Estimating Walkability of Urban Areas Using Machine Learning

Project Report

Submitted in partial fulfillment of the requirements of
HSS F266 Study Project

By

Neelay Shah
ID No. 2018A8TS0400G

Under the supervision of:

Dr. Sayantani Sarkar

BIRLA INSTITUTE OF TECHNOLOGY AND SCIENCE PILANI, GOA CAMPUS
May 2022

BIRLA INSTITUTE OF TECHNOLOGY AND SCIENCE PILANI, GOA CAMPUS

Abstract

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With the rapid pace of growth and urbanization in today's world, considerations for ensuring healthy lifestyles of citizens while planning and designing living spaces have seemingly taken a backseat. One such design consideration is walkability, which indicates how suitable and friendly an area if for commuting using walking. The first step towards making walkability an important factor for urban design is figuring out methods to estimate it. Only when stakeholders can understand what walkability essentially constitutes and what goes into making a space "walkable" can they make efforts to incorporate it in their decision making. Such estimation methods need to be scalable and not require a great amount of manual labour in order for them to be employed. The objective of this work is to propose a computational method which makes use of machine learning techniques to estimate walkability of urban areas. Our method also provides insights on what features of urban spaces are most pertinent for ensuring walkability. We describe the method in detail and also outline how it can adapted and applied for different use-cases. We evaluate our proposed method by applying it to derive insights for a collection of Indian cities, for which historically there haven't been many studies, especially using computational methods.

Acknowledgements

I wish to express my sincere gratitude to my advisor, Dr. Sayantani Sarkar, for introducing me to this interesting research problem, and for mentoring me throughout my work on this project.

I would also like to thank my colleague, B Raja Narasimhan, with whom I have collaborated on this study project.

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Chapter 1

Introduction

Walkability, a measure of how friendly an area is for walking is a vital consideration and a key challenge for urban planning, design, and development. It has previously been formally defined as *"the extent to which characteristics of the built environment and land use may or may not be conducive to residents in the area walking for either leisure, exercise or recreation, to access services, or to travel to work* ([8]). Walking is one of the most common forms of leisure-time physical activities among adults ([4]) and improving walkability has been proven to have health, economic, and environmental benefits. Hence it is critical that the aspect of walkability of urban areas is factored in while designing them. Walkability is also a key pillar and challenge of sustainable urban development [13]. Forecasting studies have predicted that 60 percent of all people globally will live in cities by 2030, thus posing great challenges for sustainable development of urban areas. Walkability, as a paradigm, is helpful in facilitating the spatial dimension of sustainability which includes transport, places for leisure and other activities, and more.

Seeing the importance of considering walkability while designing urban areas, a lot of research has gone into studying factors which influence the walkability of urban areas and researchers have developed both qualitative and quantitative methods for estimating the same. In recent years, methods which utilize statistical models such as machine learning (ML) and data from mapping technologies such as satellite imagery and Geographic Information System (GIS) data have come to the fore ([14], [13]).

In this project, we extend such work and by developing similar quantitative methods and computational approaches for estimating walkability. Particularly, we analyze the state of urban areas in India and develop methods for estimating the ease of walkability in them. Through our method, we also help identify the most pertinent factors which influence the walkability of an area. We utilize techniques such as machine learning and statistical modeling along with freely available geographical image and video data for this purpose.

Chapter 2

Background

2.1 Previous Work

Research work on urban walkability has been carried out since quite some time. [4] was one of the first studies to comprehensively measure subjective qualities of the urban street environment. The authors collected a panel of experts and used ratings from the panel to measure five urban design qualities. They factored in physical characteristics of streets and their edges: imageability, enclosure, human scale, transparency and complexity. They presented operational definitions of such urban design qualities in the context of commercial streets.

In [14], the authors were one of the first ones to introduce a computational and statistical aspect to the research problem of estimating walkability. They used traditional machine learning techniques to measure visual enclosure in street view images and studied how this quantity correlates with perceived walkability. While this study didn't proposed a method of actually estimating walkability, it offered valuable insights into how statistical techniques could be employed for this purpose.

