DEVELOPING A DECISION-SUPPORT TOOL FOR FOOTBRIDGE PLANNING AND DESIGN PHASES

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

BY

BADE ELOĞLU

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF SCIENCE
IN
BUILDING SCIENCE IN ARCHITECTURE

JANUARY 2025

Approval of the thesis:

DEVELOPING A DECISION-SUPPORT TOOL FOR FOOTBRIDGE PLANNING AND DESIGN PHASES

submitted by **BADE ELOĞLU** in partial fulfillment of the requirements for the degree of **Master of Science** in **Building Science in Architecture, Middle East Technical University** by,

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

Assoc. Prof. Dr. Ayşem Berrin Çakmaklı
Head of the Department, **Architecture** _____

Prof. Dr. Arzu Gönenç Sorguç
Supervisor, **Architecture, METU** _____

Examining Committee Members:

Assoc. Prof. Dr. Mehmet Koray Pekeriçli
Architecture, METU _____

Prof. Dr. Arzu Gönenç Sorguç
Architecture, METU _____

Assist. Prof. Dr. Işıl Ruhi Sipahioğlu
Architecture, TOBB ETÜ _____

Date: 08.01.2025

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 Last name : Bade Eloğlu

Signature :

ABSTRACT

DEVELOPING A DECISION-SUPPORT TOOL FOR FOOTBRIDGE PLANNING AND DESIGN PHASES

Eloğlu, Bade
Master of Science, Building Science in Architecture
Supervisor : Prof. Dr. Arzu Gönenç Sorguç

January 2025, 129 pages

A livable city is rooted in the quality of the pedestrian experience. Yet still, pedestrians remain one of the most vulnerable groups within built environments. With policies prioritizing motor vehicle accessibility, cities are growing increasingly centered around vehicular roads, and the spaces for pedestrians to safely and comfortably navigate around are narrowing down day by day. In such environments, footbridges, particularly on multi-lane roads with high-speed traffic, have become the most prevalent examples of the ad-hoc manner in crossing facility construction. However, imposing these structures into cities without considering site-specific constraints and pedestrian expectations further restricts pedestrian mobility. To address this challenge, this thesis proposes a decision-support tool comprising two complementary stages for footbridge planning and design phases. It employs a mixed-methods approach that integrates on-site observations and literature review findings with machine learning methods. In the first stage, a decision tree model was trained with shared built environment features of footbridge locations to predict the need for footbridges in a given location. However, constructing footbridges merely

due to the need is transforming them into urban barriers. Thus, in the second stage, the key factors affecting footbridge usage were identified through a review of literature, later incorporated with the researcher's observations on footbridge sites and mandatory design criteria. These findings were synthesized into a design guideline, translating pedestrian expectations into actionable design principles. In the final, using the guideline as the main source, the necessity and feasibility of constructing footbridges in the predicted locations were critically evaluated by the researcher.

Keywords: Footbridge, Pedestrian Preferences, Prediction Model, Machine Learning, Design Guideline

ÖZ

YAYA KÖPRÜSÜ PLANLAMA VE TASARIM AŞAMALARI İÇİN KARAR DESTEK ARACI GELİŞTİRME

Eloğlu, Bade
Yüksek Lisans, Yapı Bilimleri, Mimarlık
Tez Yöneticisi: Prof. Dr. Arzu Gönenç Sorguç

Ocak 2025, 129 sayfa

Yaşanabilir bir kentin kalitesi her zaman yaya deneyiminin kalitesine dayanmaktadır. Ancak yayalar hala inşa edilmiş çevrelerde en savunmasız gruplardan biri olmaya devam etmektedir. Motorlu taşıt erişilebilirliğini önceliklendiren politikalarla, şehirler giderek daha fazla araç yolları etrafında şekillenirken, yayaların güvenli ve konforlu bir şekilde hareket edebileceği alanlar her geçen gün daralmaktadır. Bu tür çevrelerde, özellikle trafiğin hızlı olduğu çok şeritli yollarda, yaya köprüleri yaya geçidi inşasındaki gelişigüzel tavrın en yaygın örnekleri haline gelmiştir. Bununla birlikte, alana özgü kısıtlayıcılar ve yaya beklentileri dikkate alınmaksızın bu tür yapıların kentlere empoze edilmesi, yaya hareketini daha da kısıtlamaktadır. Bu soruna çözüm üretmek amacıyla, yaya köprülerinin planlama ve tasarım evreleri için birbirini tamamlayan iki aşamalı bir karar destek aracı önermekte, yerinde gözlemleri ve literatür bulgularını makine öğrenimi yöntemleriyle entegre eden karma bir yöntem yaklaşımı sunmaktadır. İlk aşamada yaya köprülerinin konumlarına ilişkin ortak inşa edilmiş çevre özellikleri keşfedilerek belirli bir konumda yaya köprüsüne ihtiyaç olup olmadığını tahmin etmek için bir karar ağacı modeli eğitilmiştir. Ancak bu yapılar yalnızca ihtiyaca dayanarak inşa edildiğinde kentsel bariyerlere dönüşmektedirler. Bu sebeple,

yayaların yaya köprüsü kullanımını etkileyen temel faktörler literatür incelemesi aracılığıyla saptanmış, daha sonra araştırmacının yaya köprüsü konumlarına ilişkin gözlemleri ve zorunlu tasarım kriterleri ile birleştirilmiştir.Elde edilen bulgular bir tasarım kılavuzuna sentezlenmiş ve böylece yaya beklentileri, uygulanabilir tasarım ilkelerine dönüştürülmüştür. Son olarak, geliştirilen tasarım kılavuzu temel alınarak, modelin tahmin ettiği konumlarda yaya köprülerinin inşa edilme gerekliliği ve uygulanabilirliği, araştırmacı tarafından eleştirel bir yaklaşımla değerlendirilmiştir.

Anahtar Kelimeler: Yaya Köprüsü, Yaya Tercihleri, Tahmin Modeli, Makine Öğrenimi, Tasarım Kılavuzu

To my beloved mother

ACKNOWLEDGMENTS

First and foremost, I extend my deepest gratitude to Prof. Dr. Arzu Gönenç Sorguç. From our very first meeting, she not only taught me how to conduct research but also instilled in me perseverance. She inspired me to question more, explore further, and work harder. Her belief in me has been a source of encouragement throughout this journey, and her guidance allowed me to grow as a researcher, an architect, and an individual. I consider myself incredibly lucky to have had the opportunity to work with her.

I sincerely thank my jury members Assoc. Prof. Dr. Mehmet Koray Pekeriçli and Assist. Prof. Dr. Işıl Ruhi Sipahioğlu for their valuable discussions and insightful feedback. I deeply appreciate the time and effort they dedicated to this process.

I am also profoundly grateful to Dr. Müge Kruşa Yemişçioğlu and Ozan Yetkin from the DDS Team for their support and critical feedback during my research process. A special note of thanks goes to Dr. Müge Kruşa Yemişçioğlu, whose contributions extended far beyond the academic realm. Her kindness and encouragement gave me the confidence I needed to move forward.

I would like to express my deepest gratitude to my mom Elif Yıldırım, my dad Halit Eloğlu, and my grandmother Gönül Yıldırım for their unwavering love and support. I am grateful to them for taking pride in not just the outcomes of my efforts but in the dedication and perseverance I have shown throughout the journey. I owe the biggest thanks to my mom. She made everything more colorful, and every achievement more meaningful.

I also would like to thank my dearest friends Buse Ezgi Horat, Celal Can Bilgiç, Doğuhan Barlas Sevindik, and Mehmet Ali Tekçam for their presence in my life. Every success I achieve carries a reflection of their love and companionship, as they have played an undeniable role in shaping the person I am today.

Lastly, I need to express my heartfelt gratitude to two very special people, Emire Nur Solmaz and Arda Fidansoy. They kept me motivated and dedicated along the way with their constant presence and genuine interest in the process. They showed up for me at every step, made every challenge more manageable, the most difficult moments feel lighter, and happy moments even more beautiful. They both have their own special places in my heart, and I have no doubt they will remain so in the upcoming chapters of life.

TABLE OF CONTENTS

ABSTRACT v

ÖZ vii

ACKNOWLEDGMENTS x

TABLE OF CONTENTS xii

LIST OF TABLES xv

LIST OF FIGURES xviii

LIST OF ABBREVIATIONS xxi

LIST OF SYMBOLS xxii

CHAPTERS

1 INTRODUCTION 1

1.1 Problem Statement 3

1.2 Hypothesis and Research Questions 3

1.3 Scope and Objectives 4

1.4 Methodology 5

2 LITERATURE REVIEW 11

2.1 Historical Evolution of Footbridges 12

2.2 Methods in Footbridge-Focused Behavioral Research, Pedestrian Perceptions and Preferences Regarding Crossing Facilities, and Key Factors Affecting Footbridge Usage 14

2.3 Critical Review of Literature 20

3 FOOTBRIDGE LOCATION PREDICTION MODEL 25

3.1 Built Environment Features to Extract 26

3.2 Data Collection 27
3.2.1 Road Types 31
3.2.2 Functions at Starting and Ending Points 33
3.2.3 Crosswalks, Signalized Crossings, and Public Transport Stops 34
3.3 Analysis of the Dataset and Selecting the Algorithm 36
3.4 Data Preprocessing and Training 39
3.5 Decision Tree Model Performance Evaluations 47
3.5.1 Training With Train and Test Sets: Model No.1 47
3.5.2 Training With Train, Validation and Test Sets: Model No.2..... 51
3.5.3 How Different Data Splits Cause Variation in Model Performances 53
3.5.3.1 The Impact of Class Distribution and Random State..... 54
3.5.3.2 Implementing Stratified Splitting Method for Model No.2 60
3.6 Dataset Refinement and Final Model Performance Evaluations 65
3.6.1 Hyperparameter Tuning 68
3.7 Conclusion: Results and Discussions..... 71
3.7.1 Model Evaluation Results 71
3.7.2 From Model Evaluation to Decision-Support Tool Development.. 73
4 FOOTBRIDGE DESIGN GUIDELINE 79
4.1 Development Process and Sources of Information 83
4.1.1 Literature Review Findings and Integration with Researcher's Observations 83
4.1.2 Mandatory Footbridge Design Criteria 91
4.1.2.1 Ramps 92

4.1.2.2 Stairs 93
4.1.2.3 Elevators 94
4.1.2.4 Railings and Handrails 95
4.1.2.5 Clearance 96
4.2 Constructing the Guideline 96
4.3 Critical Evaluation of Constructing Footbridges: Revising the Predicted Locations 103
4.3.1 Predicted Location No.1 103
4.3.2 Predicted Location No.2 104
4.3.3 Predicted Location No.3 105
5 CONCLUSION 109
5.1 General Discussions 109
5.2 Recommendations for Future Studies 112
5.3 Limitations 113
6 REFERENCES 115
APPENDICES 121
A. Prediction Model Dataset 121

LIST OF TABLES

TABLES

Table 3.1 Prediction model dataset step 1 28
Table 3.2 Prediction model dataset step 2 30
Table 3.3 Road type names in OSM and in the dataset 32
Table 3.4 Prediction model dataset step 3 33
Table 3.5 Prediction model dataset step 4 34
Table 3.6 Prediction model dataset step 5 37
Table 3.7 Prediction model dataset step 6 40
Table 3.8 Gini impurities for each subset 43
Table 3.9 Information Gain..... 44
Table 3.10 Performance metrics for Decision Tree and Random Forest..... 46
Table 3.11 The performance metrics of the first trained model 48
Table 3.12 The performance metrics of Model No.2..... 51
Table 3.13 Class distributions between the train and test sets of Model No.1 54
Table 3.14 Ten samples of performance metrics across different random states ... 55
Table 3.15 Summary of metrics (Mean and standard deviation)..... 56
Table 3.16 Best-performing model based on test F1 Score 57
Table 3.17 Distribution of classes among different sets for Model No.1 (random state 2)..... 58
Table 3.18 Test metrics comparison of different random states 58
Table 3.19 Learning curve, confusion matrix, and decision tree comparison 59
Table 3.20 Distribution of classes among different sets for Model No.2 61
Table 3.21 Distribution of classes among overlapping data points between different sets for Model No.2..... 61
Table 3.22 Distribution of classes among overlapping data points between different sets for Model No.2 after Stratified Splitting..... 62
Table 3.23 Comparison of test metrics before and after implementing Stratified Splitting..... 62

Table 3.24 Performance metric comparison for Model No.2 before and after Stratified Splitting 63
Table 3.25 The performance metrics of Stratified Model No.2 and Model No.1 (random state 42) 64
Table 3.26 The dataset after proximity-based feature transformation 66
Table 3.27 Test metrics comparison for Model No.1 (random state 2) before and after proximity-based feature transformation 66
Table 3.28 Learning curve, confusion matrix, and decision tree comparison before and after proximity-based feature transformation 67
Table 3.29 Performance metrics of the model with The GridSearchCV hyperparameters 69
Table 3.30 Learning Curve, confusion matrix, and tree comparison before and after tuning with the best hyperparameters by GridSearchCV 70
Table 3.31 The best-performing model to validate as the prediction tool 74
Table 3.32 Misclassified data (False Positives) 76
Table 4.1 The reviewed studies on pedestrian perceptions and preferences regarding footbridges and other crossing facilities (Developed by the author) 84
Table 4.2 Integration of literature review findings and researcher observations 87
Table 4.3 Cabin width, depth, and payload correlation 94
Table 4.4 Footbridge Design Guideline categories-First stage 97
Table 4.5 Footbridge Design Guideline Categories-Second stage 98
Table 4.6 Footbridge Design Guideline Categories-Third stage 99
Table 4.7 Footbridge Design Guideline Categories-Final stage 100
Table 4.8 Footbridge Design Guideline 101
Table 4.9 AI-generated footbridge design alternatives with a simple prompt (A) Alternatives with base image, (B) Alternatives without base image (Images generated by PromeAI in 31.01.2025 https://www.promeai.pro/ai-image-generation) 106
Table 4.10 AI-generated footbridge design alternatives with a prompt created from the guideline (A) Alternatives with base image, (B) Alternatives without base

image (Images generated by PromeAI in 31.01.2025 https://www.promeai.pro/ai-image-generation) 107

LIST OF FIGURES

FIGURES

Figure 1.1 Pedestrian Crossing Facilities (A) Crosswalk, (B) Signalized crossing, (C) Underpass, (D) Footbridge (Photographs taken by the author) 2
Figure 1.2 Thesis Methodology (Developed by the author)..... 9
Figure 2.1 Analytical Hierarchy Process for the selection of the optimal type of pedestrian crossing facility (Šimunović, Grgurević & Pašagić Škrinjar, 2012)..... 19
Figure 2.2 Decision-making matrix in Multi-Criteria Decision-Making Model for identifying the most beneficial footbridge locations (Zagorskas & Turskis, 2020) 20
Figure 2.3 The Network Graphic of Keywords using the keyword “footbridges” (Last Update: 30.01.2025)..... 21
Figure 3.1 Ankara footbridges (Photographs taken by the author) 26
Figure 3.2 Extracted built environment features (Diagram developed by the author with satellite imagery of Ankara, Türkiye [39.99907222°, 32.86410278°]. Sattelite imagery source: Airbus, 2024; Google Earth Pro, 2025) 27
Figure 3.3 Pinpointed locations of footbridges in Ankara (Graphic developed by the author with sattelite imagery of Ankara. Sattelite imagery source: Airbus, CNES/Airbus, & Maxar Technologies, 2024; Google Earth Pro, 2025) 28
Figure 3.4 Distance measuring method (Sattelite imagery of Ankara, Türkiye [39.85349898 °, 32.84941771°] image source: Airbus, 2024; Google Earth Pro, 2025)..... 36
Figure 3.5 Supervised learning algorithm logic (Developed by the author, adopted from Kerner, Campbell & Strickland, 2022)..... 38
Figure 3.6 Decision Tree and Random Forest algorithms (Developed by the author) 38
Figure 3.7 Decision Tree algorithm logic (Developed by the author) 39
Figure 3.8 Data Preparation and Splitting Process..... 42
Figure 3.9 The second data preparation and splitting process..... 47
Figure 3.10 The learning curve of Model No.1..... 49

Figure 3.11 The decision tree of Model No.1 50
Figure 3.12 The confusion matrix of Model No.1 50
Figure 3.13 The learning curve of Model No.2 52
Figure 3.14 The decision tree of Model No.2 53
Figure 3.15 The learning curve after Stratified Splitting 63
Figure 3.16 The decision tree of the best-performing model 74
Figure 3.17 The feature importances of the best-performing model 75
Figure 3.18 Predicted Locations (False Positives). (A) [39.9755344°, 32.7318129°], image source: Airbus, 2024; Google Earth Pro, 2025, (B) [39.939163°, 32.877442°], image source: Airbus, 2023; Google Earth Pro, 2025, (C) [39.988133°, 32.690948°], image source: Airbus, 2024; Google Earth Pro, 2025 76
Figure 4.1 Ad-hoc Ankara Footbridges (Photographs taken by the author) 80
Figure 4.2 Ankara footbridge street view imageries (A) [39.89250439°, 32.81321738°], image source: Google, 2023; Google Earth Pro, 2025, (B) [39.98666579°, 32.89666467°], image source: Google, 2023; Google Earth Pro, 2025, (C) [39.96893078°, 32.82957183°], image source: Google, 2020; Google Earth Pro, 2025, (D) [39.95345393°, 32.81006611°], image source: Google, 2020; Google Earth Pro, 2025 81
Figure 4.3 Site-specific constraints in location selection process (Developed by the author) 82
Figure 4.4 Footbridge-sidewalk relationship (A) Photograph taken by the author, (B) Street view imagery [39.80670838°, 32.80379579°], image source: Google, 2024; Google Earth Pro, 2025 88
Figure 4.5 Application of different types of circulation elements (Photographs taken by the author) 89
Figure 4.6 Artificial lighting applications (A) METU Footbridge night photos (Arslan Selçuk, Akan, 2005), (B-C-D-E) (Photographs taken by the author) 90
Figure 4.7 Ramp Design Requirements (Edited by the author, adopted from TS 12576, 2012) 92

Figure 4.8 Ramp design requirements (Edited by the author, adopted from TS 12576, 2012)....92
Figure 4.9 Stair design requirements (Edited by the author, adopted from TS 12576, 2012)....93
Figure 4.10 Stair design requirements (Edited by the author, adopted from TS 12576, 2012)....93
Figure 4.11 Railing and handrail design requirements (edited by the author, adopted from Detection Form for Open Spaces, 2010)....95
Figure 4.12 Ramp railing requirements (edited by the author, adopted from Detection Form for Open Spaces, 2010). 96
Figure 4.13 Clearance of 4.5 meters (Photograph taken by the author)....96
Figure 4.14 Predicted Location No.1 (39.9755344°, 32.7318129°). (A) Sattelite imagery source: Airbus, 2024; Google Earth Pro, 2025, (B) Street view imagery source: Google, 2023; Google Earth Pro, 2025....103
Figure 4.15 Predicted Location No.2 (39.939163°, 32.877442°). (A) Sattelite imagery source: Airbus, 2023; Google Earth Pro, 2025, (B) Street view imagery source: Google, 2022; Google Earth Pro, 2025....104
Figure 4.16 Predicted Location No.3 (39.988133°, 32.690948°). (A) Sattelite imagery source: Airbus, 2024; Google Earth Pro, 2025, (B) Street view imagery source: Google, 2023; Google Earth Pro, 2025....105

LIST OF ABBREVIATIONS

ABBREVIATIONS	
AHP	Analytical Hierarchy Process
AI	Artificial Intelligence
ARAS	Additive Ratio Assessment
CART	Classification and Regression Tree
CBD	Central Business District
DT	Decision Tree
EDAS	Evaluation Based on Distance from Average Solution
GBM	Gradient Boosting Machine
GLM	Generalized Linear Model
KMZ	Keyhole Markup language Zipped
MCDM	Multi-Criteria Decision-Making
MEW	Multiplicative Exponential Weighting
MNL	Multinomial Logit Model
OSM	OpenStreetMap
RF	Random Forest
SWARA	Step-Wise Weight Assessment Ratio Analysis
VGI	Volunteered Geographic Information

LIST OF SYMBOLS

SYMBOLS

S	The dataset before splitting
$\|S\|$	Total number of samples in dataset
k	The total number of classes in the dataset
i	The index representing each class in the dataset
p_i	The proportion of class i in the dataset
Gini(S)	Gini impurity of the dataset before splitting
Gini(S_{left})	Gini impurity of the left subset after a split
Gini(S_{right})	Gini impurity of the right subset after a split
$\text{Gini}_{split}(S)$	The weighted sum of the impurities of the left and right subsets
$\|S_{left}\|$	Number of samples in the left subset after a split
$\|S_{right}\|$	Number of samples in the right subset after a split
IG(S)	Information Gain
h	The clear height under the bridge deck

CHAPTER 1

INTRODUCTION

The quality of pedestrian mobility lies at the heart of creating more livable cities. As pursuing livable cities is among the main objectives of architecture, fostering inclusive, safe, accessible, and uninterrupted pedestrian mobility becomes a core responsibility of architects. However, despite its critical importance, pedestrians remain one of the most vulnerable user groups within built environments. Approximately 1.19 million people lose their lives due to road traffic crashes each year, more than half of whom are vulnerable road users such as pedestrians, cyclists, and motorcyclists (WHO, 2023).

The world has been witnessing rapid expansion in motorized road networks and ever-increasing traffic. Arterial roads are cutting through settlements with active urban life, constraining spaces for pedestrians, narrowing down the areas available for their mobility, leading to the conflicts between pedestrians and motor vehicles, and ultimately resulting in the unfortunate statistics above. Reducing the reliance on motorized transport might have a significant impact on resolving this conflict, however, it has been observed that interventions to the city infrastructures are predominantly carried out in favor of motor vehicle accessibility, and what has been restructured is pedestrian accessibility. While cities are growing increasingly centered around vehicular roads, infrastructural interventions are targeting pedestrians, and pedestrian crossing facilities (Figure 1.1) are often becoming the primary alternative to reduce the negative effects of the conflict, since infrastructure interventions for motor vehicle accessibility often face social and political resistance (Anciaes & Jones, 2018).



Figure 1.1 Pedestrian Crossing Facilities (A) Crosswalk, (B) Signalized crossing, (C) Underpass, (D) Footbridge (Photographs taken by the author)

Among these facilities, particularly footbridges (Figure 1.D) have become one of the most prevalent infrastructural intervention tools in areas with intense pedestrian-motor vehicle conflicts. In theory, they minimize the potential harm caused by motor vehicles by changing the elevation of the crossing passages and providing separated mobility routes solely for pedestrians. Therefore, despite their construction, relocation, and removal significantly require more effort and higher costs, while having more excessive maintenance and repair needs compared to at-grade facilities (Figure 1.A, 1.B); and on the other hand, due to the advantages footbridges offer compared to the other grade-separated facility, underpasses (Figure 1.C), such as faster completion times and minimal ground-level intervention, their construction is frequently preferred in multi-lane roads with fast traffic. However, while the number of footbridges is increasing day by day, a review of the literature focusing on pedestrian safety, behavior, and crossing facility alternatives revealed a significant discrepancy: rather than enhancing pedestrian accessibility, these structures are often avoided by their intended audience.

Field observations conducted by the researcher throughout this research at footbridge sites further revealed that these structures are often getting “imposed” into conflict areas in an ad-hoc manner, without the guidance of future projections regarding their long-term impacts on their surrounding environments, without considering site-specific constraints and pedestrian expectations. Such a manner consequently deters

pedestrians, transforming footbridges into barriers against pedestrian mobility, and ultimately reinforcing the very consequences of pedestrian-motor vehicle conflicts.

1.1 Problem Statement

This thesis focuses on footbridges that are "imposed" into built environments in an ad-hoc manner, without being subjected to planning. The main concern is that, rather than facilitating pedestrian mobility, these footbridges are transforming into both physical and psychological barriers.

The motivation for the research arises from the need to critically evaluate where and how to construct footbridges. The answer to the question of *where* to construct footbridges is tied to *how* to construct them since it influences the decision of whether they should be constructed in the first place. Hence, by addressing the interconnected nature of location selection and design phases, this thesis puts forward the argument that footbridge site selection processes should be guided by future projections regarding their long-term impacts on built environments, and their designs should be developed within the framework of site-specific constraints, pedestrian expectations, and mandatory design criteria, or footbridges further restrict pedestrian mobility and lower the quality of life built environments.

1.2 Hypothesis and Research Questions

In response to the problem statement, this research hypothesizes that by extracting the built environment features of existing footbridge sites, locations that need footbridges can be predicted using machine learning models, and a guideline developed around predicted locations' site-specific constraints and shared pedestrian expectations can enhance footbridge design frameworks.

The hypothesis of the research will be tested by the following two research questions:

Q1: Which built environment features are determinative in footbridge location selection? How can these features be used to train a machine-learning model for the decision-making process?

Q2: How can pedestrian expectations and key factors affecting their footbridge usage be translated into actionable design principles?

Q3: How can the trained machine learning model be enhanced into a decision-support tool for footbridges by incorporating it with a design guideline, developed within the framework of site-specific constraints, pedestrian expectations, and mandatory design criteria?

1.3 Scope and Objectives

This research focuses on footbridges which are constructed as quick infrastructure interventions where pedestrian-motor vehicle conflicts are intense. Therefore, footbridges spanning over water sources and railways are excluded from the scope of the research.

Within the scope of this research and regarding the research questions, the main objectives are:

- To develop a machine learning model to predict if footbridges are needed in given locations
- To develop a footbridge design guideline that brings accessibility, functionality, and pedestrian expectations together
- To integrate the trained machine learning model with the footbridge design guideline, ultimately establish a decision-support tool for footbridge planning and design phases

1.4 Methodology

This research employs a mixed-methods approach that integrates on-site observations, theoretical frameworks, and literature review findings with artificial intelligence (AI) methods to address the stated research problem.

Within the scope of the research, first, the evolution of footbridges throughout the historical process, and their emergence as a bridge type on their own rights as a result of pedestrian-vehicle conflicts are examined. Later the existing literature focusing on pedestrian behaviors around vehicular traffic, pedestrian preferences regarding different crossing facilities, and their expectations from footbridge designs are revisited; and the key factors affecting pedestrian decisions to use or not use footbridges are revealed. These studies provided valuable insights into what pedestrians seek when using these structures, while also highlighting the trend in the use of data-driven approaches in footbridge-focused behavioral research.

However, while the existing literature focuses on pedestrian perceptions and preferences, it does not provide an in-depth focus on the effects of footbridge's relationships with their surrounding environments. Yet, the researcher's observations at ad-hoc footbridge sites revealed that constructing these structures without considering the site-specific constraints could not meet pedestrian expectations or even mandatory design criteria. Consequently, such an approach often reinforces the very consequences of pedestrian-motor vehicle conflict that they intend to mitigate.

To address this challenge, this thesis delves into the decision-making processes for footbridges in early phases and focuses on location selection and design frameworks. By emphasizing the interconnected nature of footbridges' location and designs, a two-stage decision-support tool was proposed to address the stated research problem: a prediction model for footbridge location selection and a guideline for footbridge designs. By developing such a tool, the research aims to assist architects and urban planners in the footbridge planning and design processes.

This tool comprises two complementary stages. In the first stage, a prediction model was trained to identify whether a footbridge is needed in a given location. In this regard, the built environment features that intensify pedestrian-motor vehicle conflict and result in the need for footbridges were explored by analyzing satellite and street images of the case study city Ankara, and the characteristics that need to be considered in footbridge site selection were identified. The identified features were extracted from locations with footbridges, and the same process was applied to randomly sampled locations (equal to the number of locations with footbridges) without footbridges; later brought together in a dataset. The dataset has three hundred and ten rows of data, two columns containing categorical data and five columns containing binary data, one of which is the label to be predicted by the model. Based on the size of the dataset, and the types of available data, three tree-based algorithms (Decision Tree [DT] and Random Forest [RF]) were trained in the first step. There were no significant differences among these three models with respect to their model performances. However, among these two models, the DT model was deemed the most suitable for such a task as it allows the model's decision-making process to be monitored explicitly. After selecting the algorithm, the categorical data was preprocessed and transformed into a suitable type for the algorithm. Following, a DT model was trained using the Scikit-learn library, and the model training process proceeded with the library due to its many advantages as its highly optimized CART algorithm, built-in tools, and ease of use. Later, the effects of different dataset splits (as train-test sets and train-validation-test sets) were examined, as the performance with small datasets is expected to be sensitive to data variability. The model using two sets had a balanced class distribution, thus the model’s response to data variability was systematically tested across different random state values. For the model using three sets, the number of overlapping data points was reduced and the class distribution between its sets was balanced. Following, the effects of a proximity-based feature transformation, and hyperparameter tuning were investigated. The best-performing model with an accuracy score of 0.92 is achieved by starting the decision-making process from the root question with the feature that

has the lowest Gini impurity of 0.2981 and the highest Information Gain of 0.2018. As the aim of training such a model is to develop a tool, the best-performing model was validated as the prediction tool. Lastly, the model's false positives were examined, as they are what the tool is looking for, representing the locations where a footbridge is needed in Ankara.

However, merely identifying the need for footbridges and constructing them can further restrict pedestrian mobility if the site-specific and human-centric aspects are not regarded in the planning and design phases. In this context, a footbridge design guideline that is informed by the site-specific constraints, pedestrian expectations, and mandatory design criteria was developed for the second stage of the decision-support tool. As for the prediction model, Ankara as a vehicle-oriented city with its typical ad-hoc footbridges was selected as the source of observation for the guideline. In this regard, the impacts of site-specific physical constraints on footbridge design frameworks were examined through ad-hoc Ankara examples. Following, the literature findings across the world on the key factors affecting footbridge usage, and the contexts in which these factors have an impact were grouped by the researcher according to the actions that should be taken to address them. To enrich the dialogue between theoretical understanding and practical application, how these actions can inform the footbridge designs was discovered through researcher's observations in Ankara footbridge locations. By such an approach, the design correspondences of pedestrian expectations were thus proposed. Subsequently, the mandatory design criteria were incorporated into the guideline. By integrating site-specific constraints, pedestrian expectations, and mandatory design criteria, a framework for both context-sensitive and user-centered footbridges was proposed.

