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Assessing the Pedestrian Infrastructure for Integrated Visual Walkability of Kolkata Municipal Corporation using Deep Learning based Geospatial Artificial Intelligence (Geo AI)

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Abstract

Walkability, a core element of urban mobility, is indispensable for health, liveability, and sustainability. However, it continues to face challenges in the major cities of developing countries across the Global South. Adopting a case study of the metropolitan city of Kolkata, West Bengal, India, this study aims to assess the integrated visual walkability using Mapillary Street View Imagery combined with deep learning-based semantic segmentation techniques. Four factors have been considered to study the walkability: Greenery, Openness, Pavement and Crowdedness along the selected footpaths of the study area. The semantic labels are then used to quantify the selected indicators and the areas are mapped using GeoAI techniques to reveal the intra-city variations, on a normalised scale from 0-1, where 0 indicates not walkable and 1 indicates highly walkable. The findings indicate significant discrepancies in pedestrian infrastructure, particularly within the central business districts (CBDs) of the city. These disparities are evident in inadequate footpath widths, unsafe walking spaces, and ignorance of inclusive design considerations. This shortfall in pedestrian-friendly infrastructure contributes to a less livable urban environment, impacting safety, accessibility, and overall enjoyment of the city for pedestrians. Further, the study acknowledges the potential of street view imageries and deep learning-based methods in studying urban mobility. The findings are intended to support data-driven, inclusive, and sustainable spatial planning for improved urban mobility.

1. Introduction

Walkability has been labelled as a “core urban design element” by Baobeid et al. (2021) with three major advantages being health, liveability and sustainability (Baobeid et al., 2021). Knapskog et al. (2019) defined walkability as “to what extent the surroundings are nice to walk in, as well as pleasant and interesting, and inviting walking”. Walkability can be broadly defined as the extent to which a neighbourhood is supportive of short pedestrian trips, or walking-friendly (Ruiz-Padillo et al., 2018). Leslie et al., 2007 equates walkability with “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”. Although some studies did take place in the previous decade, walkability is a concept that has become popular among Indian researchers only since the past year. However, the use of geospatial tools and techniques remains fairly low among Indian researchers. On the other hand, the European countries have gone ahead with their usage of geospatial tools to assess the visual walkability of various places. Street View Images (SVIs) have been the most commonly used image sources for map walkability (Biljecki & Ito, 2021). Along with that advanced technologies such as machine learning and deep learning have also been applied (Kang et al., 2023; Li et al., 2023).

This study attempts to use the geospatial approach to assess the visual walkability of Kolkata city in India. Unlike the conventional survey based methods and statistical indices, this methodology attempts to leverage geospatial data including SVIs, and GeoAI technology to study the indicators like Greenery, Openness, Pavement (Zhou et al., 2019) and Crowdedness (Wang et al., 2024). The factors are mapped to visualise and prioritise the areas for pedestrian infrastructural disparities.

2. Literature Review

2.1 Bibliometric Analysis

Most publications examining the walkability of the urban environment stem from the field of medical science, with particular focus on the relation between walkability and obesity (Frank et al., 2007).

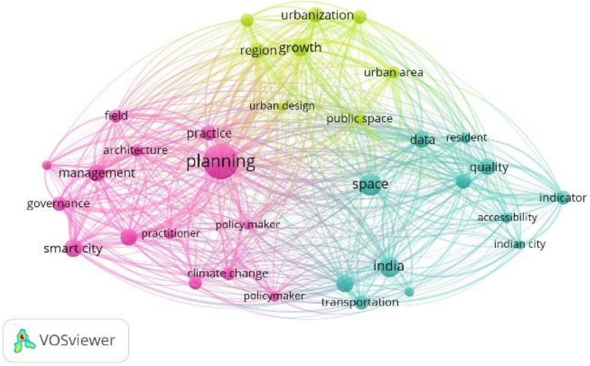


Figure 1: Network Analysis of major keyword co-occurrences. Source: Author.

The keyword co-occurrence analysis utilizes the full counting method, with the number of occurrences threshold kept at 30. The analysis brought out prominent keywords like ‘planning’, ‘management’, ‘region growth’, ‘urbanization’, ‘quality’, ‘space’, ‘architecture’, ‘governance’, ‘smart city’, etc., among which ‘planning’ has the densest cluster. The occurrence of these keywords highlights the growing emphasis on urban planning and smart cities (Tao et al., 2025).

