithms have already been mentioned in the section 3.6.1. Gradient Boosting regressor utilizes shallow trees and carries out iterations, fitting the shallow trees to the training data. The main concept behind the iterations is to reduce the residual error of the preceding learners. The logic behind GBR is that it uses a negative gradient of the loss function and fits each weak learner to it, hence reducing the residual errors successively in predictions [77]. XG Boost is also an ensemble tree-based learning that works on the gradient boosting

technique, however, with the advantage of scalability and optimization. The concept of learning is the same, with the addition of the final prediction being made by taking the sum of the outputs of all the weak learners. Hence, the final prediction is equal to the weighted sum of all trees. Equation 3.21 given below represents the final model.

$$f(x) = \sum_{i=1}^n \alpha_i \cdot f_i(x) \quad (3.21)$$

Here,  $f(x)$  represents the final prediction,  $f_i(x)$  represents the prediction from the  $i$ th weak learner, and  $\alpha_i$  is the weight assigned to the weak learner [7].

CAT Boost, short for categorical boosting, works in a similar way to most gradient boosting algorithms by fitting weak learners to minimize a loss function. It fits these shallow trees to a negative gradient of the loss function and handles the categorical variables using an encoding scheme known as ordered boosting. Using the following equation, it computes the target mean of the categorical target feature, in our case, infill pattern, based on the previous target values, hence reducing the risk of target leakage. Equation 3.22 is given below

$$\mu_i = \frac{\sum y_j}{n_i} \quad (3.22)$$

where,  $\mu_i$  represents the encoded value (mean target) for the  $i$ -th level (eg: infill pattern = Grid),  $y_j$  represents the target value (e.g., surface roughness or output label) of each row with that level and  $n_i$  represents the number of previous occurrences of that level [7] [78].

AdaBoost regressor is short for adaptive boosting regression and uses shallow trees and combines them into strong models. The algorithm starts with equal weights for all the data points, trains a weak regressor, and computes the error between the predicted and actual value. It assigns a weight to the regressor based on the performance, increases the significance of weights of data points with large errors, trains the next regressor using this reweighted dataset, and repeats this process for several iterations. Equation 3.23 summarizes the algorithm.

$$f(\mathbf{x}) = \sum_{n=1}^N \alpha_n \cdot h_n(\mathbf{x}) \quad (3.23)$$

where  $f(\mathbf{x})$  represents the final prediction,  $h_n(\mathbf{x})$  represents the prediction of the  $n$ th weak regressor,  $\alpha_n$  represents the weight assigned to the  $n$ th regressor, and  $n$  is the total number of iterations [79].

Extra Tree Regressor is a randomized tree-based algorithm similar to RF but adding additional randomization in order to reduce model variance and increase generalization. The trees are trained on random subsets of the data. It works by selecting a random subset of the training data. At each node of the tree, it selects a random subset of features and picks a split at random for each feature. The tree grows sequentially using random splits, and the final prediction is the average of predictions from all the trees [80]. The Explainable Boosting Model (EBM) is a regression-based machine learning algorithm. It builds an accurate and interpretable model by combining multiple one-dimensional learners. For predicting surface roughness, EBM trains a separate, simple model for each input parameter. This includes layer height, nozzle diameter, print speed, and depth of cut, etc. It then adds these models together to predict the final surface roughness value. This additive structure ensures that each feature's influence on the output is both independent and transparent. During training, EBM iteratively updates its prediction by fitting new models to the residual errors, allowing it to refine the prediction in each round based on the parts it previously failed to predict well. The model offers two levels of interpretability, including global interpretation that provides insights into how each process parameter (e.g., layer height or infill density) affects surface roughness across the entire dataset and local interpretation that explains how those same features contributed to the surface roughness prediction for a specific 3D printed part or surface [81].

Support Vector Regression SVR is an advanced ML whose main aim is to model a function by approximating a target variable  $y$  using a margin of tolerance [82]. In simple words, it tries to fit a line as close as possible to the actual surface roughness values, ignoring the small errors. Using the epsilon margin, the SVR tries to reduce big errors that fall outside the tolerance zone. It creates a penalty for the points lying outside the zone and tries to reduce this penalty, resulting in learning taking place. It

uses a kernel if the data is non-linear to find non-linear relationships. The following Equation 3.24 gives us the optimization function that is minimized in SVR.

$$L(\mathbf{w}, \mathbf{b}) = \min_{\mathbf{w}, \mathbf{b}, \xi_i, \xi_i^*} \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{i=1}^n (\xi_i + \xi_i^*)$$

subject to the following constraints:

$$y_i - (w \cdot x_i + b) \leq \varepsilon + \xi_i \quad (3.24)$$

$$(w \cdot x_i + b) - y_i \leq \varepsilon + \xi_i^*$$

$$\xi_i, \xi_i^* \geq 0, \quad i = 1, 2, \dots, n$$

Here  $w$  is the Weight vector that determines slope of regression function,  $b$  is the bias term coming from the intercept of the regression function, squared norm of the weight vector, encourages the model to be as flat/simple as possible,  $C$  is the regularization parameter that controls trade-off between simplicity and error tolerance,  $\xi_i, \xi_i^*$  represent slack variables that measure how much the prediction deviates from the  $\varepsilon$ -margin, and  $\sum_{i=1}^n (\xi_i + \xi_i^*)$  represents total penalty for exceeding the  $\varepsilon$ -margin; which the model tries to minimize. The symbols  $y_i, w \cdot x_i + b, \varepsilon, \xi_i$  represent the true value of the target (e.g., actual surface roughness), predicted value from the model, width of the epsilon-insensitive zone, and slack variable for the lower bound violation. The first constraint ensures that if the prediction falls below the actual value by the tolerance margin, it should be penalized. The second constraint does the same thing in the opposite direction, and the third constraint makes sure that the slack variables are non-negative.

All these models were then evaluated using the evaluation metrics, including MSE, RMSE, MAE, MAPE, and  $R^2$ . The best model was chosen which had the lowest MSE, RMSE, MAE, and MAPE values and the highest  $R^2$  values.

Chapter 3 outlines a rigorous and methodical approach for the evaluation of surface roughness across 54 PLA specimens, each comprising eight inclined surfaces spanning angles from  $10^\circ$  to  $80^\circ$ . It systematically details the experimental setup, incorporating various additive manufacturing FFF and hybrid machining parameters, and further elaborates on the machine learning methodologies employed for the prediction of surface roughness values.

## CHAPTER 4

### RESULTS AND DISCUSSION

This chapter presents a comprehensive evaluation of surface roughness measurements, following the detailed experimental methodology outlined in Chapter 3. The variation of surface roughness with increasing inclination angles, ranging from  $10^\circ$  to  $80^\circ$ , is systematically analyzed in relation to critical input parameters such as layer height and depth of cut, for both PLA-based additively manufactured components and those produced via hybrid manufacturing. Furthermore, the chapter identifies and discusses the best and worst-performing samples in terms of surface quality, under varying process conditions, providing insights into optimal and suboptimal parameter combinations. The performance of various machine learning (ML) algorithms is assessed based on predictive accuracy, robustness, and consistency. The most effective algorithm is further leveraged to generate feature importance plots, and SHAP (Shapley Additive Explanations) visualizations, which aid in identifying the most influential process parameters affecting surface roughness in both AM and hybrid fabrication contexts. The contribution of post-processing machining to surface quality improvement is critically examined, with a specific focus on the role of depth of cut when combined with other key variables. In addition, validation studies were carried out on newly fabricated samples to evaluate the generalizability and reliability of the developed ML models. Based on the findings, practical recommendations are proposed for both academic researchers and industrial practitioners on the integration of data-driven approaches for surface roughness prediction and control. Finally, initial experimental results from fluid-assisted machining trials are presented, highlighting their promising potential for further enhancing surface finish and expanding industrial applicability.

## 4.1 Surface Roughness Evaluation for AM Parts

This section deeply discusses the surface roughness results obtained from the additive manufacturing of the parts while varying input parameters such as nozzle diameter, layer height, wall thickness, top thickness, infill density, infill pattern, printing extrusion temperature, build plate temperature, print speed, and fan speed at angles ranging from 10 to 80 degrees with 10 degree increments. These input parameters are presented in Table 3.5 along with their respective levels. The findings obtained from the surface roughness measurements are given in the tables below for all 54 AM parts. The findings have been divided into two tables based on the respective nozzle diameters, similar to Table 3.7 and Table 3.8 that can be used to identify the input parameter values for each part.

Table 4.1: Surface Roughness (Ra) Values for AM Parts at Various Inclination Angles

| Part No | 10° Ra (μm) | 20° Ra (μm) | 30° Ra (μm) | 40° Ra (μm) | 50° Ra (μm) | 60° Ra (μm) | 70° Ra (μm) | 80° Ra (μm) |
|---------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| 1       | 15.816      | 18.788      | 17.517      | 15.843      | 12.762      | 11.483      | 9.945       | 9.578       |
| 2       | 16.503      | 19.699      | 17.769      | 15.396      | 11.939      | 10.771      | 9.466       | 8.750       |
| 3       | 16.791      | 18.863      | 17.675      | 14.588      | 12.343      | 9.551       | 9.334       | 8.883       |
| 4       | 17.082      | 20.363      | 18.829      | 14.785      | 11.312      | 10.175      | 9.166       | 9.346       |
| 5       | 17.065      | 20.072      | 18.240      | 15.135      | 11.378      | 9.381       | 8.650       | 9.254       |
| 6       | 17.113      | 20.360      | 17.702      | 15.046      | 11.747      | 9.888       | 8.670       | 8.506       |
| 7       | 17.737      | 19.544      | 18.246      | 15.165      | 12.127      | 9.550       | 9.411       | 9.056       |
| 8       | 17.744      | 19.696      | 17.946      | 14.783      | 11.315      | 9.111       | 8.748       | 8.768       |
| 9       | 17.681      | 19.439      | 18.173      | 14.467      | 11.761      | 9.274       | 8.411       | 8.604       |
| 10      | 13.910      | 29.517      | 33.423      | 28.774      | 22.475      | 19.855      | 18.414      | 17.528      |
| 11      | 16.578      | 27.868      | 33.264      | 28.743      | 22.430      | 19.164      | 17.922      | 16.692      |
| 12      | 16.016      | 28.918      | 32.353      | 27.885      | 22.216      | 19.185      | 17.269      | 16.301      |
| 13      | 15.445      | 30.244      | 33.027      | 28.723      | 22.537      | 18.820      | 18.207      | 16.714      |
| 14      | 16.935      | 30.088      | 32.168      | 28.280      | 22.135      | 18.415      | 17.664      | 16.371      |
| 15      | 18.699      | 29.526      | 32.945      | 28.346      | 22.559      | 18.792      | 17.573      | 16.307      |
| 16      | 15.924      | 31.181      | 32.613      | 28.866      | 22.566      | 18.892      | 18.197      | 17.283      |
| 17      | 16.941      | 29.918      | 32.983      | 28.744      | 22.840      | 18.881      | 17.915      | 16.845      |
| 18      | 18.002      | 29.014      | 32.309      | 27.970      | 21.981      | 18.213      | 17.181      | 16.296      |
| 19      | 17.106      | 27.126      | 26.809      | 22.785      | 16.957      | 13.979      | 13.172      | 12.649      |
| 20      | 17.882      | 26.432      | 26.439      | 21.722      | 16.541      | 13.414      | 12.407      | 11.700      |
| 21      | 16.745      | 25.745      | 26.296      | 21.606      | 16.222      | 13.679      | 12.359      | 11.991      |
| 22      | 16.639      | 27.737      | 25.554      | 22.785      | 17.661      | 14.187      | 13.032      | 12.464      |
| 23      | 15.936      | 26.819      | 25.357      | 22.088      | 17.183      | 13.611      | 12.757      | 11.957      |
| 24      | 17.265      | 25.108      | 25.534      | 21.644      | 16.766      | 13.352      | 12.637      | 11.799      |
| 25      | 18.099      | 28.390      | 27.890      | 21.521      | 16.625      | 14.376      | 14.346      | 13.105      |
| 26      | 17.475      | 27.534      | 26.719      | 22.316      | 16.942      | 13.736      | 12.899      | 12.676      |
| 27      | 18.083      | 26.991      | 26.538      | 21.751      | 17.353      | 14.041      | 13.449      | 12.282      |

Table 4.2: Surface Roughness (Ra) Values for AM Parts at Various Inclination Angles

| Part No | 10° Ra (μm) | 20° Ra (μm) | 30° Ra (μm) | 40° Ra (μm) | 50° Ra (μm) | 60° Ra (μm) | 70° Ra (μm) | 80° Ra (μm) |
|---------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| 28      | 16.775      | 19.863      | 18.126      | 15.514      | 12.280      | 10.659      | 10.087      | 9.419       |
| 29      | 17.460      | 20.370      | 18.199      | 15.464      | 12.419      | 10.216      | 10.268      | 9.320       |
| 30      | 16.366      | 20.173      | 17.894      | 15.737      | 12.682      | 10.505      | 9.251       | 8.634       |
| 31      | 17.715      | 20.303      | 18.165      | 15.264      | 11.878      | 10.206      | 9.912       | 9.070       |
| 32      | 17.033      | 19.958      | 17.763      | 14.781      | 11.380      | 10.391      | 9.321       | 8.642       |
| 33      | 17.388      | 19.033      | 16.041      | 15.337      | 12.801      | 10.112      | 9.530       | 9.085       |
| 34      | 17.952      | 18.764      | 16.866      | 14.724      | 12.204      | 9.530       | 8.823       | 8.607       |
| 35      | 18.086      | 19.590      | 17.205      | 14.302      | 11.283      | 9.968       | 8.605       | 8.423       |
| 36      | 16.714      | 19.963      | 16.980      | 14.098      | 11.584      | 10.083      | 8.595       | 8.505       |
| 37      | 18.536      | 29.319      | 32.393      | 29.205      | 21.068      | 18.779      | 17.568      | 17.360      |
| 38      | 18.251      | 29.233      | 32.440      | 29.495      | 22.893      | 19.035      | 17.443      | 16.940      |
| 39      | 19.466      | 28.906      | 33.053      | 30.093      | 24.701      | 19.820      | 18.416      | 16.568      |
| 40      | 16.346      | 29.728      | 34.200      | 30.262      | 23.603      | 19.665      | 17.858      | 16.482      |
| 41      | 20.734      | 30.073      | 33.555      | 30.248      | 27.596      | 21.533      | 19.714      | 17.663      |
| 42      | 21.108      | 31.178      | 33.788      | 32.984      | 30.176      | 25.423      | 24.238      | 22.871      |
| 43      | 19.273      | 30.522      | 33.548      | 30.075      | 22.942      | 19.462      | 17.629      | 17.222      |
| 44      | 19.796      | 30.197      | 33.297      | 30.880      | 25.191      | 20.505      | 18.252      | 17.116      |
| 45      | 22.577      | 30.958      | 32.667      | 31.498      | 26.020      | 21.848      | 18.358      | 17.529      |
| 46      | 16.115      | 27.069      | 26.194      | 20.806      | 16.051      | 13.589      | 12.965      | 12.763      |
| 47      | 17.225      | 28.723      | 26.331      | 21.386      | 16.947      | 14.330      | 13.299      | 12.596      |
| 48      | 17.506      | 28.194      | 28.463      | 21.220      | 18.480      | 15.247      | 13.267      | 12.115      |
| 49      | 18.799      | 26.244      | 25.321      | 20.624      | 15.669      | 13.607      | 12.988      | 12.580      |
| 50      | 19.053      | 27.168      | 25.502      | 20.107      | 16.000      | 13.585      | 12.602      | 12.207      |
| 51      | 18.615      | 28.331      | 25.658      | 21.112      | 16.704      | 13.589      | 12.878      | 12.302      |
| 52      | 18.850      | 28.392      | 25.842      | 21.268      | 17.195      | 14.296      | 13.506      | 13.023      |
| 53      | 19.236      | 27.934      | 26.884      | 21.910      | 17.526      | 14.462      | 12.808      | 12.506      |
| 54      | 25.901      | 27.884      | 32.395      | 25.302      | 18.099      | 15.370      | 13.449      | 12.957      |

The surface roughness values shown in Tables 4.1 and 4.2 are the average arithmetic mean roughness Ra values. These values come from three repeated measurements taken at each inclined surface angle. A sample is provided in Table 3.11. For a more detailed look, these tables are divided into sub-tables based on layer height and nozzle diameter. Each sub-table includes a corresponding graph that visually shows the average trend in surface roughness as the inclination angles change. The parts with the lowest Ra values, indicating the best surface finish, and the highest Ra values, indicating the worst surface finish, for each layer height and nozzle diameter combination are highlighted in the figures along with the discussion of input parameters, like layer height, extrusion temperature, and nozzle diameter contributing to these differences.

The average trend observed from Tables 4.1 and 4.2 is provided in Figure 4.1.

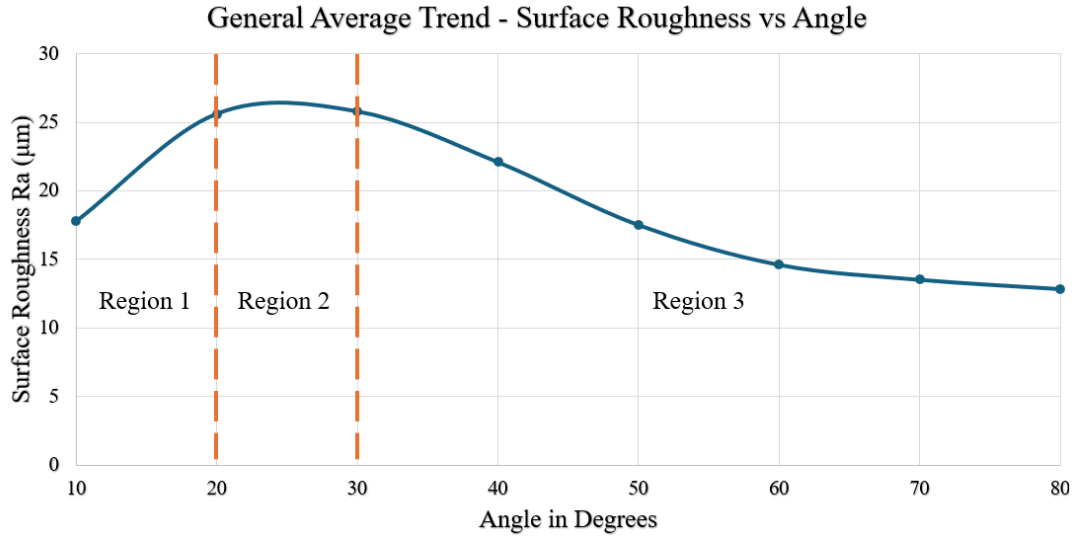


Figure 4.1: Average Trend of Ra vs Inclination Angles

The trend presented in Figure 4.1 demonstrates a sharp increase in surface roughness between 10° and 20°, followed by a peak in the range of 20° to 30°. Subsequently, a steep decline is observed from 30° to 50°, after which the surface roughness continues to decrease at a more stable and gradual rate up to 80°. Therefore, there is an increase in the surface roughness at initial angles until it reaches a peak point and then decreases at higher angles. Three regions are identified on the Figure 4.1. Region 1 is where the inclination angles are low, between 10 to 20 degrees, and there is a sharp increase in the surface roughness. The surface roughness values increase from approximately 18  $\mu\text{m}$  to 25  $\mu\text{m}$ . This trend is observed due to a stack and step effect, details of which are given in the study conducted by Kugunavar et al [34]. A step can be considered as the visible edge or stair that is quite visible at the low inclination angles. The height of the step is equal to the layer height; however, the width of the step is dependent on the inclination angle. Stacking is the number of layers that are deposited one after another. Lower inclination angles have less stacking, which means the layers are spread out more horizontally, contributing to visibly large steps. Higher inclination angles have more stacking of the layers, which reduces the horizontal distances between the layers, resulting in improved surface roughness. Figure 4.2 shows the stack and step effect on the 10 and 80 degree angles clearly in the Cura environment.



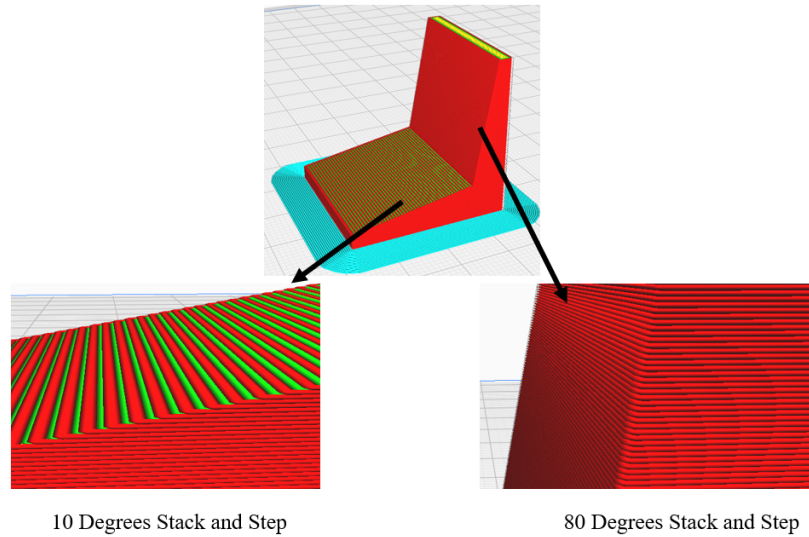
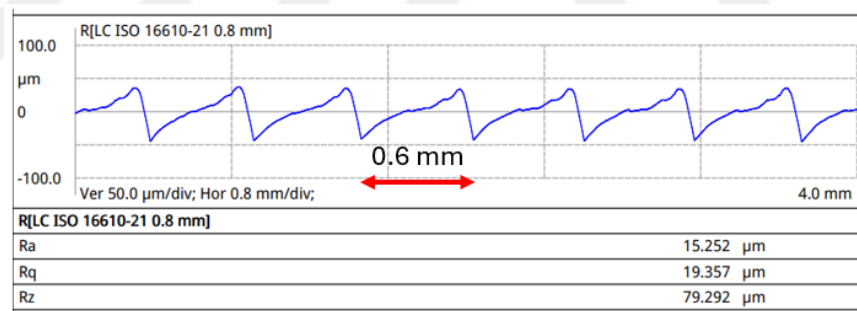
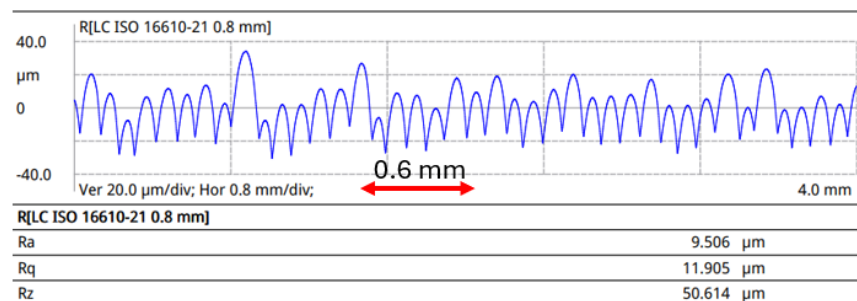


Figure 4.2: Stack and Step Effect on 10 and 80 Degrees

The stacking and stepping effects are clearly identifiable in the surface roughness profiles obtained from the profilometer measurements. Figure 4.3 illustrates the surface roughness profiles of Part 1 at inclination angles of  $10^\circ$  and  $80^\circ$ .



10 Degrees Roughness Profile (Part 1)



80 Degrees Roughness Profile (Part 1)

Figure 4.3: Stack and Step Effect on 10 and 80 Roughness profiles

In the  $10^\circ$  profile, a single layer spans a distance of approximately 0.6 mm, indicating a pronounced stacking and stepping effect due to the shallow inclination. Conversely, the  $80^\circ$  profile exhibits a much denser pattern of layers over the same surface distance, resulting in a significantly reduced stacking and stepping effect.

Region two is where the surface roughness values are the maximum and lie between 20 and 30 degrees inclination. An approximate value of  $26\text{ }\mu\text{m}$  is observed at an angle of 25 degrees from the graphical trend. In this region, there is a corner geometry effect that becomes dominant and contributes to a higher surface roughness along with the stack and step effect. Once the transition region has been passed, surface roughness values start decreasing with an increase in angle in region 3. The values decrease from  $26\text{ }\mu\text{m}$  to  $13\text{ }\mu\text{m}$  between the inclinations of  $30^\circ$  and  $80^\circ$  respectively. This is attributed to the fact that now the stack and step effect start decreasing along with the corner geometry effect as corners become less visible, making the surface smoother.

Tables 4.3, 4.4, and 4.5 have been extracted and reformatted from the original datasets presented in Tables 4.1 and 4.2 to facilitate a clearer and more targeted analysis of surface roughness behavior with respect to layer height. Such methodological distinction permits a more detailed analysis of the impacts of layer height changes on the resulting surface roughness for varying inclination angles. By delimiting these variables for their respective categories, it is then further possible to recognize clear surface quality trends that would otherwise be buried within the composite datasets. Such organized tabulation proves invaluable to making informative conclusions regarding the layer height–inclination interrelationship, as well as to recognizing the sensitivity of the resulting roughness to ostensibly small process variations.

Additional work was carried out by employing the predictive equation proposed in the study of Kugunuvar et al. [34]. This equation was applied to the present set of process parameters, and the predicted surface roughness values ( $R_a$ ) were systematically compared with the experimentally measured results. A detailed description of the methodology, along with the corresponding results, is provided in Appendix A. The comparison revealed a close agreement between the predicted and experimental  $R_a$  values, thereby strengthening the reliability of the current findings.

Table 4.3: Surface Roughness Ra for Layer Height of 0.1 mm

| Part No | 10° Ra (μm) | 20° Ra (μm) | 30° Ra (μm) | 40° Ra (μm) | 50° Ra (μm) | 60° Ra (μm) | 70° Ra (μm) | 80° Ra (μm) |
|---------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| 1       | 15.816      | 18.788      | 17.517      | 15.843      | 12.762      | 11.483      | 9.945       | 9.578       |
| 2       | 16.503      | 19.699      | 17.769      | 15.396      | 11.939      | 10.771      | 9.466       | 8.750       |
| 3       | 16.791      | 18.863      | 17.675      | 14.588      | 12.343      | 9.551       | 9.334       | 8.883       |
| 4       | 17.082      | 20.363      | 18.829      | 14.785      | 11.312      | 10.175      | 9.166       | 9.346       |
| 5       | 17.065      | 20.072      | 18.240      | 15.135      | 11.378      | 9.381       | 8.650       | 9.254       |
| 6       | 17.113      | 20.360      | 17.702      | 15.046      | 11.747      | 9.888       | 8.670       | 8.506       |
| 7       | 17.737      | 19.544      | 18.246      | 15.165      | 12.127      | 9.550       | 9.411       | 9.056       |
| 8       | 17.744      | 19.696      | 17.946      | 14.783      | 11.315      | 9.111       | 8.748       | 8.768       |
| 9       | 17.681      | 19.439      | 18.173      | 14.467      | 11.761      | 9.274       | 8.411       | 8.604       |
| 28      | 16.775      | 19.863      | 18.126      | 15.514      | 12.280      | 10.659      | 10.087      | 9.419       |
| 29      | 17.460      | 20.370      | 18.199      | 15.464      | 12.419      | 10.216      | 10.268      | 9.320       |
| 30      | 16.366      | 20.173      | 17.894      | 15.737      | 12.682      | 10.505      | 9.251       | 8.634       |
| 31      | 17.715      | 20.303      | 18.165      | 15.264      | 11.878      | 10.206      | 9.912       | 9.070       |
| 32      | 17.033      | 19.958      | 17.763      | 14.781      | 11.380      | 10.391      | 9.321       | 8.642       |
| 33      | 17.388      | 19.033      | 16.041      | 15.337      | 12.801      | 10.112      | 9.530       | 9.085       |
| 34      | 17.952      | 18.764      | 16.866      | 14.724      | 12.204      | 9.530       | 8.823       | 8.607       |
| 35      | 18.086      | 19.590      | 17.205      | 14.302      | 11.283      | 9.968       | 8.605       | 8.423       |
| 36      | 16.714      | 19.963      | 16.980      | 14.098      | 11.584      | 10.083      | 8.595       | 8.505       |

Table 4.4: Surface Roughness Ra for 0.15 mm Layer Height

| Part No | 10° Ra (μm) | 20° Ra (μm) | 30° Ra (μm) | 40° Ra (μm) | 50° Ra (μm) | 60° Ra (μm) | 70° Ra (μm) | 80° Ra (μm) |
|---------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| 19      | 17.106      | 27.126      | 26.809      | 22.785      | 16.957      | 13.979      | 13.172      | 12.649      |
| 20      | 17.882      | 26.432      | 26.439      | 21.722      | 16.541      | 13.414      | 12.407      | 11.700      |
| 21      | 16.745      | 25.745      | 26.296      | 21.606      | 16.222      | 13.679      | 12.359      | 11.991      |
| 22      | 16.639      | 27.737      | 25.554      | 22.785      | 17.661      | 14.187      | 13.032      | 12.464      |
| 23      | 15.936      | 26.819      | 25.357      | 22.088      | 17.183      | 13.611      | 12.757      | 11.957      |
| 24      | 17.265      | 25.108      | 25.534      | 21.644      | 16.766      | 13.352      | 12.637      | 11.799      |
| 25      | 18.099      | 28.390      | 27.890      | 21.521      | 16.625      | 14.376      | 14.346      | 13.105      |
| 26      | 17.475      | 27.534      | 26.719      | 22.316      | 16.942      | 13.736      | 12.899      | 12.676      |
| 27      | 18.083      | 26.991      | 26.538      | 21.751      | 17.353      | 14.041      | 13.449      | 12.282      |
| 46      | 16.115      | 27.069      | 26.194      | 20.806      | 16.051      | 13.589      | 12.965      | 12.763      |
| 47      | 17.225      | 28.723      | 26.331      | 21.386      | 16.947      | 14.330      | 13.299      | 12.596      |
| 48      | 17.506      | 28.194      | 28.463      | 21.220      | 18.480      | 15.247      | 13.267      | 12.115      |
| 49      | 18.799      | 26.244      | 25.321      | 20.624      | 15.669      | 13.607      | 12.988      | 12.580      |
| 50      | 19.053      | 27.168      | 25.502      | 20.107      | 16.000      | 13.585      | 12.602      | 12.207      |
| 51      | 18.615      | 28.331      | 25.658      | 21.112      | 16.704      | 13.589      | 12.878      | 12.302      |
| 52      | 18.850      | 28.392      | 25.842      | 21.268      | 17.195      | 14.296      | 13.506      | 13.023      |
| 53      | 19.236      | 27.934      | 26.884      | 21.910      | 17.526      | 14.462      | 12.808      | 12.506      |
| 54      | 25.901      | 27.884      | 32.395      | 25.302      | 18.099      | 15.370      | 13.449      | 12.957      |

Table 4.5: Surface Roughness Ra for 0.20 mm Layer Height

| Part No | 10° Ra (μm) | 20° Ra (μm) | 30° Ra (μm) | 40° Ra (μm) | 50° Ra (μm) | 60° Ra (μm) | 70° Ra (μm) | 80° Ra (μm) |
|---------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| 10      | 13.910      | 29.517      | 33.423      | 28.774      | 22.475      | 19.855      | 18.414      | 17.528      |
| 11      | 16.578      | 27.868      | 33.264      | 28.743      | 22.430      | 19.164      | 17.922      | 16.692      |
| 12      | 16.016      | 28.918      | 32.353      | 27.885      | 22.216      | 19.185      | 17.269      | 16.301      |
| 13      | 15.445      | 30.244      | 33.027      | 28.723      | 22.537      | 18.820      | 18.207      | 16.714      |
| 14      | 16.935      | 30.088      | 32.168      | 28.280      | 22.135      | 18.415      | 17.664      | 16.371      |
| 15      | 18.699      | 29.526      | 32.945      | 28.346      | 22.559      | 18.792      | 17.573      | 16.307      |
| 16      | 15.924      | 31.181      | 32.613      | 28.866      | 22.566      | 18.892      | 18.197      | 17.283      |
| 17      | 16.941      | 29.918      | 32.983      | 28.744      | 22.840      | 18.881      | 17.915      | 16.845      |
| 18      | 18.002      | 29.014      | 32.309      | 27.970      | 21.981      | 18.213      | 17.181      | 16.296      |
| 37      | 18.536      | 29.319      | 32.393      | 29.205      | 21.068      | 18.779      | 17.568      | 17.360      |
| 38      | 18.251      | 29.233      | 32.440      | 29.495      | 22.893      | 19.035      | 17.443      | 16.940      |
| 39      | 19.466      | 28.906      | 33.053      | 30.093      | 24.701      | 19.820      | 18.416      | 16.568      |
| 40      | 16.346      | 29.728      | 34.200      | 30.262      | 23.603      | 19.665      | 17.858      | 16.482      |
| 41      | 20.734      | 30.073      | 33.555      | 30.248      | 27.596      | 21.533      | 19.714      | 17.663      |
| 42      | 21.108      | 31.178      | 33.788      | 32.984      | 30.176      | 25.423      | 24.238      | 22.871      |
| 43      | 19.273      | 30.522      | 33.548      | 30.075      | 22.942      | 19.462      | 17.629      | 17.222      |
| 44      | 19.796      | 30.197      | 33.297      | 30.880      | 25.191      | 20.505      | 18.252      | 17.116      |
| 45      | 22.577      | 30.958      | 32.667      | 31.498      | 26.020      | 21.848      | 18.358      | 17.529      |

The following Figure 4.4 shows the average trends observed for all the surface roughness values concerning three layer heights.

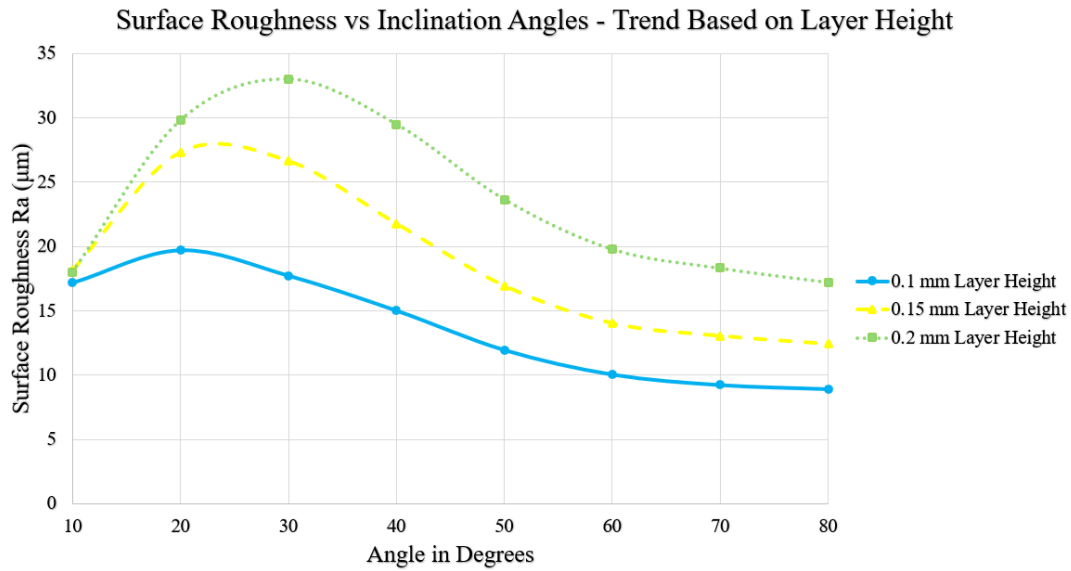


Figure 4.4: General Trend of Ra vs Inclination Angles based on Layer Heights

Figure 4.4 demonstrates the clear effect of layer height on the surface roughness Ra

for different inclination angles. The trend lines shown for the different layer heights of 0.1 mm, 0.15 mm, and 0.2 mm exhibit the common pattern where the surface roughness increases with inclination angle, reaches its maximum value, and then decreases continuously. The maximum surface roughness occurs for the 0.2 mm layer height at 30°, having a value approximately 33  $\mu\text{m}$ , while the maximum Ra values are recorded for the 0.1 mm layer height at a value of approximately 19  $\mu\text{m}$  at 20°. Therefore, it could be seen that the surface roughness at all inclination angles increases with an increase in the layer height. This reaffirms the critical role of fine selection of the layer height for applications where the surface finish is critical. In addition, a noticeable shift in the peak surface roughness is observed as a function of layer height. Specifically, as the layer height increases, the maximum surface roughness value not only becomes more pronounced but also shifts toward higher inclination angles. This shift of the peak towards the right suggests that the interaction between layer height and surface geometry becomes more dominant at steeper angles when larger layer heights are employed. This result is a significant outcome for this work's focus and has experimental value for application within industrial processes. It illustrates the significance of the careful selection of process parameters, namely layer height, when surface quality is of utmost importance because it has a direct influence on the location and magnitude of peak surface roughness on inclined geometries.

A comparative analysis of the best and worst performing parts is important for understanding the main factors that influence surface roughness. This evaluation offers useful preliminary insights into how changes in input parameters like nozzle diameter, layer height, extrusion temperature, and print speed affect the surface quality of printed components. The parts are classified into best and worst categories for each layer height, ensuring a fair and organized comparison. For each layer height, representative parts are selected by averaging surface roughness measurements across all inclination angles. This approach helped to understand performance trends under different AM parameters.

Table 4.6 explains the features and the surface roughness values for the best and the worst parts made of a 0.1 mm layer height.

