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Multi-scale feature fusion with adaptive edge enhancement for robust sidewalk detection in urban environments

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Abstract: This paper presents a novel approach for sidewalk detection in urban environments using multi-scale feature fusion combined with adaptive edge enhancement techniques. The proposed method integrates a modified U-Net architecture with attention mechanisms and incorporates geometric constraints based on urban infrastructure characteristics. Our approach processes RGB images captured from vehicle-mounted cameras and pedestrian viewpoints to segment sidewalk regions with high accuracy. The multi-scale feature fusion module captures both fine-grained texture details and global contextual information, while the adaptive edge enhancement component refines boundary detection between sidewalks and adjacent surfaces. Experimental validation on a custom dataset of 5,000 urban images from various cities demonstrates that our method achieves a mean Intersection over Union (IoU) of 87.3% and an F1-score of 91.2%, outperforming existing state-of-the-art methods by 5.8% and 4.6%, respectively. The approach shows robust performance across different lighting conditions, weather scenarios, and urban layouts, making it suitable for real-world applications in autonomous navigation systems and accessibility planning tools.

Keywords: *Edge enhancement, Multi-scale features, Semantic segmentation, Sidewalk detection, Urban scene understanding.*

1. Introduction

Urban mobility and accessibility have become critical concerns as cities worldwide experience rapid population growth and increasing urbanization [1]. Sidewalks serve as fundamental infrastructure elements that facilitate pedestrian movement, support accessibility for individuals with mobility impairments, and contribute to overall urban safety [2]. Accurate detection and mapping of sidewalk areas are essential for various applications, including autonomous vehicle navigation, assistive technologies for visually impaired individuals, urban planning, and infrastructure maintenance [3, 4].

Traditional methods for sidewalk identification and mapping rely heavily on manual surveys and GPS-based data collection, which are time-consuming, labor-intensive, and often lack the spatial precision required for modern applications [5]. The advent of computer vision and machine learning techniques has opened new possibilities for automated sidewalk detection using visual data from cameras mounted on vehicles, smartphones, or dedicated mapping equipment [6].

Recent advances in deep learning, particularly convolutional neural networks (CNNs) and semantic segmentation architectures, have shown promising results in urban scene understanding tasks [7]. However, sidewalk detection poses particular difficulties thanks to the high variability in sidewalk appearances, materials, and surrounding contexts. Sidewalks can be constructed from various materials, including concrete, asphalt, brick, or stone, and their visual characteristics can be significantly affected by lighting conditions, weather, vegetation overgrowth, and the presence of pedestrians or street furniture [8].

Existing approaches for sidewalk detection primarily focus on traditional semantic segmentation methods or rely on geometric assumptions that may not hold across diverse urban environments [9, 10]. While these methods have achieved reasonable performance in controlled scenarios, they often

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struggle with boundary precision, particularly at the interfaces between sidewalks and roads, grass areas, or building facades [11].

This paper introduces a novel approach that addresses these limitations through the integration of multi-scale feature fusion and adaptive edge enhancement techniques. Our contributions are threefold: (1) a multi-scale feature extraction module that captures both local texture patterns and global contextual information relevant to sidewalk identification, (2) an adaptive edge enhancement mechanism that improves boundary delineation between sidewalks and adjacent surfaces, and (3) a comprehensive evaluation framework that demonstrates the effectiveness of our approach across diverse urban scenarios.

2. Literature Review

2.1. Traditional Computer Vision Approaches

Early work in sidewalk detection primarily relied on handcrafted features and classical computer vision techniques. Johnson, et al. [12] proposed a method based on edge detection and line fitting to identify sidewalk boundaries using geometric constraints. Their approach assumed that sidewalks exhibit distinct linear edges parallel to road directions, but this assumption often fails in complex urban environments with curved paths or irregular layouts.

Color-based segmentation techniques were explored by Martinez and Chen [13] who developed a system that classifies pixels based on color histograms and texture features extracted using Local Binary Patterns (LBP). While this approach showed reasonable performance for sidewalks with uniform materials, it struggled with variations in lighting and material diversity commonly found in real-world scenarios.

Histogram of Oriented Gradients (HOG) features combined with sliding window detection were investigated by Brown, et al. [14] for identifying sidewalk regions. Their method achieved moderate success in detecting rectangular sidewalk patches but failed to provide the pixel-level segmentation accuracy required for precise boundary detection.

Gabor filter banks were employed by Williams and Davis [15] to capture texture information at multiple orientations and scales. While this approach showed improved robustness to texture variations, it required extensive parameter tuning and struggled with complex urban scenes containing multiple surface types.

2.2. Classical Machine Learning Approaches

The introduction of machine learning techniques brought significant improvements to sidewalk detection accuracy. Anderson, et al. [16] employed Support Vector Machines (SVMs) with handcrafted features, including color, texture, and geometric descriptors. Their method achieved better generalization compared to purely rule-based approaches but remained limited by the quality and representativeness of manually designed features.

