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Automated Evaluation of Urban Environmental Quality Using Streetscape Images Considering Component Relationships and Attributes

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ABSTRACT: Improving urban environmental quality is essential for enhancing citizens' well-being and achieving sustainable urban development. The state of urban spaces affects considerably the way people experience comfort, safety, and satisfaction. Addressing these challenges requires a systematic microscale evaluation to facilitate targeted street- or district-level improvements. While streetscape image analysis enables large-scale urban assessments by considering the influences of environmental components, existing methods often fail to consider key environmental attributes and spatial relationships that shape urban perceptions. This study enhances the existing urban evaluation frameworks by integrating these critical factors. Using computer vision, this method detects key components, classifies their attributes with 95.60% accuracy, and analyzes spatial relationships between segments. Machine-learning models predict environmental quality based on these features, with Shapley additive explanations analysis providing transparent insights into their influences. The results demonstrate that incorporating the component's attributes for maintenance quality (e.g., road quality and sticker-covered pole) and spatial relationships (e.g., sidewalk-encroaching illegal parking and road separation) improves considerably evaluation accuracy. Compared with previous studies, the proposed method incorporated component relationships and attributes and achieved an accuracy of 82.9% for pleasantness and 78.3% for unpleasantness, outperforming the corresponding outcomes of the previous model of 80.9% and 74.3%. Findings indicate that road separation and greenery positively contribute to urban pleasantness, while obstructive elements such as wire, road cracks, sidewalk-encroaching illegal parking, and sticker-covered poles negatively impact it. These results underscore the importance of considering the attributes and spatial relationships of components in assessments. This study provides precise urban evaluations and insights to improve sustainable urban infrastructure management and public space design.

1. INTRODUCTION

The quality of the urban environment impacts citizens' well-being and health considerably. Safe and pleasant public spaces enhance daily experiences, making systematic evaluation crucial. For these reasons, research aimed at the systematical evaluations and improvements of the quality of the urban environment has been ongoing. Traditionally, methods such as surveys and field studies have been primarily used to evaluate urban environments (Senlier et al., 2009; Adams et al., 2022). However, these approaches have limitations, as they are time-consuming, costly, and difficult to apply to large-scale areas. Surveys reflect subjective opinions but may introduce bias, while field studies require extensive resources. To address these limitations, automated evaluation methods using street-view images have recently gained attention (Koo et al., 2022; Lee et al., 2022; Chen & Biljecki, 2023; Liu et al., 2024). These images capture various urban elements, such as roads, buildings, and parks, enabling large-scale and efficient analyses.

These methods enhance conventional methods by providing rapid, data-driven insights into urban environmental quality.

Ma et al. (2021) analyzed street-view images using the deep learning-based SegNet model to evaluate quantitatively human visual perception of streetscapes. This study conducted a detailed analysis of the visual pleasantness of urban environments using five key indicators: greenness, openness, enclosure, walkability, and imageability. Lee et al. (2022) analyzed the visual and physical characteristics of urban environments that affect pedestrian satisfaction. Using machine-learning models and the Shapley additive explanations (SHAP) algorithm, the study examined the impact of urban design qualities such as enclosure, openness, greenery, and complexity on pedestrian satisfaction. Chen and Biljecki (2023) proposed a method to evaluate automatically public open spaces using street-view images and computer vision technology. These studies demonstrate that urban environment evaluations based on street-view images can quantify the interactions between urban environment components and citizen satisfaction.

Lee (2025) proposed an automated model to evaluate urban environments by predicting the visual pleasantness and unpleasantness of street-view images based on automatically detected urban environment components using computer vision. In this context, pleasantness refers to the perceived visual comfort and appeal of an environment, which influences individual’s willingness to walk through or stay in a space(Alfonzo, 2005; Adkins et al., 2012). The study particularly focused on the types and materials of urban environment components, such as wooden sidewalks, metal benches, and plastic signboards. This method enabled a deeper understanding of environmental quality by identifying and assessing the components that contribute to or detract from urban comfort and how different combinations of these elements influence overall perception. However, this study was limited in that it does not consider environmental attributes (such as maintenance conditions) and relationships among components (like illegally parked vehicles encroaching on sidewalks), which are essential factors influencing urban perceptions. Existing evaluation methods primarily focus on detecting the presence of urban components but fail to analyze how their attributes and spatial interactions contribute to environmental quality and citizens’ satisfaction. Therefore, this research study aims to improve the accuracy and reliability of urban environment evaluations by incorporating these attributes of environmental components, thus improving evaluation accuracy and providing more comprehensive insights into urban environmental quality.