Table 4.6: 0.1 mm Layer Height Best and Worst Parts

| Features                     | Part 36  | Part 29 |
|------------------------------|----------|---------|
| Category                     | Best     | Worst   |
| Nozzle Diameter (mm)         | 0.25     | 0.25    |
| Layer Height (mm)            | 0.1      | 0.1     |
| Wall Thickness (mm)          | 2.00     | 0.75    |
| Top Thickness (mm)           | 1.6      | 1.2     |
| Infill Density (%)           | 80       | 20      |
| Infill Pattern               | Triangle | Grid    |
| Printing Extrusion Temp (°C) | 210      | 190     |
| Build Plate Temp (°C)        | 55       | 50      |
| Print Speed (mm/s)           | 80       | 60      |
| Fan Speed                    | 100      | 75      |
| 10° Ra (μm)                  | 16.714   | 17.460  |
| 20° Ra (μm)                  | 19.963   | 20.370  |
| 30° Ra (μm)                  | 16.980   | 18.199  |
| 40° Ra (μm)                  | 14.098   | 15.464  |
| 50° Ra (μm)                  | 11.584   | 12.419  |
| 60° Ra (μm)                  | 10.083   | 10.216  |
| 70° Ra (μm)                  | 8.595    | 10.268  |
| 80° Ra (μm)                  | 8.505    | 9.320   |
| Average Ra (μm)              | 13.315   | 14.215  |

Table 4.6 provides a comparative overview of the process parameters influencing surface roughness for the best and worst performing samples fabricated using a 0.1 mm layer height. Whilst the average surface roughness measures vary by a mere 0.9 μm, with the average surface roughness of the best part being 13.315 μm compared to 14.215 μm for the worst part, this minor deviation highlights the sensitivity of the surface quality to variations in the input parameters. The peak surface roughness for the best part is on the 20° incline with an Ra of 19.963 μm, whilst the peak surface roughness for the worst part is on the same 20° incline with an Ra of 20.370 μm.

Interestingly, both samples were produced with the same 0.25 mm nozzle diameter, but the part with the best surface finish had been produced with a higher extrusion temperature of 210°C. The implication is therefore that higher extrusion temperatures improve material flow characteristics and interlayer adhesion, thus minimizing the presence of surface irregularities. Conversely, low extrusion temperatures, for instance, 190°C, were shown to degrade layer adhesion resulting in high surface roughness values. For applications where the integrity of the surface is paramount, the deployment of a 0.1 mm layer height with a 0.25 mm diameter nozzle, alongside the deployment of higher extrusion temperatures, around 210°C, would leave the parts with the best surface finish. Figure 4.5 illustrates both the best and the worst parts; however, due to a very small difference, the surface quality cannot be judged with the naked eye.

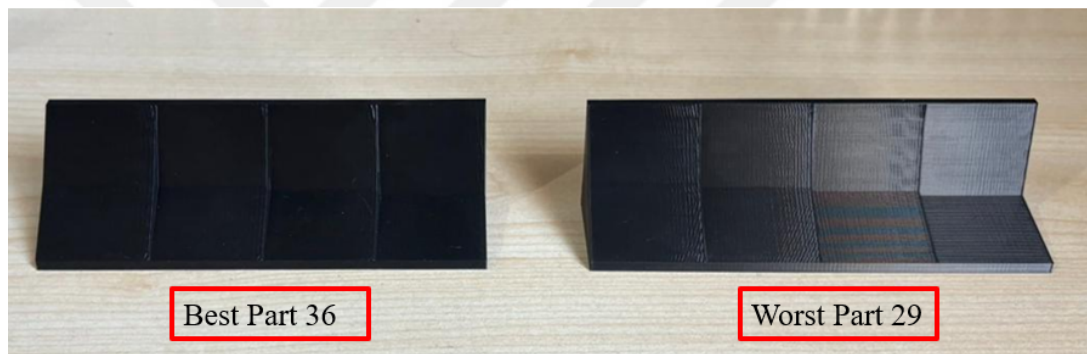


Figure 4.5: 0.1 mm Layer height Worst and Best Parts

Table 4.7 shows the comparative analysis between the best and the worst performing parts for a 0.15 mm layer height. It can be seen that the best surface quality was obtained with a 0.4 mm nozzle diameter and a printing temperature of 200°C, while the poorest surface roughness was with a 0.25 mm nozzle working at a lower 190°C temperature. The average surface roughness of best part was measured to be 18.013  $\mu\text{m}$ , and for worst-performing part, 21.420  $\mu\text{m}$ , averaging out to a significant difference of nearly 3  $\mu\text{m}$ . The highest surface roughness value on the best part was also noted at 30° inclination with an Ra of 25.534  $\mu\text{m}$ , whilst the worst part displayed an Ra value of 32.395  $\mu\text{m}$  on the same incline.

Table 4.7: 0.15 mm Layer Height Best and Worst Parts

| Features                     | Part No: 24 | Part No: 54 |
|------------------------------|-------------|-------------|
| Category                     | Best        | Worst       |
| Nozzle Diameter (mm)         | 0.4         | 0.25        |
| Layer Height (mm)            | 0.15        | 0.15        |
| Wall Thickness (mm)          | 1           | 2           |
| Top Thickness (mm)           | 1.2         | 1.2         |
| Infill Density (%)           | 80          | 80          |
| Infill Pattern               | Grid        | Cubic       |
| Printing Extrusion Temp (°C) | 200         | 190         |
| Build Plate Temp (°C)        | 55          | 60          |
| Print Speed (mm/s)           | 80          | 80          |
| Fan Speed                    | 75          | 50          |
| 10° Ra (µm)                  | 17.265      | 25.901      |
| 20° Ra (µm)                  | 25.108      | 27.884      |
| 30° Ra (µm)                  | 25.534      | 32.395      |
| 40° Ra (µm)                  | 21.644      | 25.302      |
| 50° Ra (µm)                  | 16.766      | 18.099      |
| 60° Ra (µm)                  | 13.352      | 15.370      |
| 70° Ra (µm)                  | 12.637      | 13.449      |
| 80° Ra (µm)                  | 11.799      | 12.957      |
| Average Ra (µm)              | 18.013      | 21.420      |

Figure 4.6 represents the surface quality problems present on the worst part, numbered 54. The right part of this figure of the 0.15 mm layer height category shows visible surface irregularities. These defects typically appear from under-extrusion and poor thermal bonding. Figure 4.7 presents the surface roughness profiles for both the best and worst parts within this category. The roughness profile corresponding to Part 54 exhibits pronounced peaks and valleys accompanied by irregularities, with significantly higher amplitude values, thereby confirming the presence of surface discontinuities.



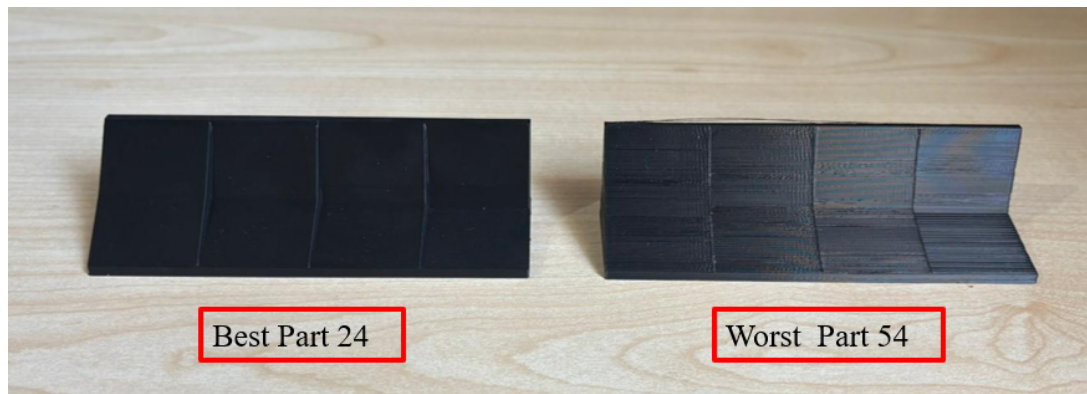
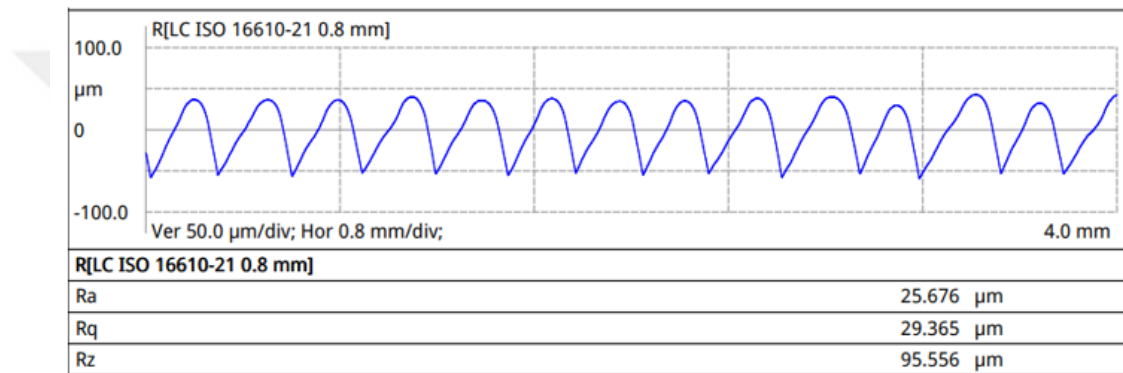
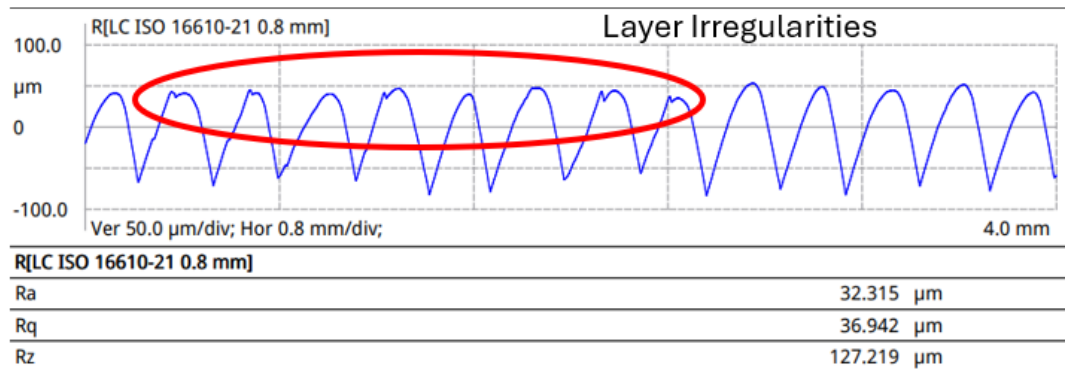


Figure 4.6: 0.15 mm Layer height Worst and Best Parts



30 Degrees Roughness Profile (Part 24)



30 Degrees Roughness Profile (Part 54)

Figure 4.7: 0.15 mm Layer height Worst and Best Parts Surface Roughness Profiles

The inclined surfaces on the worst part 54 show a rough, non-smooth aspect, compared to the shiny finish on the best part 24. The part 54 obtained its rough surface quality primarily by the combination of a 0.25 mm nozzle diameter, low printing tem-

perature of 190°C, and 0.15 mm layer height. Although there is a potential for 0.25 mm nozzle to produce detailed features, with a smaller extruded volume it is also more prone to sub-optimal processing conditions. At a rather low extrusion temperature of 190°C, the PLA filament could not achieve full melting, leading to incomplete layer adhesions and higher roughness on the surface, particularly on inclined surfaces where the angle of deposition additionally worsens layer adhesion.

Table 4.8 shows a comparison between the best and worst surface roughness results of specimens made at a constant layer height of 0.2 mm. The best surface finish occurred with a 0.4 mm nozzle at 210°C extrusion temperature, producing the lowest average Ra value of 22.518  $\mu\text{m}$  for the 0.2 mm layer height category. The worst surface finish occurred with a 0.25 mm nozzle at 190°C extrusion temperature, producing an average Ra value of 27.721  $\mu\text{m}$ . At an angle of 30°, both parts reached their highest Ra values, with the best part recording 32.353  $\mu\text{m}$  and the worst part measuring 33.788  $\mu\text{m}$ . The results show that nozzle size, together with extrusion temperature, strongly affects surface roughness measurements even when layer height remains at 0.2 mm.

Figure 4.8 shows the underextrusion and stringing effect on the worst-performing printed part (Part 42). A similar trend is evident in the surface roughness profiles obtained for the worst-performing part, as shown in Figure 4.9. The profile corresponding to the 40° inclined surface of Part 42 displays significant irregularity and lack of uniformity in the amplitude of surface features. The waveform is highly inconsistent, with sporadic peaks and valleys, which indicates poor surface quality due to the dominant underextrusion phenomenon. These defects collectively contribute to the elevated roughness parameters observed in Part 42, including a higher Ra of 33.015  $\mu\text{m}$  for 40°, and as compared to Part 12, which exhibits more regular and periodic surface features for the same inclination. The smoother and more consistent profile in Part 12, with a lower Ra of 27.772  $\mu\text{m}$ , further validates the influence of optimized printing parameters on surface finish quality. It should be kept in mind that the surface roughness profiles are one of the three profiles for the 40° inclination obtained by carrying out three measurements on each inclination angle, as mentioned in Section 3.4.2. The part was manufactured using a 0.25 mm nozzle with 190°C extrusion temperature and 0.2 mm layer height. Stringing results when the printer moves across open spaces, the nozzle leaks small amounts of molten filament, which results

in fine strings of material being deposited unintentionally between print features, thus creating stringing, also known as "oozing" or "hairy prints" [83]. The combination of 0.25 mm nozzle diameter and 190°C extrusion temperature leads to insufficient extrusion control. A 0.25 mm nozzle has a restricted volumetric flow rate because of its tight bore dimension, so it cannot reliably extrude material at lower temperatures. A 0.25 mm nozzle with 0.2 mm layer height usage reaches the maximum recommended ratio. The proper ratio for layer height to nozzle diameter is to stay below 75–80% for maintaining adequate bonding and flow properties. The 0.2 mm layer height sits at the highest recommended point.

Table 4.8: 0.2 mm Layer Height Best and Worst Parts

| Features                     | Part No: 12 | Part No: 42 |
|------------------------------|-------------|-------------|
| Category                     | Best        | Worst       |
| Nozzle Diameter (mm)         | 0.4         | 0.25        |
| Layer Height (mm)            | 0.2         | 0.2         |
| Wall Thickness (mm)          | 0.75        | 1           |
| Top Thickness (mm)           | 1.4         | 1.4         |
| Infill Density (%)           | 80          | 80          |
| Infill Pattern               | Grid        | Triangle    |
| Printing Extrusion Temp (°C) | 210         | 190         |
| Build Plate Temp (°C)        | 60          | 50          |
| Print Speed (mm/s)           | 80          | 80          |
| Fan Speed                    | 50          | 100         |
| 10° Ra (µm)                  | 16.016      | 21.108      |
| 20° Ra (µm)                  | 28.918      | 31.178      |
| 30° Ra (µm)                  | 32.353      | 33.788      |
| 40° Ra (µm)                  | 27.885      | 32.984      |
| 50° Ra (µm)                  | 22.216      | 30.176      |
| 60° Ra (µm)                  | 19.185      | 25.423      |
| 70° Ra (µm)                  | 17.269      | 24.238      |
| 80° Ra (µm)                  | 16.301      | 22.871      |
| Average Ra (µm)              | 22.518      | 27.721      |

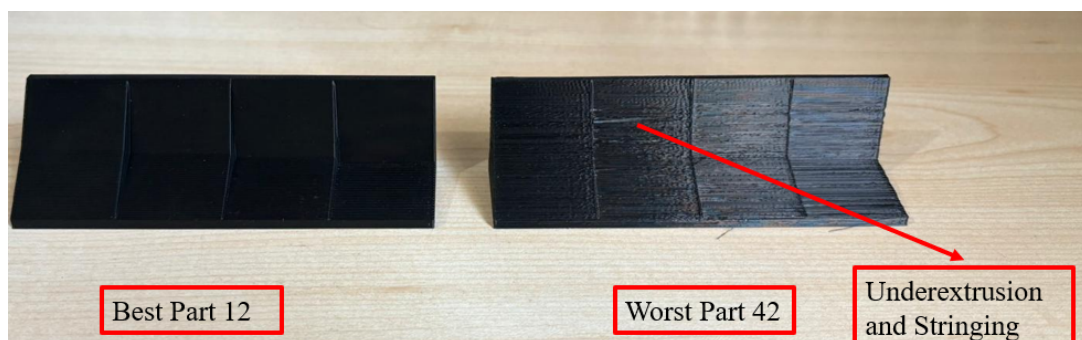
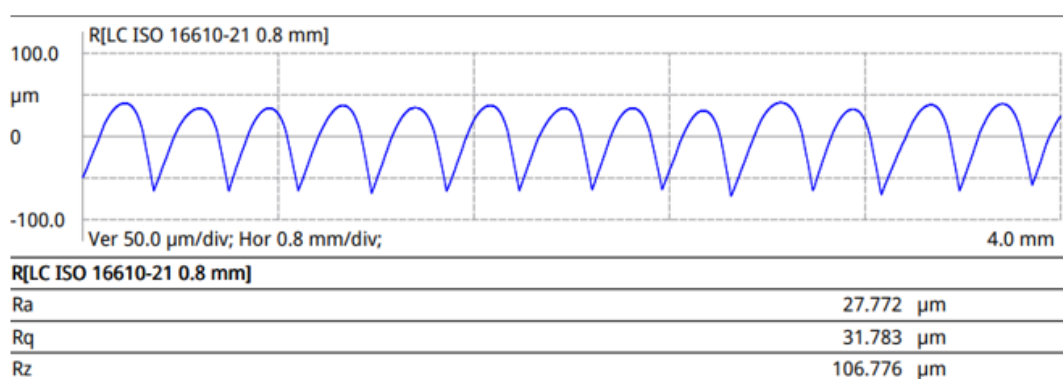
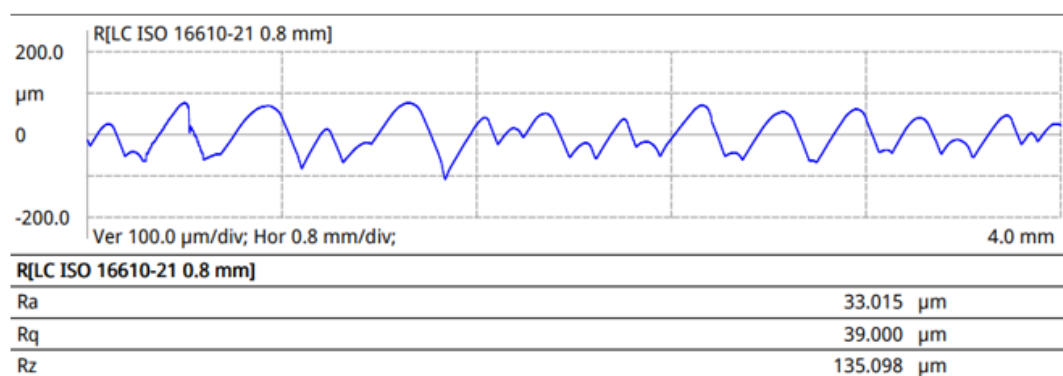


Figure 4.8: 0.2 mm Layer height Worst and Best Parts



#### 40 Degrees Roughness Profile (Part 12)



#### 40 Degrees Roughness Profile (Part 42)

Figure 4.9: 0.2 mm Layer height Worst and Best Parts Surface Roughness Profiles

Using this parameter at its maximum point weakened layer adhesion and created un-

der extrusion problems because of insufficient material not properly extruding out of the nozzle at a lower temperature and smaller nozzle diameter. This resulted in surface defects that appeared in Part 42.

Therefore, it can be concluded that the optimal surface roughness was achieved using a 0.25 mm nozzle in conjunction with a 0.1 mm layer height and a printing temperature of 210°C. Conversely, the poorest surface roughness values were obtained using the same nozzle diameter at higher layer heights of 0.15 mm and 0.2 mm, particularly when the extrusion temperature was set to 190°C. Other process parameters have been excluded from this specific analysis, as their influence will be more comprehensively evaluated through feature importance and SHAP plots generated by machine learning algorithms. A practical recommendation for industrial practitioners is that if superior surface quality is the primary objective, utilizing a smaller nozzle diameter of 0.25 mm in combination with a lower layer height of 0.1 mm and elevated printing temperature of 210°C is advised to minimize surface roughness. However, in scenarios where printing time is a critical factor, employing a 0.4 mm nozzle at layer heights of 0.15 mm or 0.2 mm and printing temperatures between 200°C and 210°C offers a more time-efficient alternative with high surface quality results as compared to using a 0.25 mm nozzle with the same layer height settings for PLA.

## **4.2 Surface Roughness Evaluation for Hybrid (AM+CNC) Parts**

This section examines the critical role of CNC milling in enhancing the surface quality of additively manufactured (AM) PLA components. As outlined in Section 3.5.2, the depth of cut was systematically varied from 0.2 mm to 0.4 mm in increments of 0.1 mm for each inclination angle. The objective was to evaluate the extent of improvement in surface roughness that can be achieved through post-processing under the selected milling parameters and to observe the effect of the depth of cut variation. A comparative analysis is presented between the best-performing and worst-performing parts, based on the mean surface roughness values calculated across all inclination angles. Furthermore, attention is given to specific cases where certain parts could not undergo CNC post-processing due to defects originating during the AM stage. These manufacturing-related issues are examined in detail, with a discussion of the poten-

tial contributing factors and their implications for subsequent hybrid manufacturing operations.

Tables 4.9, 4.10, 4.11, and 4.12 present the surface roughness measurements obtained from CNC machined parts at three levels of depth of cut corresponding to different inclination angle ranges. Tables 4.9 and 4.10 report the surface roughness Ra values for parts fabricated using a 0.4 mm nozzle diameter, covering inclination angles of 10°–40° and 50°–80°, respectively.

Table 4.9: Surface Roughness Measurements for 10°–40° inclinations at Different Depths of Cuts (Parts 1-27)

| Part No | 10° Ra ( $\mu\text{m}$ ) |        |        | 20° Ra ( $\mu\text{m}$ ) |        |        | 30° Ra ( $\mu\text{m}$ ) |        |        | 40° Ra ( $\mu\text{m}$ ) |        |        |
|---------|--------------------------|--------|--------|--------------------------|--------|--------|--------------------------|--------|--------|--------------------------|--------|--------|
|         | 0.2 mm                   | 0.3 mm | 0.4 mm | 0.2 mm                   | 0.3 mm | 0.4 mm | 0.2 mm                   | 0.3 mm | 0.4 mm | 0.2 mm                   | 0.3 mm | 0.4 mm |
| 1       | 1.540                    | 1.608  | 1.517  | 2.367                    | 2.225  | 2.294  | 2.522                    | 2.526  | 2.476  | 1.751                    | 1.585  | 2.254  |
| 2       | 1.593                    | 1.384  | 1.393  | 2.029                    | 2.366  | 2.036  | 2.103                    | 2.091  | 2.112  | 1.276                    | 1.788  | 1.376  |
| 3       | 1.112                    | 1.224  | 1.234  | 1.870                    | 2.291  | 2.365  | 1.774                    | 1.782  | 2.226  | 1.911                    | 1.329  | 1.387  |
| 4       | 1.732                    | 1.464  | 1.550  | 2.166                    | 2.090  | 2.291  | 2.234                    | 2.055  | 2.174  | 1.233                    | 1.845  | 1.374  |
| 5       | 1.691                    | 1.511  | 1.418  | 2.056                    | 2.487  | 2.453  | 2.280                    | 2.263  | 2.386  | 1.299                    | 1.975  | 1.535  |
| 6       | 1.501                    | 1.411  | 1.687  | 2.540                    | 2.261  | 2.398  | 2.283                    | 2.140  | 2.150  | 1.591                    | 1.418  | 1.343  |
| 7       | 1.543                    | 1.381  | 1.812  | 2.181                    | 2.248  | 2.662  | 1.763                    | 2.181  | 2.115  | 1.599                    | 1.373  | 2.144  |
| 8       | 1.565                    | 1.710  | 1.495  | 2.230                    | 2.188  | 2.309  | 1.884                    | 2.102  | 2.455  | 1.696                    | 1.526  | 1.956  |
| 9       | 1.473                    | 1.393  | 1.263  | 2.341                    | 2.182  | 2.283  | 2.175                    | 2.478  | 1.931  | 1.409                    | 1.279  | 1.283  |
| 10      | 1.508                    | 1.530  | 1.654  | 2.030                    | 2.069  | 2.104  | 2.021                    | 2.315  | 2.340  | 2.371                    | 1.422  | 1.399  |
| 11      | 1.596                    | 1.813  | 1.666  | 2.325                    | 2.643  | 2.583  | 2.413                    | 2.665  | 2.709  | 1.437                    | 1.605  | 1.720  |
| 12      | 1.908                    | 1.830  | 1.762  | 2.609                    | 2.853  | 2.418  | 2.411                    | 2.168  | 2.122  | 1.781                    | 1.719  | 1.655  |
| 13      | 1.912                    | 1.880  | 1.629  | 2.697                    | 2.746  | 2.617  | 2.648                    | 2.860  | 2.576  | 1.820                    | 1.526  | 1.755  |
| 14      | 2.198                    | 2.060  | 1.689  | 2.621                    | 2.764  | 2.401  | 2.344                    | 2.674  | 2.665  | 1.641                    | 1.593  | 1.727  |
| 15      | 2.075                    | 1.964  | 1.760  | 2.525                    | 2.504  | 2.793  | 2.548                    | 2.583  | 2.831  | 1.647                    | 1.586  | 1.534  |
| 16      | 1.345                    | 1.656  | 1.368  | 2.003                    | 2.358  | 2.371  | 2.278                    | 2.188  | 1.938  | 1.245                    | 1.119  | 1.739  |
| 17      | 1.385                    | 1.946  | 1.802  | 2.048                    | 2.293  | 2.672  | 1.904                    | 2.259  | 2.406  | 1.259                    | 1.269  | 1.598  |
| 18      | 1.735                    | 1.489  | 1.257  | 2.213                    | 2.586  | 2.460  | 2.009                    | 2.138  | 1.964  | 1.179                    | 1.388  | 1.317  |
| 19      | 1.415                    | 1.571  | 1.393  | 2.290                    | 2.081  | 2.438  | 2.124                    | 2.441  | 2.274  | 1.500                    | 1.015  | 1.409  |
| 20      | 1.125                    | 1.751  | 1.576  | 2.269                    | 2.120  | 2.010  | 1.789                    | 2.442  | 2.311  | 1.212                    | 0.986  | 1.036  |
| 21      | 1.232                    | 1.370  | 1.361  | 2.257                    | 2.775  | 2.610  | 1.892                    | 2.326  | 2.405  | 1.208                    | 1.278  | 1.619  |
| 22      | 1.282                    | 1.573  | 1.392  | 2.098                    | 2.362  | 2.292  | 2.235                    | 2.306  | 2.371  | 2.557                    | 1.391  | 1.329  |
| 23      | 1.220                    | 1.777  | 1.534  | 2.320                    | 2.430  | 2.251  | 2.103                    | 1.980  | 2.386  | 1.728                    | 1.235  | 1.331  |
| 24      | 1.122                    | 1.621  | 1.521  | 2.380                    | 2.203  | 2.355  | 2.245                    | 2.214  | 2.447  | 1.121                    | 1.422  | 1.759  |
| 25      | 1.568                    | 1.833  | 1.878  | 2.550                    | 2.204  | 2.495  | 1.982                    | 2.026  | 2.501  | 1.430                    | 1.681  | 1.235  |
| 26      | 1.570                    | 2.278  | 1.472  | 2.442                    | 2.769  | 2.649  | 2.060                    | 2.445  | 2.370  | 1.225                    | 1.823  | 1.292  |
| 27      | 1.588                    | 2.138  | 1.999  | 2.442                    | 2.648  | 2.460  | 1.812                    | 2.559  | 2.443  | 1.087                    | 1.702  | 1.288  |

Table 4.10: Surface Roughness Measurements for 50°–80° inclinations at Different Depths of Cuts (Parts 1-27)

| Part No | 50° Ra ( $\mu\text{m}$ ) |        |        | 60° Ra ( $\mu\text{m}$ ) |        |        | 70° Ra ( $\mu\text{m}$ ) |        |        | 80° Ra ( $\mu\text{m}$ ) |        |        |
|---------|--------------------------|--------|--------|--------------------------|--------|--------|--------------------------|--------|--------|--------------------------|--------|--------|
|         | 0.2 mm                   | 0.3 mm | 0.4 mm | 0.2 mm                   | 0.3 mm | 0.4 mm | 0.2 mm                   | 0.3 mm | 0.4 mm | 0.2 mm                   | 0.3 mm | 0.4 mm |
| 1       | 1.709                    | 2.115  | 2.105  | 2.476                    | 2.600  | 2.050  | 2.126                    | 2.589  | 2.081  | 1.865                    | 1.959  | 1.762  |
| 2       | 1.308                    | 1.577  | 1.504  | 2.208                    | 2.239  | 2.326  | 2.138                    | 2.380  | 2.409  | 1.399                    | 1.406  | 1.443  |
| 3       | 1.371                    | 1.300  | 1.173  | 1.762                    | 2.106  | 2.071  | 2.131                    | 2.296  | 2.057  | 1.608                    | 1.675  | 1.804  |
| 4       | 1.610                    | 1.426  | 1.820  | 2.118                    | 2.249  | 2.329  | 2.290                    | 1.938  | 2.714  | 1.627                    | 1.578  | 1.379  |
| 5       | 1.446                    | 1.475  | 1.574  | 2.193                    | 2.376  | 2.364  | 1.883                    | 2.162  | 2.145  | 1.596                    | 1.458  | 1.464  |
| 6       | 1.425                    | 1.331  | 1.594  | 2.449                    | 2.174  | 1.994  | 2.158                    | 2.516  | 2.444  | 1.526                    | 1.393  | 1.454  |
| 7       | 1.155                    | 1.299  | 1.517  | 1.907                    | 1.864  | 2.027  | 2.007                    | 2.224  | 2.386  | 1.919                    | 1.415  | 1.686  |
| 8       | 1.338                    | 1.316  | 1.541  | 1.639                    | 1.969  | 2.059  | 2.246                    | 2.082  | 1.993  | 1.643                    | 1.463  | 1.591  |
| 9       | 1.575                    | 1.373  | 1.238  | 2.127                    | 1.988  | 2.446  | 1.942                    | 1.958  | 2.421  | 1.608                    | 1.666  | 1.532  |
| 10      | 1.279                    | 1.350  | 1.580  | 1.973                    | 2.050  | 2.094  | 2.309                    | 1.948  | 2.576  | 2.180                    | 1.690  | 1.795  |
| 11      | 1.533                    | 1.554  | 1.758  | 2.460                    | 2.522  | 2.794  | 2.895                    | 2.060  | 2.623  | 1.698                    | 1.900  | 2.226  |
| 12      | 1.419                    | 1.305  | 1.219  | 2.090                    | 2.402  | 2.172  | 2.189                    | 2.576  | 2.751  | 1.704                    | 1.290  | 1.838  |
| 13      | 1.370                    | 1.307  | 1.288  | 2.063                    | 1.945  | 2.832  | 2.785                    | 2.060  | 2.416  | 1.825                    | 1.384  | 1.918  |
| 14      | 1.416                    | 1.206  | 1.311  | 2.328                    | 2.160  | 2.572  | 2.146                    | 2.486  | 2.525  | 1.400                    | 1.851  | 1.811  |
| 15      | 1.184                    | 1.301  | 1.208  | 1.980                    | 2.249  | 2.076  | 2.117                    | 2.427  | 2.573  | 1.285                    | 1.092  | 1.709  |
| 16      | 1.199                    | 1.087  | 1.283  | 1.986                    | 2.037  | 1.965  | 2.110                    | 2.168  | 2.209  | 1.913                    | 1.440  | 2.025  |
| 17      | 1.189                    | 1.504  | 1.172  | 2.075                    | 1.815  | 1.917  | 1.974                    | 2.270  | 2.124  | 1.820                    | 1.843  | 1.520  |
| 18      | 1.035                    | 1.024  | 1.297  | 1.779                    | 2.018  | 2.230  | 2.261                    | 2.074  | 2.201  | 1.176                    | 1.299  | 1.996  |
| 19      | 1.212                    | 1.432  | 1.327  | 2.021                    | 2.117  | 2.398  | 2.100                    | 2.334  | 2.457  | 1.418                    | 1.664  | 1.891  |
| 20      | 1.189                    | 1.470  | 1.238  | 2.164                    | 1.970  | 2.471  | 2.057                    | 2.214  | 1.968  | 1.610                    | 1.478  | 1.791  |
| 21      | 1.475                    | 1.476  | 1.447  | 2.051                    | 1.961  | 2.845  | 2.154                    | 2.340  | 2.482  | 1.227                    | 1.672  | 1.444  |
| 22      | 1.852                    | 1.307  | 1.449  | 2.143                    | 1.968  | 2.142  | 1.971                    | 2.848  | 2.529  | 2.188                    | 1.738  | 1.467  |
| 23      | 1.239                    | 1.352  | 1.279  | 2.241                    | 2.249  | 2.329  | 2.576                    | 2.496  | 2.521  | 1.379                    | 1.284  | 1.807  |
| 24      | 1.106                    | 1.470  | 1.497  | 2.260                    | 2.114  | 2.356  | 2.485                    | 2.374  | 2.194  | 1.284                    | 1.197  | 1.931  |
| 25      | 1.281                    | 1.258  | 1.299  | 2.199                    | 2.213  | 2.374  | 1.836                    | 2.081  | 1.984  | 1.167                    | 1.302  | 2.154  |
| 26      | 1.542                    | 1.295  | 1.444  | 2.026                    | 1.797  | 2.186  | 2.450                    | 2.289  | 2.458  | 1.332                    | 1.597  | 2.451  |
| 27      | 1.317                    | 1.551  | 1.373  | 2.262                    | 2.857  | 2.607  | 2.403                    | 2.232  | 2.350  | 1.586                    | 1.521  | 1.911  |

Tables 4.11 and 4.12 list the measured values for the surface roughness for parts produced with a nozzle of diameter 0.25 mm, measured for inclination angles between 10°–40° and 50°–80° respectively, at various values of depth of cut. It would be worth highlighting the fact that the part numbers for these tables run parallel to those given for Tables 3.7 and 3.8, so as to keep the identification of samples uniform throughout the experiment. The scheme of numbers has been decided on the basis of the selected input parameters while designing the experiment, so as to uniquely allocate every part to its desired parameter combination. The uniform designation has been followed throughout all the datasets as well as the analysis conducted throughout this research, thus keeping the trackability along with uniformity intact.