At the final stage, three predicted locations were revisited, and the model was tested using the design guideline. Although the model labeled these locations as "footbridge needed", this research does not encourage constructing footbridges. On the contrary, the research emphasizes that pedestrian accessibility should not be overshadowed by the prioritization of motor vehicle accessibility, and that safe and uninterrupted

mobility at ground level is a fundamental right for all pedestrians. However, in built environments where such structures are deemed necessary due to the constraints in modifying the existing city road networks, it is emphasized that they should be integrated into the planning process; and this study proposes a methodology to be followed for this purpose. Therefore, by revisiting the predicted locations, the necessity and feasibility of constructing a footbridge at the predicted locations were critically evaluated by the researcher using the design guideline as the main source. The methodology of this thesis is presented in the diagram below (Figure 1.2).

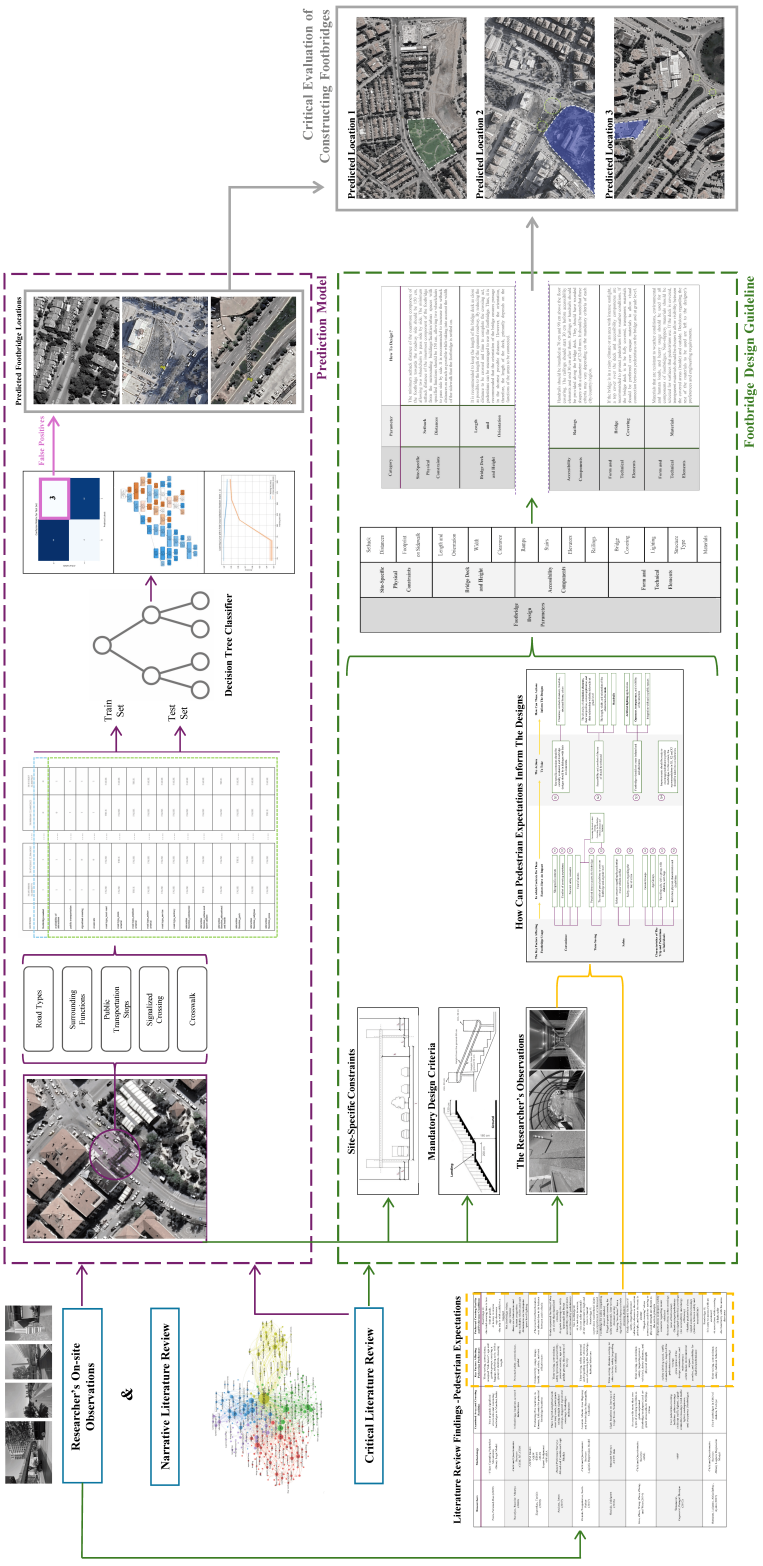


Figure 1.2 Thesis Methodology (Developed by the author)

CHAPTER 2

LITERATURE REVIEW

The emergence of bridges for non-pedestrian use and the transformation of footbridges into a bridge type in their rights are linked with the social, economic, and technological developments that underlie them (Baus and Schlaich, 2007). Starting from the primitive examples constructed with available materials found in nature to the structures of 21st-century technological advancements, the evolution of bridges represents the evolution of human history. Hence, the first section of the literature review examines the evolution of footbridges within the broader concept of bridges. This historical narrative emphasizes that footbridges are infrastructural intervention tools to provide separated mobility networks for pedestrians that emerged in pedestrian-motor vehicle conflict areas in built environments. However, despite being designated specifically for pedestrians, these structures are still avoided by their intended audience. Even on multi-lane roads with excessive traffic, pedestrians prefer to cross on ground level rather than using footbridges (Räsänen, Lajunen, Alticafarbay, Aydin, 2007). Hence, the second section of this chapter examines why footbridges are not favored by pedestrians and delves into behavioral research focusing on pedestrian perceptions and preferences regarding different crossing facilities, key factors affecting their decisions in conflict areas, and the reasons to use or not use footbridges. While the reviewed studies explore the reasons for using or avoiding footbridges, and what pedestrians expect from these structures from a user-centered perspective, they also reveal the trend of machine learning-based approaches in footbridge-related behavioral research.

Lastly, this chapter comes to an end with a critical review of the literature in the third section.

2.1 Historical Evolution of Footbridges

The evolution of bridges from the Paleolithic Age to the 21st century and the separation of footbridges as a bridge type in their rights reflect both the advances in construction technology and the changes in social landscapes. The earliest ancestors of bridges go back to the stepping stones and log bridges of the Paleolithic Age, where stones were arranged one after the other, and logs, which are probably felled trees, spanning over natural water (Bennet, 2008). Later, ropes and vines were added to the ancestors of bridges, giving rise to the early examples of suspension bridges (Tang, 2007).

The era in which bridges started to evolve more into their current contemporary meaning is when the potential of the arch form is realized. Although the arch form, perfectly suitable for compression materials such as stone, brick, and concrete that have been available for thousands of years (Tang, 2007), was used in different structures until the Roman Era. A significant transformation took place in bridge-building when the Romans applied arch form in bridge and viaduct construction (Tyrrell, 1911). During and after this period, the use of timber continued until the Renaissance, covering the Middle Ages, however, the dominant construction material was still stone.

Later, with the Age of Enlightenment in the 17th and 18th centuries, and especially with the 18th and 19th centuries Industrial Revolutions, technological demands began to encourage innovations on bigger scales, and footbridges evolved along a separate path (Baus, et al., 2007). Expanding trade, growing cities, and increased mobility demanded the development of city infrastructures, constructions, and improvements of railways, roads, bridges, and canals, which necessitated faster construction using lightweight but durable components; thus bridge-building was reshaped by the use of iron, steel and reinforced concrete (Bennet, 2008; Tyrrell, 1911). In the 18th century, iron as a building material and timber trusses as a construction principle were replacing masonry arc construction which had reached its peak in this period (Bennet, 2008). Iron has a higher strength than stone but a

lower tensile capacity than steel, and it was used in bridge construction until steel was mass-produced and used as a building material around the mid-19th century (Tang, 2007). The arrival of steel and the suitability of structural steel for constructing all types of bridges (Parke, Harding, 2008) completely changed bridge-building. Steel also paved the way for concrete to become one of the most widely used materials in bridge construction today. Reinforcing concrete, which is brittle like stone, good in compression but not in tension, with steel allowed it to be used in long-span bridges (Bennet, 2008).

Today, in addition to all the materials listed above, recyclable materials are used in bridge construction. The changes in construction techniques and dominant construction materials affected the types of classification, and now bridges can be classified in several ways, such as the construction materials, usage, structural form, geometric shape, span length, and span types, deck location, and if movable, superstructure's position (Lin, Yoda, 2017).

The journey of materials is not solely related to the evolution of bridge-building practices but also other infrastructure facilities. The increasing need for the expansion of infrastructure with the Industrial Revolutions, the necessity for bridges to serve freight transport, and especially the rapid spread of motor vehicles in the 20th century have changed the infrastructures of cities to a great extent. The increase in the number of motor vehicles and their speed has resulted in the expansion of highway networks within cities and gave rise to pedestrian-motor vehicle conflict. This conflict led to the separation of pedestrian and vehicular traffic, and necessitated interventions in built environments that can serve for safe pedestrian mobility. Thus, the bridges that are specifically designated for pedestrians have become a bridge type of their own.

2.2 Methods in Footbridge-Focused Behavioral Research, Pedestrian Perceptions and Preferences Regarding Crossing Facilities, and Key Factors Affecting Footbridge Usage

The previous section highlights that footbridges emerged to provide separated mobility routes solely for pedestrians to minimize the negative impacts of pedestrian-motor vehicle conflicts, and today, footbridges are often constructed as infrastructural interventions in built environments where this conflict is particularly intense. Yet, these structures have neither become a solution to the conflicts nor are they preferred by pedestrians.

There is a growing body of literature asking why pedestrians avoid these structures, focusing on their behaviors around conflict areas, their perceptions, and preferences regarding different crossing facilities. In line with the problem statement of this thesis, footbridge-related behavioral research across the world has been reviewed, and key factors affecting pedestrian decisions around vehicular traffic areas, and the reasons for choosing/not choosing footbridges were revealed.

In a study by Guo, Zhao, Wang, Zhou, Zhang, and Wets (2014), the researchers emphasized that traffic conditions and human factors have a significant impact on the crossing behavior of pedestrians, and the decision to cross a road is fundamentally influenced by the characteristics of the trip, the infrastructure, and pedestrians' characteristics. They analyzed pedestrian crossing behaviors around different crossing facilities, conducted field and questionnaire surveys in Beijing, and later used the data in a multinomial logit (MNL) model. The model revealed the most influential and critical factors in pedestrian decisions. According to the results, when safety concerns regarding motor vehicles were prioritized, the majority of pedestrians preferred grade-separated facilities, however, when pedestrians prioritized time-saving and convenience, grade-separated facilities were the least preferred, followed by at-grade facilities, and the majority of pedestrians preferred to jaywalk. The detour distance also had a notable effect, in a parallel vein with the previous result, pedestrians tended to jaywalk when the detour distance increased.

Another study finding was that pedestrians unfamiliar with the area were more selective in their facility choices.

Familiarity with the area was found to be an influential factor in pedestrian decision-making in another study conducted by Räsänen et al. (2007). The researchers investigated the key factors affecting the use or non-use of footbridges by selecting five footbridges that span over 3-4 lanes of vehicular traffic in the central business district (CBD) of Ankara Türkiye. They conducted field and questionnaire surveys at the selected footbridge sites on pedestrians who used footbridges, crossed under them, and crossed within 25 meters distance of them. Pedestrians were asked how they perceive footbridges as crossing facilities, their familiarity with the CBD, the frequency of using the selected footbridges, and their perception of safety regarding vehicle traffic in the area. Additionally, they were asked about how "safe" these structures are, their ease of use, and whether using them saves time. These questions were also asked about the “unofficial” crossings in the same area. According to the results, the footbridge usage rates varied between 6.3% and 62.9%. The collected data were then used for a binary logistic regression model, and the results indicated that convenience is a key factor, and the ease of access to the bridge increases the likelihood of preferring footbridges. Time-saving was another key factor. Pedestrians preferred footbridges if they see them as a time-saving option, compared to the time to cross on street level. Besides, the pedestrians who were familiar with the areas were less likely to prefer footbridges, and the results indicated that footbridge usage is a habitual behavior rather than coincidental. The sense of safety did not play a key role according to the results of this study.

However, another study by Oviedo-Trespalacios & Scott-Parker (2017) highlighted a significant point that perceived footbridge safety is linked with the social context of the footbridge locations, and fear of crime and violence is one of the factors affecting pedestrian crossing preferences. This research investigated the influencing factors on pedestrian crossing behavior by using a footbridge in Barranquilla, Colombia, around the "Avenida Alberto Assa" highway, which is exposed to high vehicular traffic flow, and constant and mixed-aged groups of pedestrians. The

researchers collected data by conducting a questionnaire survey on pedestrians who used the footbridge to cross and preferred to cross by the highway. Survey participants were asked about their crossing habits, how they perceive risks, and the footbridge itself, along with their socio-demographic information. Later, the researchers used the data to first calculate the response frequencies for both of the crossing modes and then used a backward stepwise regression model to identify the factors influencing crossing preferences. Only 18% of pedestrians used the footbridge, and the outcomes indicated that the strongest predictor was the frequency of prior footbridge usage, which supports Räsänen et al. (2007). The footbridge was not found convenient, and the footbridge accessibility elements were unfavored as they were in close proximity to the highway. The perceived crossing time when using a footbridge was not considered an outstanding factor, while the perceived distance from the illegal crossing at street level was decisive. The climatic conditions also affected the usage, showing that high temperatures and humidity deterred footbridge usage.

Patra et al. (2020) also investigated the pedestrian crossing facility preferences in two areas where at-grade signalized crosswalks and footbridges coexist in Mumbai, India by video-capturing pedestrian movements. They collected data by extracting the number of pedestrians using the facilities, crossing time for both facilities, waiting time at the signal, and personal characteristics of the pedestrians by visual observation. Only 26% of pedestrians preferred to use the footbridge, and they investigated the low usage of the footbridge using a binary logit model to find the key influential factors in their decisions. The proportions of crossing facility preferences were determined, the possibility of preference reasons was analyzed and common characteristics in pedestrian behaviors were grouped. The outcomes demonstrated that the key factors affecting pedestrian decisions depend on the "risk factor" that pedestrians accept before attempting to cross, that pedestrians tend to reduce the crossing time and time to wait for crossing (valid for both of the facilities), and that an increase in pedestrian age decreases the rate of footbridge use (thought to be due to the necessity of climbing the structure). Pedestrians preferred to use a

footbridge when traveling with a child. Additionally, male pedestrians had a higher rate of preferring footbridges compared to female pedestrians, and young pedestrians to old pedestrians, which aligns with the previous findings by Anciaes et al. (2018). The researchers conducted a two-stage survey in three English neighborhoods near busy roads. They investigated pedestrian choices between grade-separated and at-grade facilities, without introducing illegal crossing as an option. While the safety concerns regarding motor vehicles were a factor for pedestrians to choose footbridges or underpasses, the findings of the preliminary qualitative survey demonstrated that pedestrians preferred using at-grade facilities due to inconvenience, lack of accessibility, and personal safety concerns, especially women, older people, and disadvantaged pedestrians. In the quantitative phase, the researchers conducted a rating exercise and stated preference survey, to investigate the trade-offs in pedestrian preferences of different facilities and walking distances. The outcomes demonstrated that pedestrians preferred to walk even additional distances to avoid grade-separated facilities. The willingness to walk depended on many individual characteristics, the purpose of the trip, carrying luggage or not, and climate conditions. The outcomes of this study support many aspects of the other studies, indicating that time-saving, convenience, accessibility, fear of crime, individual characteristics, and the purpose of the trip have key roles in pedestrian decision-making processes.

Another study by Sinclair and Zuidgeest (2016) highlighted that along with time-saving and convenience, the perception of risk was a significant factor in crossing decisions. The research is based on intercept surveys in eight locations on Cape Town freeways, selected by monitoring 9 freeway locations (one of the locations was later excluded from the research due to safety concerns) with high pedestrian activity, focusing on pedestrian motivations to choose at-grade facilities or footbridges. The pedestrians were asked about their primary and secondary motivations for crossing at-grade or by a footbridge. They were later asked about how they perceive risks. According to the outcomes, safety concerns regarding motor vehicles were the primary motivation for footbridge users, followed by having “no

choice" and time-saving. For at-grade crossers from the areas with a footbridge nearby, the primary motivation was time-saving and distance-saving, followed by having "no choice", while traffic-related safety concerns were rarely mentioned.

Another study conducted by Banerjee, Raoniar & Maurya (2020) emphasized the importance of understanding the factors affecting footbridge usage and conducted field and questionnaire surveys at 14 footbridge locations across 6 Indian cities. The researchers investigated the key factors under four main contexts: mobility friction (ease of mobility), safety and security (perceived security and fear of crime), vertical connectivity (accessibility elements), and horizontal connectivity (connected destinations by footbridges). They collected data in adequate pedestrian flow areas on footbridges that have single entry and exit, covering demographic characteristics, existing conditions of the footbridges, future usability of the footbridges, and field observations such as walkable width, riser dimension, and land-use type. They employed and compared three machine learning algorithms, Generalized Linear Model (GLM), Random Forest (RF), and Gradient Boosting Machine (GBM), to predict key factors affecting pedestrian footbridge usage. According to the results, GBM performed as the best algorithm for the task. The outcomes demonstrated that safety and security had the most influence on pedestrian decisions, and gender had a key role in this context. Male pedestrians were more likely to prefer footbridges. Age also had an effect particularly regarding to the ease of using a footbridge, as age increased, the usage of footbridges decreased. Inadequate walkable widths, availability of obstructions and human congestion, in adequate stair dimensions, and poor lighting were common issues, however, this study highlighted the need for location-specific footbridge designs.

Another study that underscores the need for location-specific footbridge designs, as well as the importance of considering diverse pedestrian groups' preferences regarding different crossing facilities was conducted in 2012 by Šimunović, Grgurević & Pašagić Škrinjar. The researchers proposed a multi-criteria decision-making process using the Analytical Hierarchy Process (AHP) for the selection of the optimal type of pedestrian crossing facility (Figure 2.1).

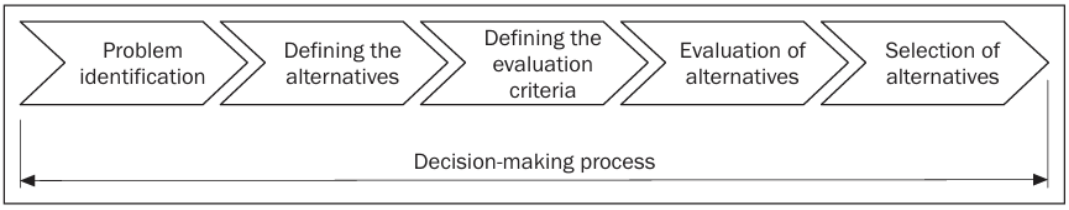


Figure 2.1 Analytical Hierarchy Process for the selection of the optimal type of pedestrian crossing facility (Šimunović, Grgurević & Pašagić Škrinjar, 2012)

The researchers evaluated four pedestrian crossing facilities: zebra crossings (without traffic lights), signal-controlled crossings (with traffic lights), underpasses, and overpasses (footbridges). The main criteria for the decision-making process (what do pedestrians prioritize for crossing action) were safety (driving speed, traffic volume/intensity, length of the pedestrian crossing), energy, price (prices of the design, construction, and maintenance), and other (noise, environmental impact, comfort, and accessibility for disabled pedestrians). These criteria were evaluated using stakeholder-specific priorities through comparisons between four scenarios: experts, investors, pedestrians with disabilities, and healthy pedestrians. AHP was employed to calculate the weighted score for each crossing facility; later how the changes in criteria weight affected the final alternative rankings were assessed by sensitivity analysis. According to the results, experts prioritized safety and selected underpasses, investors prioritized cost-effectiveness and selected zebra crossings, pedestrians with disabilities prioritized accessibility and energy efficiency and selected signal-controlled crossings, and lastly, healthy pedestrians also selected signal-controlled crossings due to the balance between safety and accessibility.

A particular study in footbridge related literature was study conducted in 2020 by Zagorskas & Turskis emphasizing that footbridges are often constructed without considering their necessity and usefulness and proposed a machine learning-based decision-making process to identify the most beneficial footbridge locations to avoid redundant bridges in the future in Kaunas, Lithuania. The authors viewed footbridges as tools to improve the pedestrian mobility networks; thus they evaluated the benefits and feasibility of these structures using a hybrid Multi-Criteria Decision-Making

(MCDM) model (Figure 2.2), incorporating five decision-making methods: Multiplicative Exponential Weighting (MEW), method of Evaluation Based on Distance from Average Solution (EDAS), an Additive Ratio Assessment (ARAS) method, expert judgment, and Step-Wise Weight Assessment Ratio Analysis (SWARA).

$$X = \begin{bmatrix} x_{01} & \cdots & x_{0j} & \cdots & x_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix}; \qquad i = \overline{0,\ m};\ j = \overline{1,\ n},$$

Figure 2.2 Decision-making matrix in Multi-Criteria Decision-Making Model for identifying the most beneficial footbridge locations (Zagorskas & Turskis, 2020)

Using such a model enabled the decision-maker to actively participate in the decision-making process. Using this opportunity, an expert panel identified six key criteria to evaluate the alternative footbridge locations. The criteria used in the research are as follows: Connectivity, usage, image, health, road safety, and cost-effectiveness. Each criteria was ranked by the experts including urban planners, transportation planners, architects, and municipal officials familiar with local conditions; later these criteria were weighted using the SWARA method. Following, the researchers proposed five different locations in Kaunas, Lithuania as footbridge location alternatives, and these locations were ranked based on their alignment with these criteria. In the end, the best location was identified based on its balance across the criteria. The study is particularly noteworthy as it highlights the importance of expert judgment and community perspectives in decision-making processes in footbridge location processes.

2.3 Critical Review of Literature

In the previous section, footbridge-related literature that remains within this thesis's scope and problem definition were presented. However, footbridge-related literature

covers a wide range of studies from diverse disciplines and perspectives. Hence, a broad range of were sourced from the Scopus database using only “footbridges” as the keyword without incorporating additional terms.

Initially, the search was performed on the following subject areas among available areas: “Engineering”, “Computer Science”, “Social Sciences”, “Psychology”, “Multidisciplinary”, and “Decision Sciences”, and performed on the following document types among available types: “Article”, “Conference paper”, “Review”, “Book chapter”, “Conference review”, and “Book”. The number of publications in the field of engineering was 8,687, computer science was 1,741, social sciences was 891, psychology was 151, multidisciplinary was 122, and decision sciences was 121. After the filtering, the total number of exported publications decreased to 9,558. Using this bibliographic data, a keyword co-occurrence map was created with VOSviewer (https://www.vosviewer.com/). The minimum number of occurrences of a keyword was set to 50 out of 42,052 keywords, and 364 of them met the threshold. The first network graphic of keywords is as follows:

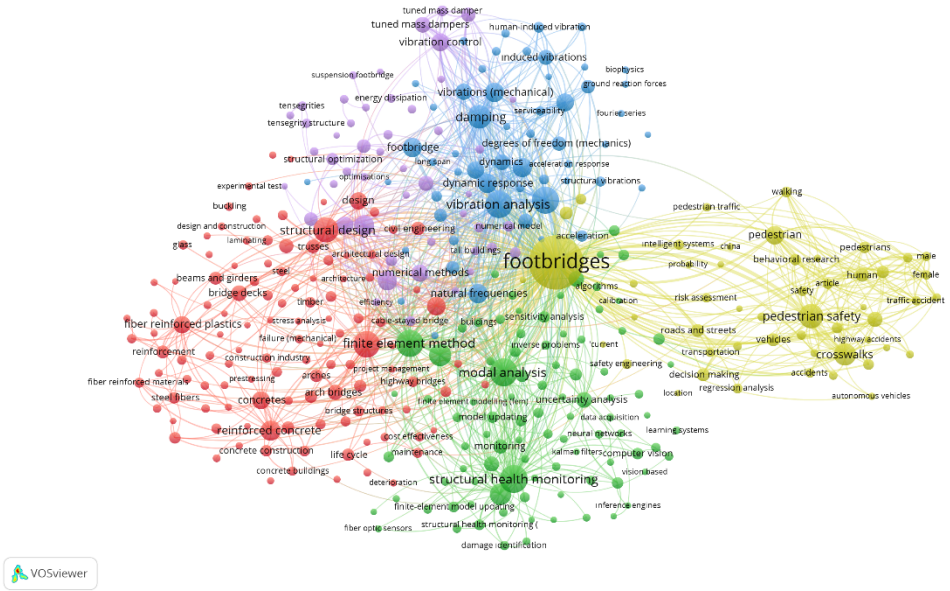


Figure 2.3 The Network Graphic of Keywords using the keyword “footbridges” (Last Update: 30.01.2025)

By not limiting the initial search to additional keywords, the wide spectrum of footbridge-related studies was illustrated. As shown in the graphic, the “footbridges” appear as the central node, while the engineering and design-focused studies tend to be more clustered, and pedestrian-focused studies tend to have a distinct branch (yellow cluster). The size of the nodes represents the significance of the keywords within the network. For the yellow cluster, the sizes of the nodes highlight that pedestrian safety, crosswalks, decision-making, vehicles, roads, and streets are central themes in footbridge-related pedestrian research.

As presented in the previous section of the literature review, the majority of the research within the body of footbridge-related pedestrian behavioral literature shares common perspectives and methods, focusing on pedestrian decision-making processes in conflict areas, their perceptions regarding footbridges, and the key factors affecting footbridge usage. These studies are of great importance as they provide context and subjective insights into pedestrians' motivations to use or not use these structures. Yet, the site-specific factors and the relationships that footbridges establish with their surrounding environments, which inherently shape the footbridge designs, and thus, pedestrian expectations, have not been studied in existing literature. However, as stated in the problem statement of this thesis, footbridges that are not constructed and designed without careful evaluation of site-specific constraints also fail to meet pedestrian expectations and even mandatory design criteria.

This thesis underscores the importance of considering the interplay between built environmental features and pedestrian expectations to ensure these structures are not transforming into urban barriers; puts forward the argument that pedestrian-focused studies get connected to other fields and offers a more comprehensive approach to enrich the overall discourse.

Another notable point in the reviewed literature is the trend in using machine learning-based methods for footbridges and behavioral research. Majority of these studies combine qualitative and quantitative approaches, obtain pedestrian

preferences through questionnaires, and employ machine-learning models to understand the most influential factors in decision-making processes, capture the patterns in the data, and predict future decisions and preferences of pedestrians. While these studies mainly focus on existing facilities, the outcomes demonstrate the actions to take in footbridge designs. As presented in the section above, a particular study focused on the location selection process, again employing machine learning methods.

Drawing on the findings from studies across the world, both the first and second objectives of this thesis were refined as it can address the shared needs at urban scale for both location selection and design processes: to develop a machine learning model to predict if a given location needs a footbridge and to develop a design guideline that addresses site-specific constraints identified through the initial prediction model while also incorporating pedestrian expectations obtained from research across the world and mandatory design criteria.

By incorporating observational findings, data-driven approaches, and user-centered approaches, this thesis provides a comprehensive understanding of footbridge planning and design and aims to become a resource for future studies.

CHAPTER 3

FOOTBRIDGE LOCATION PREDICTION MODEL

The main concern of this thesis is the ad-hoc manner in footbridge construction, which overlooks the interplay between built environmental features and pedestrian expectations. The footbridges constructed by disregarding their surrounding site-specific constraints also fail to satisfy pedestrian expectations and mandatory design criteria, transforming footbridges into urban barriers for their intended users. To address this challenge, this research aims to provide a comprehensive understanding of footbridge planning and design. It proposes a decision-support tool comprising two complementary stages: a prediction model for location selection and a guideline for design phases.

The first stage of the decision-support tool begins with developing a machine learning model to predict the need for footbridges in a given location. To train such a model, first, the built environment features that intensify conflict, position pedestrians in a vulnerable situation, thus resulting in the need for these structures to be discovered. To identify the shared characteristics of footbridge locations, Ankara, Türkiye was selected as the observation, thus, the data collection source for this discovery. Ankara is the capital of Türkiye and the second most populated city, with a population of approximately 5.8 million (Türkiye İstatistik Kurumu [TÜİK], 2024). Ankara is a notable example of a vehicle-oriented city, with its narrow sidewalks that force pedestrians to navigate around multi-laned arterial roads cutting through high pedestrian activity areas and with its typical ad-hoc footbridges in high conflict areas.



Figure 3.1 Ankara footbridges (Photographs taken by the author)

3.1 Built Environment Features to Extract

As outlined in the above sections of this thesis, footbridges have become infrastructural interventions to separate pedestrian mobility from the potential harm posed by motor vehicles. Thus, the data collection process first started by examining the types of vehicular roads (e.g. arterial road, local road) that footbridges are constructed on. However, even if vehicular roads maintain their same high-risk features over long distances, footbridges are constructed only at certain points. This situation indicates that in addition to the road characteristics, the building functions and human activities located in the vicinity are important determinants in footbridge location selection. Thus, the function of areas that footbridges connect at grade were collected as data.

In a parallel vein, the role of public transportation stations should be taken into account, since these facilities periodically facilitate human flow at certain points within cities. Hence, along with the data on the functions at the start and end points of footbridges, data on the existence of public transportation facilities was collected.