2. RESEARCH METHODS

2.1 Overview of the Existing Model

As shown in Figure 1, this research was extended based on the previous model by Lee (2025) for evaluating urban environments by predicting visual pleasantness and unpleasantness based on street-view images. The existing model utilized computer vision techniques to detect automatically and classify 56 microscale environmental components, including roads, sidewalks, trees, fences, and cars. Additionally, several key component materials, such as asphalt, concrete, stone, metal, plastic, and wood were identified using You Only Look Once (YOLO)v8, a real-time object detection algorithm. In this study, YOLOv8 showed fast processing speed and high detection performance for material classification.

To assess urban environment quality, Lee (2025) conducted a survey based on street-view images to build a training dataset for the pleasantness–unpleasantness prediction model. The survey involved 10000 participants and evaluated 5000 street-view images on a three-category nominal scale (1: unpleasant, 2: neutral, 3: pleasant). The dataset included 2500 Google Street views, 300 Kakao Road views, 1,500 AI Hub walkway images, 300 Cityscapes dataset images, and 400 photographs captured by vehicles. Machine-learning models, including logistic regression, XGBoost, and LightGBM, were then trained using this dataset.

Based on the survey results, two separate prediction models were developed: a pleasantness evaluation model (pleasant vs. other) and an unpleasantness evaluation model (unpleasant vs. other). This approach was chosen because pleasantness and unpleasantness are not direct opposites but independent factors, implying that the absence of unpleasantness does not necessarily indicate pleasantness, and vice versa (Herzberg et al., 1993). By modeling them separately, the framework captures the distinct environmental characteristics that contribute to each perception type, enabling a more refined evaluation of urban environmental quality. SHAP analysis was used to interpret the model's predictions and identify components that influenced pleasantness and unpleasantness considerably. The results showed that elements such as green spaces, brick walls, and wooden benches contributed to pleasantness, whereas components like trucks, the absence of curbs, and the absence of trees were associated with unpleasantness.

However, Lee (2025) did not incorporate critical environmental attributes (such as maintenance conditions) and the impact of obstructive elements (like illegally parked vehicles encroaching on sidewalks). This limitation reduced the model's ability to capture fully the complexity of urban environments and their influences on perceived pleasantness.

