GEOMATICS AND ENVIRONMENTAL ENGINEERING • Volume 17 • Number 6 • 2023

https://doi.org/10.7494/geom.2023.17.6.5

Gitisree Biswas[1], Tusar Kanti Roy[2]

Measuring Objective Walkability from Pedestrian-Level Visual Perception Using Machine Learning and GSV in Khulna, Bangladesh

Abstract: Walkability entails measuring the degree of walking activity, a non-motorized mode of active transportation crucial in fast-developing urban settings and combating sedentary lifestyles. While there has been extensive objective research focusing on factors related to the physical environment that influence walkability, there has been a comparatively limited exploration into objectively evaluating a pedestrian's visual perception. This study in Khulna, Bangladesh, aimed to develop a novel method for objectively measuring walkability based on pedestrian-level visual perception using machine learning. In this research, ResNet, a computer vision model, analyzed 127 panoramic Google Street View images taken at 200-meter intervals from seven major roads. The model, trained with the "deeplabv3plusResnet18CamVid" algorithm, quantified five selected visual features. The results, including walkability rankings, correlation analysis, and spatial mapping, highlighted that greenery and visual enclosures significantly influenced the walkability index. However, the impact of other visual features was less distinctive due to an overall poor streetscape condition. This study bridged the gap between human perception and scientific intelligence, allowing for the evaluation of previously "unmeasurable" streetscape designs. It provides valuable insights for more human-centered planning and transportation strategies, addressing the challenges of modern urbanization and sedentary behavior.

Keywords: walkability, streetscapes features, visual perception, machine learning, Google Street View (GSV)

Received: 21 March 2023; accepted: 17 July 2023

[1] Khulna University of Engineering & Technology (KUET), Department of Urban and Regional Planning, Khulna, Bangladesh, email: giti181biswas@gmail.com (corresponding author), https://orcid.org/0000-0002-4230-1624

[2] Khulna University of Engineering & Technology (KUET), Department of Urban and Regional Planning, Khulna, Bangladesh, email: tusarkroy@urp.kuet.ac.bd, https://orcid.org/0000-0001-6543-5126

1. Introduction

According to [1], 27.5% of the Earth's population is not efficiently physically active. Rapid urbanization and vehicular dependency tend to result in sedentary lifestyles, which increases the risk of cardiovascular disease, stroke, Type-2 diabetes, and other non-communicable diseases [2–4]. Walking is considered to be an active mode of non-motorized transportation, as it requires greater physical exertion, promotes walking behavior as a mode of transportation for short trips or errands, and highlights human-oriented transportation. However, walkability is a measurable quality that is distinct from simple walking [5]. Walkability refers to the degree of friendliness to which an area is designed and accessible for walking [6]. Research on walkability (a widely studied topic) has shown a two-fold connection between walkability and the built environment: a well-designed environment promotes walking as a mode of transportation and contributes to health benefits from the mutual convenience of an economic aspect [7].

Walkability is variably influenced by walking environments that consist of physical and non-physical elements. Physical components like street connectivity, accessibility, block size, land use, street amenities, retail floor area ratio, vegetation, and horizontal-vertical road elements are generally measured at a macro-scale using GIS or Point of Interest data [8]. Non-physical elements constitute the perceptual judgment of the feeling of attractiveness, comfort, pleasurability, place proximity, safety from crime, and social cohesion. Human-oriented walkability refers to the perspective of pedestrians, which deals with the non-physical qualitative design and functionality of a built environment. According to [9, 10], walkability components can be categorically measured into direct and indirect approaches of objective and subjective measures. Also, [11, 12] explored that physical elements alone might not be attributed to the walking experience. Arguably, walking behavior may be implicitly impacted by the subjective dimension of perceptual opinions, visual intuitions, and environmental psychology. Eventually, [13] critically addressed that the challenge to moving from a subjective measure to an objective one is to ensure technical reliability. In developing countries, this challenge is unbeatable without a standard objective method that can counter the limitations of time, cost-effectiveness, micro-scale data availability, and the inconsistency of judgments among the raters for any individual qualities.

Google Maps and Google Earth's Google Street View (GSV) feature offer users' images of cities from more than 20 nations worldwide. This allows users to see panoramic images of public streets as if they were walking down the streets in person [14]. It is easily accessible to anyone with internet connectivity and can be used to objectively determine pedestrian counts on a street and analyze walkability trends to gain insights into the pedestrian activity in a city. The advancement of machine-learning technology combined with GSV images significantly contributes to urban research [15, 16].

The use of GSV for evaluating streetscape elements was reliable for micro-scale analysis according to [17]. The greenery and building-to-street ratio (enclosure) [18] and sidewalk-to-street proportion [19] showed a correlation with the walk score. Some GSV-based studies estimated only greenery pixels to find their influence on walking behavior more specifically over walking time [20–24]. The evaluation of urban design quality in three ways using sky proportion as calculated by [16] also showed itself to be reliable with pedestrian counts and walk scores. An alternative method for manual pedestrian counting through object detection has been proposed [25]. However, focusing on only one or two physical features fails to provide a comprehensive understanding of a visual environment's impact on walkability. Much of the walkability research was correlation-oriented; the researchers analyzed complex visual environments using GSV image detection and showed their concordance with manual walking behavior data from their field observation. Very few of the studies were able to provide a direct method where walkability was measured by and correlated with the same variables that were processed by image segmentation [26]. Developed countries have predominantly adopted objective measures for walkability, while in the developing countries of South America, Africa, Southeast Asia, and Southern Asia, it is subjectively oriented [27]. For Bangladesh, existing walking-related studies are incommensurate, qualitative, and policy review-oriented [28–32]; even more, none of the studies have applied a computer vision model and GSVs to measure micro-scale walkability in Khulna to date.

Considering the study gaps, this study aims to propose a comprehensive programmatic walkability index that takes the design factors of streetscapes into account and converts subjective assessments into objective ones. The index ranks walkability based on visual factors and examines the correlations between different features; the results are presented in terms of percentage and spatial analysis for all of the studied roads. The study hypothesizes that the visual appearances of streetscapes have a significant impact on walkability, and the proposed index provides an objective measure through sensing technology. The research questions that are addressed by this study are related to how street design affects walkability and the effectiveness of the objective measure:

– How can visual streetscape features be quantified objectively?
– How can visual streetscape features be applied to measure walkability?
– How is walkability correlated to visual streetscape features?

The study's outcomes can guide urban planners, architects, and policymakers in addressing walkability and improving urban health by incorporating the findings into developmental plans. It may also inspire similar studies for walkability in other metropolitan cities in Bangladesh.

2. Study Area

Situated in the southwest of Bangladesh, Khulna is the third-largest city and is bounded by the Bay of Bengal to its south. Khulna City Corporation (KCC) consists of a population of 720,000 with an area of 45.17 km^2. Khulna has a robust multimodal transportation system that includes roads, rivers, and railways; over time, however, the road network is gaining a competitive advantage over maritime and rail transportation. The total road network of Khulna includes 1215 roads that total 824.47 km (primary, secondary, and tertiary roads). Several inclusive transportation development projects have been conducted over time that have facilitated convenient walking behavior via the construction of footpaths/walkways and extensions of existing roads (including 88 km of separate slow-moving vehicle lanes) [33]. Researchers have found that main roads that cover mixed land use areas, roads that connect multiple destinations over short distances, and access to primary roads that have potential streetscape infrastructure encourage pedestrians regarding both leisure and utilitarian walking [34]. In the city areas of Bangladesh, secondary and tertiary roads are usually poorly attributed to road enclosures (disproportionate street-building ratios) [35], openness (congested roads with low sky proportions), and attractiveness elements (greenery); these are the significant influential features that demotivate pedestrians due to comfort and safety concerns. Considering these facts, only seven major primary roads were selected as study roads, and a total of 127 GSV images were accepted as study samples (Fig. 1). The total lengths of the study roads are described in Table 1.

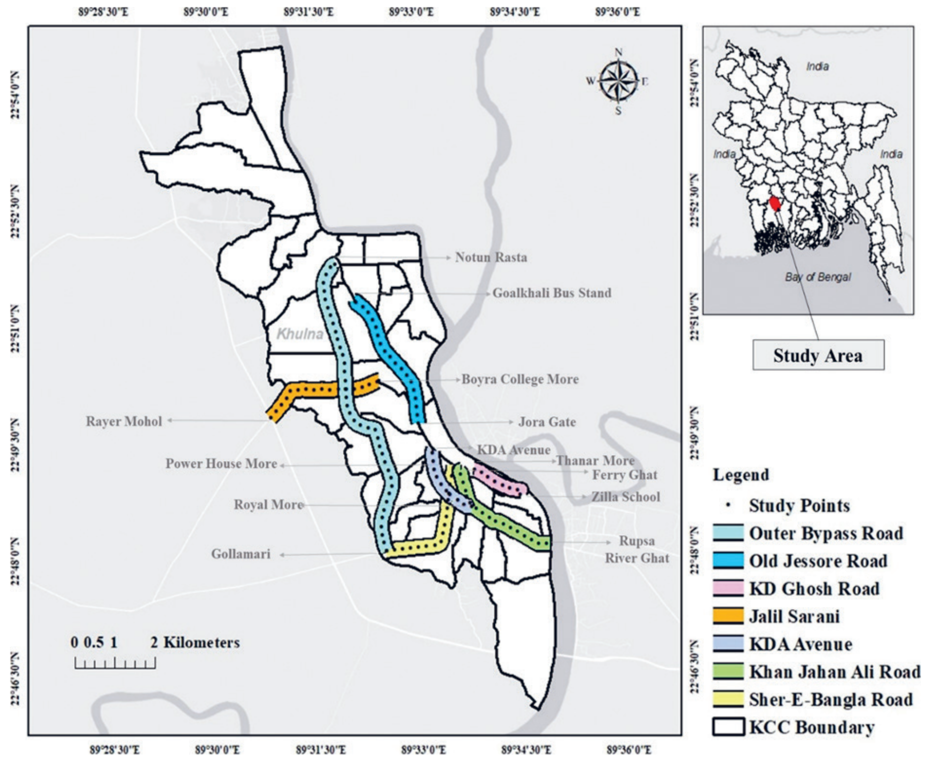


Fig. 1. Study road map of Khulna

Table 1. Selected study roads

Study Roads	Start and End Points	Lengths [km]
Outer Bypass Road	Notun Rasta to Gollamari	7.1
Old Jessore Road	Goalkahli Bus Stand to Jora Gate	3.4
KD Ghosh Road	Thanar More to Zilla School	1.6
Jalil Sarani	Boyra Girls' College to Rayer Mahal	2.2
Khan Jahan Ali Road	Rupsa Ghat Road to Ferry Ghat Road	3.1
KDA Avenue	Shibbari More to Royal More	2.0
Sher-E-Bangla Road	Gollamari to Power House More	3.2

3. Methodology

3.1. Methodological Framework

The methodology was initiated by conceptualizing a "street level" walkability study design that incorporated four phases, including street view data collection, image processing, calculating and evaluating visual walkability, and addressing the evaluative impact (Fig. 2). First, a data set that was comprised of 127 panoramic street view images was created by using Google Earth. Second, the potential physical components that impacted or might impact the contextual built environment and physical activity were classified pixel-wise by applying the ResNet computer vision model after an extensive literature review. Classified physical components were converted into five visual features by applying the proposed formulas, and the walkability was analyzed by calculating the OVW index. The evaluation part was comprised of three parts, including walkable road-rank determination, mapping representation of visual features, and a correlation analysis of the visual features and OVW.