2.2 Past Methodologies

The study and method of measuring walkability depend mainly on the definition and on what factors we consider important in shaping a pedestrian-friendly environment (Telega et al., 2021).

Based on the previous literatures, the methods of research on walkability can be mainly divided into the following (Telega et al., 2021): -

- Survey based methods- interviews and questionnaires (subjective) (Telega et al., 2021);
- Direct audit tools or stock taking (subjective), most often conducted by trained observers (Craig et al., 2002, Pikora et al., 2002)
- GIS tools (objective) (Leslie et al., 2007, Frank et al., 2011)
- Mixed methods containing data from both primary and secondary sources (Giles-Corti & Donovan, 2002)

2.3 Street view imagery for studying walkability

Remote sensing images are commonly used for studying long term city dynamics and short-term dynamics rely on SVIs and video data (Biljecki & Ito, 2021). Kang et al. (2020) summarises how SVI differentiates itself from other forms of urban data: (i) large coverage; (ii) homogenous quality, sampling and resolution; (iii) free access to data; (iv) reliable and rich metadata and, (v) urban scenery captured from human perspective.

Doiron et al. (2022) leveraged SVIs and deep learning to predict walking-to-work in seven Canadian cities. Two deep learning methods have been used in this study: (i) image segmentation-extracts the percent pixel coverage of a feature and (Doiron et al., 2022), (ii) object detection- extracts counts of features (Doiron et al., 2022).

2.4 Types of Walkability

Three types of walkability have been talked about by researchers over the world, namely, visual walkability (Wang et al., 2024; Li et al., 2022), perceived walkability (De Vos et al., 2022; Kang et al., 2023), and physical walkability (Kang et al., 2023). Perceived walkability is the “perceived ease of reaching destinations” (De Vos et al., 2022) or “how easy people find it to walk” (De Vos et al., 2022). Perceived walkability has been assessed with a survey or onsite participant questionnaire (De Vos et al., 2022; Lee & Dean, 2018; Kim & Lee, 2016). Visual walkability has been subdivided further into two types: Integrated Visual Walkability (IVW) (Li et al., 2022; Zhou et al., 2019) and Total Visual Walkability (TVW) (Wang et al., 2024). Walkability that gets affected by physical design features of neighbourhoods, such as residential density, land use mix, and street network connectivity (Frank et al., 2005) is called physical walkability. In this case also, the factors affecting walking were extracted through field surveys and site visits (Mateo-Babiano, 2010; Arellana et al., 2020; Lee et al., 2006; Weiss et al., 2010; Kim et al., 2014; Quercia et al., 2015).

3. Methodology

3.1 Study area

Kolkata one of the oldest metro cities of India, with its Municipal Corporation sprawling over an area of 205 sq. km (Census of India, 2011). However, it is still an unplanned city and suffers from “unplanned higher built up areas”, poor transport connectivity and weak spatial integration (Haque et al., 2019). Not only that, walkability or pedestrian accessibility remains inadequate in Kolkata in terms of pedestrian infrastructure (Das Mahapatra et al., 2021).

In our day-to-day movements through the city, we often come across the market areas where vendors have taken up the sidewalks to set up their temporary shops. Mukherjee (2025) states that, “a 1% increase in footpath encroachment by street vendors leads to an 18% rise in footpath underutilization.” Pedestrians tend to avoid designated locations at bus stops due to “lack of essential amenities and poor accessibility” (Mukherjee, 2025). A practising architect in Kolkata, Mr. Subhasish mentioned that despite the rising number of vehicles and traffic the footpath width in Central Kolkata is fixed which poses a challenge to the pedestrians (Das Mahapatra et al., 2023). Architect Shreya Ghosh Dastidar, an officer of the Public Works Department in the Government of West Bengal highlighted the critically poor conditions of footpaths in Central Kolkata (Das Mahapatra et al., 2023).

Land Use Land Cover map of Kolkata for the most recent year, i.e., 2024, was sourced from ESRI. Geoprocessing was done to get the percentage of ward wise Built-Up area. The results (Figure 3) show that Ward 58, 108, 63, 90 and 94 have the lowest percentage of built-up area. Ward 19, 32, 33, 45, 97, 109 and 144 have medium built up area and almost 75% wards exhibit high to very high percentage of built-up area. Following this observation streets were selected to cover at least one ward each with low, medium and high percentage of built up.