Table 4.11: Surface Roughness Measurements for 10°–40° inclinations at Different Depths of Cuts (Parts 28-54)

| Part No | 10° Ra ( $\mu\text{m}$ ) |        |        | 20° Ra ( $\mu\text{m}$ ) |        |        | 30° Ra ( $\mu\text{m}$ ) |        |        | 40° Ra ( $\mu\text{m}$ ) |        |        |
|---------|--------------------------|--------|--------|--------------------------|--------|--------|--------------------------|--------|--------|--------------------------|--------|--------|
|         | 0.2 mm                   | 0.3 mm | 0.4 mm | 0.2 mm                   | 0.3 mm | 0.4 mm | 0.2 mm                   | 0.3 mm | 0.4 mm | 0.2 mm                   | 0.3 mm | 0.4 mm |
| 28      | 1.684                    | 1.888  | 1.942  | 2.261                    | 2.676  | 2.568  | 2.214                    | 2.431  | 2.484  | 1.376                    | 1.421  | 1.326  |
| 29      | 1.397                    | 1.929  | 1.533  | 2.569                    | 2.393  | 2.156  | 2.240                    | 2.587  | 2.351  | 1.196                    | 1.547  | 1.522  |
| 30      | 1.453                    | 1.585  | 1.642  | 2.609                    | 2.332  | 2.465  | 2.182                    | 2.289  | 2.683  | 1.303                    | 1.638  | 1.724  |
| 31      | 1.560                    | 1.659  | 1.288  | 2.550                    | 2.374  | 2.542  | 2.196                    | 2.531  | 1.965  | 1.437                    | 1.593  | 1.248  |
| 32      | 1.940                    | 1.750  | 1.666  | 2.375                    | 2.586  | 2.572  | 2.432                    | 2.426  | 2.576  | 1.442                    | 1.477  | 1.580  |
| 33      | 1.511                    | 1.707  | 1.634  | 2.424                    | 2.153  | 2.727  | 2.236                    | 2.567  | 2.237  | 1.220                    | 1.660  | 1.394  |
| 34      | 1.900                    | 1.417  | 2.243  | 2.374                    | 2.560  | 2.475  | 2.578                    | 2.466  | 1.853  | 1.438                    | 1.292  | 1.350  |
| 35      | 1.469                    | 1.612  | 1.479  | 2.092                    | 2.462  | 2.338  | 2.424                    | 2.616  | 2.593  | 1.598                    | 1.689  | 1.441  |
| 36      | 1.519                    | 1.674  | 1.410  | 2.123                    | 2.331  | 2.236  | 2.137                    | 2.434  | 2.422  | 1.645                    | 1.283  | 1.477  |
| 37      | 2.021                    | 1.951  | 2.248  | 2.011                    | 2.593  | 3.832  | 1.909                    | 2.424  | 2.477  | 2.495                    | 1.466  | 1.914  |
| 38      | 2.445                    | 1.917  | 1.889  | 2.330                    | 2.256  | 2.354  | 1.923                    | 1.970  | 1.727  | 1.186                    | 1.240  | 1.265  |
| 39      | 1.494                    | 1.780  | 1.705  | 2.382                    | 2.486  | 2.718  | 1.952                    | 2.090  | 2.107  | 1.023                    | 1.477  | 1.686  |
| 40      | 1.542                    | 3.135  | 3.591  | 2.822                    | 3.913  | 2.843  | 5.263                    | 2.648  | 2.865  | 2.810                    | 2.576  | 2.228  |
| 41      | –                        | –      | –      | –                        | –      | –      | –                        | –      | –      | –                        | –      | –      |
| 42      | –                        | –      | –      | –                        | –      | –      | –                        | –      | –      | –                        | –      | –      |
| 43      | 1.835                    | 2.215  | 2.245  | 2.291                    | 2.287  | 2.604  | 1.790                    | 2.434  | 2.765  | 1.443                    | 1.125  | 2.593  |
| 44      | 1.897                    | 1.784  | 2.530  | 2.750                    | 2.625  | 3.016  | 1.767                    | 2.793  | 2.686  | 1.194                    | 2.608  | 2.086  |
| 45      | 2.737                    | 2.893  | 2.404  | 2.611                    | 4.314  | 3.032  | 2.380                    | 2.265  | 1.885  | 1.186                    | 1.376  | 3.263  |
| 46      | 1.976                    | 1.767  | 1.593  | 2.230                    | 2.383  | 2.211  | 1.761                    | 2.073  | 2.381  | 1.163                    | 1.319  | 1.396  |
| 47      | 1.722                    | 2.236  | 1.667  | 2.202                    | 2.095  | 2.920  | 1.694                    | 2.343  | 2.368  | 1.045                    | 1.661  | 1.109  |
| 48      | 1.460                    | 1.686  | 2.075  | 2.084                    | 2.198  | 2.659  | 2.260                    | 2.184  | 2.177  | 1.602                    | 2.203  | 1.848  |
| 49      | 1.657                    | 1.204  | 1.405  | 2.397                    | 2.284  | 2.298  | 2.308                    | 2.052  | 2.476  | 1.639                    | 1.429  | 1.420  |
| 50      | 1.798                    | 1.594  | 1.793  | 1.891                    | 2.900  | 2.393  | 2.198                    | 2.458  | 2.004  | 1.388                    | 1.546  | 1.657  |
| 51      | 1.294                    | 1.059  | 1.468  | 2.305                    | 2.857  | 2.536  | 2.107                    | 2.424  | 2.439  | 2.095                    | 1.334  | 1.357  |
| 52      | 1.837                    | 1.433  | 1.850  | 2.515                    | 2.563  | 3.262  | 1.988                    | 2.400  | 1.823  | 1.434                    | 1.614  | 1.245  |
| 53      | 1.746                    | 1.972  | 1.856  | 2.981                    | 2.708  | 3.511  | 2.147                    | 2.550  | 2.646  | 1.866                    | 2.445  | 2.377  |
| 54      | –                        | –      | –      | –                        | –      | –      | –                        | –      | –      | –                        | –      | –      |

From both Tables 4.11 and 4.12, it can be observed that parts numbered 41, 42, and 54 do not exhibit any Ra values. This absence of data is attributed to the lack of surface roughness measurements, which in turn resulted from the problems encountered during the application of CNC finishing operations. The omission of CNC machining for these parts was due to manufacturing defects, primarily caused by severe stringing and under-extrusion. It is noteworthy that all three parts exhibiting these defects also possessed the highest surface roughness values in their as-printed condition. These defective parts were fabricated using a 0.25 mm nozzle at layer heights of 0.20 mm and 0.15 mm, respectively, combined with a relatively low extrusion temperature of 190°C.



Table 4.12: Surface Roughness Measurements for 50°–80° inclinations at Different Depths of Cuts (Parts 28-54)

| Part No | SR 50 Ra ( $\mu\text{m}$ ) |        |        | SR 60 Ra ( $\mu\text{m}$ ) |        |        | SR 70 Ra ( $\mu\text{m}$ ) |        |        | SR 80 Ra ( $\mu\text{m}$ ) |        |        |
|---------|----------------------------|--------|--------|----------------------------|--------|--------|----------------------------|--------|--------|----------------------------|--------|--------|
|         | 0.2 mm                     | 0.3 mm | 0.4 mm | 0.2 mm                     | 0.3 mm | 0.4 mm | 0.2 mm                     | 0.3 mm | 0.4 mm | 0.2 mm                     | 0.3 mm | 0.4 mm |
| 28      | 1.313                      | 1.757  | 1.602  | 2.478                      | 2.283  | 2.284  | 2.523                      | 2.382  | 2.463  | 1.908                      | 1.852  | 1.678  |
| 29      | 1.586                      | 1.574  | 1.633  | 2.301                      | 2.222  | 2.411  | 2.485                      | 2.601  | 2.869  | 1.580                      | 2.280  | 1.944  |
| 30      | 1.438                      | 1.374  | 1.527  | 2.201                      | 2.620  | 2.368  | 2.246                      | 2.591  | 2.783  | 2.082                      | 1.837  | 1.709  |
| 31      | 1.223                      | 1.421  | 1.280  | 2.418                      | 2.414  | 2.600  | 2.021                      | 2.321  | 2.809  | 1.467                      | 2.106  | 1.776  |
| 32      | 1.418                      | 1.571  | 1.635  | 2.445                      | 2.430  | 2.496  | 2.585                      | 2.423  | 2.788  | 1.525                      | 2.084  | 2.040  |
| 33      | 1.105                      | 1.666  | 1.775  | 2.307                      | 2.266  | 2.487  | 2.625                      | 2.472  | 2.115  | 1.739                      | 2.175  | 1.928  |
| 34      | 1.538                      | 1.536  | 1.855  | 2.319                      | 2.531  | 2.435  | 2.611                      | 2.576  | 1.740  | 1.496                      | 1.592  | 2.108  |
| 35      | 1.401                      | 1.669  | 1.785  | 2.016                      | 2.273  | 2.572  | 2.386                      | 2.621  | 2.429  | 1.658                      | 1.191  | 1.398  |
| 36      | 1.423                      | 1.770  | 1.646  | 2.148                      | 2.487  | 2.743  | 2.387                      | 2.567  | 2.179  | 1.512                      | 1.240  | 1.394  |
| 37      | 1.053                      | 1.366  | 1.807  | 1.907                      | 2.437  | 2.105  | 2.256                      | 2.952  | 2.526  | 1.512                      | 1.753  | 2.142  |
| 38      | 1.166                      | 1.572  | 2.888  | 1.970                      | 4.196  | 2.340  | 2.258                      | 3.170  | 2.222  | 1.239                      | 2.095  | 2.316  |
| 39      | 3.086                      | 1.663  | 1.792  | 1.581                      | 2.030  | 2.899  | 2.139                      | 2.054  | 2.141  | 1.454                      | 1.607  | 2.406  |
| 40      | 1.087                      | 1.228  | 1.694  | 2.241                      | 2.715  | 3.077  | 2.569                      | 2.719  | 2.985  | 1.614                      | 1.583  | 2.211  |
| 41      | –                          | –      | –      | –                          | –      | –      | –                          | –      | –      | –                          | –      | –      |
| 42      | –                          | –      | –      | –                          | –      | –      | –                          | –      | –      | –                          | –      | –      |
| 43      | 1.879                      | 1.233  | 2.102  | 2.096                      | 2.260  | 2.654  | 2.439                      | 2.538  | 2.645  | 1.741                      | 1.428  | 2.448  |
| 44      | 1.850                      | 1.372  | 2.099  | 1.946                      | 2.268  | 3.135  | 2.305                      | 2.038  | 2.897  | 1.970                      | 1.867  | 2.738  |
| 45      | 2.051                      | 1.295  | 2.459  | 2.581                      | 3.230  | 2.968  | 2.065                      | 3.536  | 2.286  | 1.751                      | 3.150  | 2.957  |
| 46      | 1.281                      | 1.518  | 1.636  | 1.930                      | 2.079  | 2.143  | 2.328                      | 2.401  | 2.529  | 1.505                      | 1.572  | 1.663  |
| 47      | 1.147                      | 1.295  | 2.565  | 2.000                      | 2.550  | 2.166  | 2.133                      | 2.075  | 2.442  | 1.828                      | 1.502  | 1.849  |
| 48      | 2.181                      | 1.646  | 1.659  | 1.916                      | 2.102  | 2.378  | 2.546                      | 2.079  | 2.346  | 1.739                      | 1.973  | 1.765  |
| 49      | 1.185                      | 1.060  | 1.215  | 2.069                      | 2.451  | 2.801  | 2.395                      | 2.464  | 2.338  | 1.274                      | 1.887  | 1.772  |
| 50      | 1.511                      | 1.629  | 1.704  | 1.906                      | 2.403  | 2.506  | 2.237                      | 2.811  | 2.324  | 1.926                      | 2.112  | 1.578  |
| 51      | 1.422                      | 1.220  | 2.052  | 1.975                      | 1.983  | 2.449  | 2.546                      | 2.184  | 2.784  | 1.814                      | 1.395  | 1.692  |
| 52      | 1.393                      | 1.912  | 2.403  | 2.454                      | 2.208  | 2.243  | 2.268                      | 2.572  | 2.418  | 1.642                      | 1.511  | 3.270  |
| 53      | 1.249                      | 1.359  | 2.251  | 2.021                      | 2.456  | 2.484  | 2.386                      | 2.661  | 2.646  | 1.970                      | 1.462  | 1.819  |
| 54      | –                          | –      | –      | –                          | –      | –      | –                          | –      | –      | –                          | –      | –      |

To capture the problems encountered during machining, part numbered 54 was machined unsuccessfully, and is presented in Figure 4.10, displaying the part before and after machining. Part numbered 54 is already the worst part in the 0.15 mm layer category due to the reasons mentioned above. Following CNC finishing, the printed part exhibits patch formation, uneven cutting, and layer ripping and tearing. Patch formation is indicative of non-uniform material removal, potentially arising from inconsistent engagement of the milling cutter with the irregular AM surface. Uneven cutting is attributed to the poor surface topology inherited from the AM process. Layer ripping and tearing occur when the machining forces exceed the interlayer bonding strength, leading to delamination and localized tearing of the PLA layers. This

effect is exacerbated in regions already compromised by under-extrusion, where adhesion between adjacent layers is weak, resulting in a porous internal structure. The unsuccessful CNC machining outcome of Part 54, despite the application of identical milling conditions to those used on successfully machined specimens, can be attributed primarily to deficiencies originating from the additive manufacturing stage. Collectively, the observed defects highlight the interdependence between AM process quality and CNC post-processing outcomes. The poor initial surface integrity of AM Part 54 compromised the machinability of the part, resulting in additional surface deterioration during CNC finishing. This underscores the necessity of optimizing AM parameters (layer height, nozzle diameter, printing extrusion temperature) prior to machining in order to improve surface uniformity and ultimately, post-machining quality.

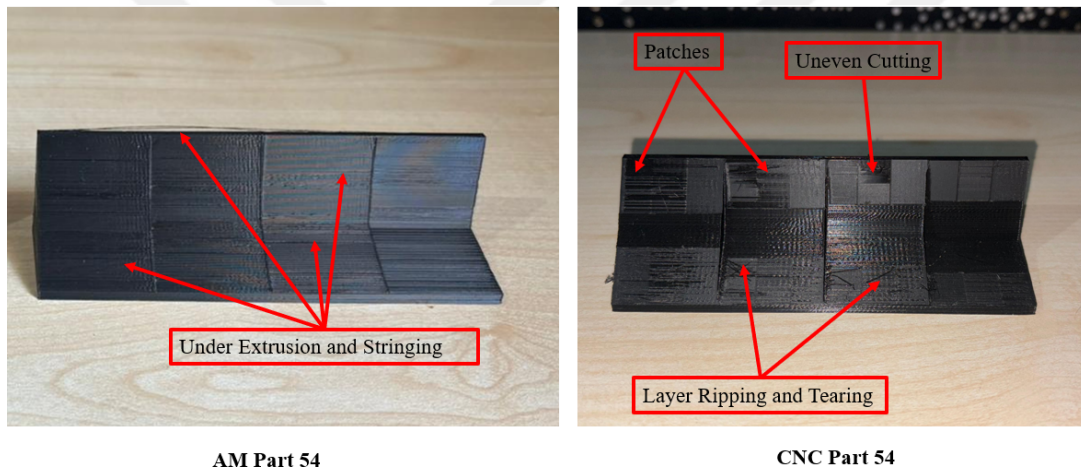


Figure 4.10: Pre and Post Machining Part 54 - Surface Defects

Based on the post-machining results of Part 54, it was determined that machining of Parts 41 and 42 would not be pursued. These two specimens represent the poorest surface quality within the 0.20 mm layer height category and already exhibit pronounced surface defects in their as-printed condition. Given a higher layer height at the upper end coupled with a low temperature of 190°C and a 0.25 mm nozzle known to produce under-extrusion, weak interlayer adhesion, and high void content, it was reasonably anticipated that CNC finishing would reproduce the same detrimental effects observed in Part 54. Consequently, these parts were excluded from the post-processing stage to avoid redundant outcomes and unnecessary resource expenditure.

The data presented in Tables 4.9, 4.10, and 4.11, 4.12 demonstrates that CNC finishing led to better surface roughness outcomes throughout all tested samples. The evaluation of surface roughness can become more practical by selecting the CNC-machined components with minimum and maximum roughness values. The results should be organized to compare the surfaces with minimum and maximum roughness from the CNC process against their corresponding surfaces with minimum and maximum roughness from the additive manufacturing (AM) stage. To enable a clear and balanced comparison, the same evaluation methodology was applied to both the additive manufacturing and hybrid manufacturing stages. The parts were first grouped according to their respective layer heights to ensure an equitable basis for comparison between the two manufacturing approaches. For each group, the surface roughness (Ra) values were averaged across all tested depths of cut and inclination angles. This approach provides a representative mean roughness value for each part category, thereby facilitating a direct and unbiased assessment of the effect of CNC finishing on surface quality relative to the as-printed condition.

Tables 4.13 and 4.14 show a comparison between the AM and hybrid process for the best and the worst parts, numbered 36 and 29, belonging to 0.1 mm layer height category, respectively. The printing parameters are provided in Table 4.6.

Table 4.13: Surface roughness improvement after CNC machining for Part No. 36 at different depths of cut.

| Angle (°)      | AM Ra (μm)    | Hybrid Ra (μm) |              |              | % Improvement |               |               |
|----------------|---------------|----------------|--------------|--------------|---------------|---------------|---------------|
|                |               | 0.2 mm         | 0.3 mm       | 0.4 mm       | 0.2 mm        | 0.3 mm        | 0.4 mm        |
| 10°            | 16.714        | 1.519          | 1.674        | 1.410        | 90.91%        | 89.98%        | 91.56%        |
| 20°            | 19.963        | 2.123          | 2.331        | 2.236        | 89.37%        | 88.32%        | 88.80%        |
| 30°            | 16.980        | 2.137          | 2.434        | 2.422        | 87.41%        | 85.66%        | 85.74%        |
| 40°            | 14.098        | 1.645          | 1.283        | 1.477        | 88.33%        | 90.90%        | 89.53%        |
| 50°            | 11.584        | 1.423          | 1.770        | 1.646        | 87.72%        | 84.72%        | 85.79%        |
| 60°            | 10.083        | 2.148          | 2.487        | 2.743        | 78.70%        | 75.33%        | 72.80%        |
| 70°            | 8.595         | 2.387          | 2.567        | 2.179        | 72.23%        | 70.14%        | 74.65%        |
| 80°            | 8.505         | 1.512          | 1.240        | 1.394        | 82.22%        | 85.42%        | 83.61%        |
| <b>Average</b> | <b>13.315</b> | <b>1.862</b>   | <b>1.973</b> | <b>1.938</b> | <b>86.02%</b> | <b>85.18%</b> | <b>85.44%</b> |

Table 4.14: Surface roughness improvement after CNC machining for Part No. 29 at different depths of cut.

| Angle (°)      | AM Ra (μm)    | Hybrid Ra (μm) |              |              | % Improvement |               |               |
|----------------|---------------|----------------|--------------|--------------|---------------|---------------|---------------|
|                |               | 0.2 mm         | 0.3 mm       | 0.4 mm       | 0.2 mm        | 0.3 mm        | 0.4 mm        |
| 10°            | 17.460        | 1.397          | 1.929        | 1.533        | 92.00%        | 88.95%        | 91.22%        |
| 20°            | 20.370        | 2.569          | 2.393        | 2.156        | 87.39%        | 88.25%        | 89.42%        |
| 30°            | 18.199        | 2.240          | 2.587        | 2.351        | 87.69%        | 85.78%        | 87.08%        |
| 40°            | 15.464        | 1.196          | 1.547        | 1.522        | 92.27%        | 90.00%        | 90.16%        |
| 50°            | 12.419        | 1.586          | 1.574        | 1.633        | 87.23%        | 87.32%        | 86.85%        |
| 60°            | 10.216        | 2.301          | 2.222        | 2.411        | 77.48%        | 78.25%        | 76.40%        |
| 70°            | 10.268        | 2.485          | 2.601        | 2.869        | 75.80%        | 74.67%        | 72.06%        |
| 80°            | 9.320         | 1.580          | 2.280        | 1.944        | 83.04%        | 75.53%        | 79.14%        |
| <b>Average</b> | <b>14.215</b> | <b>1.919</b>   | <b>2.142</b> | <b>2.052</b> | <b>86.50%</b> | <b>84.93%</b> | <b>85.56%</b> |

The surface finish improvement patterns for Part 36 and Part 29 demonstrate that CNC milling provides substantial surface quality improvement for additively manufactured parts at all measured inclination angles. The printed surfaces of Part 36 showed average roughness measurements of 13.315 μm with maximum values appearing at low angles (20° at 19.963 μm) and minimum values at high angles (80° at 8.505 μm). CNC machining decreased these measurements to 1.862–1.938 μm on average, which resulted in 85%–86% surface quality enhancement for all depths of cut, with the 0.2 mm depth producing slightly better outcomes. The average AM roughness of Part 29 started at 14.215 μm with the highest roughness measurements occurring at low inclination angles (20° at 20.370 μm). The surface roughness improved by 85% - 86% after CNC machining, averaging between 1.919 and 2.052 μm. Although the two parts' improvement magnitudes are similar, Part 36 performs more consistently across inclination angles, while Part 29 demonstrates somewhat more variability, especially at 70° where the improvement falls to about 72%. According to the data, CNC finishing is very successful in lowering surface roughness in both situations. Shallower depths of cut (such as 0.2 mm) typically yield slightly better results than the other two depths of cut.

For the 0.15 mm layer height category, Part 54 could not be measured due to the se-

were surface defects previously described. Consequently, in order to enable a meaningful comparison, the second worst-performing part within this category, Part 53, was selected for detailed analysis. Tables 4.15 and 4.16 provide a comparative assessment of the Ra values obtained for the additively manufactured (AM) and hybrid-manufactured versions of the best-performing part (Part 24) and the second worst-performing part (Part 53) in the 0.15 mm layer height category.

For Part No. 24, the initial AM Ra values were between 11.799  $\mu\text{m}$  at 80° to 25.534  $\mu\text{m}$  at 30°. By CNC machining, these were largely brought down to the range of 1.750  $\mu\text{m}$ –2.007  $\mu\text{m}$  on average, leading to high percentage improvements throughout all the depths of the cut, with averages of 90.28%, 89.86%, and 88.86%, for the 0.2 mm, 0.3 mm, and 0.4 mm, respectively. Conversely, Part No. 53 had higher initial AM Ra values, between 12.506  $\mu\text{m}$  at 80° to 27.934  $\mu\text{m}$  at 20°, but after the process of CNC machining, the hybrid Ra values were diminished to 2.046  $\mu\text{m}$ –2.449  $\mu\text{m}$  on average. Though the percentage improvement for Part No. 53 stayed high, with averages of 89.32%, 88.51%, and 87.22%, for the three depth-of-cuts, these values were throughout lower than those for Part No. 24 by about 1–2%.

Table 4.15: Surface roughness improvement after CNC machining for Part No. 24 at different depths of cut.

| Angle (°)      | AM Ra ( $\mu\text{m}$ ) | Hybrid Ra ( $\mu\text{m}$ ) |              |              | % Improvement |               |               |
|----------------|-------------------------|-----------------------------|--------------|--------------|---------------|---------------|---------------|
|                |                         | 0.2 mm                      | 0.3 mm       | 0.4 mm       | 0.2 mm        | 0.3 mm        | 0.4 mm        |
| 10°            | 17.265                  | 1.122                       | 1.621        | 1.521        | 93.50%        | 90.61%        | 91.19%        |
| 20°            | 25.108                  | 2.380                       | 2.203        | 2.355        | 90.52%        | 91.22%        | 90.62%        |
| 30°            | 25.534                  | 2.245                       | 2.214        | 2.447        | 91.21%        | 91.33%        | 90.42%        |
| 40°            | 21.644                  | 1.121                       | 1.422        | 1.759        | 94.82%        | 93.43%        | 91.87%        |
| 50°            | 16.766                  | 1.106                       | 1.470        | 1.497        | 93.40%        | 91.23%        | 91.07%        |
| 60°            | 13.352                  | 2.260                       | 2.114        | 2.356        | 83.07%        | 84.17%        | 82.35%        |
| 70°            | 12.637                  | 2.485                       | 2.374        | 2.194        | 80.33%        | 81.21%        | 82.64%        |
| 80°            | 11.799                  | 1.284                       | 1.197        | 1.931        | 89.12%        | 89.86%        | 83.64%        |
| <b>Average</b> | <b>18.013</b>           | <b>1.750</b>                | <b>1.827</b> | <b>2.007</b> | <b>90.28%</b> | <b>89.86%</b> | <b>88.86%</b> |

Table 4.16: Surface roughness improvement after CNC machining for Part No. 53 at different depths of cut.

| Angle (°)      | AM Ra (μm)    | Hybrid Ra (μm) |              |              | % Improvement |               |               |
|----------------|---------------|----------------|--------------|--------------|---------------|---------------|---------------|
|                |               | 0.2 mm         | 0.3 mm       | 0.4 mm       | 0.2 mm        | 0.3 mm        | 0.4 mm        |
| 10°            | 19.236        | 1.746          | 1.972        | 1.856        | 90.92%        | 89.75%        | 90.35%        |
| 20°            | 27.934        | 2.981          | 2.708        | 3.511        | 89.33%        | 90.30%        | 87.43%        |
| 30°            | 26.884        | 2.147          | 2.550        | 2.646        | 92.01%        | 90.51%        | 90.16%        |
| 40°            | 21.910        | 1.866          | 2.445        | 2.377        | 91.48%        | 88.84%        | 89.15%        |
| 50°            | 17.526        | 1.249          | 1.359        | 2.251        | 92.87%        | 92.25%        | 87.16%        |
| 60°            | 14.462        | 2.021          | 2.456        | 2.484        | 86.03%        | 83.02%        | 82.82%        |
| 70°            | 12.808        | 2.386          | 2.661        | 2.646        | 81.37%        | 79.23%        | 79.34%        |
| 80°            | 12.506        | 1.970          | 1.462        | 1.819        | 84.25%        | 88.31%        | 85.46%        |
| <b>Average</b> | <b>19.158</b> | <b>2.046</b>   | <b>2.202</b> | <b>2.449</b> | <b>89.32%</b> | <b>88.51%</b> | <b>87.22%</b> |

For Part 53, some angles, for instance, 20°, where the values of the roughness of the surfaces become 3.511 μm, exhibit slightly lower efficiency, suggesting the possibility that initial AM defects could be constraining the potential for the gain to be made by CNC improvement.

Similarly, within the 0.20 mm layer height category, the worst-performing parts, namely Parts 41 and 42, were excluded from CNC machining due to the presence of pronounced surface defects and elevated surface roughness values, as reported in Table 4.5 and mentioned in the above paragraphs. This decision was informed by the observation that a layer height of 0.20 mm lies at the upper operational limit for a 0.25 mm nozzle. When combined with a relatively low extrusion temperature of 190 °C, these settings promoted under-extrusion, which in turn resulted in inadequate interlayer bonding, the formation of voids, surface irregularities, and ultimately poor as-printed surface quality. The severity of these defects made post-processing by CNC machining impractical for these parts. Consequently, for comparison, the third worst-performing part (Part 40) and the best-performing part (Part 12) within this category were selected for detailed analysis. Their Ra values, obtained in the AM condition and following CNC finishing, were compared to quantify the improvement in surface quality. The corresponding tables 4.17 and 4.18 provide a comparative as-

assessment highlighting the differences in initial and post-machining surface roughness for both Parts 12 and 40.

Table 4.17: Surface roughness improvement after CNC machining for Part No. 12 at different depths of cut.

| Angle (°)      | AM Ra (μm)    | Hybrid Ra (μm) |              |              | % Improvement |               |               |
|----------------|---------------|----------------|--------------|--------------|---------------|---------------|---------------|
|                |               | 0.2 mm         | 0.3 mm       | 0.4 mm       | 0.2 mm        | 0.3 mm        | 0.4 mm        |
| 10°            | 16.016        | 1.908          | 1.830        | 1.762        | 88.09%        | 88.58%        | 89.00%        |
| 20°            | 28.918        | 2.609          | 2.853        | 2.418        | 90.98%        | 90.13%        | 91.64%        |
| 30°            | 32.353        | 2.411          | 2.168        | 2.122        | 92.55%        | 93.30%        | 93.44%        |
| 40°            | 27.885        | 1.781          | 1.719        | 1.655        | 93.61%        | 93.84%        | 94.06%        |
| 50°            | 22.216        | 1.419          | 1.305        | 1.219        | 93.61%        | 94.13%        | 94.51%        |
| 60°            | 19.185        | 2.090          | 2.402        | 2.172        | 89.11%        | 87.48%        | 88.68%        |
| 70°            | 17.269        | 2.189          | 2.576        | 2.751        | 87.32%        | 85.08%        | 84.07%        |
| 80°            | 16.301        | 1.704          | 1.290        | 1.838        | 89.55%        | 92.08%        | 88.73%        |
| <b>Average</b> | <b>22.518</b> | <b>2.014</b>   | <b>2.018</b> | <b>1.992</b> | <b>91.06%</b> | <b>91.04%</b> | <b>91.15%</b> |

Table 4.18: Surface roughness improvement after CNC machining for Part No. 40 at different depths of cut.

| Angle (°)      | AM Ra (μm)    | Hybrid Ra (μm) |              |              | % Improvement |               |               |
|----------------|---------------|----------------|--------------|--------------|---------------|---------------|---------------|
|                |               | 0.2 mm         | 0.3 mm       | 0.4 mm       | 0.2 mm        | 0.3 mm        | 0.4 mm        |
| 10°            | 16.346        | 1.542          | 3.135        | 3.591        | 90.56%        | 80.82%        | 78.03%        |
| 20°            | 29.728        | 2.822          | 3.913        | 2.843        | 90.51%        | 86.84%        | 90.44%        |
| 30°            | 34.200        | 5.263          | 2.648        | 2.865        | 84.61%        | 92.26%        | 91.62%        |
| 40°            | 30.262        | 2.810          | 2.576        | 2.228        | 90.72%        | 91.49%        | 92.64%        |
| 50°            | 23.603        | 1.087          | 1.228        | 1.694        | 95.39%        | 94.80%        | 92.82%        |
| 60°            | 19.665        | 2.241          | 2.715        | 3.077        | 88.61%        | 86.20%        | 84.35%        |
| 70°            | 17.858        | 2.569          | 2.719        | 2.985        | 85.61%        | 84.78%        | 83.28%        |
| 80°            | 16.482        | 1.614          | 1.583        | 2.211        | 90.21%        | 90.40%        | 86.59%        |
| <b>Average</b> | <b>23.518</b> | <b>2.494</b>   | <b>2.565</b> | <b>2.687</b> | <b>89.40%</b> | <b>89.10%</b> | <b>88.58%</b> |

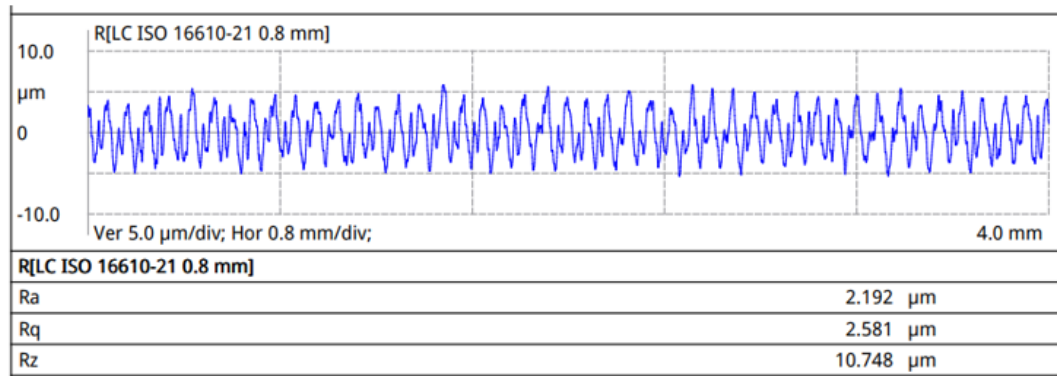
For Part 12, the as-printed AM Ra values range from 16.016 μm at 10° to a maximum of 32.353 μm at 30°, indicating that this inclination exhibited the poorest surface

quality in the AM condition. Following CNC machining, Ra values decreased substantially across all depths of cut, with average percentage improvements of 91.06%, 91.04%, and 91.15%, showing consistent performance across inclination angles and depths of cut. Conversely, Part 40 generally had higher AM Ra values, between 16.346  $\mu\text{m}$  at 10° and 34.200  $\mu\text{m}$  at 30°, and made lower mean improvements of 89.40%, 89.10%, and 88.58%. Additionally, some disparities were noted for Part 40, specifically for 10°, 60°, and 70°, where the improvements were lower than the part mean, indicating deeper AM defects were generating a higher layer height, low temperature, with corresponding weakened layer adhesion, which lowered the efficiency of the CNC finishing process. In general, Part 12 reliably showed superior post-machining surface quality and higher percentage improvements compared to Part 40, likely because it has better initial AM surface quality with fewer severe localized faults. These results show that both parts respond to CNC finishing advantageously but to differing extents, with the extents being larger for higher original AM surface qualities, highlighting the significance of AM process parameter optimization prior to applying the CNC postprocessing.

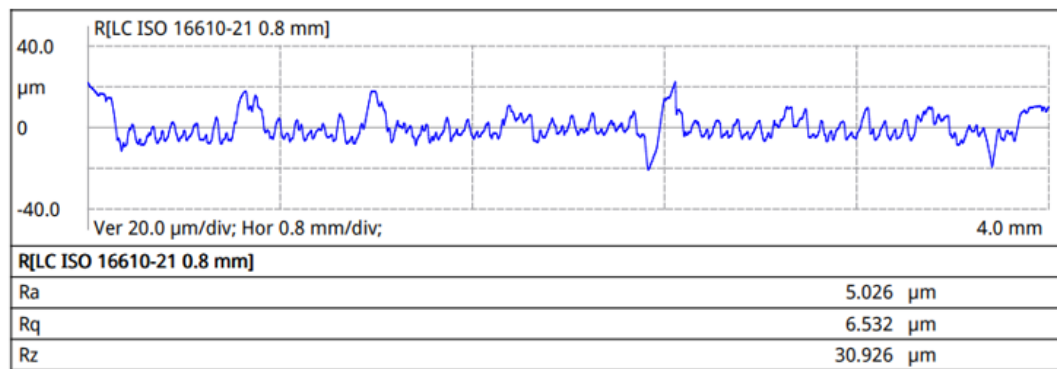
Among all the parts exhibiting the poorest surface quality, Part 40 recorded the highest surface roughness values across all depths of cut among the 51 parts subjected to CNC machining. The most severe case was observed at a depth of cut of 0.2 mm, where the surface roughness reached 5.263  $\mu\text{m}$  at a 30° inclination. As highlighted in Table 4.18, the elevated surface roughness at 30° can be attributed to the combined effects of stack and step effect and influence of corner geometry, and process-induced factors such as the use of a 0.25 mm nozzle, a 0.20 mm layer height, and a relatively low extrusion temperature of 190°C. These conditions collectively contributed to increased inadequate surface fusion and pronounced surface irregularities that persisted even after CNC finishing. Figure 4.11 show the surface profiles obtained from one of the three readings of both part 36 made of 0.1 mm layer height and 40 made of 0.2 mm layer height respectively. Both were produced using the same nozzle with a diameter of 0.25 mm for the inclination angles of 30° at a depth of cut of 0.2 mm.

The comparison between the surface roughness profiles of Part 36 and Part 40 at 30° inclination and 0.2 mm depth of cut highlights a clear distinction in post-machining surface quality.





Part 36



Part 40

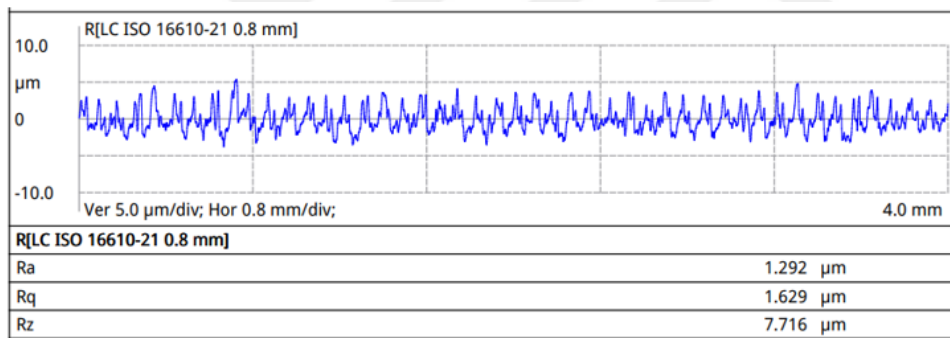
Figure 4.11: Surface Roughness Profiles of Parts 36 and 40 at 0.2 mm depth of cut and 30° inclination

The surface roughness profiles of Part 36 and Part 40 show a noticeable difference in post-machining performance at a 30° inclination and 0.2 mm depth of cut. A highly uniform and periodic surface profile with low amplitude fluctuations is shown for Part 36, which corresponds to  $Ra = 2.192 \mu\text{m}$  (one of the three readings). This consistency is attributed to the fact that the material was effectively removed during CNC finishing, resulting in a smooth surface with few traces left over from the AM process. The steady waveform of the profile indicates that the cutting parameters and tool engagement were appropriately matched to the material condition, allowing for the effective removal of layer-induced asperities.

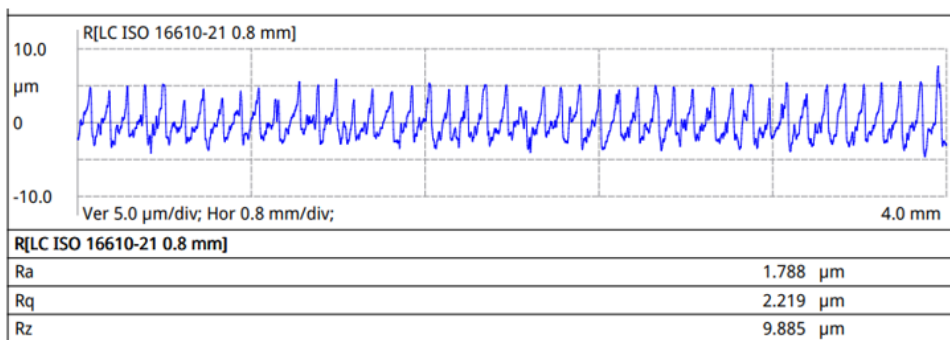
With  $Ra = 5.026 \mu\text{m}$  (one of the three readings), more than twice the average roughness parameters of Part 36, Part 40, on the other hand, showed a profile dominated by

irregular, high amplitude variations. Significant AM-related flaws, including uneven layer bonding and possible thermal distortion, persisted after machining, as evidenced by the deep valleys and sharp peaks. Since under-extrusion and poor interlayer adhesion are known to be encouraged by the combination of a 0.25 mm nozzle, 0.20 mm layer height, and 190 °C extrusion temperature, these defects most likely resulted from the original AM process parameters. Overall, the comparison shows that while CNC finishing substantially improves surface quality for both parts, its effectiveness is heavily dependent on the starting AM surface condition. The superior finish of Part 36 can be attributed to a more uniform and defect-free as-printed surface, whereas the poorer outcome for Part 40 reflects the persistence of deep-rooted AM irregularities that could not be fully removed during the machining process.

Figure 4.12 gives the profiles (one of the three readings) of both parts at 80° inclination and 0.3 mm depth of cut.