[8] and [13] both made use of satellite and geographical data in their studies. The former was one of the pioneer works which dealt with Geographic Information Systems (GIS) data by utilizing it to objectively measure features of the environment that may influence adults' physical activity. They showcased how GIS data has the potential to be used to construct measures of environmental attributes and to develop indices of walkability for cities, regions or local communities. They suggested that the walkability index applied in their work and its component measures, provides a useful tool for the selection of communities for household recruitment that can maximize the variability in the built environment and result in an improved ability to detect differences in physical activity levels that likely occur in objectively different environments.

[13] suggested a comprehensive approach of measuring walkability from GIS data based on density maps of specific urban functions and networks of generally accessible pavements and paths. Their methodology could be also used to forecast different states of land use and to predict the impact of changes in the location of various functions and pedestrian infrastructure on walkability. Their method also relied completely on open-source data and was distinguished by its simplicity and ease of application.

In related work, [12] also employed GIS data to develop models to compute a 'bikeability' index akin to a walkability index. Their major focus was on the creation of a novel experimental bikeability index for a specific part of the city of Munich based on applying GIS methodologies. They also identified the contributing factors and explained existing methods with indices for measuring bikeability.

2.1.1 Limitations

While previous works have provided insights into how computational techniques can be used to analyze walkability, they have typically limited to themselves to a narrow geographic scope or have focused on dealing with limited aspects of walkability. In our work, we wish to carry out a study which takes inspiration from previous approaches to develop a method to estimate walkability and analyze factors influencing in a less constrained fashion. We also aim to utilize recent advances in statistical techniques like machine learning (ML) to derive insights and create predictive models.

2.2 The Indian Context

As previously described, a significant amount of research has gone into studying walkability of urban areas, what influences it, and ways to estimate it. However, none of the aforementioned works have approached this problem in the Indian context. To our best knowledge, a report published in 2008 by the Ministry of Urban Development titled "Study on Traffic and Transportation Policies and Strategies in Urban Areas in India" is the only study which addressed this problem from the Indian point of view. This report used surveying techniques to calculate walkability scores of some select Indian cities of national importance.

Through our work, we aim to develop computational approaches which objectively estimate walkability and apply them to Indian cities.

Chapter 3

Preliminaries

3.1 Machine Learning

Machine Learning (ML) is the science (and technology) of developing computer algorithms than can do not have to be explicitly specified but rather can 'learn' from data. More formally, it is the study of computer algorithms that can improve automatically through experience and by the use of data [9]. It is the science of enabling computers to carry out tasks we desire without having to explicitly and meticulously program them to do so. Arthur Samuel, an American computer science researcher first coined the term *machine learning* in the year 1959. Since it's advent in the 20th century, the field of machine learning has advanced broadly and rapidly, and today finds applications in all walks of life. Some examples include recommendation systems, speech recognition and translation, face recognition, and path planning.

To define machine learning more simply, it's the study and development of algorithms which are able to recognize patterns in data [1]. 'Patterns' here can be broadly defined. They can range from visual cues and structural similarities in image (and video) data to sentences which are close in meaning for textual data, and more. All these kinds of data are high dimensional in nature, that is they are characterized by a lots of variables and parameters. The biggest utility of machine learning algorithms is their ability to recognize patterns in such dimensional data without having to be explicitly programmed to do so. This way, one can develop algorithms to perform tasks akin to humans.

In essence, machine learning algorithms are function approximators or representation learners [10]. They are algorithms which are 'trained' to approximate mappings from input to output by recognizing patterns in data as mentioned above and producing similar output for similar kinds of inputs. Alternatively, they are made to learn structures in data regardless of a mapping to develop so called representations of the data. The function approximators are mathematical models parameterized by real numbers called 'weights'. The training process comprises of tuning these weights (adjusting their values) so that the model can approximate a mapping present between inputs and outputs in the data supplied.

Machine learning as a field can be broadly split into 3 categories or types: supervised learning, unsupervised learning and reinforcement learning [5]. This categorization is based on the way machine learning algorithms are 'supervised' during training. As described earlier, machine learning approximators are essentially models which are trained either to approximate mappings or to learn representations of data. Supervision during training alludes to the kind of mapping we wish to learn.

