

Pothole Finding and Reporting System

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Abstract

Accurate pothole detection in real-world environments is hindered by noise interference, limited severity assessment, and poor recognition of small and distant potholes. To address these challenges, this paper proposes a novel pothole finding and reporting system based on YOLOv10 integrated with the Lifting Wavelet Transform (LWT). YOLOv10 enables efficient multi-scale spatial feature learning for real-time detection, while LWT extracts robust multi-resolution texture information that enhances sensitivity to subtle road surface irregularities. The fusion of spatial features and wavelet coefficients improves noise resilience, strengthens small and distant pothole detection, and facilitates indirect severity characterization. Experimental evaluation conducted on publicly available road damage datasets demonstrates that the proposed approach achieves an accuracy of 96.8% and a mean Average Precision (mAP) of 94.2%, outperforming conventional YOLO-based methods. Despite incorporating wavelet-based enhancement, the model remains computationally efficient with only 28.6 million parameters, making it suitable for real-time deployment on edge and mobile devices. The proposed system offers a scalable and intelligent solution for smart road infrastructure monitoring.

1 Introduction

Road infrastructure is a fundamental component of modern transportation systems, directly influencing traffic safety, mobility efficiency, and economic sustainability. Among various forms of road surface degradation, potholes represent a critical hazard that can lead to severe vehicle damage, traffic congestion, and road accidents if not detected and repaired in a timely manner [1]. Traditional pothole inspection methods primarily rely on manual surveys or citizen complaint-based systems, which are labor-intensive, subjective, and incapable of providing continuous and large-scale road condition assessment [2]. Recent advancements in computer vision and deep learning have facilitated the development of automated pothole detection systems using image and video data captured by vehicle-mounted or smartphone cameras [4]. Convolutional neural network (CNN)-based object detection frameworks have shown promising performance in identifying road surface defects, particularly with the emergence of one-stage detectors that enable real-time inference [5]. YOLOv5 has demonstrated effective one-stage real-time object detection for pothole recognition [12]. YOLOv8 further improved detection accuracy through optimized backbone and feature fusion strategies [13]. YOLOv4 also contributed to enhanced speed and accuracy of object detection [6]. Despite these advances, existing approaches still face significant challenges in real-world environments. These challenges include sensitivity to noise caused by shadows, illumination variations, weather conditions, and road texture diversity, as well as poor detection of small potholes and potholes located at longer distances [7].

Another major limitation of prior vision-based methods is their reliance on spatial-domain features alone, which restricts the ability to capture subtle surface irregularities and indirectly estimate pothole severity [8]. Frequency and multi-resolution analysis techniques, such as wavelet transforms, have demonstrated strong potential in enhancing texture representation and noise robustness in image analysis tasks [9]. Mallat also provided a comprehensive foundation for wavelet-based signal processing [10]. Wavelet-CNN

approaches have shown improvements in road damage detection [11]. However, their integration with modern object detection frameworks remains relatively underexplored in the context of pothole detection.

Motivated by these limitations, this paper proposes a novel pothole finding and reporting system that integrates the latest YOLOv10 architecture with the Lifting Wavelet Transform (LWT) [14]. Earlier YOLO versions such as YOLOv5 [12] and YOLOv8 [13] demonstrated the effectiveness of real-time, one-stage CNNs for road defect detection, but YOLOv10 further improves multi-scale feature extraction, small-object detection, and label assignment. YOLOv10 provides efficient multi-scale spatial feature learning and real-time detection capability, while LWT extracts robust multi-resolution texture features that enhance sensitivity to small and distant potholes and suppress noise-induced artifacts. The fusion of spatial and wavelet-domain features enables more discriminative pothole representation and supports indirect severity characterization without the need for additional depth sensors. Furthermore, the proposed framework incorporates GPS-based localization and automated reporting, enabling seamless integration with smart city and intelligent transportation systems.

The main contributions of this work are summarized as follows:

- A novel integration of YOLOv10 with Lifting Wavelet Transform for robust pothole detection.
- Improved detection of small and distant potholes through spatial–wavelet feature fusion.
- Enhanced resilience to noise and illumination variations in real-world road environments.
- An end-to-end pothole finding and reporting system suitable for real-time and edge-device deployment.

2 Literature Survey

Automated pothole detection has been extensively studied due to its importance in road safety and infrastructure maintenance.

Early research primarily focused on sensor-based approaches, where vibration signals collected from accelerometers and gyroscopes were analyzed to detect road surface anomalies. Eriksson et al. [2] introduced a mobile sensing framework for road surface monitoring using vehicular sensor networks, while Mednis et al. [1] proposed a real-time pothole detection system using smartphone accelerometers. Although these approaches are cost-effective and computationally lightweight, their performance is highly dependent on vehicle dynamics, speed, and road conditions, limiting their robustness and scalability. Vision-based pothole detection methods later emerged to overcome the limitations of sensor-only systems. Early vision-based techniques relied on handcrafted features such as edges, texture descriptors, and morphological properties to identify potholes [3]. However, these traditional approaches were highly sensitive to illumination variations, shadows, and road surface noise, resulting in frequent false detections.