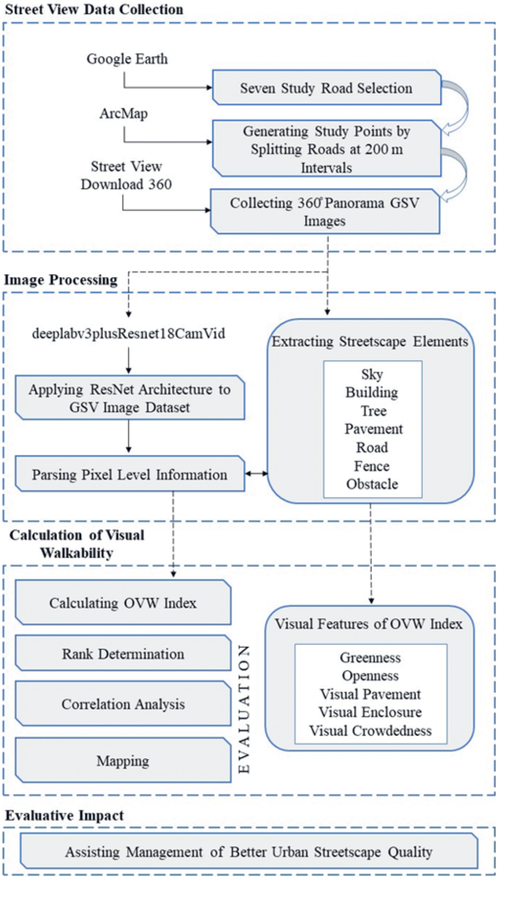


Fig. 2. Methodological framework

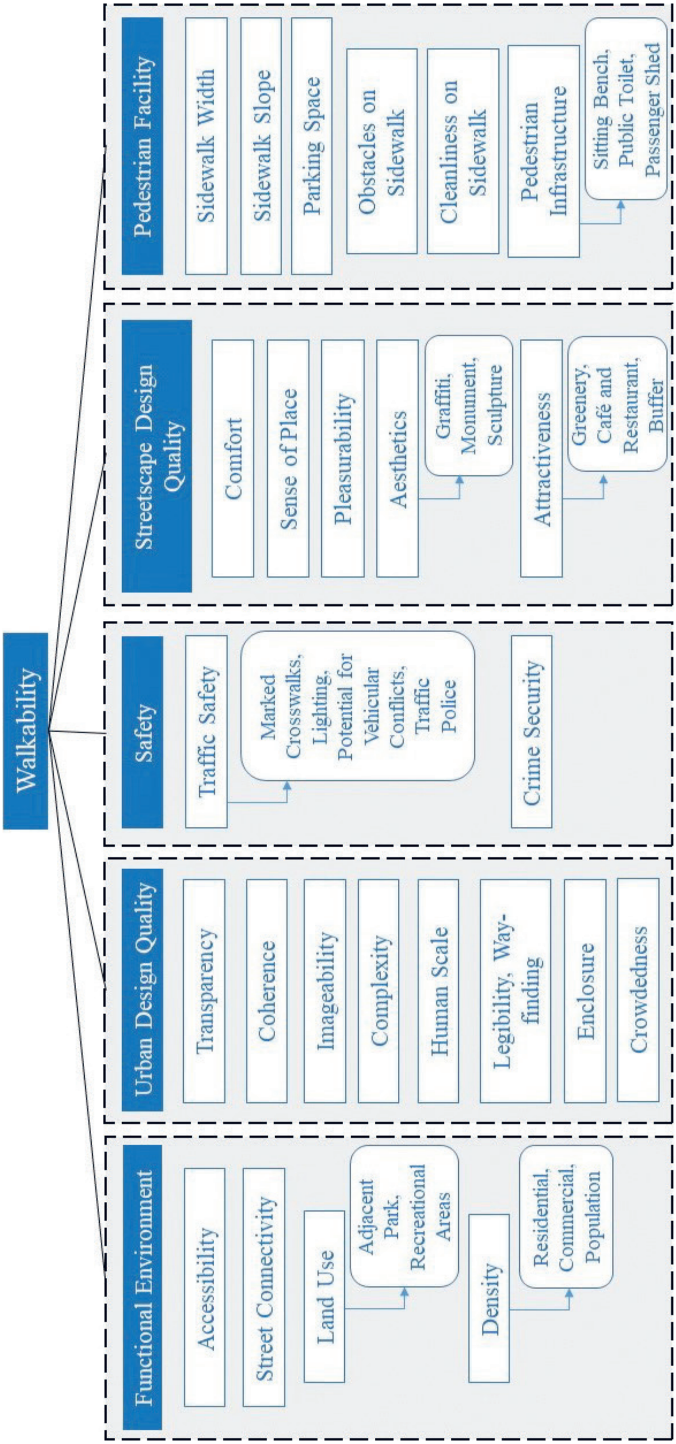


Fig. 3. Reviewed streetscape features and sub-features to measure walkability

3.2. Overview of Streetscape Features

Understanding its multidimensional nature, walkability has become a complex concept that encompasses multiple factors that influence pedestrian walkability. In recent years, this topic has been examined from different perspectives (such as urban planning, public health, and analytical techniques), and researchers have explored numerous features and sub-features in order to assess walkability based on these perspectives in attempts to capture its comprehensive nature (Fig. 3) [36, 37].

All of these streetscape features and sub-features have been previously used in the literature (categorized in Table 2).

Table 2. List of walkability literature using reviewed streetscape features and sub-features

Streetscape features	Studies
Functional Environment (Accessibility, Street Connectivity, Land Use, Density)	[2], [38], [39], [40], [41], [42], [43], [44], [45]
Urban Design Quality (Transparency, Coherence, Imageability, Complexity, Human Scale, Legibility, Enclosure, Crowdedness)	[9], [16], [25], [26], [27], [46], [47], [48], [49], [50]
Safety (Traffic Safety, Crime Security)	[39], [40], [44], [45], [51], [52], [53]
Streetscape Design Quality (Comfort, Sense of Place, Pleasurability, Aesthetics, Attractiveness)	[17], [23], [38], [39], [44], [45], [54]
Pedestrian Facility (Sidewalk Widths, Sidewalk Slopes, Parking Spaces, Obstacles on Sidewalks, Cleanliness on Sidewalks, Pedestrian Infrastructures)	[17], [27], [39], [44], [52], [53], [54]

Functional Definition of Key Streetscape Visual Features

Before the image processing and pixel calculation, five key visual design features were generated from the 11 initial physical features that were viewed in the panoramic GSV image. This selection focused on how frequently the features were used in urban design studies, how easily their functional definitions could be understood, and their computational compatibility with existing machine-learning models (including SegNet, ResNet, DeepLab, and YOLO) [55–58]. Publications [12, 13, 59] first addressed the visual characteristics that covered a majority of the complex urban design and spatial analytics.

Greenness

Street vegetation has been shown to act as a stimulant for the promotion of outdoor activity, and researchers significantly emphasize this factor in the assessment of walkability. More precisely, it has been shown that an increase in the amount of visible flora in an area has a positive impact on easing unpleasant psychological symptoms [60]. The counterpart ascendancy of greenness and visual crowdedness on walking is positively attributed to greenness; on the other hand, crowding the obstacles of streets limit smooth walking activities. Greenness is the strongest visual attribute that directly captivates pedestrians' visual senses of aesthetics and beauty. Even though vegetation is being measured by the conventional GIS-based NDVI indices, advanced machine learning and GSV are being employed to objectively quantify subjective greenery in health, social, environmental, and psychological studies [61–63].

Openness

Though openness is related to an enclosure, it conceptually refers to the degree of the exposure to the sky. Openness generates a wide and well-lit visionary impact that induces comfort and relaxation in users [64]. In this study, openness has been quantified as the sky proportion that is visible from a standing stance to the total environment's pixel number. The presence of proportionate vertical structures and trees with wide horizontal elements of roads, sidewalks, and setbacks creates a relatively high exposure of openness [65]. Also, a road with a relatively higher openness may question the feeling of safety and create discomfort and emptiness.

Visual Enclosure

In the walkability study, enclosure defines how pedestrians visualize a street's walking environment to be separated and surrounded by its horizontal and vertical elements [66]. The visual enclosure is estimated with the proportions of the road widths, sidewalks, setbacks, and vertical structures and canopies. The majority of the time, vertical features determine how roadways are enclosed; it will be a more successful place when the outdoor area is distinctively proportioned in shape as compared to the nearby buildings [67]. The visual confinement of the enclosure has a profound impact on walking willingness; a higher vertical and lower horizontal ratio can be oppressive and discomforting [9].

Visual Crowdedness

Street elements like vehicles, billboards, signboards, electric poles, lamp posts, and sign-symbols (which tend to create disquietness and unwillingness to walk) are compositely considered to be obstacles. A higher number of obstacles tend to make a walking environment noisier and visually crowded. From some conceptual aspects, crowdedness and complexity represent the same meaning but are different in their direction of perception [68, 69]. Complexity refers to the aesthetical diversity of streetscape and architectural embellishments [9]; on the contrary, pedestrian environments with higher complexities or that are monotonously established are discouraging to walkers. Two methods for evaluating complexity have been suggested by a thorough architectural study on visual complexity: the first involves ambiguı ÖÜÚpatterns, and the second involves patterns that are created by environmental ÍÈÊtors [70].