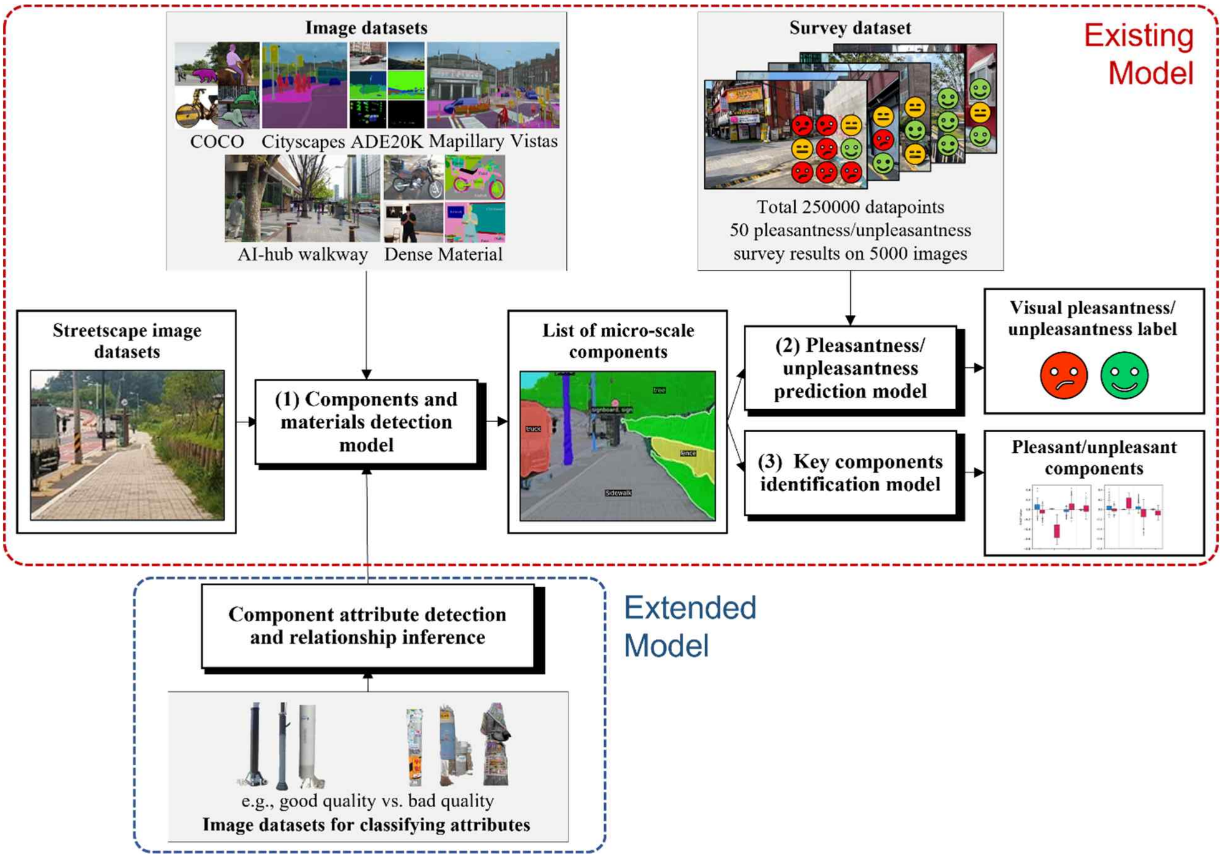
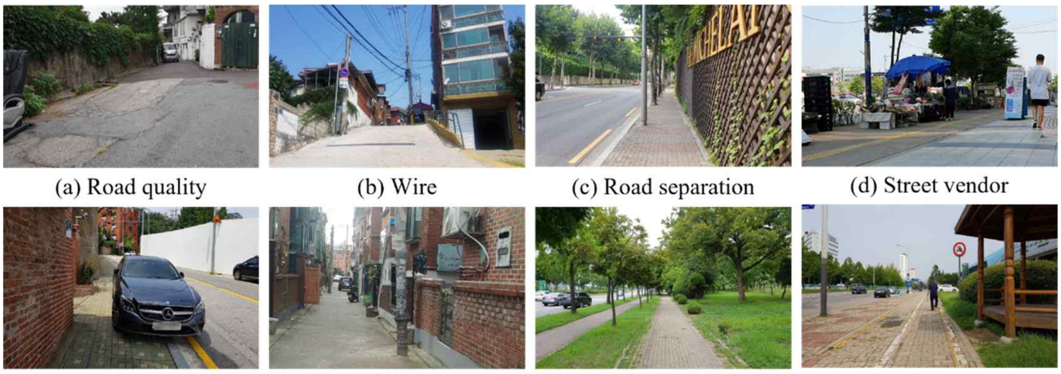


Figure 1: Framework of the Existing Model (Lee, 2025) and the Extended Model of This Study

2.2 Extension of the Existing Model

This study aims to enhance urban environment evaluation by expanding the detection model of components and materials, as illustrated in Figure 1. By analyzing environmental attributes and relationships among components that influence pleasantness and unpleasantness considerably, this study incorporates newly identified factors, such as road quality (Wang et al., 2023), wire, road separation, street vendor, sidewalk-encroaching illegal parking (Ujjwal & Bandyopadhyaya, 2023), sticker-covered pole, greenery (Han et al., 2023; Tang et al., 2023), and openness (Chen et al., 2022). Figure 2 represents these features regarding the attributes and relationships of the analyzed components.



(a) Road quality (b) Wire (c) Road separation (d) Street vendor
(e) Sidewalk-encroaching illegal parking (f) Sticker-covered pole (g) Greenery (h) Openness

Figure 2: Examples of Urban Environment Components Included in This Study That Require Consideration of Their Attributes and Interrelationships in Street-view Images

To improve the accuracy of urban environmental quality evaluation, this study utilized the survey data from Lee (2025) and applied advanced computer vision techniques to detect and analyze attributes and relationships of additional environmental components in street-view images. Panoptic segmentation, a technique that simultaneously performs instance segmentation (distinguishing individual objects) and semantic segmentation (classifying entire regions), was utilized for comprehensive identification of urban components. In this study, the segmentation was performed using OneFormer, which is based on a transformer architecture for unified segmentation, enhancing the accuracy and efficiency of identifying both existing and newly introduced elements (Jain et al., 2023). Supplementary classification and spatial analysis techniques were incorporated to refine detection accuracy and contextual understanding of environmental components. Relationships between components, including sidewalk-encroaching illegal parking and road separation, were analyzed by examining the spatial positioning of segments. The attributes, including sticker-covered pole and road quality, were classified by evaluating the state of segmented components identified through panoptic segmentation (e.g., good quality vs. bad quality of a detected segment). Additionally, greenery and openness were quantified by calculating the proportion of sky and vegetation in the images, providing insights into environmental openness and natural elements.