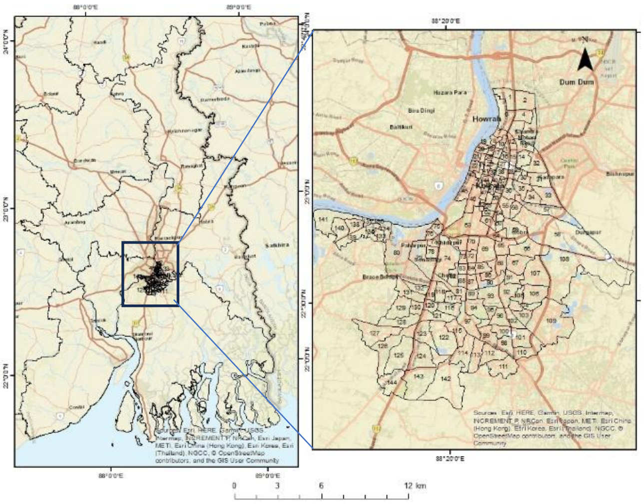


Figure 2: Study Area Map. Source: Author.

The Eastern Metropolitan Bypass covers the ward numbers 57, 58, 108 and 109. Dufferin Road and Chowringhee Road are present in ward 46 and 63 respectively. Rest all the other roads parse through wards with high built-up area.

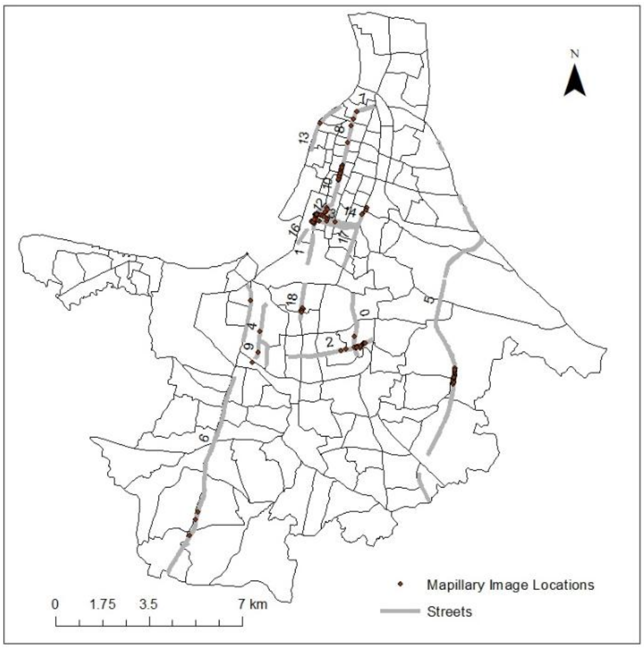


Figure 3: Selected Streets and Mapillary Image Locations. Source: Author.

Mapillary has considerably low coverage of areas with low built-up area which has resulted in inequal amount of SVI acquired for the three categories. Figure 3 shows the selected streets and Mapillary Image locations.

FID	Street Names
0	Gariahat Road
1	Chowringhee Road
2	Rash Behari Avenue
3	Surendra Nath Banerjee Road
4	Alipore Road
5	Eastern Metropolitan Bypass
6	Diamond Harbour Road
7	Bhupendra Bose Avenue
8	Jatindra Mohan Avenue
9	Alipore Park Road
10	Chittaranjan Avenue
11	Hospital Street
12	Chandni Chowk Street
13	Strand Bank Road
14	Lenin Sarani
15	Abhoy Sarkar Lane
16	Dufferin Road
17	AJC Bose Road
18	Ashutosh Mukherjee Road

Table 1: Selected Streets

3.2 Data Collection and Preparation

The road network data was sourced from OpenStreetMap via BBBike extracts. The selected streets were further extracted by selecting attributes. Some of the localities from the selected wards were used for collecting Mapillary SVIs using the API token through the bounding boxes. The localities are, namely, Gariahat, College Street and Chowringhee (high built up), Bhawanipur (medium built up) and VIP Nagar (low built up). The streets extracted are given in Table 1. Initially, a total of 208 images were collected. However, since Mapillary is a crowdsourced platform, the data are heterogenous with different users using different GPS-enables devices (Wang et al., 2024). After plotting the 208 image points, it was found that 43 images were falling outside the bounds of the study area. Hence, they were discarded are finally, 165 images have been used for this study.