Lastly, as reviewed in the previous research, another important determinant is the coexistence of other pedestrian crossing facilities, which affects pedestrians' footbridge usage preferences. Hence, the data on the existence of other pedestrian crossing facilities was collected. The extracted features of built environments are given in the diagram below (Figure 3.2).



Figure 3.2 Extracted built environment features (Diagram developed by the author with satellite imagery of Ankara, Türkiye [39.99907222°, 32.86410278°]. Sattelite imagery source: Airbus, 2024; Google Earth Pro, 2025)

3.2 Data Collection

After identifying the built environment features that play key roles in footbridge location selection processes, and selecting the case study city, the data collection process began by Ankara footbridge locations. In this regard, a KMZ file containing 170 pinpointed locations was obtained from the Ankara Metropolitan Municipality in 2024, March by email. This KMZ file consists of footbridges that have been constructed and are currently in use, footbridges that have been designed but not yet constructed, along with several underpass locations in Ankara. Based on the scope of the research and the problem statement, 12 underpasses, 2 footbridges that cross above railways, and 1 footbridge that is integrated with a motor vehicle road are excluded from the data, which resulted in the number of the pinpointed locations decreasing to 155. The pinpointed locations of footbridges in Ankara are given below (Figure 3.3).

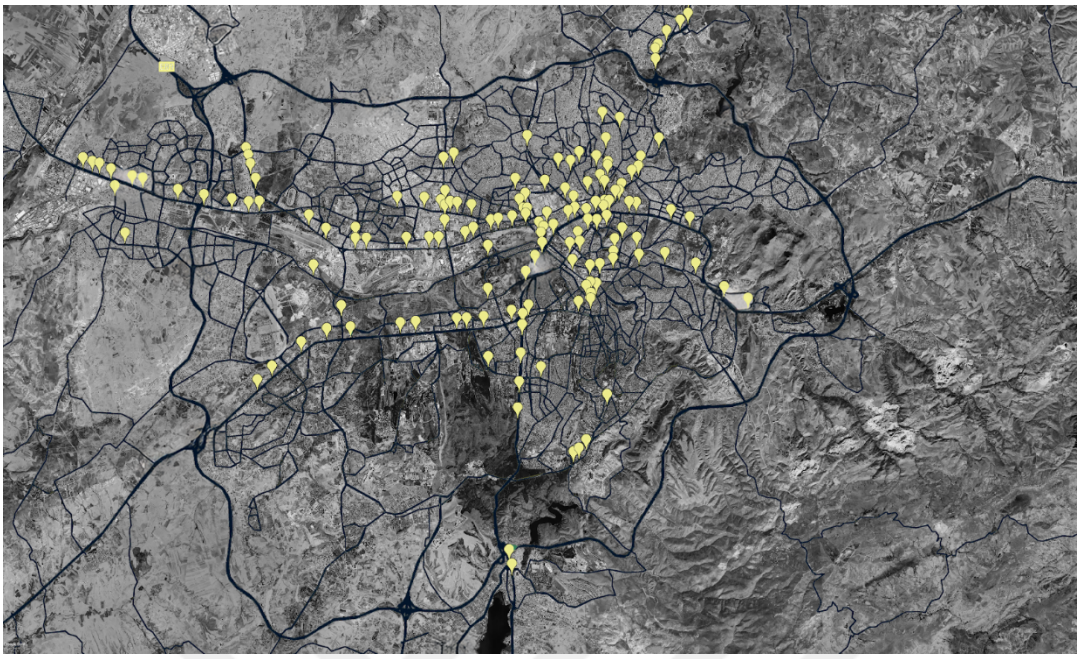


Figure 3.3 Pinpointed locations of footbridges in Ankara (Graphic developed by the author with sattelite imagery of Ankara. Sattelite imagery source: Airbus, CNES/Airbus, & Maxar Technologies, 2024; Google Earth Pro, 2025)

By creating a new dataset, the remaining 155 locations were exported as coordinate values and presented under the “coordinates” column. Following, the second column “footbridge needed” is added to the dataset. This column indicates the presence of a footbridge, thus, the rows under this column corresponding to their coordinates of are added to the dataset and presented in the dataset with “1” (Table 3.1).

Table 3.1 Prediction model dataset step 1

coordinates	footbridge needed
39.85349898 32.84941771	1
39.97420183 32.59614303	1

To train a model that predicts the need for footbridges, it is essential to provide the features of locations both with and without footbridges to the model. This allows the model to learn the patterns in built environments that do and do not necessitate footbridges. Therefore, in the second step of constructing a dataset, along with the locations with footbridges, the locations without footbridges were added to the dataset. The coordinates of locations without footbridges were obtained by downloading the road network data of Ankara (Data source: OpenStreetMap contributors, 2025. Contains information from OpenStreetMap, made available under the Open Database License [ODbL]) from OpenStreetMap (OSM) in 2024, April. OSM is a free and open-access spatial database containing geographic data and information, and the most famous example of Volunteered Geographic Information (VGI) online (Mooney & Minghini, 2017). It is a resource that can be updated by residents who experience the city firsthand and witness the changes taking place in the environment. Therefore, it was deemed appropriate to use it as a data source.

This road network dataset consists of 17 columns and 88.343 rows. In this dataset, the roads of Ankara are divided into different road segments. To clarify what is meant by the road segment, a single highway in Ankara is divided into various road segments, and a numerical identifier (osm_id) is given to each separated segment. Each row refers to a different road segment, and following the same logic, the other columns in the dataset contain various information about these road segments.

The coordinate pairs that create the corresponding road segment with the same osm_id are found under the “geometry” column. The x-coordinate and the y-coordinate for a coordinate are separated by space, and different coordinates are separated from each other by commas. As has been done for locations with footbridges, coordinates of roads without footbridges should be obtained from this dataset. Among the coordinates under the “geometry” column, 155 coordinate pairs (equal to the footbridge locations) were selected from different rows using a Python script that randomly samples the coordinates. These coordinates were then checked with the footbridge coordinates to see if there were any overlaps, and no overlaps

were detected. Subsequently, these coordinate values were added to the dataset under the “coordinates” column and were given the value “0” under the “footbridge needed” column.

It should be noted that the “coordinates” column was placed in the dataset to facilitate the data collection process, therefore it was not included in the model training process. On the other hand, the “footbridge needed” column that indicates the the presence of footbridges with “1” and absence of them with “0” is the label that the model will be predicting (Table 3.2).

Table 3.2 Prediction model dataset step 2

Coordinates	Footbridge Needed
39.85349898 32.84941771	1
39.97420183 32.59614303	1
⋮	⋮
39.9950169 32.84852021	0
39.9334287 32.8687625	0

After obtaining the locations with and without footbridges in Ankara, the following step was to collect further data (built environment features to extract), which will be the features that the model tries to learn for predicting the label. Due to the lack of open-access data, the features of interest were collected by the researcher. Using the coordinates in the dataset, satellite and street images of Ankara were analyzed by the

researcher, and the relevant information on OSM, Google Maps, and Google Earth Pro were accessed, if available.

3.2.1 Road Types

The first step when expanding the dataset was to collect data on the road types as mentioned in the upper sections. Since the data will be collected from Ankara, Türkiye, the definitions of the Turkish General Directorate of Highways were examined regarding the road types in Türkiye.

Türkiye Highway Traffic Regulation defines a highway as “a strip of land, bridges, and areas open to public use for traffic” (1997). In this document, highways are divided into two-way highways, one-way highways, divided highways, access-controlled highways (motorways), express roads, passage roads, connection roads, bicycle paths, pedestrian roads, main roads, and secondary roads. While these broad definitions contain details about the general characteristics of roads in any city in Türkiye, further information is needed to understand the hierarchical relationship of all roads in the road network of Ankara. Thus, further information about the relevant roads is collected via OSM, which labels the road types according to their “importance” in the road network hierarchy. The process is as follows:

First, the OSM website (https://www.openstreetmap.org/) was accessed, and the 'Map Data' option under the 'Layers' section was activated. Later, the coordinates were searched using the search bar, with one coordinate per search. Thus, the road segment to the corresponding coordinate was accessed. By clicking on the road segment on the map, an information box appeared on the left-hand side of the screen. Then, the corresponding road type to the “highway” tag in this information box was taken and added to the dataset under the “road type” column. This process was repeated for all coordinates in the dataset.

The road type names obtained from OSM were revised and later added to the dataset. The road type names in OSM and their corresponding names in the dataset are as follows:

Table 3.3 Road type names in OSM and in the dataset

Road Type Names in OSM	Road Type Names in the Dataset
trunk	main arterial
primary	medium arterial
secondary	minor arterial
service	service road

The reason behind the revision is to provide easier understanding of the hierarchical order of the roads for the readers. Trunk roads (referring to intercity roads within Türkiye), primary roads that generally connect large towns and secondary roads that connect smaller towns. For this reason, trunk roads are added to the dataset as main arterial, primary roads as medium arterial, and secondary roads as minor arterial. Additionally, mid-block roads and roads that do not connect neighborhoods, arteries, or settlements were added to the dataset as "local roads" regardless of the functions that they were surrounded by. Due to its specific function that it refers to, the service road retained its name. Since pedestrian access is not allowed, freeways (tagged as “motorway” in OSM) were not considered as data collection sources and were excluded from the scope of the research.

It is worth noting that the accuracy of the data collected via OSM was cross-checked by Google Maps and Google Earth Pro (web and desktop versions). The outdated and missing data were corrected and then added to the dataset. Further, the footbridge locations were visited in person, and the accuracy of the data was reconfirmed. This

process is valid for all information under all columns in the dataset. The third step of the dataset is given in the table below (Table 3.4).

Table 3.4 Prediction model dataset step 3

coordinates	footbridge needed	road type
39.85349898 32.84941771	1	medium arterial
39.97420183 32.59614303	1	main arterial
⋮	⋮	⋮
39.9950169 32.84852021	0	local road
39.9334287 32.8687625	0	medium arterial

3.2.2 Functions at Starting and Ending Points

The following step was to discover the interplay between footbridges and human activity. Thus, the data on the functions at the starting and end points of footbridges were added to the dataset. The functions that correspond to dense human activity throughout the day or at certain intervals such as educational and healthcare, commercial, parks, culture and sports centers, and religious buildings were represented with “1” under the “availability of attractions” column and represented by their functions under “attraction function” column. Residential, military, and industrial zones and governmental office buildings were presented under the “availability of attractions” column with “0” and the “attraction function” column with “none” (Table 3.5).

Table 3.5 Prediction model dataset step 4

coordinates	footbridge needed	road type	availability of attractions	attraction function
39.85349898 32.84941771	1	medium arterial	1	culture and sports centers
39.97420183 32.59614303	1	main arterial	1	park
⋮	⋮	⋮	⋮	⋮
39.9950169 32.84852021	0	local road	0	none
39.9334287 32.8687625	0	medium arterial	1	educational and health

3.2.3 Crosswalks, Signalized Crossings, and Public Transport Stops

Previously reviewed studies focusing pedestrian preferences in the act of crossing have been discussed through the facilities of crosswalks, signalized crossings, and footbridges. Building upon these studies, the relevant data is collected, and the interplay between the coexistence of footbridges and these facilities was explored. Besides, the existence of public transportation stops, and the “walkable distance” for pedestrians are of significant factors in footbridge usage. By collecting data on these features, it was aimed to gain insights into whether footbridges are preferred in the presence or absence of these facilities or to discover whether there is a correlation or not. In this regard, first, the distance limits between these facilities were decided.

The necessity of these facilities, the parameters that contribute to the walkability of a city, and most fundamentally, the act of walking are associated with a diverse range of factors such as the individual characteristics of the pedestrians, the purpose of the

trip, ‘actual’ and ‘perceived’ security, and the physical and social characteristics of built environments (Loutzenheiser, 1997; Daniels, Mulley, 2013; Akkar Ercan, Belge, 2016; Yang & Diez-Roux, 2012). Therefore, defining a walkable distance through a metric measurement alone would be insufficient. The same measurement would not suit the character of every environment. However, determining a distance limit as a frame for observation can be a step towards discovering relationships between these facilities with each other. For this reason, it was decided to use distances of 400-meter (for bus stops), and 800 meters (for rail stations), which are commonly accepted as the walkable distance to a transportation facility by the public transit industry (El-Geneidy, Grimsrud, Wasfi, Tétreault, Surprenant-Legault, 2013).

The choice of using 400 and 800 meters as limits does not imply that this measure definitively determines walkable and not-walkable distances for every location. While using these measures, the literature focusing on the errors that occur when using the Euclidean distance (El-Geneidy et al., 2013) has not been ignored; rather, these measures only serve as a filter for collecting data. Following this decision, the coordinates in the dataset are measured by rulers on Google Earth (Figure 3.4). Public transportation stops located within the limit dimensions are added to the dataset with the value of “1”, corresponding to their relevant coordinates. The facilities outside of the circle were added with the value of “0”. On the other hand, for crosswalks and signalized crossings, a 200-meter limit was applied with a 50-meter measurement error margin. Thus, crosswalks and signalized crossings located within 250 meters were added to the dataset with the value of “1”.

Additionally, if crosswalks and signalized crossings are not located on the exact road that the coordinates belong to, regardless of whether they are located within the limited distance or not, they are given a value of “0” in the dataset. There is no obligation for public transportation stops to be located on the exact road, only the distance requirement must be met to give the value “1”.



Figure 3.4 Distance measuring method (Sattelite imagery of Ankara, Türkiye [39.85349898 °, 32.84941771°] image source: Airbus, 2024; Google Earth Pro, 2025)

3.3 Analysis of the Dataset and Selecting the Algorithm

The data on built environment features of existing footbridge locations and randomly sampled locations without footbridges in Ankara were collected; and later brought together into a dataset and presented in the section above. The extracted features are as follows:

The type of roads that footbridges cross above, (e.g. arterial roads or local roads), the availability of attractions and their specific functions at the areas connected by the footbridges, the presence of public transportation stations, crosswalks, and signalized crossings. A portion of the dataset is given below (Table 3.6).

Table 3.6 Prediction model dataset step 5

coordinates	footbridge needed	road type	availability of attractions	attraction function	public transportation	signalized crossing	crosswalk
39.85349898 32.84941771	1	medium arterial	1	culture and sports centers	1	1	1
39.97420183 32.59614303	1	main arterial	1	park	1	0	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
39.9950169 32.84852021	0	local road	0	none	1	1	1
39.9334287 32.8687625	0	medium arterial	1	educational and health	1	1	1

The dataset has 310 rows (excluding the column names row), 2 columns containing categorical data (“road type” and “attraction function”), and 4 columns containing binary data (“presence of crosswalk”, “presence of signalized crossing”, “presence of public transportation”, “availability of attraction function”). The binary data under the “footbridge needed” column is the label to be predicted by the model. As mentioned above, the “coordinates” column was not included in the training process.

Thus, by using this dataset, the model to be trained will produce two binary predictions: “footbridge needed” and “no need for footbridge”. In order to perform such a task using labels, the model should be selected from supervised learning algorithms (Figure 3.5).

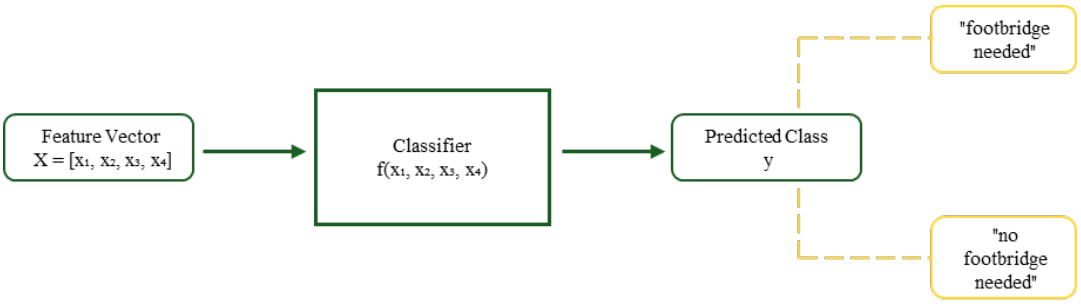


Figure 3.5 Supervised learning algorithm logic (Developed by the author, adopted from Kerner, Campbell & Strickland, 2022)

However, the characteristics, type, and number of data to be used are key factors in choosing the appropriate algorithm. Considering the structure of this dataset, tree-based algorithms for classification tasks that are capable of handling both categorical, numerical, and binary data stand out as suitable choices. (Figure 3.6).

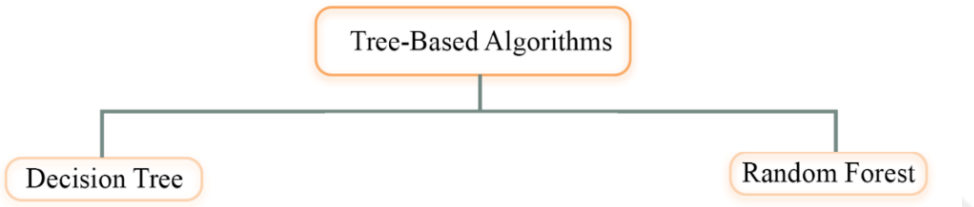


Figure 3.6 Decision Tree and Random Forest algorithms (Developed by the author)

Decision Tree and Random Forest algorithms are both supervised learning algorithms used for classification and regression tasks that split the data into subsets based on feature vectors until no further split can be produced, or when the stopping criteria are met. The tree-like structure of Decision Tree algorithm is demonstrated in the diagram below (Figure 3.7).

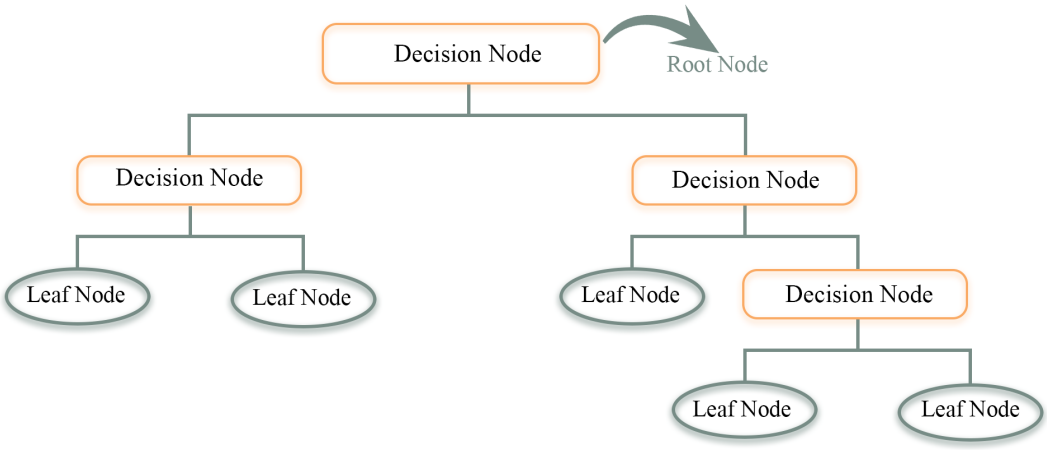


Figure 3.7 Decision Tree algorithm logic (Developed by the author)

Decision Trees provide human-readable rules for classification (Ali, Khan, Ahmad & Maqsood, 2012) and create tree-like structures by selecting the feature with the lowest Gini impurity or Entropy, and the highest Information Gain as the root node that starts the first split and decides the splits of the entire dataset (Talekar & Agrawal, 2020). Decision Trees are easy to read, computationally less expensive, however prone to overfit. Random Forests combine n' number of decision trees, use random subsets in each split, create unique trees, make the final prediction by majority voting across all the trees for classification tasks, and reduce the overfitting tendency of decision trees, however, they are less interpretable compared to Decision Trees. By considering the strengths and weaknesses, it was decided to train two models using these two algorithms and interpret the performance results first.

3.4 Data Preprocessing and Training

Before working further on the models, Python was selected as the programming language, and Google Colab was selected as the coding environment. Google Colab offers several advantages such as providing free access to computing resources, including GPUs and TPUs (Google Colab, n.d.), and providing several pre-installed

libraries. Besides, it is Cloud-based, thus it requires no local installations, which means the projects can be accessed from any device with an internet connection.

After setting the coding language and environment, the dataset was accessed, and the data was preprocessed by applying one-hot encoding to the categorical columns ("road type", "attraction function"), transforming them into Boolean data. By using one-hot encoding, categorical variables were represented as independent features without assumptions about ordinal relationships between categories. Since each category was preserved as an independent feature, no information was lost during the process. Following, the data under the "coordinates" column was excluded, the data under the "footbridge needed" was defined as the target variable (the label to predict) and rest of the data was defined as the feature vectors. The dataset after applying one-hot encoding is given below (Table 3.7).

Table 3.7 Prediction model dataset step 6

coordinates	39.85349898 32.84941771	39.97420183 32.59614303	…	39.9950169 32.84852021	39.9334287 32.8687625
footbridge needed	1	1	…	0	0
availability of attractions	1	1	…	0	1
public transportation	1	1	…	1	1
signalized crossing	1	0	…	1	1
crosswalk	1	0	…	1	1
road type_local road	FALSE	FALSE	…	TRUE	FALSE
road type_main arterial	FALSE	TRUE	…	FALSE	FALSE

road type_medium arterial	TRUE	FALSE	...	FALSE	TRUE
road type_minor arterial	FALSE	FALSE	...	FALSE	FALSE
road type_service	FALSE	FALSE	...	FALSE	FALSE
road type_tertiary	FALSE	FALSE	...	FALSE	FALSE
attraction function_commercial	FALSE	FALSE	...	FALSE	FALSE
attraction function_culture and sport centers	TRUE	FALSE	...	FALSE	FALSE
attraction function_educational and health	FALSE	FALSE	...	FALSE	TRUE
attraction function_park	FALSE	TRUE	...	FALSE	FALSE
attraction function_religious	FALSE	FALSE	...	FALSE	FALSE
attraction function_none	FALSE	FALSE	...	TRUE	FALSE

After preprocessing the data and defining the target variable and feature vectors, the dataset was split into two sets for training the model both with Decision Tree and Random Forest algorithms: a train set (70%) to capture the data patterns and a test set (30%) to evaluate the model's performance on new and unseen data. A random

state of 42 was given for reproducibility, and the initial hyperparameters were defined as follows:

{'min_samples_split': 2, 'min_samples_leaf': 1, 'max_depth': 15, 'criterion': 'gini'}

Given the limited number of data, one of the main concerns is to obtain a shallow tree. Therefore, the minimum number of samples required to split a node, and the minimum number of samples guaranteed in a leaf node are defined as low as possible to ensure tree growth. The process starting from data collection to dataset splitting is given in the following diagram (Figure 3.8).

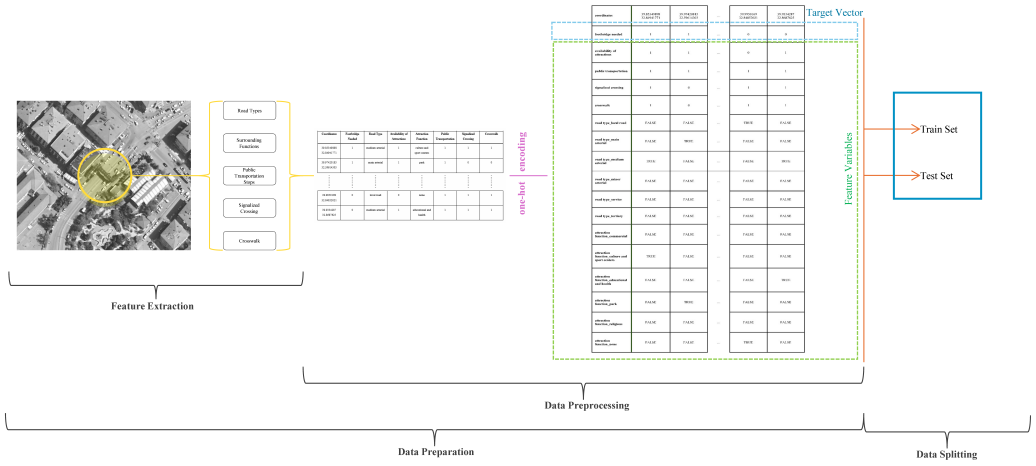


Figure 3.8 Data Preparation and Splitting Process

In the following step, the Gini impurity of the entire dataset was calculated before splitting the data with the formula as follows:

$$\text{Gini}(S) = 1 - \sum_{i=1}^{k} p_i^2$$

Thus, the Gini impurity of the dataset is as follows:

$$\text{Gini}(S) = 1 - (0.5^2 + 0.5^2) = 1 - (0.25 + 0.25) = 1 - 0.5 = 0.5$$

Subsequently, the models were trained and fitted using the Scikit-learn library in Python, which provides necessary tools for preprocessing, training, and evaluating processes for a wide range of algorithms, including the algorithms of interest. Later,

the data was split into train and test sets, the weighted average of Gini impurities for each subset, and the Information Gain was calculated to understand the selection of the optimal feature for a split and to find out which feature is the best to use as the root question.

The formula for weighted average Gini impurities for each subset is as follows:

$$\text{Gini}_{\text{split}}(S) = \frac{|S_{\text{left}}|}{|S|} \times \text{Gini}(S_{\text{left}}) + \frac{|S_{\text{right}}|}{|S|} \times \text{Gini}(S_{\text{right}})$$

The formula for Information Gain is as follows:

$$\text{IG}(S) = \text{Gini}(S) - \text{Gini}_{\text{split}}(S)$$

The Gini impurities for each subset (Table 3.8) and the impurity reduction (Information Gain) (Table 3.9) are given below.

Table 3.8 Gini impurities for each subset

Feature	Gini Index
road type_local road	0.3026704478317382
road type_main arterial	0.3231314880585479
road type_medium arterial	0.4253936464794057
availability of attractions	0.4333816556075446
attraction function_none	0.43678880885269855
road type_tertiary	0.4500719852435415
attraction function_commercial	0.46800736170467677
attraction function_educational and health	0.4721324758191118

crosswalk	0.48108413325804633
road type_service	0.4929152848959903
road type_minor arterial	0.4975724462506466
attraction function_culture and sport centers	0.4976515420063807
signalized crossing	0.49812372914261194
public transportation	0.4996269475532148
attraction function_park	0.4999875451488355
attraction function_religious	0.49998918240626555

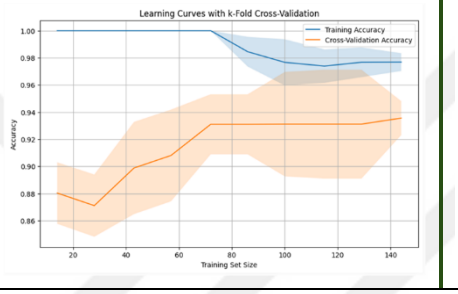
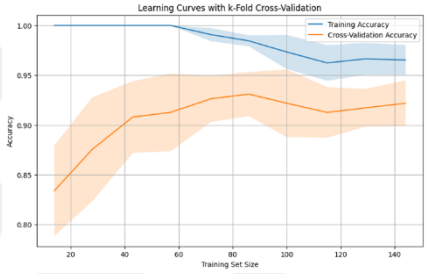
Table 3.9 Information Gain

Feature	Information Gain
road type_local road	0.1973
road type_main arterial	0.1769
road type_medium arterial	0.0746
availability of attractions	0.0666
attraction function_none	0.0632
road type_tertiary	0.0499
attraction function_commercial	0.0320
attraction function_educational and health	0.0279

crosswalk	0.0189
road type_service	0.0071
road type_minor arterial	0.0024
attraction function_culture and sport centers	0.0023
signalized crossing	0.0019
public transportation	0.0004
attraction function_park	0
attraction function_religious	0

According to the results, the feature “road type_local road” has the highest impurity reduction measure, therefore, it is validated as the root question of the trees. Following this stage, the performance metrics of both algorithms and their learning curves were evaluated and are presented in the table below.

Table 3.10 Performance metrics for Decision Tree and Random Forest

	Decision Tree	Random Forest
Train Accuracy	0.967742	0.958525
Cross-Validation Accuracy	0.935566	0.921804
Test Accuracy	0.827957	0.892473
Learning Curve		

To select the optimal algorithm for the prediction task, a decision tree model, and a random forest model were trained. The random forest model demonstrated higher accuracy scores and a better learning curve with a narrower gap. Yet, the performance difference between the models was not found to be significant against one of the advantages that decision tree models have. Decision tree models offer a transparent decision-making process that can be fully monitored. The utilized features, the order of their utilization, the number of times that they have been used as questions, and their relative importance in classification can be examined explicitly. In line with the objective of training such a model, this level of interpretability is of great importance to understanding the model's behavior. Thus, the decision tree model was deemed suitable for this research.

3.5 Decision Tree Model Performance Evaluations

The information regarding the case study city, details on feature extraction, data collection, and data preprocessing are presented in the above section. Following, the model performances were comprehensively evaluated, and the Decision Tree algorithm was selected for the prediction task, as it allows to explicitly monitor its decision-making processes.

After this stage, the focus shifted to the impact of data variability on the performances. Given the small size of the dataset, the main concern was the models' sensitivity to data variability. In this regard, the impact of different data splits (Figure 9), and class distributions was systematically tested; later, feature engineering was performed on the data. The outcomes are detailed in this section, and presented by performance metric tables, learning curves, decision trees, and confusion matrices.