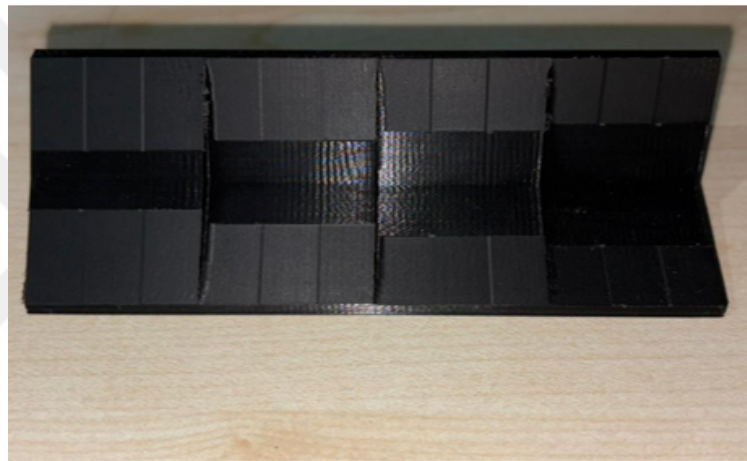
Part 36



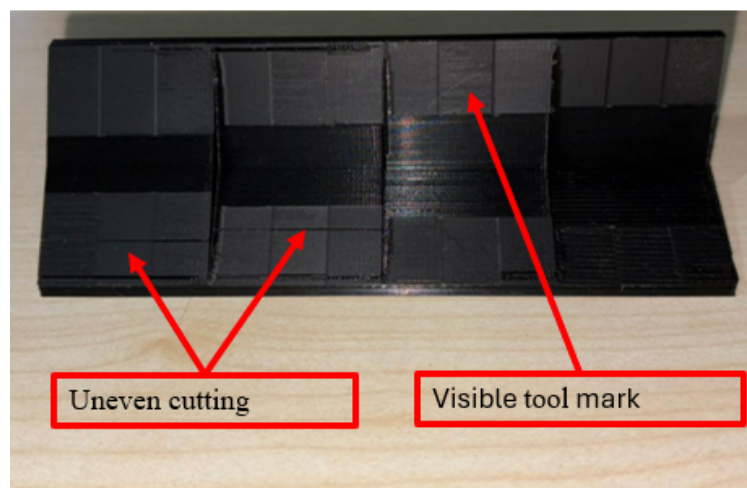
Part 40

Figure 4.12: Surface Roughness Profiles of Parts 36 and 40 at 0.2 mm depth of cut and 80° inclination

The surface roughness values for the inclination angle of 80° for both parts 36 and 40 have the best value at a depth of cut of 0.3 mm as indicated in Tables 4.13 and 4.18 displaying values of 1.240  $\mu\text{m}$  and 1.583  $\mu\text{m}$ . As seen from 4.12, the surface roughness values have decreased with an increase in the inclination angles from 30° to 80°. Part 36 consistently exhibits lower surface roughness compared to Part 40, a trend largely attributable to the superior as-built surface quality achieved during the additive manufacturing stage. The improved initial surface condition of Part 36 facilitated more efficient material removal during CNC finishing, resulting in fewer visible tool marks and a smoother final surface as evidenced by Figure 4.13.



Part 36



Part 40

Figure 4.13: Part 36 and Part 40 after CNC Machining

As evidenced from the preceding analysis, it is challenging to discern a definitive influence of the depth of cut on the resulting surface roughness values. Despite the CNC machining parameters being held constant for all specimens, as outlined in Table 3.12, variations in the measured Ra values are still observed. This variability can be attributed to the inherent differences in the as-built surface quality produced during the additive manufacturing stage. In particular, the worst surface roughness values following CNC machining are associated with Part 40, which exhibited pre-existing surface defects originating from its AM process parameters. These defects, when compared to its counterpart, Part 36, contributed to a less effective material removal process and diminished the achievable post-machining surface finish.

To observe the influence of the depth of cut on the surface roughness values, Tables 4.9, 4.10, 4.11 and 4.12 were analyzed in depth and averages were found for all the angles at each level of the depth of cut given in Table 4.19. The depth of cut of 0.2 mm has provided the lowest average Ra for all the angles. In FFF printing, each wall is formed by one or more parallel extrusion lines whose width is approximately equal to the nozzle diameter. For a wall thickness of 0.75 mm, this corresponds to either three lines with a 0.25 mm nozzle or two lines with a 0.4 mm nozzle. At a shallow machining depth of cut, such as 0.2 mm, the tool primarily engages with the outermost extrusion line, effectively removing the surface stair-steps while remaining within a single shell. This light finishing pass avoids cutting into the internal interfaces where adjacent extrusion lines bond together, which are typically less uniform and may contain voids or seams. When the depth of cut is increased to 0.3 mm or 0.4 mm, however, the cutter penetrates deeper into these internal bonding regions, leading to tearing, smearing, or exposure of voids, all of which contribute to higher Ra values. Figure 4.14 illustrates an enlarged view from the Cura slicing environment, highlighting the wall structure and subsequent finishing operation. The part is manufactured using a 0.25 mm nozzle, resulting in a total wall thickness of 0.75 mm composed of three distinct walls, each with an extrusion width of 0.25 mm. As shown in the figure, the outer, middle, and inner walls are clearly distinguished, with the infill pattern lying adjacent to the innermost wall. The schematic further demonstrates the machining operation, where the tool performs a finishing pass at a depth of cut of 0.2 mm. Importantly, this cut is confined within the region of the outermost

wall, ensuring that only the surface material is removed. This prevents unintended engagement with the subsequent walls, thereby reducing the cutting forces and improving the surface finish. However, the increase in the depth of cut from 0.3 to 0.4 mm does not necessarily increase or decrease the surface roughness as evidenced by the Ra value of 1.745  $\mu\text{m}$  at 0.3 mm and 1.711  $\mu\text{m}$  at 0.4 mm for 10° inclination. The same observation is concluded for the 30° inclination, having average Ra values of 2.346  $\mu\text{m}$  at 0.3 mm and 2.335  $\mu\text{m}$  at 0.4 mm. While other inclination angles, such as 20°, 40°, 50°, 60°, 70°, and 80°, show an increase in the average Ra with an increase in the depth of cut. Within the range of 0.2-0.4 mm, machining can be done safely at 10°-80° with a correct combination of CNC parameters highlighted in Table 3.12 and AM parameters such as nozzle diameter, layer height, and high temperature as proposed in the concluding paragraph of section 4.1. With the application of this depth of cut range, the Ra values can be improved by 85% – 91% which is a significant improvement in terms of surface quality. Furthermore, it can also be concluded that a depth of cut of 0.2 mm can safely be used to obtain optimal Ra values, further reinforcing the claims in [29] and [30] that shallow depths of cut provide better Ra values.

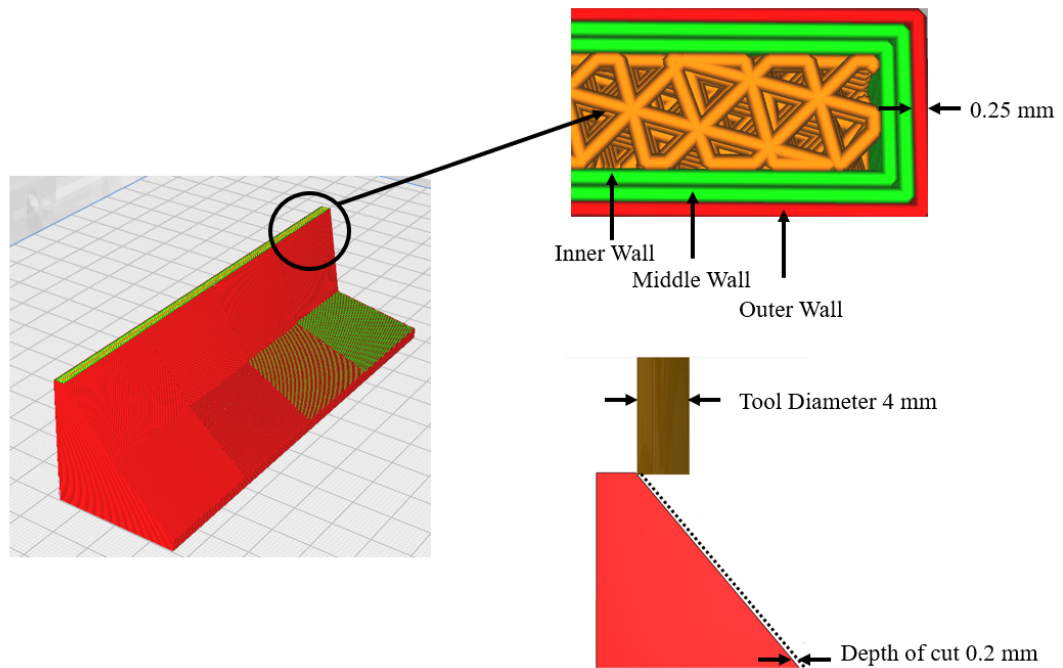


Figure 4.14: Depth of Cut and Wall thickness

Table 4.19: Average Ra for different inclination angles and depths of cut.

| Angle (°) | Depth of Cut, $a_p$ (mm) | Average Ra ( $\mu\text{m}$ ) |
|-----------|--------------------------|------------------------------|
| 10°       | 0.2                      | 1.636                        |
|           | 0.3                      | 1.745                        |
|           | 0.4                      | 1.711                        |
| 20°       | 0.2                      | 2.335                        |
|           | 0.3                      | 2.492                        |
|           | 0.4                      | 2.536                        |
| 30°       | 0.2                      | 2.195                        |
|           | 0.3                      | 2.346                        |
|           | 0.4                      | 2.335                        |
| 40°       | 0.2                      | 1.518                        |
|           | 0.3                      | 1.547                        |
|           | 0.4                      | 1.606                        |
| 50°       | 0.2                      | 1.427                        |
|           | 0.3                      | 1.434                        |
|           | 0.4                      | 1.641                        |
| 60°       | 0.2                      | 2.118                        |
|           | 0.3                      | 2.292                        |
|           | 0.4                      | 2.407                        |
| 70°       | 0.2                      | 2.282                        |
|           | 0.3                      | 2.408                        |
|           | 0.4                      | 2.417                        |
| 80°       | 0.2                      | 1.626                        |
|           | 0.3                      | 1.656                        |
|           | 0.4                      | 1.889                        |

### 4.3 Machine Learning Results and Analysis

Machine learning algorithms were implemented following the pipeline illustrated in Figure 3.57, as described in Section 3.6.2. The surface roughness measurements ob-

tained from both AM and hybrid manufacturing processes—reported in Tables 4.1 and 4.2 for AM, and in Tables 4.9, 4.10, 4.11, and 4.12 for hybrid—were combined with the corresponding input parameters listed in Tables 3.27 and 3.28 to form the dataset for ML model training. The data restructuring process was carried out so that each surface roughness (Ra) value constituted a single data point, paired with its corresponding set of input parameters (features). Consequently, for the AM dataset, a total of 432 rows were generated, derived from the combination of eight inclination angles and 54 experimental runs. Each row, therefore, represented a distinct combination of inclination angle, input parameters, and the associated measured Ra value. Similarly, for the hybrid process, a total of 51 experiments were conducted, excluding parts 41, 42, and 54 for which Ra measurements were not obtained, as discussed in the preceding section. The combination of 51 experimental conditions with 8 inclination angles and 3 depth-of-cut levels yielded a total of 1,224 rows, with each row corresponding to a unique Ra value. The resulting Excel files for AM and Hybrid were uploaded to the drive and can be accessed by following the link provided in Appendix B.

Machine learning algorithms were evaluated using the performance metrics outlined in Section 3.6.1. Following the restructuring of the dataset, an 80:20 ratio was adopted for the training and testing sets, respectively. This data split for a single run, in conjunction with 10-fold cross-validation, was employed to mitigate the risks of overfitting and underfitting, thereby enhancing the generalizability of the models. The evaluation metrics were computed for both the training and testing phases across all ten ML algorithms for both the AM and hybrid datasets. Tables 4.20 and 4.21 give the evaluation metrics for both training and testing dataset of the AM process for a single run respectively.

Table 4.20: AM-Training Evaluation Metrics

| Metrics              | PR (4 Degree) | DT    | RFR   | GBR   | XG Boost | CAT Boost | AdaBoost | ETR   | EBM   | SVR   |
|----------------------|---------------|-------|-------|-------|----------|-----------|----------|-------|-------|-------|
| <b>MSE</b>           | 0.408         | 0.303 | 0.177 | 0.479 | 0.017    | 0.016     | 3.511    | 0.311 | 0.369 | 0.586 |
| <b>RMSE</b>          | 0.639         | 0.550 | 0.420 | 0.692 | 0.129    | 0.127     | 1.874    | 0.557 | 0.608 | 0.765 |
| <b>MAE</b>           | 0.473         | 0.318 | 0.274 | 0.495 | 0.089    | 0.093     | 1.649    | 0.317 | 0.431 | 0.381 |
| <b>MAPE</b>          | 2.58%         | 1.66% | 1.45% | 2.63% | 0.51%    | 0.54%     | 10.86%   | 1.67% | 2.31% | 1.87% |
| <b>R<sup>2</sup></b> | 0.991         | 0.993 | 0.996 | 0.989 | 0.987    | 0.988     | 0.921    | 0.993 | 0.992 | 0.987 |

Table 4.21: AM-Testing Evaluation Metrics

| Metrics              | PR (4 Degree) | DT    | RFR   | GBR   | XG Boost | CAT Boost | AdaBoost | ETR   | EBM   | SVR    |
|----------------------|---------------|-------|-------|-------|----------|-----------|----------|-------|-------|--------|
| <b>MSE</b>           | 2.703         | 1.079 | 0.813 | 0.752 | 0.945    | 0.922     | 3.602    | 1.040 | 0.791 | 11.595 |
| <b>RMSE</b>          | 1.644         | 1.039 | 0.902 | 0.867 | 0.972    | 0.960     | 1.898    | 1.020 | 0.889 | 3.405  |
| <b>MAE</b>           | 1.201         | 0.690 | 0.631 | 0.625 | 0.615    | 0.614     | 1.644    | 0.702 | 0.616 | 2.164  |
| <b>MAPE</b>          | 6.86%         | 4.07% | 3.63% | 3.57% | 3.40%    | 3.35%     | 10.88%   | 4.06% | 3.48% | 11.95% |
| <b>R<sup>2</sup></b> | 0.942         | 0.977 | 0.983 | 0.984 | 0.980    | 0.980     | 0.922    | 0.978 | 0.983 | 0.750  |

During the training phase, ensemble-based machine learning models, particularly Random Forest Regressor (RFR), Extra Trees Regressor (ETR), Explainable Boosting Machine (EBM), Gradient Boosting Regressor (GBR), XGBoost, and CatBoost, demonstrated superior predictive accuracy for estimating the surface roughness (Ra) in the AM dataset. Among these, XGBoost and CatBoost achieved the lowest MSE values (0.017 and 0.016, respectively) and RMSE values (0.127–0.129), indicating an exceptional fit to the training data. RFR (MSE = 0.177) and ETR (MSE = 0.311) also performed strongly, with  $R^2$  values of 0.996 and 0.993, respectively, suggesting a high ability to capture complex nonlinear relationships between process parameters and Ra. EBM maintained strong performance (MSE = 0.369,  $R^2$  = 0.992), indicating that interpretable boosting methods can also match the predictive capability of less interpretable ensemble techniques. Polynomial Regression (PR) with a fourth-degree term yielded a high  $R^2$  (0.991) but larger errors compared to ensemble methods, reflecting its limited flexibility for highly nonlinear patterns. In contrast, AdaBoost showed substantially higher errors and a lower  $R^2$  (0.921), indicating weaker predictive capability during training for Ra estimation.

In the testing phase, EBM, RFR, ETR, and gradient boosting models (GBR, XGBoost, CatBoost) maintained high predictive accuracy, confirming strong generalization capability for predicting Ra on unseen AM data. EBM achieved a low MSE (0.791) and RMSE (0.889), along with a low MAPE (3.48%) and a high  $R^2$  of 0.983, closely matching RFR ( $R^2$  = 0.983, MAPE = 3.63%) and ETR ( $R^2$  = 0.978, MAPE = 4.06%). Gradient boosting models produced MSE values between 0.752 and 0.945, MAPE ranging from 3.35%–3.57%, and  $R^2$  values around 0.980–0.984, demonstrating robust and stable predictions of Ra. Decision Tree (DT) and PR exhibited moderate performance, with slightly higher errors, but still acceptable  $R^2$  values (0.977



and 0.942, respectively). AdaBoost suffered from relatively higher prediction errors (MSE = 3.602, MAPE = 10.88%), while Support Vector Regression (SVR) performed the worst, showing the highest errors (MSE = 11.595, MAPE = 11.95%) and the lowest  $R^2$  (0.750), indicating its unsuitability for Ra prediction in the AM process.

Model selection in this study is based primarily on the testing phase results rather than the training phase performance. This approach ensures that the selected model demonstrates strong generalization capability rather than memorization of the training data. The testing dataset contains unseen samples that were not used during model development, providing an unbiased measure of predictive performance. By evaluating models on this independent dataset, the likelihood of overfitting where a model performs exceptionally well on training data but poorly on new data is significantly reduced. Furthermore, the testing phase evaluation more accurately reflects real-world applicability, as the model will ultimately be required to predict surface roughness Ra for new additively manufactured parts under potentially different process conditions.

Based on the testing-phase results of the single run, the Explainable Boosting Machine (EBM) stands out as the most effective model for predicting surface roughness Ra in the AM process. EBM achieved a low testing MSE (0.791) and RMSE (0.889) while maintaining a high  $R^2$  of 0.983 and a low MAPE of (3.48%). These results indicate that EBM not only provides highly accurate predictions but also generalizes well to unseen data. Moreover, EBM offers the advantage of interpretability through feature importance and interaction plots, allowing for a better understanding of how each process parameter influences Ra. Tables 4.22 and 4.23 represents the mean and standard deviation of the evaluation metrics of all ten ML models by carrying out a 10-fold cross validation.

Table 4.22: 10-fold Cross-Validation (mean  $\pm$  SD) for AM — Part I

| Metrics                 | PR (4 Degrees)    | DT                | RFR               | GBR               | XG Boost          |
|-------------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| <b>MSE</b>              | 2.025 $\pm$ 0.607 | 1.837 $\pm$ 1.004 | 1.071 $\pm$ 0.543 | 0.957 $\pm$ 0.456 | 0.889 $\pm$ 0.491 |
| <b>RMSE</b>             | 1.404 $\pm$ 0.232 | 1.314 $\pm$ 0.334 | 1.003 $\pm$ 0.255 | 0.955 $\pm$ 0.211 | 0.913 $\pm$ 0.236 |
| <b>MAE</b>              | 1.054 $\pm$ 0.153 | 0.831 $\pm$ 0.160 | 0.690 $\pm$ 0.105 | 0.682 $\pm$ 0.100 | 0.621 $\pm$ 0.084 |
| <b>MAPE (%)</b>         | 5.993 $\pm$ 0.829 | 4.565 $\pm$ 0.626 | 3.700 $\pm$ 0.489 | 3.623 $\pm$ 0.430 | 3.382 $\pm$ 0.375 |
| <b><math>R^2</math></b> | 0.952 $\pm$ 0.016 | 0.955 $\pm$ 0.032 | 0.974 $\pm$ 0.017 | 0.977 $\pm$ 0.014 | 0.978 $\pm$ 0.015 |

Table 4.23: 10-fold Cross-Validation (mean  $\pm$  SD) for AM — Part II

| Metrics              | Cat Boost         | Ada Boost          | ETR               | EBM               | SVR               |
|----------------------|-------------------|--------------------|-------------------|-------------------|-------------------|
| <b>MSE</b>           | 1.898 $\pm$ 0.433 | 3.991 $\pm$ 0.834  | 1.317 $\pm$ 0.625 | 0.863 $\pm$ 0.377 | 4.917 $\pm$ 2.259 |
| <b>RMSE</b>          | 1.378 $\pm$ 0.222 | 1.987 $\pm$ 0.205  | 1.119 $\pm$ 0.253 | 0.909 $\pm$ 0.189 | 2.161 $\pm$ 0.497 |
| <b>MAE</b>           | 0.679 $\pm$ 0.075 | 1.703 $\pm$ 0.159  | 0.726 $\pm$ 0.093 | 0.652 $\pm$ 0.101 | 1.507 $\pm$ 0.318 |
| <b>MAPE (%)</b>      | 3.320 $\pm$ 0.329 | 10.796 $\pm$ 1.444 | 3.894 $\pm$ 0.323 | 3.539 $\pm$ 0.434 | 8.287 $\pm$ 1.781 |
| <b>R<sup>2</sup></b> | 0.946 $\pm$ 0.013 | 0.905 $\pm$ 0.029  | 0.968 $\pm$ 0.020 | 0.979 $\pm$ 0.012 | 0.886 $\pm$ 0.048 |

Building on the single-run testing results, the 10-fold cross-validation in Tables 4.22 and 4.23 leads to the same conclusion. EBM attains the best overall generalization with the lowest RMSE (0.909  $\pm$  0.189) and MSE (0.863  $\pm$  0.377) and the highest R<sup>2</sup> (0.979  $\pm$  0.012). XGBoost and GBR form a close second tier: XGBoost gives the lowest MAE/MAPE (0.621  $\pm$  0.084 and 3.382%  $\pm$  0.375), while GBR is marginally behind (MAE = 0.682  $\pm$  0.100; RMSE = 0.955  $\pm$  0.211). However, XGBoost's slight advantage in MAE/MAPE comes with RMSE/MSE that are a touch higher than EBM's, and the gaps are within one standard deviation, suggesting practical parity. RFR and ETR are competitive but clearly behind the top group (RMSE = 1.00–1.12; R<sup>2</sup> = 0.968–0.974).

In contrast, DT and the polynomial baseline (PR-4°) underperform the ensembles, and SVR and AdaBoost are the weakest overall (e.g., SVR RMSE = 2.161  $\pm$  0.497; AdaBoost MAPE = 10.796%  $\pm$  1.444). Overall, cross-validation corroborates selecting EBM as the primary model—offering the best error–variance trade-off and interpretability—while XGBoost is a strong runner-up when absolute-error metrics (MAE/MAPE) are prioritized.

While numerical evaluation metrics provide a quantitative assessment of model performance, visualizing the relationship between predicted and actual Ra values offers additional insights into the model's predictive behavior.

Figures 4.15, 4.16, 4.17, 4.18, 4.19, 4.20, 4.21, 4.22, 4.23, and 4.24 represents the predicted vs actual plots for all the MLs algorithms employed in this study belonging to the AM process.

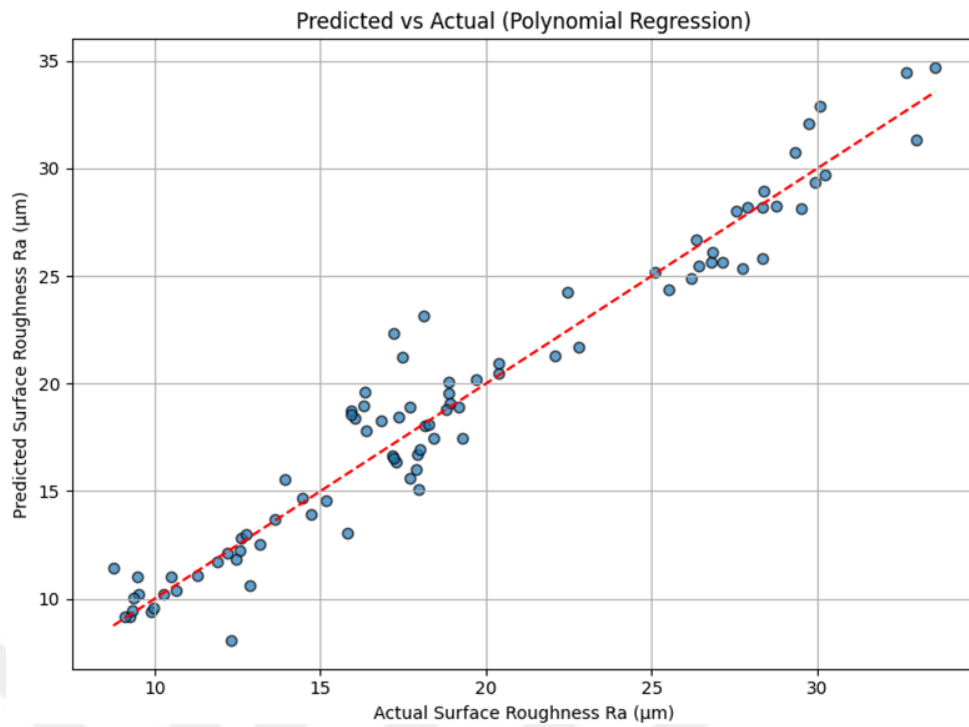


Figure 4.15: Polynomial Regression Predicted vs Actual Plot

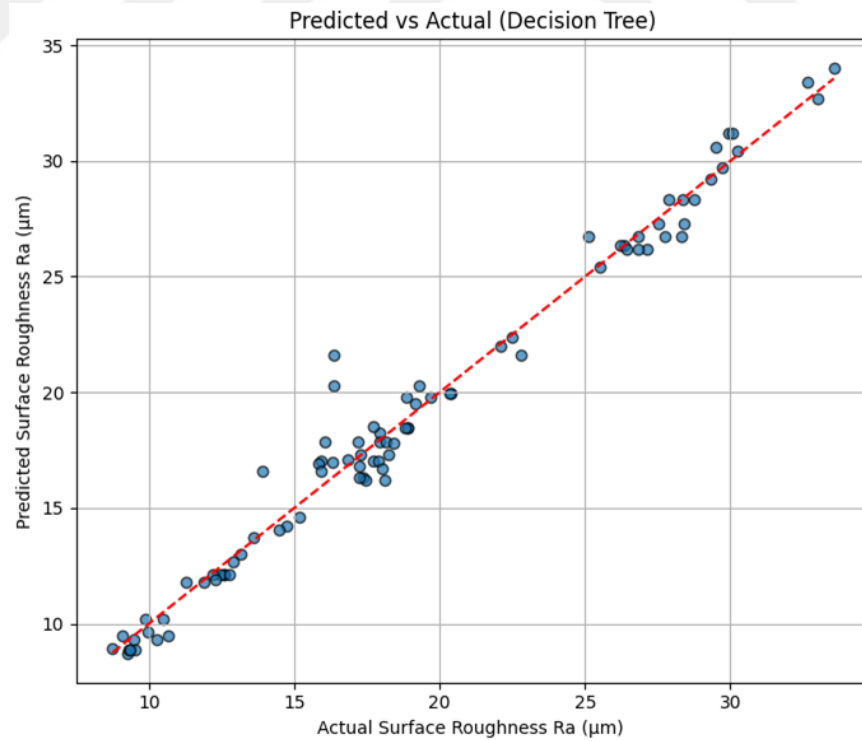


Figure 4.16: Decision Tree Predicted vs Actual Plot

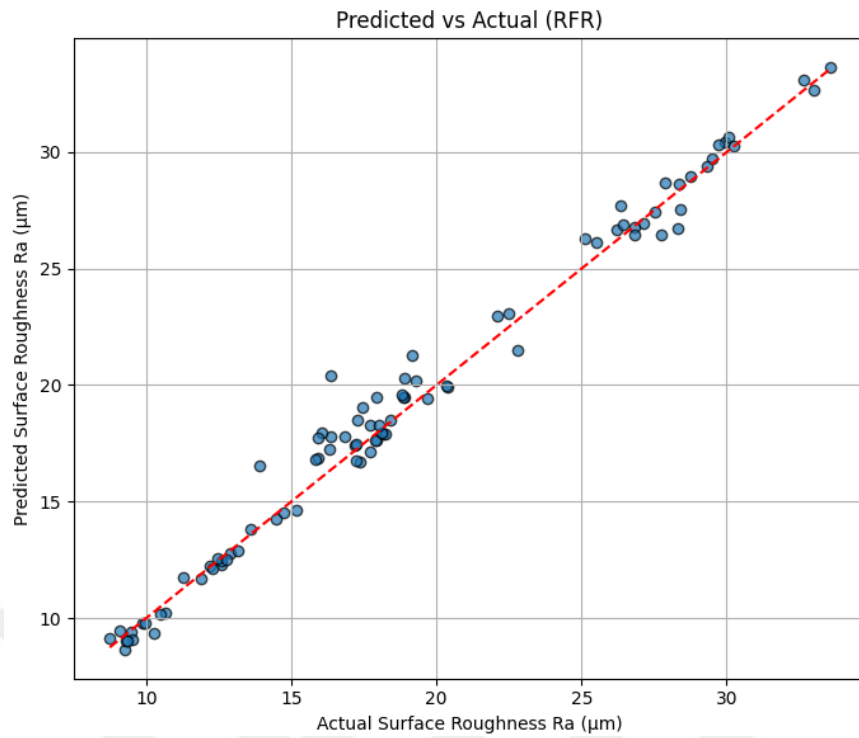


Figure 4.17: Random Forest Regressor Predicted vs Actual Plot

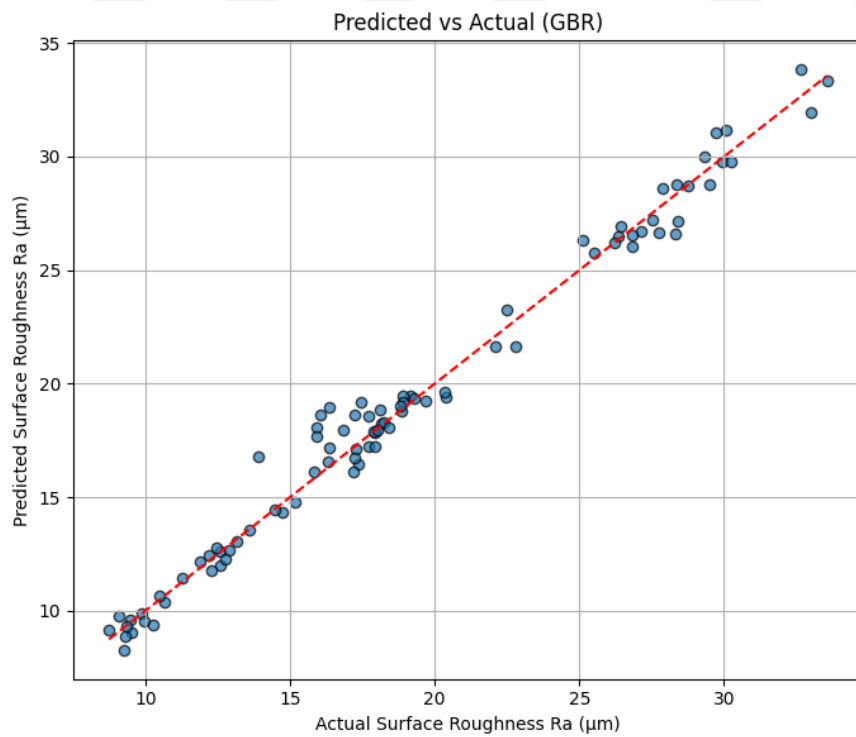


Figure 4.18: Gradient Boosting Regressor Predicted vs Actual Plot

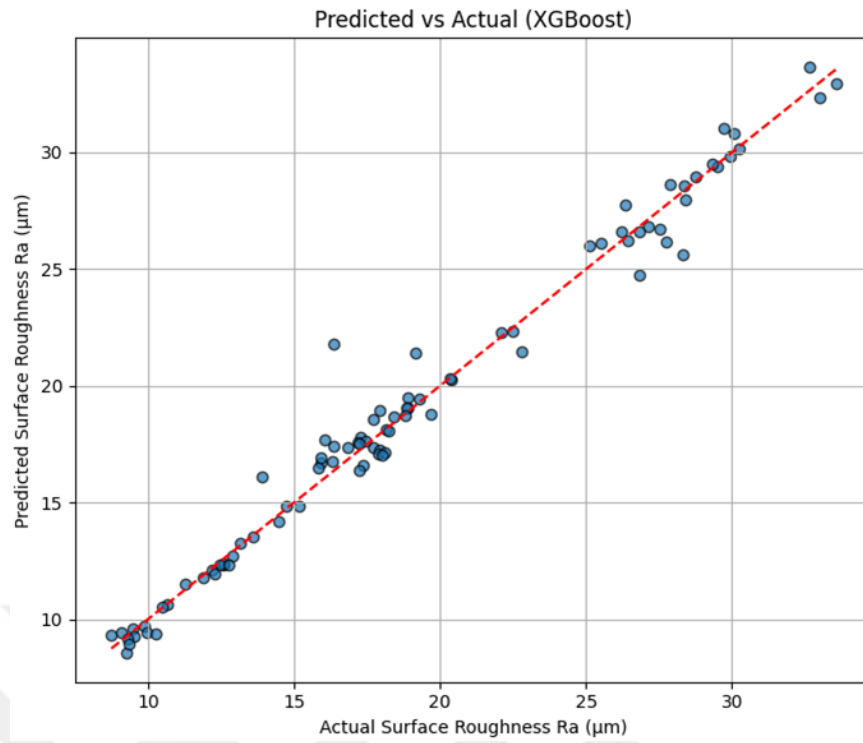


Figure 4.19: Extreme Gradient Boosting Regressor Predicted vs Actual Plot

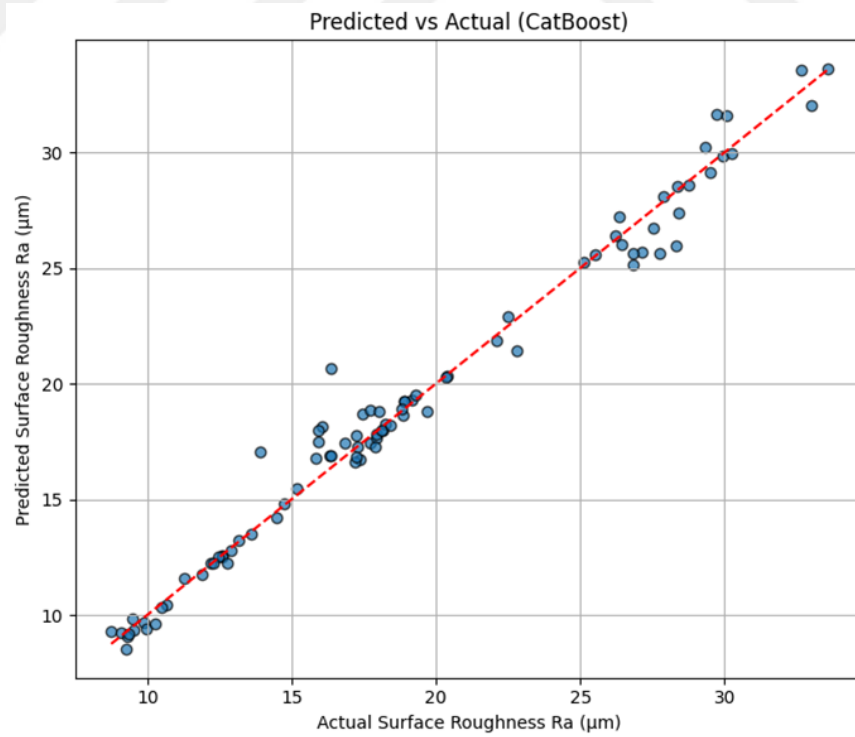


Figure 4.20: Category Boosting Regressor Predicted vs Actual Plot

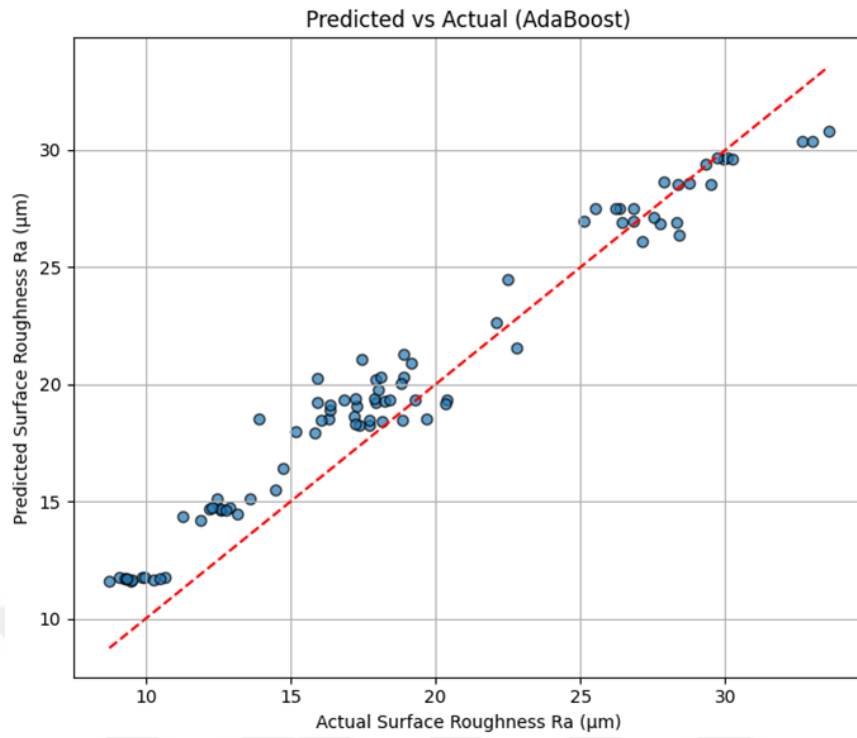


Figure 4.21: Adaptive Boosting Regressor Predicted vs Actual Plot

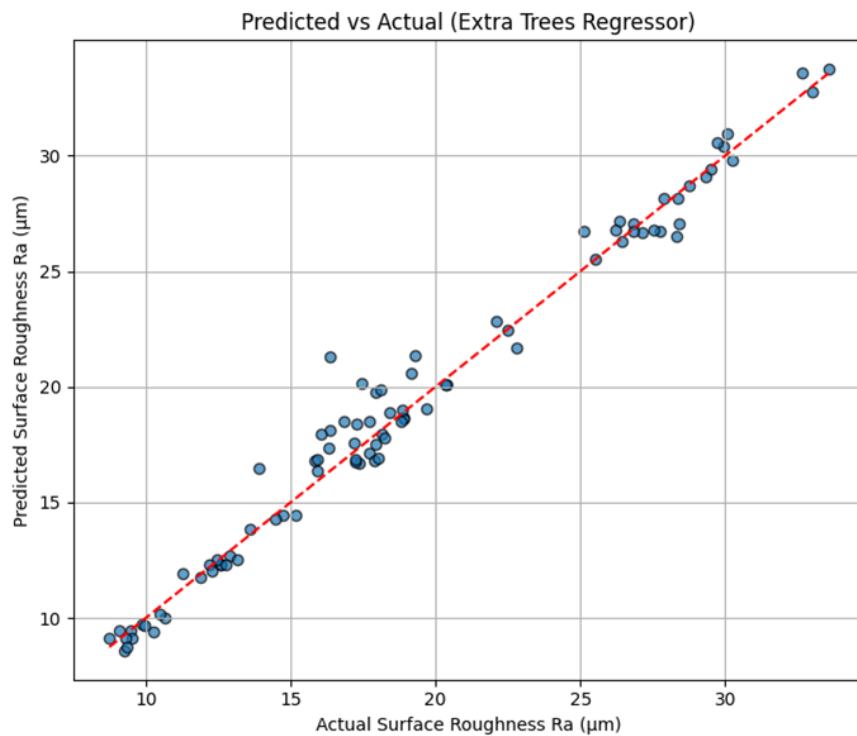


Figure 4.22: Extra Tree Regressor Predicted vs Actual Plot

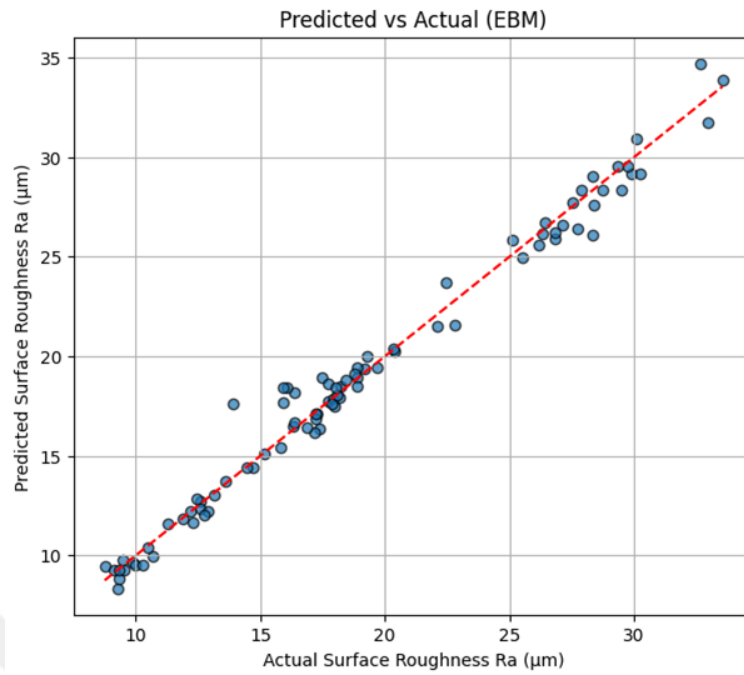


Figure 4.23: Explainable Boosting Machine Predicted vs Actual Plot

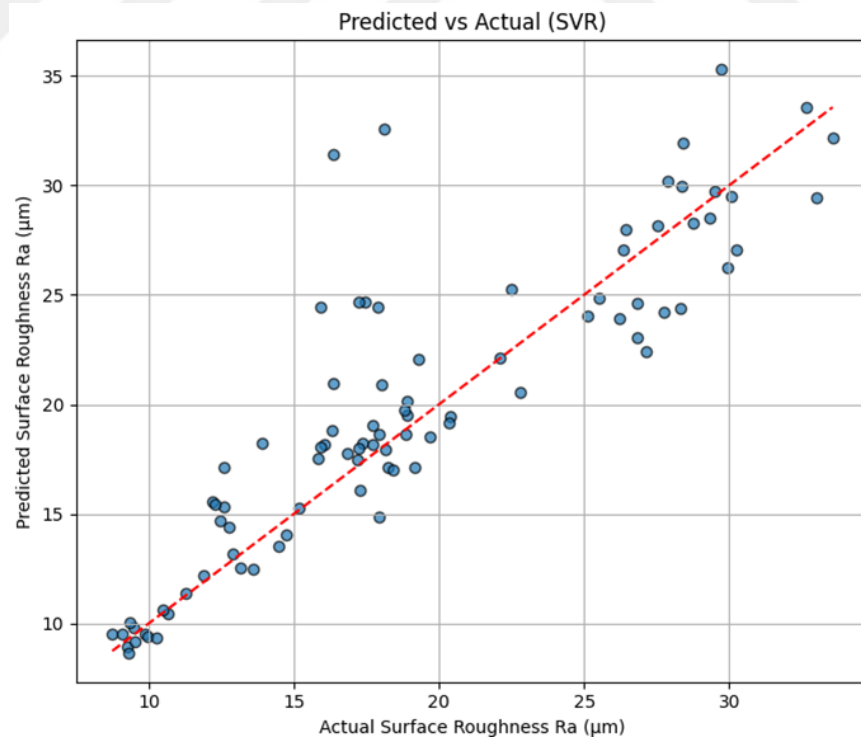


Figure 4.24: Support Vector Regression Predicted vs Actual Plot

Predicted vs. actual plots show how well the ML predicted values are matching the observations. The x-axis represents the actual observations, while the y-axis represents the predicted ones. Points falling closer to the line of 45 degree mean that the model is performing well for those points. An ideal ML has all the points lying on the 45 degree diagonal.