Data	Source
Shapefile of Kolkata Municipal Corporation	Administrative Boundary Database, Survey of India
Road Network	OpenStreetMap via BBBike Extracts (accessed on 16 May 2025).
Land Use Land Cover (2024)	ESRI Land Use- ArcGIS Living Atlas (accessed on 23 April 2025).
Street View Images	Mapillary

Table 2: Data Sources

(a)

(b)

(c)

Figure 4 (a, b, & c): Examples of Street View Images.

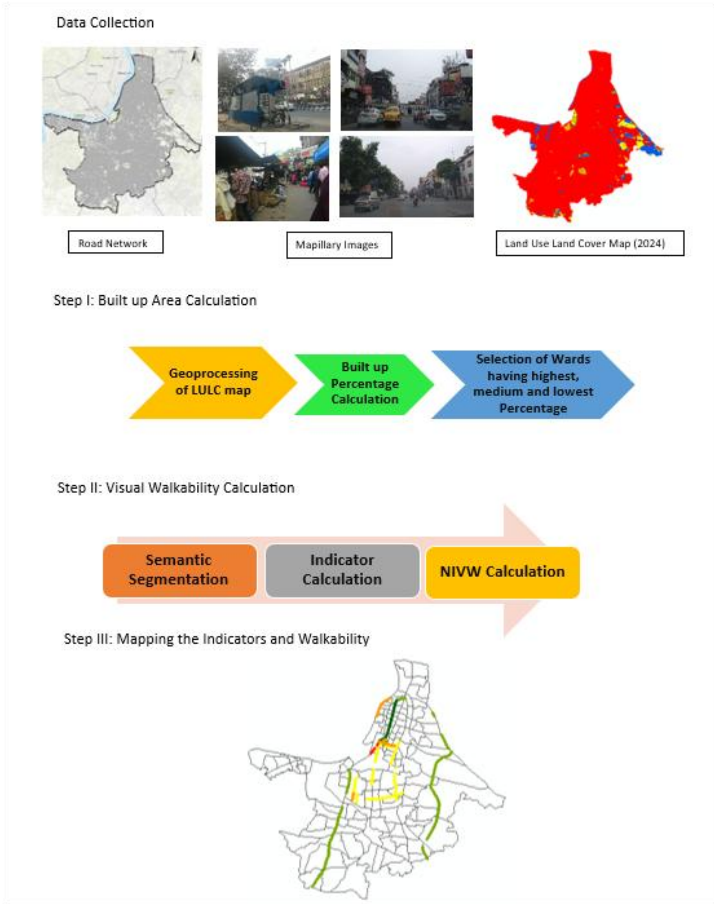


Figure 5: Overview of Methodology. Source: Author.

3.3 Visual Walkability Calculation

3.3.1 Semantic Segmentation

Four labels were used to segment the data using the DeepLabV3-MobileNetV3 architecture. The model is pretrained on the Cityscapes dataset (Howard et al., 2019; Cheng et al., 2018). It is the most lightweight, fast and efficient model for working with limited data and computes (Howard et al., 2019).

Vehicles, pedestrians, shops and temporary establishments were labelled as ‘crowdedness’, grasslands and trees were labelled as ‘greenery’, sky was labelled as ‘openness’ and roads, sidewalks, lanes etc of such type were labelled as ‘pavements.’ The model was run four times, each for one of the objects, keeping all the other objects anonymous.