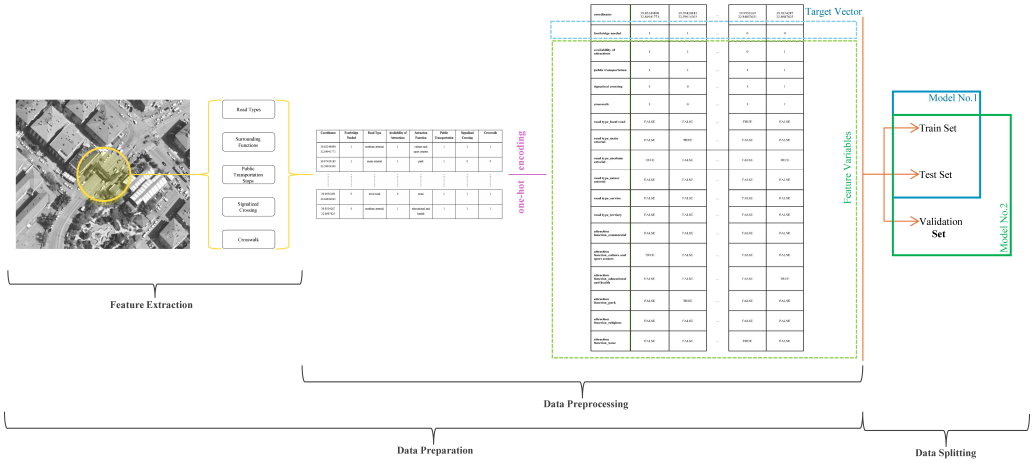


Figure 3.9 The second data preparation and splitting process

3.5.1 Training With Train and Test Sets: Model No.1

The performance metrics of the first trained using the feature with the lowest Gini impurity of 0.3026 and the highest Information Gain of 0.1973 model with train (70%) and test sets (50%) are given in the below table (Table 3.11).

Table 3.11 The performance metrics of the first trained model

	Cross Validation	Training	Test
Accuracy	0.935566	0.967742	0.827957
Precision	0.938391	0.968104	0.837670
Recall	0.935566	0.967742	0.827957
F1 Score	0.935525	0.967738	0.826511

Promising test accuracy of approximately 83% and cross-validation accuracy of 93.5% were obtained. However, approximately a 10% difference between test and cross-validation accuracies, and the high training accuracy scores are raising concerns in two different contexts.

The model learns the data patterns in the training process, thus, a training accuracy higher than other accuracy scores is an expected result. A high training accuracy does not always indicate that the model is overfitting, however, an overly optimistic accuracy close to 100% should be investigated. Similarly, the 10% difference between test and cross-validation scores might indicate the tendency to overfit. In this context, the learning curve (Figure 3.10), the decision tree of the model (Figure 3.11), and confusion matrix (Figure 3.12) were used for interpreting the results.

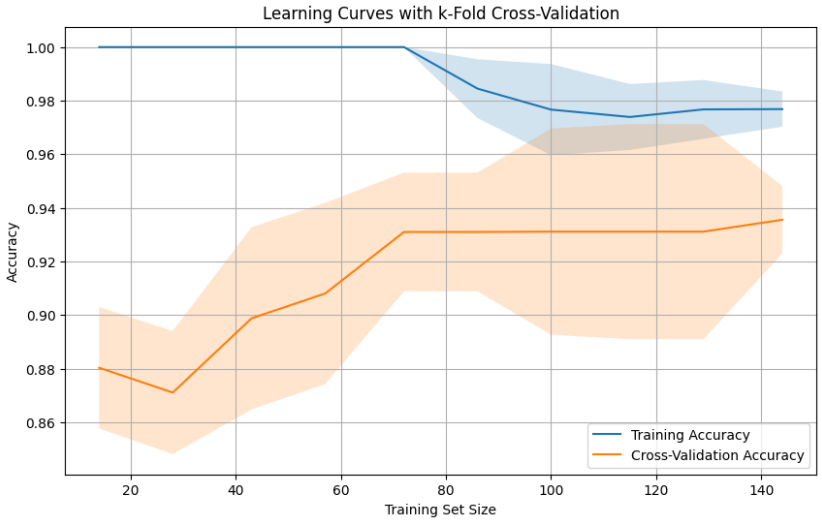


Figure 3.10 The learning curve of Model No.1

When the learning curve is examined, the gap between accuracies narrows down as the number of training data increases, which indicates the model is moving towards a good generalization ability. The training accuracy starts at 100%, remains steady for a certain amount of data, and later gradually decreases. The cross-validation curve has a decline in the beginning (which is not concerning at this stage); it later steadily increases; however, it has an early plateau.

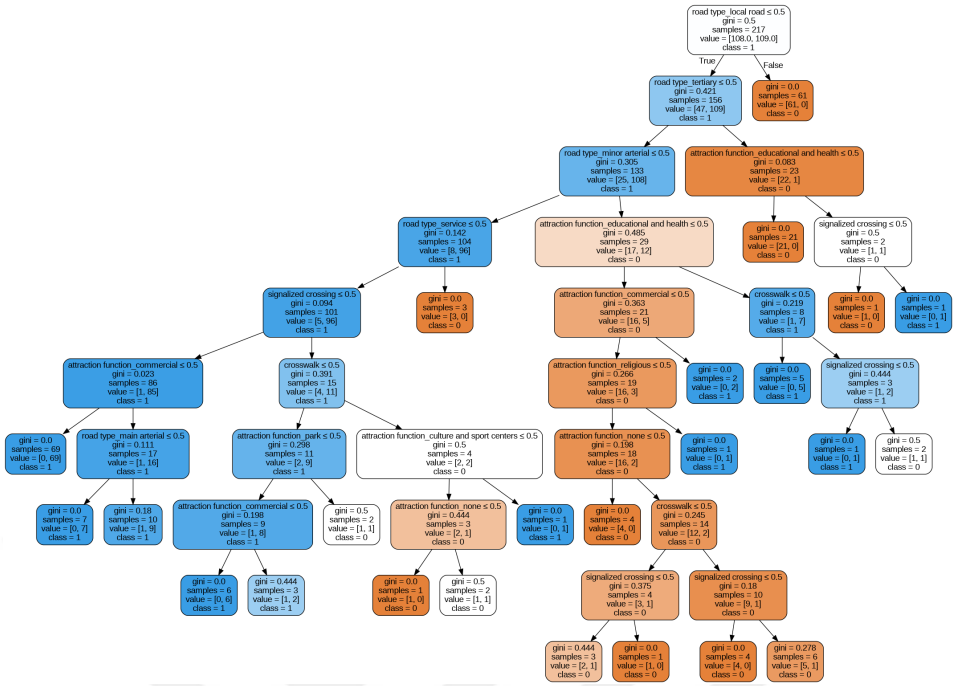


Figure 3.11 The decision tree of Model No.1

The decision tree shows that the model can use every feature as a question. The depth is neither too deep nor too shallow; however, it hasn't reached the maximum depth limit determined in the training process.

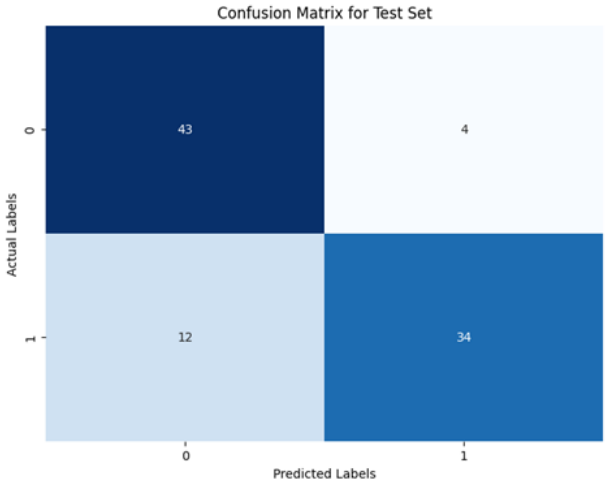


Figure 3.12 The confusion matrix of Model No.1

There is an imbalance in the false positives and false negatives, which is investigated in the upcoming sections. However, when the overall performance is examined, the

model is demonstrating sensitivity due to its dataset size, rather than an overfitting tendency. When training with small datasets, the model becomes sensitive to changes in data splits. Using cross-validation provides a robust estimation of the generalization success of the models since it takes the average results of multiple data splits. Therefore, it was decided to further explore how data split variations affect the model performance. In this regard another model was trained using the same dataset, but with an additional validation set for tuning the model with unseen data on the training process.

3.5.2 Training With Train, Validation and Test Sets: Model No.2

The learning curve and the decision tree of Model No.1 indicated that the model shows sensitivity to different data folds, rather than an overfitting tendency. Therefore, in the following step, the effects of adding a validation set to the model performance were investigated; and Model No.2 with three datasets, a train set (70%), a validation set (15%), and a test set (15%), was trained.

Since the dataset was split into three sets, Gini impurities and Information Gains were calculated again. The root question of this model was again 'road type_local road' with the lowest Gini impurity of 0.2948 and the highest Information Gain of 0.2049. The performance metrics of Model No.2 are as follows (Table 3.12):

Table 3.12 The performance metrics of Model No.2

	Cross Validation	Training	Validation	Test
Accuracy	0.903222	0.958525	0.956522	0.829787
Precision	0.906949	0.959460	0.956522	0.829787
Recall	0.903222	0.958525	0.956522	0.829787
F1 Score	0.903096	0.958481	0.956522	0.829787

The gap between training and test accuracies slightly narrowed down, which can be interpreted as adding a validation set helps to fine-tune the model during the training

process. However, the 95.65% accuracy of the validation set is again a highly optimistic score, which supports that the model is sensitive to data distributions. The results indicate that the model tends to memorize data patterns instead of learning. For small datasets, slight differences in data patterns can lead to such a result. In this context, the learning curve (Figure 3.13), and decision tree (Figure 3.14) of the model are used for interpreting the results.

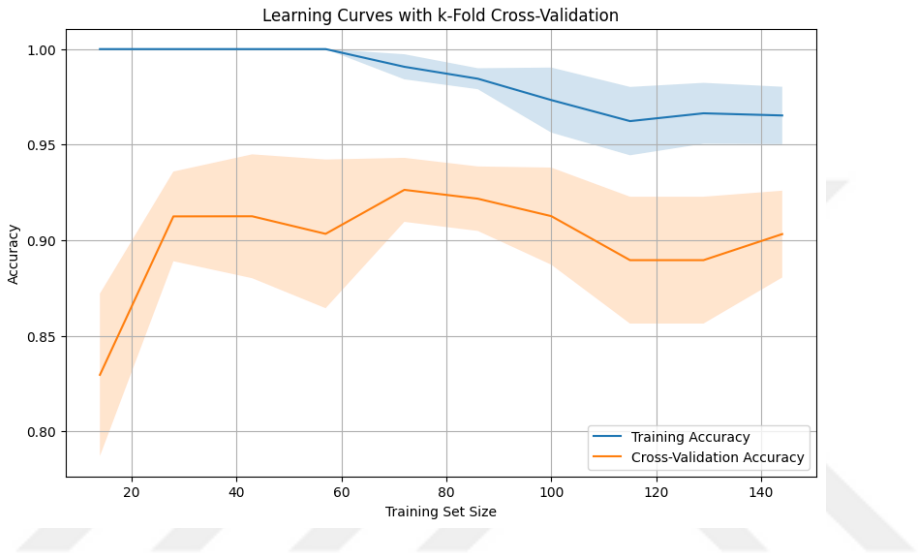


Figure 3.13 The learning curve of Model No.2

In terms of the gap between training and cross-validation curves, no significant difference was observed, however, the fluctuations in the cross-validation curve behavior indicate instability and support the possibility that the model is sensitive to data variability.

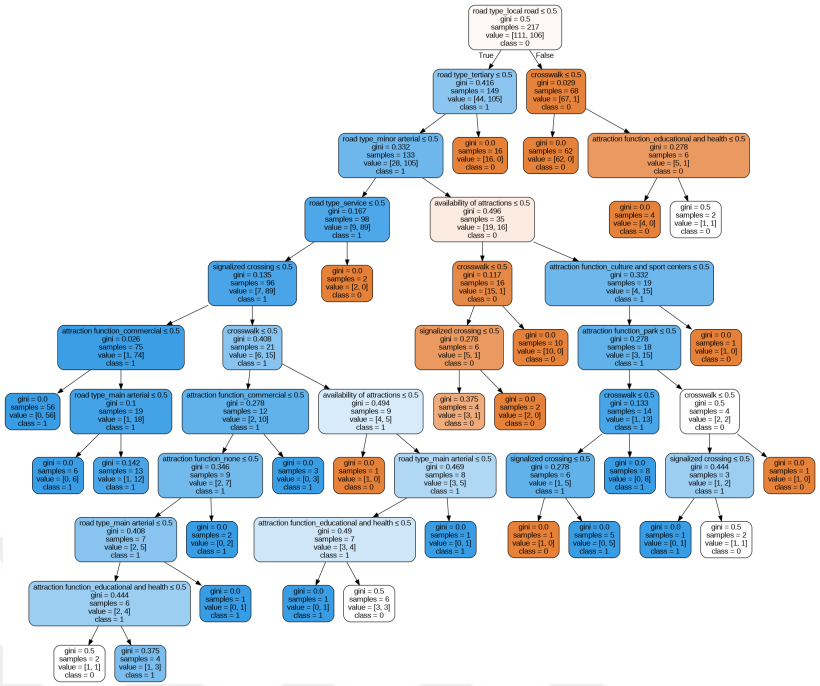


Figure 3.14 The decision tree of Model No.2

3.5.3 How Different Data Splits Cause Variation in Model Performances

Both model performance results indicated that the model is sensitive to data variability. In small datasets, even slight changes in the data can strongly affect the model performance. Therefore, it was decided to examine how different data splits cause variation in the model performances.

In the first step, the splitting processes of both models were checked to see if there was data leakage, which could lead to the above-mentioned results. It was ensured that rows with the same index were not repeated in different sets. Following, the class distributions between different sets were obtained, and later, the effects of changes in data splits were examined. Lastly, the overlapping data points (the data with different indices that share nearly the same values for features) in different sets were identified. For both models, balanced class distributions were ensured, and again, their effects on the performances were examined.

3.5.3.1 The Impact of Class Distribution and Random State

The class distribution between the train and test sets of Model No.1 is given in Table 3.13.

- Overall overlap between training and test sets: 10

Table 3.13 Class distributions between the train and test sets of Model No.1

Class Label	Overall Class Distribution in the Dataset	Class Distribuiton for Train Set	Class Distribuiton for Test Set	Distribution of Classes Among Overlapping Data
0	0.5	0.502304	0.505376	0.5
1	0.5	0.497696	0.494624	0.5

The class distributions within training and test sets are almost equal, as it is with the overlapping data points. The sets are balanced, as is desired for data splits. However, the data distribution can be rearranged by changing the random state value.

Random state shuffles the data and splits it into different sets. In this case, 42 random state values were systematically tested while splitting train and test sets, training the model, and performing cross-validation; later reported. Ten of the tested values and corresponding cross-validation metrics were displayed to illustrate the effects of random state values and the model's robustness in the below tables (Table 3.14, Table 3.15).

Table 3.14 Ten samples of performance metrics across different random states

Metrics		Random State				
		0	2	4	40	41
Train	Accuracy	0.958525	0.953917	0.949309	0.958525	0.967742
	Precision	0.959510	0.954527	0.949345	0.958881	0.968104
	Recall	0.958525	0.953917	0.949309	0.958525	0.967742
	F1	0.958508	0.953897	0.949307	0.958520	0.967738
Test	Accuracy	0.881720	0.924731	0.881720	0.903226	0.870968
	Precision	0.883396	0.924910	0.881870	0.904976	0.871714
	Recall	0.881720	0.924731	0.881720	0.903226	0.870968
	F1	0.881638	0.924714	0.881693	0.903159	0.870938
Cross Validation	Accuracy	0.847920	0.885147	0.884830	0.894089	0.907851
	Precision	0.851748	0.886668	0.888227	0.897908	0.909530
	Recall	0.847920	0.885147	0.884830	0.894089	0.907851
	F1	0.847829	0.885034	0.885002	0.893982	0.907860

Table 3.15 Summary of metrics (Mean and standard deviation)

Metrics		Mean	Standard Deviation
Train	Accuracy	0.957757	0.007003
	Precision	0.958179	0.006962
	Recall	0.957757	0.007003
	F1	0.957747	0.007006
Test	Accuracy	0.886329	0.024661
	Precision	0.889430	0.024024
	Recall	0.886329	0.024661
	F1	0.886099	0.024797
Cross Validation	Accuracy	0.890398	0.019013
	Precision	0.893690	0.018506
	Recall	0.890398	0.019013
	F1	0.890326	0.019032

The mean training metrics around 95.8% ± 0.7% indicate that the model's performance is consistent across different training splits. Compared to the training metrics, test metrics show a slight decrease with scores around 88% ± 0.25%, however they are still stable across different splits. The decrease is expected, as the model performs better on seen data compared to unseen data. Cross-validation metrics are similar to test metrics with scores around 89%, which indicates that the model shows consistency across different folds. However, the cross-validation

standard deviation of approximately 1.9 % is relatively higher than the test splits. The overall performance of the model shows consistency, and the high mean values for accuracy, precision, recall, and F1 score across different splits suggest that the model does not tend to overfit or underfit. However, the results once again confirm the model's sensitivity to data variability.

The model's average behavior was highlighted in this section. Following this stage, the best-performing model was selected among the above-presented models to further improve performance. The aim of training such a model is to develop a decision-support tool for the research-specific objectives. Therefore, after performance evaluations, the best model should be selected for the model deployment process.

While selecting the best model, using an accuracy score is a reasonable choice while training with such a balanced dataset as it provides a general sense of the model's overall performance. However, on the other hand, both the false positives (predicting a footbridge is needed when it is not) and especially, false negatives (predicting a location does not need a footbridge when it is needed) are critical regarding the specific aim of the model. Therefore, the F1 score has been selected as the performance evaluation metric. The best-performing model based on the test F1 score is presented in the table below (Table 3.16). The class distributions of the best-performing model are presented in the table below (Table 3.17).

Table 3.16 Best-performing model based on test F1 Score

Random State	Train F1 Score	Test F1 Score	Cross-Validation F1 Score
2	0.953897	0.924714	0.885034

Table 3.17 Distribution of classes among different sets for Model No.1 (random state 2)

Class Label	Overall Class Distribution in the Dataset	Class Distribution for Training Set	Class Distribution for Test Set
0	0.5	0.502304	0.505376
1	0.5	0.497696	0.494624

The class distributions within training and test sets are almost equal in the best model trained with a random state value of 2. Since the splits were changed by changing the random state, the Gini impurities and Information Gains were calculated again. The root question of this model was once again 'road type_local road' with the lowest Gini impurity of 0.2981 and the highest Information Gain of 0.2018. The table below is provided to compare the test metrics of Model No.1 with random state 42, and random state 2 (Table 3.18):

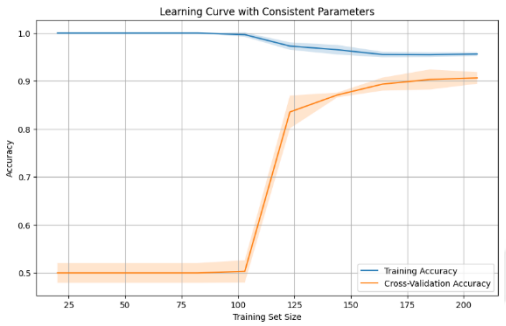
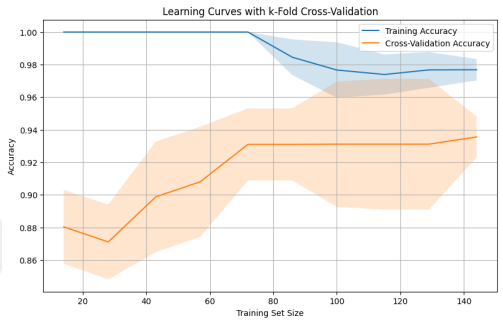
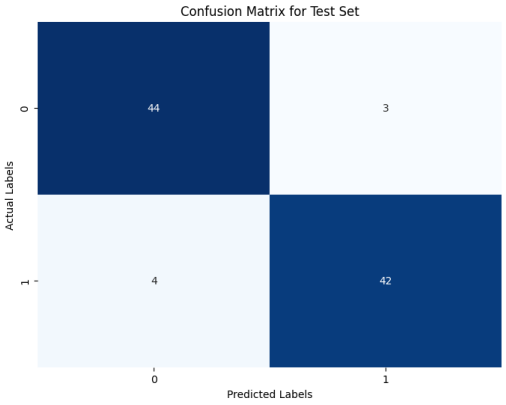
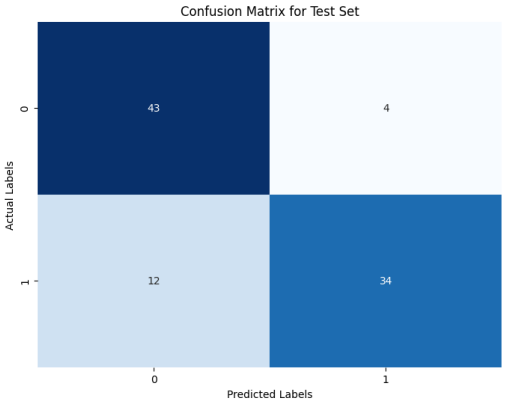
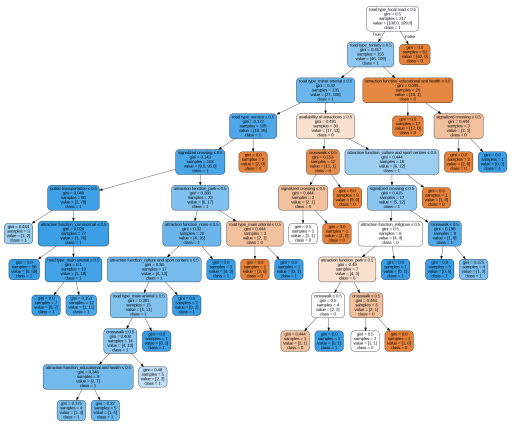
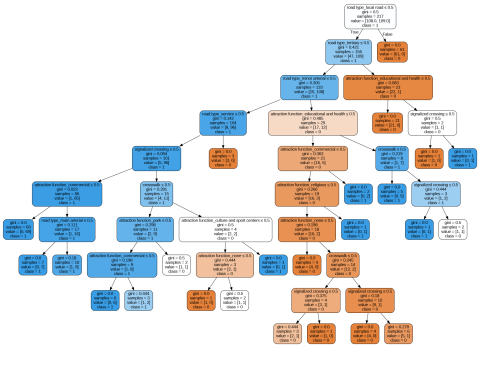
Table 3.18 Test metrics comparison of different random states

Test Metrics	Accuracy	Precision	Recall	F1 Score
Model No.1 (random state 2)	0.924731	0.924910	0.924731	0.924714
Model No.1 (random state 42)	0.827957	0.837670	0.827957	0.826511

The model with random state 2 shows an increase of approximately 10% in test accuracy, however, high test accuracy does not always suggest that the model generalizes well. The following table of learning curves, confusion matrices, and the decision trees of Model No.1 with random state 2, and Model No.1 with random state

42 are provided for a more comprehensive interpretation of the performances (Table 3.19).

Table 3.19 Learning curve, confusion matrix, and decision tree comparison

Model No.1 (random state 2)	Model No.1 (random state 42)
	
	
	

According to the comparison table above, the learning curve of the model with random state 2 shows a consistent increase in cross-validation scores, smoothly narrowing its gap between training scores as the training size increases, which suggests that the model generalizes well and performs consistently on unseen data. In the confusion matrix, it has fewer misclassified samples both in false positives and false negatives, suggesting a better classification performance. The decision tree of the model with random state 2 is slightly deeper, having more branches, however, there are no significant differences between the trees. These outcomes indicate that the model with random state 2 performs consistently high scores on both validation and test sets, with no signs of overfitting.

3.5.3.2 Implementing Stratified Splitting Method for Model No.2

The data of Model No.1 was split into two sets as training and testing sets. The effects of different data splits were examined by changing the random state value. The data of Model No.2 was split into three sets as training, validation, and testing. In order to examine the effects of different data splits for this model, first, the overlapping data points between these sets were identified, along with the class distributions. The results are given below:

- Overall overlap between training and validation sets: 5
- Overall overlap between training and test sets: 7
- Overall overlap between validation and test sets: 3

Table 3.20 Distribution of classes among different sets for Model No.2

Class Label	Overall Class Distribution in the Dataset	Class Distribution for Training Set	Class Distribution for Validation Set	Class Distribution for Test Set
0	0.5	0.511521	0.521739	0.574465
1	0.5	0.488479	0.478561	0.425532

Table 3.21 Distribution of classes among overlapping data points between different sets for Model No.2

Class Label	Training and Validation Sets	Training and Test Sets	Validation and Test Sets	Distribution of Classes Among Overlapping Data
0	0.8	0.571429	1.0	0.733333
1	0.2	0.428571	0.0	0.266667

As shown in the above tables, the class distributions within the sets and overlapping data points are unbalanced, which might be leading the model to overfit and estimate overly optimistic performance scores. Therefore, for Model No.2, it was decided to examine the effects of reducing the number of overlapping data points and ensuring mutually exclusive sets as possible, using the “Stratified Splitting” method. The results after implementing the method are given below.

- Overall overlap between training and validation sets: 4
- Overall overlap between training and test sets: 3
- Overall overlap between validation and test sets: 1

Table 3.22 Distribution of classes among overlapping data points between different sets for Model No.2 after Stratified Splitting

Class Label	Class Distribution for Training Set	Class Distribution for Validation Set	Class Distribution for Test Set
0	0.497696	0.5	0.510638
1	0.502304	0.5	0.489362

By implementing this method, the number of overlapping data points was reduced, and the overall class distribution of different sets was balanced, resulting in a significant difference in the test set. The comparison of performance metrics before and after implementing the method is given below.

Table 3.23 Comparison of test metrics before and after implementing Stratified Splitting

	Cross Validation	Training	Validation	Test
Accuracy	0.903222	0.958525	0.956522	0.829787
Precision	0.906949	0.959460	0.956522	0.829787
Recall	0.903222	0.958525	0.956522	0.829787
F1 Score	0.903096	0.958481	0.956522	0.829787

Table 3.24 Performance metric comparison for Model No.2 before and after Stratified Splitting

	Training Accuracy	Cross Validation Accuracy	Validation Accuracy	Test Accuracy
With Unbalanced Sets	0.958525	0.903222	0.956522	0.829787
With Balanced Sets	0.967742	0.935566	0.804348	0.851064

Stratification resulted in higher training and cross-validation accuracies, while the test accuracy remained the same. There is a notable drop in the validation accuracy. Along with this table, the effects of stratification are interpreted with the model's learning curve (Figure 3.15).

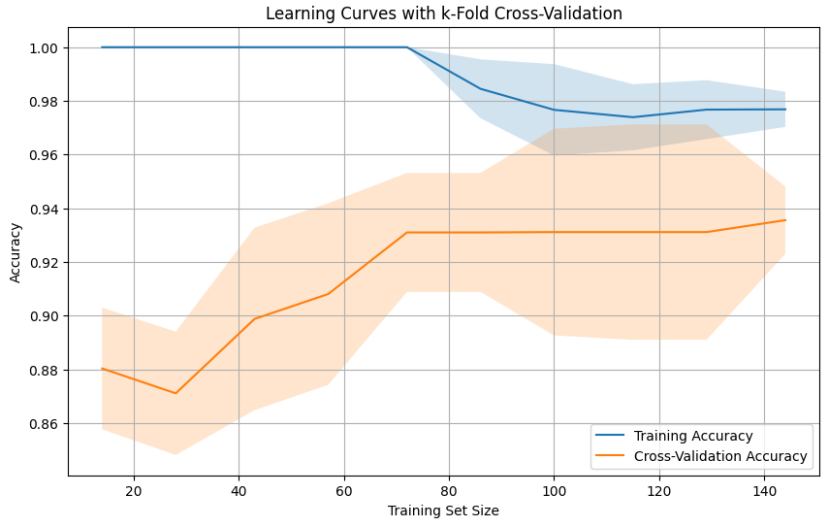


Figure 3.15 The learning curve after Stratified Splitting

A significant similarity between this model and the first trained Model No.1 (with random state value 42) was revealed after plotting the learning curve. Additionally, the decision tree of this model and Model No.1 are identical (Figure 3.10).

The performance metrics of stratified Model No.2 and Model No.1 (random state 42) are as follows (Table 3.25):

Table 3.25 The performance metrics of Stratified Model No.2 and Model No.1 (random state 42)

	Training Accuracy	Test Accuracy	Cross Validation Accuracy	Validation Accuracy
Model No.1 (random state 42)	0.967742	0.827957	0.935566	-
Model No.2 (stratified)	0.967742	0.851064	0.935566	0.804348

Model No.1(random state 42) and stratified Model No.2 perform very similarly, sharing the same training and cross-validation accuracies, learning curves, and decision trees. The class distribution between sets for these models is nearly identical, which indicates that while stratification ensured balanced class distribution, it did not change the overall decision-making process of the model.

While training and cross-validation accuracies and the learning curve remained the same, stratified Model No.2 had a higher test accuracy. Adding a validation set to Model No.1 (random state 42) increased the test accuracy but resulted in the model overfitting the validation set. Following, the class distribution of Model No.2 sets was balanced, and a higher test accuracy was obtained (stratified Model No.2) while decreasing the validation accuracy to a notable extent. The validation set has become more representative of the entire data, and with a higher test accuracy, the model improved its generalization ability. These results support the previous claim that data splits have a significant effect on model performances in small datasets.

As stated in previous sections, this thesis aims to develop a decision-support tool, hence after evaluating the model performances, the best-performing models are selected for the model deployment process. In this regard, since stratified Model

No.2 shows a very similar performance to Model No.1 (random state 42), and Model No.1(random state 2) suggests a better generalization ability than Model No.1 (random state 42), the development process proceeded with the Model No.1 (random state 2).