The supervised learning paradigm involves having a collection of labelled examples $(x_i, y_i)_{i=1}^{N}$. x_i is an input element of the dataset which is mapped to a label y_i. Each x_i among N is commonly called a feature vector. A feature vector is a vector whose each value describes the example x_i in a representative way. The goal of a supervised learning algorithm is to use the dataset to produce a model that takes a feature vector x as input and outputs information that allows deducing the label for this feature vector [2].

Unsupervised learning, on the other hand, is the process of learning from a dataset of unblablled examples. The dataset now comprised only of feature vectors x_i but not any labels y_i. The goal in this learning paradigm is create a model which by means of mathematical transforms is able to learn a good representation of the input data. This representation almost always is another continuous real-valued vector, often with fewer dimensions than the original input vector.

Reinforcement learning, meanwhile, is a learning system wherein an 'agent' interacts with it's 'environment' and takes 'actions' in it to achieve rewards in return.

3.2 Decision Trees

A decision tree [7] is a kind of supervised learning machine learning algorithm which can be used for both classification and regression problems. Decision trees were one of the first ML models widely used by the community and they trace their origin back to the late 20th century. While they can be used for both kinds of prediction tasks, they have traditionally found more success and usage for classification problems. Succinctly put, a decision tree is a tree-structured classifier, where internal nodes represent the features of a dataset, branches represent the decision rules and each leaf node represents the outcome.

Figure 3.1 illustrates the general structure of a decision tree. It starts with the root node, which expands on further branches and constructs a tree-like structure. The tree has two kinds of nodes: decision nodes and leaf nodes. Decision nodes are used to make splitting decisions based on features and have multiple branches. Leaf nodes, on the other hand, are terminal nodes of a tree which are used to infer an outcome. They don't have any further branches.

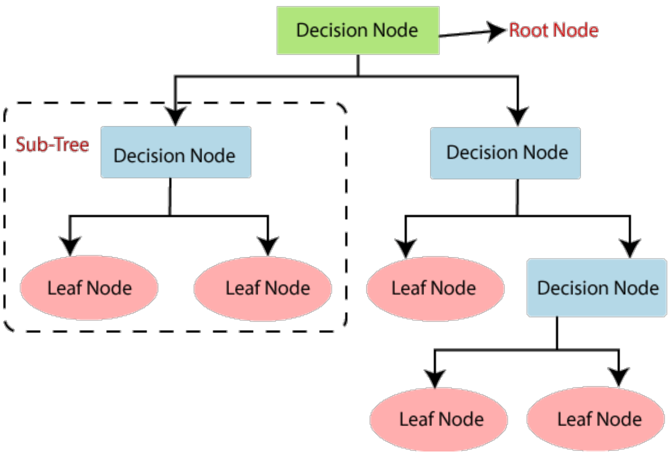

FIGURE 3.1: General structure of a decision tree

Figure 3.2 showcases an example of a decision tree model for predicting the occurrence of rain. It utilizes features such as *Outlook*, *Humidity*, and *Wind* for the task. The tree has three decision nodes corresponding to the three features. For making a prediction on whether it will rain or not, the algorithm makes splitting decisions based on the decision nodes sequentially from top to bottom. At the bottom-most level of the tree are leaf nodes which make the final predictions.

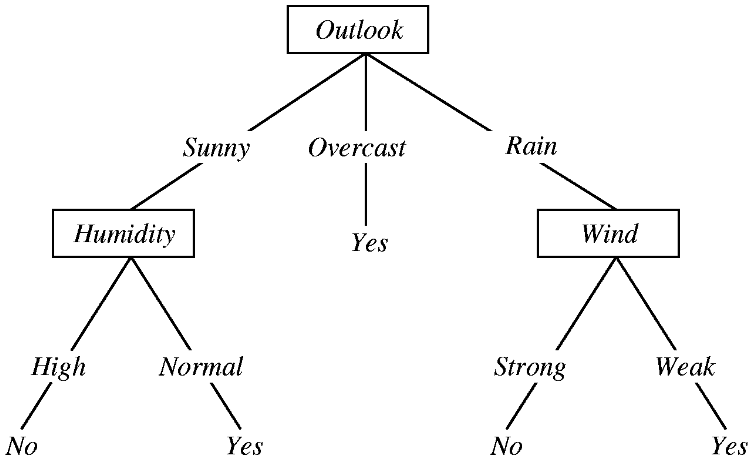

FIGURE 3.2: An example of a very simple decision tree for a rain forecasting task

3.3 Image Segmentation

Image segmentation is an image processing task in which a digital image is partitioned into multiple image segments, also known as image regions or image objects. The goal of image segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. The process consists of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics. Image segmentation can be used to locate objects and boundaries of scenes in images.