Visual Pavement

Visual pavement represents the degree of the arrangement of horizontal components. The proportionate appearance between the road width and the sideways elements like sidewalks, footpaths, and fences are calculated to measure the visual pavement. A higher proportion of the sideways parts allows for suitably arranged pathways for walking [71].

3.3. Data Processing: Objective Visual Walkability (OVW)

Street View Image Collection

The data-collection phase started by selecting seven study roads from the united road network of Khulna (using Google Earth) and generating the study points by splitting the roads into 200 m intervals (using ArcGIS 10.5). A reconnaissance survey on the study roads revealed that a 200-meter-distance interval was sufficient for capturing relevant information on roadside features, traffic density, land use, transportation infrastructure, and key points of interest. This interval was aligned with the standard practices in related studies [72] and was systematically effective for minimizing data overload. Choosing this interval was practical and feasible in terms of time, budget, and computing resources while allowing for efficient data collection and maintaining the necessary level of detail for analysis. Accordingly, the data set was created by capturing a 360° panoramic-street-view image for each of the study points by compiling Google Maps and Street View Download 360. Google Maps is an open-accessible street-view image resource that is available in Bangladesh; it is provided with high resolution and substantial detailed information on the studied roads. This study required panoramic views of the roads to make them equivalent to the visual experiences of pedestrians. So, iStreetView software was used to get the panorama URL link of the study points, and the 360° panoramic images were downloaded from Street View Download 360 software using Panorama ID. These 360° panoramic images were dimensioned with 360° horizontal and 180° vertical coverage of the street sites. However, for those points where landmarks and structures were changed or erected over time, GSV was not appropriate for showing accurate views. For those points, real-time 360° panoramic images were captured using Google Camera, and both types of images from Google Maps and Google Camera were resized. In this method, the field-of-view (FoV) (or the central field of human vision for the panoramic image boxes) was set to 60°. FoV generally refers to the extent of the angle that is viewed in a virtual image that is equivalent to the eye-level pedestrian experience for a specific study point. This is how six 60° images can cover a 360° horizontal surrounding area [73]. Figure 4 shows that the FoV that was extracted from the panorama was represented in the frames of the vision boxes for analyzing the visual perspectives of pedestrians. Setting the necessary FoV is important for achieving real-time perspectives from each part of the images.

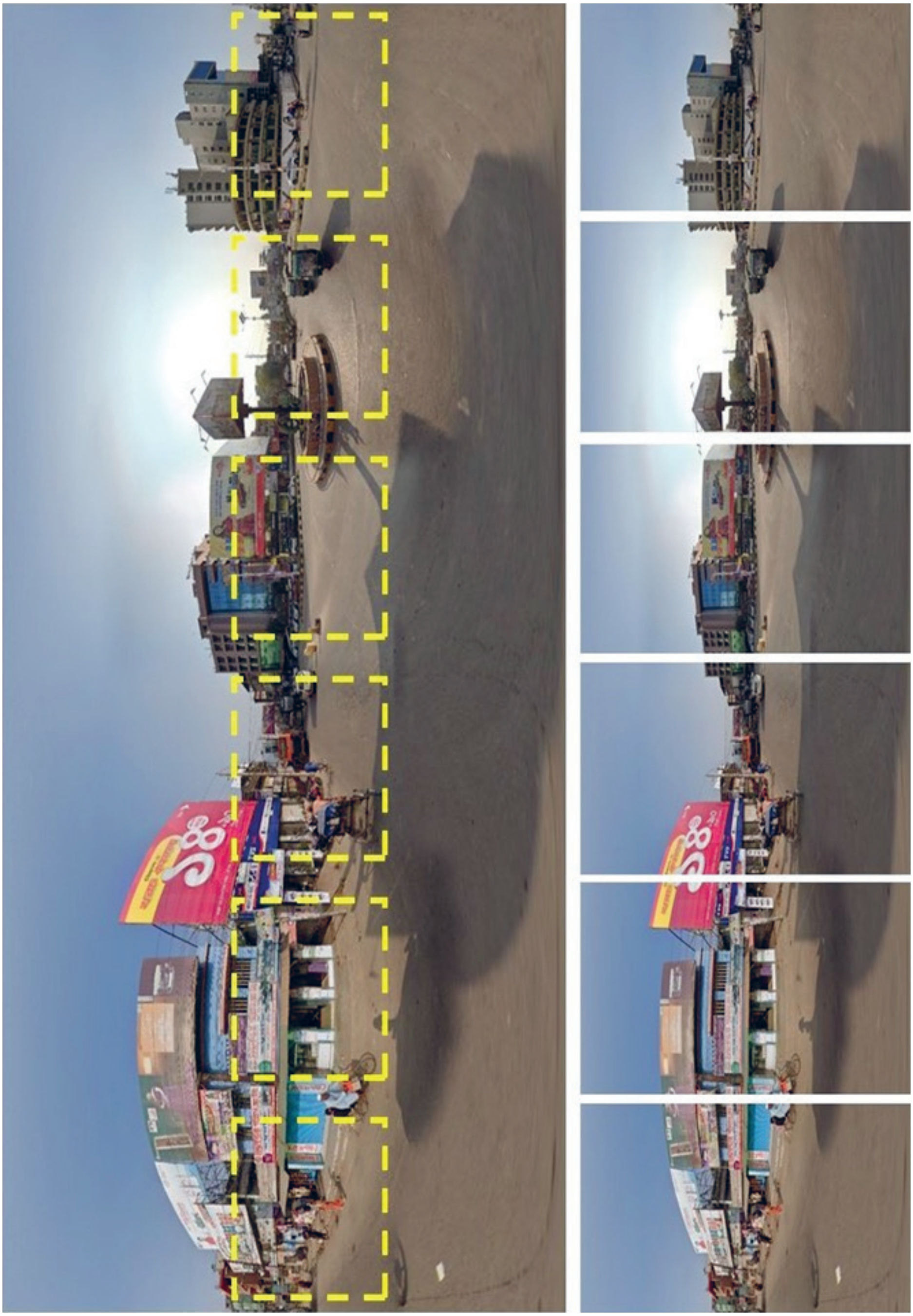


Fig. 4. Field-of-view (FoV) determination in frames of vision boxes from panoramic image

Image Feature Recognition:
ResNet Training, Image Segmentation, and Pixel Quantification

MATLAB was used for the segmentation process, where a machine-learning algorithm was utilized to make the machine recognize streetscape features according to the classified pixels. To operate these algorithms, an artificial neural network (ANN) called a residual neural network (ResNet) was devised. This is the first fully functional very deep feedforward neural network with hundreds of layers with a deep convolutional encoder-decoder architecture for semantic pixel-wise labeling for increasing segmentation accuracy (far better than prior neural networks) [74]. There are 18 deep layers in the architecture's 72 tiers; first, a convolution layer of a size of 33 receives the input, while the batch normalization, activation, and pooling layers are the following three layers. ReLU (rectified linear unit) is the activation function that is utilized. The pooling layer has a stride of 2 and measures 33. There is a "residual learning unit" that makes use of any skip connections between two such units. The "fully connected" layer with the "Softmax" activation function is employed at the network's termination. The network's input size is 224 × 224 × 3, which has been predetermined. Due to its intricate layer structure and the fact that each layer receives input from other layers and outputs to other layers, the network is considered to be a DAG network. Its goal is to make it possible for numerous convolutional layers to operate well. ResNet's main concept is the usage of jumping connections – often known as identity connections or shortcut connections. Most of the time, these connections work by jumping over one or more levels to provide shortcuts between them. The purpose of establishing these shortcut connections was to address the primary problem of disappearing gradients that deep networks commonly experience. By reusing the activations from the prior layer, these shortcut connections fix the vanishing gradient problem.

ResNet uses reinforcement learning to infer pixel-wise class labels, where it requires a training data set that consists of a large number of GSV images. For this current image segmentation, a pre-trained network algorithm called "deeplabv3plusResnet18CamVid" (developed by Cambridge University) was used for validation; it contained a data set of 701 training images, 140 test images, and 140 images. This whole mechanism is represented in Figure 4; it shows the application of the pre-trained "deeplabv3plusResnet18CamVid" network algorithm on its training set in the convolutional encoder-decoder of the ResNet architecture, which optimizes the machine to recognize the features and segment a whole image into feature-wise pixel classification according to the designated RGB colors. This involves the whole process of image training, testing, and validation. When the machine was optimized with supervision learning, the study area's GSV image was inserted as input, and the final segmented output was derived (shown in Figure 5).

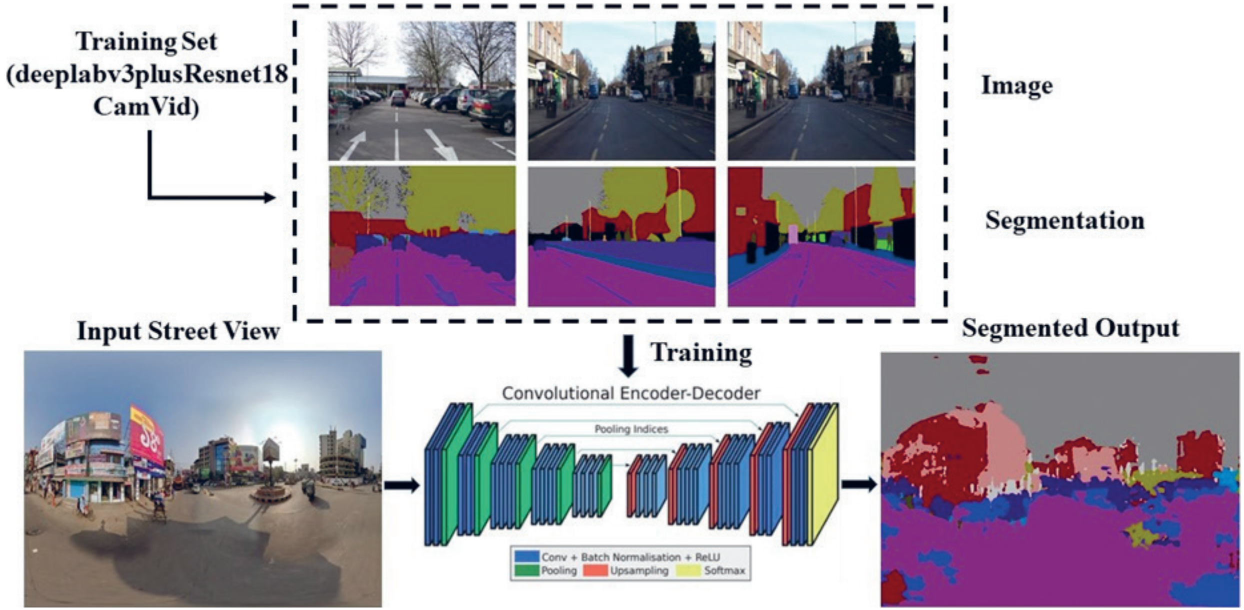


Fig. 5. ResNet architecture

Source: Basic ResNet architecture of this research (encoder-decoder architecture collected from [56])