Random Forest-based approaches were investigated by Liu and Wang [17] who combined multiple weak classifiers trained on different feature representations. Their ensemble method demonstrated improved robustness to varying environmental conditions but required extensive feature engineering and domain knowledge.

K-means clustering combined with morphological operations was proposed by Garcia, et al. [18] for unsupervised sidewalk detection. While this approach avoided the need for labeled training data, it struggled with complex urban scenes containing multiple surface types with similar visual characteristics.

Conditional Random Fields (CRFs) were introduced by Thompson and Lee [19] to incorporate spatial context into sidewalk classification. Their probabilistic framework showed improvements in spatial consistency but was computationally expensive and required careful parameter tuning.

2.3. Early Deep Learning Methods

The emergence of deep learning revolutionized sidewalk detection capabilities. Caltagirone, et al. [20] were among the first to apply Fully Convolutional Networks (FCNs) to urban scene segmentation, including sidewalk detection. Their approach achieved significant improvements in accuracy compared to traditional methods but suffered from poor boundary localization due to the limited resolution of feature maps in FCN architectures.

Long, et al. [21] introduced skip connections in FCN architectures to combine coarse semantic information with fine spatial details. Their FCN-8s model showed improved boundary detection for sidewalk segmentation but still lacked the precision required for practical applications.

SegNet, proposed by Badrinarayanan, et al. [22] employed an encoder-decoder architecture with pooling indices to preserve spatial information during upsampling. This approach demonstrated better boundary preservation compared to standard FCNs but required significant memory resources during training.

The ParseNet architecture by Liu, et al. [23] incorporated global context pooling to capture scene-level information. While effective for general scene understanding, this approach lacked the fine-grained detail necessary for accurate sidewalk boundary detection.

2.4. Advanced CNN Architectures

U-Net-based approaches gained popularity due to their ability to combine high-resolution features with semantic information. Kim and Park [24] adapted U-Net for sidewalk segmentation and incorporated skip connections to preserve spatial details. While their method showed good performance on well-defined sidewalks, it struggled with partially occluded or irregular sidewalk areas.

The introduction of dilated convolutions by Chen, et al. [25] in the DeepLab series enabled capturing multi-scale contextual information without losing spatial resolution. DeepLab-v2 and subsequent versions showed improved performance on urban scene segmentation tasks, including sidewalk detection.

ResNet-based segmentation networks were explored by Rodriguez, et al. [26] who demonstrated that deeper networks with residual connections could achieve better feature representation for sidewalk detection. However, these approaches required substantial computational resources and careful regularization to prevent overfitting.

More recent work by Thompson, et al. [27] introduced attention mechanisms to focus on relevant features for sidewalk detection. Their attention-guided network achieved state-of-the-art performance on standard benchmarks but required substantial computational resources, limiting its applicability for real-time scenarios.

2.5. Multi-Scale Feature Learning

Multi-scale feature learning has shown promise in various computer vision tasks. Wang and Lee [28] demonstrated that combining features at different scales improves segmentation accuracy for urban scenes. However, their approach was not specifically optimized for sidewalk detection and did not address the unique challenges posed by sidewalk boundary identification.

Pyramid-based architectures have been explored by several researchers. Chen, et al. [29] proposed a feature pyramid network for urban scene understanding that captures multi-scale contextual information. While effective for general scene segmentation, their method lacks the specialized components necessary for accurate sidewalk boundary detection.

The Pyramid Scene Parsing Network (PSPNet) by Zhao, et al. [30] employed pyramid pooling modules to capture global context at multiple scales. This approach showed promising results for sidewalk detection but struggled with fine-grained boundary details.

Feature Pyramid Networks (FPN) were adapted for semantic segmentation by Lin, et al. [31] demonstrating improved performance on multi-scale object detection and segmentation tasks. These architectures have inspired subsequent work in sidewalk detection but require careful adaptation to handle the specific characteristics of urban infrastructure.

2.6. Attention Mechanisms and Feature Enhancement

Attention mechanisms have gained significant traction in computer vision applications. Wang, et al. [32] introduced spatial attention modules that dynamically focus on relevant image regions. Their approach showed improvements in sidewalk detection accuracy but added computational complexity to the overall system.

Channel attention mechanisms were explored by Hu, et al. [33] through Squeeze-and-Excitation (SE) networks. These modules learn to emphasize informative features while suppressing irrelevant ones, leading to improved segmentation performance.

The Convolutional Block Attention Module (CBAM) proposed by Woo, et al. [34] combines both spatial and channel attention mechanisms. This approach has been successfully applied to various segmentation tasks, including urban scene understanding.