Specifically, sidewalk-encroaching illegal parking, a representative example of the components' relationship, was identified by computing the Intersection over Union between sidewalk and car segments. This method was adopted based on the assumption that illegally parked vehicles on sidewalks have a greater impact on pleasantness and unpleasantness than moving vehicles. This approach ensures reliable differentiation between legally parked and obstructive vehicles. Road separation was inferred based on the concurrent presence of road and sidewalk segments; their coexistence indicated proper separation, whereas the absence of one of the two segments signified a lack of division, contributing to infrastructure assessment. Sticker-covered poles, an example of a component's attribute for maintenance quality, were detected by classifying the cleanness or dirtiness of pole segments. To this end, a dataset (composed of 10000 images) from the AI Hub polygon segmentation datasets (AI Hub, 2021) was used from which 4000 pole segments were extracted. These segments were analyzed using a ResNet-18 classification model (He et al., 2016) that was trained to distinguish clean poles from sticker-covered ones. ResNet-18 was selected for its efficiency and high performance in the image classification tasks of this study. The detailed pole analysis process, including segmentation and classification, is illustrated in Figure 3. The training process involved the isolation of pole segments from the dataset and the refinement of the model's capacity to recognize visual differences, contributing to improved detection accuracy. Road quality was assessed using a process similar to pole analysis, focusing on the classification of cracked or deteriorated, well-maintained surfaces. Annotated road segments were used to train a classification model, enabling the identification of poor road conditions, such as surface degradation and structural irregularities. The image classification model using ResNet-18 achieved an accuracy of 95.60%, demonstrating reliable performance. Additionally, the model was not overfitted, demonstrating that it maintains high-classification accuracy while it adapts to new data.

Wires and street vendors were detected using panoptic segmentation to enhance the identification of obstructive urban elements. Greenery and openness were quantified based on image segmentation, quantifying the proportion of detected vegetation and sky visibility to assess their contributions to urban comfort. These metrics were integrated into the evaluation framework to analyze their influences on perceived urban comfort.

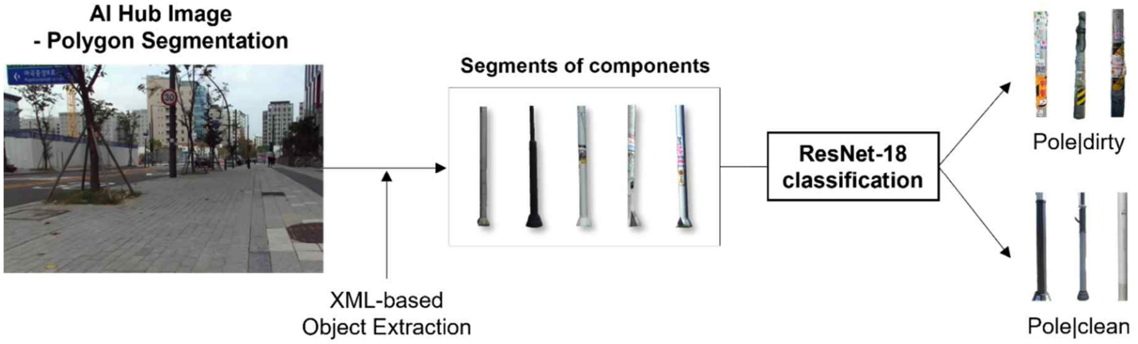


Figure 3: Process of Detecting and Classifying Sticker-Covered Poles (Dirty vs. Clean Poles) Combining Panoptic Segmentation and Image Classification

Subsequently, an environmental evaluation was conducted to predict the pleasantness and unpleasantness of urban environments using LightGBM and XGBoost—the machine-learning methods applied in Lee (2025)—incorporating the 56 microscale environmental components from previous study in conjunction with the additional eight component attributes and relationship features introduced in this study (i.e., 64 features in total). Performance metrics, including accuracy, precision, recall, and F1-score, were calculated to assess the models' effectiveness. Improvements in prediction accuracy were compared with those reported in the previous study, demonstrating the enhanced capability of the proposed framework to capture complex urban attributes and their influences on perceived pleasantness and unpleasantness.