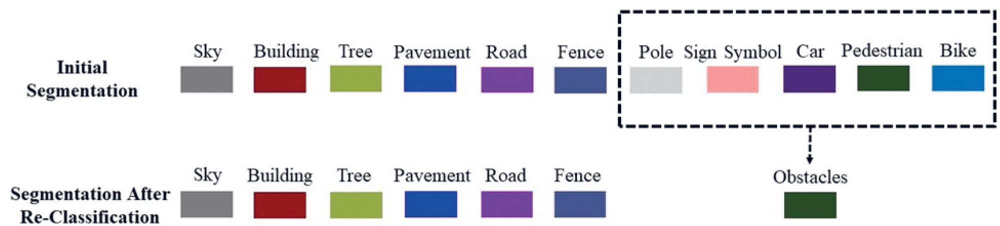


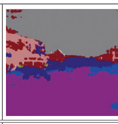
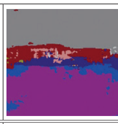
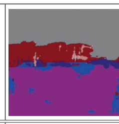
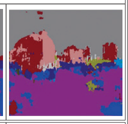
Fig. 6. Streetscape attribute declaration and re-classification

Objective Visual Walkability (OVW) Calculation

The ResNet architecture was supervised for feature-wise pixel segmentation according to RGB inferences. Using the necessary codes in MatLab, the feature-wise pixel number from each segmented image was extracted. A total of 11 features were defined in the initial segmentation and, thereafter, re-classified into a total of seven features (shown in Figure 6) for the calculative convenience of the OVW index (shown in Table 3). After the total 11 features were recognized by the RGB characterizations, their pixel numbers were estimated.

Table 3 shows that the feature-wise classified pixel numbers from all six 60° parted sub-images of Royal More were calculated in order to obtain the total pixel number of the panoramic image. In the same way, the total pixel count was determined from all of the sample images.

Table 3. Estimated pixel counts of segmented features (Royal More)

Features	Images						
							
Sky	199,377	128,303	238,332	241,860	280,436	241,330	1,336,917
Buildings	75,507	99,633	19,374	39,303	41,354	62,561	482,591
Poles	125	315	63	549	1412	88	673
Roads	216,276	238,098	266,439	269,601	225,859	276,977	1,529,158
Sidewalks	46,495	24,075	12,392	28,734	26,083	28,595	77,038
Trees	207	102	367	355	3141	32	40,886
Sign symbols	21,082	44,051	31,442	6051	50	2460	22,258
Fences	695	542	400	638	642	591	2166
Cars	18,366	26,913	40,051	27,847	34,557	13,441	236,712
Pedestrians	497	185	118	112	175	110	1216
Bikes	660	476	343	502	520	492	2385
Total pixels	641,750	621,591	628,747	608,383	623,128	608,401	3,732,000

To calculate the objectively measured walkability, these features were compiled to build five key formulas that indicated five key features; these five features constructed a walkability formula called "objective visual walkability" (shown in Table 4), which is a modified adaptation from [26]. Greenness, openness, visual crowdedness, visual enclosure, and visual pavement were the five key features for calculating the OVW index. The calculated values were the pixel numbers where the higher the values were, the better the level that the features represented (except for the visual crowdedness feature). In the same way, a higher index value represented the better walkability of that location (for this study, this ranged between 3 and 8 on a scale of 1–10).

Table 4. Formulations and definitions of OVW Index

Key features	Functional definition	Formula
Openness	Degree to which sky portion is exposed to pedestrians	$\text{O-level} = \dfrac{\text{Sum of sky pixels}}{\text{Sum of total pixels}}$
Greenness	Degree to which street greenery exposure can affect how pedestrians feel	$\text{G-level} = \dfrac{\text{Sum of tree pixels}}{\text{Sum of total pixels}}$
Visual crowdedness	Degree to which obstruction visibility can affect how pedestrians feel	$\text{C-level} = \dfrac{\text{Sum of obstacle (Pole, sign-symbols, car, pedestrian, and bike) pixels}}{\text{Sum of total pixels}}$
Visual enclosure	Way outdoor area resembles room (ratio of vertical objects to horizontal features)	$\text{E-level} = \dfrac{\text{Sum of vertical objective (Building and tree) pixels}}{\text{Sum of horizontal featured (Pavement, road and fence) pixels}}$
Visual pavement	Effects of proportions of sideways and roads on perceptions of pedestrians	$\text{P-level} = \dfrac{\text{Sum of sideway (Pavement and fence) pixels}}{\text{Sum of road pixels}}$
Objective visual walkability (OVW) = $(O+G+C+E+P)\cdot 5$		

The objective visual walkability (OVW) index calculation was started by applying the formula that was constructed by assembling the five visual indices that are shown in Equation (1). Next, the OVW values of each study point of each study road were summed up, and this cumulative value was averaged by the total number of study points that existed on that study road.

$$\text{OVW for each road} = \frac{\sum \text{OVW of study points}}{\text{No. of study points}} \tag{1}$$

4. Results

4.1. Walkability Ranking

After the composite OVW index calculations for the seven study roads, a ranking is illustrated in Table 5 according to their value priority. Here, KD Ghosh Road appears to be ranked first (with the highest walkability index value – 6.0046), and KDA Avenue ranks last (with the lowest index score – 4.1753). KD Ghosh Road is a popular route for leisure walking for locals, despite the fact that it is the shortest route; this is due to its location near important government buildings (like Circuit House, Khulna Divisional Court, and the police station) and its abundance of street amenities and greenery. On the contrary, KDA Avenue is less inviting for walking because it is surrounded by fast-growing economic development, high-rise infrastructure, and multiple mixed crowds (making it even more visually less enclosed). Ongoing disruptions throughout the year for road maintenance and repair by various authorities make it unable to walk due to a lack of adequate coordination. The study showed that walkability is influenced by the visual appeal of a street, which is affected by factors like the availability of street amenities and the level of maintenance.

Table 5. OVW calculation and ranking of study roads

Study roads	∑OVW of study points	No. of study points	∑OVW of study points/ No. of study points	Ranking
Outer Bypass Road	199.3215	41	4.8615	4
Old Jessore Road	95.9934	18	5.3329	2
KD Ghosh Road	42.0322	9	6.0046	1
Jalil Sarani Road	86.6761	16	5.0985	3
Khan Jahan Ali Road	76.4345	16	4.7771	5
Sher-E-Bangla Road	73.5244	17	4.3249	6
KDA Avenue Road	45.9284	10	4.1753	7

Figure 7 represents one set of sample images from each study road; these images provide insight into how real-time pedestrian environments have been segmented by feature-wise pixel classification.

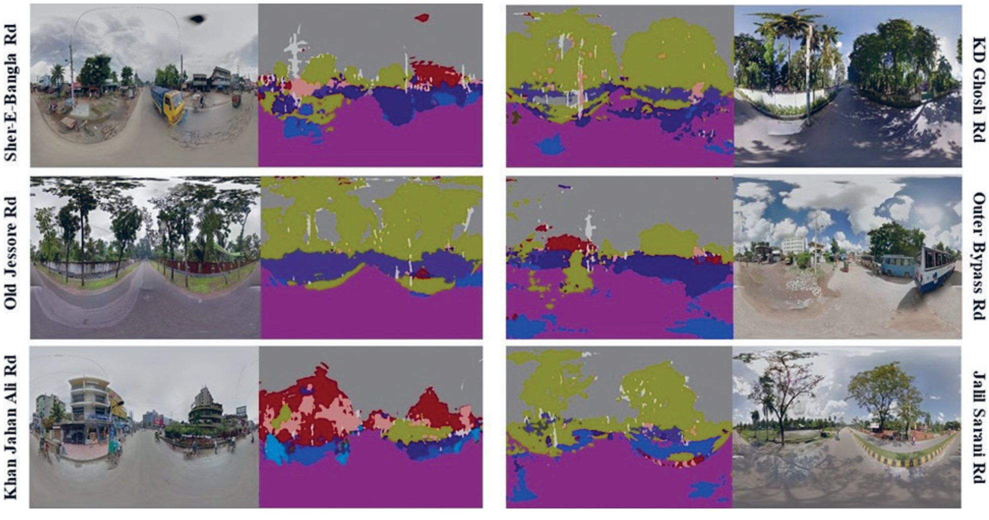


Fig. 7. Sample segmented images of study roads

4.2. Correlation Analysis of Initial Elements and Generated Key Visual Features

To identify the statistically meaningful relationship among multiple variables, a two-tailed significance-tested multiple correlation analysis was conducted over a sample data set of 127 GSV images (shown in Table 6). The corresponding relationship was represented as the Pearson correlation coefficient in a comparison matrix. The first part of the four-stage correlation analysis evaluated the multi-collinearity among the visual indices and the degree of influence of the independent visual indices on the dependent variable ("walkability"). The relatively low (or negative) correlation among the visual indices indicates that the seven initial explanatory elements were individual, and the five key visual indices that were generated from the initial components did not overlap (independently influencing the walkability). This made the comparison matrix valid without an interpretation bias. The correlation coefficients (0.614, 0.750, 0.483) showed that greenness and visual enclosure had a strong positive effect, and visual pavement had a moderate positive influence on walkability. Conversely, openness (−0.511) and visual crowdedness (−0.070) had a negative correlation with walkability, which was systematically valid because congested roads with crowds make it disturbing for walking.