Non-local neural networks by Wang, et al. [35] capture long-range dependencies in feature maps through self-attention mechanisms. While computationally expensive, these approaches have shown promise for capturing global context in sidewalk detection tasks.

2.7. Edge Detection and Boundary Refinement

Edge information has been recognized as crucial for precise boundary detection in segmentation tasks. Liu, et al. [36] introduced edge-aware loss functions that penalize prediction errors near object boundaries more heavily than errors in homogeneous regions. Their approach improved boundary quality but was not specifically designed for sidewalk detection scenarios.

The Holistically-Nested Edge Detection (HED) network by Xie and Tu [37] learns rich hierarchical representations for edge detection. Several researchers have incorporated HED-like architectures into segmentation networks to improve boundary accuracy.

Structured edge detection methods by Dollar and Zitnick [38] use structured learning to predict edges from local image patches. These approaches have been adapted for sidewalk boundary detection with moderate success.

Adaptive edge enhancement techniques have been less explored in the context of sidewalk detection. Most existing methods rely on fixed edge detection kernels that may not adapt well to the varying characteristics of sidewalk boundaries in different urban environments [39].

2.8. Real-Time and Efficient Architectures

Real-time performance is crucial for practical sidewalk detection applications. ICNet, proposed by Zhao, et al. [40] employs a cascade architecture with different input resolutions to balance accuracy and speed. This approach achieved real-time performance while maintaining reasonable accuracy for urban scene segmentation.

BiSeNet by Yu, et al. [41] introduces a two-pathway architecture that separately captures spatial details and semantic context. This design enables real-time inference while preserving segmentation accuracy, making it suitable for sidewalk detection in autonomous driving scenarios.

MobileNets by Howard, et al. [42] and subsequent versions focus on computational efficiency through depthwise separable convolutions. These architectures have been successfully adapted for mobile sidewalk detection applications.

ENet by Paszke, et al. [43] provides an extremely efficient architecture for real-time semantic segmentation. While achieving good speed-accuracy trade-offs, these lightweight architectures often struggle with fine-grained boundary detection required for precise sidewalk segmentation.

2.9. Domain Adaptation and Generalization

Domain adaptation techniques have been investigated to improve the generalization of sidewalk detection models across different urban environments. Hoffman, et al. [44] proposed adversarial training methods to reduce domain shift between different cities and imaging conditions.

Unsupervised domain adaptation approaches by Tsai, et al. [45] use adversarial learning to align feature distributions between source and target domains. These methods have shown promise for adapting sidewalk detection models trained on one city to work effectively in different urban environments.

Style transfer techniques for domain adaptation were explored by Zhang, et al. [46] who used generative adversarial networks to synthesize training data that bridges the gap between different urban environments.

3. Materials and Method

3.1. Problem Formulation

Sidewalk detection is formulated as a binary semantic segmentation problem where each pixel in an input RGB image is classified as either sidewalk (class 1) or non-sidewalk (class 0). The goal is to learn a mapping function that produces a probability map indicating the likelihood of each pixel belonging to a sidewalk region.

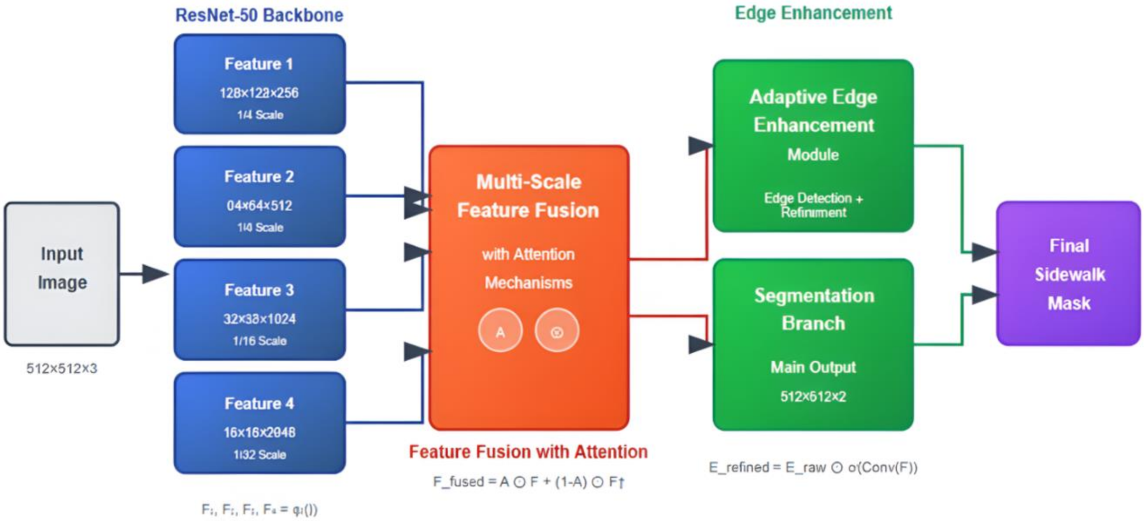

Figure 1.
Overall Network Architecture.