3.6 Dataset Refinement and Final Model Performance Evaluations

After experimenting with the effects of different data splits on the performance, the effects of the changes in the dataset itself were examined. Due to the data source limitations, the dataset size remained the same. However, the structure of the dataset was modified by performing proximity-based feature transformation for three binary variables, which indicate the presence of public transportation stops, crosswalks, and signalized crossings around footbridge locations. In this regard, these binary variables were transformed into numeric variables, indicating their respective proximities to footbridges.

In the context of the research problem, crosswalks, and signalized crossings that have a distance exceeding 200 meters to footbridges were represented as “0” in the dataset. Later, this distance was increased to 250 meters, considering the measurement error margin. After proximity-based feature transformation, distances within 250 meters were converted into their respective numerical value. For values exceeding 250 meters, the distance difference is exaggerated by giving “11111” meters. The dataset after proximity-based feature transformation is given below (Table 3.26).

Table 3.26 The dataset after proximity-based feature transformation

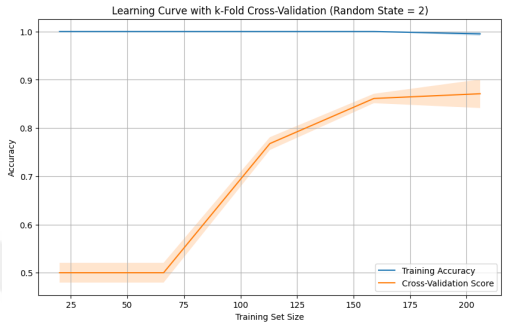
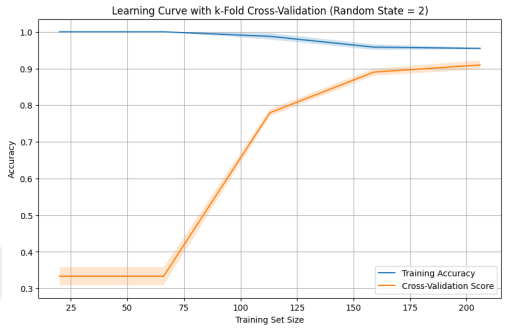
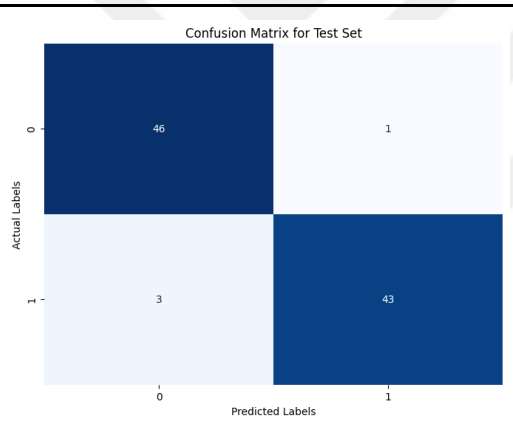
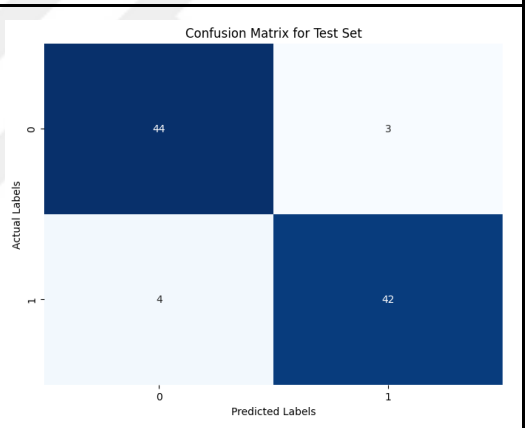
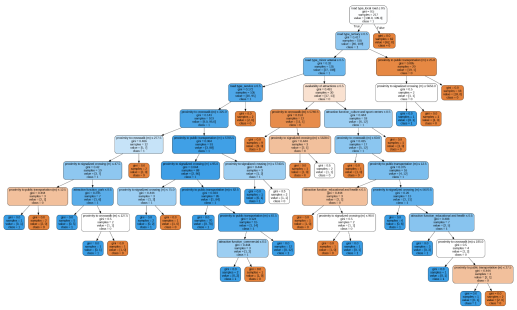
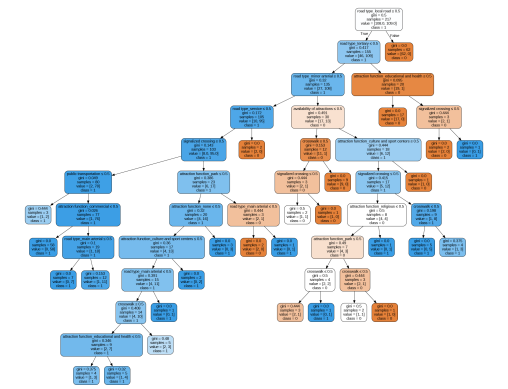
coordinates	footbridge needed	road type	availability of attractions	attraction function	proximity to public transportation (m)	proximity to signalized crossing (m)	proximity to crosswalk (m)
39.85349898 32.84941771	1	medium arterial	1	culture and sports centers	150	85	245
39.97420183 32.59614303	1	main arterial	1	park	45	11111	11111
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
39.9950169 32.84852021	0	local road	0	none	40	40	11111
39.9334287 32.8687625	0	medium arterial	1	educational and health	20	10	60

The impact of the data type transformation on the model's performance is presented below in comparison tables (Table 3.27, Table 3.28).

Table 3.27 Test metrics comparison for Model No.1 (random state 2) before and after proximity-based feature transformation

Test Metrics	Accuracy	Precision	Recall	F1 Score
Model No.1 (random state 2, modified dataset)	0.956989	0.957817	0.956989	0.956959
Model No.1 (random state 2)	0.924731	0.924910	0.924731	0.924714

Table 3.28 Learning curve, confusion matrix, and decision tree comparison before and after proximity-based feature transformation

Model No.1 (random state 2, modified dataset)	Model No.1 (random state 2)
	
	
	

The motivation for transforming binary variables into numeric variables was to richen the information to the model and introduce new variability and complexity to the dataset. However, the transformation had a negative impact on the model's performance, as it increased sensitivity to scaling. An increase in test metrics was observed, however, training scores remained almost the same as the training size increased, which indicates that the model overfitted to the training data.

On the contrary, the confusion matrix after the transformation has fewer misclassifications. However, since their number is satisfactorily low for Model No.1 (random state 2), and the model has a good generalization ability, it was decided to continue the study with Model No.1 (random state 2) without data transformation. It is important to highlight that the model's false positives are valuable for the task, as they indicate that a footbridge is needed in a location where there is no existing footbridge.

3.6.1 Hyperparameter Tuning

As the last step of model evaluation, it was investigated how the selected model would react to the changes in its hyperparameters. In this regard, first, GridSearchCV was implemented in the model. This hyperparameter optimization technique (available in the sci-kit-learn library) evaluates a model's performance by testing the hyperparameter combinations within a predefined range and selecting the best set. The predefined hyperparameter ranges are as follows:

'min_samples_split': [2, 5, 10],
'min_samples_leaf': [1, 2, 5],
'max_depth': [None, 3, 5, 10, 15, 20],
'criterion': ['gini', 'entropy']
'max_features': [None, 'sqrt', 'log2']

The initial hyperparameters that have been used for training are as follows:

{'min_samples_split': 2, 'min_samples_leaf': 1, 'max_depth': 15, 'criterion': 'gini'}

The best hyperparameters for the model by GridSearchCV are as follows:

{'min_samples_split': 10, 'min_samples_leaf': 2, 'max_depth': 10, 'criterion': 'gini', 'max_features': 'sqrt'}

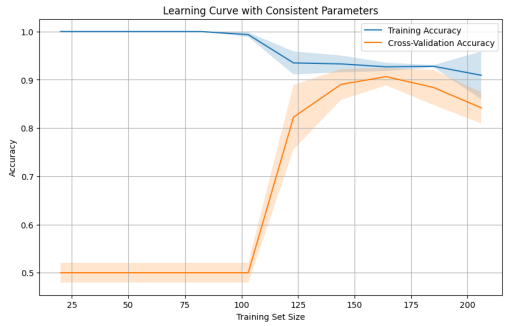
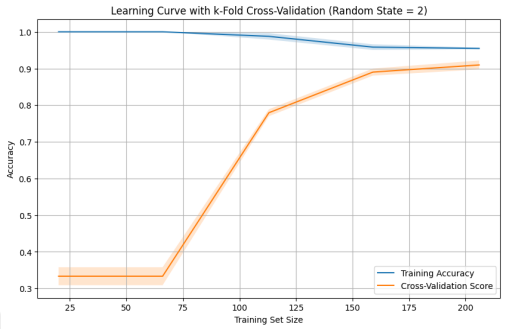
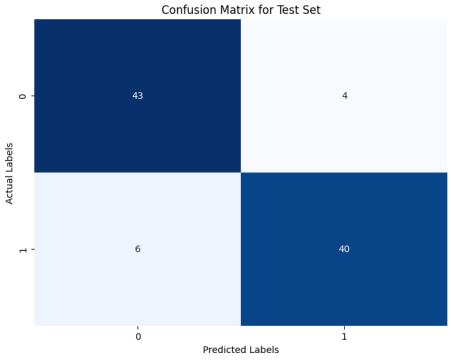
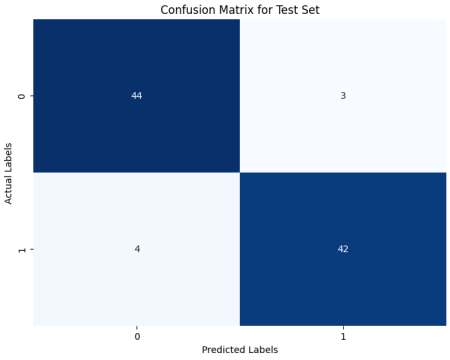
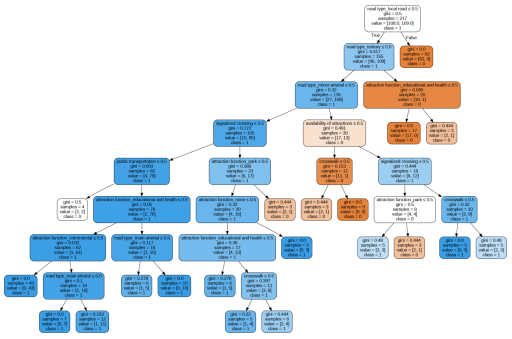
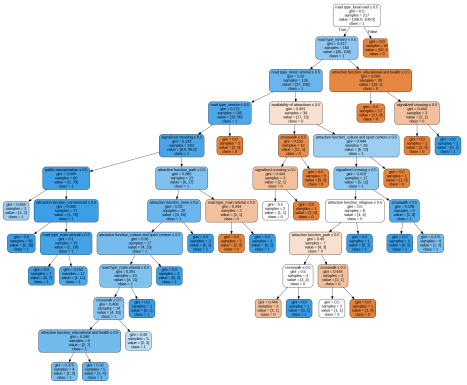
The performance metrics of the model with the best hyperparameters for the model by GridSearchCV are given in the below Table 3.29.

Table 3.29 Performance metrics of the model with The GridSearchCV hyperparameters

Test Metrics	Accuracy	Precision	Recall	F1 Score
Model No.1 (random state 2, tuned)	0.892473	0.893151	0.892473	0.892398
Model No.1 (random state 2)	0.924731	0.924910	0.924731	0.924714

A test accuracy difference of 3% was observed between the model trained with the initial hyperparameters and the model trained with the hyperparameters obtained from GridSearchCV. However, the overall performance should be further evaluated by learning curves, and the decision trees after hyperparameter tuning are given below (Table 3.30).

Table 3.30 Learning Curve, confusion matrix, and tree comparison before and after tuning with the best hyperparameters by GridSearchCV

Model No.1 (random state 2, tuned)	Model No.1 (random state 2)
	
	
	

Decreasing the depth of the decision tree and increasing the minimum number of samples required for a split have not resulted in a significant difference in the test accuracy. However, when the learning curve and confusion matrix were observed, it had a negative impact on the overall performance. The training curve remains stable at 1.0, and the curves get oriented in an undesired way as the number of data increases. Besides, the model has higher false negatives compared to the previous hyperparameters.

3.7 Conclusion: Results and Discussions

The model training process started by encoding the dataset consisting of 310 rows, 2 categorical, and 4 binary feature variables. Initially, the model hyperparameters were determined, and the encoded dataset was used to train a decision tree classifier. Given the small size of the dataset, the model was expected to be sensitive to data variability. To address this, two types of dataset splitting were performed, and the effects of data distribution on model performance were examined. The data was first split into train and test sets (70%-30%) for Model 1, and into train, validation, and test sets (70%-15%-15%) for Model 2.

3.7.1 Model Evaluation Results

When evaluating Model No.1 performance metrics after the initial training, a difference of approximately 10% was observed between the test and training accuracies. Analysis of the learning curve showed that although the training and validation curves converged slightly, the final gap remained wide. Examination of the confusion matrix further revealed a notable imbalance between false positives and false negatives. To investigate the data distribution impact on the model, a two-stage analysis was conducted:

First, the class distributions within the training and test sets were analyzed, revealing a balanced class distribution, approximately equal (50%-50%) across both sets.

Thus, for the second step, the model's response to varying data splits across the train and test sets was investigated. In this regard, the model's performance was tested across 42 different random states. Across these 42 variations, the training, test, and cross-validation scores were found to be consistent, indicating stable model performance. The best performance among variations was observed at random state = 2. The F1 score was chosen as the primary criterion to identify the best-performing model. For datasets with balanced class distributions, the accuracy score is also an appropriate measure. However, due to the high false positive and false negative outcomes of the initial model, the F1 score was deemed the most reliable criterion as a metric that accounted for both misclassifications.

When the models with random state = 42 (initial model) and random state = 2 were compared, it was observed that the learning curves in the random state = 2 model converged closely, with a notably reduced gap compared to the other model. Additionally, analysis of the confusion matrix revealed a notable decrease in misclassification cases, particularly in false negatives. The depth of the tree also increased, resulting in an approximately 10% improvement in test accuracy. However, test accuracy alone is not sufficient to interpret whether the model generalizes well or overfits. Therefore, the learning curve, confusion matrix, and depth of the decision tree were evaluated collectively, revealing that the 10% improvement stemmed from enhanced generalization ability rather than overfitting.

Further investigations into data splits focused on Model No.2, which included a validation set in addition to the training and test sets. Initial results indicated that the model overfitted to the validation set, as a common issue with small datasets that are sensitive to data distribution. Upon examining the class distributions across the partitions, a significant imbalance was identified. To address this issue, the stratified splitting method was applied, ensuring balanced class distribution across each set, while also reducing the overlap of data points between the sets. After this method, the model’s test accuracy remained stable, while training accuracy improved. However, a significant decrease in validation accuracy was observed. The ultimate

results after stratified splitting were almost identical to Model No.1 (random state = 42).

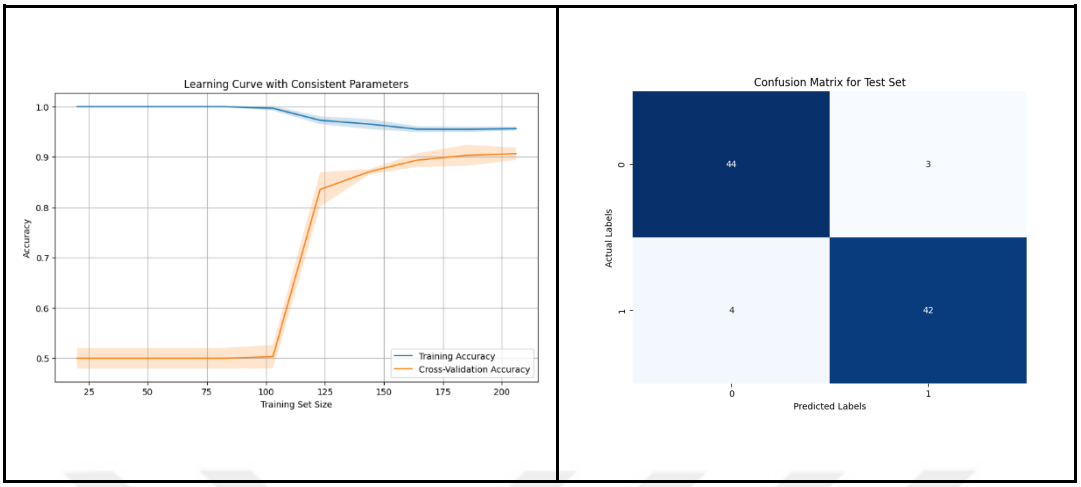
3.7.2 From Model Evaluation to Decision-Support Tool Development

The first stage of developing a decision-support is to develop a machine learning model to predict whether a footbridge is needed at a given location. Therefore, after comprehensively evaluating the model performances, testing different data splits systematically, investigating class distributions, and performing feature engineering on the dataset, the best-performing model with fewer misclassifications, consistent performance metrics, and high generalization ability was selected to finalize the tool. Based on the above-presented evaluations, Model 1 (random state = 2) was identified as the best-performing model among the four models tested.

Subsequently, the effects of data type transformation on the performance of Model 1 (random state = 2) were analyzed. Specifically, a proximity-based transformation was applied to three binary features in the dataset and transformed into numerical variables. This transformation aimed to enrich the information available to the model and introduce variability beyond the initial data. However, due to the model's sensitivity to data variability, this transformation caused the model to show an overfitting tendency.

Finally, the model's response to hyperparameter changes was investigated. Using GridSearchCV, various hyperparameter combinations were tested, and the combination that suggested the best performance was identified. However, tuning the hyperparameters did not have a significant positive effect on the performance. The best hyperparameters by GridSearchCV reduced the number of branches of the decision tree, increased the number of misclassifications, and resulted in a learning curve that converged slightly but later showed a negative trend as the training size increased. In conclusion, Model 1 (random state = 2) was confirmed as the best-performing model and selected for the decision support tool (Table 3.31).

Table 3.31 The best-performing model to validate as the prediction tool



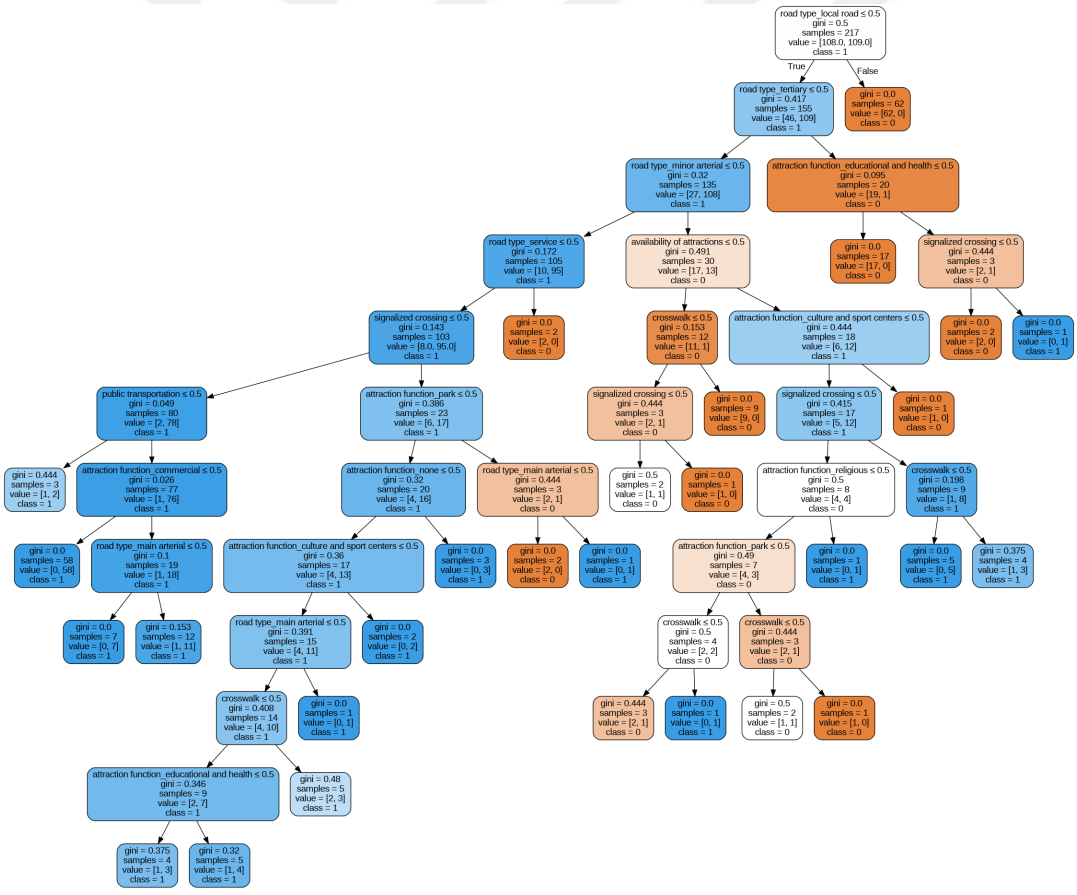


Figure 3.16 The decision tree of the best-performing model

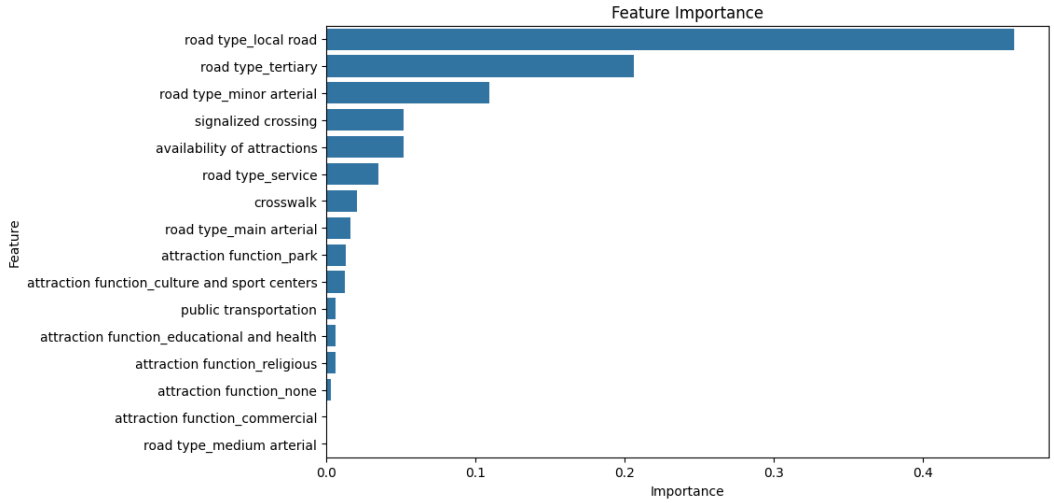


Figure 3.17 The feature importances of the best-performing model

The final step in validating the model as the decision support tool was to analyze the data that the model has misclassified. The primary aim of the model is to identify whether a footbridge is needed in a location. Hence, the false positives are particularly important in the context of this study, as they represent the locations where a footbridge is needed and highlight the locations where pedestrian-motor vehicle conflict is a concern. The misclassified locations with the label “0” are given in Table 3.32 (in the initial dataset format):

Table 3.32 Misclassified data (False Positives)

coordinates	footbridge needed	road type	availability of attractions	attraction function	public transportation	signalized crossing	crosswalk
39.9755344 32.7318129	0	minor arterial	1	park	1	1	0
39.939163 32.877442	0	medium arterial	1	educational and health	1	1	1
39.988133 32.690948	0	medium arterial	0	none	1	1	1



Figure 3.18 Predicted Locations (False Positives). (A) [39.9755344°, 32.7318129°], image source: Airbus, 2024; Google Earth Pro, 2025, (B) [39.939163°, 32.877442°], image source: Airbus, 2023; Google Earth Pro, 2025, (C) [39.988133°, 32.690948°], image source: Airbus, 2024; Google Earth Pro, 2025

The first false positive suggested a footbridge to an area with high human activity (park), combined with a road that has a high feature importance ranking. However, the availability of other pedestrian crossing facilities did not have a notable effect on the prediction. The second prediction suggests that the presence of an educational-health-related function, despite its low importance in the feature ranking, combined with a public transportation stop, and a medium arterial road resulted in a "footbridge needed" prediction. Again, the availability of other pedestrian crossing facilities did not have a notable effect on the prediction. However, this prediction is consistent with real-life examples by suggesting a footbridge on a high-risk type of road around

a primarily important function without being affected by the presence of other crossing facilities. In the third false positive, despite the availability of other pedestrian crossing facilities and no attraction functions, the road type combined with the presence of public transportation stops resulted in a “footbridge needed” prediction.

While the prediction model suggested that these three locations need footbridges, the question of “how” to design a footbridge influences the decision of whether a footbridge should be constructed. To prevent footbridges from becoming urban barriers, certain criteria must be met in their design frameworks. This demonstrates the interconnected nature of location selection and design phases. Therefore, the need for footbridges in predicted locations will be re-evaluated after answering “how” to design.

CHAPTER 4

FOOTBRIDGE DESIGN GUIDELINE

In the first stage of the decision-support tool, a prediction model was developed to identify whether a footbridge is needed in a location. Simultaneously, the underlying reasons for pedestrian-motor vehicle conflict in high pedestrian activity areas and the characteristics that resulted in the need for these structures are revealed through Ankara's footbridge locations. However, as stated in the research problem, merely identifying the need for footbridges and building these structures in an ad-hoc manner, without evaluating site-specific constraints and pedestrian expectations, is transforming these structures into physical and psychological barriers for pedestrians. Hence, after identifying the need, the development of the decision-support tool proceeds with developing a guideline to enhance footbridge design frameworks based on the locations predicted by the model.

In Chapter 3, Ankara was recognized as a suitable case as a data collection source to train the prediction model. At the same time, Ankara is a noteworthy case with its numerous footbridges built in an ad-hoc manner. To support the claim that footbridges that are imposed into built environments without considering site-specific constraints and pedestrian expectations further restrict pedestrian mobility, Chapter 4 begins with the researcher's observations on Ankara's footbridges, and focuses on how the site-specific constraints influence footbridge designs. In this regard, the following images of typical Ankara footbridges around high-risk roads and intensive human activity areas are provided to demonstrate the ad-hoc building manner (Figure 4.1).



Figure 4.1 Ad-hoc Ankara Footbridges (Photographs taken by the author)

The images above belong to one of the most frequently used footbridges in Ankara, located near a metro station and the Middle East Technical University. This footbridge spans eight lanes of traffic on Dumlupınar Boulevard, an intercity road that connects Ankara and Eskişehir. The road is one of the busiest roads in Ankara and is surrounded by diverse functions such as educational and healthcare buildings, commercial centers, and residential areas. Consequently, the road passes through high human activity zones, creating significant pedestrian-motor vehicle conflict.

Based on the research conducted during this thesis, it has been concluded that the heavy use of the footbridge is the lack of alternative crossing facility options to cross the arterial road. This conclusion aligns with the findings of the reviewed literature, which highlighted having “no other option” is a key factor (Sinclair et al., 2016) in footbridge usage.

The deck of the footbridge is connected to a stair on one side, and a ramp on the other that leads to the university entrance. The footbridge does not have another circulation element such as an elevator that would facilitate access for disadvantaged pedestrians. However, as captured in the above images, despite having one type of circulation element on both sides, the bridge occupies nearly all the space on the sidewalk, forcing pedestrians to navigate extremely close to the dangerous traffic (Figure 4.1). Besides, this configuration drops pedestrians off adjacent to the road, again exposing them to vehicular hazards. Therefore, reducing the ground-level footprints of footbridges might be a recommendation, however, it might also mean

compromising the circulation components that ensure accessibility. Thus, the balance must be ensured.

This footbridge is a notable example of how footbridges become barriers to pedestrian mobility when site-specific constraints are not regarded in decision-making processes. The below images of different footbridges in Ankara are given as examples of the same context (Figure 4.2). In areas where a footbridge is needed to cross a vehicular road, it is critical first to evaluate whether the site provides sufficient infrastructural support for building such a structure.



Figure 4.2 Ankara footbridge street view imageries (A) [39.89250439°, 32.81321738°], image source: Google, 2023; Google Earth Pro, 2025, (B) [39.98666579°, 32.89666467°], image source: Google, 2023; Google Earth Pro, 2025, (C) [39.96893078°, 32.82957183°], image source: Google, 2020; Google Earth Pro, 2025, (D) [39.95345393°, 32.81006611°], image source: Google, 2020; Google Earth Pro, 2025

The first step after identifying the need for these structures is to develop their designs around site-specific constraints (Figure 4.3), such as the setback distances from

vehicular roads (l_1) and surrounding buildings (l_2, l_4) the distance to be crossed by the bridge (l), including the setback distances of the bridge components (footprints of the bridge) like abutments and circulation elements (l_3, l_5).

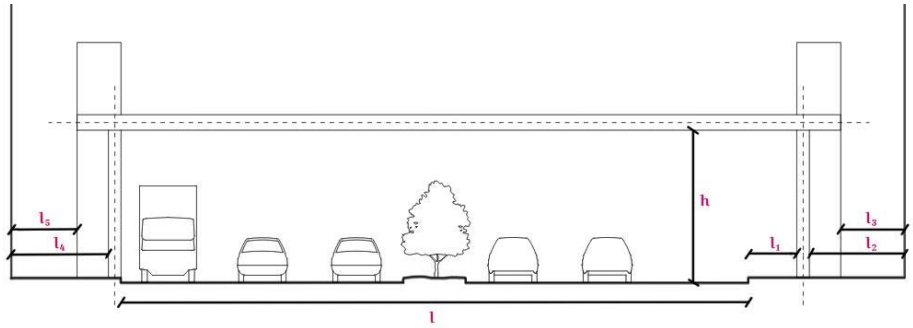


Figure 4.3 Site-specific constraints in location selection process (Developed by the author)

As outlined above, site-specific constraints are the primary parameters influencing footbridge designs. However, both as individuals and as groups, pedestrians have specific expectations from these structures. Even the safety concerns regarding motor vehicles are not enough to encourage pedestrians to use footbridges. Consequently, footbridges that only provide a safe crossing are still not favorable for pedestrians. Literature findings also support this claim, revealing that pedestrians tend to cross "illegally" or only prefer to use footbridges if there are no other alternatives.