Table 6. Correlation analysis of walkability index, key walkability features, and initial elements

Part A: Correlation coefficient of five streetscape features and walkability (OVW)						
Features	Openness	Greenness	Visual crowdedness	Visual enclosure	Visual pavement	IVW
Openness	1	−0.651**	−0.001	−.0754**	0.014	−0.511**
Greenness	−0.651**	1	−0.400**	0.765**	−0.204*	0.614**
Visual crowdedness	−0.001	−0.400**	1	−0.213*	0.200*	−0.070
Visual enclosure	−0.754**	0.765**	−0.213*	1	−0.142	0.750**
Visual pavement	0.014	−0.204*	0.200*	−0.142	1	0.483**
IVW	−0.511**	0.614**	−0.070	0.750**	0.483**	1
Part B: Correlation coefficient of visual crowdedness and its visual elements						
Features	Visual crowdedness	Pole	Sign-symbols	Car	Pedestrian	Bike
Visual crowdedness	1	−0.124	0.164	0.863**	0.247**	0.236**
Pole	−0.124	1	−0.060	−0.142	−0.092	−0.033
Sign-symbol	0.164	−0.060	1	−0.010	0.167	0.259**
Car	0.863**	−0.142	−0.010	1	0.187*	0.141
Pedestrian	0.247**	−0.092	0.167	0.187*	1	0.051
Bike	0.236**	−0.033	0.259**	0.141	0.051	1
Part C: Correlation coefficient of visual enclosure and its visual elements						
Features	Visual enclosure	Building	Tree	Sidewalk	Road	Fence
Visual enclosure	1	0.216*	0.662**	−0.225*	−0.023	0.203*
Building	0.216*	1	−0.456**	0.117	−0.130	−0.142
Tree	0.662**	−0.456**	1	−0.262**	0.165	0.325**
Sidewalk	−0.225*	0.117	−0.262**	1	−0.584**	0.295**
Road	−0.023	−0.130	0.165	−0.584**	1	−0.095
Fence	0.203*	−0.142	0.325**	0.295**	−0.095	1

Part D: Correlation coefficient of visual pavement and its visual elements				
Features	Visual pavement	Sidewalk	Road	Fence
Visual pavement	1	0.914**	−0.682**	0.315**
Sidewalk	0.914**	1	−0.584**	0.295**
Road	−0.682**	−0.584**	1	−0.095
Fence	0.315**	0.295**	−0.095	1

* Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).

The next three parts of the correlation analysis evaluated the relationships among the visual indices and the streetscape elements from which they were generated. Openness and greenness were not included in this analysis, as they were determined using a single component.

Part B revealed that the sub-elements of car, pedestrian, bike, and sign-symbol had strong (correlation coefficient range of 0.7 to 0.9), moderate (range of 0.5 to 0.7), and weak (range of 0.2 to 0.5) positive correlations with visual crowdedness, respectively. The pole had a negative relationship (with a coefficient range of −0.1 to −0.3), as it was considered to be less disruptive to walkability as a vertical infrastructure. Pedestrians and bikes had the highest correlation, with a maximum of four co-elements.

Part C found that the vertical features of buildings, trees, and fences had strong influences on the visual enclosure, with positive correlations ranging from 0.2 to 0.65. Meanwhile, horizontal elements were found to have a negative correlation, indicating that the construction and combination of vertical elements were more important for a proportionate streetscape design. All of the co-elements were individually important for the visual enclosure, resulting in negative or zero interactive correlations among them.

In the comparison matrix for visual pavement, pavement, and fence, it had a positive correlation (coefficient range from 0.3 to 0.9), while road had a negative correlation. The interactive correlations among the co-elements followed a similar trend, with sidewalks and fences positively correlating, and roads negatively correlating.

4.3. Percentage-Level Representation of Visual Walkability Features

The stacked columns in Figure 8 show at what percentages all of the five visual indices are present and viewed from a totality of vision from a standpoint. So, the percentage level of the five visual indices at each of the study points for all of the study roads is shown. Since the walkability index for each study point is derived by compositing the five visual indices, the degree of the walkability of a study point is combinedly dependent on all of the five key features. In the OVW ranking, KD Ghosh Road ranked first, with a comparatively higher degree of proportioned greenness, enclosure, and sidewalk (which made the road visually open, comfortable, and pleasant). Although the lowest level of greenery reduced the shades resulted in increasing openness, a comparatively lower degree of road pavement, enclosure, and greater crowdedness compositely made KDA Avenue the least walkable in the OVW index.

A correlation analysis of enclosure suggested vertical elements to be influential, which is reflected in the graphical representation of road-wise feature distribution. Also, the study roads with approximately the same widths and sidewalks impacted relatively the same over the horizontal part of the enclosure. Accordingly, the buildings with comparatively lower building heights and the higher setbacks of the residential building along with the trees on Old Jessore Road represented higher ranges of the enclosure.