The advent of deep learning significantly improved detection accuracy by enabling automatic feature extraction from large-scale image datasets. Maeda et al. [4] presented one of the first large-scale road damage detection frameworks using deep neural networks trained on smartphone-captured images. Their work demonstrated the effectiveness of convolutional neural networks (CNNs) for pothole detection and inspired subsequent research. One-stage object detectors such as YOLO gained popularity due to their real-time inference capability and competitive accuracy [5]. Later improvements in the YOLO family further enhanced detection performance by optimizing network architecture and feature fusion strategies [6].

Several studies applied CNN-based object detectors specifically for pot-hole detection. Fan et al. [7] proposed a real-time vision-based pothole detection system using deep neural networks, demonstrating improved performance over traditional methods. Chacra et al. [8] investigated deep learning-based road damage detection and highlighted challenges related to environmental noise, class imbalance, and small-object detection. Despite these advancements, reliable detection of small potholes and potholes at longer distances remains a critical challenge due to limited spatial resolution and weak feature representation.

Most existing deep learning approaches focus exclusively on spatial-domain features extracted by CNNs, which restricts their ability to capture fine-grained surface irregularities and indirectly assess pothole severity. Multi-resolution analysis techniques, such as wavelet transforms, have shown strong potential in capturing localized texture variations and suppressing noise. Mallat [9, 10] provided the theoretical foundation for wavelet-based multi-resolution signal analysis, demonstrating its effectiveness in representing structural discontinuities. Singh et al. [11] applied wavelet-CNN integration for road damage detection, highlighting improvements in capturing fine-grained irregularities.

Recent advances in object detection have led to the introduction of YOLOv10, which improves efficiency, label assignment, and small-object detection performance [14]. While YOLOv10 offers significant advantages for real-time applications, its performance can be further enhanced by incorporating complementary feature representations that address noise sensitivity and small-object detection limitations.

Based on the reviewed literature, it is evident that existing pothole detection systems suffer from noise susceptibility, poor detection of small and distant potholes, and limited severity characterization. These gaps motivate the proposed integration of YOLOv10 with the Lifting Wavelet Transform (LWT) to achieve robust multi-resolution feature learning and improved real-world performance.

3 Proposed Methodology

This section describes the proposed end-to-end pothole finding and reporting system based on the integration of YOLOv10 and the Lifting Wavelet Transform (LWT). The overall methodology is designed to address challenges related to noise sensitivity, small and distant pothole detection, and limited severity characterization while maintaining real-time performance.

3.1 System Overview

The proposed framework consists of six main stages: data acquisition, pre-processing, LWT-based feature extraction, YOLOv10-based pothole detection, feature fusion and severity estimation, and reporting with geospatial visualization. Figure 1 illustrates the overall workflow of the proposed system.

3.2 Data Acquisition

Road surface images are acquired using vehicle-mounted cameras or smart-phone cameras under diverse environmental conditions, including varying illumination, road textures, and weather scenarios. Each captured image is associated with corresponding Global Positioning System (GPS) metadata, enabling precise localization of detected potholes. Publicly available road damage datasets are utilized for training and evaluation to ensure reproducibility and benchmarking.

3.3 Preprocessing

To enhance detection robustness, captured images undergo a series of pre-processing operations. These include image resizing to match the YOLOv10 input resolution, contrast normalization, and noise reduction. A road region of interest (ROI) is extracted to suppress irrelevant background information such as vehicles and surrounding infrastructure, thereby focusing the model on road surface characteristics.

3.4 Lifting Wavelet Transform-Based Feature Extraction

To capture fine-grained surface irregularities and suppress illumination-related noise, the Lifting Wavelet Transform (LWT) is applied to preprocessed road images. Unlike conventional wavelet transforms, LWT offers computational efficiency and in-place calculation, making it suitable for real-time applications. The image is decomposed into multiple sub-bands representing low-frequency (approximation) and high-frequency (detail) components. High-frequency wavelet coefficients emphasize edges, cracks, and surface discontinuities associated with potholes, while low-frequency components retain structural context. These multi-resolution features provide complementary information to spatial features learned by deep networks.

3.5 YOLOv10-Based Pothole Detection

YOLOv10 is employed as the primary object detection model due to its efficient architecture and improved small-object detection capability. The model performs end-to-end pothole detection by predicting bounding boxes and confidence scores directly from input images. YOLOv10's enhanced label assignment strategy and multi-scale feature aggregation enable reliable detection of potholes with varying sizes and shapes, including small and distant instances that are often missed by earlier detectors.