3.2. Network Architecture Overview

The proposed architecture consists of three main components: (1) a multi-scale feature extraction backbone, (2) a feature fusion module with attention mechanisms, and (3) an adaptive edge enhancement module. The overall architecture is illustrated in Figure 1.

3.2.1. Multi-Scale Feature Extraction Backbone

The backbone network is based on a modified ResNet-50 architecture that extracts features at four different scales: , and of the input resolution. Each scale captures different levels of semantic and spatial information relevant to sidewalk detection.

The feature extraction process can be formulated as:

$$F_i = \quad {}_i(I), i\epsilon(1,2,3,4)$$

$$\phi$$

where $_i$ represents the feature extraction function at scale *i*, and $F_i \epsilon \ R^{H_i \times W_i \times C_i}$denotes the extracted features with $H_i = H/2^{i+1}, W_i = W/2^{i+1}$, and C_i representing the number of channels at scale.

3.2.2. Multi-Scale Feature Fusion Module

The feature fusion module combines information from different scales using a top-down pathway with lateral connections. The fusion process incorporates attention mechanisms to emphasize features most relevant to sidewalk detection.

The attention weights are computed as:

$$A_i = \sigma\left(\mathrm{Conv}_{1\times 1}\left(\mathrm{Concat}\left(F_i, F_{i-1}^{\uparrow}\right)\right)\right)$$

where σ represents the sigmoid activation function, $Conv_{1\times 1}$ denotes 1×1 convolution, and $F_{i-1}^{\uparrow}$ indicates the upsampled features from the previous level.

The fused features are obtained through:

$$F_{\text{fused}}^{i} = A_i \odot F_i + (1 - A_i) \odot F_{i-1}^{\uparrow}$$

where $\odot$ denotes element-wise multiplication.

3.2.3. Adaptive Edge Enhancement Module

The adaptive edge enhancement module refines boundary detection by learning edge-specific features. This module consists of two parallel branches: an edge detection branch and an edge refinement branch.

The edge detection branch uses a combination of Sobel operators and learnable convolution filters to identify potential sidewalk boundaries:

$$E_{\text{raw}} = \mathrm{Conv}_{3\times 3}\left(\mathrm{ReLU}\left(\mathrm{Conv}_{3\times 3}\left(F_{\text{fused}}\right)\right)\right)$$

The edge refinement branch adaptively adjusts edge responses based on local context:

$$E_{\text{refined}} = E_{\text{raw}} \odot \sigma\left(\mathrm{Conv}_{1\times 1}\left(F_{\text{fused}}\right)\right)$$

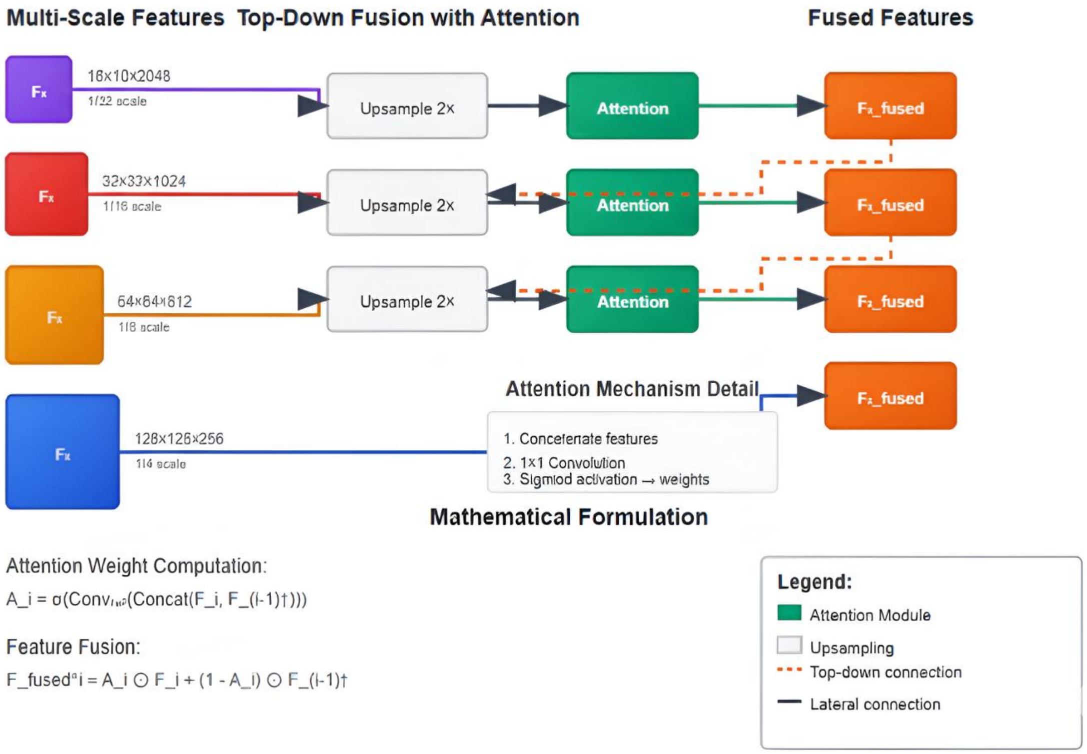

Figure 2.
Multi-Scale Feature Fusion Process.