Thus, after identifying the locations where footbridges are needed and emphasizing which physical constraints of these locations directly affect their designs, pedestrian expectations regarding these structures should be incorporated into footbridge design processes. Additionally, it is important to note that each footbridge must comply with mandatory design criteria defined by official standards/regulations governing their locations.

In this context, as the second stage of the decision-support tool, it was decided to develop a design guideline for footbridges around site-specific constraints, pedestrian expectations, and mandatory design criteria to enhance their design

frameworks, using the locations predicted by the model in the first stage. The development process, sources of information, and guideline matrices are provided in the following headings.

4.1 Development Process and Sources of Information

During the guideline development process, the parameters affecting footbridge design frameworks are explored. The literature findings on pedestrian expectations, the researcher's observations in Ankara, and footbridge design regulations governing Ankara informed the guideline in this exploration. During the testing process, three false positives of the prediction model were selected as case studies. Site-specific constraints of these locations were integrated with the design guideline; later the necessity and feasibility of constructing footbridges in these locations were evaluated by the researcher.

4.1.1 Literature Review Findings and Integration with Researcher's Observations

The statement that footbridges are not embraced by pedestrians and that this situation leads to a poor-quality pedestrian experience is grounded on the researcher's observation in Ankara. Still, previous studies across the world focus on pedestrian perceptions and preferences regarding different crossing facilities, and the key factors affecting footbridge usage support this discourse and indicate that the problem addressed in this thesis is not specific to Ankara alone. These findings on pedestrian expectations play a crucial role in the development of the design guideline. By integrating these findings with researcher's on-site observations, pedestrian needs and expectations can be directly incorporated into the footbridge design processes, while also offering a user-centered approach to footbridge design processes. The table below outlines the examined areas and specific crossing

facilities, the investigation methods, and the findings of these reviewed studies. (Table 4.1).

Table 4.1 The reviewed studies on pedestrian perceptions and preferences regarding footbridges and other crossing facilities (Developed by the author)

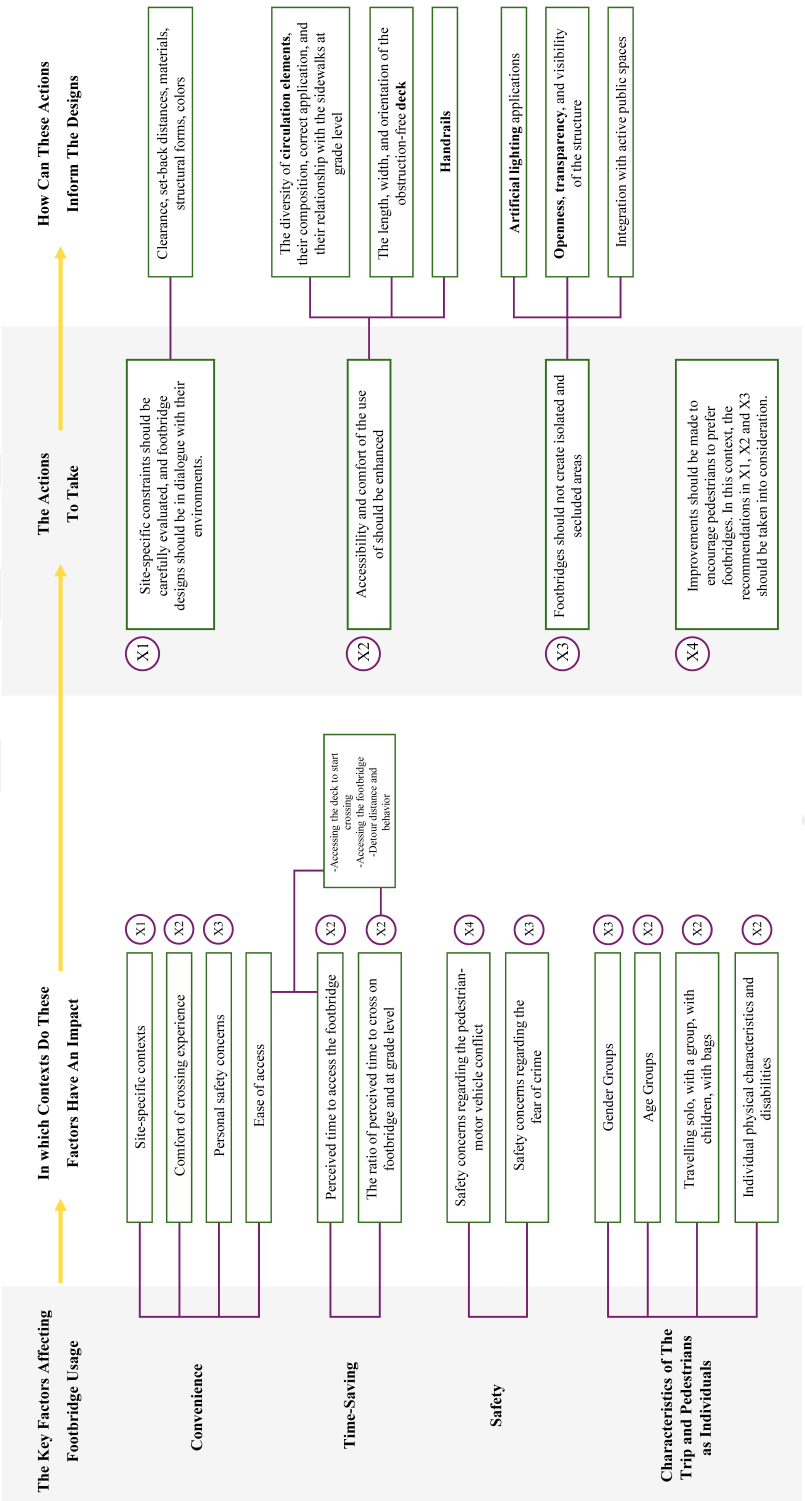
Researchers	Methodology	Examined Area and Crossing Facilities	Key Factors Affecting Pedestrian Preferences	Preferred Crossing Facility and Preference Conditions
Patra, Perumal, Rao (2020)	-Video Capturing Pedestrian Movements -Binary Logit Model	Two at-grade signalized crosswalks and coexisting footbridges in Mumbai, India	Time-saving, convenience, accepted "risk factor", age and gender groups, carrying a luggage, trip being solo, with a group or children, crossing length	Footbridge if; -the total crossing time is less than at-grade, -it is easy to access -age decreases -the trip is with a child or a luggage
Banerjee, Raoniar, Maurya (2020)	-Field and Questionnaire Surveys -GLM, RF, GBM	14 footbridge locations across 6 Indian cities	Personal safety, convenience, gender	Not footbridge when; -age increase -there are obstructions and human congestion -the walkable widths and stair dimensions are inadequate -poor level lighting
Zagorskas, Turskis (2020)	-MCDM Model: -MEW -EDAS -ARAS Expert Judgement -SWARA	Evaluating five locations in Kaunas, Lithuania for potential footbridge locations	Connectivity, usage, image, health, road safety, and cost effectiveness	-The most beneficial location was selected due to its balance between each criteria
Anciaes, Jones (2018)	-Stated Preference Surveys -Mixed and Conditional Logit Models	Three English neighborhoods near busy roads, participants rating straight signalized crossings, staggered signalized crossings, footbridges, underpasses	Time-saving, convenience, safety (personal), accessibility, personal security, age and gender groups, the purpose of the trip	Grade-separated facilities if they are closer than signalized crossings At-grade crossings for safety (personal) and better accessibility (ramps and stairs are not favored by pedestrians)
Oviedo-Trespalacios, Scott-Parker (2017)	-Field and Questionnaire Surveys -Logistic Regression Model	Avenida Alberto Assa Highway and Footbridge in Barranquilla, Colombia	Time-saving, safety (personal and regarding motor vehicles), ease of accessing the footbridge, habitual behaviors	Not footbridge if; -it is not easy to access, -it is not safer (personal) -if the temperature is high and there is humid Footbridge if; -a previous road-related injury was experienced or witnessed

Sinclair, Zuidgeest (2016)	-Intercept Surveys -CCTV data	Eight locations on freeways of Cape Town, South Africa	Time-saving, distance-saving, no other choice, safety (regarding motor vehicles)	Footbridge for safety (regarding motor vehicles) Illegal at-grade crossing for safety (personal), time-saving, distance saving Having "no choice" has a significant influence on both crossing choices
Guo, Zhao, Wang, Zhou, Zhang, and Wets (2014)	-Field and Questionnaire Surveys -MNL	An area with more than two types of crossing facilities as grade-separated (footbridge/underpass) and at-grade crosswalks in Beijing, China	Time-saving, convenience, safety (regarding motor vehicles), detour distance, and physical strength	Grade-separated facilities if safety (regarding motor vehicles) is chosen as the action principle, and when the route is shorter "Illegal crossing" when convenience and time-saving or physical strength are chosen as the action principle
Šimunović, Grgurević, Pašagić Škrinjar (2012)	-AHP	Four pedestrian crossing facilities: zebra crossings (without traffic lights), signal-controlled crossings (with traffic lights), underpasses, and overpasses (footbridges)	-safety (driving speed, traffic volume/intensity, length of the pedestrian crossing) -energy -price (prices of the design, construction, and maintenance) -other (noise, environmental impact, comfort, and accessibility for disabled pedestrians)	-Experts chose underpass (safety concerns regarding motor vehicles) -Investors chose zebra crossings (cost-effectiveness) -Disadvantaged pedestrians chose signal-controlled crossings (for accessibility and energy efficiency) -Healthy pedestrians chose signal-controlled crossings (balance between safety and accessibility)
Räsänen, Lajunen, Alticafarbay, Aydin (2007)	-Field and Questionnaire Surveys -Binary Logistic Regression Model	Five Footbridges in CBD of Ankara, Turkiye	Time-saving, convenience, safety, habitual behaviors	Footbridge if; -it is easy to access (with an escalator) -it saves time while crossing -it feels safer -the familiarity with the areas decreases

While each study has its unique characteristics, they share several common elements; these include conducting field surveys by selecting specific areas within a city or different cities, where pedestrian-motor vehicle conflicts are intense, and collecting data on pedestrian perceptions and preferences through questionnaires. In such a research topic shaped by individuals' experiences, the answers provided by pedestrians about their footbridge usage experiences are of great importance as a source of insight into common needs.

These studies examine the key factors behind the use and non-use of footbridges. Building upon these findings, it is aimed to expand the scale to the urban scale and to address the shared expectations at the urban scale. In this regard, literature findings are incorporated with the researcher's observations of footbridges in Ankara. The table below demonstrates the key factors affecting footbridge usage, the contexts that these factors have an impact on, the actions to address them, and how these actions can inform the footbridge designs (Table 4.2):

Table 4.2 Integration of literature review findings and researcher observations



According to the outcomes of these studies, pedestrians expect a comfortable crossing experience and easy access to the footbridge itself and the footbridge deck to start crossing. In terms of accessibility and ease of use, the variety, configuration, and correct application of the circulation elements such as ramps, stairs, elevators, and escalators that provide access to the decks directly affect the user-friendliness of these structures. The applicability of circulation elements is closely related to the relationship between these structures and the sidewalks that they are located on. To provide easy access to the footbridge, it has to be ensured that the bridge abutments and circulation elements do not occupy the space on the sidewalks (Figure 4.4).



Figure 4.4 Footbridge-sidewalk relationship (A) Photograph taken by the author, (B) Street view imagery [39.80670838°, 32.80379579°], image source: Google, 2024; Google Earth Pro, 2025

On the other hand, the availability of different types of circulation elements affects the ease of use and accessibility of these structures. For physically disadvantaged and older pedestrians, the bridge should offer options such as elevators or escalators that minimize physical effort while using these structures. However, these elements are dependent on energy power, thus in case of failure, alternative circulation elements such as ramps and stairs should be offered (Figure 4.5). In addition, since the usage capacity of elevators is limited compared to other alternatives, the lack of different types of circulation elements can lead to human congestion on the ground level. In this context, the balance of different circulation elements is crucial. Lastly,

in terms of ease of use and accessibility, an obstruct-free bridge deck and the presence of handrails to ease movement also positively affect the user experience.



Figure 4.5 Application of different types of circulation elements (Photographs taken by the author)

Another key finding of these studies is that pedestrians prefer time-saving crossing options. Thus, the perceived time to access the footbridge, and the ratio of perceived time for the crossing act on the footbridge and at grade level are influential in their decisions. The distance to be crossed by the footbridge being longer than the crossing distance at grade level often deters pedestrians from using these structures. Thus, it is recommended to keep the length of the deck as short as possible. However, the functions connected by the bridge are another key parameter while defining the bridge orientation and, therefore, its length. A site-specific optimized proposal should be provided that takes both contexts into account.

The reviewed studies also revealed that pedestrians prefer using footbridges when their primary concern is motor vehicle traffic. However, when personal safety becomes a concern, they prefer to cross at grade level. Footbridges that create dark and isolated areas are strengthening their concerns regarding personal safety (Figure 4.6A). Both for open and covered footbridges, it is essential to provide an adequate level of artificial lighting (Figure 4.6B). As has been emphasized in the literature, the ratio of using a footbridge decreases when there is a poor level of lighting.

In this regard, footbridges that allow a clear visual connection between pedestrians on the bridge and at grade level are preferred, thus designing open footbridges can be recommended. It should also be mentioned that placing billboards on bridges may

block the visual connection, even on open bridges (Figure 4.6C). However, the decision to design an open or covered bridge is closely tied to the climate conditions. In such cases where covering the bridge is necessary, using transparent materials for the cover can be recommended (Figure 4.6D, 4.6E); but as the cleaning needs of such materials are higher compared to opaque materials, a balance between the functionality and costs should be carefully considered.

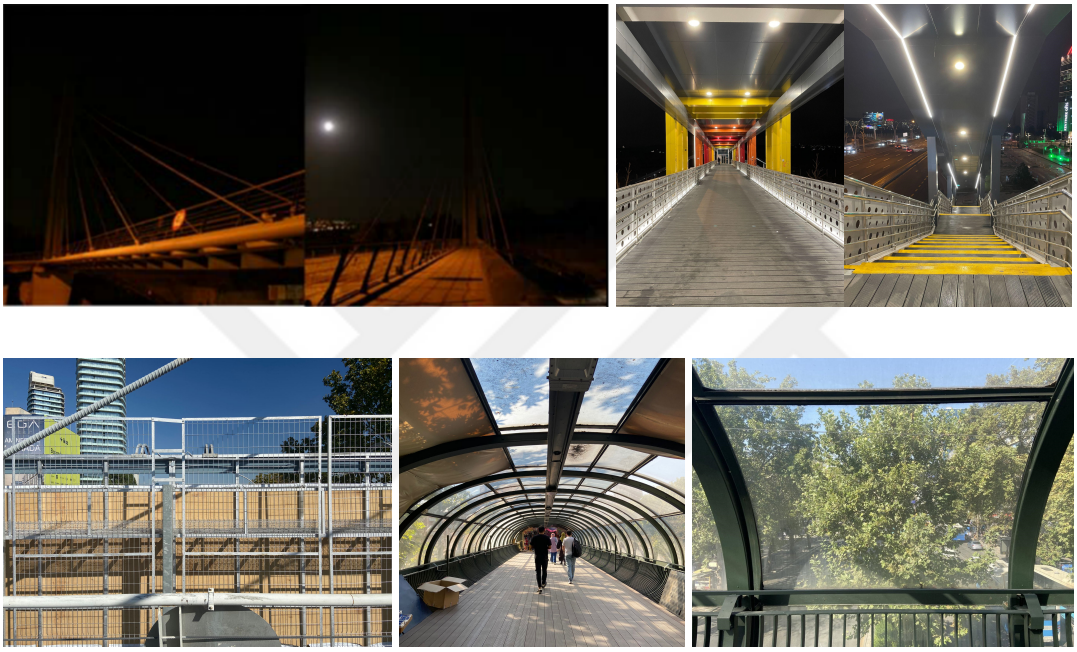


Figure 4.6 Artificial lighting applications (A) METU Footbridge night photos (Arslan Selçuk, Akan, 2005), (B-C-D-E) (Photographs taken by the author)

Lastly, it became evident that the characteristics of both the trip and pedestrians as individuals play a significant role in the decision-making processes. Pedestrians' physical strength and disadvantages are closely related to their usage preferences. As age increases, the likelihood of using a footbridge decreases. In line, while ramps and stairs are less favored by pedestrians due to the physical effort required, incorporating circulation elements such as elevators and escalators increases the usage rates. However, as mentioned in the upper sections, energy dependency should be taken into account. A similar result to age groups has been revealed in a different context. The social environment surrounding the footbridge locations has a strong

impact on the preferences. For instance, it has been reported in various studies that female pedestrians tend to cross at grade level due to their safety concerns regarding fear of crime. However, specific travel contexts can reverse these trends. For instance, when pedestrians carry luggage or travel with children, the likelihood of using a footbridge increases despite the previously noted preferences.

4.1.2 Mandatory Footbridge Design Criteria

The fundamental design criteria of footbridges are drawn around official documents such as standards and regulations. These documents define the mandatory design requirements in an area that each footbridge must meet. However, with the typical footbridge examples of Ankara, it has been demonstrated that footbridges built without considering site-specific constraints cannot even meet these criteria. The criteria defined in these documents constitute the basic components for accessible footbridges. Therefore, failing to meet these criteria results in footbridges not being preferred by pedestrians.

In this regard, the fundamental design criteria within the scope of the thesis are outlined in this section. The outlined documents are as follows:

- TS 12576: “Urban Roads-Structural preventive and sign design criteria on accessibility in sidewalks and pedestrian crossings” (2012)
- TS 9111: “The requirements of accessibility in buildings for people with disabilities and mobility constraints” (2011)
- TS EN 81-70: “Safety rules for the construction and installations of lifts - Particular applications for passenger and good passenger lifts- Part 70: Accessibility to lifts for persons including person with disability” (2007)
- “Açık alanlar uygunluk tespit formu” (Detection Form for Open Spaces) (2010)
- “Highway Traffic Regulations” (1997)

4.1.2.1 Ramps

The ramp slope must not exceed 5%; a minimum width of 150 centimeters along the ramp and flat spaces of 150x150 centimeters should be provided to allow wheelchair maneuvers (TS 12576), (Figure 4.7).

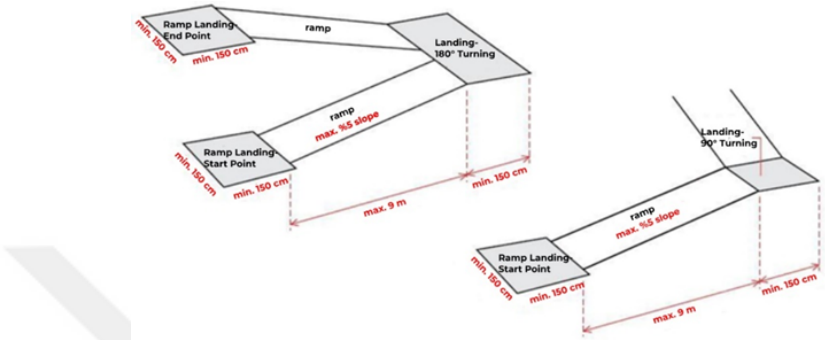


Figure 4.7 Ramp Design Requirements (Edited by the author, adopted from TS 12576, 2012)

For ramps exceeding 9 meters in total length and transition areas between two separate ramps, an additional landing of a minimum of 150x150 centimeters, and for ramps exceeding 30 meters in total length, an additional landing of 250x250 centimeters should be provided (TS 12576), (Figure 4.8).

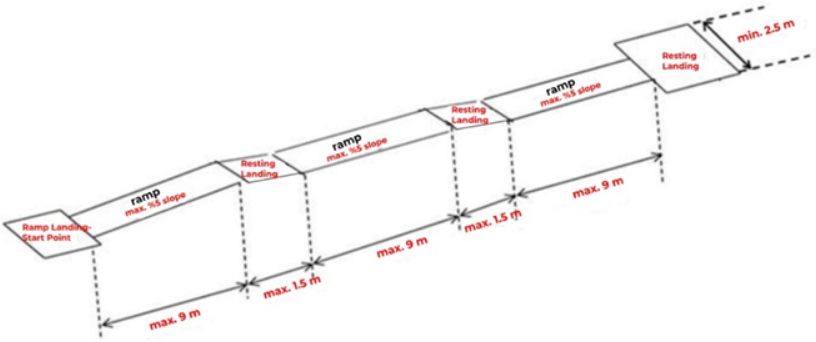


Figure 4.8 Ramp design requirements (Edited by the author, adopted from TS 12576, 2012)

4.1.2.2 Stairs

As described in TS 12576, all stairs must have a minimum step width of 30 cm and a maximum step height of 15 cm, with the same measurements specified for each step of a single stair; all step risers should have a closed design and no protrusions, as open risers and ledges may increase the risk of a fall (TS 12576, 2012). Similar to the ramp requirements, landings should be implemented on stairs that exceed specific dimensions. For each 180 cm vertical distance in a single direction, landings of a minimum 200 cm depth should be provided (TS 12576, 2012) (Figure 4.9).

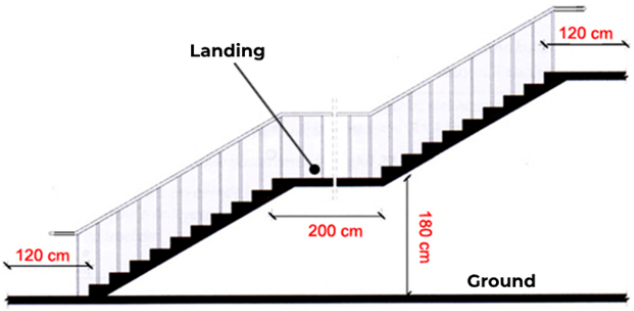


Figure 4.9 Stair design requirements (Edited by the author, adopted from TS 12576, 2012)

For visually impaired pedestrians, the gap under the stairs should be closed up to 220 cm height, as it is the minimum height to prevent people from hitting their heads (TS 12576, 2012), (Figure 4.10).

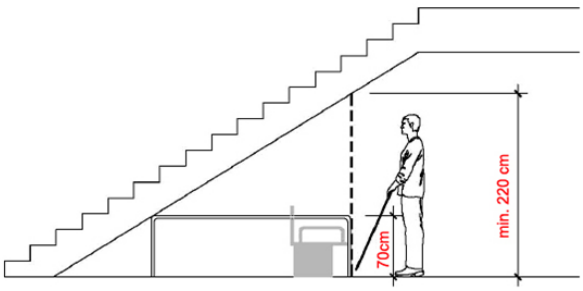


Figure 4.10 Stair design requirements (Edited by the author, adopted from TS 12576, 2012)

Regardless of the size of the stairs, the 120 cm area before the first step and the 120 cm area after the last step must be considered as inseparable components (TS 12576, 2012).

4.1.2.3 Elevators

All the criteria for elevators are taken from TS EN 81-70: "Safety rules for the construction and installations of lifts - Particular applications for passenger and good passengers' lifts - Part 70: Accessibility to lifts for persons including persons with disability" which TS 1276 guided for the accessibility requirements in elevators.

According to the relevant standard, the elevator floor should align with the entrance floor, free from obstacles, and the elevator entrance width should be a minimum of 80 cm; however, it is recommended to extend the threshold to allow wheelchair maneuvers (TS EN 81-70, 2007).

The cabin dimensions should also be determined to accommodate accessibility for disabled users (TS EN 81-70, 2007). The required dimensions for single-entry or double-way elevator cabins are given in Table 4.3 below.

Table 4.3 Cabin width, depth, and payload correlation

Cabin Width x Cabin Depth (mm)	**Payload (kg)**
1000 x 1250	450
1100 x 1400	630
2000 x 1400	1257

4.1.2.4 Railings and Handrails

All criteria under this heading are valid for handrails on bridge decks, ramps, and stairs.

According to TS 9111, railings must be installed on both sides of circulation elements, and handrails must be installed at 70 cm and 90 cm above the floor covering, and 30 cm before and after the circulation elements (TS 9111, 2011), (Figure 4.11). In the presence of a flat surface, such as a wall adjacent to the circulation element, the gap between the surface and the handrail should be between 4-6 cm, and must have a rounded shape, with a diameter of 32-40 mm, made of non-slippery and robust materials (TS 9111, 2011).

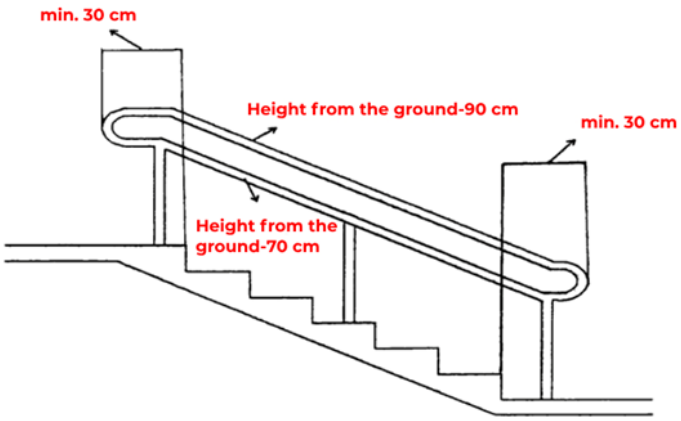


Figure 4.11 Railing and handrail design requirements (edited by the author, adopted from Detection Form for Open Spaces, 2010)

For the ramps that exceed 3 meters in length, a third handrail dividing the ramp into two as 90-140 cm should be provided (TS 12576) (Figure 4.12).

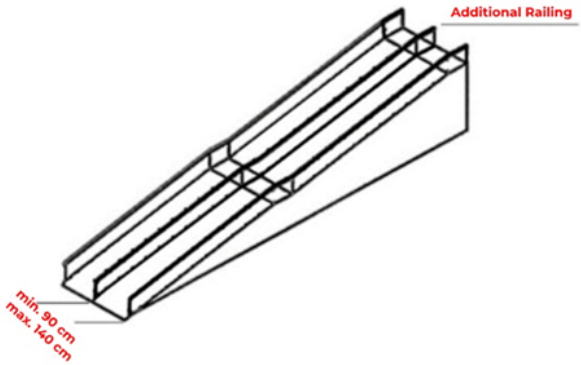


Figure 4.12 Ramp railing requirements (edited by the author, adopted from Detection Form for Open Spaces, 2010).

4.1.2.5 Clearance

According to the criteria of Türkiye General Directorate of Highways, it is mandatory to maintain a minimum clearance of 4.5 meters beneath every bridge and comparable structure (Karayolları Trafik Yönetmeliği, 1997), (Figure 4.13).



Figure 4.13 Clearance of 4.5 meters (Photograph taken by the author)

4.2 Constructing the Guideline

The researcher's observations on footbridges in Ankara regarding their relationships with their surrounding environments, literature review findings on what pedestrians expect from these structures, and mandatory design criteria that every footbridge (in

the case of this thesis, footbridges in Türkiye) must comply with are presented in previous sections.

The key factors affecting footbridge usage, the contexts that these factors have an impact on, the actions to take to address them, and how to inform the design frameworks according to those actions are detailed; later gathered together to construct a design guideline for footbridges, that will enhance their design frameworks. The followed methodology is as follows:

The guideline begins with addressing site-specific constraints, such as setback distances from roads and surrounding buildings, as well as the footprint of the footbridge at grade level. This includes ensuring the availability of sufficient sidewalk width to accommodate an adequate number and variety of circulation elements, thereby facilitating access for all pedestrian groups (Table 4.4).

Table 4.4 Footbridge Design Guideline categories-First stage

Footbridge Design Parameters	**Site-Specific Physical Constraints**	Setback Distances
		Footprint on Sidewalk

If the parameters related to site-specific constraints are deemed satisfactory, the guideline advances to its fundamental function: enabling pedestrian crossing. To this end, the second parameter, titled “Bridge Deck and Height,” is introduced to the guideline (Table 4.5). The first parameter under this section is the “length and orientation”, which is informed by the literature findings but is inherently tied to the site-specific characteristics since the minimum distance to be crossed is predetermined by the width of the road to cross above. In order to encourage pedestrians to use the bridges, the deck length should be as short as possible, and the orientation should be determined to result in the ideal length. The second critical parameter for the deck is its “width”, which is similarly informed by the literature.

To ensure a comfortable crossing experience, the deck must provide sufficient width for pedestrian flow. The final parameter in this section is the clear span, or "clearance," beneath the footbridge. This parameter is dictated by mandatory design requirements and is included in the guideline to ensure compliance with relevant standards.

Table 4.5 Footbridge Design Guideline Categories-Second stage

Footbridge Design Parameters	**Site-Specific Physical Constraints**	Setback Distances
		Footprint on Sidewalk
	Bridge Deck and Height	Length and Orientation
		Width
		Clearance

After forming the framework of the bridge deck and its height, the guideline focused on the accessibility component. In this context, the third section titled "Accessibility Components" is included in the guideline (Table 4.6). This section covers ramps, stairs, and elevators that provide access to the deck, as well as handrails that enhance accessibility and usability. Each component under this heading is dominantly informed by mandatory design criteria but with additional recommendations from the literature and researcher's observations.

Table 4.6 Footbridge Design Guideline Categories-Third stage

Footbridge Design Parameters	**Site-Specific Physical Constraints**	Setback Distances
		Footprint on Sidewalk
	Bridge Deck and Height	Length and Orientation
		Width
		Clearance
	Accessibility Components	Ramps
		Stairs
		Elevators
		Railings

Following, the guideline focused on “Form and Technical Elements” (Table 4.7). The decisions about whether the footbridge should be designed open or covered are addressed under this section with the “Bridge Covering” title. The decision to design an open or closed bridge is tied to the climatic conditions of the footbridge locations, however further informed by the literature, particularly the findings on personal safety concerns. Following, the guideline incorporated “Lighting” recommendations, which are guided by the literature findings. In the final, the design parameters such as the structural type of the bridge, and the materials to be used are considered. These parameters are shaped by a combination of designer preferences, engineering requirements, and environmental factors.