Figure 3.3 displays an example of image segmentation applied to an image of a neighbourhood street. As can be seen, the different regions/objects present in the scene such as vehicles, sidewalk, etc. have been segregated and have been assigned representative labels.

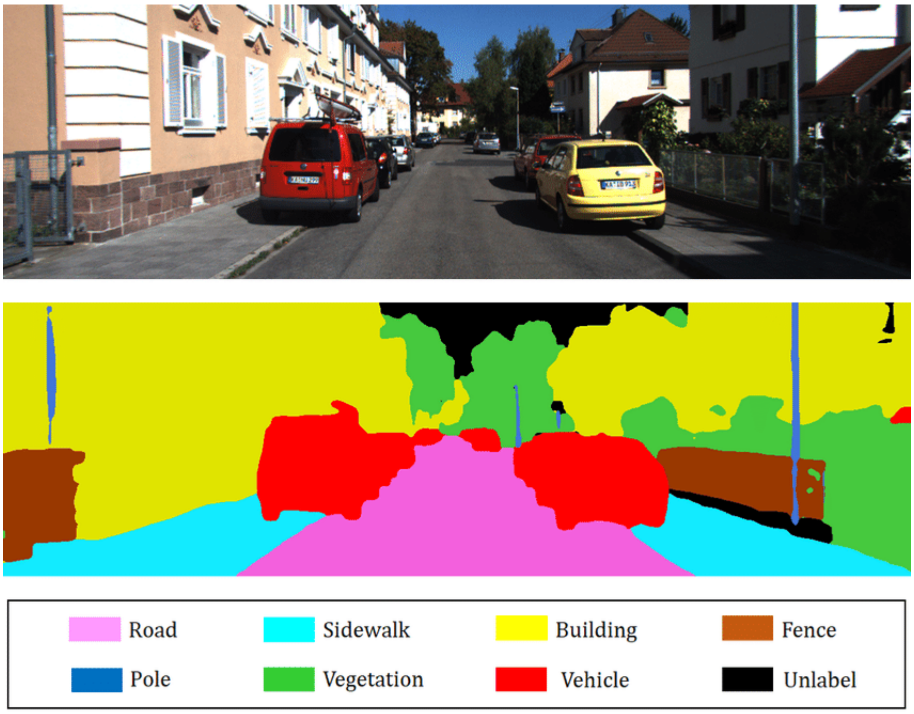

FIGURE 3.3: An example of segmentation for an image of a neighbourhood street

In recent years, machine learning techniques have become the go-to methods for the task of image segmentation. Supervised ML algorithms are employed for this task and they have proven to outperform more traditional computer vision and image processing methods.

In particular, a class of ML models called convolutional neural networks (CNNs) [11], are widely used for image segmentation and are known to be highly accurate. Some examples of established CNN-based models for image segmentation include MobileNet [6], PSPNet [15], and DeepLab [3].

Chapter 4

Methodology

As alluded to earlier, our goal in this work is to develop a computational method to estimate walkability of urban spaces in a manner which is resource-efficient, scalable, and easily extensible. Apart from estimating walkability, we also wish to be able to identify what specific factors are most influential in ensuring that urban areas are 'walkable'.

We took inspiration from previous works which have used computational and statistical techniques to develop an approach based on machine learning for the task of estimating walkability. We utilized openly available geographical and satellite imagery data for this purpose. Our method can be broken down into two major sequential stages: i) feature extraction and ii) model fitting.

4.1 Feature Extraction

In this stage, we extracted features pertaining to urban areas for a collection of cities from image data. We achieved this by first obtaining streetview images from various parts of different cities and then using image segmentation and further processing to extract features of interest.