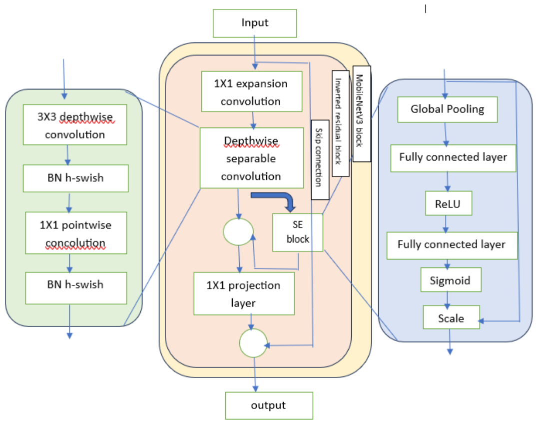
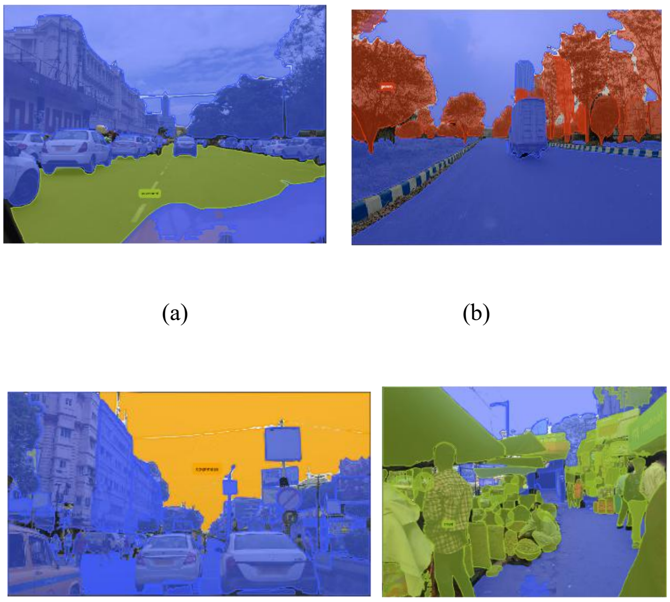


Figure 6: MobileNetV3 Structure. Source: Elaziz et al., 2021.



(a) (b)

(c) (d)

Figure 7: Examples of Segmented Images. (a) Pavement, (b) Greenery, (c) Openness, (d) Crowd. Source: Author

3.3.2 Description and Calculation of Indicators

Visual Walkability is measured by based on the calculation of indicators of visual walkability (Wang et al., 2024). The four environment indicators are greenery, openness, pavements and crowdedness (Zhou et al., 2019).

In this framework, greenery refers to "the extent of visible street greenery" (Wang et al., 2024). Openness is the visible extent of sky (Wang et al., 2024). Visual pavement includes visible sidewalks, roads etc. and crowdedness is reflected by visual obstacles such as vehicles, pedestrians, temporary shops etc (Wang et al., 2024) These four indicators are represented by G_i, S_i, V_i *and* N_i respectively (Wang et al., 2024). The formulae for each indicator are given in Table 3. The masks were exported in json format and later converted to png format for pixel calculation using PIL and NumPy. The pixels were calculated in each image for each of the indicators.

Indicators	*Formula*	*Explanation*
Greenery*	$G_i = \frac{Gn}{Sum}$	G_n= Total number of vegetation pixels Sum= Total number of pixels
Openness*	$S_i = \frac{Sn}{Sum}$	S_n= Total number of sky pixels Sum= Total number of pixels
Visual Pavement	$Vi = \frac{Pn}{Sum}$	P_n= Total number of pavement pixels Sum= Total number of pixels
Crowdedness*	N_i	N_i= Total number of crowdedness pixels

Table 3: Calculation of Indicators in Visual Walkability

*Note: * represents indicators generated from previous work proposed by Wang et al., 2024.*

3.3.4 Normalised Integrated Visual Walkability Index Calculation

Integrated Visual Walkability (IVW) is the level of walkability generated from the four indicators (Wang et al., 2024). The indicators of each image were calculated using pixel level segmentation. After the calculations are done for individual images, the average for each indicator along the streets they are located upon are calculated.

Then, in order to compare the results of each indicator they have been normalised using the min-max normalisation method. The formula for normalisation is given below (1).

$$V_i\ nor = \frac{Vi - Vi\ min}{Vi\ max - Vi\ min}, \qquad (1)$$

where, *Vi =variable*
Vi nor= normalised variable
Vi min= minimum value of the variable
Vi max= maximum *value* of the variable

The values range from 0-1, where 0 indicates *no occurrence* and 1 indicates *complete occurrence*. However, the situation gets reversed in the case of crowdedness because a 0 for crowdedness indicates *no crowd* which is a positive indicator. Thus, the normalisation has been reversed for crowdedness using the following formula (2):

$$\text{Reversed } V_i\ nor = 1 - V_i\ nor \qquad (2)$$

Finally, the normalised indicator values are summed using the following formula (3):

$$IVW = G_i\ nor + S_i\ nor + V_i\ nor + N_i\ nor \qquad (3)$$

The IVW values are again normalised for the final Normalised Integrated Visual Walkability Index.