Table 4.7 Footbridge Design Guideline Categories-Final stage

Footbridge Design Parameters	**Site-Specific Physical Constraints**	Setback Distances
		Footprint on Sidewalk
	Bridge Deck and Height	Length and Orientation
		Width
		Clearance
	Accessibility Components	Ramps
		Stairs
		Elevators
		Railings
	Form and Technical Elements	Bridge Covering
		Lighting
		Structure Type
		Materials

After forming the general framework of the guideline, all information given in this section regarding literature findings, researcher observations, and mandatory design criteria is integrated into the guideline as descriptions/requirements, corresponding to their categories (Table 4.8).

Table 4.8 Footbridge Design Guideline

Category	Parameter	How To Design?
Site-Specific Physical Constraints	**Setback Distances**	The minimum setback distance of the outermost component of the footbridge towards the roadway side should be 150 cm, allowing two wheelchairs to pass side by side. The minimum setback distance of the innermost component of the footbridge from the surrounding buildings/facilities/urban spaces with specified functions should be 150 cm, allowing two wheelchairs to pass side by side. It is recommended to increase the setback distances as much as possible while taking into account the width of the sidewalk that the footbridge is settled on.
Site-Specific Physical Constraints	**Footprint on Sidewalk**	The abutments and the accessibility components of footbridges should be in sizes that do not occupy the sidewalk width to ensure while the footbridge is offering accessibility, the sidewalks maintain their functions for pedestrians at grade level. The sizes of such components should leave a gap equal to or greater than the minimum setback distances, while the dimensions of such components also comply with the mandatory design criteria.
Bridge Deck and Height	**Length and Orientation**	It is recommended to keep the length of the bridge deck as close as possible to the length of the spanned roadway. By reducing the distance to be crossed and time to complete the crossing act, pedestrians can be encouraged to use the footbridge. Thus, it is recommended that the orientation of the bridge ensures passage in the shortest possible distance. However, the orientation, therefore, the length of the deck, primarily depends on the functions of the areas to be connected.
Bridge Deck and Height	**Width**	The minimum width of the bridge deck should be 150 cm, allowing two wheelchairs to pass side by side, however, it is recommended to increase the available space.
Bridge Deck and Height	**Clearance**	The minimum clear height (clearance) under the bridge deck should be 4.5 meters. However, it should be noted that this measure may vary depending on the mandatory criteria of each city/country/region.
Accessibility Components	**Ramps**	The slope of footbridge ramps should not exceed %6, allowing disadvantaged pedestrians to comfortably use the bridge. A minimum of 150 centimeters width should be provided along the ramps. Flat areas of 150×150 cm should be placed at the starting and ending areas of ramps and for every 9 meters. If the total ramp length exceeds 30 m, additional landings of 250x250 are placed on the ramps. It should be noted that these criteria may vary depending on the mandatory criteria of each city/country/region. If ramps are selected as accessibility elements, it is recommended to also include other accessibility components that minimize physical effort such as elevators.

Accessibility Components	**Stairs**	The minimum step tread should be 30 cm, and the maximum riser height should be 15 cm. Risers should be closed designed with no protrusions that can cause falling accidents. These criteria should be maintained on each step of the stairs. Landings of a minimum of 200 cm should be placed for each 180 cm vertical distance. The gap under the stairs should be closed up to 220 cm in height to prevent people from hitting their heads. It should be noted that these criteria may vary depending on the mandatory criteria of each city/country/region. If stairs are selected as accessibility components, it is recommended to also include other accessibility elements that minimize physical effort such as elevators.
Accessibility Components	**Elevators**	If elevators are selected as accessibility components, it is recommended to also include other accessibility elements that do not rely on energy sources thus, in case of a failure, the structure can remain accessible at a certain level. If elevators are selected, the following cabin dimensions should be provided: -For 6 people: 100 x 125 cm -For 8 people: 110 x 140 cm -For 17 people: 200 x 140 cm It should be noted that these criteria may vary depending on the mandatory criteria of each city/country/region.
Accessibility Components	**Railings**	Handrails should be installed at 70 cm and 90 cm above the floor covering. The railings should start 30 cm before accessibility elements and end 30 cm after them. Railings or handrails should be provided along the bridge deck. They should have rounded shapes with a diameter of 32-40 mm. It should be noted that these criteria may vary depending on the mandatory criteria of each city/country/region.
Form and Technical Elements	**Bridge Covering**	If the bridge is in a rainy climate or an area with intense sunlight, a top cover over the deck and accessibility components are recommended to protect pedestrians from weather conditions. If the bridge deck is to be fully covered, transparent materials should be preferred over opaque materials to allow visual connection between pedestrians on the bridge and at grade level.
Form and Technical Elements	**Lightings**	The structure should not create dark and isolated areas that cause fear of crime; thus, an adequate level of lighting is crucial. Artificial lighting should be applied, and bright environments should be created. If the surrounding environments are bright enough to also brighten footbridges, the decision to install additional artificial lighting might be considered along with energy consumption and costs, however, it is recommended to provide an adequate level of brightness to reduce the fear of crime without depending on the surrounding environment. Aside from artificial light, openings or transparent coverage should be provided for natural light to pass through the bridge deck and accessibility components.
Form and Technical Elements	**Structure Type**	Decisions regarding the structure type of footbridges are left to the designer's preferences and engineering requirements. Furthermore, it is worth noting that designer preferences and engineering requirements guide the designs in each design aspect.
Form and Technical Elements	**Materials**	Materials that are resistant to weather conditions, environmental and human loads, and heavy usage should be used for all components of footbridges. Non-slippery materials should be selected for surfaces that pedestrians use. If the deck is covered, transparent materials should be chosen to allow visibility between the covered areas (inside) and outside. Decisions regarding the rest of the materials to be used are left to the designer's preferences and engineering requirements.

4.3 Critical Evaluation of Constructing Footbridges: Revising the Predicted Locations

In the first stage of the decision-support tool, the prediction model suggested footbridges in three locations. However, how to design footbridges affects the decision of where to construct, and in fact, whether to construct them or not. Hence, following the development of the two-stage decision-support tool for the footbridge site selection and design phases, the predicted locations were revisited, and the necessity and feasibility of constructing footbridges at these locations were critically evaluated by the researcher using the design guideline as the main source.

4.3.1 Predicted Location No.1



Figure 4.14 Predicted Location No.1 (39.9755344°, 32.7318129°). (A) Sattelite imagery source: Airbus, 2024; Google Earth Pro, 2025, (B) Street view imagery source: Google, 2023; Google Earth Pro, 2025

The predicted footbridge area is located on a four-lane local road, divided by a narrow and shallow median strip. Although a park is located near the site, which initially might suggest the need for a footbridge since parks are active urban spaces, further analysis does not support this prediction. The predicted area is in a residential zone with relatively low road-crossing demand and low pedestrian-motor vehicle conflict. Additionally, the sidewalks, measuring approximately 1.5 meters on both sides, are too narrow to accommodate a footbridge's mandatory accessibility criteria, while also maintaining the sidewalk's functionality. Despite the model's prediction,

on-site analysis shows that a footbridge is neither necessary nor feasible in that area. Building upon the literature reviewed in this thesis, it is recommended to install a crosswalk, or a signalized crossing next to the park rather than constructing a footbridge.

4.3.2 Predicted Location No.2



Figure 4.15 Predicted Location No.2 (39.939163°, 32.877442°). (A) Sattelite imagery source: Airbus, 2023; Google Earth Pro, 2025, (B) Street view imagery source: Google, 2022; Google Earth Pro, 2025

hThe predicted footbridge area is located on a six-lane minor arterial road, divided by a wide median strip, adjacent to a public transportation stop (bus stop), and lies between a crosswalk (within 10 meters), and a signalized crossing (within 50 meters). The predicted location is in front of a university (Ankara University, Faculty of Nursing).

The presence of an educational building and an arterial road might be suggesting the need for a footbridge for the prediction model. Additionally, despite they were not provided to the model as data (since the same data was not available nor collectible for every road in the dataset), the number of lanes and the presence of a wide median strip align with real-life scenarios. However, considering the availability of other crossing facilities, slowing down the vehicle traffic with a speed bump between the two crossings, and converting the crosswalk into a signalized crossing can be recommended.

4.3.3 Predicted Location No.3



Figure 4.16 Predicted Location No.3 (39.988133°, 32.690948°). (A) Sattelite imagery source: Airbus, 2024; Google Earth Pro, 2025, (B) Street view imagery source: Google, 2023; Google Earth Pro, 2025

The last predicted footbridge area is located on a seven-lane medium arterial road, divided by a wide median strip, and in between two residential zones, with one high-school building nearby. The distance to the closest public transportation stop (bus stop) is approximately 50 meters, the nearest crosswalk is about 50 meters away, and the closest signalized crossing is approximately 120 meters away. Despite the availability of other crossing facilities, constructing a footbridge could be beneficial for this area due to the volume and speed of an arterial road, not exactly on the predicted coordinate, but closer to the high school nearby.

The sidewalk widths in the area (approximately 3 meters and 3.5 meters on either side) meet the minimum measures defined in the guideline, however, still they might present a challenge while ensuring accessibility to the deck and maintaining sidewalk functionality since the available space is very close to the limits.

The developed guideline draws the framework of how to design a footbridge in this location. However, as an exploratory step, the following preliminary design alternatives for the predicted location were generated using AI image generation tool PromeAI (https://www.promeai.pro/ai-image-generation). AI-generated design alternatives are not a part of this study's methodology, they have only employed to try and illustrate how different design frameworks might manifest by transforming the information in the guideline into prompts.

Table 4.9 AI-generated footbridge design alternatives with a simple prompt (A) Alternatives with base image, (B) Alternatives without base image (Images generated by PromeAI in 31.01.2025 https://www.promeai.pro/ai-image-generation)

"Design a highly realistic footbridge connecting two sidewalks, spanning a roadway. The whole structure should be visible."		
		
		

Table 4.10 AI-generated footbridge design alternatives with a prompt created from the guideline (A) Alternatives with base image, (B) Alternatives without base image (Images generated by PromeAI in 31.01.2025 https://www.promeai.pro/ai-image-generation)

"Design a highly realistic footbridge connecting two sidewalks, spanning a roadway. The whole structure should be visible. The minimum setback distance of the outermost component of the footbridge towards the roadway side is 150 cm, and the minimum setback distance of the innermost component of the footbridge from the surrounding building is 150 cm. The bridge deck is perpendicular to the roadway. The width of the bridge deck is 350 cm, and the clear height under the bridge is 4.5 m. Place one stair and one elevator on both sides of the footbridge, connecting the deck to the ground level. For the stairs, the minimum step tread is 30 cm, and the maximum riser height is 15 cm. Risers are closed designed with no protrusions. These criteria should be maintained on each step of the stairs. Landings of a minimum of 200 cm are placed for each 180 cm vertical distance. The gap under the stairs is closed up to 220 cm in height. The elevators will be for six people. Thus, the cabin dimensions are 100 x 125 cm. For accessibility, railings should start 30 cm before the stairs and end 30 cm after them. Railings or handrails are provided on the bridge deck. The handrails have rounded shapes with a diameter of 32-40 mm. The top of the bridge is covered with an opaque material. Artificial lights are applied along the deck and stairs. The footbridge is a steel arch bridge."


The AI-generated design alternatives have not shown the ability to integrate site-specific imagery, accurate design components, contextual factors, and realistic scaling into the outputs. The prompts used for generating the outputs were not reflected in the designs. To offer preliminary design ideas, further enhancements are needed in the tool.

CHAPTER 5

CONCLUSION

5.1 General Discussions

Nowadays, footbridges have become one of the most prevalent infrastructural intervention tools in urban settings, where motor vehicle accessibility is often prioritized over pedestrian accessibility. By elevating pedestrians from ground-level traffic, footbridges create separate pedestrian mobility routes. However, reviewing the literature on pedestrian safety, behavior, and crossing facility alternatives revealed a significant discrepancy: rather than enhancing pedestrian accessibility, these structures are often avoided by their intended audience. Field observations conducted by the researcher at footbridge sites further reveal that these structures are often built in an ad-hoc manner as quick solutions to pedestrian-vehicle conflict areas. This approach overlooks long-term projections regarding the integration of footbridges with their surrounding environments and fails to account for their relationship with pedestrians. To address this challenge, this thesis delved into the decision-making processes for footbridges in early phases and focuses on location selection and design frameworks. It emphasized that in built environments where footbridges are deemed necessary, the site selection and design processes of these structures should be adhered to a structured planning framework.

To this end, this study proposes a two-stage decision-support tool comprising two complementary steps: a machine learning model to predict the need for footbridges in given locations for location selection processes, and a guideline for design processes. While the prediction model responds to *where* to construct footbridges, the guideline responds to *how* to design these structures. This approach not only underscores the fact that location selection and design phases are tied to each other,

but it also guides the decision of *whether* they should be constructed or not. In this regard, the first research question is revisited:

"Which built environment factors are determinative in footbridge location selection? How can these factors be used to train a machine-learning model for the decision-making process?"

To answer this question, Ankara, Türkiye as a notable example of a vehicle-oriented city was selected as the main observation and data collection source. The shared built environment features and the patterns in Ankara footbridge locations were explored and collected as data. The same features were extracted from Ankara locations without footbridges, and the prediction model was trained using real-world data. The decision Tree algorithm was selected for the task as it allows clear monitoring of its decision-making process while producing the predictions. After evaluation of the effects of different data splits, data type transformations, and hyperparameter tuning, the best-performing model starting the tree with the feature with the lowest Gini index and the highest Information Gain was validated as the prediction tool. While the selected best-performing model is tailored to meet the objectives of this thesis, the whole process of developing the tool provides a valuable resource for similar tasks, outlining the methodological steps for developing prediction models with small datasets.

At the end of the model evaluation process, the final model suggested footbridges in three different locations. However, the location selection and design processes are interconnected by their nature, hence, the thesis continued with the second stage of the decision-support tool, which is the main contribution of this thesis to the footbridge-related study field. By evaluating where and how to design footbridges together, this thesis offers a comprehensive understanding of footbridge planning that enriches the overall discourse.

In this regard, the second research question of the thesis is revisited:

"How can the trained machine learning model be enhanced into a decision-making tool for footbridges by incorporating it with a design guideline, developed within the framework of site-specific constraints, pedestrian expectations, and mandatory design criteria?"

Footbridges confront the risk of further restricting pedestrian mobility if the site-specific and human-centric aspects are not regarded in the planning and design phases. In this regard, as in the prediction model development process, Ankara was selected as the observation source in discovering the influence of site-specific constraints on the design frameworks. By examining ad-hoc Ankara footbridges, the site-specific constraints such as the setback distances from the roadway and surroundings, and the footprints of footbridge components at grade level were explored.

Following, the key factors affecting footbridge usage were identified through a comprehensive review of the existing literature on pedestrian behavioral studies, focusing on their preferences regarding crossing facility alternatives. While these studies are of great importance since they provide pedestrians' motivations to use or not to use footbridges, they do not provide a focus on the interplay between built environmental features and pedestrian expectations. Hence, to enrich the dialogue between theoretical understanding and practical application, this thesis incorporates the literature findings regarding the key factors such as time-saving, convenience, safety, and the characteristics of both the trip and pedestrians as individuals with researcher's on-site observations. After identifying the key factors and the contexts that influence pedestrian decisions, the actions to take in footbridge designs and how to reflect those actions in footbridge designs were proposed. Subsequently, mandatory design criteria were incorporated into the guideline, offering a framework for translating these expectations into actionable design principles. By combining these findings with site-specific observations, this study proposes design correspondences of pedestrian expectations in footbridge design frameworks,

proposes a sequential decision-making frame, and outlines how to design footbridges.

This two-stage methodological framework that acknowledges the interplay between built environmental features and pedestrian expectation not only uncovers the relationships between built environment characteristics that lead to pedestrian-vehicle conflicts and pedestrian expectations, it brings accessibility, functionality, user expectations, and designer preferences together, ensuring that footbridge designs comply with site-specific conditions, while also complying with mandatory criteria.

5.2 Recommendations for Future Studies

This research proposed a mixed-methods approach, by integrating multiple perspectives across different domains. By leveraging data-driven approaches, theoretical frameworks, literature findings, and observational studies, it has the potential to broaden the existing literature and serve as a valuable resource for future studies.

As illustrated by the network of keywords graphics (Figure 2.3), the intersection of two distinct research domains: structural engineering (e.g., structural dynamics, vibration analysis) and behavioral research (e.g., pedestrian safety, crosswalks). Notably, the structural engineering and human-centric branches are largely disconnected from each other. Building upon the two-stage decision-support tool, future studies can develop integrative frameworks that contribute to both domains, integrating structural design aspects and user-centric aspects during the planning and design phases.

The scope of the decision-support tool can also be expanded by including these structures' environmental impacts and construction and maintenance costs, which could refine site selection and design processes.

Besides, the scope of the proposed methodological framework (prediction model and design guideline) can be extended to other pedestrian crossing facilities, and how different crossing alternatives perform under similar built-environment constraints and user expectations could be explored. By providing data on other pedestrian crossing facilities, such prediction models can suggest not only the construction of footbridges but also the most suitable facility options for given areas. By allowing user feedback, the guideline can be refined, enhancing the user-friendliness of the design principles.

5.3 Limitations

While this study proposes a novel framework for the decision-making processes of footbridges, several constraints should be acknowledged. One major limitation was the lack of open-access, large-scale datasets. Despite the efforts to manually collect data, the size of the dataset remained small, and the model remained sensitive to data variability. More robust insights regarding the model's generalization ability could be achieved by more extensive datasets.

Secondly, Ankara is a noteworthy city to examine the footbridges built in an ad-hoc manner. The on-site observations in the city provided an in-depth look at the urban context, and by integrating these observation-based insights with literature findings across the world, the thesis provided a source for studies outside the city. However, future research in other geographical locations might require additional adaptation for both stages of the decision-support tool.

Lastly, despite the AI design generation tools have advanced significantly in recent years, these tools still face limitations. The main challenges encountered during this study were the lack of contextual alignment of the outputs produced with real-world applications, and inconsistent and unrealistic scaling has been experienced across all images. The prompts used for generating outputs could not reflected in the designs.

The future advancements in contextual awareness and scaling can be valuable for research as this thesis.

REFERENCES

Airbus, CNES/Airbus, & Maxar Technologies. (2024). *Satellite imagery [Ankara, Türkiye]*. Google Earth Pro (Version 7.3.6). Retrieved on 30.01.2025, from https://www.google.com/earth/

Airbus. (2023, December 29). *Satellite imagery [Location: 39.85349898°, 32.84941771°].* Google Earth Pro (Version 7.3.6). Retrieved on 30.01.2025, from https://www.google.com/earth/

Airbus. (2023, December 29). *Satellite imagery [Location: 39.939163°, 32.877442°].* Google Earth Pro (Version 7.3.6). Retrieved on 30.01.2025, from https://www.google.com/earth/

Airbus. (2024, April 4). *Satellite imagery [Location: 39.99907222°, 32.86410278°].* Google Earth Pro (Version 7.3.6). Retrieved on 30.01.2025, from https://www.google.com/earth/

Airbus. (2024, July 19). *Satellite imagery [Location: 39.975534°, 32.731813°].* Google Earth Pro (Version 7.3.6). Retrieved on 30.01.2025, from https://www.google.com/earth/

Airbus. (2024, July 19). *Satellite imagery* [Location: 39.988133°, 32.690948°]. Google Earth Pro (Version 7.3.6). Retrieved on 30.01.2025, from https://www.google.com/earth/

Akkar Ercan, M., & Belge, Z. S. (2016). Daha Yaşanabilir kentler için mikro ölçek Bir Yürünebilirlik Modeli. *METU JOURNAL OF THE FACULTY OF ARCHITECTURE*. https://doi.org/10.4305/metu.jfa.2016.2.11

Ali, J., Khan, R., Ahmad, N., & Maqsood, I. (2012). Random forests and Decision Trees. *IJCSI International Journal of Computer Science Issues*, 9(5)

Anciaes, P. R., & Jones, P. (2018). Estimating preferences for different types of pedestrian crossing facilities. Transportation Research Part F: Traffic Psychology and Behaviour, 52, 222–237. https://doi.org/10.1016/j.trf.2017.11.025

Arslan Selçuk, S., Akan, Er, A. (2005). Bir Şehir İkonu Olma Yolunda Yaya Üst Geçitleri ve Aydınlatmaları ODTU Yaya Üst Geçiti Örneği. 3. Ulusal Aydınlatma Sempozyumu, Turkey.

Banerjee, A., Raoniar, R., & Maurya, A. K. (2020). Pedestrian overpass utilization modeling based on mobility friction, safety and security, and connectivity using Machine Learning Techniques. Soft Computing, 24(22), 17467–17493. https://doi.org/10.1007/s00500-020-05277-w

Baus, U., Schlaich, M. (2007) Footbridges: Construction, Design, History. (1st ed). Birkhäuser Architecture. DOI: 10.1680/mobe.34525.0235

Bennet, D. (2008) The history and aesthetic development of bridges. *ICE Manual of Bridge Engineering*. 1-15. (11) ICE manual of bridge engineering SECOND EDITION | Jonggyun Paik - Academia.edu DOI: 10.1680/mobe.34525.0235

Daniels, R., & Mulley, C. (2013). Explaining walking distance to public transport: The dominance of public transport supply. *Journal of Transport and Land Use*, *6*(2), 5–20. https://doi.org/10.5198/jtlu.v6i2.308

El-Geneidy, A., Grimsrud, M., Wasfi, R., Tétreault, P., & Surprenant-42 Legault, J. (2014). New evidence on walking distances to transit stops: Identifying redundancies and gaps 43 using variable service areas. Transportation, 41(1), 193-210. http://dx.doi.org/10.1007/s11116-013-9508-z

Google. (2020, July). *Street view [Location: 39.95345393°, 32.81006611°],* Google Earth Pro (Version 7.3.6). Retrieved on 30.01.2025, from https://www.google.com/earth/

Google. (2020, July). *Street view [Location: 39.96893078°, 32.82957183°],* Google Earth Pro (Version 7.3.6). Retrieved on 30.01.2025, from https://www.google.com/earth/

Google. (2022, October). *Street view [Location: 39.939163°, 32.877442°].* Google Earth Pro (Version 7.3.6). Retrieved on 30.01.2025, from https://www.google.com/earth/

Google. (2023, April). *Street view [Location: 39.89250439°, 32.81321738°],* Google Earth Pro (Version 7.3.6). Retrieved on 30.01.2025, from https://www.google.com/earth/

Google. (2023, April). *Street view [Location: 39.9755344°, 32.7318129°].* Google Earth Pro (Version 7.3.6). Retrieved on 30.01.2025, from https://www.google.com/earth/

Google. (2023, April). *Street view [Location: 39.98666579°, 32.89666467°],* Google Earth Pro (Version 7.3.6). Retrieved on 30.01.2025, from https://www.google.com/earth/

Google. (2023, April). *Street view [Location: 39.988133°, 32.690948°].* Google Earth Pro (Version 7.3.6). Retrieved on 30.01.2025, from https://www.google.hcom/earth/

Google. (2024, June). *Street view [Location: 39.80670838°, 32.80379579°],* Google Earth Pro (Version 7.3.6). Retrieved on 30.01.2025, from https://www.google.com/earth/

Google. (n.d.). Google Colaboratory FAQ. Retrieved on November 16, 2024 from https://research.google.com/colaboratory/faq.html

Guo, H., Zhao, F., Wang, W., Zhou, Y., Zhang, Y., Wets, G. (2014). Discrete Dynamics in Nature and Society, 2014, 1–8. https://doi.org/10.1155/2014/949475

Herkes İçin Alanya. (n.d.). Açık alanlar uygunluk tespit formu [PDF document]. Retrieved on November 22, 2024 from https://admin.herkesicinalanya.org/Upload/Docs/330639072.pdf

Lin, W., Yoda, T. (2017). Arch bridges. *Bridge Engineering: Classifications, Design Loading, and Analysis Methods*. 155–173. Butterworth-Heinemann. https://doi.org/10.1016/B978-0-12-804432-2.00009-8

Loutzenheiser, D. R. (1997). Pedestrian access to transit: model of walk trips and their design and urban form determinants around Bay Area rapid transit stations. *Transportation Research Record Journal of the Transportation Research Board*, *1604*(1), 40–49. https://doi.org/10.3141/1604-06

Mooney, P., & Minghini, M. (2017). A review of OpenStreetMap data. In G. Foody, L. See, S. Fritz, P. Mooney, A.-M. Olteanu-Raimond, C. C. Fonte, & V. Antoniou (Eds.), Mapping and the citizen sensor (pp. 37–59). Ubiquity Press. DOI: 10.5334/bbf.c

OpenStreetMap contributors. (2024*). Road network data of Ankara, Turkey* [Road Network Dataset]. OpenStreetMap. Retrieved on 17.04.2024, from https://www.openstreetmap.org

Oviedo-Trespalacios O, Scott-Parker B (2017). Footbridge usage in high-traffic flow highways: the intersection of safety and security in pedestrian decision-making. Transportation Research Part F: Traffic Psychology and Behavior. (49). 177–187. https://doi.org/10.1016/j.trf.2017.06.010

Park, R., Paulay, T. (1975). Concrete, Reinforced. *Reinforced Concrete Structures*. (pp. 583-602). 1975. John Wiley & Sons, Inc. DOI:10.1002/9780470172834

Parke, G. A. R, Harding, J. E. (2008). Design of steel bridges. *ICE Manual of Bridge Engineering*. 235-280. (11) ICE manual of bridge engineering SECOND EDITION | Jonggyun Paik - Academia.edu DOI: 10.1680/mobe.34525.0235

Patra, M., Perumal, V., & Rao, K. V. K. (2020). Modelling the effects of risk factors and time savings on pedestrians' choice of crossing facilities at signalized

intersections. Case Studies on Transport Policy, 8(2), 460–470. https://doi.org/10.1016/j.cstp.2019.10.010

Räsänen, M., Lajunen, T., Alticafarbay, F., & Aydın, C. (2007). Pedestrian self-reports of factors influencing the use of pedestrian bridges. Accident Analysis & Prevention, 39(5), 969–973. https://doi.org/10.1016/j.aap.2007.01.004

Šimunović, L., Grgurević, I., & Pašagić Škrinjar, J. (2012). Selecting optimal pedestrian crossing using multi-criteria decision-making. PROMET - Traffic&Transportation, 22(2), 105–116. https://doi.org/10.7307/ptt.v22i2.169

Sinclair, M., & Zuidgeest, M. (2016). Investigations into pedestrian crossing choices on Cape Town Freeways. Transportation Research Part F: Traffic Psychology and Behaviour, 42, 479–494. https://doi.org/10.1016/j.trf.2015.07.006

T.C. Cumhurbaşkanlığı Mevzuat Sistemi. *Karayolları Trafik* Yönetmeliği (1997). Retrieved December 9, 2024, from https://www.mevzuat.gov.tr/mevzuat?MevzuatNo=8182&MevzuatTur=7&MevzuatTertip=5

Talekar, B., Agrawal (2020). A Detailed Review on Decision Tree and Random Forest. Bioscience Biotechnology Research Communications, 13(14), 245–248. https://doi.org/10.21786/bbrc/13.14/57

Tang, M.-C. (2007). Evolution of bridge technology. IABSE Reports, 93. https://doi.org/10.2749/222137807796119500

Türk Standartları Enstitüsü. (2011). TS 9111*: The requirements of accessibility in buildings for people with disabilities and mobility constraints.* Retrieved on December 7, 2024, from https://intweb.tse.org.tr/Standard/Standard/Standard.aspx?081118051115108051104119110104055047105102120088111043113104073097107103081101066102086100073109

Türk Standartları Enstitüsü. (TSE). (2012). TS 12576: *Urban roads-Structural preventive and sign design criteria on accessibility in sidewalks and pedestrian crossings.* Retrieved on November 18, 2024, from https://intweb.tse.org.tr/standard/standard/Standard.aspx?081118051115108051104119110104055047105102120088111043113104073098112067083103080405708811708605 4

Türk Standartları Enstitüsü. Institution (TSE). (2007). TS EN 81-70: *Safety rules for the construction and installations of lifts - Particular applications for passenger and good passenger lifts - Part 70: Accessibility to lifts for persons including persons with disabilities.* Retrieved on November 18, 2024, from https://intweb.tse.org.tr/standard/standard/Standard.aspx?081118051115108051104119110104055047105102120088111043113104073102057101050073052114099051118100

Türkiye İstatistik Kurumu (TÜİK). (2024). *Yıllara göre illerin yıllık nüfus artış hızı ve nüfus yoğunluğu* [Dataset]. Accessed on 30.01.2025 from https://data.tuik.gov.tr/Search/Search?text=n%C3%BCfus

Tyrrell, H. G. (1911). History of bridge engineering. The author. Retrieved on September 21, 2024 from https://archive.org/details/historyofbridgee00tyrrrich/page/n5/mode/2up

World Health Organization (WHO). (n.d.). *Road traffic injuries*. Retrieved on December 20, 2024 from https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries

Yang, Y., & Diez-Roux, A. V. (2012a). Walking distance by trip purpose and population subgroups. American Journal of Preventive Medicine, 43(1), 11–19. https://doi.org/10.1016/j.amepre.2012.03.015