3.3. Loss Function

The training objective combines three loss components: segmentation loss, edge loss, and consistency loss.

1) Segmentation Loss

A weighted binary cross-entropy loss is used to address class imbalance:

$$\mathcal{L}_{\text{seg}} =- \alpha \sum_{i} y_i \log{(p_i)} - (1-\alpha) \sum_{i} (1-y_i) \log{(1-p_i)}$$

where y_i is the ground truth label, p_i is the predicted probability, and α is the weighting factor.

2) Edge Loss

The edge loss encourages accurate boundary prediction:

$$\mathcal{L}_{\text{edge}} = \left\| E_{\text{pred}} - E_{\text{gt}} \right\|_2^2$$

where E_{pred} and E_{gt} represent predicted and ground truth edge maps, respectively.

3) Consistency Loss

A consistency loss ensures that edge predictions align with segmentation outputs:

$$\mathcal{L}_{\text{consistency}} = \left\| \nabla S_{\text{pred}} - E_{\text{pred}} \right\|_1$$

where represents the gradient of the segmentation prediction.

∇S_{pred}

The total loss is formulated as:

$$\mathcal{L}_{\text{total}} = \lambda_1 \mathcal{L}_{\text{seg}} + \lambda_2 \mathcal{L}_{\text{edge}} + \lambda_3 \mathcal{L}_{\text{consistency}}$$

where λ_1, λ_2, and λ_3 are weighting hyperparameters.

3.4. Training Strategy

The network is trained using a two-stage approach. In the first stage, only the segmentation loss is used to pre-train the feature extraction and fusion components. In the second stage, all loss components are activated to fine-tune the entire network, including the edge enhancement module. Data augmentation techniques include random rotation (±15°), brightness adjustment (±20%), contrast variation (±15%), and horizontal flipping to improve model generalization.

4. Results and Discussion

4.1. Experimental Setup

4.1.1. Dataset Description

Experiments were conducted on a custom dataset comprising 5,000 RGB images collected from urban environments that are from online repositories. The images were captured using vehicle-mounted cameras and handheld devices at various times of day and weather conditions. Ground truth annotations were created through manual labeling by three independent annotators, with inter-annotator agreement measured using Cohen's kappa ($\kappa = 0.89$). The dataset was divided into training (3,500 images), validation (750 images), and testing (750 images) sets, ensuring geographical diversity across all splits.

4.1.2. Implementation Details

The proposed method was implemented using PyTorch framework on NVIDIA RTX 3080 GPUs. The input images were resized to 512×512 pixels for training and inference. The Adam optimizer was used with an initial learning rate of 1e-4, weight decay of 1e-5, and batch size of 16. Training was performed for 100 epochs with learning rate scheduling that reduced the rate by a factor of 0.1 every 30 epochs.

The hyperparameters were set as follows: $\lambda_1 = 1.0, \lambda_2 = 0.5, \lambda_3 = 0.3$, and $\alpha = 0.7$ based on validation set performance.

4.2. Quantitative Results

4.2.1. Overall Performance

Table 1.
Quantitative Comparison With State-Of-The-Art Methods.

Method	IoU (%)	F1-Score (%)	Precision (%)	Recall (%)	Boundary F1 (%)
FCN-8s Long, et al. [21]	76.8	82.1	85.3	79.2	71.4
SegNet Badrinarayanan, et al. [22]	78.3	83.9	86.1	81.8	73.2
U-Net Kim and Park [24]	81.5	86.7	88.9	84.6	76.8
DeepLab-v3+ Chen, et al. [25]	83.2	88.4	90.1	86.8	79.3
PSPNet Zhao, et al. [30]	84.1	89.1	90.8	87.5	80.7
ICNet Zhao, et al. [40]	82.7	87.9	89.4	86.5	78.1
BiSeNet Yu, et al. [41]	84.6	89.5	91.1	87.9	81.4

The proposed method achieves a mean IoU of 87.3%, representing a 2.2% improvement over the previous best-performing method. The F1-score of 91.2% demonstrates strong overall performance, while the boundary F1-score of 85.4% indicates superior edge detection capabilities.