4. Results and Discussions

4.1 Analysis of Greenery

Figure 8 shows the greenery levels of the selected streets. Bhupendra Bose Avenue, Diamond Harbour Road and Alipore

Road show maximum greenery, followed by Chittaranjan Avenue and Ashutosh Mukherjee Road. Eastern Metropolitan Bypass, despite being located in a low built up area, has less than expected greenery around the streets. AJC Bose Road and Strand Bank Road are devoid of any greenery. Almost 70% of streets fall under the category of less to no greenery. This indicates a lack of comfort for walkability.

30% of the selected streets have a fair amount of vegetation. It is advisable to have trees and vegetation around the streets as they result in reduced air pollution levels that are created by vehicles (NIH, 2019). Additionally, it also adds to the aesthetic value of the localities. It has been observed that trees and grasslands provide comfortable urban places and result in increased urban walkability (Estacio et al., 2022).

Figure 9 demonstrates some examples from the dataset with greenery dominated images.

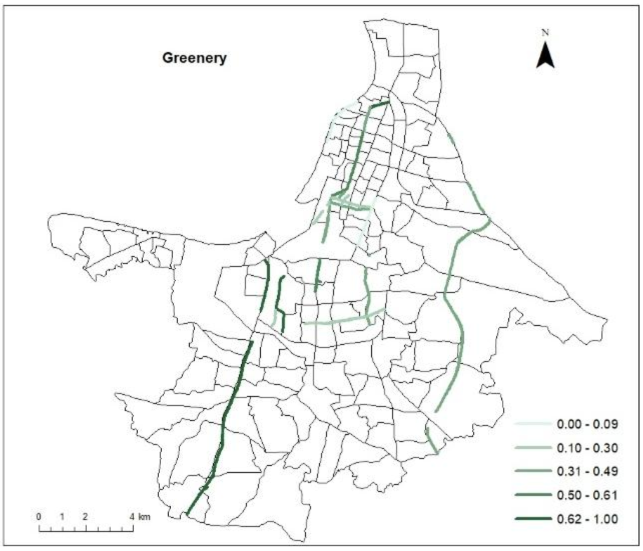


Figure 8: Greenery. Source: Author.

(a) Location: 22.594911, 88.364819

(b) Location: 22.52548, 88.330903.

Figure 9 (a & b): Examples of Greenery dominated streets.

4.2 Openness Analysis

Openness refers to the amount of sky pixels visible in an image. Highest amounts of openness have been observed in Jatindra Mohan Avenue. Hospital Street, Chittaranjan Avenue, Eastern Metropolitan Bypass and AJC Bose Road also exhibit high level of openness. However, out of 20 selected streets, only 5 streets have openness suitable for comfortable walkability. That makes up only 25% of the area. Rest 75% have less to no openness. Refer to figure 10.

Similar to greenery, openness also provides a psychological comfort to pedestrians (Zhang et al., 2018). In a study conducted by Zhang et al., 2018, it was observed that visible extent of sky positively correlates with safety and openness.

Besides, more openness means better air circulation and less urban heat trap (Oke, 1988).