Across all tested models, the Explainable Boosting Machine (EBM) clearly emerges as the best performer, as its predictions align closely with the ideal 1:1 relationship between actual and predicted surface roughness Ra values as shown in Figure 4.23. The scatter is minimal across the full Ra range, showing that EBM consistently captures the complex nonlinear dependencies between input process parameters and the output. This stability results from EBM's ability to combine the strengths of boosted decision trees with an interpretable additive model, which allows it to learn both simple and interaction effects effectively. Among the other models, GBR, XGBoost, CatBoost, and Extra Trees Regressor also show strong predictive performance, with relatively tight clustering around the ideal line. However, they exhibit slightly higher scatter compared to EBM, particularly in the mid-range Ra values, which suggests slightly less stability in generalization.

Support Vector Regression (SVR) performs the worst among the tested methods as shown in the Figure 4.24. While it follows the general trend, its scatter is much larger, especially between 15  $\mu\text{m}$  and 25  $\mu\text{m}$  Ra, where it significantly underpredicts or overpredicts. This is chiefly because SVR is founded on the application of kernel functions, the adjustment of whose hyperparameters and kernel parameters is sensitive to tuning for adapting to a complex dataset. Here, SVR cannot learn the subtle nonlinear relationships as ensemble-based methods do, so it is not as optimal for the prediction of surface roughness with additively manufactured parts. Briefly, while gradient boosting and ensemble-based tree structures typically perform well, the high accuracy, low bias, stable generalization, and interpretability of the EBM put it clearly out front, while the sensitivity to parameter tuning alongside weaker handling for complex nonlinearities by the SVR puts it the least effective ML within this comparison.

Figure 4.25 represents the predicted vs actual plot with residuals of the EBM model



selected to be the best one among all others.

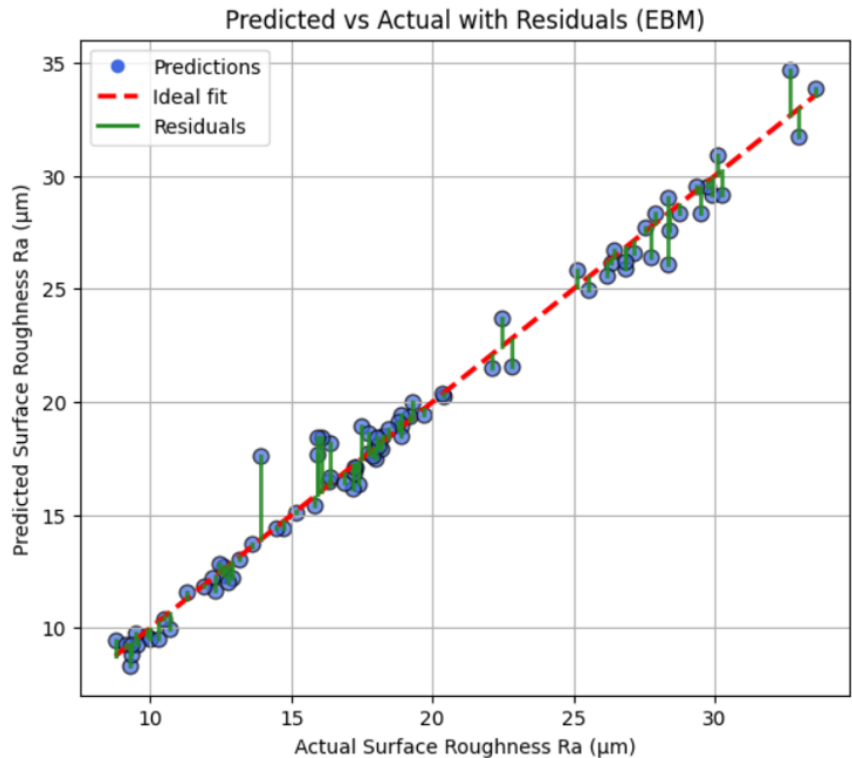


Figure 4.25: EBM Predicted vs Actual plot (AM) with residuals

In this plot, the residuals are illustrated as vertical green lines connecting each prediction to its corresponding actual value. These residuals represent the prediction errors of the model, and their magnitude and orientation provide valuable diagnostic insight. Lines extending upward indicate cases where the model over-predicted the surface roughness, while lines extending downward represent under-prediction. The majority of these lines are relatively short, which demonstrates that the EBM model achieves consistently small deviations from the experimental values across most of the dataset. Only a limited number of points, particularly those in the mid-range (around 16–20  $\mu\text{m}$ ) and upper roughness range (above 28  $\mu\text{m}$ ), display slightly longer residuals, indicating localized regions where the predictions deviate slightly from the actual values. Overall, this residual-enhanced visualization not only confirms the strong predictive performance of the EBM model but also highlights its robustness, as the vast majority of predictions are characterized by small, well-distributed errors.

Similarly, for the Hybrid case, Tables are formed for both the evaluation metrics for the training and the testing phases for a single run as given in 4.24, 4.25

Table 4.24: Hybrid-Training Evaluation Metrics

| Metrics              | PR (4 Degree) | DT     | RFR   | GBR    | XG Boost | CAT Boost | AdaBoost | ETR   | EBM    | SVR    |
|----------------------|---------------|--------|-------|--------|----------|-----------|----------|-------|--------|--------|
| <b>MSE</b>           | 0.064         | 0.080  | 0.013 | 0.068  | 0.021    | 0.048     | 0.119    | 0.044 | 0.073  | 0.213  |
| <b>RMSE</b>          | 0.253         | 0.282  | 0.114 | 0.260  | 0.144    | 0.220     | 0.345    | 0.210 | 0.271  | 0.461  |
| <b>MAE</b>           | 0.190         | 0.212  | 0.083 | 0.192  | 0.103    | 0.162     | 0.281    | 0.153 | 0.199  | 0.398  |
| <b>MAPE</b>          | 9.97%         | 11.09% | 4.40% | 10.14% | 5.38%    | 8.59%     | 15.98%   | 8.03% | 10.53% | 21.92% |
| <b>R<sup>2</sup></b> | 0.744         | 0.681  | 0.948 | 0.729  | 0.917    | 0.806     | 0.524    | 0.823 | 0.707  | 0.147  |

Table 4.25: Hybrid-Testing Evaluation Metrics

| Metrics              | PR (4 Degree) | DT     | RFR    | GBR    | XG Boost | CAT Boost | AdaBoost | ETR    | EBM    | SVR    |
|----------------------|---------------|--------|--------|--------|----------|-----------|----------|--------|--------|--------|
| <b>MSE</b>           | 0.197         | 0.152  | 0.145  | 0.120  | 0.133    | 0.120     | 0.189    | 0.147  | 0.109  | 0.274  |
| <b>RMSE</b>          | 0.444         | 0.390  | 0.380  | 0.346  | 0.365    | 0.346     | 0.435    | 0.383  | 0.331  | 0.524  |
| <b>MAE</b>           | 0.314         | 0.263  | 0.249  | 0.233  | 0.253    | 0.234     | 0.321    | 0.254  | 0.226  | 0.432  |
| <b>MAPE</b>          | 16.31%        | 13.52% | 13.07% | 12.27% | 13.18%   | 12.24%    | 17.79%   | 13.39% | 11.92% | 23.53% |
| <b>R<sup>2</sup></b> | 0.308         | 0.466  | 0.492  | 0.580  | 0.533    | 0.579     | 0.335    | 0.486  | 0.616  | 0.038  |

From the Table 4.24, we can see that in all models, Random Forest Regressor (RFR) has the best results with the smallest MSE (0.013), RMSE (0.114), MAE (0.083), and MAPE (4.40%), and the largest R<sup>2</sup> (0.948). This represents a supreme degree of prediction capability and little or no overfitting during the training phase. XGBoost has comparably low errors (MSE = 0.021, RMSE = 0.144) and a high R<sup>2</sup> (0.917), indicating to be powerful in fitting the model. XGBoost also performs very well, with comparably low errors (MSE = 0.021, RMSE = 0.144) and a high R<sup>2</sup> (0.917), suggesting strong fitting ability. Extra Trees Regressor (ETR) and CatBoost also achieve competitive performance, though slightly behind RFR and XGBoost. Explainable Boosting Machine (EBM) demonstrates respectable performance, though it is not the top performer in the training phase. With an MSE of 0.073, RMSE of 0.271, MAE of 0.199, and MAPE of 10.53%, EBM achieves a moderate R<sup>2</sup> of 0.707. Conversely, SVR struggles in training with the highest MAPE (21.92%) and lowest R<sup>2</sup> (0.147), indicating poor fit and a substantial deviation from the actual values. Polynomial Regression (PR) and Decision Tree (DT) perform moderately, while AdaBoost exhibits weaker training accuracy, with relatively high error metrics and a lower R<sup>2</sup> (0.524).

In the Testing Evaluation phase, from Table 4.25, generalization ability becomes more evident. While RFR retains a good balance between accuracy and generalization ( $MSE = 0.145$ ,  $R^2 = 0.492$ ), its performance drops compared to training, indicating overfitting. Interestingly, EBM achieves the best generalization, with the lowest MSE (0.109), lowest RMSE (0.331), and highest  $R^2$  (0.616), showing that it handles unseen data more reliably than others. GBR and CatBoost also fail to generalize well ( $R^2 = 0.579$ – $0.580$ ) with relatively high errors, making them unsuitable. Despite being robust during training, XGBoost exhibits a discernible decline in performance during testing, indicating mild overfitting. The worst-performing models in testing are SVR and AdaBoost, which have high error metrics (SVR MAPE = 23.53%,  $R^2 = 0.038$ ; AdaBoost MAPE = 17.79%,  $R^2 = 0.335$ ), indicating that they are unable to capture the underlying patterns adequately. Overall, while RFR dominates in training, EBM is the most reliable choice for testing due to its ability to maintain high accuracy on unseen data, while SVR is the weakest model for both training and testing phases. Tables 4.26 and 4.27 represent the mean and standard deviation of the evaluation metrics for all ten ML models after carrying out a 10 fold cross validation.

Table 4.26: 10-fold Cross-Validation for Hyrbid (mean  $\pm$  SD) — Part I

| Metrics              | PR (4 Degrees)     | DT                 | RFR                | GBR                | XG Boost           |
|----------------------|--------------------|--------------------|--------------------|--------------------|--------------------|
| <b>MSE</b>           | 0.377 $\pm$ 0.033  | 0.109 $\pm$ 0.033  | 0.105 $\pm$ 0.029  | 0.091 $\pm$ 0.024  | 0.107 $\pm$ 0.030  |
| <b>RMSE</b>          | 0.281 $\pm$ 0.013  | 0.327 $\pm$ 0.047  | 0.322 $\pm$ 0.042  | 0.300 $\pm$ 0.038  | 0.325 $\pm$ 0.041  |
| <b>MAE</b>           | 0.143 $\pm$ 0.026  | 0.237 $\pm$ 0.021  | 0.229 $\pm$ 0.018  | 0.217 $\pm$ 0.015  | 0.235 $\pm$ 0.019  |
| <b>MAPE (%)</b>      | 14.825 $\pm$ 0.571 | 12.384 $\pm$ 1.035 | 12.060 $\pm$ 0.852 | 11.438 $\pm$ 0.785 | 12.269 $\pm$ 0.833 |
| <b>R<sup>2</sup></b> | 0.441 $\pm$ 0.055  | 0.579 $\pm$ 0.076  | 0.590 $\pm$ 0.079  | 0.646 $\pm$ 0.053  | 0.583 $\pm$ 0.077  |

Table 4.27: 10-fold Cross-Validation for Hybrid (mean  $\pm$  SD) — Part II

| Metrics              | Cat Boost          | Ada Boost          | ETR                | EBM                | SVR                |
|----------------------|--------------------|--------------------|--------------------|--------------------|--------------------|
| <b>MSE</b>           | 0.093 $\pm$ 0.023  | 0.173 $\pm$ 0.046  | 0.100 $\pm$ 0.032  | 0.091 $\pm$ 0.019  | 0.239 $\pm$ 0.032  |
| <b>RMSE</b>          | 0.303 $\pm$ 0.035  | 0.413 $\pm$ 0.054  | 0.313 $\pm$ 0.047  | 0.299 $\pm$ 0.031  | 0.488 $\pm$ 0.033  |
| <b>MAE</b>           | 0.218 $\pm$ 0.014  | 0.318 $\pm$ 0.033  | 0.225 $\pm$ 0.021  | 0.216 $\pm$ 0.013  | 0.415 $\pm$ 0.020  |
| <b>MAPE (%)</b>      | 11.484 $\pm$ 0.708 | 18.091 $\pm$ 2.134 | 11.842 $\pm$ 0.996 | 11.378 $\pm$ 0.679 | 22.769 $\pm$ 1.384 |
| <b>R<sup>2</sup></b> | 0.639 $\pm$ 0.049  | 0.326 $\pm$ 0.137  | 0.613 $\pm$ 0.076  | 0.647 $\pm$ 0.043  | 0.063 $\pm$ 0.047  |

Expanding on the single-run discussion, the 10-fold cross-validation in Tables 4.26 and 4.27 provides a more robust ranking by averaging performance across ten disjoint test splits and revealing stability via the standard deviations. The top cluster consists of EBM and GBR, which are essentially tied on squared-error metrics (both  $MSE = 0.091$ ,  $RMSE = 0.30$ ); EBM has a marginal edge on goodness-of-fit ( $R^2 = 0.647 \pm 0.043$  vs.  $0.646 \pm 0.053$ ) and slightly lower MAE ( $0.216$  vs.  $0.217$ ). CatBoost follows very closely ( $MSE = 0.093 \pm 0.023$ ,  $RMSE = 0.303 \pm 0.035$ ,  $R^2 = 0.639 \pm 0.049$ ). ETR forms a competitive second tier ( $MSE = 0.100 \pm 0.032$ ,  $RMSE = 0.313 \pm 0.047$ ,  $R^2 = 0.613 \pm 0.076$ ), while RFR and XGBoost sit mid-pack with slightly higher errors ( $RMSE = 0.322\text{--}0.325$ ,  $R^2 = 0.583\text{--}0.590$ ). DT trails the ensembles ( $RMSE = 0.327 \pm 0.047$ ,  $R^2 = 0.579 \pm 0.076$ ). The weakest models are AdaBoost and SVR, which show large errors and low fit (e.g., SVR  $R^2 = 0.063 \pm 0.047$ ,  $MAPE = 22.769 \pm 1.384\%$ ; AdaBoost  $R^2 = 0.326 \pm 0.137$ ,  $MAPE = 18.091 \pm 2.134\%$ ), indicating difficulty capturing the underlying relationships.

The standard deviations add useful context: the leading models (EBM/GBR/CatBoost) exhibit small RMSE SDs  $= 0.031\text{--}0.038$ , implying consistent generalization across splits; differences among them are often within one SD, so performance is practically similar. EBM also combines low error with the lowest variance on several metrics, strengthening its case when stability matters. By contrast, AdaBoost shows relatively high variability (e.g.,  $R^2$  SD  $0.137$ ), and while PR ( $4^\circ$ ) has modest SDs, its means are much worse (e.g.,  $MSE = 0.377 \pm 0.033$ ,  $R^2 = 0.441 \pm 0.055$ ), reflecting systematic underfitting rather than stability. Interpreting magnitudes, the best models'  $RMSE = 0.30 \mu m$  corresponds to roughly 11–12% MAPE, which is a reasonable prediction error given the roughness scale measured. Overall, the cross-validated evidence reinforces the single-run conclusion: EBM remains the preferred model because it delivers the best error–variance trade-off with strong  $R^2$  and low MAE/RMSE, while also being interpretable. GBR and CatBoost are strong, stable alternatives; ETR is serviceable but a step behind; RFR/XGB/DT are middling under cross-validation; and SVR/AdaBoost are not recommended for deployment on this task.

This becomes evident when examining the predicted vs actual machine learning plots presented in Figures 4.26, 4.27, 4.28, 4.29, 4.30, 4.31, 4.32, 4.33, 4.34, and 4.35.

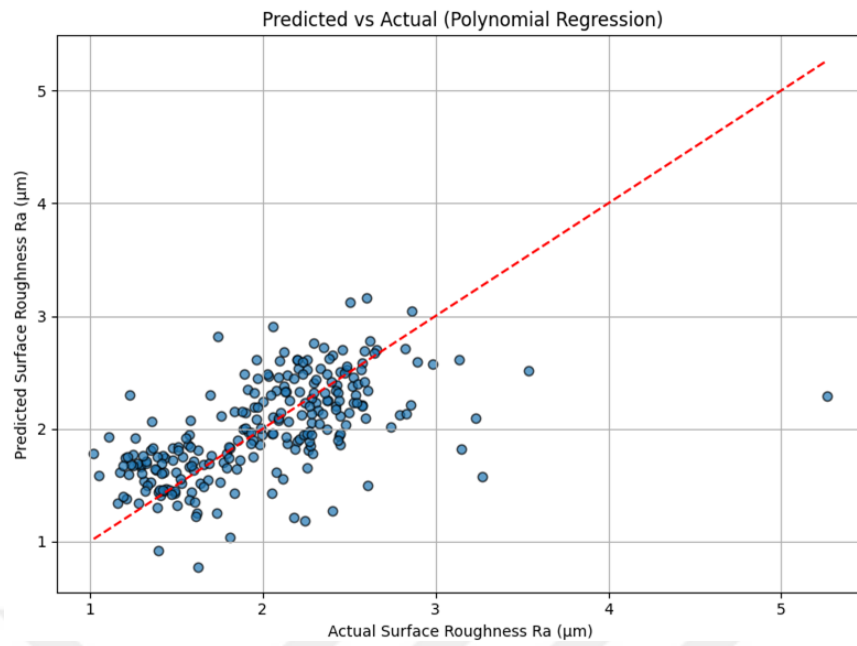


Figure 4.26: Hybrid - Polynomial Regression (4 Degree) Predicted vs Actual Plot

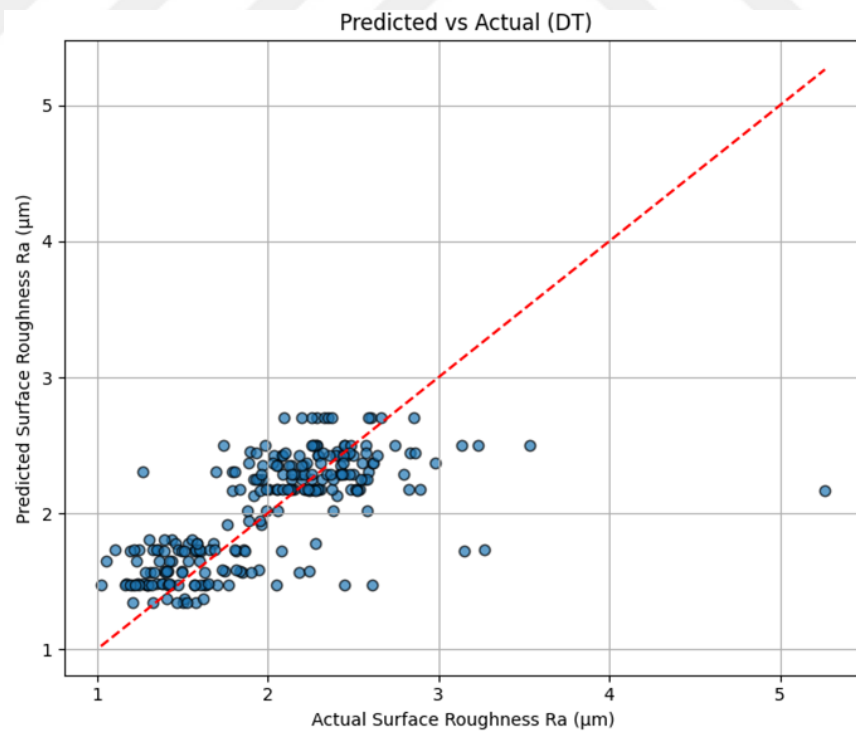


Figure 4.27: Hybrid - Decision Tree Predicted vs Actual Plot

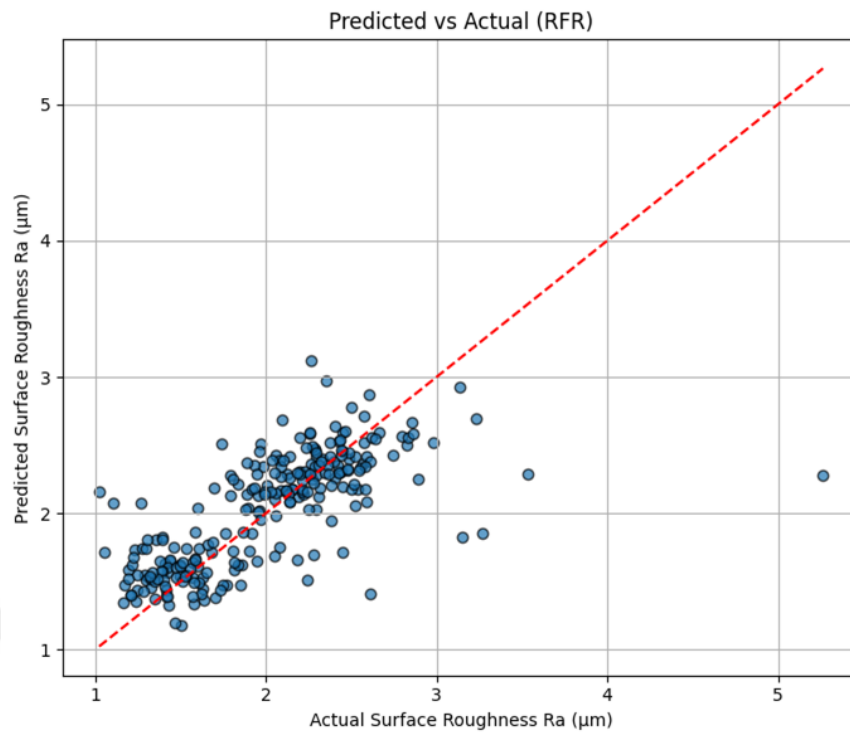


Figure 4.28: Hybrid - Random Forest Regression Predicted vs Actual Plot

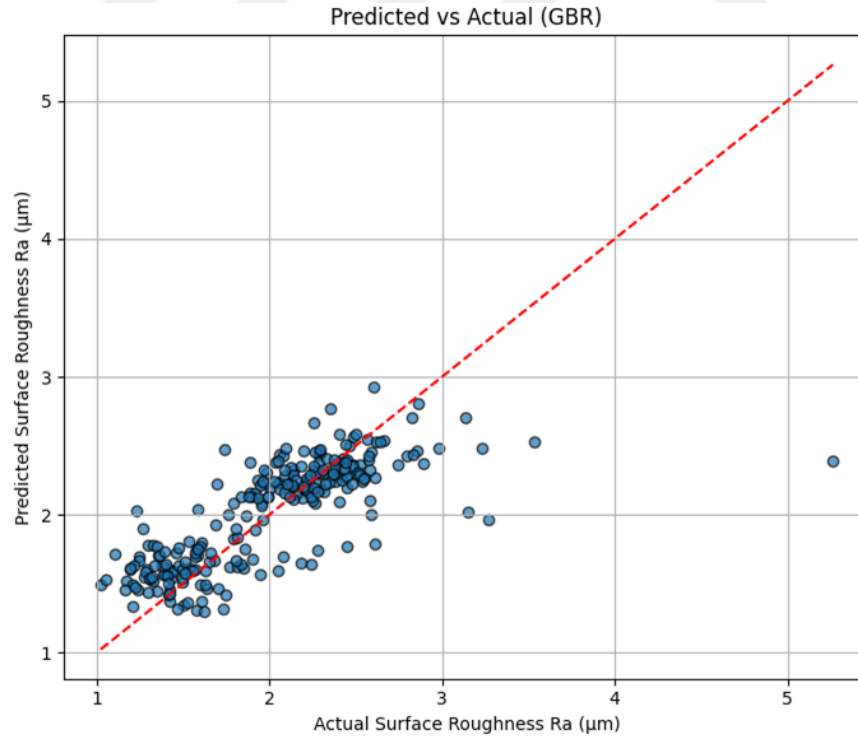


Figure 4.29: Hybrid - Gradient Boosting Regression Predicted vs Actual Plot

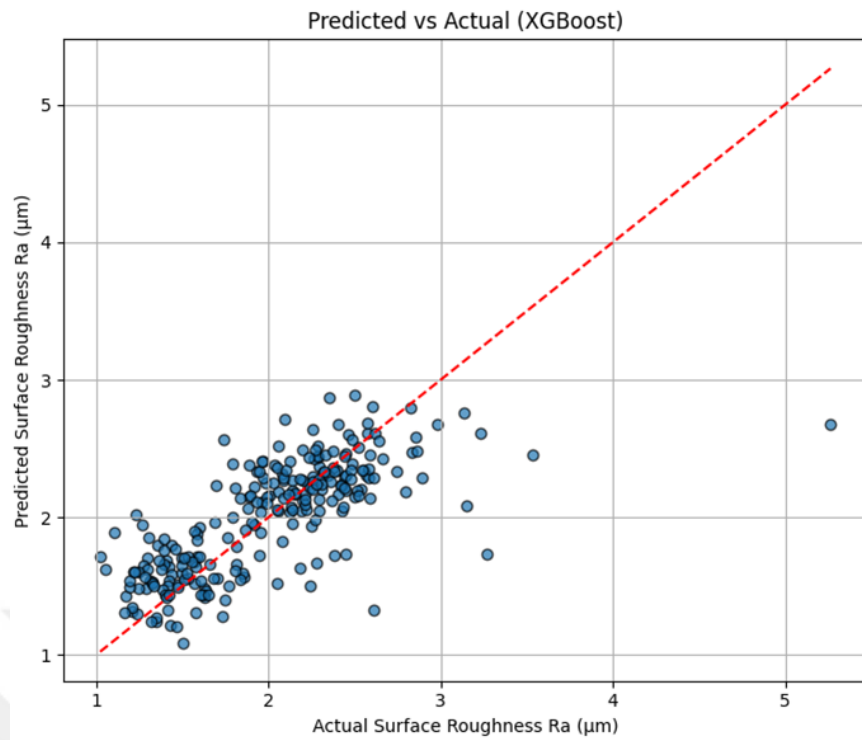


Figure 4.30: Hybrid - Extreme Gradient Boosting Predicted vs Actual Plot

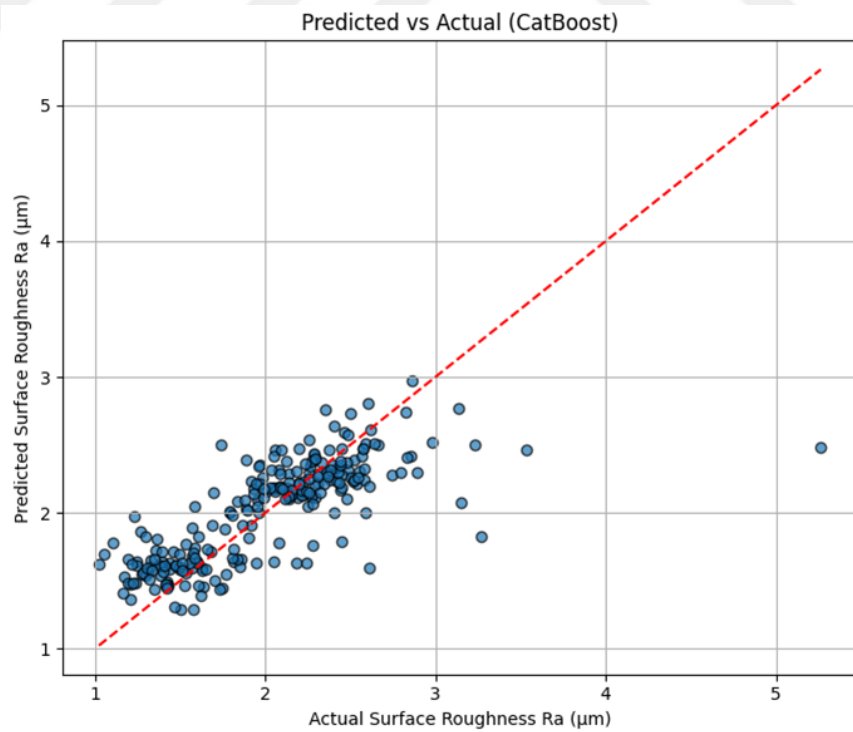


Figure 4.31: Hybrid - Category Boosting Predicted vs Actual Plot

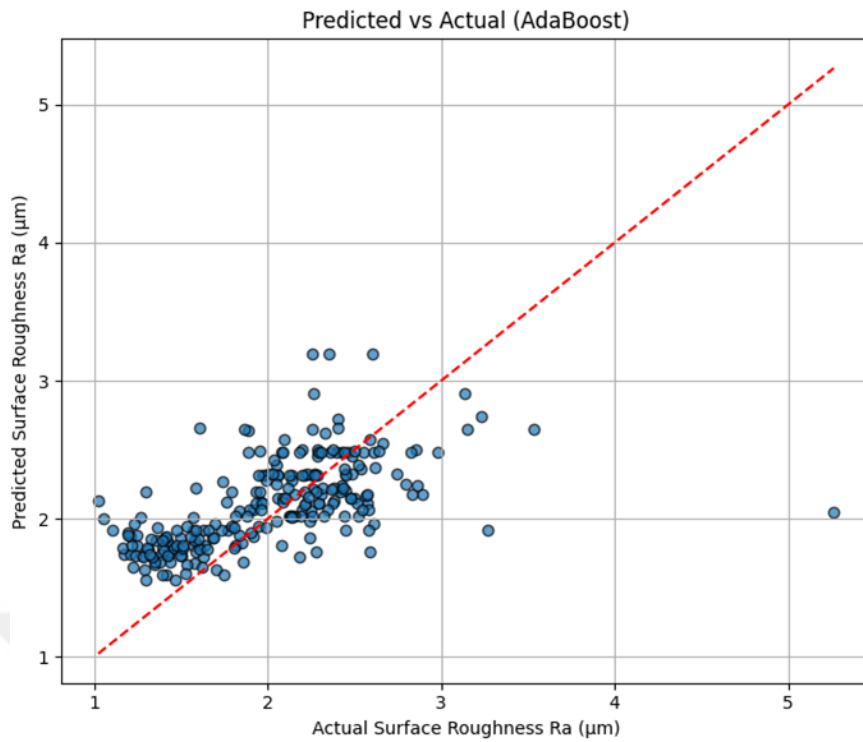


Figure 4.32: Hybrid - Adaptive Boosting Predicted vs Actual Plot

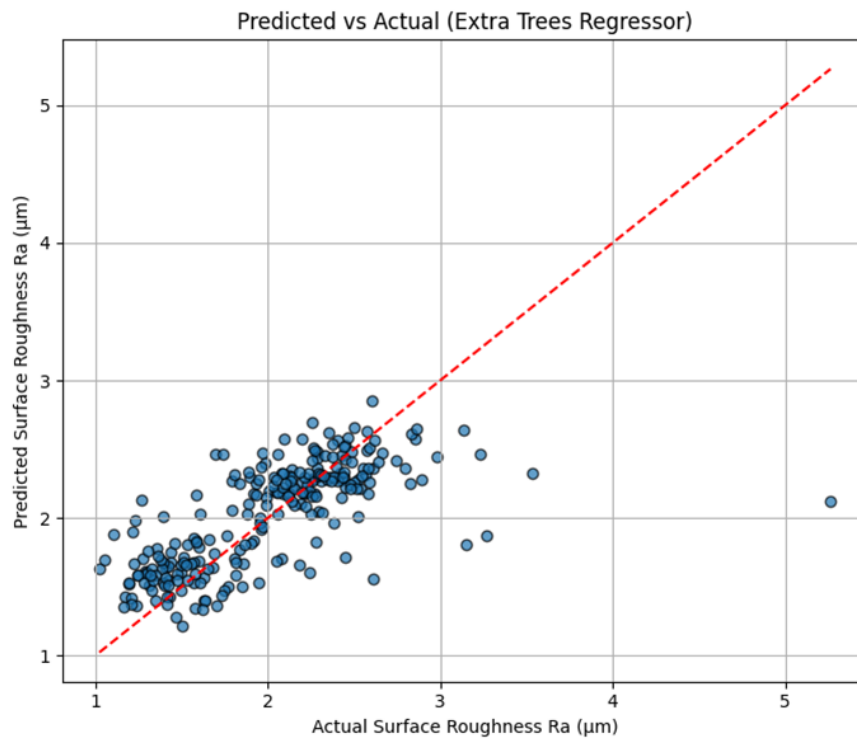


Figure 4.33: Hybrid - Extra Tree Regressor Predicted vs Actual Plot



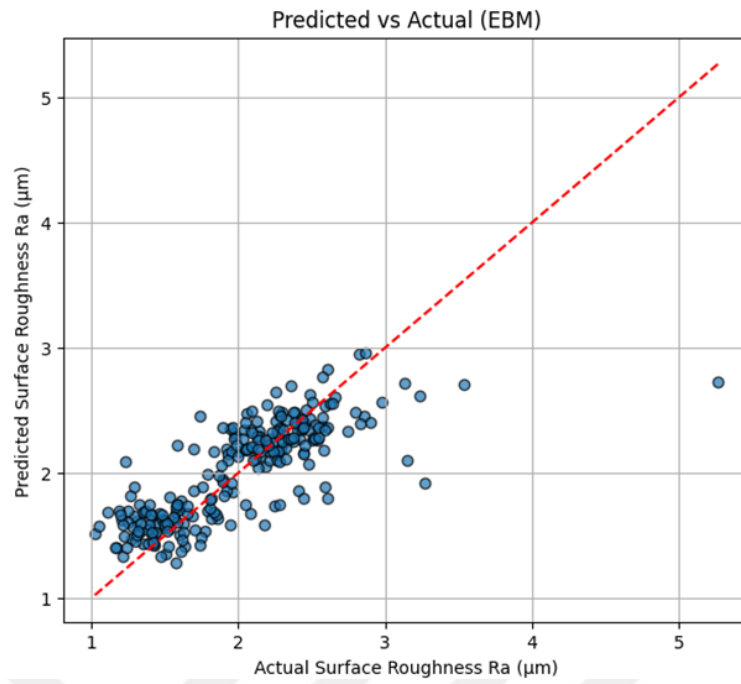


Figure 4.34: Hybrid - Explainable Boosting Predicted vs Actual Plot

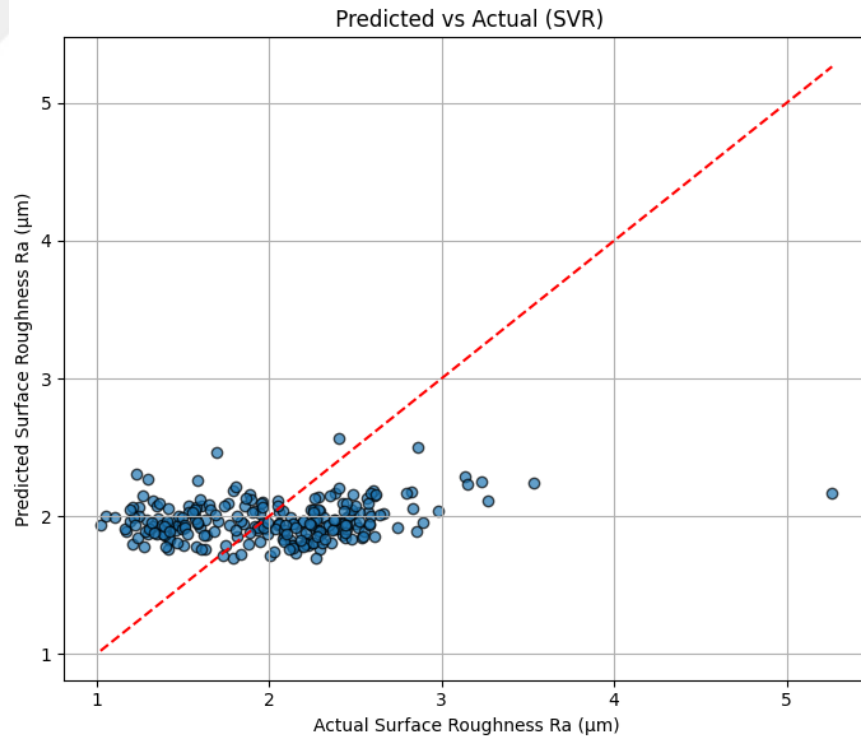


Figure 4.35: Hybrid - Support Vector Regression Predicted vs Actual Plot

These plots serve as a crucial diagnostic tool for assessing the predictive capability of the ML models trained on the hybrid dataset by facilitating the identification of systematic deviations and the presence of outliers, which may indicate areas where the model struggles to generalize effectively.