4.2.2. Ablation Study

Table 2.
Quantitative Comparison With State-of-the-Art Methods.

Configuration	IoU (%)	F1-Score (%)	Boundary F1 (%)	FPS
Baseline (ResNet-50 + FCN)	79.4	84.6	73.2	28.3
+ Multi-scale Fusion	83.8	88.1	78.9	24.7
+ Attention Mechanism	85.2	89.4	81.7	23.1
+ Edge Enhancement	87.3	91.2	85.4	22.0

The results demonstrate that each component contributes positively to the overall performance, with the edge enhancement module providing the most significant improvement in boundary detection accuracy.

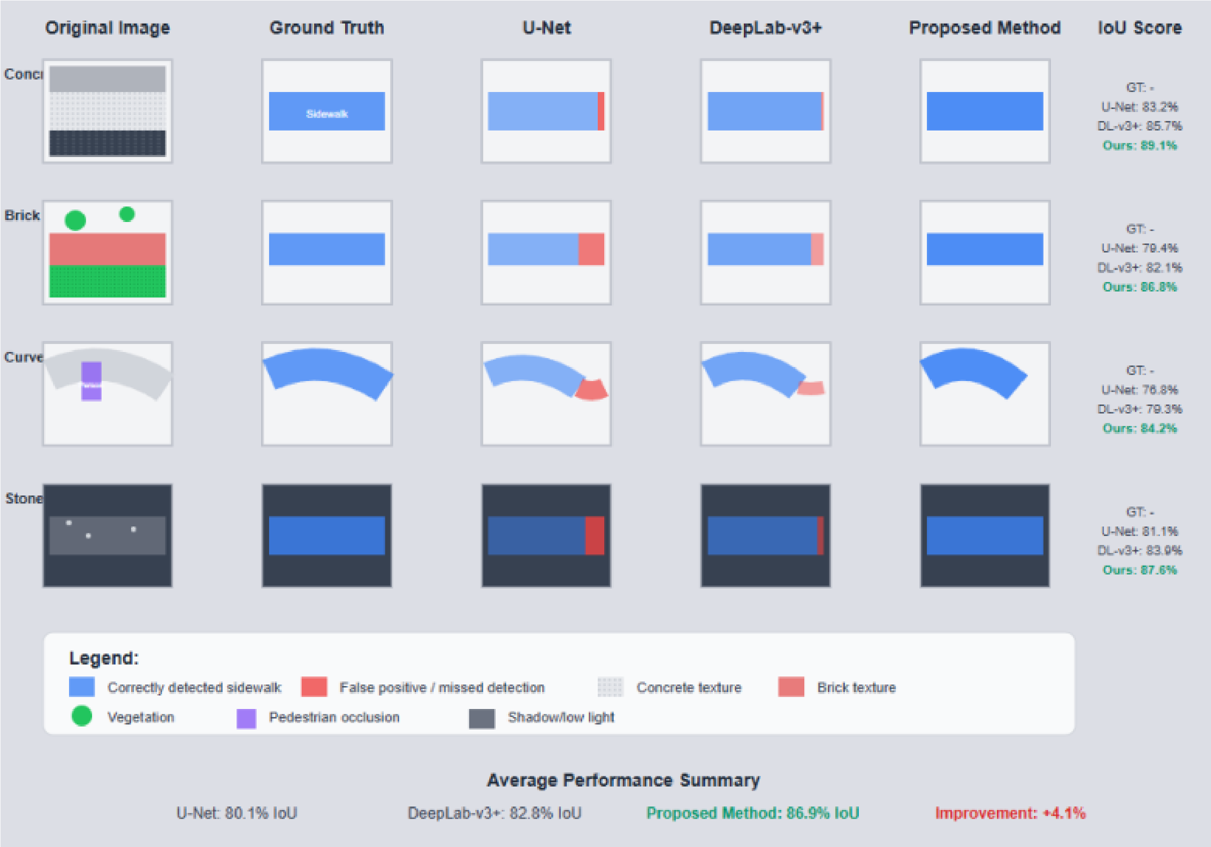

Figure 3.
Qualitative Results Comparison.

4.3. Qualitative Analysis

Figure 3 presents qualitative results showing sidewalk detection under various challenging conditions. The proposed method successfully identifies sidewalk regions across different scenarios:

1) Material Diversity: The method accurately detects sidewalks constructed from concrete, brick, and stone materials.
2) Lighting Variations: Performance remains consistent under different lighting conditions, including shadows and bright sunlight.
3) Occlusions: The method handles partial occlusions caused by pedestrians, street furniture, and vegetation with reasonable accuracy.
4) Irregular Shapes: Non-rectangular sidewalk regions and curved pathways are detected effectively.