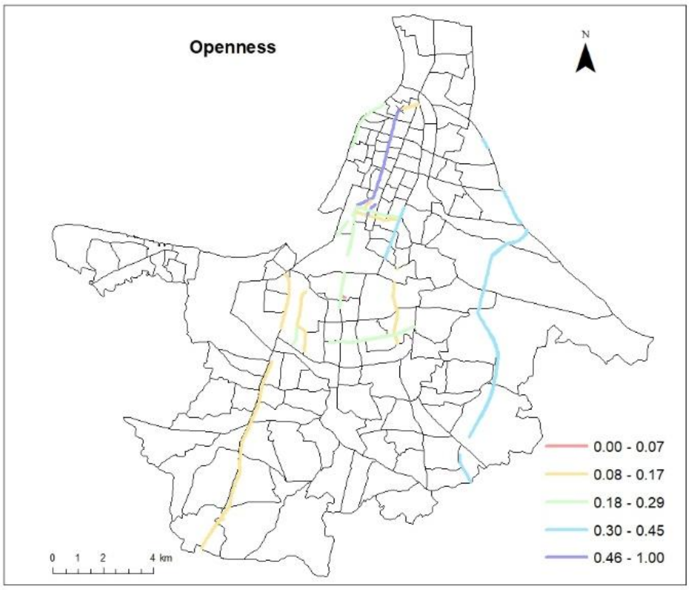


Figure 10: Openness. Source: Author.

(a) Location: 22.59741, 88.365703

(b) Location: 22.594911, 88.364819

Figure 11 (a & b): Examples of Openness dominated streets

4.3 Visual Pavement

The number of pavement pixels to the total number of pixels is called the visual pavement. Diamond Harbour Road, Eastern Metropolitan Bypass, AJC Bose Road, Dufferin Road, Chandni Chowk Street, Chittaranjan Avenue, Surendra Nath Banerjee Road, Hospital Street, Rash Behari Avenue, Alipore Park Road and Bhupendra Bose Avenue have high visual pavement, which constitutes about 60% of the total number of streets selected. However, Strand Bank Road, which is located in low density area, lags behind in this aspect as well.

A higher visual pavement measure means less vehicle congestion and more area available for walking (Tiwari, 2022).

Figure 12 and 13 show map of visual pavement and examples of images with high visual pavement.

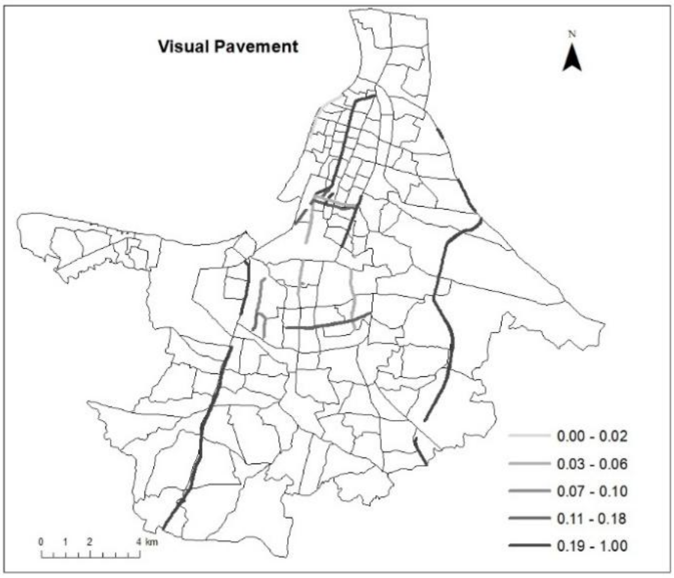


Figure 12: Visual Pavements. Source: Author.

(a) Location: 22.578278, 88.36051

(b) Location: 22.57879, 88.360721

Figure 13 (a & b): Examples of Pavement dominated streets

4.4 Crowdedness

Crowdedness consists of vehicles, shops, pedestrians and every other obstacle that hinders walkability. Strand Bank Road, Gariahat Road and Chowringhee Road are leading in this aspect. Gariahat and Chowringhee are known to be market hubs. Looking at the images given in figure 15, it is clear that almost the entire space has been taken up by the temporary shops and vendors, leaving little to no space for walking.

Vehicles also create obstacles for the mobility of pedestrians, especially in cases where traffic jams are common, or by parking along the road sides. This compels pedestrians to jostle with vehicles for space, thereby exposing them to injury (Tiwari, 2022).

Diamond Harbour Road, Bhupendra Bose Avenue and Alipore Road have low crowdedness which is a positive indicator.