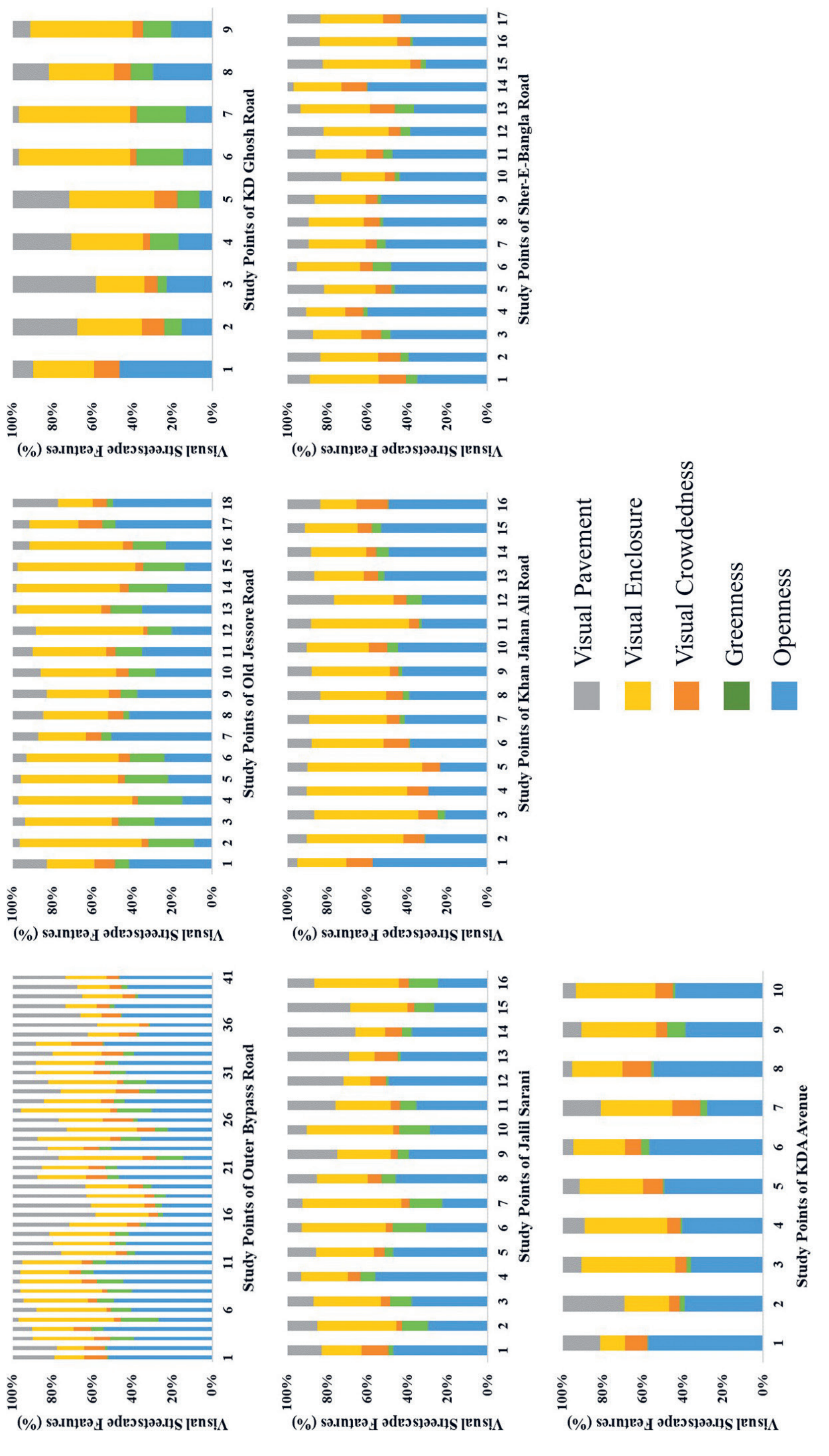


Fig. 8. Stacked bar chart of visual feature percentages

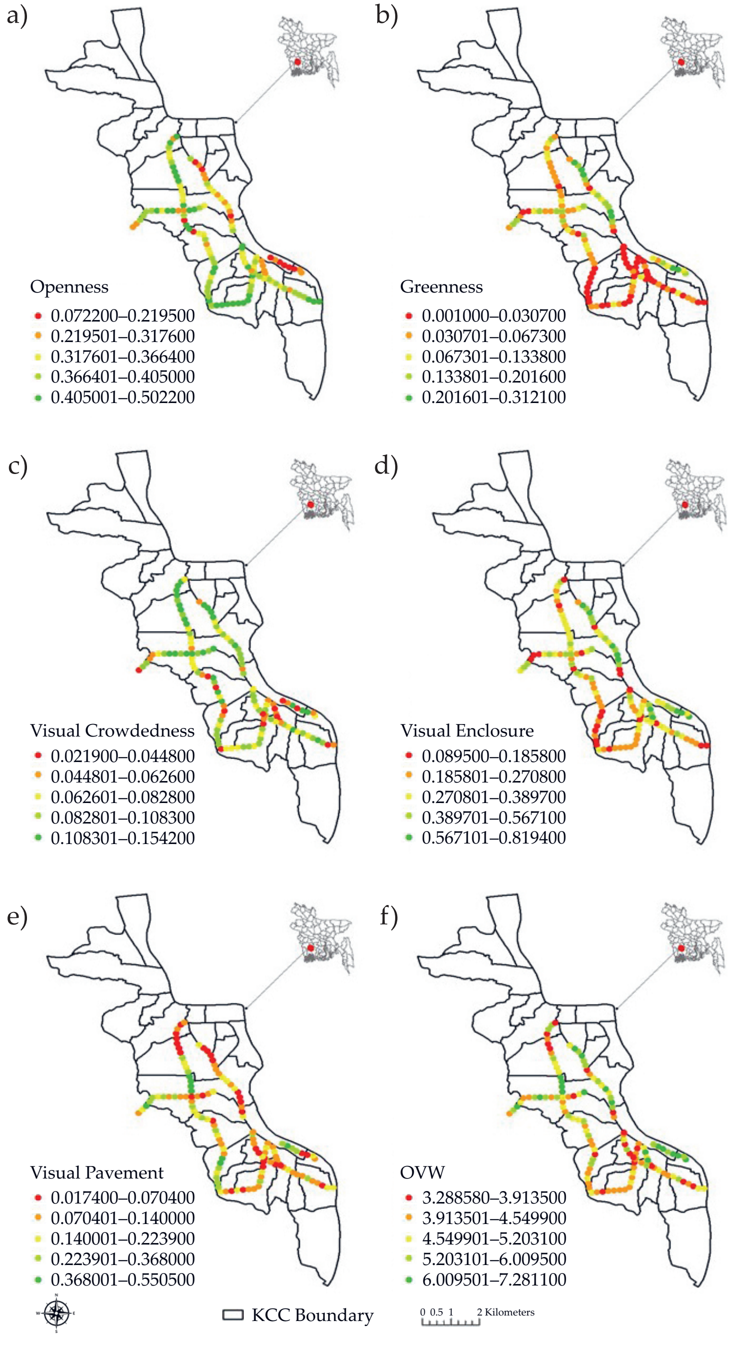


Fig. 9. Spatial distribution of visual features and walkability index: a) openness; b) greenness; c) visual crowdedness; d) visual enclosure; e) visual pavement; f) objective visual walkability (OVW)

4.4. Spatial Distribution of Visual Walkability

The study conducted a spatial analysis where the choropleth mapping in Figure 8 showed how the five walkability measuring indices values varied spatially within the 127 study points. Figure 9a represents a lower degree of openness in KD Ghosh and Old Jessore Roads. In contrast, these two roads had a higher degree of greenness with trees and canopies in Figure 9b, which minimized sky exposure. This implied a fact that, even though a road that has a moderate horizontal-vertical enclosure can be distorted by lower openness, large vertical canopies provide shading and reduce sky exposure. However, the greenness mapping indicated that roads that were ranked less-walkable in the OVW index had lower ranges of greenness. In Figure 9c, the values are quite interspersed where Old Jessore Road is the least-crowded road because it is surrounded by residential land use (where the human crowd and vehicular movement was less). Oppositely, Khan Jahan Ali Road, KDA Avenue, and Sher-E-Bangla Road had a higher range of crowdedness because they run across the CBD and the major economic hub of Khulna. The enclosure mapping in Figure 9d tends to illustrate a similar trend of crowdedness in Outer Bypass Road, since this long route covers multiple land uses. Theoretically and functionally, the overall pavement conditions of Khulna's roads are not suitable for overall walking, so the overall values in Figure 9e are distorted. Finally, Figure 9f illustrates the aggregated OVW index scores that were obtained from the respective five indices. This is the final understanding of the spatial walkable conditions for all of the study points, where KD Ghosh Road appeared to be the most-walkable road, and KDA Avenue was the least-walkable.

5. Discussions

Studies from various fields such as behavioral geography, urban planning, and cognitive psychology have discovered the concept of a "sense of place" that involves how individuals visually perceive and connect with their surroundings. Despite this, visual street design elements have been less explored – only 5% [27]; this is due to the lack of a standard and user-friendly objective method. An objective measure combined with an advanced machine-learning algorithm and GSVs for assessing the visual designs of streets offers a robust tool. For this objective approach, it is no longer obscured to relate visionary notions for cityscape designing and planning – even at a micro-scale level – as visual elements are calculated through human-scale observation (which is automated and can be replicated without manual observation). The image-segmentation process that is applied through the ResNet architecture has enormous advantages for achieving the study goal, as ResNet models can be pre-trained on large data sets and then fine-tuned on smaller data sets; this can be useful in built-environment analysis where labeled data is limited [75]. The deeper network principle makes it capable to extract a detailed number of features to alleviate the vanishing gradient problem. The current study used 11 physical features synthesized into five key visual features that were compositely framed for pedestrian-oriented comfort; this has significantly contributed to visual cognitive studies, urban planning, and architectural design. The results showed that roads that are close to CBD or economic-commercial zones distress its visual comfort for crowded sidewalks, multi-modal traffic flow, and high-rise infrastructure. The roads with higher walkable values ranked the presence of visible greenness and enclosure higher than other features, which attributed them as the predominant features. The remaining features could not resonate with distinctive influence, as the overall roads were not accommodating enough with diversified and standard streetscape facilities. This is the perverse effect of prioritizing motorized transportation over non-motorized traffic. In contrast with human scale intelligence, this method can supplementarily be used as a technical tool for zoning rules, land-use resizing, and architectural design guidelines like "Active Design Guidelines" [76]; to identify problematic roads and determine the features that were difficult to examine. It can be simulated in the comparative analysis with the conventional subjective approach and a GIS-based objective measure. The current research can be extended to evaluate socio-economic behavioral and planning studies. Also, it scopes up the opportunities to integrate multidimensional research interests, including public health, real estate, medical research [77], and cycling behavior. From a futuristic viewpoint, a global online system can be generated that enables image-segmentation services to be available for relevant types of image data sets and integrated into walkability indexes like Neighborhood Environment Walkability Scale (NEWS) [78] and Walkscore® [79].

Policies and strategies that address sustainability and transportation are essential for promoting a walkable city. The BRT (Bus Rapid Transit) Walkability Strategy aims to promote a sustainable and walkable city through improved access, security, and vibrancy in its streets, parks, and public spaces [80]. National transportation policies such as the National Land Transport Policy (2004) and the Integrated Multi-Modal Transport Policy (2013) focus on safe and developed transportation systems and infrastructure investment [32]. However, market-driven land-use policies and financial interests can hinder progress. Major cities in Bangladesh (like Khulna) face challenges in promoting walkability due to their heavy traffic flows and inadequate road infrastructures. This is due to the lack of coordination between urban and transportation planning authorities, which prioritize automotive mobility over pedestrian needs. The proposed visual walkability may encourage planners and policymakers to prioritize walkability as a sustainable planning strategy and approach it from a technologically driven human-centered visual perspective.

The study of the visual walkability index has limitations, as it only analyzed certain aspects of the walking environment and did not take other sensory factors like smell, sound, and mental perception into account. It also did not consider subjectively measured elements such as social cohesion, comfort, safety, and pleasurability [2]. Vision-oriented perceptual features were analyzed without the inclusion of other sensual features that are oriented to smells, sounds, and cognitive sensitivity. Conventional methods of assessing walkability use spatial factors like land-use mix, road networks, dwellings, and intersection densities, which is a different approach from this study. This study is not a complete replacement for other methods of assessing the multidimensional aspects of walkability. In addition, conducting GSV-based studies in developing countries like Bangladesh can be challenging due to the lack of updated Street View images in Google Maps and the unavailability of GSVs in rural areas (which restricts the study's reach).

6. Conclusion

To conclude, this objective approach proposed a visual walkability in Khulna that was intended to quantitatively measure "unmeasurable" visual streetscape elements using an artificial pedestrian's visual level perception, which was difficult with a subjective approach. The application of a machine learning-based ResNet model with the input of Google Street View images was able to extract five key visual streetscape features through image segmentation, providing a cost-effective and scalable solution to objectively measure walkability. A quantitative analysis of classified features and the OVW index showed quite satisfactory real-time performance. This study highlights the potential for using machine-learning technology to support urban planning and design efforts by providing objective data on the walkability of a given area, which can help when making decisions to ensure diversified cityscape design elements, greenery, and other pedestrian-friendly infrastructures. With the responsive supervision of planners, scholars, and decision-makers, this scopes up the further development and research opportunities that are related to a "sense of place."

References

[1] Guthold R., Stevens G.A., Riley L.M., Bull F.C.: *Worldwide trends in insufficient physical activity from 2001 to 2016: A pooled analysis of 358 population-based surveys with 1.9 million participants*. The Lancet Global Health, vol. 6(10), 2018, pp. e1077–e1086. https://doi.org/10.1016/S2214-109X(18)30357-7.

[2] Alfonzo M.A.: *To walk or not to walk? The hierarchy of walking needs.* Environment and Behavior, vol. 37(6), 2005, pp. 808–836. https://doi.org/10.1177/0013916504274016.

[3] Litman T.: *Evaluating Public Transportation Health Benefits*. 2011. http://site.ebrary.com/lib/sfu/docDetail.action?docID=10534560 [access: 1.09.2019].

[4] Hallal P.C., Lee I.M.: *Prescription of physical activity: An undervalued intervention*. The Lancet, vol. 381(9864), 2013, pp. 356–357. https://doi.org/10.1016/S0140-6736(12)61804-2.

[5] Southworth M.: *Designing the walkable city*. Journal of Urban Planning and Development, vol. 131(4), 2005, pp. 246–257. https://doi.org/10.1061/(ASCE)0733-9488(2005)131:4(246).

[6] Lwin K.K., Murayama Y.: *Modelling of urban green space walkability: Eco-friendly walk score calculator*. Computers, Environment and Urban Systems, vol. 35(5), Sep. 2011, pp. 408–420. https://doi.org/10.1016/J.COMPENVURBSYS.2011.05.002.

[7] Imani M.: *City sustainability: The influence of walkability on built environments*. Transportation Research Procedia, vol. 24, 2017, pp. 97–104. https://doi.org/10.1016/j.trpro.2017.05.074.

[8] Telega A., Telega I., Bieda A.: *Measuring walkability with GIS-methods overview and new approach proposal*. Sustainability, vol. 13(4), 2021, 1883. https://doi.org/10.3390/su13041883.

[9] Ewing R., Handy S., Brownson R.C., Clemente O., Winston E.: *Identifying and measuring urban design qualities related to walkability*. Journal of Physical Activity and Health, vol. 3(1), 2006, pp. s223–s240. https://doi.org/10.1123/jpah.3.s1.s223.

[10] Ewing R., Hajrasouliha A., Neckerman K.M., Purciel-Hill M., Greene W.: *Streetscape features related to pedestrian activity*. Journal of Planning Education and Research, vol. 36(1), 2016, pp. 5–15. https://doi.org/10.1177/0739456X15591585.