Additionally, SHAP analysis was performed to examine the impact of each component on pleasantness and unpleasantness. SHAP analysis provided visual interpretations of feature contributions, offering transparent insights into which elements had the greatest impact on the predictions (Lundberg & Lee, 2017). This process identified the urban environment components with the greatest impact on pedestrian pleasantness, further refining the understanding of urban space evaluation and improvement.

3. RESULTS

This study utilized the LightGBM and XGBoost models to predict the pleasantness and unpleasantness of urban environments, incorporating additional urban features beyond those considered in previous research (Lee, 2025). Table 1 presents the accuracy, precision, recall, and F1-score values for both models, demonstrating an overall improvement in performance compared with Lee (2025)'s study.

Regarding the LightGBM model, the accuracy for the "Pleasant/other" label increased from 0.816 in Lee (2025) to 0.829 in this study, while the F1-score improved from 0.796 to 0.819. Similarly, for the "Unpleasant/other" label, the accuracy increased from 0.737 to 0.783, and the F1-score from 0.719 to 0.778. The XGBoost model exhibited comparable improvements. The accuracy for the "Pleasant/other" label improved from 0.799 to 0.815, and the F1-score increased from 0.782 to 0.806. For the "Unpleasant/other" label, the accuracy increased from 0.737 to 0.779, and the F1-score improved from 0.724 to 0.775. Across both models, the results confirm that the integration of additional components enhanced predictive accuracy.

To analyze further the contribution of individual components, SHAP analysis was conducted. The analysis visually illustrates the relative impact of each detected element on the model's predictions. Figure 4 shows the results of the SHAP analysis for the components in the pleasantness and unpleasantness models. Features on the right side increase the probability of prediction as pleasant (Figure 4(a)) or unpleasant (Figure 4(b)) predictions, while those on the left decrease these probabilities. The color represents the feature value: red indicates the presence of a component (with), while blue represents its absence (without). The spread of points in the plot provides additional insights into the consistency of each feature's effect. Densely clustered points suggest that a feature has a uniform influence across multiple data points, whereas a broader spread indicates variability in impact. For example, in Figure 4(a), greenery (with) increases considerably the probability of being predicted as pleasant, while in Figure 4(b), its absence (without) increases the probability of being predicted as unpleasant.

Table 1: Comparison of LightGBM and XGBoost Model Performance in Predicting Urban Pleasantness and Unpleasantness (Lee (2025) vs. Current Study)

Model	Study	Labels	Accuracy	Precision	Recall	F1-score
LightGBM	Lee (2025)	Pleasant/ Other	0.816	0.792	0.816	0.796
		Unpleasant/ Other	0.737	0.717	0.737	0.719
	Current Study	Pleasant/ Other	0.829	0.815	0.829	0.819
		Unpleasant/ Other	0.783	0.776	0.783	0.778
XGBoost	Lee (2025)	Pleasant/ Other	0.799	0.774	0.799	0.782
		Unpleasant/ Other	0.737	0.720	0.737	0.724
	Current Study	Pleasant/ Other	0.815	0.801	0.815	0.806
		Unpleasant/ Other	0.779	0.773	0.779	0.775