The predicted vs actual plots shown in the Figures 4.26, 4.27, 4.28, 4.29, 4.30, 4.31, 4.32, 4.33, 4.34, and 4.35 for all machine learning models trained on the hybrid dataset reveal substantial differences in predictive accuracy and generalization capability. Polynomial Regression (PR), Figure 4.26, shows considerable scatter with numerous deviations from the 45° reference line, particularly at higher Ra values, indicating its inability to capture the dataset's non-linear interactions. Decision Tree (DT), Figure 4.27, demonstrates visible clustering at discrete predicted values, a typical symptom of overfitting to training data, with poor interpolation between points. Random Forest Regressor (RFR), Figure 4.28, reduces this discretization effect, offering tighter clustering along the diagonal, yet still exhibits underestimation for higher Ra values. Gradient Boosting Regressor (GBR), Figure 4.29, and XGBoost, Figure 4.30 both improve alignment along the diagonal, reflecting better handling of complex non-linearities; however, they still show dispersion and underprediction for extreme Ra values, with XGBoost being slightly more robust. CatBoost, Figure 4.31, delivers similar behavior to XGBoost but with marginally reduced spread in mid-range Ra predictions, benefiting from better categorical handling. AdaBoost, Figure 4.32, in contrast, shows a compressed prediction range with a tendency to regress toward the mean, severely underestimating high Ra values and spreading predictions widely for mid-range values, reflecting its weakness in noisy, weakly correlated multi-parameter settings. Explainable Boosting Machine (EBM), Figure 4.34, also has the tightest grouping around the diagonal, least amount of systematic bias, and fewest number of extreme outliers which highlights its tradeoff between interpretability and variance for difficult, noisy data. Support Vector Regression (SVR), Figure 4.35 has the worst performance, constraining predictions to a narrow horizontal band about the mean Ra value, while being wildly unresponsive to changes in actual Ra, indicating significant underfitting. Overall, the plots visually confirm the ranking suggested by the evaluation metrics: EBM, GBR, XGBoost, and RFR perform relatively well; CatBoost remains competitive; PR, DT, and AdaBoost are less reliable; and SVR is the weak-

est, with performance heavily limited by the hybrid dataset's noise, narrow Ra range, and weak feature–target correlations.

Figure 4.36 represent the predicted vs actual plot along with the residuals displayed for the EBM model in the hybrid stage.

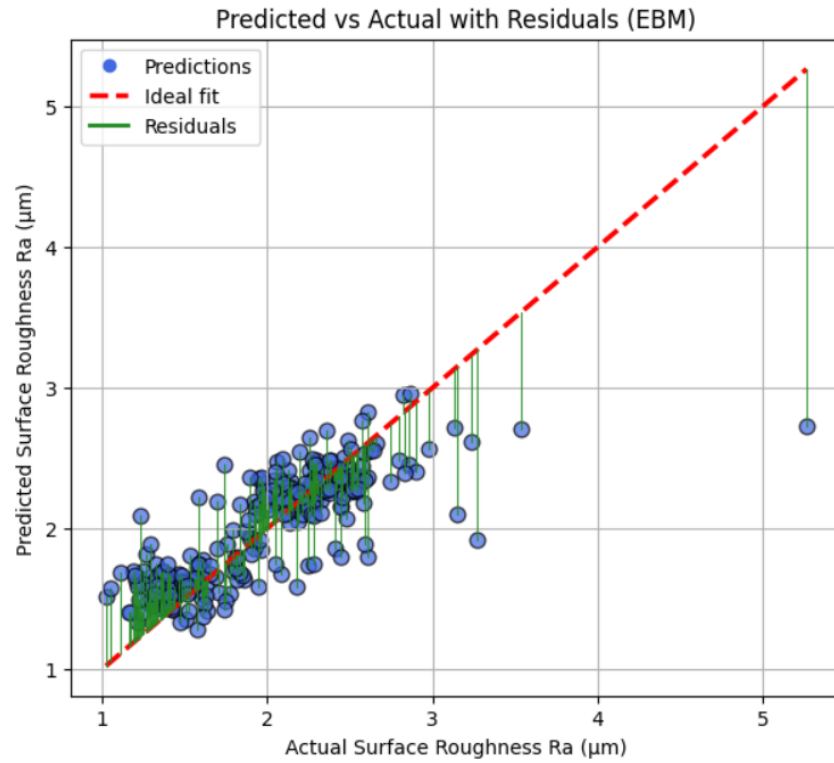


Figure 4.36: Hybrid - Predicted vs Actual Plot EBM with Residuals

According to the Figure the predicted versus actual plot for the EBM model in the hybrid stage explicitly shows the residuals vertical green lines. The predictions remain tightly clustered along the 45° reference line, confirming the superior generalization ability of EBM compared to the other models. The majority of residuals are short and evenly distributed, indicating that errors are both small in magnitude and free from systematic bias across the full range of Ra values. Only a limited number of outliers exhibit longer deviations, primarily at the extremes of the dataset, which is expected in a noisy multi-parameter environment. Importantly, even with these deviations, EBM maintains the lowest overall dispersion around the diagonal and demonstrates consistent accuracy where other models showed underprediction, clustering, or con-

straining in a horizontal band. This residual-enhanced visualization therefore reinforces the earlier evaluation metrics, confirming EBM as the most robust and reliable predictive model for the hybrid stage among the tested machine learning algorithms.

From Tables 4.21, 4.22, 4.23, 4.25 4.26, and 4.27 the comparative evaluation of the AM and hybrid datasets clearly demonstrates a substantial disparity in predictive performance between the two manufacturing approaches. Despite the hybrid dataset containing 1224 observations compared to only 432 for the AM dataset, its testing-stage accuracy is significantly lower. For the best-performing Explainable Boosting Machine (EBM) model in a single run, the AM dataset achieved an  $R^2$  of 0.983 with an RMSE of 0.889  $\mu\text{m}$  and MAPE of 3.48%, whereas the hybrid dataset achieved only an  $R^2$  of 0.616 with a higher RMSE of 0.331  $\mu\text{m}$  and MAPE of 11.92%. From Figures 4.23 and 4.34, comparing the predicted EBM vs. actual plots for the AM and hybrid datasets, several key differences help explain why the performance scores of the hybrid model are lower. In the AM case, the data points are tightly clustered along the diagonal line, indicating strong alignment between predicted and actual values, with minimal deviation. Outliers are rare and only slightly removed from the main trend. Additionally, the AM dataset spans a relatively wide range of  $R_a$  values (roughly 9  $\mu\text{m}$  to 35  $\mu\text{m}$ ), which allows the model to better capture variance patterns and develop a stronger correlation between inputs and outputs. On the contrary, the Hybrid plot exhibits a much smaller range of  $R_a$ -values (roughly 1  $\mu\text{m}$  to 5  $\mu\text{m}$ ), thereby reducing the variance from which the model could learn. What is more, Hybrid plots are scattered and contain distinct outliers substantially away from the diagonal, especially mid-ranges, which serve to worsen the error metrics. Such deviations underpin weaker parameter-to-output correlations and a greater influence of noise relative to the signal since the hybrid data represents a combination of different process influences, AM plus the depth of cut parameters, which may thus not correlate as straightforwardly as the AM-only data. Hence, while there might be more training samples in the hybrid dataset, it does give higher prediction errors and lower  $R^2$  values when compared with AM, as evidenced in the evaluation metrics.

Similar results are reported for other models for a single run; for instance, RFR obtains an  $R^2$  of 0.983 in the AM but just 0.492 in the hybrid; XGBoost, for its part, obtains 0.980 in AM as opposed to 0.533 in the hybrid. Several factors contribute

to this reduced prediction ability. The hybrid process has a higher noise-to-signal level because the final surface roughness  $R_a$  is affected not only by AM parameters but also by machining-related parameters such as tool wear, vibration, clamping, and environmental conditions, the majority of which may not be recorded in the dataset. Machining-related effects such as tool wear can progressively deteriorate cutting performance and increase roughness while tool vibration especially at inclined surfaces can lead to chatter marks and irregularities evident in Figure 4.13. Similarly, workpiece clamping conditions introduce variability; even minor misalignments or insufficient rigidity can cause deflection during cutting, amplifying surface errors. Moreover, environmental conditions, such as machine stability, or external disturbances, can subtly affect the machining precision. Since many of these parameters are either difficult to measure directly or are not systematically recorded in the dataset, they contribute to unexplained variance, thereby increasing prediction uncertainty in hybrid AM–CNC processes. The other factor is that the range of  $R_a$  values in the hybrid dataset is less wide than in AM, thereby compressing the variation available for learning by the models. Narrow target ranges make prediction more sensitive to measurement errors and noise, as even small absolute deviations cause large relative changes in evaluation metrics such as MAPE. Third, the influence of AM parameters is diluted during the hybrid process, as machining modifies or partially overrides the as-printed surface features, weakening the correlation between recorded inputs and measured  $R_a$ . Fourth, the hybrid process introduces more complex non-linear interactions between the additive and subtractive stages, making it more challenging for machine learning algorithms to capture stable patterns without overfitting. This is evident in the pronounced generalization gap, where hybrid models show a sharp decline in  $R^2$  from training to testing, unlike AM models, which maintain consistently high performance. Lastly, although the hybrid dataset is larger, it contains redundancy from repeated or closely spaced parameter combinations, limiting effective diversity and further constraining model generalization. Collectively, these factors, including higher noise, compressed  $R_a$  range, weaker parameter output correlation, and redundant combinations explain why, across the provided evaluation metric tables, AM models consistently achieve higher predictive accuracy, and lower error rates than their hybrid counterparts.

Therefore, it can be concluded that the EBM emerges as the most effective machine learning algorithm for predicting surface roughness in both AM and hybrid processes. This assertion is substantiated by the results presented in Tables 4.21, 4.22, 4.23, 4.25, 4.26, 4.27, and elaborated upon in the preceding discussion. Although a disparity is observed in the evaluation metrics and  $R^2$  values of EBM between the AM and hybrid processes, the model consistently outperforms the other evaluated machine learning algorithms in both scenarios. Consequently, EBM can be considered a robust and reliable tool for reliably predicting surface roughness Ra values across both AM and hybrid manufacturing approaches. Therefore, the Explainable Boosting Machine (EBM) was employed to generate feature importance plots, encompassing top ten features affecting the Ra, along with SHAP (SHapley Additive exPlanations) plots. These visualizations illustrate the relative significance of each input parameter and provide insights into how variations in these parameters influence the predicted surface roughness Ra values.

Figure 4.37 displays the important features affecting the Ra of the AM process. Angle is the most influential parameter affecting Ra, which aligns well with the observations and findings presented in Section 4.1. This makes sense, as the inclination of the surface directly influences how each printed layer is stacked and stepped, which in turn impacts the final Ra. Next in line is Layer Height, which affects Ra as an increase in layer height contributes to the increase in the vertical distance (peak) of the Ra.

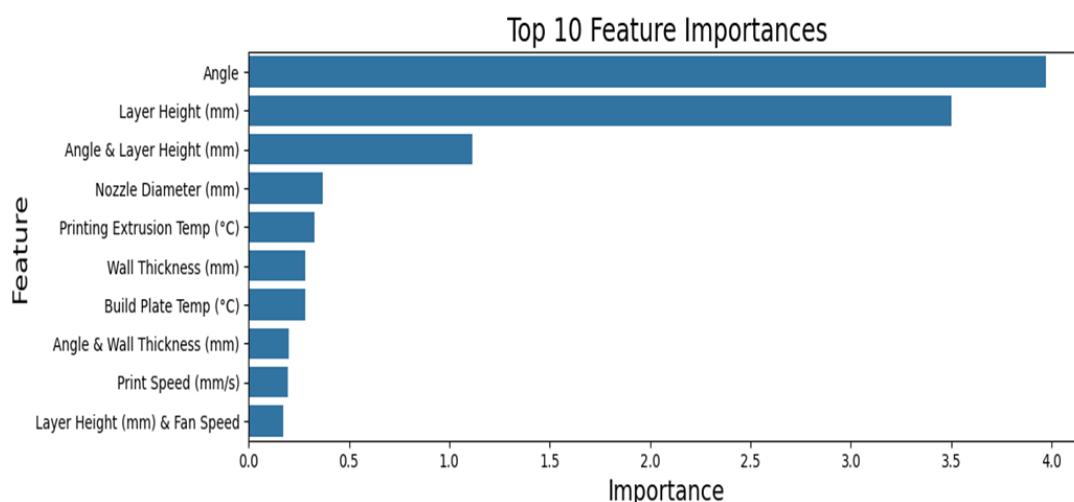


Figure 4.37: AM - EBM Top Ten Feature Importances

The mix of Angle and Layer Height comes third, showing that these two together have a big joint effect on roughness. They are followed by parameters like Nozzle Diameter and the Printing Extrusion temperature. Wall thickness is also displayed as a critical parameter, however, not as much as compared to the angle, layer height, nozzle diameter, and printing temperature. Factors like Build Plate Temperature, Angle and Wall Thickness interaction, Print Speed, and the Layer Height and Fan Speed interaction contribute the least in this model.

Overall, the results confirm that geometric, deposition, and thermal parameters, especially when considered together, are the key drivers of surface quality. Individual plots displaying the top three features affecting the Ra values are provided in Figures 4.38, 4.39, 4.40 to assess and explain their effect using EBM local feature importance plots.

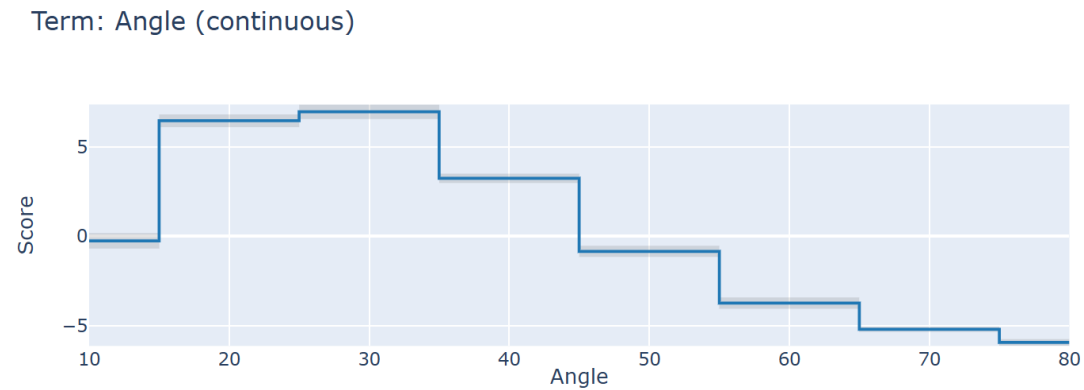


Figure 4.38: AM - Local Feature Importance Plot Displaying Effect of Angle

The Explainable Boosting Machine (EBM) local feature importance plot for the Angle parameter in the additive manufacturing process, presented in Figure 4.38, illustrates the variation in model prediction scores as a function of build inclination. The score axis represents the magnitude and direction of the Angle’s contribution to the predicted surface roughness Ra, where positive values indicate an increase and negative values indicate a decrease relative to the model’s baseline prediction. The Ra values start increasing as the angle increases from 10° to 20°. Between approximately 17° and 31°, the score sharply increases, indicating a pronounced tendency for these mid-low angles to deteriorate surface finish, likely due to intensified stack and step

effect as well as corner geometries. As the angle increases from  $31^\circ$  to  $45^\circ$ , the positive impact remains but with reduced magnitude, followed by a transition towards neutrality around  $45^\circ$ – $52^\circ$ . Beyond  $52^\circ$ , the score progressively declines into negative values, suggesting that higher inclination angles ( $> 60^\circ$ ) tend to improve the predicted surface finish as the stack and step effect becomes less dominant. These findings highlight the critical influence of build orientation on surface roughness in AM parts and provide quantitative support for optimizing part orientation to achieve superior surface quality with minimal post-processing. The plot also aligns well with the plot 4.1, displaying three critical regions where Ra influence can be observed.

Term: Layer Height (mm) (continuous)

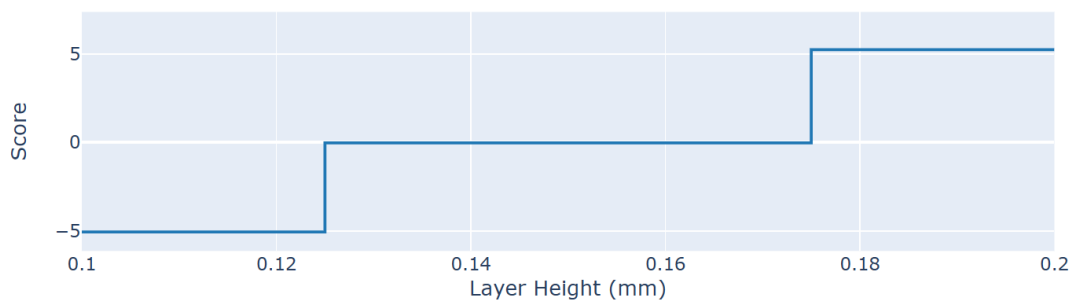


Figure 4.39: AM - Local Feature Importance Plot Displaying Effect of Layer Height

The Explainable Boosting Machine (EBM) local feature importance plot for the Layer Height parameter in the AM process, presented in Figure 4.39, demonstrates the influence of layer thickness on the predicted surface roughness Ra. The score axis quantifies the marginal effect of Layer Height relative to the model's baseline prediction. For low layer heights in the range of 0.10 – 0.12 mm, the model exhibits a strong negative score, suggesting a pronounced improvement in surface quality due to finer vertical resolution and reduced stair-stepping effects. As the layer height increases to approximately 0.13 – 0.17 mm, the score approaches zero, indicating that mid-range values exert a minimal direct influence on surface roughness. However, for larger layer heights exceeding 0.18 mm, the score rises sharply into positive values, signifying a deterioration in predicted surface quality, likely caused by increased layer line prominence with an increase in the vertical height affecting resolution in the build direction. These findings align with established additive manufacturing principles



and Figure. 4.4, where finer layer deposition generally enhances surface finish, while coarser layers compromise surface quality. Consequently, when surface smoothness is a priority, adopting lower layer heights is recommended, whereas higher layer heights should be reserved for cases prioritizing build speed over surface finish.

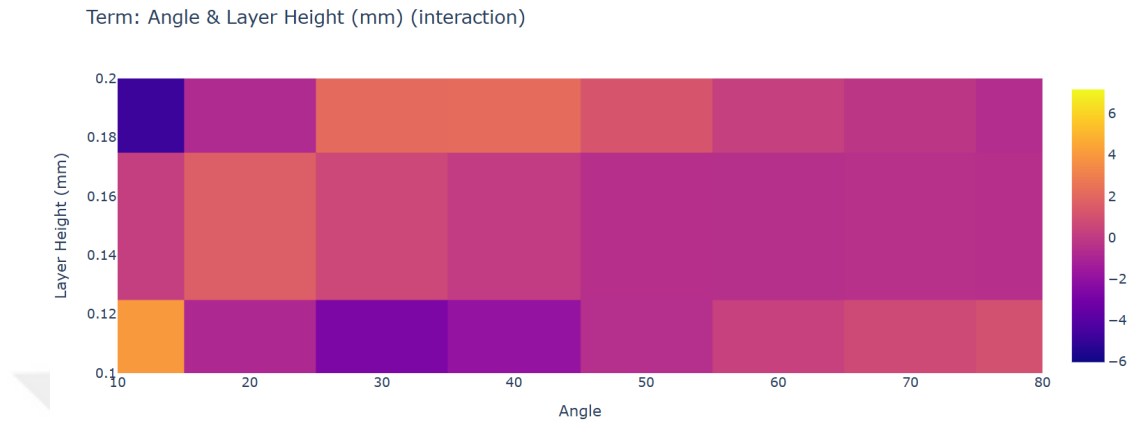


Figure 4.40: AM - Local Feature Importance Plot Displaying Interaction of Angle and Layer Height

The interaction plot between Angle and Layer Height in Figure 4.40 shows how these two parameters work together to affect surface roughness  $R_a$  in the AM process. The colors represent whether the combination increases or decreases the predicted surface roughness. Yellow/orange areas indicate rougher surfaces, while purple/blue areas indicate smoother surfaces compared to the baseline prediction. For very small layer heights 0.10 mm, the model predicts rougher surfaces when the build angle is very low 10°, but the effect becomes neutral or even smoother as the angle increases. On the other hand, for large layer heights 0.18 – 0.20 mm, the opposite trend appears: these produce smoother surfaces at low angles, but as the angle increases, the predicted roughness becomes slightly worse. Medium layer heights 0.14 – 0.16 mm generally show little to no strong effect, meaning they do not interact much with angle in terms of roughness prediction. Overall, this means that the best layer height depends on the angle of the surface: fine layers are better for steep angles, while coarser layers may work surprisingly well for shallow angles by reducing the visible stair-step effect.

The SHAP plot in Figure 4.41 is from the Gradient Boosting Regressor (GBR) model, which was plotted in order to confirm the reliability of the findings. This was done

inorder to ensure if other well performing models provided similar feature importance trends.

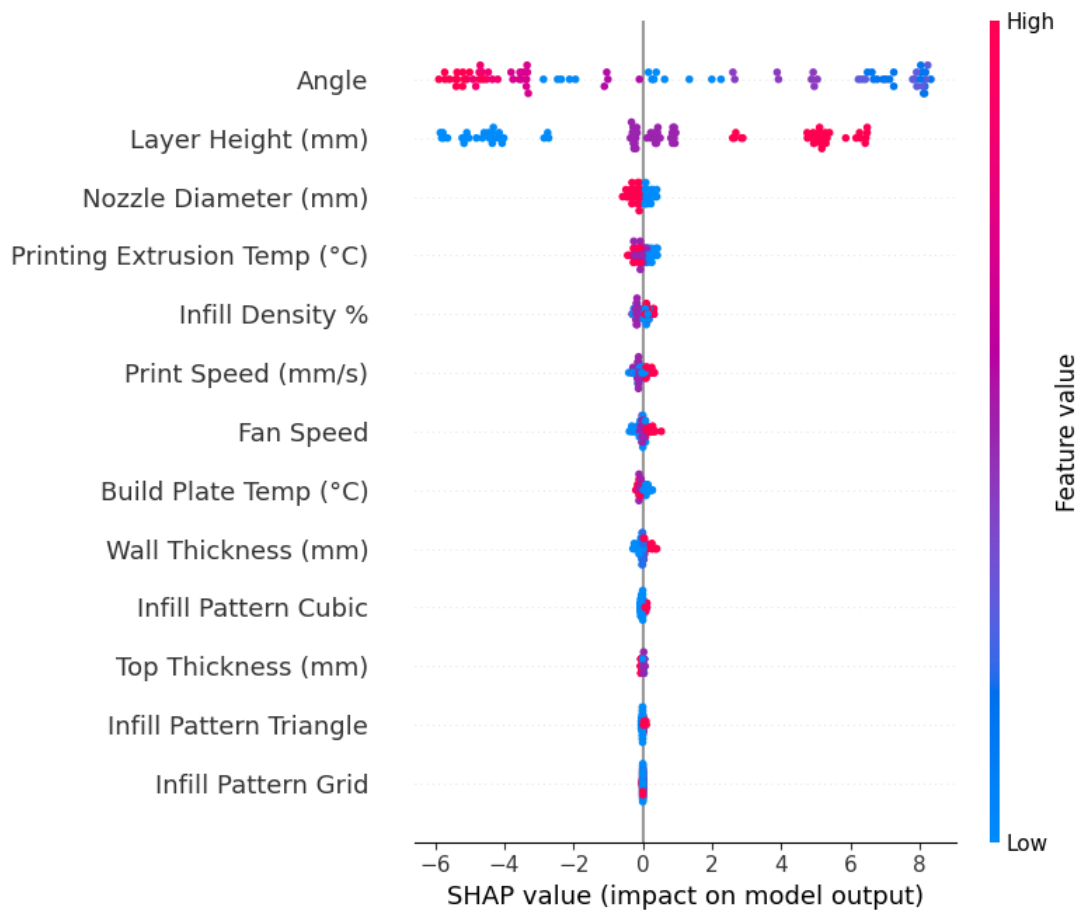


Figure 4.41: AM - SHAP Plot Taken from GBR ML

From the Figure 4.41, the top 4 features are the same and the feature importance effect is clear. SHapley Additive exPlanations (SHAP) is a model-agnostic interpretability technique for estimating the contribution of every single input feature to the individual prediction of the model. The SHAP values indicate by how much the feature raises or lowers the prediction of the model with respect to the base case; positive values increase the prediction, whereas negative values decrease it. In a SHAP summary plot, the features appear on the y-axis, sorted in descending order by the mean absolute importance of the features, whereas the x-axis presents the range of the SHAP values, indicating the size and sign of each feature's contribution. Each point represents an observation from the data, and the color is high (red) or low (blue) for the value of

the feature. The visualization enables you to observe the importance of features, the size of the effect, and the association between the magnitude of the features and the direction of the prediction. In Figure 4.41, Angle is the most influential parameter, where higher angle values (red) generally result in negative SHAP values, indicating a decrease in predicted surface roughness, whereas lower angles (blue) produce positive SHAP values associated with higher surface roughness. Layer Height follows an opposite trend, with higher values contributing to rougher predictions and lower values improving surface quality. Nozzle Diameter and Printing Extrusion Temperature also influence predictions, but to a lesser extent. Using a higher nozzle diameter can lower surface roughness, combined with proper layer height and printing extrusion temperature settings, as evidenced by layer heights of 0.15 mm and 0.2 mm displaying a better surface roughness with a nozzle diameter of 0.4 mm compared to 0.25 mm. Printing Extrusion Temperature increases the surface roughness with a decrease in the value, while decreasing the surface roughness with an increase in the value. Parameters such as infill density, Print Speed, Fan Speed, and Build Plate Temperature show minimal impact, with SHAP values concentrated near zero. Infill-related parameters exhibit negligible influence in this dataset. Overall, the SHAP analysis reinforces the conclusion that build orientation, layer height, nozzle diameter, and printing extrusion temperature are the dominant factors governing surface roughness, consistent with the trends observed in the EBM feature importance plots.

In the same manner, the hybrid results were processed using the same visualization techniques and plots. The Explainable Boosting Machine (EBM) feature importance plot for the hybrid manufacturing process, presented in Figure 4.42, ranks the input parameters according to their relative contribution to the prediction of surface roughness Ra. Angle emerges as the most dominant factor, with an importance value substantially higher than all other features, indicating that build orientation plays a decisive role in determining surface finish in hybrid-produced parts. Nozzle Diameter ranks second, suggesting that extrusion width has a significant influence on the post-machined surface quality, potentially due to its impact on the as-3D printed surface quality.

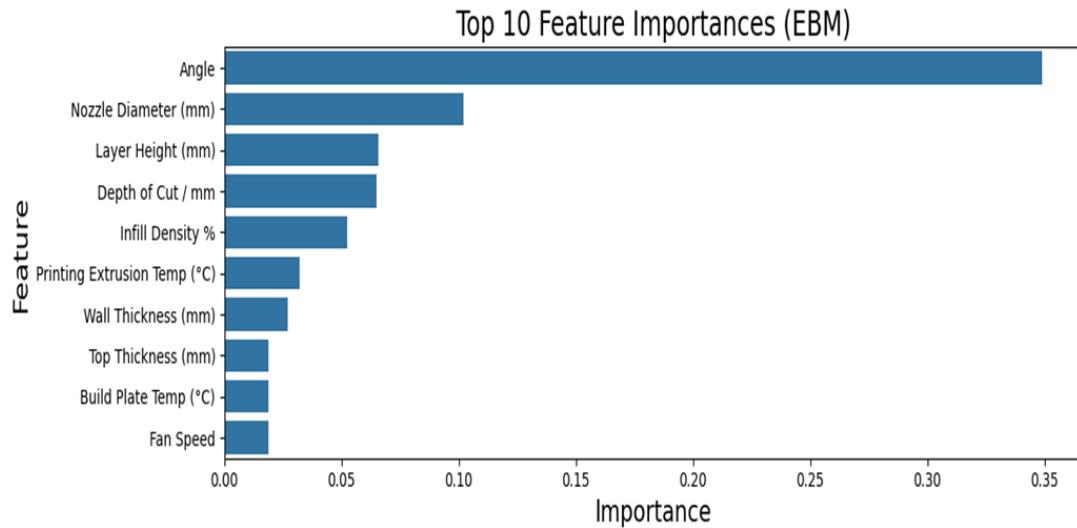


Figure 4.42: Hybrid-Top Ten Feature Importances

Layer Height is positioned third, reinforcing the notion that layer resolution in the additive stage remains an important determinant of hybrid surface finish. Beyond these primary parameters, Depth of Cut is the fourth most important variable, reflecting the influence of subtractive machining parameters in refining the as-printed surface according to specified range (0.2-0.4 mm). Infill Density also contributes noticeably, which may be attributed to its indirect effect on part rigidity during machining, influencing vibration and chip formation. Printing extrusion temperature is also considered to be an important factor in the hybrid process. These factors further reinforce the claim that a proper combination of input parameters during the AM stage is very important to have an optimal surface roughness. The best combination is achieved by using a smaller layer height, suitable nozzle diameter according to the layer height (e.g 0.1 mm layer height with a 0.25 mm nozzle, and 0.15 and 0.2 mm layer height with a 0.4 mm nozzle diameter), higher infill densities, and print temperatures greater than 200 °C. The remaining features, including Wall Thickness, Top Thickness, Build Plate Temperature, and Fan Speed, exhibit relatively lower importance scores, indicating that they play a more secondary role in predicting final surface roughness for hybrid-manufactured components. Overall, the EBM analysis highlights that for hybrid processing, a combination of key additive manufacturing settings (Angle, Nozzle Diameter, Layer Height, Infill, Printing Extrusion Temperature) and machining parameter Depth of Cut are the primary drivers of surface quality, with other variables

exerting comparatively minor effects.

Local feature importance plot is provided in Figure 4.43 for the depth of cut, other local feature importance plots (Angle, Nozzle Diameter, Layer Height, Infill Density, Print Temperature) are not provided since their effect is already known from the above paragraph discussing the AM parameters.

Term: Depth of Cut / mm (continuous)

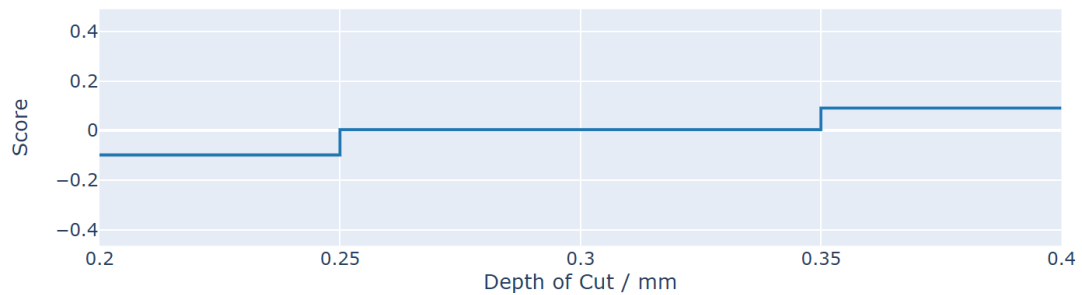


Figure 4.43: Hybrid-Local Feature Importance Plot for the Effect of the Depth of Cut

The local feature importance plot for Depth of Cut in the hybrid manufacturing process, shown in Figure 4.43, illustrates the marginal effect of varying this parameter on the predicted surface roughness  $R_a$ . The score shows the contribution of Depth of Cut to the prediction relative to the model's baseline, where positive value indicates an increase in  $R_a$  and negative value indicates a decrease in  $R_a$ . For smaller depths of cut (0.20 – 0.25 mm) the score is slightly negative, so a small decrease in  $R_a$ , probably due to less tool engagement and lower cutting forces resulting in a smoother finish. As the depth of cut increases to mid-range (0.25–0.35 mm) the score is zero, so no effect. For higher depths of cut (> 0.35 mm) the score is slightly positive, so a small increase in  $R_a$ , probably due to more tool engagement, higher cutting forces and potential chatter or vibration. Overall the effect of Depth of Cut on  $R_a$  in the hybrid process is small and influenced by other features like Angle, Nozzle Diameter, Layer Height, Infill Density and Printing Extrusion Temperature. However, the trend suggests that lower depths of cut might be better for smoother surfaces in the subtractive stage of hybrid manufacturing.

The SHAP summary plot in Figure 4.44 illustrates the relative importance and di-

rectional influence of each process parameter on the predicted surface roughness Ra for the hybrid manufacturing process. Angle is the most influential parameter, with high angle values (red) clustered on the positive SHAP side, indicating that steeper orientations tend to increase predicted surface roughness in the hybrid process.