[11] Lee C., Moudon A.V.: *Physical activity and environment research in the health field: Implications for urban and transportation planning practice and research*. Journal of Planning Literature, vol. 19(2), 2004, pp. 147–181. https://doi.org/10.1177/0885412204267680.

[12] Ewing R., Handy S.: *Measuring the unmeasurable: Urban design qualities related to walkability*. Journal of Urban Design, vol. 14(1), 2009, pp. 65–84. https://doi.org/10.1080/13574800802451155.

[13] Ewing R., Clemente O., Neckerman K.M., Purciel-Hill M., Quinn J.W., Rundle A.: *Measuring Urban Design: Metrics for Livable Places*. Metropolitan Planning + Design, Island Press, Washington – Covelo – London 2013. https://doi.org/10.5822/978-1-61091-209-9.

[14] Anguelov D., Dulong C., Filip D., Frueh Ch., Lafon S., Lyon R., Ogale A., Vincent L., Weaver J.: *Google Street View: Capturing the world at street level*. Computer, vol. 43(6), 2010, pp. 32–38. https://doi.org/10.1109/MC.2010.170.

[15] Nagata S., Nakaya T., Hanibuchi T., Amagasa S., Kikuchi H., Inoue S.: *Objective scoring of streetscape walkability related to leisure walking: Statistical modeling approach with semantic segmentation of Google Street View images*. Health & Place, vol. 66, 2020, 102428. https://doi.org/10.1016/j.healthplace.2020.102428.

[16] Yin L., Wang Z.: *Measuring visual enclosure for street walkability: Using machine learning algorithms and Google Street View imagery*. Applied Geography, vol. 76, 2016, pp. 147–153. https://doi.org/10.1016/j.apgeog.2016.09.024.

[17] Steinmetz-Wood M., Velauthapillai K., O'Brien G., Ross N.A.: *Assessing the micro-scale environment using Google Street View: The Virtual Systematic Tool for Evaluating Pedestrian Streetscapes (Virtual-STEPS)*. BMC Public Health, vol. 19(1), 2019, 1246. https://doi.org/10.1186/s12889-019-7460-3.

[18] Li X., Santi P., Courtney T.K., Verma S.K., Ratti C.: *Investigating the association between streetscapes and human walking activities using Google Street View and human trajectory data*. Transactions in GIS, vol. 22(4), 2018, pp. 1029–1044. https://doi.org/10.1111/tgis.12472.

[19] Koo B.W., Guhathakurta S., Botchwey N.: *How are neighborhood and street-level walkability factors associated with walking behaviors? A big data approach using street view images*. Environment and Behavior, vol. 54(1), 2022, pp. 211–241. https://doi.org/10.1177/00139165211014609.

[20] Lu Y.: *The association of urban greenness and walking behavior: Using Google Street View and deep learning techniques to estimate residents' exposure to urban greenness*. International Journal of Environmental Research and Public Health, vol. 15(8), 2018, 1576. https://doi.org/10.3390/ijerph15081576.

[21] Yang Y., He D., Gou Z., Wang R., Liu Y., Lu Y.: *Association between street greenery and walking behavior in older adults in Hong Kong*. Sustainable Cities and Society, vol. 51, 2019, 101747. https://doi.org/10.1016/j.scs.2019.101747.

[22] Ki D., Lee S.: *Analyzing the effects of Green View Index of neighborhood streets on walking time using Google Street View and deep learning*. Landscape and Urban Planning, vol. 205, 2021, 103920. https://doi.org/10.1016/j.landurbplan.2020.103920.

[23] Yang L., Ao Y., Ke J., Lu Y., Liang Y.: *To walk or not to walk? Examining non-linear effects of streetscape greenery on walking propensity of older adults*. Journal of Transport Geography, vol. 94, 103099. https://doi.org/10.1016/j.jtrangeo.2021.103099.

[24] Yang L., Liu J., Liang Y., Lu Y., Yang H.: *Spatially varying effects of street greenery on walking time of older adults*. ISPRS International Journal of Geo-Information, vol. 10(9), 2021, 596. https://doi.org/10.3390/ijgi10090596.

[25] Yin L., Cheng Q., Wang Z., Shao Z.: *'Big data' for pedestrian volume: Exploring the use of Google Street View images for pedestrian counts*. Applied Geography, vol. 63, 2015, pp. 337–345. https://doi.org/10.1016/j.apgeog.2015.07.010.

[26] Zhou H., He S., Cai Y., Wang M., Su S.: *Social inequalities in neighborhood visual walkability: Using street view imagery and deep learning technologies to facilitate healthy city planning*. Sustainable Cities and Society, vol. 50, 2019, 101605. https://doi.org/10.1016/j.scs.2019.101605.

[27] Fonseca F., Ribeiro P.J.G., Conticelli E., Jabbari M, Papageorgiou G., Tondelli S., Ramos R.A.R.: *Built environment attributes and their influence on walkability*. International Journal of Sustainable Transportation, vol. 16(7), 2022, pp. 660-679. https://doi.org/10.1080/15568318.2021.1914793.

[28] Shumi S., Zuidgeest M.H.P., Martinez J.A., Efroymson D., van Maarseveen M.F.A.M.: *Understanding the relationship between walkability and quality-of-life of women garment workers in Dhaka, Bangladesh*. Applied Research Quality Life, vol. 10(2), 2015, pp. 263–287. https://doi.org/10.1007/s11482-014-9312-8.

[29] Siddiqua F., Kabir S., Taher M.T.: *Assessing walkability of planned and historical streetscape of urban Dhaka*. AIUB Journal of Science and Engineering, vol. 16(1), 2017, pp. 19–28. https://doi.org/10.53799/ajse.v16i1.28.

[30] Al Mamun M.M., Begum A.A., Mowla Q.A.: *Walkability for urban sustainability: Study of pedestrian traffic in Chittagong*. Jahangirnagar University Plannind Review, vol. 16, 2018, pp. 87–102. https://doi.org/10.13140/RG.2.2.35300.63367.

[31] Nasrin S., Afifah F.: *Walkability assessment tool for a developing country*. IOP Conference Series: Materials Science and Engineering, vol. 527(1), 2019, 012073. https://doi.org/10.1088/1757-899X/527/1/012073.

[32] Al Noman A., Sharna F.K.: *An overview of pedestrian service relevant standards and guidelines: Correlative approaches of international examples with existing policies of Bangladesh*. Bangladesh Institute of Planners (BIP), November 2019, pp. 44–51.

[33] Moniruzzaman M.: *Sustainable and inclusive transport development of Khulna City*. Khulna City Corporation, Khulna 2013.

[34] Kowaleski-Jones L., Zick C., Smith K.R., Brown B., Hanson H., Fan J.: *Walkable neighborhoods and obesity: Evaluating effects with a propensity score approach*. SSM – Population Health, vol. 6, 2018, pp. 9–15. https://doi.org/10.1016/j.ssmph.2017.11.005.

[35] Leather J., Fabian H., Gota S., Mejia A.: *Walkability and Pedestrian Facilities in Asian Cities: State and Issues*. ADB Sustainable Development Working Paper Series, no. 17, Asian Development Bank, 2011.

[36] Blečić I., Congiu T., Fancello G., Trunfio G.A.: *Planning and design support tools for walkability: A guide for urban analysts*. Sustainability, vol. 12(11), 2020, 4405. https://doi.org/10.3390/su12114405.

[37] Hasan M.M., Oh J.S., Kwigizile V.: *Exploring the trend of walkability measures by applying hierarchical clustering technique*. Journal of Transport & Health, vol. 22, 2021, 101241. https://doi.org/10.1016/j.jth.2021.101241.

[38] Rafiemanzelat R., Emadi M.I., Kamali A.J.: *City sustainability: the influence of walkability on built environments*. Transportation Research Procedia, vol. 24, 2017, pp. 97–104. https://doi.org/10.1016/j.trpro.2017.05.074.

[39] Arellana J., Saltarín M., Larrañaga A.M., Alvarez V., Henao C.A.: *Urban walkability considering pedestrians' perceptions of the built environment: A 10-year review and a case study in a medium-sized city in Latin America*. Transport Reviews, vol. 40(2), 2020, pp. 183–203. https://doi.org/10.1080/01441647.2019.1703842.

[40] Oreskovic N.M., Roth P., Charles S.L., Tsigaridi D., Shepherd K., Nelson K.P., Bar M.: *Attributes of form in the built environment that influence perceived walkability*. Journal of Architectural and Planning Research, vol. 31(3), 2014, pp. 218–232. https://www.jstor.org/stable/44114605.

[41] Zhu W., Nedovic-Budic Z., Olshansky R.B., Marti J., Gao Y., Park Y., McAuley E., Chodzko-Zajko W.: *Agent-based modeling of physical activity behavior and environmental correlations: An introduction and illustration*. Journal of Physical Activity and Health, vol. 10(3), 2013, pp. 309–322. https://doi.org/10.1123/jpah.10.3.309.

[42] Lotfi S., Koohsari M.J.: *Neighborhood walkability in a city within a developing country*. Journal of Urban Planning and Development, vol. 137(4), 2011, pp. 402–408. https://doi.org/10.1061/(asce)up.1943-5444.0000085.

[43] Fan P., Wan G., Xu L., Park H., Xie Y., Liu Y., Yue W., Chen J.: *Walkability in urban landscapes: A comparative study of four large cities in China*. Landscape Ecology, vol. 33(2), 2018, pp. 323–340. https://doi.org/10.1007/s10980-017-0602-z.

[44] Ramakreshnan L., Fong C.S., Sulaiman N.M., Aghamohammadi N.: *Motivations and built environment factors associated with campus walkability in the tropical settings*. Science of the Total Environment, vol. 749, 2020, 141457. https://doi.org/10.1016/j.scitotenv.2020.141457.

[45] Khder H.M., Mousavi S.M., Khan T.H.: *Impact of street's physical elements on walkability: A case of Mawlawi Street in Sulaymaniyah, Iraq*. International Journal of Built Environment and Sustainability, vol. 3(1), 2016, pp. 18–26. https://doi.org/10.11113/ijbes.v3.n1.106.