To collect streetview image data, we made use of two sources: video blogs from online sharing platform like YouTube and satellite imagery obtained from public sources such as the Google Street View service within Google Maps. We manually searched up video blogs of dashboard camera footage on vehicles being driven by people on urban streets in cities. Once we had collected the videos, we sampled frames at equal intervals from them to get streetview images. Apart from video blogs on YouTube, we also used the Google Street View service to obtain streetview images for which there were no videos on YouTube. We manually sampled street locations and made use of a freely available web API downloading images. Our aim during this image collection step was to ensure as much diversity as possible in the streets/areas sampled from the various cities.

After we collected streetview images for a set of cities, we performed a feature extraction step. Specifically, we carried out image segmentation on every streetview image in our collection by using a machine learning model called MobileNet [6]. By doing this, we obtained pixel-wise labels for images which denoted what category a pixel belonged to. Categories here comprised sidewalks, roads, vehicles, pedestrians, and more. We used this information to calculate the proportion of pixels belonging to a particular category to the total number of pixels in an image. This way we were able to extract six features, namely the proportions of **road, sidewalk, vegetation, buildings, terrain, and sky** in images.

Figure 4.1 shows an example of a streetview image obtained for the city of Bengaluru. The image segmentation results have been overlaid on top the image by colour compositing. The different semi-transparent regions indicate the different regions in the image identified by image segmentation.

FIGURE 4.1: Segmentation results overlaid on top of an image of a street in Bengaluru

4.2 Model Fitting

Once we had aggregated a variety of features for roads sampled from a collection of cities, we constructed a dataset which mapped these features of city roads to the how walkable the roads are. A report by the Ministry of Urban Development titled "Study on Traffic and Transportation Policies and Strategies in Urban Areas in India" contains walkability scores for cities which range between 0.0 and 1.0. These scores were assigned by manual surveying procedures carried out by the competent authorities. We categorized these scores into five bins and hence obtained walkability class labels for every city. For scores between 0.0 and 0.20, a label of 1 was assigned, 2 for scores between 0.21 and 0.40. and so on. This way, 1 indicated the lowest level of walkability and 5 the highest. We thus assigned to each image for which we had extracted features a walkability class label based on which city the image belonged to. For all images belonging to a city, we assigned the same walkability class label corresponding to that city. An important thing to note is that since the report contains data for cities as a whole and not for individual roads, we assumed that the score for a city is representative of its individual roads. Hence, we mapped all the roads in a particular city to the same walkability category.

After this step, we had obtained a dataset containing a mapping from features of roads to their level of walkability. This dataset was suitable for training a machine learning model for the classification task of predicting the walkability. We split our entire dataset into a training set and a test set. We fitted a decision tree [7] model to the training set. Once we had obtained the learned model, we evaluated its accuracy on the test set. We also analyzed the learned model by computing the relative importance of the six different features for the classification task. By doing this, we were able to identify the features which are most important in determining how 'walkable' an area is.

Overall, our method can be summarized by the following sequence of steps:

1. Obtain streetview images for a collection of cities using openly available data.
2. Extract features of interest from the images using image segmentation.
3. Create a dataset mapping these features to walkability scores for cities.
4. Fit a machine learning classification model (decision tree) to this dataset.
5. Analyze this learned model to identify the relative importance of features.

Chapter 5

Results and Discussion

We built our dataset by collecting images and corresponding features for urban areas from a variety of cities spanning the geography of India. Some of the cities for which we collected include Chandigarh, Delhi, Kanpur, Guwahati, Kolkata, Chennai, Kochi, Bangalore, Mumbai, Ahmedabad, and more. A full list of the cities for which data was collected can be found in the A along with their published walkability scores and the bins we categorized them into.

We split our entire dataset into a training set which comprised 80% of the images and a test which contained the remaining 20%. We fitted a decision tree model to the training set. We configured the model to have a maximum depth of 5. We evaluated the fitted model on the test set. We achieved an accuracy of **68.42%** on the test set for the walkability score classification task.

We also analyzed the results of the model and computed the normalized relative importance of the different features as shown in table 5.1.