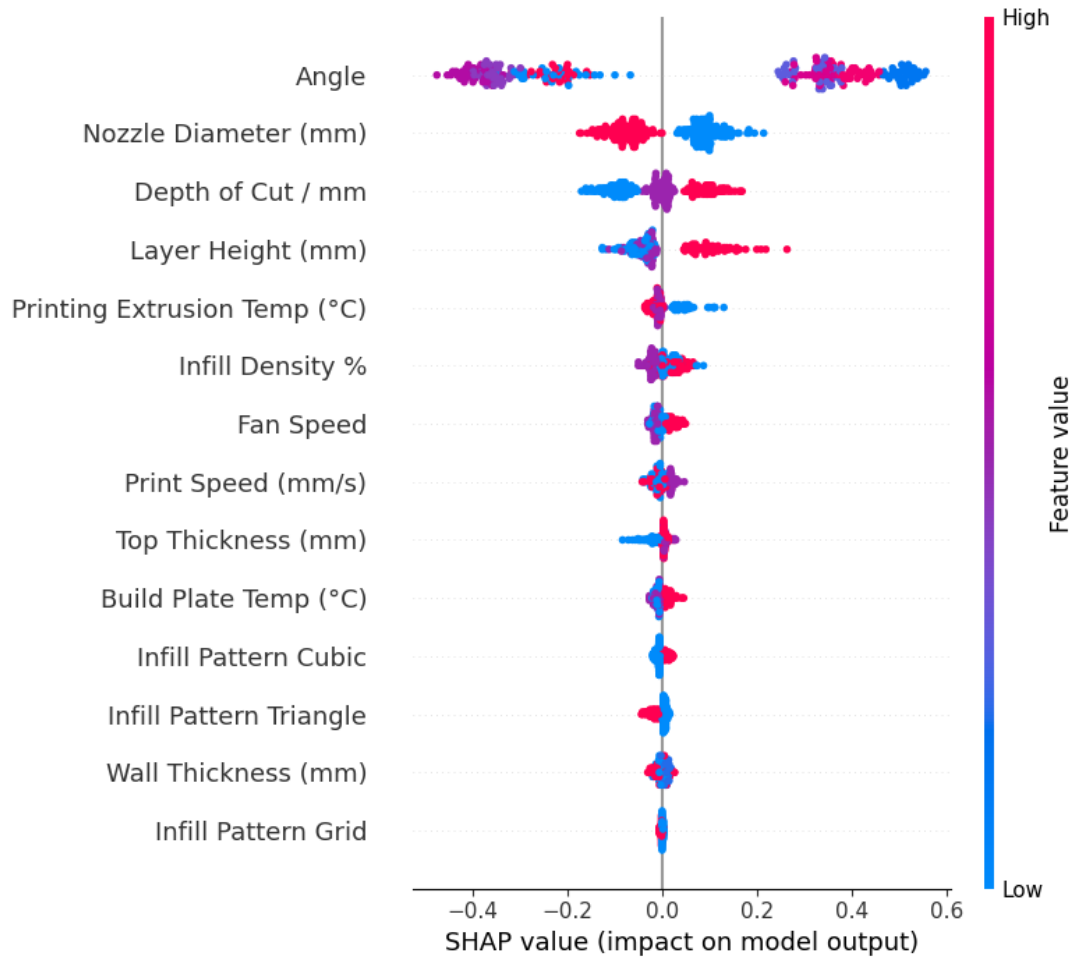


Figure 4.44: Hybrid - SHAP Plot Taken from GBR ML

Conversely, lower angles (blue) are associated with negative SHAP values, contributing to smoother predicted surfaces. Nozzle Diameter ranks second in importance: larger diameters (red) generally push predictions toward the negative SHAP side, suggesting a tendency to reduce surface roughness, whereas smaller diameters (blue) shift predictions upward. Depth of Cut is the third most important feature, with higher values (red) often linked to small positive SHAP values, indicating a mild increase in roughness, and lower values (blue) generally associated with reductions in pre-

dicted Ra. Layer Height follows, where lower values (blue) tend to reduce surface roughness, while higher values (red) increase it. Printing Extrusion Temperature exert effects where Ra increases with a decrease in Print Extrusion Temperature. Other parameters such as Fan Speed, Print Speed, Top Thickness, Build Plate Temperature, and infill pattern types, show negligible impact in the model's predictions. Overall, the SHAP analysis highlights that for hybrid manufacturing, a combination of additive parameters (Angle, Nozzle Diameter, Layer Height, Print Temperature, Infill Density) and machining parameter (Depth of Cut) are the primary drivers of surface roughness, aligning with trends observed in the EBM feature importance results.

Based on the comparative evaluation of multiple machine learning models, the Explainable Boosting Machine (EBM) consistently demonstrated superior predictive performance for surface roughness Ra in both additive manufacturing (AM) and hybrid manufacturing processes. Across all evaluation metrics, including  $R^2$ , RMSE, and MAE, EBM outperformed other models while providing inherently interpretable feature importance plots verified by SHAP plots from GBR, verifying the surface quality relationships. Its ability to capture non-linear effects and feature interactions, while maintaining high transparency, makes it a robust and reliable tool for modeling surface roughness in both manufacturing contexts. Consequently, EBM can be regarded as the most effective and trustworthy predictive model for Ra in AM and hybrid manufacturing, enabling both accurate forecasting and meaningful process insight.

In summary, the analysis for both the additive manufacturing (AM) and hybrid manufacturing processes, with the help of the mentioned plots above, reveals that build orientation and layer height consistently emerge as the most influential parameters affecting surface roughness, although their effects differ between the two processes. In AM, higher angles tend to reduce predicted surface roughness, whereas in hybrid manufacturing, their trend is a bit dubious, as the inclines ( $10^\circ$ - $80^\circ$ ,  $40^\circ$ - $50^\circ$ ) present on the corners of the part displayed lower Ra during hybrid processing compared to the angles ( $20^\circ$ - $70^\circ$ ,  $30^\circ$ - $60^\circ$ ). One of the reasons could be that the change in inclination can cause a change in the cutting direction relative to the stiffness of the tool, which can cause vibrations or chatter. For both processes, Nozzle Diameter and Printing Extrusion Temperature have notable but secondary effects, with larger nozzle sizes

generally improving surface quality when paired with appropriate layer height and temperature settings. However, the best surface roughness should be obtained with a nozzle diameter of 0.25 mm, coupled with a layer height of 0.1 mm, and printing extrusion temperature of 210 °C if build time is not crucial. In the hybrid process, subtractive machining parameters such as Depth of Cut also play a measurable role in improving the surface roughness within the ranges of 85% to 91%. Overall, while the dominant factors are similar in both processes, the hybrid approach introduces additional machining-related dependencies, reflecting the combined influence of additive and subtractive stages on the final surface finish.

#### **4.4 Verification and Validation**

In this section, the EBM model is put to the test after its development to see how well it can predict the surface roughness of both AM and hybrid parts made with randomly chosen input parameters but lying well within the range specified in Tables 3.7, and 3.8. The results from actual surface roughness measurements for both AM and Hybrid processes are compared with the model's predictions to check its accuracy on data it has never seen before. This step helps confirm that the EBM model can reliably handle new cases, showing its potential for use not only in research but also in real-world industrial applications.

After the training and testing procedures, the EBM model predicting surface roughness was tested on cases it had never seen before for practical verification. This was done by producing eight new parts through the FFF process, representing sixteen surfaces with different inclination angles. There were two inclinations on each part with such combinations as 10°–80°, 13°–77°, 20°–70°, 25°–65°, 30°–60°, 37°–53°, 40°, 50°, and 42°–48°. The chosen angle values were selected by taking into account the values already within the original DOE range and those in between to test how well a model can interpolate for unseen geometries. This step was, therefore, a very stringent measure of whether the model is usable in real applications: a check if it can predict for many more different part geometries.

The input parameters were randomly chosen for these 16 geometries and are provided



in Table 4.28. The methodology to manufacture these parts using FFF was followed step by step as mentioned in Section 3.3.2. The FFF-AM manufactured parts are shown in Figure 4.45

Table 4.28: AM Input Parameters for Verification Parts

| Angle Group | ND (mm) | LH (mm) | WT (mm) | TT (mm) | ID (%) | IP       | PET (°C) | BPT (°C) | PS (mm/s) | FS  |
|-------------|---------|---------|---------|---------|--------|----------|----------|----------|-----------|-----|
| 10°–80°     | 0.25    | 0.15    | 2.00    | 1.60    | 80     | Cubic    | 210      | 50       | 40        | 50  |
| 13°–77°     | 0.25    | 0.10    | 2.00    | 1.20    | 20     | Cubic    | 210      | 60       | 60        | 75  |
| 20°–70°     | 0.40    | 0.20    | 2.00    | 1.60    | 50     | Cubic    | 200      | 50       | 80        | 75  |
| 25°–65°     | 0.40    | 0.10    | 0.75    | 1.60    | 20     | Triangle | 190      | 55       | 40        | 75  |
| 30°–60°     | 0.40    | 0.10    | 0.75    | 1.20    | 20     | Grid     | 210      | 50       | 80        | 100 |
| 37°–53°     | 0.40    | 0.15    | 0.75    | 1.20    | 80     | Grid     | 200      | 50       | 60        | 50  |
| 40°–50°     | 0.25    | 0.10    | 1.00    | 1.60    | 50     | Triangle | 190      | 55       | 80        | 100 |
| 42°–48°     | 0.25    | 0.15    | 0.75    | 1.40    | 80     | Grid     | 200      | 60       | 80        | 75  |

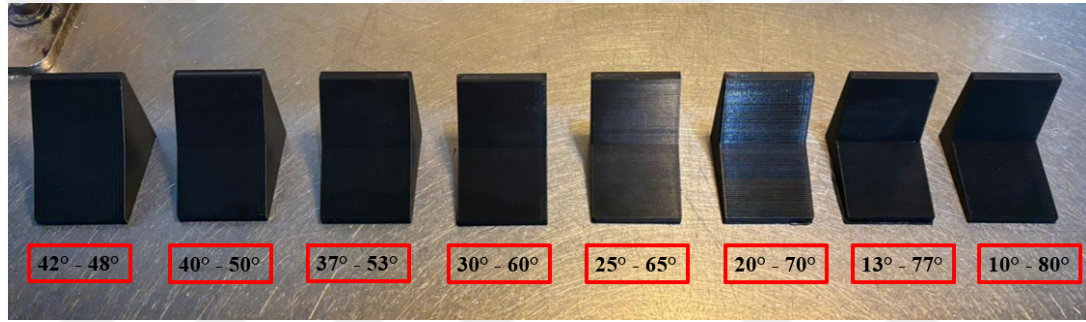


Figure 4.45: AM - Verification Parts

The parts corresponding to the angle groups 13°–77°, 25°–65°, 37°–53°, and 42°–48° were equipped with specifically designed fixtures to ensure precise and reliable measurement of the surface roughness Ra values. The measurement procedure followed the methodology described in Section 3.4.2, with three independent readings taken for each inclination to enhance measurement accuracy. For the CNC machining process, eight separate G-code files were generated for each part, as presented in Appendix A, to address the specific machining requirements. Each inclination angle was divided into three faces corresponding to values of depth of cut 0.2 mm, 0.3 mm, and 0.4 mm. The machining procedure and cutting tool selection were consistent with those detailed in Section 3.5.2, ensuring methodological consistency throughout the experiments. In accordance with this approach, three separate Ra measurements were taken for each depth of cut and subsequently averaged to obtain representative values for

further analysis.

Table 4.29 compares the actual measured  $R_a$  values with those predicted by the Explainable Boosting Machine (EBM) model for the additive manufacturing (AM) process, along with the corresponding residuals, and absolute errors. Moreover Table 4.30 shows a comparison of the evaluation metrics between the unseen data, single run (80-20% split), and 10 fold CV. These tables prove that the EBM model can predict the AM surface roughness with high accuracy since most errors are less than 2  $\mu\text{m}$ . The lowest error has been achieved at  $53^\circ$  with a deviation of only 0.046  $\mu\text{m}$ , which practically shows a perfect match between prediction and actual measurement. The maximum deviation is observed at  $42^\circ$  with an error of 2.312  $\mu\text{m}$ .

Table 4.29 lists per-sample results for the external validation set: in 15 of 16 cases the absolute error is below  $\pm 2 \mu\text{m}$ . Errors are balanced and generally small across angles, indicating that the model is tracking trends in  $R_a$  rather than regressing to the mean.

Table 4.29: External validation (EBM): per-sample errors on unseen AM data

| Angle ( $^\circ$ ) | Actual $R_a$ ( $\mu\text{m}$ ) | EBM Predicted $R_a$ ( $\mu\text{m}$ ) | Residual ( $\mu\text{m}$ ) | Absolute Error ( $\mu\text{m}$ ) |
|--------------------|--------------------------------|---------------------------------------|----------------------------|----------------------------------|
| 10                 | 17.785                         | 19.524                                | 1.739                      | 1.739                            |
| 80                 | 12.118                         | 12.640                                | 0.522                      | 0.522                            |
| 13                 | 19.920                         | 19.213                                | -0.707                     | 0.707                            |
| 77                 | 9.375                          | 8.729                                 | -0.646                     | 0.646                            |
| 20                 | 30.553                         | 29.474                                | -1.079                     | 1.079                            |
| 70                 | 16.397                         | 17.905                                | 1.508                      | 1.508                            |
| 25                 | 18.799                         | 18.159                                | -0.640                     | 0.640                            |
| 65                 | 9.185                          | 9.382                                 | 0.197                      | 0.197                            |
| 30                 | 17.874                         | 16.200                                | -1.674                     | 1.674                            |
| 60                 | 9.580                          | 8.340                                 | -1.240                     | 1.240                            |
| 37                 | 23.557                         | 21.794                                | -1.763                     | 1.763                            |
| 53                 | 16.432                         | 16.491                                | 0.059                      | 0.059                            |
| 40                 | 15.928                         | 14.954                                | -0.974                     | 0.974                            |
| 50                 | 13.163                         | 12.549                                | -0.614                     | 0.614                            |
| 42                 | 20.382                         | 22.721                                | 2.339                      | 2.339                            |
| 48                 | 17.356                         | 18.119                                | 0.763                      | 0.763                            |

These row-level findings are mirrored by the dataset-level metrics in Table 4.30: on

the external unseen data EBM attains MAE = 1.03  $\mu\text{m}$ , RMSE = 1.20  $\mu\text{m}$ , MAPE = 6.22%, and a high  $R^2 = 0.951$ , while 10-fold CV confirms stability across splits (RMSE  $0.909 \pm 0.189 \mu\text{m}$ , MAE  $0.652 \pm 0.101 \mu\text{m}$ ,  $R^2 = 0.979 \pm 0.012$ ). The slightly stronger single 80–20 split is expected from a favorable partition, whereas the external test demonstrates that accuracy holds when confronted with new parts and process settings. Considering the inherent variability in AM surface roughness measurements due to factors such as material heterogeneity and measurement uncertainty, a prediction tolerance within  $\pm 2 \mu\text{m}$  is generally acceptable for engineering evaluation. The results indicate that the EBM predictions for AM fall well within this tolerance in nearly 94% of the cases for the unseen data with a MAPE value of 6.22%, confirming the model’s robustness and reliability for accurate surface roughness prediction in additively manufactured components.

Table 4.30: EBM performance comparison across evaluation settings

| Metric                  | EBM Unseen Data | EBM Single Run (80-20% split) | EBM 10-Fold CV      |
|-------------------------|-----------------|-------------------------------|---------------------|
| <b>MSE</b>              | 1.433           | 0.791                         | $0.863 \pm 0.377$   |
| <b>RMSE</b>             | 1.197           | 0.889                         | $0.909 \pm 0.189$   |
| <b>MAE</b>              | 1.029           | 0.616                         | $0.652 \pm 0.101$   |
| <b>MAPE (%)</b>         | 6.22%           | 3.48%                         | $3.539 \pm 0.434\%$ |
| <b><math>R^2</math></b> | 0.951           | 0.983                         | $0.979 \pm 0.012$   |

Tables 4.31 and 4.32 compare the Ra values obtained from measurements and the ones predicted by the EBM model for the hybrid stage at different depths of cuts. Overall, the Explainable Boosting Machine (EBM) demonstrates high predictive accuracy, with the majority of errors remaining below 0.5  $\mu\text{m}$ .

In several cases, such as 80° at 0.3 mm and 0.4 mm, 65° at 0.2 mm, and 0.4 mm, and 25° at 0.4 mm, the deviation between predicted and measured values is negligible. Some larger discrepancies are observed at specific combinations of inclination and depth of cut, particularly 50° at 0.4 mm (0.949  $\mu\text{m}$ ), 37° at 0.4 mm (0.441  $\mu\text{m}$ ), 42° at 0.4 mm (0.435  $\mu\text{m}$ ), and 48° at 0.4 mm (0.447  $\mu\text{m}$ ). These cases likely reflect increased variability due to the interaction of cutting forces, chip formation, and tool–part engagement as well as uncertainties in measurements coupled with human

errors due to the usage of a hand-held profilometer. The highest error is found to be at 50° at 0.4 mm with a magnitude of 0.949  $\mu\text{m}$ . The lowest error has been found at 80° at a depth of cut of 0.4 mm with a magnitude of 0.003  $\mu\text{m}$ .

Table 4.31: External validation (EBM): hybrid per-sample errors by depth of cut

| Angle (°) | Depth of Cut (mm) | Actual $R_a$ ( $\mu\text{m}$ ) | EBM Predicted $R_a$ ( $\mu\text{m}$ ) | Residual ( $\mu\text{m}$ ) | Absolute Error ( $\mu\text{m}$ ) |
|-----------|-------------------|--------------------------------|---------------------------------------|----------------------------|----------------------------------|
| 10        | 0.2               | 1.761                          | 1.742                                 | -0.019                     | 0.019                            |
|           | 0.3               | 1.673                          | 1.863                                 | 0.190                      | 0.190                            |
|           | 0.4               | 1.847                          | 1.922                                 | 0.075                      | 0.075                            |
| 80        | 0.2               | 1.666                          | 1.701                                 | 0.035                      | 0.035                            |
|           | 0.3               | 1.817                          | 1.822                                 | 0.005                      | 0.005                            |
|           | 0.4               | 1.937                          | 1.934                                 | -0.003                     | 0.003                            |
| 13        | 0.2               | 1.672                          | 1.702                                 | 0.030                      | 0.030                            |
|           | 0.3               | 1.782                          | 1.837                                 | 0.055                      | 0.055                            |
|           | 0.4               | 1.730                          | 1.900                                 | 0.170                      | 0.170                            |
| 77        | 0.2               | 1.728                          | 1.695                                 | -0.033                     | 0.033                            |
|           | 0.3               | 1.964                          | 1.829                                 | -0.135                     | 0.135                            |
|           | 0.4               | 2.047                          | 1.946                                 | -0.101                     | 0.101                            |
| 20        | 0.2               | 1.861                          | 2.270                                 | 0.409                      | 0.409                            |
|           | 0.3               | 2.202                          | 2.375                                 | 0.173                      | 0.173                            |
|           | 0.4               | 2.432                          | 2.450                                 | 0.018                      | 0.018                            |
| 70        | 0.2               | 2.226                          | 2.125                                 | -0.101                     | 0.101                            |
|           | 0.3               | 2.338                          | 2.224                                 | -0.114                     | 0.114                            |
|           | 0.4               | 2.464                          | 2.325                                 | -0.139                     | 0.139                            |
| 25        | 0.2               | 2.015                          | 2.081                                 | 0.066                      | 0.066                            |
|           | 0.3               | 2.065                          | 2.145                                 | 0.080                      | 0.080                            |
|           | 0.4               | 2.196                          | 2.177                                 | -0.019                     | 0.019                            |
| 65        | 0.2               | 2.173                          | 2.179                                 | 0.006                      | 0.006                            |
|           | 0.3               | 2.116                          | 2.241                                 | 0.125                      | 0.125                            |
|           | 0.4               | 2.300                          | 2.294                                 | -0.006                     | 0.006                            |

Table 4.33 shows that the EBM model predicts hybrid-machining surface roughness with small and consistent errors across all validation schemes. On the external (unseen) set, EBM attains the lowest errors—MAE = 0.160  $\mu\text{m}$  and RMSE = 0.234  $\mu\text{m}$  (MAPE = 9.17%)—with  $R^2 = 0.654$ , indicating that the model explains about two-thirds of the variability while keeping the typical absolute deviation well below a quarter micron. The single 80–20 split is slightly worse (MAE = 0.226  $\mu\text{m}$ , RMSE = 0.331  $\mu\text{m}$ ,  $R^2 = 0.616$ ), whereas 10-fold CV yields nearly the same accuracy (MAE  $0.216 \pm 0.013$   $\mu\text{m}$ , RMSE  $0.299 \pm 0.031$   $\mu\text{m}$ , and  $R^2 = 0.647 \pm 0.043$ ), with tight standard deviations showing stability across folds.

Table 4.32: External validation (EBM): hybrid per-sample errors by depth of cut (cont.)

| Angle (°) | Depth of Cut (mm) | Actual $R_a$ (μm) | EBM Predicted $R_a$ (μm) | Residual (μm) | Absolute Error (μm) |
|-----------|-------------------|-------------------|--------------------------|---------------|---------------------|
| 30        | 0.2               | 2.083             | 1.979                    | -0.104        | 0.104               |
|           | 0.3               | 2.026             | 2.037                    | 0.011         | 0.011               |
|           | 0.4               | 2.153             | 2.055                    | -0.098        | 0.098               |
| 60        | 0.2               | 1.911             | 2.044                    | 0.133         | 0.133               |
|           | 0.3               | 2.185             | 2.102                    | -0.083        | 0.083               |
|           | 0.4               | 2.094             | 2.142                    | 0.048         | 0.048               |
| 37        | 0.2               | 1.819             | 1.406                    | -0.413        | 0.413               |
|           | 0.3               | 1.276             | 1.461                    | 0.185         | 0.185               |
|           | 0.4               | 1.969             | 1.528                    | -0.441        | 0.441               |
| 53        | 0.2               | 1.565             | 1.348                    | -0.217        | 0.217               |
|           | 0.3               | 1.699             | 1.407                    | -0.292        | 0.292               |
|           | 0.4               | 1.782             | 1.482                    | -0.300        | 0.300               |
| 40        | 0.2               | 1.427             | 1.488                    | 0.061         | 0.061               |
|           | 0.3               | 1.383             | 1.607                    | 0.224         | 0.224               |
|           | 0.4               | 1.423             | 1.662                    | 0.239         | 0.239               |
| 50        | 0.2               | 1.475             | 1.433                    | -0.042        | 0.042               |
|           | 0.3               | 1.688             | 1.556                    | -0.132        | 0.132               |
|           | 0.4               | 2.568             | 1.619                    | -0.949        | 0.949               |
| 42        | 0.2               | 1.716             | 1.560                    | -0.156        | 0.156               |
|           | 0.3               | 1.619             | 1.664                    | 0.045         | 0.045               |
|           | 0.4               | 1.350             | 1.786                    | 0.436         | 0.436               |
| 48        | 0.2               | 1.235             | 1.532                    | 0.297         | 0.297               |
|           | 0.3               | 1.426             | 1.640                    | 0.214         | 0.214               |
|           | 0.4               | 1.322             | 1.769                    | 0.447         | 0.447               |

Table 4.33: EBM performance comparison across evaluation settings (hybrid data)

| Metric               | EBM Unseen Data | EBM (Training & Testing) | EBM 10-Fold CV       |
|----------------------|-----------------|--------------------------|----------------------|
| <b>MSE</b>           | 0.055           | 0.109                    | $0.091 \pm 0.019$    |
| <b>RMSE</b>          | 0.234           | 0.331                    | $0.299 \pm 0.031$    |
| <b>MAE</b>           | 0.160           | 0.226                    | $0.216 \pm 0.013$    |
| <b>MAPE (%)</b>      | 9.17%           | 11.92%                   | $11.378 \pm 0.679\%$ |
| <b>R<sup>2</sup></b> | 0.654           | 0.616                    | $0.647 \pm 0.043$    |

Considering the inherent variability in hybrid CNC finishing contributing to a low  $R^2$  value compared to the AM stage, a  $\pm 1$  μm prediction tolerance is reasonable for

engineering assessment; EBM remains within this tolerance for almost all measurements, displaying a MAPE of 9.17% and demonstrating robust and practically useful predictive accuracy for hybrid process. Overall, these results confirm that EBM generalizes reliably to new hybrid parts, delivering sub-micron average errors and robust performance suitable for engineering use.

The Explainable Boosting Machine (EBM) model demonstrated high predictive accuracy for surface roughness Ra in both additive manufacturing (AM) and hybrid CNC machining. In AM, for the unseen data 94% of the errors were below  $\pm 2 \mu\text{m}$  with a MAPE of 6.22% and well within the acceptable tolerance, while in the hybrid stage, nearly all predictions were within  $\pm 1 \mu\text{m}$  with a MAPE of 9.17%, despite process and measurement variability. The smallest deviations approached zero, and even the largest errors remained within practical engineering limits. These results confirm the EBM's robustness and reliability for accurate Ra prediction across both manufacturing stages.

#### **4.5 Coolant Assisted Wet Machining**

A preliminary investigation was conducted to evaluate the influence of coolant application during the CNC machining of the parts described in Section 3.5.2. The primary objective was to assess whether the use of coolant could lead to measurable improvements in the surface roughness Ra values compared to dry cutting conditions. Tables 4.34 and 4.35 present the Ra measurements obtained for Parts 4 and 5, respectively, under both dry and coolant-assisted machining conditions.

Table 4.34 presents a comparison of surface roughness Ra values obtained under dry and coolant-assisted (wet) hybrid CNC machining conditions for Part 4, along with the corresponding percentage improvements. Across all angles and depths of cut, the majority of cases exhibit a measurable reduction in Ra with the use of coolant, indicating an overall positive effect on surface quality. The improvement is most pronounced at  $10^\circ$  with 0.3 mm depth of cut (41.45%) and  $70^\circ$  with 0.4 mm depth of cut (30.82%), while the lowest gains occur at  $70^\circ$  with 0.3 mm depth of cut (0.77%). On average, the application of coolant results in an Ra reduction of 21.28%, 18.34%,

and 18.80% for depths of cut of 0.2 mm, 0.3 mm, and 0.4 mm, respectively.

Table 4.35 compares the surface roughness  $R_a$  values for Part 5 under dry and coolant-assisted (wet) hybrid CNC machining conditions and presents the corresponding percentage improvements.

The highest percentage improvement is observed at 30° with a 0.4 mm depth of cut (31.73%) and 20° with a 0.4 mm depth of cut (29.58%), while some conditions, such as 20° at 0.2 mm (3.88%) and 50° at 0.3 mm (0.87%), show minimal gains. On average, coolant application improves  $R_a$  by 19.35% at 0.2 mm, 15.74% at 0.3 mm, and 21.30% at 0.4 mm depth of cut.

The findings obtained from both Tables 4.34 and 4.35 clearly highlight that the usage of coolant during CNC machining is quite critical for application areas where extreme surface roughness control is required. As mentioned in [29], thermoplastics have a glass transition temperature  $T_g$  below which the polymer chains are immobilized and material behaves stiff and brittle. However, if the  $T_g$  is exceeded, thermoplastics start behaving rubber like and can result in viscous folding. The  $T_g$  of PLA is around 60°C, therefore cutting parameters should be selected to keep the temperature during machining below this temperature. Although, in this study the cutting parameters as mentioned in Table 3.13 are selected according to the guidelines mentioned in [29], the usage of coolant further helps to keep the temperature below 60°C i.e  $T_g$  of PLA.

Table 4.34: Comparison of  $R_a$  Values and Percentage Improvement for Dry and Coolant-Assisted (Wet) Hybrid CNC Machining Part 4

| Angle (°)      | Dry Hybrid $R_a$ (μm) |        |        | Wet Hybrid $R_a$ (μm) |        |        | % Improvement |        |        |
|----------------|-----------------------|--------|--------|-----------------------|--------|--------|---------------|--------|--------|
|                | 0.2 mm                | 0.3 mm | 0.4 mm | 0.2 mm                | 0.3 mm | 0.4 mm | 0.2 mm        | 0.3 mm | 0.4 mm |
| 10             | 1.732                 | 1.464  | 1.550  | 1.111                 | 0.857  | 1.541  | 35.85%        | 41.45% | 0.62%  |
| 20             | 2.166                 | 2.090  | 2.291  | 1.333                 | 1.868  | 1.823  | 38.44%        | 10.64% | 20.42% |
| 30             | 2.234                 | 2.055  | 2.174  | 1.844                 | 1.821  | 1.728  | 17.48%        | 11.40% | 20.50% |
| 40             | 1.233                 | 1.845  | 1.374  | 1.280                 | 1.541  | 1.376  | 3.81%         | 16.47% | 0.17%  |
| 50             | 1.610                 | 1.426  | 1.820  | 1.218                 | 1.056  | 1.289  | 24.34%        | 25.97% | 29.21% |
| 60             | 2.118                 | 2.249  | 2.329  | 1.854                 | 1.745  | 1.954  | 12.45%        | 22.40% | 16.09% |
| 70             | 2.290                 | 1.938  | 2.714  | 1.764                 | 1.923  | 1.878  | 22.98%        | 0.77%  | 30.82% |
| 80             | 1.627                 | 1.578  | 1.379  | 1.412                 | 1.148  | 1.104  | 13.20%        | 27.26% | 19.92% |
| <b>Average</b> | 1.876                 | 1.831  | 1.954  | 1.477                 | 1.495  | 1.587  | 21.28%        | 18.34% | 18.80% |

Table 4.35: Comparison of  $Ra$  Values and Percentage Improvement for Dry and Coolant-Assisted (Wet) Hybrid CNC Machining Part 5

| Angle (°)      | Dry Hybrid $Ra$ ( $\mu\text{m}$ ) |        |        | Wet Hybrid $Ra$ ( $\mu\text{m}$ ) |        |        | % Improvement |        |        |
|----------------|-----------------------------------|--------|--------|-----------------------------------|--------|--------|---------------|--------|--------|
|                | 0.2 mm                            | 0.3 mm | 0.4 mm | 0.2 mm                            | 0.3 mm | 0.4 mm | 0.2 mm        | 0.3 mm | 0.4 mm |
| 10             | 1.691                             | 1.511  | 1.418  | 1.178                             | 1.385  | 1.205  | 30.34%        | 8.34%  | 15.02% |
| 20             | 2.056                             | 2.487  | 2.453  | 1.976                             | 2.239  | 1.727  | 3.88%         | 9.95%  | 29.58% |
| 30             | 2.280                             | 2.263  | 2.386  | 1.672                             | 1.849  | 1.629  | 26.68%        | 18.31% | 31.73% |
| 40             | 1.299                             | 1.975  | 1.535  | 1.107                             | 1.148  | 1.313  | 14.78%        | 41.88% | 14.48% |
| 50             | 1.446                             | 1.417  | 1.530  | 0.942                             | 1.430  | 1.258  | 34.85%        | 0.87%  | 17.74% |
| 60             | 1.993                             | 2.376  | 2.364  | 1.700                             | 1.892  | 1.811  | 14.70%        | 20.36% | 23.39% |
| 70             | 1.803                             | 2.205  | 2.217  | 1.838                             | 1.984  | 1.871  | 1.90%         | 10.04% | 15.62% |
| 80             | 1.596                             | 1.495  | 1.464  | 1.154                             | 1.253  | 1.129  | 27.69%        | 16.19% | 22.86% |
| <b>Average</b> | 1.771                             | 1.966  | 1.921  | 1.446                             | 1.647  | 1.493  | 19.35%        | 15.74% | 21.30% |

In addition, the coolant also prevents the chips from getting stuck to the workpiece and results in taking the chips away from the workpiece during machining. With these improvements, the  $Ra$  values decrease. It should be noted that although the coolant usage was carried out with promising results contributing to the surface roughness improvement, a future study should focus on maximizing the experimental dataset to a larger number of parts having different AM parameters for more reliable results.



## CHAPTER 5

### CONCLUSION AND FUTURE RESEARCH ROADMAP

#### 5.1 Summary of the Findings

The study was conducted based on an identification of a crucial research gap from the literature regarding the prediction of surface roughness of additively manufactured (FFF) and machined (hybrid) PLA parts using supervised regression based machine learning algorithms at various inclinations. Only a few studies namely [18, 27, 30] have considered inclination angle as a design parameter for PLA parts, with CNC machining as a post-processing method reported exclusively in [27, 30]. Among these, only [30] applied an ML technique, specifically an artificial neural network, to predict surface roughness in hybrid-manufactured PLA parts, and even then, the analysis was restricted to four inclination angles (30°, 45°, 60°, and 90°). In contrast, the present study addresses this gap by employing a more comprehensive experimental design involving 54 parts designed using Taguchi L54 DOE methodology, extending the inclination angle range from 10° to 80°, incorporating CNC machining for surface quality enhancement, and applying ten different supervised regression-based ML algorithms and choosing the best one to model and predict surface roughness with greater accuracy and generalizability.

This study concludes that PLA components produced via AM using the FFF technique require careful selection of processing parameters to achieve optimal surface quality. The analysis of surface roughness  $R_a$  trends reveals three distinct regions. Region 1 comprises shallow or lower inclination angles, where  $R_a$  increases up to a point typically corresponding to an inclination of approximately 20° - 30°. Region 2 corresponds to the peak inclination angle, at which  $R_a$  reaches its maximum. Region

3 covers higher inclination angles, where Ra progressively decreases, as illustrated in Figure 4.1. These variations are primarily attributed to the stack-and-step effect and the influence of corner geometries inherent to AM processes. The analysis further identifies layer height as the most influential parameter affecting Ra. Increasing the layer height not only elevates Ra values but also shifts the peak position in Region 2 towards higher inclination angles, as shown in Figure 4.4. Results indicate optimal surface roughness is obtained with a suitable layer height, nozzle diameter, and extrusion temperature. For applications requiring high surface roughness control, a 0.10 mm layer height, 0.25 mm nozzle, and 210°C extrusion temperature produce low Ra values for all inclinations. For applications where build time is of importance, 0.15 or 0.20 mm layer heights, with a 0.40 mm nozzle, along with 210°C print extrusion temperature, offer a useful trade-off between build time and a good surface finish.

During the hybrid CNC machining phase, it was observed that the AM input parameters significantly influence the machinability and finishing quality of PLA parts. Inadequate AM settings such as the combination of a low extrusion temperature of 190°C, a high layer height of 0.20 mm, and a nozzle diameter of 0.25 mm tend to promote under-extrusion and stringing. These defects can lead to layer ripping, tearing, and uneven cutting during CNC finishing, thereby negating the intended benefits of the post-processing stage. Furthermore, the cutting parameters must be selected to ensure that the cutting temperature does not exceed the glass transition temperature ( $T_g$ ) approximately 60°C of PLA. The present study recommends the use of a spindle speed ( $N$ ) of 4000 rpm and a feed rate ( $V_f$ ) of 360 mm/min in combination with a three-flute cutting tool of 4 mm diameter. Using these parameters with depth of cut values between 0.20 mm and 0.40 mm resulted in a reduction of Ra by approximately 85–91%, demonstrating substantial improvement in surface finish. While variations in depth of cut did not produce a statistically significant effect on Ra, the average of the Ra values for all the inclinations at a 0.2 mm depth of cut was found to be 1.8  $\mu\text{m}$ . Therefore, for optimal results, the recommended AM parameter set (outlined in the preceding paragraph) should be combined with the aforementioned cutting parameters, employing a 0.20 mm depth of cut to achieve superior surface quality in hybrid CNC machining of PLA components.

Ten supervised regression-based machine learning (ML) algorithms were applied to

predict Ra values based on the given input parameters. For the AM dataset, for a single run, the Explainable Boosting Machine (EBM) emerged as the most reliable model, achieving a low testing MSE of 0.791 and RMSE of 0.889, alongside a high  $R^2$  value of 0.983. It also recorded low MAE and MAPE values of 0.616 and 3.48%, respectively for a single run. This was followed closely by ensemble tree-based algorithms such as GBR, RFR, XGBoost, ETR, and CatBoost, all of which demonstrated competitive prediction accuracy. In contrast, SVR was the poorest performer, exhibiting the highest errors (MSE = 11.95, RMSE = 3.405, MAE = 2.164, MAPE = 11.95%) and the lowest  $R^2$  of 0.750. A similar trend was observed in the evaluation metrics obtained from the 10 fold cross validation. For the hybrid dataset, EBM again outperformed the other algorithms, for a single run, achieving the highest  $R^2$  value of 0.616 and the lowest errors (MSE = 0.109, RMSE = 0.331, MAE = 0.226, MAPE = 11.92%). Similar results were obtained from the comparison of the evaluation metrics from the 10 fold cross validation in the hybrid stage. However, the evaluation metrics for the hybrid case were substantially weaker than for AM. Several factors account for this disparity. Firstly, the hybrid dataset exhibits a higher noise-to-signal ratio due to unrecorded influences such as machine vibrations, clamping effects, and environmental variations. Secondly, the range of Ra values in the hybrid dataset is narrower (1–5  $\mu\text{m}$ ), limiting the variability from which the model can learn. Thirdly, the presence of outliers, particularly values near 5  $\mu\text{m}$ , reduces correlation strength and negatively impacts predictive performance. Lastly, the combined effects of AM and machining introduce more complex non-linear interactions, making it more challenging for ML models to identify stable patterns without overfitting. Despite these challenges, EBM provided valuable insights into parameter importance and their influence on Ra for both AM and hybrid processes, reinforcing its suitability as a robust predictive model across different manufacturing stages.