[46] Ye Y., Zeng W., Shen Q., Zhang X., Lu Y.: *The visual quality of streets: A human-centred continuous measurement based on machine learning algorithms and street view images*. Environment and Planning B: Urban Analytics and City Science, vol. 46(8), 2019, pp. 1439–1457. https://doi.org/10.1177/2399808319828734.

[47] Ma X. Ma C., Wu C., Xi Y., Yang R., Peng N., Zhang C., Ren F.: *Measuring human perceptions of streetscapes to better inform urban renewal: A perspective of scene semantic parsing*. Cities, vol. 110, 2021, 103086. https://doi.org/10.1016/j.cities.2020.103086.

[48] Dai L., Zheng C., Dong Z., Yao Y., Wang R., Zhang X., Ren S., Zhang J., Song X., Guan Q.: *Analyzing the correlation between visual space and residents' psychology in Wuhan, China using street-view images and deep-learning technique*. City and Environment Interactions, vol. 11, 2021, 100069. https://doi.org/10.1016/j.cacint.2021.100069.

[49] Tao Y., Wang Y., Wang X., Tian G., Zhang S.: *Measuring the correlation between human activity density and streetscape perceptions: An analysis based on Baidu street view images in Zhengzhou, China*. Land, vol. 11(3), 2022, 400. https://doi.org/10.3390/land11030400.

[50] Huang G., Yu Y., Lyu M., Sun D., Zeng Q., Bart D.: *Using Google Street View panoramas to investigate the influence of urban coastal street environment on visual walkability*. Environmental Research Communications, vol. 5(6), 2023, 065017. https://doi.org/10.1088/2515-7620/acdecf.

[51] Dong H.: *Does walkability undermine neighbourhood safety?* Journal of Urban Design, vol. 22(1), 2017, pp. 59–75. https://doi.org/10.1080/13574809.2016.1247644.

[52] Reisi M., Nadoushan M.A., Aye L.: *Local walkability index: Assessing built environment influence on walking*. Bulletin of Geography Socio-economic Series,, vol. 46(46), 2019, pp. 7–21. https://doi.org/10.2478/bog-2019-0031.
[53] Adkins A., Dill J., Luhr G., Neal M.: *Unpacking walkability: Testing the influence of urban design features on perceptions of walking environment attractiveness*. Journal of Urban Design, vol. 17(4), 2012, pp. 499–510. https://doi.org/10.1080/13574809.2012.706365.
[54] Moayedi F., Zakaria R., Bigah Y., Mustafar M., Che Puan O., Zin I.S., Klufallah M.M.A.: *Conceptualising the indicators of walkability for sustainable transportation*. Jurnal Teknologi, vol. 65(3), pp. 85–90, 2013. https://doi.org/10.11113/jt.v65.2151.
[55] He K., Zhang X., Ren S., Sun J.: *Deep residual learning for image recognition*. [in:] *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2016), Las Vegas, Nevada, USA, 27–30 June 2016*, IEEE, Poscataway 2016, pp. 770–778. https://doi.org/10.1109/CVPR.2016.90.
[56] Badrinarayanan V., Kendall A., Cipolla R.: *SegNet: A deep convolutional encoder-decoder architecture for image segmentation*. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39(12), 2017, pp. 2481–2495. https://doi.org/10.1109/TPAMI.2016.2644615.
[57] Chen L.-C., Papandreou G., Kokkinos I., Murphy K., Yuille A.L.: *DeepLab: Semantic image segmentation with deep convolutional nets, atrous convolution, fully connected CRFs*. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 40(4), 2018, pp. 834–848. https://doi.org/10.1109/TPAMI.2017.2699184.
[58] Diwan T., Anirudh G., Tembhurne J.V.: *Object detection using YOLO: Challenges, architectural successors, datasets and applications*. Multimedia Tools and Applications, vol. 82, 2023, pp. 9243–9275. https://doi.org/10.1007/s11042-022-13644-y.
[59] Montgomery J.: *Making a city: urbanity, vitality and urban design*. Journal of Urban Design, vol. 3(1), 1998, pp. 93–116. https://doi.org/10.1080/13574809808724418.
[60] Li X., Ghosh D.: *Associations between body mass index and urban 'Green' streetscape in Cleveland, Ohio, USA*. International Journal of Environmental Research and Public Health, vol. 15(10), 2018, 2186. https://doi.org/10.3390/ijerph15102186.
[61] Villeneuve P.J. et al.: *Comparing the normalized difference vegetation index with the google street view measure of vegetation to assess associations between greenness, walkability, recreational physical activity, and health in Ottawa, Canada*. International Journal of Environmental Research and Public Health, vol. 15(8), 2018, 1719. https://doi.org/10.3390/ijerph15081719.
[62] Dong R., Zhang Y., Zhao J.: *How green are the streets within the sixth ring road of Beijing? An analysis based on tencent street view pictures and the green view index*. International Journal of Environmental Research and Public Health, vol. 15(7), 2018, 1367. https://doi.org/10.3390/ijerph15071367.

[63] Zhang J., Heng C.K., Malone-Lee L.C., Hii D.J.C., Janssen P., Leung K.S., Tan B.K.: *Evaluating environmental implications of density: A comparative case study on the relationship between density, urban block typology and sky exposure*. Automation in Construction, vol. 22, 2012, pp. 90–101. https://doi.org/10.1016/j.autcon.2011.06.011.

[64] Tang J., Long Y.: *Measuring visual quality of street space and its temporal variation: Methodology and its application in the Hutong area in Beijing*. Landscape and Urban Planning, vol. 191, 2019, 103436. https://doi.org/10.1016/J.LANDURBPLAN.2018.09.015.

[65] Molaei P., Tang L., Hardie M.: *Measuring walkability with street connectivity and physical activity: A case study in Iran*. World, vol. 2(1), 2021, pp. 49–61. https://doi.org/10.3390/world2010004.

[66] Edirisinghe T., Hewawasam D.C.: *An investigation of the relationship of streetscape visual enclosure and the pedestrian movement in selected case studies in Colombo*. Journal of Engineering and Architecture, vol. 8(1), 2020, pp. 10–30. https://doi.org/10.15640/jea.v8n1a2.

[67] Imamoglu Ç.: *Complexity, liking and familiarity: architecture and non-architecture turkish students' assessments of traditional and modern house facades*. Journal of Environmental Psychology, vol. 20(1), 2000, pp. 5–16. https://doi.org/10.1006/JEVP.1999.0155.

[68] Stamps A.E.: *Advances in visual diversity and entropy*. Environment and Planning B: Planning and Design, vol. 30(3), 2003, pp. 449–463. https://doi.org/10.1068/B12986.

[69] Tucker C., Ostwald M.J., Chalup S.K.: *A method for the visual analysis of streetscape character using digital image processing*. [in:] Bromberek Z. (ed.), *Contexts of Architecture: Proceedings of the 38th Annual Conference of the Architectural Science Association ANZAScA and the International Building Performance Simulation Association – Australasia, Launceston, 10–12 November 2004*, School of Architecture, University of Tasmania, Locked Bag, Launceston 2004, pp. 134–141.

[70] Adams M.A., Phillips C.B., Patel A., Middel A.: *Training computers to see the built environment related to physical activity: Detection of microscale walkability features using computer vision*. International Journal of Environmental Research and Public Health, vol. 19(8), 2022, 4548. https://doi.org/10.3390/ijerph19084548.

[71] Lichstein J.W., Simons T.R., Franzreb K.E.: *Landscape effects on breeding songbird abundance in managed forests*. Ecological Applications, vol. 12(3), 2002, pp. 836–857. https://doi.org/10.1890/1051-0761(2002)012[0836:LEOBSA]2.0.CO;2.

[72] Fourie P.J., Jittrapirom P., Binder R.B., Tobey M.B., Medina S.O., Maheshwari T., Yamagata Y.: *Modeling and Design of Smart Mobility Systems*. [in:] Yamagata Y., Yang P.P.J. (eds.), *Urban Systems Design: Creating Sustainable Smart Cities in the Internet of Things Era*, Elsevier, 2020, pp. 163–197. https://doi.org/10.1016/B978-0-12-816055-8.00006-3.

[73] Agarwal P., Burgard W., Spinello L.: *Metric localization using Google Street View*. [in:] *IROS: IEEE/RSJ International Conference on Intelligent Robots and Systems: September 28-October 2, 2015, Hamburg, Germany*, IEEE, Piscataway 2015, pp. 3111–3118. https://doi.org/10.1109/IROS.2015.7353807.

[74] Dhillon A., Verma G.K.: *Convolutional neural network: a review of models, methodologies and applications to object detection*. Progress in Artificial Intelligence, vol. 9(2), 2020, pp. 85–112. https://doi.org/10.1007/s13748-019-00203-0.

[75] Zaeemzadeh A., Rahnavard N., Shah M.: *Norm-preservation: Why residual networks can become extremely deep?* IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 43(11), 2021, pp. 3980–3990. https://doi.org/10.1109/TPAMI.2020.2990339.

[76] Lee K.K.: *Developing and implementing the Active Design Guidelines in New York City*. Health & Place, vol. 18(1), 2012, pp. 5–7. https://doi.org/10.1016/j.healthplace.2011.09.009.

[77] Sarwinda D., Paradisa R. H., Bustamam A., Anggia P.: *Deep learning in image classification using Residual Network (ResNet) variants for detection of colorectal cancer*. Procedia Computer Science, vol. 179, 2021, pp. 423–431. https://doi.org/10.1016/j.procs.2021.01.025.

[78] Cerin E., Saelens B.E., Sallis J.F., Frank L.D.: *Neighborhood environment walkability scale: Validity and development of a short form*. Medicine & Science in Sports & Exercise, vol. 38(9), 2006, pp. 1682–1691. https://doi.org/10.1249/01.mss.0000227639.83607.4d.

[79] Hall C.M., Ram Y.: *Walk score® and its potential contribution to the study of active transport and walkability: A critical and systematic review*. Transportation Research Part D: Transport and Environment, vol. 61(part B), 2018, pp. 310–324. https://doi.org/10.1016/j.trd.2017.12.018.

[80] Efroymson D. et al.: *Moving Dangerously, Moving Pleasurably: Improving Walkability in Dhaka: Using a BRT Walkability Strategy to Make Dhaka's Transportation Infrastructure Pedestrian-Friendly*. 2012. https://healthbridge.ca/dist/library/BRT_Walkability_Strategy_Summary_final.pdf.