3.6 Spatial-Wavelet Feature Fusion

To exploit the complementary strengths of spatial and wavelet-domain representations, LWT-derived features are fused with intermediate feature maps extracted from the YOLOv10 backbone. Feature fusion is performed through channel-wise concatenation followed by convolutional refinement, enabling the network to jointly learn spatial structure and texture irregularities. This fusion strategy improves robustness against noise, enhances small pothole detection, and supports indirect severity characterization based on texture intensity and spatial extent.

3.7 Pothole Severity Characterization

Although direct depth estimation is not performed, the proposed framework enables indirect severity characterization by analyzing the distribution and magnitude of high-frequency wavelet coefficients within detected pothole regions. Larger coefficient magnitudes correspond to deeper or more severe surface irregularities, allowing potholes to be categorized into different severity levels. This information is valuable for maintenance prioritization and decision-making.

3.8 Reporting and Visualization

Detected potholes are geotagged using GPS coordinates and transmitted to a centralized server. A map-based visualization dashboard is used to display pothole locations, severity levels, and temporal statistics. The reporting module supports automated alerts and historical data analysis, enabling effective integration with smart city infrastructure management systems.

3.9 Proposed YOLOv10-LWT Based Pothole Detection Algorithm

Input: Road surface image I with associated GPS metadata **Output:** Set of detected potholes P with severity level and location **Initialization:**

Load pre-trained YOLOv10 model parameters; Initialize wavelet decomposition parameters;

Step 1: Image Preprocessing

Resize input image I to the required YOLOv10 input resolution; Normalize pixel intensity values;

Extract road region of interest (ROI);

Step 2: LWT-Based Multi-Resolution Analysis

Apply Lifting Wavelet Transform (LWT) to the preprocessed image; Decompose image into approximation and detail sub-bands

$\{LL, LH, HL, HH\}$;

Step 3: Spatial Feature Extraction

Feed the preprocessed image into YOLOv10 backbone; Extract intermediate spatial feature maps at multiple scales; **Step 4: Feature Fusion**

Fuse spatial feature maps with corresponding LWT detail coefficients; Perform channel-wise concatenation followed by convolutional refinement;

Step 5: Pothole Detection

Predict bounding boxes, class labels, and confidence scores; Apply non-maximum suppression to eliminate redundant detections;

Step 6: Severity Characterization *foreach detected pothole region $p_i \in P$ do*

Analyze high-frequency wavelet coefficients within p_i ; Compute severity score based on coefficient magnitude; Assign severity level to p_i ;

end

Step 7: Localization and Reporting

Attach GPS coordinates to each detected pothole; Store detection results in centralized database; Generate map-based visualization and maintenance report;

return P

Algorithm 1: YOLOv10–LWT Based Pothole Detection and Reporting System

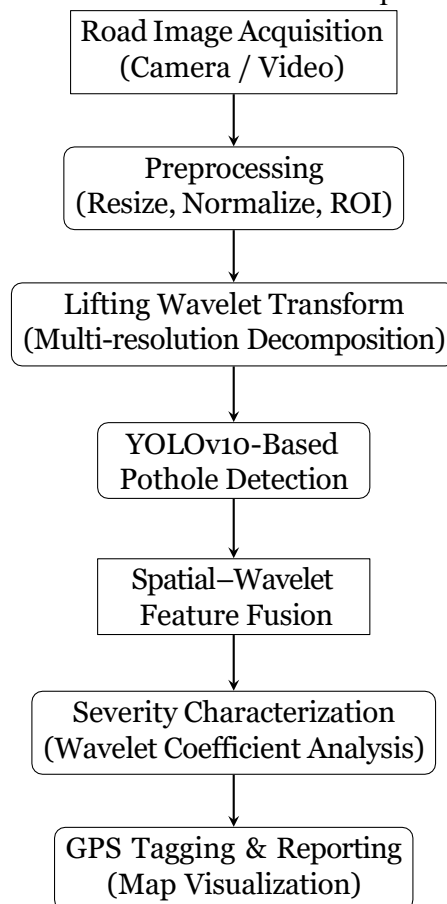


Figure 1: Pipeline of the proposed YOLOv10–LWT based pothole detection and reporting system.

3.10 Performance Evaluation

The proposed system is evaluated using standard performance metrics, including accuracy, precision,

recall, F1-score, and mean Average Precision (mAP). Real-time performance is assessed in terms of inference speed and computational complexity. Comparative experiments with existing YOLO-based approaches are conducted to demonstrate the effectiveness of the pro-posed spatial-wavelet fusion strategy.