For the AM stage, the EBM model identified the top five most influential factors affecting Ra values as: Angle, Layer Height, the interaction between Angle and Layer Height, Nozzle Diameter, and Printing Temperature. Other parameters exhibited negligible influence on Ra. An increase in layer height consistently resulted in higher Ra values. While a smaller nozzle diameter performed effectively for lower layer heights (e.g., 0.10 mm), optimal surface quality was achieved when it was paired

with a higher extrusion temperature of 210°C. Furthermore, increasing the printing temperature from 190°C to 210°C reduced Ra values, indicating a beneficial thermal effect on interlayer bonding and surface finish. These trends are clearly visible in the SHAP plot (Figure 4.41). In the hybrid stage, the most influential parameters identified were Angle, Nozzle Diameter, Layer Height, Depth of Cut, Infill Density, and Printing Temperature. Applications of small nozzle diameter, high layer heights, low infill percentage values, and low extrusion temperature values were correlated to high values of Ra. Conversely, the usage of lower depth of cut reduced the roughness of the generated surface, as depicted in Figure 4.44. These results again emphasize the need for optimal parameter setting for both AM and hybrid techniques to achieve desirable characteristics of the generated surface.

To further validate the effectiveness of the EBM model for continuous prediction of a Ra values, verification parts with randomly selected input parameters were employed. The results demonstrated that, for the AM stage, EBM could reliably predict Ra values within a tolerance of  $\pm 2 \mu\text{m}$  and MAPE of 6.22% for the unseen data, thereby satisfying the requirements for engineering evaluation. In the hybrid stage, despite the lower Ra values obtained during model evaluation, EBM successfully predicted Ra values for the unseen data within a tighter tolerance of  $\pm 1 \mu\text{m}$  and MAPE of 9.17%, further reinforcing its suitability for practical and industrial applications. Additionally, a preliminary investigation into coolant-assisted machining was conducted, revealing improvements in Ra values in the range of 15–21%, as reported in Tables 4.34 and 4.35. The application of water soluble coolant emulsion helps maintain cutting temperatures below the glass transition temperature ( $T_g$ ) of PLA and facilitates effective chip evacuation, both of which contribute to enhanced surface quality.

In conclusion, this study provides a comprehensive framework for predicting the surface roughness of PLA components fabricated via AM and Hybrid processes. The findings recommend that optimal surface roughness can be achieved using a layer height of 0.10 mm, a nozzle diameter of 0.25 mm, and an extrusion temperature of 210°C during the AM stage. These parameters promote better interlayer bonding and reduce print-induced defects that may affect post-processing. In the CNC finishing stage, a spindle speed of 4000 rpm, feed rate of 360 mm/min, and a 3-flute, 4 mm di-

ameter flat end mill were found to be the most effective, particularly when used with a depth of cut of 0.20 mm, which yielded an average surface roughness (Ra) of 1.8  $\mu\text{m}$ . The majority of the parts fell within the range of 1-3.5  $\mu\text{m}$  for varying inclinations and depths of cut. An improvement of 85% - 91% was observed in the surface roughness with the application of CNC milling in the hybrid stage as compared to the AM stage. Additionally, the application of coolant during machining resulted in a further 15–21% improvement in surface finish, demonstrating a practical enhancement easily adaptable in industrial settings. The Explainable Boosting Machine (EBM) emerged as the most accurate and robust model for Ra prediction in both AM and hybrid processes, offering reliable predictions within prediction tolerances of  $\pm 2 \mu\text{m}$  for AM and  $\pm 1 \mu\text{m}$  for hybrid cases.

The results and findings discussed in this study have a high significance for industry and practical manufacturing application where careful control of surface roughness is required especially in the sectors of aerospace and biomedical devices. By systematically analyzing and optimizing both AM and hybrid AM–CNC machining parameters, and integrating advanced predictive modeling using ML EBM model, this work demonstrates a reliable pathway to achieve targeted surface roughness levels with minimal trial-and-error. The ability of the EBM model to accurately predict Ra values within tight engineering tolerances  $\pm 2 \mu\text{m}$  for AM and  $\pm 1 \mu\text{m}$  for hybrid machining enables manufacturers to pre-emptively adjust process parameters, resulting in less material consumption and scrap, and lower production costs. Moreover, the experimental evidence for coolant-assisted machining to enhance the surface quality represents a practical, low-cost intervention easily deployable on actual manufacturing lines. Each among these contributions, on its own, represents a good decision-support tool for enhancing the surface integrity of PLA-based parts, by accelerating the scale-up of the additive and hybrid manufacturing from the prototype level to high-value, industrial-scale manufacturing.

## **5.2 Future Research Roadmap**

The scope of the research is limited to the FFF technology in AM employing PLA as the targeted material. According to the PLA material, the input parameters have

been selected based on manufacturers recommendations. To minimize the time consumption, a total of 54 experiments have been conducted and supervised regression based MLs have been employed for continuous prediction. The Ra values have been measured using a handheld skidded profilometer which allows for a certain degree of human error. In the hybrid stage, the cutting parameters have carefully been selected to allow the cutting temperature to stay below the glass transition temperature  $T_g$  of PLA. Hence, these limitations can become a significant starting point for future research. A systematic roadmap for future research is provided below.

- Investigation of Ra values for widely used materials in the industry such as ABS, TPU, PEEK.
- Enlargement of the experimental data set using different DOE approaches such as fractional factorial design, Latin Hyper Cube Sampling or RSM
- Application of direct slicing on shallow inclinations to reduce the stack and step effect and corner geometry effect
- Exploration of inclinations beyond  $90^\circ$  and upto  $180^\circ$
- Exploration of other AM input parameters such as infill overlap percentage, outer and inner wall speed, infill jerk, wall jerk, as well as initial and final printing temperatures
- Employment of non-contact optical scanners and skidless type profilometers to measure Ra providing high accuracy and precision
- Arrangement of Ra values into classes and employment of classification based ML algorithms such as Naive Bayes, KNNs etc
- Employment of a 5-axis CNC machine can be investigated for decreasing Ra values
- Employment of ball-nose end mills instead of flat end mills. Spherical geometry of the ball end mill might reduce surface roughness more
- Investigation of other processes such as grinding, vibratory surface treatment or laser machining for enhancing Ra values

- Exploration of coolant assisted machining on a large number of experiments
- Investigation on technologies other than FFF, such as SLA, SLS, SLM or DED with proper input parameters







## REFERENCES

- [1] M. Usama and U. Yaman, "Embedding information into or onto additively manufactured parts: a review of qr codes, steganography and watermarking methods," *Materials*, vol. 15, no. 7, p. 2596, 2022.
- [2] M. Ahmadifar, A. S. R. Badr, A. A. Zein, A. Shanmugam, and M. U. A. Khan, "Additive manufacturing of polymer-based composites using fused filament fabrication (fff): a review," *Applied Composite Materials*, vol. 28, pp. 1335–1380, 2021.
- [3] U. B.V., "Ultimaker s5 - professional 3d printer." <https://ultimaker.com/3d-printers/ultimaker-s5>, 2024. Accessed: Apr. 19, 2025.
- [4] A. J. Arockiam, A. S. Jawahar, M. Irshad, B. Manikandan, and N. Elanchezhian, "A review on pla with different fillers used as a filament in 3d printing," *Materials Today: Proceedings*, vol. 50, pp. 2057–2064, 2022.
- [5] A. Boschetto, V. Giordano, and F. Veniali, "Surface roughness prediction in fused deposition modelling by neural networks," *The International Journal of Advanced Manufacturing Technology*, vol. 67, pp. 2727–2742, 2013.
- [6] I. Buj-Corral, A. Bagheri, and M. Sivatte-Adroer, "Effect of printing parameters on dimensional error, surface roughness and porosity of fff printed parts with grid structure," *Polymers*, vol. 13, no. 8, p. 1213, 2021.
- [7] A. Mishra, S. Sharma, V. Kumar, S. Kumar, P. Kumar, and S. Pathak, "Explainable artificial intelligence (xai) and supervised machine learning-based algorithms for prediction of surface roughness of additively manufactured polylactic acid (pla) specimens," *Applied Mechanics*, vol. 4, no. 2, pp. 668–698, 2023.
- [8] P. M. Pandey, N. V. Reddy, and S. G. Dhande, "Slicing procedures in layered manufacturing: a review," *Rapid Prototyping Journal*, vol. 9, no. 5, pp. 274–288, 2003.

- [9] S. Badillo, B. Banfai, F. Birzele, I. I. Davydov, L. Hutchinson, T. Kam-Thong, J. Siebourg-Polster, B. Steiert, and J. D. Zhang, "An introduction to machine learning," *Clinical Pharmacology & Therapeutics*, vol. 107, no. 4, pp. 871–885, 2020.
- [10] Z. Li, J. Wang, X. Wang, Y. Gao, and Y. Yin, "Prediction of surface roughness in extrusion-based additive manufacturing with machine learning," *Robotics and Computer-Integrated Manufacturing*, vol. 57, pp. 488–495, 2019.
- [11] J. M. Barrios and P. E. Romero, "Decision tree methods for predicting surface roughness in fused deposition modeling parts," *Materials*, vol. 12, no. 16, p. 2574, 2019.
- [12] A. Cerro, L. N. L. de Lacalle, Álvaro Rodríguez, O. Perurena, E. Ukar, E. Fernández, and A. Lamikiz, "Use of machine learning algorithms for surface roughness prediction of printed parts in polyvinyl butyral via fused deposition modeling," *The International Journal of Advanced Manufacturing Technology*, vol. 115, no. 7-8, pp. 2465–2475, 2021.
- [13] K. Kandananond, "Surface roughness prediction of fff-fabricated workpieces by artificial neural network and box-behnken method," *International Journal of Metrology and Quality Engineering*, vol. 12, p. 17, 2021.
- [14] A. Yaseer and H. Chen, "Machine learning based layer roughness modeling in robotic additive manufacturing," *Journal of Manufacturing Processes*, vol. 70, pp. 543–552, 2021.
- [15] M. S. Saad, M. H. Musa, Z. Mohamad, S. Sulaiman, N. M. Mohamed, and M. S. Salleh, "Optimization of fdm process parameters to minimize surface roughness with integrated artificial neural network model and symbiotic organism search," *Neural Computing and Applications*, vol. 34, no. 20, pp. 17423–17439, 2022.
- [16] F. García-Martínez, A. J. Fernández-Prieto, R. Ángel García-León, and E. Cano, "Toward data-driven research: preliminary study to predict surface roughness in material extrusion using previously published data with machine learning," *Rapid Prototyping Journal*, 2023.

- [17] O. Ulkir and G. Akgun, “Predicting and optimising the surface roughness of additive manufactured parts using an artificial neural network model and genetic algorithm,” *Science and Technology of Welding and Joining*, pp. 1–10, 2023.
- [18] M. Huang, X. Luo, L. Zhou, B. Zhang, and X. Yuan, “A method for predicting surface finish of polylactic acid parts printed using fused deposition modeling,” *Processes*, vol. 11, no. 6, p. 1820, 2023.
- [19] A. Saxena, Q. Murtaza, and P. Kumar, “Prediction of surface roughness in additively manufactured samples in pla+ polymer material through machine learning,” *European Chemical Bulletin*, vol. 12, no. 7, pp. 2096–2112, 2023.
- [20] D. Wu, Y. Wei, and J. Terpenney, “Predictive modelling of surface roughness in fused deposition modelling using data fusion,” *International Journal of Production Research*, vol. 57, no. 12, pp. 3992–4006, 2019.
- [21] A. Mishra and V. S. Jatti, “Novel coupled genetic algorithm–machine learning approach for predicting surface roughness in fused deposition modeling of polylactic acid specimens,” *Journal of Materials Engineering and Performance*, pp. 1–10, 2023.
- [22] E. Vahabli and S. Rahmati, “Improvement of fdm parts’ surface quality using optimized neural networks–medical case studies,” *Rapid Prototyping Journal*, vol. 23, no. 4, pp. 825–842, 2017.
- [23] S. Djurović, I. Pasti, I. Bogojević, M. Kovačević, M. Ranković, S. Vučetić, and D. Spasić, “Modeling and prediction of surface roughness in hybrid manufacturing–milling after fdm using artificial neural networks,” *Applied Sciences*, vol. 14, no. 14, p. 5980, 2024.
- [24] U. B.V., “Ultimaker cura: Powerful, easy-to-use 3d printing software.” <https://ultimaker.com/software/ultimaker-cura>, 2024. Accessed: Apr. 19, 2025.
- [25] A. Kumar, P. Choudhary, S. Kumar, P. V. M. Rao, and S. K. Pal, “Investigations and predictions for mechanical and surface properties of fff prints using doe, ml and fea,” *Advances in Materials and Processing Technologies*, vol. 10, no. 3, pp. 1767–1783, 2024.

- [26] J. B. Deb, S. Chowdhury, and N. M. Ali, “An investigation of the ensemble machine learning techniques for predicting mechanical properties of printed parts in additive manufacturing,” *Decision Analytics Journal*, p. 100492, 2024.
- [27] L. Li, A. Haghighi, and Y. Yang, “Theoretical modelling and prediction of surface roughness for hybrid additive–subtractive manufacturing processes,” *IISE Transactions*, vol. 51, no. 2, pp. 124–135, 2019.
- [28] International Organization for Standardization, “ISO 4287:1997 — Geometrical Product Specifications (GPS) — Surface texture: Profile method — Terms, definitions and surface texture parameters.” International Standard, 1997. ISO, Geneva, Switzerland.
- [29] U. M. Dilberoglu, U. Yaman, and M. Dolen, “A comprehensive guide to milling techniques for smoothing the surfaces of 3d-printed thermoplastic parts,” *Rapid Prototyping Journal*, vol. 30, no. 8, pp. 1648–1662, 2024.
- [30] S. Pascu and N. Balci, “Process parameter optimization for hybrid manufacturing of pla components with improved surface quality,” *Polymers*, vol. 15, no. 17, p. 3610, 2023.
- [31] Siemens Digital Industries Software, “Siemens NX, Version 2306.” <https://plm.sw.siemens.com/en-US/nx/>, 2025. Accessed: Apr. 19, 2025.
- [32] C.-C. Kuo, C.-M. Chen, and S.-X. Chang, “Polishing mechanism for abs parts fabricated by additive manufacturing,” *The International Journal of Advanced Manufacturing Technology*, vol. 91, pp. 1473–1479, 2017.
- [33] P. E. Reeves and R. C. Cobb, “Reducing the surface deviation of stereolithography using in-process techniques,” *Rapid Prototyping Journal*, vol. 3, no. 1, pp. 20–31, 1997.
- [34] S. Kugunavar, M. Viralka, and K. S. Sangwan, “Development of a hybrid model to estimate surface roughness of 3d printed parts,” *Additive Manufacturing*, vol. 92, p. 104368, 2024.
- [35] M. Pérez, E. Suárez, N. Carou, T. Concheiro, R. Taboada-Crispi, and A. Díaz-Álvarez, “Surface quality enhancement of fused deposition modeling (fdm)

- printed samples based on the selection of critical printing parameters,” *Materials*, vol. 11, no. 8, p. 1382, 2018.
- [36] B. N. Turner and S. A. Gold, “A review of melt extrusion additive manufacturing processes: Ii. materials, dimensional accuracy, and surface roughness,” *Rapid Prototyping Journal*, vol. 21, no. 3, pp. 250–261, 2015.
- [37] I. J. Solomon, P. Sevvel, and J. J. M. T. P. Gunasekaran, “A review on the various processing parameters in fdm,” *Materials Today: Proceedings*, vol. 37, pp. 509–514, 2021.
- [38] A. Alafaghani, A. Qattawi, A. Alrawi, and A. Guzman, “Experimental optimization of fused deposition modelling processing parameters: a design-for-manufacturing approach,” *Procedia Manufacturing*, vol. 10, pp. 791–803, 2017.
- [39] A. Dey and N. Yodo, “A systematic survey of fdm process parameter optimization and their influence on part characteristics,” *Journal of Manufacturing and Materials Processing*, vol. 3, no. 3, p. 64, 2019.
- [40] L. Kačergis, R. Mitkus, and M. Sinapius, “Influence of fused deposition modeling process parameters on the transformation of 4d printed morphing structures,” *Smart Materials and Structures*, vol. 28, no. 10, p. 105042, 2019.
- [41] Ultimaker B.V., “Technical data sheet: Ultimaker pla,” 2022. Accessed: Apr. 19, 2025.
- [42] Ultimaker B.V., “Ultimaker print core aa 0.25 mm.” <https://store.ultimaker.com/ultimaker-print-core-aa-0-25mm>, 2024. Accessed: Apr. 19, 2025.
- [43] F. M. Fernández and M. J. M. Sánchez, “Analysis of the effect of the surface inclination angle on the roughness of polymeric parts obtained with fused filament fabrication technology,” *Polymers*, vol. 15, no. 3, p. 585, 2023.
- [44] A. H. Kadhum, S. Al-Zubaidi, and S. S. Abdulkareem, “Effect of the infill patterns on the mechanical and surface characteristics of 3d printing of pla, pla+ and petg materials,” *ChemEngineering*, vol. 7, no. 3, p. 46, 2023.

- [45] M. D. Oliveira *et al.*, “Experimental planning factorial: a brief review,” *International Journal of Advanced Engineering Research and Science*, vol. 5, no. 6, p. 264164, 2018.
- [46] D. C. Montgomery and C. M. Borror, “An examination of effect estimation in factorial and standardly-tailored designs,” *Journal of Quality Technology*, vol. 29, no. 3, pp. 300–308, 1997.
- [47] S. Boonyuen and P. Prasertsan, “Using response surface methodology (rsm) to optimize 2g bioethanol production: A review,” *Industrial Crops and Products*, vol. 154, p. 112740, 2020.
- [48] A. Valente, R. C. A. Guedes, M. C. U. Araújo, and R. J. Poppi, “Experimental designs for modeling retention patterns and separation efficiency in analysis of fatty acid methyl esters by gas chromatography–mass spectrometry,” *Journal of Chromatography A*, vol. 1218, no. 32, pp. 5457–5464, 2011.
- [49] A. K. Das and S. Dewanjee, “Optimization of extraction using mathematical models and computation,” in *Mathematical Modeling and Computational Tools*, ch. 3, pp. 49–70, Academic Press, 2020.
- [50] J. Antony, “Taguchi or classical design of experiments: a perspective from a practitioner,” *Sensor Review*, vol. 26, no. 3, pp. 227–230, 2006.
- [51] M. Heidari-Rarani, M. J. Ezati, and M. A. Shabani, “Optimization of fdm process parameters for tensile properties of polylactic acid specimens using taguchi design of experiment method,” *Journal of Thermoplastic Composite Materials*, vol. 34, no. 7, pp. 1009–1023, 2021.
- [52] J. Antony, S. Warwood, K. Fernandes, and H. Rowlands, “Process optimisation using taguchi methods of experimental design,” *Work Study*, vol. 50, no. 2, pp. 51–58, 2001.
- [53] R. N. Kacker, E. S. Lagergren, and J. J. Filliben, “Taguchi’s orthogonal arrays are classical designs of experiments,” *Journal of Research of the National Institute of Standards and Technology*, vol. 96, no. 5, pp. 577–591, 1991.

- [54] S. Singh, G. Singh, C. Prakash, and W.-M. Yang, "Current status and future directions of fused filament fabrication," *Journal of Manufacturing Processes*, vol. 55, pp. 288–306, 2020.
- [55] M. F. Arif and A. E. Cinar, "Gaining a better understanding of the extrusion process in fused filament fabrication 3d printing: A review," *Additive Manufacturing*, vol. 66, p. 102904, 2023.
- [56] S. Soni and M. Taufik, "Design and assembly of fused filament fabrication (fff) 3d printers," *Materials Today: Proceedings*, vol. 46, pp. 5233–5241, 2021.
- [57] T.-M. Wang, J.-T. Xi, and Y. Jin, "A model research for prototype warp deformation in the fdm process," *The International Journal of Advanced Manufacturing Technology*, vol. 33, no. 11–12, pp. 1087–1096, 2007.
- [58] S. Bansod, A. Patil, S. Patil, S. Patil, S. Patil, and A. Patil, "Design and development of large scale fdm based 3d printer," *Journal of Physics: Conference Series*, vol. 2272, no. 1, p. 012016, 2022.
- [59] T. A. Ruzova and B. Haddadi, "Surface roughness and its measurement methods: Analytical review," *Results in Surfaces and Interfaces*, vol. 10, p. 100441, 2025.
- [60] S. Xia, "Classification and interpretation of surface roughness," 2024. Accessed: May 13, 2024.
- [61] E. S. Gadelmawla, M. M. Koura, T. M. A. Maksoud, I. M. Elewa, and H. H. Soliman, "Roughness parameters," *Journal of Materials Processing Technology*, vol. 123, no. 1, pp. 133–145, 2002.
- [62] Mahr GmbH, "Mobiles Rauheitsmessgerät MarSurf PS 10." <https://metrology.mahr.com/tr/ueruen/article/6910230-mobiles-rauheitsmessgeraet-marsurf-ps-10>, n.d. Accessed: 2025-07-19.
- [63] H. Zhou, X. Cheng, X. Jiang, G. Zheng, J. Zhang, Y. Li, M. Tang, and F. Lv, "Green manufacturing-oriented polyetheretherketone additive manufacturing and dry milling post-processing process research," *Processes*, vol. 10, no. 12, p. 2561, 2022.

- [64] G. Gu, S. Wu, D. Wang, S. Zhou, L. Zhu, Q. An, H. Guo, and C. Li, “A review of the research on the variation of tool’s motion trajectory and its influence on the formation mechanism of surface quality in ultrasonic vibration machining,” *Journal of Manufacturing Processes*, vol. 107, pp. 294–319, 2023.
- [65] M. P. Groover, *Fundamentals of Modern Manufacturing: Materials, Processes, and Systems*. Hoboken, NJ: Wiley, 5th ed., 2013. See Chapter 21, pp. 557–580.
- [66] R. G. Pămărac and R. E. Petrus, “Study regarding the optimal milling parameters for finishing 3d printed parts from abs and pla materials,” *Acta Universitatis Cibiniensis – Technical Series*, vol. LXX, pp. 57–62, 2018. Faculty of Engineering, Department of Industrial Engineering and Management.
- [67] D. Grguraš and D. Kramar, “Optimization of hybrid manufacturing for surface quality, material consumption and productivity improvement,” *Tehnički Glasnik*, vol. 17, no. 1, pp. 120–125, 2023.
- [68] M. Carta, G. Loi, M. El Mehtedi, P. Buonadonna, and F. Aymerich, “Improving surface roughness of fdm-printed parts through cnc machining: A brief review,” *Journal of Composites Science*, vol. 9, no. 6, p. 296, 2025.
- [69] Haas Automation, Inc., “VF-1 Technical Specifications.” <https://www.haascnc.com/machines/vertical-mills/vf-series/models/vf-1.html>, 2024. Accessed: July 20, 2025.
- [70] Seco Tools, “Solid Carbide End Mill - Jabro HPM JH770.” [https://www.secotools.com/article/p\\_02679360?language=en](https://www.secotools.com/article/p_02679360?language=en), 2024. Accessed: July 20, 2025.
- [71] Autodesk Inc., “Fusion 360 cam for cnc milling.” <https://www.autodesk.com/products/fusion-360/overview>, 2024. Accessed: July 20, 2025.
- [72] A. Géron, *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems*. Sebastopol, CA: O’Reilly Media, 2nd ed., 2019.



- [73] M. Verleysen and D. François, “The curse of dimensionality in data mining and time series prediction,” in *Proceedings of the International Work-Conference on Artificial Neural Networks (IWANN)*, pp. 758–770, Springer, 2005.
- [74] J. D. Rodriguez, A. Perez, and J. A. Lozano, “Sensitivity analysis of k-fold cross validation in prediction error estimation,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 32, no. 3, pp. 569–575, 2010.
- [75] T. Hastie, R. Tibshirani, and J. Friedman, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. New York: Springer, 2 ed., 2009.
- [76] T. Carneiro, R. N. Albuquerque, T. Nepomuceno, P. A. Tavares, A. L. M. Júnior, and V. H. C. de Albuquerque, “Performance analysis of google colaboratory as a tool for accelerating deep learning applications,” *IEEE Access*, vol. 6, pp. 61677–61685, 2018.
- [77] U. Singh, M. Rizwan, M. Alaraj, and I. Alsaidan, “A machine learning-based gradient boosting regression approach for wind power production forecasting: A step towards smart grid environments,” *Energies*, vol. 15, no. 3, p. 1252, 2022.
- [78] Y. Zhang, J. Ma, S. Liang, X. Li, and M. Li, “An evaluation of eight machine learning regression algorithms for forest aboveground biomass estimation from multiple satellite data products,” *Remote Sensing*, vol. 14, no. 9, p. 2242, 2022.
- [79] Q. Liu, X. Wang, X. Huang, and X. Yin, “Prediction model of rock mass class using classification and regression tree integrated adaboost algorithm based on tbn driving data,” *Tunnelling and Underground Space Technology*, vol. 106, p. 103595, 2020.
- [80] M. Hammed, M. AlOmar, F. Khaleel, and N. Al-Ansari, “An extra tree regression model for discharge coefficient prediction: Novel, practical applications in the hydraulic sector and future research directions,” *Mathematical Problems in Engineering*, vol. 2021, p. 7001710, 2021.
- [81] I. Ilic, B. Görgülü, M. Cevik, and M. G. Baydoğan, “Explainable boosted linear regression for time series forecasting,” *Expert Systems with Applications*, vol. 221, p. 119729, 2023.

- [82] Z. Zhang, S. Ding, and Y. Sun, “A support vector regression model hybridized with chaotic krill herd algorithm and empirical mode decomposition for regression task,” *Neurocomputing*, vol. 410, pp. 185–201, 2020.
- [83] O. Charia, H. Rajani, I. F. Real, M. Domingo-Espin, and N. Gracias, “Real-time stringing detection for additive manufacturing,” *Sensors*, vol. 23, no. 19, p. 8549, 2023.



## APPENDICES

### A Additional Validation Equation, stylus uncertainty, G-codes (AM and CNC), Excel File DOE, and Surface Roughness Data

#### Appendix A

Equation A.1 presented in the study carried out by Kugunuvar et al [34] is given below:

$$R_a = a \times \sin^2(\theta_b) + b \times \cos^2(\theta_b) + c \times \frac{\sin(\theta_b)}{d} \times R \times (\theta_2 - \theta_1) \quad (\text{A.1})$$

- $R_a$  = arithmetic average surface roughness ( $\mu\text{m}$ )
- $a, b, c$  = empirical coefficients obtained from regression fitting
- $\theta_b$  = build orientation (inclination) angle (degrees)
- $d$  = layer height (mm)
- $R$  = filament radius, taken as half of nozzle diameter (mm)
- $\theta_2 - \theta_1$  = accessible angular span of the filament corner geometry captured by the profilometer stylus, accounting for tip radius and obstruction

The following table gives us the  $R_a$  values taken experimentally for parts 1-9 manufactured with a nozzle diameter of 0.4 mm and a layer height of 0.1 mm at all inclination angles ranging from 10 to 80 °.

Table A.1: Surface Roughness  $R_a$  for 0.10 mm Layer Height and 0.4 mm nozzle)

| Part No | 10° Ra (μm) | 20° Ra (μm) | 30° Ra (μm) | 40° Ra (μm) | 50° Ra (μm) | 60° Ra (μm) | 70° Ra (μm) | 80° Ra (μm) |
|---------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| 1       | 15.816      | 18.788      | 17.517      | 15.843      | 12.762      | 11.483      | 9.945       | 9.578       |
| 2       | 16.503      | 19.699      | 17.769      | 15.396      | 11.939      | 10.771      | 9.466       | 8.750       |
| 3       | 16.791      | 18.863      | 17.675      | 14.588      | 12.343      | 9.551       | 9.334       | 8.883       |
| 4       | 17.082      | 20.363      | 18.829      | 14.785      | 11.312      | 10.175      | 9.166       | 9.346       |
| 5       | 17.065      | 20.072      | 18.240      | 15.135      | 11.378      | 9.381       | 8.650       | 9.254       |
| 6       | 17.113      | 20.360      | 17.702      | 15.046      | 11.747      | 9.888       | 8.670       | 8.506       |
| 7       | 17.737      | 19.544      | 18.246      | 15.165      | 12.127      | 9.550       | 9.411       | 9.056       |
| 8       | 17.744      | 19.696      | 17.946      | 14.783      | 11.315      | 9.111       | 8.748       | 8.768       |
| 9       | 17.681      | 19.439      | 18.173      | 14.467      | 11.761      | 9.274       | 8.411       | 8.604       |

The average of these values have been computed for all the inclination angles in order to find out the values for coefficients using regression fitting. The values for the inputs in the above equation are given in the table below:

Table A.2: Input Parameters and Corresponding Values

| Input Parameters       | Values |
|------------------------|--------|
| $d$ (mm)               | 0.1    |
| $R = ND/2$ (mm)        | 0.2    |
| Stylus Tip Radius (μm) | 2.0    |
| Scan Speed (mm/s)      | 0.5    |
| $a$                    | 8.117  |
| $b$                    | 19.623 |
| $c$                    | -0.789 |

For the accessibility span  $\theta_2 - \theta_1$ , there are three cases presented in [34]. The following equation presents all three cases.

$$(\theta_2 - \theta_1) = \begin{cases} \theta_b + (90 - l_\theta) & \text{if } \frac{d}{\sin(\theta_b)} - 2R > 2t_r \\ \theta_b + 90 - (\alpha + l_\theta) & \text{if } \frac{d}{\sin(\theta_b)} - 2R < 2t_r \\ \theta_b + 90 - 2\alpha & \text{if } l_\theta < \alpha \end{cases} \quad (\text{A.2})$$

In our case,  $l_\theta$  which is the leaving angle of the stylus has been assumed to be  $5^\circ$ . The following equations are computed for each inclination angle to check which case does it belong to along with the computation of alpha as given below

$$\alpha = \cos^{-1} \left( \frac{d / \sin \theta_b}{2(R + t_r)} \right) \quad (\text{A.3})$$

With the selection of each case, Table gives us the accessibility span  $\theta_2 - \theta_1$ , experimental and predicted Ra values using this equation for all the inclination angles.

Table A.3: Comparison of Experimental and Predicted  $R_a$  values using the Hybrid Model

| Angles ( $^\circ$ ) | $\theta_2 - \theta_1$ (rad) | Experimental $R_a$ Avg ( $\mu\text{m}$ ) | Predicted $R_a$ ( $\mu\text{m}$ ) |
|---------------------|-----------------------------|------------------------------------------|-----------------------------------|
| 10                  | 1.658                       | 17.059                                   | 18.821                            |
| 20                  | 0.397                       | 19.647                                   | 18.912                            |
| 30                  | -0.011                      | 18.011                                   | 16.755                            |
| 40                  | -0.082                      | 15.023                                   | 14.952                            |
| 50                  | -0.040                      | 11.854                                   | 12.920                            |
| 60                  | 0.056                       | 9.909                                    | 10.917                            |
| 70                  | 0.184                       | 9.089                                    | 9.190                             |
| 80                  | 0.334                       | 8.972                                    | 7.946                             |

The results show that the model successfully reproduces the overall trend observed experimentally Ra peaks around  $20^\circ$  and decreases steadily towards  $80^\circ$ . At  $10^\circ$ , the model slightly overpredicts roughness (+1.8  $\mu\text{m}$ ), while between  $20^\circ$  and  $30^\circ$  it slightly underpredicts. Beyond  $40^\circ$ , the predictions closely match the experimental values, with differences generally within  $\pm 1 \mu\text{m}$ . The largest discrepancies occur at the extremities ( $10^\circ$  and  $80^\circ$ ), where staircase effects and probe accessibility have a stronger influence on measurement.

While this equation A.1 provides a physically interpretable framework to estimate

surface roughness based on build orientation, layer geometry, and probe accessibility, it is limited in several ways compared to machine learning (ML) models. The analytical formulation is restricted to a narrow set of geometric parameters and requires refitting of coefficients for each material or process setup, making it less adaptable across different printing conditions. Moreover, its rigid functional form cannot fully capture nonlinear interactions arising from factors such as extrusion temperature, print speed, or infill density, which ML models can incorporate seamlessly. The equation also shows systematic deviations at extreme angles and is dependent on measurement instrument parameters such as stylus tip radius, reducing its generalizability. In contrast, ML models can learn flexible mappings directly from experimental data, achieve higher predictive accuracy, and provide additional interpretability tools such as feature importance rankings. Thus, while this model is valuable for explaining physical mechanisms, ML approaches are generally more robust for accurate and generalized prediction of surface roughness.

The stylus uncertainty equation has been derived by using the well known equation for calculating the scallop height during a finishing process provided below.

$$h = \frac{m^2}{8R} |\sin \alpha| \quad (\text{A.4})$$

where

- $h$  = scallop (cusp) height (mm),
- $m$  = stepover (distance between adjacent tool passes) (mm),
- $R$  = Tool radius (mm),
- $\alpha$  = surface inclination angle with respect to the horizontal (degrees or radians).

Over one stepover  $m$  across passes ( $y \in [-m/2, m/2]$ ), approximate the scallop cusp by a parabola passing through  $(0, 0)$  and  $(\pm m/2, h)$ :

$$z(y) = \frac{4h}{m^2} y^2, \quad y \in \left[-\frac{m}{2}, \frac{m}{2}\right]. \quad (\text{A.5})$$

The mean line over one stepover is given by the equation:

$$z_{mean} = \frac{1}{m} \int_{-m/2}^{m/2} z(y) dy = \frac{1}{m} \int_{-m/2}^{m/2} \frac{4h}{m^2} y^2 dy = \frac{h}{3}. \quad (\text{A.6})$$

The cross over point  $y_c$  needs to be found by solving  $z(y_c) = \bar{z} = h/3$  to split the absolute-value integral:

$$\frac{4h}{m^2} y_c^2 = \frac{h}{3} \Rightarrow y_c = \frac{m}{2\sqrt{3}}. \quad (\text{A.7})$$

The  $Ra$  value can be split into  $Ra_x$  and  $Ra_y$  representing arithmetic mean roughness along the tool path and across the tool path.  $Ra_y$  is given by the equation below.

$$Ra_y = \frac{1}{m} \int_{-m/2}^{m/2} |z(y) - z_{mean}| dy \quad (\text{A.8})$$

By symmetry,

$$Ra_y = \frac{2}{m} \left[ \int_0^{y_c} \left( \frac{h}{3} - z(y) \right) dy + \int_{y_c}^{m/2} \left( z(y) - \frac{h}{3} \right) dy \right]. \quad (\text{A.9})$$

Substituting (A.5) and evaluating both integrals gives

$$Ra_y = \frac{4}{9\sqrt{3}} h \approx 0.257 h. \quad (\text{A.10})$$

If the stylus is misaligned by  $\varepsilon$  (sway angle) relative to the tool-path direction, the measured  $Ra$  mixes the along/across components. A common small-angle model is

$$Ra(\varepsilon) \approx Ra_x \cos^2 \varepsilon + Ra_y \sin^2 \varepsilon, \quad (\text{A.11})$$

so the bias when one intends  $Ra_x$  is

$$\Delta Ra \equiv Ra(\varepsilon) - Ra_x = (Ra_y - Ra_x) \sin^2 \varepsilon. \quad (\text{A.12})$$

Using (A.10) and (A.4),

$$\Delta Ra \approx \left( \frac{4}{9\sqrt{3}} h - Ra_x \right) \sin^2 \varepsilon = \left( \frac{4}{9\sqrt{3}} \frac{m^2}{8R} |\sin \alpha| - Ra_x \right) \sin^2 \varepsilon. \quad (\text{A.13})$$

If  $Ra_x \ll Ra_y$  (conservative),

$$\Delta Ra \approx \frac{4}{9\sqrt{3}} \frac{m^2}{8R} |\sin \alpha| \sin^2 \varepsilon. \quad (\text{A.14})$$

In theory, the roughness across adjacent tool passes can be estimated from the scallop geometry, which for the finishing parameters in this study would correspond to sub-micrometer values. However, the actual measurements in this work come from a hybrid process, where additively manufactured PLA parts are subsequently machined at different inclination angles. In such a case, the measured roughness is not governed solely by scallop height but also by the influence of AM input parameters, material response, and machining dynamics. This explains why the experimentally obtained roughness along the tool path is considerably higher than the geometric across-pass estimate. Nevertheless, because the additional contribution of a small stylus misalignment ( $\pm 2^\circ$ ) scales only as a fraction of the across-pass roughness, the resulting uncertainty is extremely small and does not affect the validity of the Ra measurements in this study.

The AM G-codes for all 54 parts are publicly available and can be accessed using the link below:

<https://github.com/usamamuhammad01/AM-G-Codes-Prints.git>

The CNC G-codes for the experimental parts can be accessed and are publicly available by clicking the links given below:

<https://github.com/usamamuhammad01/CNC-G-codes.git>

The Surface Roughness Measurements Ra for both AM and Hybrid stages are publicly available at the following link:

[https://bit.ly/Ra\\_data](https://bit.ly/Ra_data)

The Excel file containing the Taguchi L54 DOE, along with Ra measurements for both AM and Hybrid is publicly available by following the link below:

<https://github.com/usamamuhammad01/Main-Excel-File.git>

The CNC G-codes for the extra validation parts are publicly available and can be accessed with the following link:

<https://github.com/usamamuhammad01/GcodesCNC-Verification.git>



## **B Machine Learning Codes**

### Appendix B

The excel files for both AM and Hybrid dataset can be accessed and are publicly available using the following link:

<https://github.com/usamamuhammad01/AM-Hybrid-ML-Data.git>

The codes for the 10 machine learning algorithms for the AM and Hybrid stage used in this research can be accessed and are publicly available using the following link:

<https://github.com/usamamuhammad01/ML-Codes.git>

The excel file containing the dataset for the verification parts is publicly available by following the link below:

<https://github.com/usamamuhammad01/Verification-Data.git>