Zagorskas, J., & Turskis, Z. (2020). Location preferences of new pedestrian bridges based on multi-criteria decision-making and GIS-based estimation. The Baltic Journal of Road and Bridge Engineering, 15(2), 158–181. https://doi.org/10.7250/bjrbe.2020-15.478

APPENDICES

A. Prediction Model Dataset

coordinates	footbridge needed	road type	median strip	public transportation	proximity to public transportation (m)	signalized crossing	proximity to signalized crossing (m)	cross walk	proximity to crosswalk (m)	attraction function	availability of attractions
39.97294101 32.66149396	1	main arterial	1	1	140	0	11111	0	11111	none	0
40.0737002 32.94678449	1	main arterial	1	1	40	0	11111	0	11111	none	0
39.95005338 32.82531433	1	medium arterial	1	1	10	0	11111	0	11111	commercial	1
39.98135281 32.57088554	1	main arterial	1	1	20	0	11111	0	11111	educational and health	1
39.85349898 32.84941771	1	medium arterial	1	1	150	1	85	1	245	culture and sport centers	1
39.97420183 32.59614303	1	main arterial	1	1	45	0	11111	0	11111	park	1
39.96385665 32.64787968	1	main arterial	1	1	45	0	11111	0	11111	commercial	1
39.98924326 32.81975984	1	medium arterial	1	1	115	1	105	0	490	educational and health	1
40.08909782 32.9724304	1	medium arterial	1	1	5	0	420	0	450	commercial	1
39.94815299 32.82788044	1	medium arterial	1	1	55	0	11111	0	11111	none	0
39.8834553 32.66172352	1	main arterial	1	1	5	0	420	0	11111	none	0
39.88931608 32.67017401	1	main arterial	1	1	10	0	490	0	11111	none	0
39.89966466 32.68712653	1	main arterial	1	1	20	0	11111	0	11111	park	1
39.90524132 32.70192382	1	main arterial	1	1	5	0	11111	0	11111	commercial	1
39.90575169 32.71555919	1	main arterial	1	1	20	0	11111	0	11111	none	0
39.90706783 32.74427136	1	main arterial	1	1	25	0	11111	0	11111	none	0
39.90836933 32.77669698	1	main arterial	1	1	5	0	11111	0	11111	commercial	1
39.90844628 32.78241799	1	main arterial	1	1	5	0	11111	0	11111	educational and health	1
39.90901566 32.79228485	1	main arterial	1	1	10	0	11111	0	11111	none	0
39.9113376 32.80839844	1	main arterial	1	1	5	0	11111	0	11111	commercial	1
39.9135221 32.81829125	1	medium arterial	1	1	5	0	520	0	11111	none	0
39.9146054 32.84700567	1	medium arterial	1	1	250	1	160	0	11111	none	0
39.80063416 32.80520418	1	main arterial	1	1	5	0	11111	0	11111	culture and sport centers	1
39.80670838 32.80379579	1	main arterial	1	1	15	0	11111	0	11111	park	1
39.86836279 32.81066562	1	main arterial	1	1	30	0	11111	0	11111	educational and health	1
39.87986014 32.81189741	1	main arterial	1	1	20	0	11111	0	11111	culture and sport centers	1
39.89250439 32.81321738	1	main arterial	1	1	145	0	11111	0	11111	commercial	1
39.90495531 32.81426931	1	main arterial	1	1	5	0	11111	0	11111	educational and health	1
39.90979022 32.81467454	1	main arterial	1	1	65	0	11111	0	11111	educational and health	1
39.92852043 32.81709577	1	main arterial	1	1	30	0	11111	0	11111	commercial	1
39.93547023 32.82263927	1	main arterial	1	1	65	0	11111	0	11111	educational and health	1
39.94121712 32.82707869	1	main arterial	1	1	5	0	11111	0	11111	educational and health	1

39.94929612 32.83365035	1	main arterial	1	1	75	0	11111	0	11111	commercial	1
39.9551739 32.84255075	1	main arterial	1	1	240	0	11111	0	11111	none	0
39.95669483 32.84628919	1	main arterial	1	1	60	0	11111	0	11111	none	0
39.95878073 32.85864322	1	main arterial	1	1	125	0	11111	0	11111	park	1
39.95925493 32.86377809	1	main arterial	1	1	300	0	11111	0	11111	educational and health	1
39.95923034 32.86652641	1	main arterial	1	1	50	0	11111	0	11111	none	0
39.9544278 32.90215868	1	main arterial	1	1	70	0	11111	0	11111	commercial	1
39.95846852 32.87804594	1	main arterial	1	1	25	0	290	0	11111	educational and health	1
39.95826259 32.88212671	1	main arterial	1	1	25	0	11111	0	11111	culture and sport centers	1
39.91950789 32.93130217	1	main arterial	1	1	5	0	11111	0	11111	park	1
39.95088227 32.91280429	1	main arterial	1	1	5	0	11111	0	460	none	0
39.91422446 32.94481262	1	main arterial	1	1	5	0	11111	0	11111	none	0
39.89122371 32.79446294	1	medium arterial	1	1	215	0	11111	0	11111	educational and health	1
39.88629633 32.82456161	1	medium arterial	1	0	11111	0	370	0	11111	none	0
39.95248158 32.77100352	1	medium arterial	1	1	5	1	250	0	11111	educational and health	1
39.98041711 32.77107172	1	medium arterial	1	0	11111	0	11111	0	11111	none	0
39.95902759 32.77131467	1	medium arterial	1	1	25	0	11111	0	11111	commercial	1
39.96550051 32.77159614	1	medium arterial	1	1	5	0	11111	0	11111	none	0
39.96359333 32.87033512	1	main arterial	1	1	30	1	60	1	11111	educational and health	1
39.97249406 32.88008692	1	main arterial	1	1	15	0	11111	1	190	religious	1
39.97876568 32.88572798	1	main arterial	1	1	30	0	11111	0	11111	none	0
39.96668219 32.87390865	1	main arterial	1	1	5	1	170	0	380	park	1
39.98666579 32.89666467	1	main arterial	1	1	15	0	11111	1	240	none	0
39.95691022 32.86316498	1	main arterial	1	1	20	0	380	0	11111	educational and health	1
39.98364554 32.65731748	1	main arterial	1	1	5	0	11111	0	11111	none	0
39.94122588 32.84866138	1	medium arterial	1	1	15	1	170	0	11111	culture and sport centers	1
39.95474627 32.83022105	1	main arterial	1	1	5	0	11111	0	11111	commercial	1
39.94491698 32.76174433	1	main arterial	1	1	5	0	11111	0	11111	commercial	1
39.94515728 32.74867957	1	main arterial	1	1	5	0	11111	0	11111	none	0
39.97968508 32.65850458	1	main arterial	1	1	5	0	11111	0	11111	none	0
39.98699094 32.65659879	1	main arterial	1	1	40	0	11111	0	11111	none	0
39.95611744 32.69245407	1	main arterial	1	1	5	0	11111	0	11111	none	0
39.94519768 32.72546891	1	main arterial	1	1	40	0	11111	0	11111	commercial	1
39.94484893 32.76735327	1	main arterial	1	1	45	0	11111	0	11111	religious	1
39.94998245 32.70221644	1	main arterial	1	1	5	0	11111	0	11111	none	0
39.95192715 32.7976455	1	main arterial	1	1	110	0	450	0	11111	none	0
39.95257752 32.80195477	1	main arterial	1	1	5	0	11111	0	11111	park	1
39.94882123 32.78728806	1	main arterial	1	1	5	0	390	0	11111	park	1

39.95429404 32.81792645	1	main arterial	1	1	10	0	11111	0	11111	park	1
39.94699196 32.78263689	1	main arterial	1	1	10	0	11111	0	11111	park	1
39.94524299 32.71912741	1	main arterial	1	1	5	0	560	0	11111	none	0
39.95345393 32.81006611	1	main arterial	1	1	15	0	11111	0	11111	none	0
39.94538296 32.82626363	1	medium arterial	1	1	5	0	11111	0	11111	educational and health	1
39.94052616 32.79565445	1	medium arterial	1	1	10	0	11111	0	11111	none	0
39.9331975 32.84423937	1	medium arterial	1	1	300	0	300	0	11111	commercial	1
39.94555198 32.84783828	1	medium arterial	1	1	15	0	11111	0	11111	commercial	1
39.94094433 32.84282479	1	medium arterial	1	1	25	0	520	0	11111	park	1
39.95100599 32.85390398	1	medium arterial	1	1	65	0	11111	0	11111	commercial	1
39.96339471 32.74374609	1	medium arterial	1	1	35	0	330	0	11111	park	1
39.96135955 32.76892378	1	medium arterial	1	1	15	0	11111	0	11111	commercial	1
39.95874278 32.7865981	1	medium arterial	1	1	5	0	270	0	11111	park	1
39.96065462 32.77439492	1	medium arterial	1	1	290	0	570	0	11111	commercial	1
39.96261555 32.75943279	1	medium arterial	1	1	5	0	320	0	11111	none	0
39.9602765 32.77852064	1	medium arterial	1	1	15	1	210	0	11111	park	1
40.02734719 32.8962071	1	main arterial	1	1	30	0	11111	0	11111	commercial	1
40.04985553 32.91665793	1	main arterial	1	1	5	0	11111	0	11111	none	0
40.04307634 32.9159742	1	main arterial	1	1	5	0	11111	0	11111	none	0
40.09059203 32.97532416	1	main arterial	1	1	5	0	11111	0	11111	none	0
40.02931947 32.89773331	1	main arterial	1	1	65	0	430	0	11111	park	1
40.06407039 32.92077948	1	main arterial	1	1	20	0	11111	0	11111	none	0
40.0400164 32.91137625	1	main arterial	1	1	105	0	11111	0	11111	none	0
40.02261973 32.89629055	1	main arterial	1	1	40	0	11111	0	11111	park	1
40.07990354 32.96663873	1	main arterial	1	1	5	0	11111	0	11111	commercial	1
40.03526668 32.90330247	1	main arterial	1	1	90	0	350	0	11111	religious	1
40.07722255 32.95813897	1	main arterial	1	1	55	0	11111	0	11111	none	0
39.93066382 32.85449491	1	medium arterial	1	1	5	0	11111	0	11111	educational and health	1
39.91581276 32.85417181	1	medium arterial	1	1	45	0	495	0	11111	commercial	1
39.92302564 32.85431653	1	medium arterial	1	1	5	1	140	0	11111	commercial	1
39.91811143 32.85425741	1	medium arterial	1	1	10	1	240	0	11111	commercial	1
39.91757006 32.8545379	1	minor arterial	0	1	30	0	11111	1	65	commercial	1
39.92155217 32.85179077	1	medium arterial	1	1	55	1	145	0	370	commercial	1
39.92247552 32.85766542	1	minor arterial	0	1	140	0	290	1	130	commercial	1
39.96142539 32.84564096	1	medium arterial	1	1	5	0	11111	0	11111	none	0
39.95565751 32.85291101	1	minor arterial	1	1	30	0	11111	0	11111	none	0
39.96518949 32.84098128	1	medium arterial	1	1	5	0	325	0	11111	educational and health	1
39.95082718 32.85901928	1	minor arterial	0	1	170	1	11111	0	11111	park	1

39.97664628 32.86651692	1	medium arterial	0	1	145	1	110	0	330	commercial	1
39.97505115 32.86612581	1	medium arterial	0	1	95	0	290	0	510	educational and health	1
39.96818635 32.86411572	1	medium arterial	1	1	45	0	280	0	11111	park	1
39.98744831 32.86564125	1	medium arterial	1	1	45	1	95	0	255	none	0
39.97873934 32.83761969	1	minor arterial	1	1	80	1	115	0	430	educational and health	1
39.99907222 32.86410278	1	minor arterial	1	1	70	1	50	1	40	none	0
39.98146629 32.8498679	1	minor arterial	0	1	40	1	60	1	140	educational and health	1
39.97763798 32.84480243	1	minor arterial	0	1	75	1	180	1	170	educational and health	1
39.97092107 32.86163309	1	minor arterial	0	1	30	0	11111	0	11111	park	1
39.97950367 32.85983004	1	minor arterial	0	1	75	0	11111	0	275	park	1
39.9678986 32.85422888	1	minor arterial	0	1	25	0	11111	0	290	educational and health	1
39.99642889 32.87401111	1	tertiary	1	1	20	1	195	0	280	educational and health	1
39.93025717 32.91533388	1	medium arterial	1	1	5	1	250	0	345	educational and health	1
39.93481111 32.88276111	1	medium arterial	0	1	30	1	105	0	11111	educational and health	1
39.94236256 32.88182478	1	medium arterial	1	1	25	1	200	1	150	educational and health	1
39.93534722 32.89780556	1	minor arterial	1	1	100	1	45	1	11111	educational and health	1
39.8500117 32.84503287	1	medium arterial	1	1	5	0	310	0	11111	none	0
39.87317524 32.86195012	1	medium arterial	1	1	5	1	10	1	115	educational and health	1
39.84847222 32.84175833	1	medium arterial	1	1	170	1	65	1	11111	none	0
39.95007502 32.71932831	1	medium arterial	1	1	70	0	11111	1	95	park	1
39.98229048 32.77702785	1	minor arterial	0	1	45	0	11111	1	115	educational and health	1
39.960889 32.81451162	1	medium arterial	1	1	50	1	150	0	11111	educational and health	1
39.95667905 32.81898757	1	medium arterial	1	1	200	0	450	0	11111	educational and health	1
39.95667222 32.81653056	1	medium arterial	1	1	5	0	11111	0	11111	none	0
39.96337641 32.81797926	1	minor arterial	1	1	5	0	11111	1	110	educational and health	1
39.9701309 32.81240807	1	local road	0	1	60	0	11111	1	150	educational and health	1
39.96893078 32.82957183	1	minor arterial	1	1	80	1	170	0	11111	educational and health	1
39.98424448 32.56138511	1	main arterial	1	1	15	0	330	0	11111	educational and health	1
39.96643512 32.63167816	1	main arterial	1	1	35	0	350	0	11111	commercial	1
39.96268351 32.65752912	1	main arterial	1	1	5	0	11111	0	11111	none	0
39.96274578 32.66377748	1	main arterial	1	1	5	0	11111	0	11111	educational and health	1
39.96892277 32.61652023	1	main arterial	1	1	5	0	11111	0	11111	none	0
39.97555796 32.59001943	1	main arterial	1	1	5	0	11111	0	11111	park	1
39.97897131 32.57771509	1	main arterial	1	1	20	0	11111	0	11111	culture and sport centers	1
39.98247585 32.56683723	1	main arterial	1	1	15	0	11111	0	11111	commercial	1
39.94996389 32.58579722	1	minor arterial	1	1	15	1	230	1	235	educational and health	1
39.93374882 32.69469021	1	medium arterial	1	1	45	0	11111	0	11111	none	0
39.97122061 32.57999479	1	minor arterial	1	1	30	1	160	0	11111	educational and health	1

39.91534553 32.7104966	1	medium arterial	1	1	5	0	11111	0	11111	none	0
39.92142441 32.79495101	1	medium arterial	1	1	25	0	360	0	11111	educational and health	1
39.93112767 32.86004877	1	minor arterial	1	1	40	1	220	0	11111	educational and health	1
39.95258056 32.86474722	1	minor arterial	1	1	75	1	105	0	11111	educational and health	1
39.94675833 32.87353056	1	minor arterial	1	1	15	0	11111	1	70	educational and health	1
39.96361744 32.87242705	1	minor arterial	0	1	5	1	115	0	11111	educational and health	1
39.94208442 32.86902197	1	minor arterial	1	1	60	0	11111	1	130	religious	1
39.93337688 32.86762532	1	medium arterial	1	1	65	1	85	1	160	educational and health	1
39.9365155 32.86802955	1	minor arterial	0	0	11111	1	210	0	11111	educational and health	1
39.9950169 32.8485202	0	local road	0	1	40	1	40	1	365	none	0
39.9334287 32.8687625	0	medium arterial	1	1	20	1	10	1	60	educational and health	1
39.9914504 32.7969361	0	local road	0	1	10	0	11111	1	100	none	0
39.9946135 32.815294	0	local road	0	1	235	0	11111	0	11111	park	1
39.9681187 32.8134804	0	local road	0	1	340	0	11111	0	11111	none	0
39.944897 32.7625611	0	main arterial	1	1	65	0	11111	0	11111	commercial	1
39.9838401 32.7722013	0	local road	0	0	11111	0	11111	0	400	none	0
39.9615673 32.7392702	0	local road	0	1	235	0	11111	0	11111	none	0
39.932447 32.8276722	0	medium arterial	1	1	30	1	110	1	160	park	1
39.9679121 32.8692871	0	local road	0	1	120	0	11111	0	11111	none	0
39.9588085 32.7056192	0	local road	0	1	265	0	11111	0	11111	educational and health	1
39.96535 32.7382718	0	local road	0	1	155	0	11111	0	11111	none	0
39.9585711 32.8310058	0	minor arterial	0	1	10	0	11111	0	11111	park	1
39.9501144 32.7241085	0	local road	0	1	440	0	11111	0	11111	park	1
39.950589, 32.871105	0	local road	1	1	75	0	11111	0	11111	none	0
39.9745181 32.8111781	0	local road	0	0	135	0	11111	0	11111	none	0
39.9914504 32.7969361	0	minor arterial	0	1	10	0	11111	1	115	none	0
39.9937957 32.8162348	0	local road	0	1	265	0	11111	0	11111	none	0
39.9220324 32.8512263	0	medium arterial	1	1	130	1	225	0	300	commercial	1
39.9803521 32.8402395	0	local road	0	1	570	0	11111	0	11111	park	1
39.997028 32.832438	0	local road	0	1	180	0	11111	0	11111	none	0
39.9948965 32.8112763	0	local road	0	1	60	1	40	1	11111	none	0
39.988133 32.690948	0	medium arterial		1	180	1	15	1	185	none	0
39.9746629 32.6901822	0	local road	0	1	340	0	11111	0	11111	park	1
39.9905779 32.7132424	0	local road	0	1	240	0	11111	0	11111	park	1
40.0107443 32.864773	0	local road	0	1	125	0	11111	0	11111	none	0
39.9670422 32.8731349	0	tertiary	0	1	80	0	11111	0	11111	none	0
39.9934687 32.8806491	0	tertiary	0	1	90	1	120	1	195	none	0
39.9915237 32.8584666	0	local road	0	1	180	0	11111	0	11111	none	0

40.0244617 32.8579791	0	local road	0	1	135	0	11111	0	11111	none	0
39.95448 32.7413615	0	local road	0	0	11111	0	11111	0	11111	none	0
39.9960681 32.7661954	0	service	0	1	300	0	11111	0	11111	none	0
39.9287748 32.8903034	0	minor arterial	1	1	105	1	145	0	11111	none	0
40.0035464 32.8061643	0	local road	0	1	125	0	11111	0	11111	none	0
40.0234707 32.8636692	0	local road	0	1	125	0	11111	0	11111	none	0
40.0506938 32.8556873	0	local road	0	1	225	0	11111	0	11111	none	0
40.0054321 32.855084	0	minor arterial	0	1	90	1	20	1	125	culture and sport centers	1
39.987761 32.8103385	0	local road	0	1	100	0	11111	0	11111	none	0
39.9681629 32.8694373	0	local road	0	1	120	0	11111	0	11111	none	0
39.9729599 32.7430939	0	local road	0	1	350	0	11111	0	11111	park	1
39.9736759 32.844877	0	local road	0	1	280	1	70	1	185	none	0
40.0219676 32.8599047	0	local road	0	1	115	0	11111	0	11111	none	0
39.9584816 32.8306298	0	tertiary	0	1	20	0	11111	1	55	educational and health	1
39.9505511 32.8712444	0	minor arterial	1	1	145	0	450	1	85	none	0
39.9972451 32.862813	0	medium arterial	1	1	125	1	5	1	165	educational and health	1
40.0041452 32.876758	0	local road	0	1	365	0	11111	0	11111	educational and health	0
39.9281165 32.8253868	0	local road	0	1	150	0	11111	0	11111	none	0
40.0019981 32.8760466	0	local road	0	1	405	0	11111	0	11111	none	0
39.9726035 32.8631492	0	local road	0	1	310	0	11111	0	11111	none	0
40.0033506 32.8743054	0	local road	0	1	135	0	11111	0	11111	none	0
40.0081523 32.8621169	0	local road	0	1	155	0	11111	0	11111	none	0
39.9795196 32.8576565	0	tertiary	0	1	120	0	11111	1	235	commercial	1
39.9816902 32.788951	0	local road	0	0	11111	0	11111	0	11111	none	0
39.9977705 32.8503188	0	tertiary	0	1	235	0	11111	0	11111	none	0
39.9959667 32.7973231	0	local road	0	1	120	0	11111	0	11111	none	0
39.9887202 32.8414851	0	local road	0	1	75	0	11111	0	11111	none	0
39.9750633 32.810427	0	minor arterial	1	1	40	1	230	1	50	none	0
39.96999 32.7977924	0	local road	0	1	100	0	11111	1	45	educational and health	1
39.9342443 32.8688469	0	local road	0	1	165	0	11111	0	11111	none	0
39.9934982 32.7927997	0	minor arterial	0	1	125	0	11111	0	275	educational and health	1
39.965492 32.721895	0	local road	0	1	235	0	11111	0	285	culture and sport centers	1
39.9475471 32.8867495	0	minor arterial	0	1	250	1	150	1	35	none	0
39.9837282 32.73035	0	tertiary	1	1	185	1	50	1	250	none	0
39.9365647 32.865618	0	local road	0	0	500	0	11111	0	11111	none	0
39.9855044 32.8907109	0	local road	0	1	320	0	11111	0	11111	none	0
40.0012601 32.8029398	0	local road	0	1	130	0	11111	0	11111	none	0
39.9280564 32.8891463	0	local road	0	1	145	0	11111	0	11111	none	0
40.0744357 32.823119	0	minor arterial	0	1	40	0	11111	0	11111	none	0

39.9759557 32.8880129	0	tertiary	0	1	290	0	11111	0	11111	none	0
40.0493591 32.8457862	0	local road	0	1	55	0	11111	0	11111	none	0
40.0415322 32.6954347	0	tertiary	0	1	255	0	11111	0	11111	none	0
39.983968 32.6877306	0	tertiary	0	1	30	0	11111	0	11111	educational and health	1
39.939163 32.877442	0	medium arterial	1	1	15	1	10	1	50	educational and health	1
40.0397987 32.844575	0	local road	0	1	70	0	11111	0	11111	none	0
39.9355603 32.824926	0	medium arterial	1	1	30	1	80	0	320	educational and health	1
39.9800118 32.8045038	0	local road	0	1	230	0	11111	0	11111	none	0
39.9755344 32.7318129	0	minor arterial	1	1	75	1	250	0	11111	park	1
39.9407559 32.8779351	0	local road	0	1	85	0	11111	0	11111	religious	1
39.9541585 32.7933878	0	local road	0	1	30	0	11111	1	165	park	1
39.9985679 32.8777283	0	local road	0	1	220	0	11111	0	11111	none	0
39.9442849 32.8172316	0	local road	0	1	165	0	11111	0	11111	none	0
39.9837752 32.6908623	0	minor arterial	0	1	265	0	455	1	5	park	1
39.9753842 32.6571227	0	local road	0	1	125	0	11111	0	11111	park	1
39.9726758 32.8582214	0	tertiary	0	1	65	0	11111	0	11111	none	0
39.9643196 32.8457301	0	service	0	1	310	0	11111	0	11111	educational and health	1
39.9815795 32.8187041	0	local road	0	1	190	0	11111	0	11111	none	0
39.9661399 32.8044972	0	local road	0	1	70	0	11111	0	11111	park	1
39.9957341 32.7996445	0	local road	0	1	60	0	11111	0	11111	park	1
40.0721012 32.8361522	0	local road	0	0	11111	0	11111	0	11111	none	0
39.9553751 32.853142	0	minor arterial	1	1	30	0	11111	0	11111	educational and health	1
39.940609 32.7118608	0	local road	0	1	220	0	11111	0	11111	none	0
39.9861635 32.8567093	0	minor arterial	1	1	235	1	180	1	140	none	0
39.9253745 32.7355746	0	medium arterial	1	0	11111	0	11111	0	11111	none	0
39.9912861 32.8794159	0	local road	0	1	40	0	11111	0	11111	none	0
40.0052075 32.7508641	0	local road	0	1	125	0	11111	0	11111	none	0
39.9615917 32.7381438	0	local road	0	1	230	0	11111	0	11111	none	0
39.9747592 32.7183811	0	local road	0	1	165	0	11111	0	11111	none	0
40.0232023 32.7708409	0	minor arterial	1	1	30	0	11111	0	11111	none	0
39.9620337 32.7626015	0	medium arterial	1	1	5	1	85	0	11111	park	1
39.9626761 32.7479698	0	minor arterial	1	1	45	1	130	1	35	none	0
39.9768577 32.7959148	0	local road	0	1	115	0	11111	0	11111	none	0
39.9763065 32.8484974	0	tertiary	0	1	60	1	215	0	11111	none	0
39.9755694 32.8158039	0	local road	0	1	115	0	11111	0	11111	none	0
39.9761673 32.8756294	0	minor arterial	0	1	95	0	260	1	85	none	0
40.0338113 32.8902112	0	local road	0	1	230	0	11111	0	11111	educational and health	1
39.9842159 32.65937	0	local road	0	1	100	0	11111	0	11111	none	0
39.9270104 32.8794611	0	local road	0	1	450	0	11111	0	11111	none	0

39.9790535 32.7052966	0	tertiary	0	1	170	1	145	1	95	none	0
39.9952111 32.7981012	0	local road	0	1	170	0	11111	0	11111	none	0
39.9856725 32.8456134	0	tertiary	0	1	30	1	125	0	11111	none	0
39.9777801 32.8175981	0	local road	0	1	55	0	11111	0	11111	none	0
39.9669791 32.7686426	0	tertiary	0	1	390	0	11111	0	11111	culture and sport centers	1
40.0047339 32.8666301	0	tertiary	0	1	110	1	65	0	560	none	0
39.9902314 32.816504	0	local road	0	1	195	0	11111	0	11111	park	1
39.9827072 32.7095116	0	local road	0	1	265	0	11111	0	11111	park	1
39.9651036 32.7085569	0	local road	0	1	265	0	11111	0	11111	educational and health	1
39.9806696 32.7227911	0	tertiary	0	1	220	0	11111	0	11111	park	1
39.9799167 32.7067676	0	tertiary	0	1	100	0	11111	0	11111	none	0
39.9834925 32.7805393	0	local road	0	1	445	0	11111	0	11111	none	0
39.9870916 32.8730629	0	local road	0	1	195	1	170	1	65	none	0
40.0069641 32.8702333	0	local road	0	1	80	0	11111	0	11111	religious	1
39.9782204 32.7489706	0	minor arterial	1	1	125	1	175	0	11111	none	0
40.0038816 32.8745011	0	local road	0	1	225	0	11111	0	11111	none	0
39.99363 32.7696178	0	tertiary	0	1	305	0	11111	0	11111	none	0
39.9317987 32.8817249	0	local road	0	1	370	0	11111	0	11111	none	0
39.9793866 32.7737206	0	local road	0	0	11111	0	11111	0	11111	none	0
39.9691129 32.7227719	0	tertiary	1	1	375	0	345	0	11111	park	1
39.9427065 32.8162655	0	minor arterial	1	1	110	1	55	1	370	none	0
40.0064379 32.8773142	0	local road	0	1	210	0	11111	0	11111	none	0
39.9696327 32.8541629	0	local road	0	1	210	0	11111	0	11111	none	0
39.9466076 32.7337019	0	tertiary	0	1	405	0	11111	0	11111	none	0
39.9892563 32.8570577	0	minor arterial	1	1	205	0	265	1	45	none	0
40.0050861 32.8032784	0	tertiary	0	1	65	0	11111	0	11111	none	0
39.9367874 32.8665901	0	local road	0	0	11111	0	11111	0	11111	none	0
39.9852471 32.6871486	0	local road	0	1	185	0	11111	1	10	educational and health	1
39.9689761 32.8410259	0	minor arterial	0	1	5	1	65	1	11111	educational and health	1
39.9900319 32.7180763	0	tertiary	1	1	70	1	150	1	90	park	1
39.9550688 32.8717029	0	local road	0	1	215	0	11111	0	11111	none	0
39.9883468 32.8130591	0	local road	0	1	60	0	11111	0	11111	park	1
39.9533949 32.7221858	0	minor arterial	1	1	75	1	5	1	200	none	0
39.9819137 32.705467	0	tertiary	0	1	200	0	11111	1	170	none	0
39.9433916 32.7082658	0	local road	0	0	455	0	11111	0	11111	none	0
39.9814696 32.7384163	0	tertiary	1	1	65	1	50	1	85	none	0
40.0114668 32.8329652	0	local road	0	1	55	0	11111	0	11111	none	0
39.9416599 32.829039	0	tertiary	1	1	170	1	100	0	11111	none	0
39.9791879 32.8882715	0	tertiary	0	1	65	0	11111	0	11111	religious	1

39.9563543 32.7153878	0	local road	0	0	490	0	11111	0	11111	educational and health	1
40.0020812 32.8401649	0	local road	0	1	190	0	11111	0	11111	none	0
40.0202209 32.7627656	0	service	0	0	11111	0	11111	0	11111	none	0
40.0486853 32.8380024	0	local road	0	1	275	0	11111	0	11111	none	0
40.0503403 32.8518978	0	minor arterial	0	1	105	0	11111	0	11111	none	0
40.0347011 32.771939	0	minor arterial	1	1	15	0	11111	1	65	none	0
39.9805869 32.7233051	0	tertiary	0	1	170	0	11111	0	11111	park	1
39.9723266 32.7294968	0	local road	0	1	115	0	11111	0	11111	none	0
39.9818557 32.6960867	0	tertiary	0	1	275	0	11111	0	11111	none	0