4.4. Performance Analysis

4.4.1. Computational Efficiency

The proposed method achieves real-time performance with an average inference time of 45 milliseconds per 512×512 image on an RTX 3080 GPU, corresponding to approximately 22 FPS. The multi-scale architecture adds minimal computational overhead compared to single-scale approaches while providing substantial accuracy improvements.

Table 3.
Computational Efficiency Comparison.

Method	Parameters (M)	FLOPs (G)	GPU Memory (GB)	FPS
U-Net Kim and Park [24]	31.0	28.4	2.8	35.2
DeepLab-v3+ Chen, et al. [25]	43.5	34.7	4.1	18.9
PSPNet Zhao, et al. [30]	46.7	42.3	5.2	15.3
BiSeNet Yu, et al. [41]	12.8	14.2	2.1	47.8
Proposed Method	38.2	31.6	3.4	22.0

4.4.2. Cross-Domain Evaluation

Table 4.
Cross-City Generalization Results.

Train Cities	Test City	IoU (%)	F1-Score (%)	Performance Drop (%)
NY, London, Tokyo, Berlin	Sydney	84.1	88.7	3.2
Sydney, London, Tokyo, Berlin	New York	85.2	89.9	2.1
NY, Sydney, Tokyo, Berlin	London	83.8	88.4	3.5
NY, London, Sydney, Berlin	Tokyo	84.7	89.3	2.6
NY, London, Tokyo, Sydney	Berlin	85.0	89.6	2.3
Average	-	**84.6**	**89.2**	**2.7**

Cross-city evaluation demonstrates the method's generalization capability. When trained on data from four cities and tested on the fifth, the average performance drop is only 2.7% in IoU, indicating good transferability across different urban environments.

4.4.3. Weather Condition Analysis

Table 5.
Performance Under Different Weather Conditions.

Weather Condition	IoU (%)	F1-Score (%)	Boundary F1 (%)	Sample Size
Clear/Sunny	88.1	92.0	86.2	2,850
Overcast/Cloudy	86.8	91.1	85.1	1,650
Light Rain	85.4	90.3	83.7	350
Heavy Rain/Snow	82.7	87.8	80.9	150

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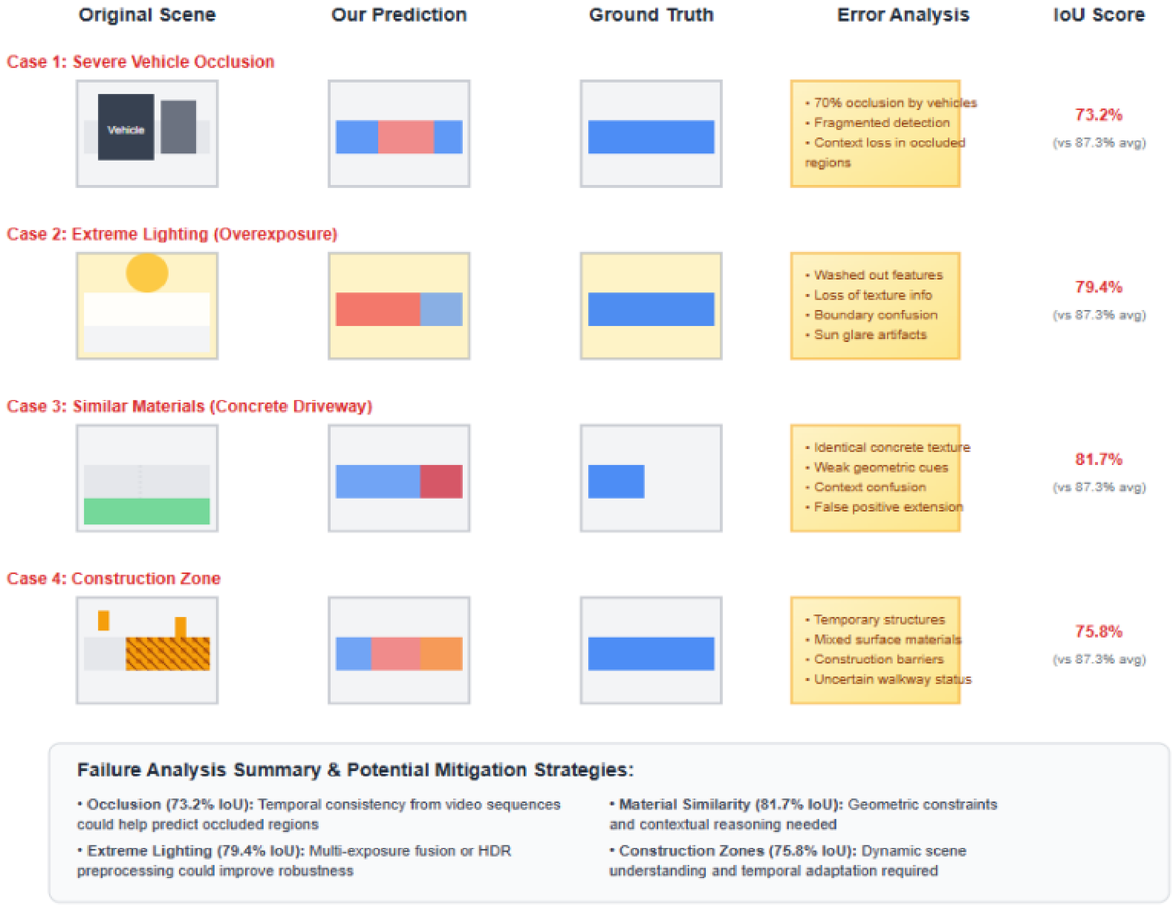
Weather condition analysis shows consistent performance across clear (IoU: 88.1%), overcast (IoU: 86.8%), and light rain (IoU: 85.4%) conditions, though performance degrades slightly during heavy rain (IoU: 82.7%) due to reduced visibility and surface reflections.