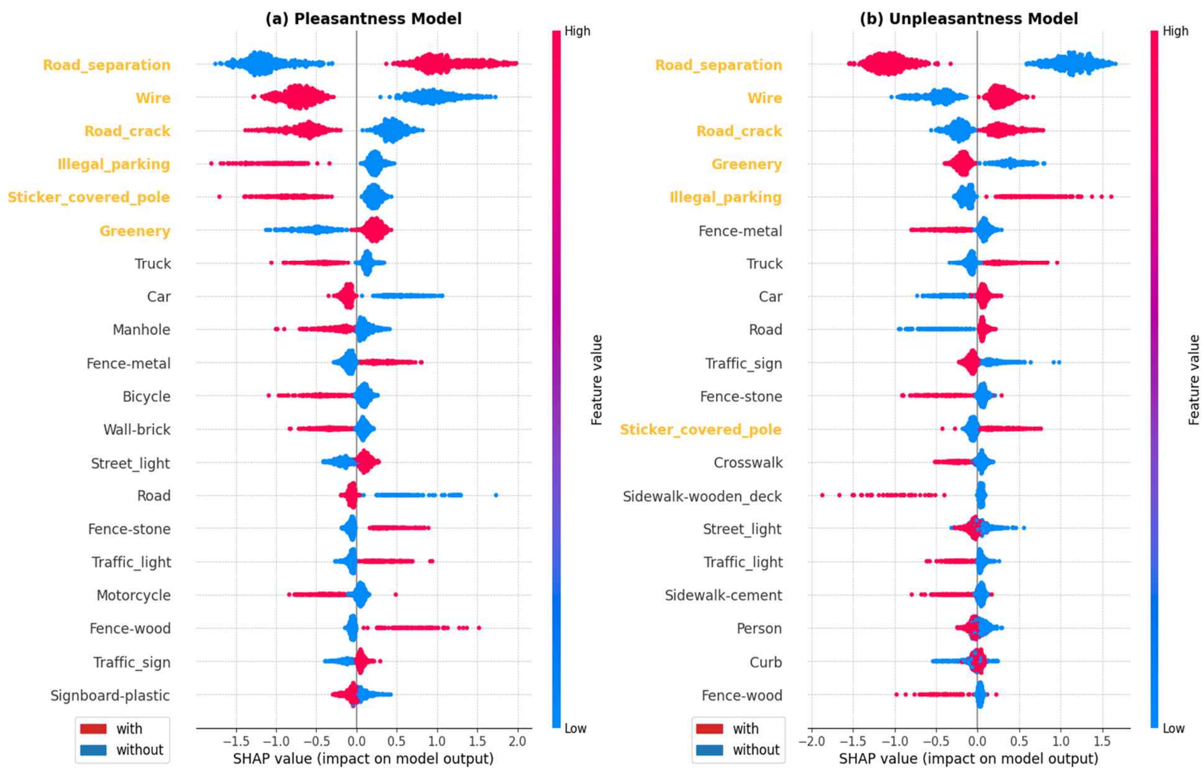


Figure 4: Results of the Shapley Additive Explanations (SHAP) Analysis of the Prediction Model: (a) Pleasantness Model; (b) Unpleasantness Model

Based on this interpretation, road separation (with), wire (without), road crack (without), sidewalk-encroaching illegal parking (without), sticker-covered pole (without), and greenery (with) play a major role in increasing the probability of being predicted as pleasant. Conversely, road separation (without), wires (with), road cracks (with), greenery (without), sidewalk-encroaching illegal parking (with), and sticker-covered poles (with) increase the probability of being predicted as unpleasant. In particular, it can be observed that these attributes have a greater impact on the evaluation than most existing component types or materials. These findings confirm that incorporating additional environmental attributes and relationships improves prediction accuracy considerably, offering in-depth insights into urban environmental quality. These findings highlight the critical need to address maintenance and obstruction issues in urban planning.

4. DISCUSSION AND CONCLUSIONS

This study proposed a refined framework for evaluating urban environments using street-view images and machine-learning models, focusing on the predictions of urban pleasantness and unpleasantness. By incorporating additional component attributes for maintenance quality (e.g., road quality and sticker-covered pole) and analyzing components' relationships (e.g., sidewalk-encroaching illegal parking and road separation), this study demonstrated notable improvements in model performance compared with previous research. The results confirmed that features like road separation and greenery enhance considerably urban pleasantness, while obstructive elements such as wires, road cracks, sidewalk-encroaching illegal parking, and sticker-covered poles detract from it.

This research contributes to urban environment evaluation by expanding previous frameworks that primarily focused on the types and materials of environmental components, to incorporate their spatial relationships and additional attributes. By integrating these factors, the study improved considerably the accuracy of urban environmental evaluations and provided more comprehensive insights into the relationships among urban components and perceived environmental quality. These enhancements not only improve predictive performance but also provide insights that are actionable for real-world applications. For example, city planners and policymakers can utilize this model to prioritize the maintenance of deteriorated components (e.g., road cracks and dirty poles) and to improve walkability by addressing obstructive components (e.g., sidewalk-encroaching illegal parking). From a pedestrian perspective, this framework helps clarify how specific environmental features directly affect walking comfort, pleasurability, and street-level quality. The findings highlighted the value of integrating automated detection methods for large-scale data analysis to identify and address key factors affecting urban comfort.

However, the study primarily considered negative attributes affecting urban comfort, which may limit a balanced understanding of factors that enhance pleasantness. The approach also depends on available street-view images, which may not fully capture real-time urban dynamics and temporary changes in environmental conditions. By considering these factors, future research can develop more precise urban environment evaluation methods, offering a balanced approach that accounts for both negative and positive contributors. This would allow for a more comprehensive framework to guide urban planning and policy decisions, ultimately leading to more effective and sustainable urban improvements.

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