Feature (proportion of)	Normalized Importance
Road	0.2333
Vegetation	0.2144
Sidewalk	0.1870
Sky	0.1619
Building	0.1547
Terrain	0.0487

Table 5.1: Normalized feature importances

As can be seen in the table, the proportions of road, vegetation, and sidewalk are the top three most important features for determining the walkability of an area.

Our results corroborate insights from previous work in suggesting that roads are important factors which greatly influence the walkability of urban areas. Width of sidewalks is obviously a very pertinent factor for walkability since it provides the infrastructure for pedestrians while ensuring comfort and safety. Adequate road width and condition is also an important consideration for walkability to ensure that vehicles have the requisite amount of space to commute. This ensures that the path of vehicles doesn't encroach upon that of pedestrians.

Our results also match insights obtained from previous which suggest that apart from the necessary infrastructure for commuting by walking, aesthetic and environment factors like vegetation also play a part in determining how suitable an area is for walking and how willing people are to walk [13]. Lastly, our results also confirm with previous work in suggesting that visual enclosure is a moderately important factor influencing walkability [14].

As mentioned in previous work as well [8], a method like ours which can be used to estimate walkability in a resource-efficient manner provides considerable opportunity for other applied policy research. For example, analyzing what factors are most influential in determining walkability can assist decision making authorities in city planning and design.

5.1 Limitations

The biggest limitation of our method is that it is dependent on having an accurate image segmentation model for the feature extraction stage. While state-of-the-art machine learning models like MobileNet [6] and DeepLabV3 [3] do a pretty good job in general, they aren't perfect and can lead to inaccurate results when faced with challenging images. Inaccurate image segmentation could lead to noisy feature extraction which would hamper the entire downstream method.

One other limitation of our work is that we assume that the walkability score for a city applied to all urban areas in the city in order to create a dataset for the model training procedure. While ideally this would be true for most cases, this can again lead to introduction of noise in the dataset if the sample streetview images aren't really representative of a city's overall walkability score.

Lastly, because we use a decision tree and treat the task of estimating walkability as a classification problem, we are only able to predict what bin / band (eg. between 0.21 and 0.4) an area's walkability score would fall him while using the model for inference. Ideally, we would like to predict an exact walkability score, but due to the challenges associated with training ML models for regression when dealing with small datasets, we are forced to resort to classification and hence can only estimate a range of walkability for an area, and not an exact score.

Chapter 6

Conclusion

In this work, we developed a method to estimate the walkability of urban areas using computational and statistical modelling techniques. Our method deals with streetview image data and uses machine learning techniques to extract features of interest from images by segmentation. A machine learning model - decision tree - is then trained to estimate walkabilty from the features of the images and evaluated on test data. The model's results can also be analyzed to compute the relative importance of the different features for the walkability estimation task.

We have demonstrated our the working of our method on a dataset which comprised images from a variety of Indian cities. Our trained model can be used to estimate the walkability of a new city of choice by following similar feature extraction steps and then directly using the model for inference without having to re-train it.

A possible extension to our work would be to extract more features other than the ones from images obtained by segmentation. These could potentially from other data sources such as traffic data, weather data, and more. Once could also try to build a larger dataset for training models following our method in an effort to acheive greater accuracy.

Appendix A

Complete List of Cities in the Dataset and their Walkability Scores

City	Walkability Score	Walkability Label / Bin
Bengaluru	0.63	4
Chennai	0.77	4
Kochi	0.57	3
Kolkata	0.81	5
Mumbai	0.85	5
Varanasi	0.33	2
Shimla	0.22	2
Bhubaneswar	0.28	2
Delhi	0.87	5
Guwahati	0.39	2
Madurai	0.40	2
Panaji	0.32	2
Ahmedabad	0.85	5
Amritsar	0.31	2
Bikaner	0.43	3
Chandigarh	0.91	5
Gangtok	0.30	2
Jaipur	0.64	4
Kanpur	0.59	3
Madurai	0.40	2
Pune	0.40	2
Surat	0.62	4
Trivandrum	0.34	2

Table A.1: Cities and their corresponding walkability scores and assigned bins

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