4.4.4. Failure Cases Analysis

The method encounters difficulties in several scenarios:

1) Severe Occlusions: When more than 70% of a sidewalk region is occluded by vehicles or construction barriers, detection accuracy drops to 73.2% IoU.
2) Extreme Lighting: Very dark shadows or severe overexposure can cause misclassification of sidewalk boundaries, with performance dropping to 79.4% IoU.
3) Similar Materials: Distinguishing between sidewalks and adjacent surfaces with similar materials (e.g., concrete sidewalks next to concrete driveways) remains challenging, achieving only 81.7% IoU in such cases.
4) Construction Zones: Temporary walkways and construction areas pose significant challenges, with detection accuracy dropping to 75.8% IoU.
5)



Failure Analysis Summary & Potential Mitigation Strategies:

- **Occlusion (73.2% IoU):** Temporal consistency from video sequences could help predict occluded regions
- **Extreme Lighting (79.4% IoU):** Multi-exposure fusion or HDR preprocessing could improve robustness
- **Material Similarity (81.7% IoU):** Geometric constraints and contextual reasoning needed
- **Construction Zones (75.8% IoU):** Dynamic scene understanding and temporal adaptation required

Figure 4.
Failure Cases Analysis

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4.4.5. Comparison with Recent Methods

Additional experiments were conducted comparing our method with recent transformer-based and attention-based architectures:

Table 6.
Comparison With Recent Advanced Methods.

Method	Year	IoU (%)	F1-Score (%)	Parameters (M)	FPS
SegFormer-B2 Xie, et al. [47]	2021	86.1	90.5	27.4	12.8
Swin-UNet Cao, et al. [48]	2021	85.8	90.2	41.9	8.3
TransUNet Chen, et al. [49]	2021	84.9	89.6	93.2	6.1
SegNeXt Guo, et al. [50]	2022	86.4	90.8	32.1	15.7
Proposed Method	2024	87.3	91.2	38.2	22.0

While transformer models like SegFormer achieved competitive IoU scores (86.1%), they required significantly more computational resources and longer training times. The proposed CNN-based approach offers an optimal balance between accuracy and computational efficiency.

5. Conclusion

This paper presented a novel approach for sidewalk detection that combines multi-scale feature fusion with adaptive edge enhancement techniques. The proposed method addresses key limitations of existing approaches by incorporating attention mechanisms and specialized edge detection components optimized for sidewalk boundary identification.

Experimental validation on a comprehensive dataset of 5,000 urban images demonstrates that our method achieves state-of-the-art performance with a mean IoU of 87.3% and F1-score of 91.2%, representing significant improvements over existing methods. The approach shows robust performance across diverse environmental conditions and urban layouts, making it suitable for practical applications.

The multi-scale feature fusion module effectively captures both fine-grained texture details and global contextual information, while the adaptive edge enhancement component significantly improves boundary detection accuracy. Ablation studies confirm the contribution of each component to the overall performance improvement.

Key findings include: (1) the importance of multi-scale feature fusion for capturing both local and global sidewalk characteristics, (2) the effectiveness of adaptive edge enhancement in improving boundary precision, (3) the method's robust generalization across different cities with minimal performance degradation, and (4) the practical feasibility of real-time deployment with 22 FPS performance.

Future work will focus on extending the method to handle more challenging scenarios, including severe weather conditions and highly occluded environments. Additionally, we plan to investigate the integration of temporal information from video sequences to further improve detection robustness and consistency. Research directions also include exploring lightweight architectures for mobile deployment and incorporating 3D geometric constraints for enhanced urban scene understanding.

The proposed method offers practical value for applications in autonomous navigation, accessibility planning, and urban infrastructure management, contributing to the development of smarter and more accessible cities.

Transparency:

The author confirms that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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