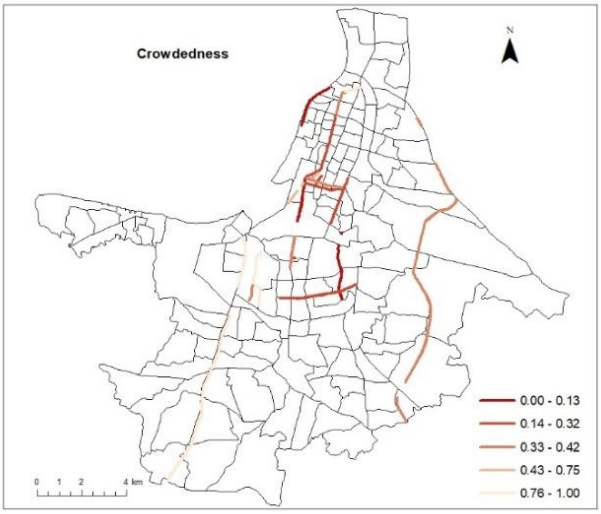


Figure 14: Crowdedness. Source: Author.

(a) Location: 22.595947, 88.353428

(b) Location: 22.564424, 88.351573

Figure 15 (a & b): Examples of Crowdedness dominated streets.

4.5 Spatial Distribution of NIVWI

Diamond Harbour Road, Chittaranjan Avenue, Bhupendra Bose Avenue, Alipore Road, Hospital Street and Eastern Metropolitan Bypass exhibit maximum visual walkability. Strand Bank Road has no walkability. Rest of the streets have medium to low walkability.

40% streets have high walkability; 55% streets have medium to low walkability and 5% have no walkability.

Figure 17 (a) and (b) shows examples of images with high and low walkability respectively.

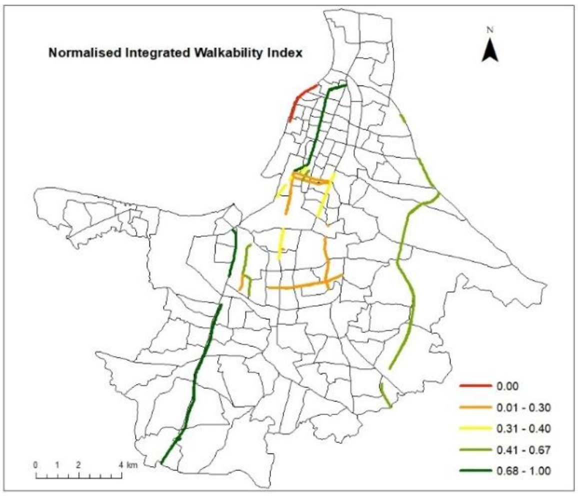


Figure 16: NIVWI. Source: Author.

(a) Location: 22.594911, 88.364819

(b) Location: 22.563054, 88.351352

Figure 17 (a & b): Examples of (a) Highly Walkable and (b) Not Walkable Streets.

5. Conclusion and Future Scopes

Walkability is a comparatively new theme among Indian Researchers. The existing studies rely heavily on on-site surveys for studying walkability, especially in the Indian context. To address these issues, this study leverages advanced GeoAI techniques to study walkability. Firstly, this paper attempted a new methodology to study the short term urban dynamics. Visual walkability is the degree to which to a street is perceived as appealing based on visual characteristics. From all the calculations we can conclude that the CBD faces challenges in providing a safe environment for pedestrian mobility. Site surveys lack in area based calculations which provide a comprehensive and clear view of how each and every indicator affects walkability.

This study is first of its kind in Indian academia, as far as the use of street view images is concerned. Mapillary is a crowdsourced platform for acquiring street view images. Mapillary is known to have coverage in areas where Google Street View fails to capture (Wang et al., 2024). While it is the most easily accessible SVI source, it also has its shortcomings. The data here is contributed by individuals who lack in professional training for data capturing (Wang et al., 2024). The dense areas with increased human activities have more coverage than the less dense or rural areas (Wang et al., 2024). At times, the images are captured from moving vehicles which result in blurred and hazy images thus reducing the data size (Wang et al., 2024). Compared to GSVs the coverage is much lower, especially in the case of Kolkata Municipal Corporation. This resulted in unequal dataset.

In the future, IVW can be calculated for the entire Kolkata Municipal Corporation. Further, other types of walkability, such as physical walkability and type of visual walkability can also be studied in the Indian context. More users, particularly pedestrians can be trained to capture street view images for the sole purpose of studying walkability. In addition, other data sources such as CCTV footages traffic flow can be integrated with SVIs for even better results (Wang et al., 2024).

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