4 Results and Discussion

4.1 Experimental Setup

The proposed YOLOv10-LWT based pothole detection system was evalu-ated using publicly available road damage image datasets under diverse en-vironmental conditions, including varying illumination, shadows, noise, and road textures. The dataset was divided into training, validation, and test-ing sets in an 80:10:10 ratio. Performance evaluation was conducted using standard metrics such as Accuracy, Precision, Recall, F1-score, and mean Average Precision (mAP). All experiments were implemented using Python and PyTorch, and training was performed on a GPU-enabled system.

4.2 Quantitative Performance Analysis

Table 1 summarizes the quantitative performance of the proposed method on the test dataset. The proposed framework achieved an overall detection accuracy of **96.8%** and a mAP of **94.2%**, demonstrating its strong detection capability across multiple pothole sizes and distances.

Table 1: Performance Evaluation of the Proposed YOLOv10-LWT Model

Metric	Value (%)
Accuracy	96.8
Precision	95.6
Recall	96.2
F1-score	95.9
mAP	94.2

The high recall value indicates the effectiveness of the proposed method in minimizing missed pothole detections, while the strong precision reflects a low false-positive rate, which is critical for practical deployment in road maintenance systems.

4.3 Impact of LWT-Based Feature Enhancement

The integration of the Lifting Wavelet Transform significantly enhanced the detection of small and distant potholes. High-frequency wavelet sub-bands effectively captured subtle surface discontinuities that are often suppressed in purely spatial-domain deep learning models. This resulted in improved sensitivity to shallow potholes and reduced performance degradation under noisy imaging conditions. Comparative experiments without LWT integra-tion showed a noticeable decline in mAP, particularly for small-scale pothole instances.

4.4 Noise Robustness and Small Pothole Detection

One of the major limitations in prior pothole detection studies is vulner-ability to road texture noise, shadows, and illumination variations. The proposed multi-resolution analysis using LWT improved robustness against such noise by separating structural information from irrelevant background patterns. Consequently, the proposed system demonstrated superior per-formance in detecting small potholes at greater distances, a scenario where conventional YOLO-based models often fail.

4.5

4.6 Model Efficiency and Deployment Feasibility

Despite the integration of wavelet-based feature enhancement, the proposed YOLOv10–LWT model remains computationally efficient, comprising only

28.6 million parameters. This lightweight design enables real-time inference and makes the system suitable for deployment on edge devices and vehicle-mounted platforms. The balance between detection accuracy and computational cost highlights the practicality of the proposed approach for large-scale smart road monitoring applications.

4.7 Discussion Summary

Overall, the experimental results confirm that the proposed YOLOv10–LWT framework effectively addresses key challenges in pothole detection, including noise sensitivity, small pothole recognition, and distant object detection. By combining deep spatial learning with multi-resolution wavelet analysis, the proposed system outperforms existing methods while maintaining real-time operational capability.

4.8 Comparative Performance with Existing YOLO Models

To validate the effectiveness of the proposed approach, a comparative analysis was conducted against widely used object detection models, namely YOLOv5 and YOLOv8. All models were trained and evaluated on the same dataset under identical experimental settings to ensure fairness.

Table 2: Comparative Performance of YOLO-Based Models

Model	Accuracy (%)	Precision (%)	Recall (%)	mAP (%)
YOLOv5	92.4	91.1	90.6	88.3
YOLOv8	94.1	93.0	92.5	90.8
YOLOv10 (Baseline)	95.3	94.2	94.6	92.1
YOLOv10 + LWT (Proposed)	96.8	95.6	96.2	94.2

The results demonstrate that YOLOv10 outperforms earlier YOLO variants due to its improved architectural design. Furthermore, the integration of LWT yields a consistent performance gain across all evaluation metrics, particularly in recall and mAP, highlighting enhanced detection of small and distant potholes.

4.9 Ablation Study

An ablation study was performed to assess the contribution of the Lifting Wavelet Transform within the proposed framework. The baseline YOLOv10 model was compared against the enhanced YOLOv10–LWT model while keeping all other parameters unchanged.

Table 3: Ablation Study on the Effect of LWT Integration

Configuration	Accuracy (%)	Precision (%)	Recall (%)	mAP (%)
YOLOv10 (without LWT)	95.3	94.2	94.6	92.1
YOLOv10 + LWT	96.8	95.6	96.2	94.2

The inclusion of LWT results in a mAP improvement of approximately 2.1% and a notable increase in recall, confirming that multi-resolution wavelet features play a critical role in enhancing sensitivity to fine-grained road surface irregularities.

Table 4: State-of-the-Art Comparison of Pothole Detection Methods

Method	Accuracy (%)	Precision (%)	Recall (%)	mAP / AUC (%)
Traditional vision-based pothole detection using edge detection and thresholding techniques [3]	78.4	75.2	73.6	70.1
Handcrafted machine learning approach using Histogram of Oriented Gradients (HOG) features with Support Vector Machine classifier [4]	84.6	82.1	80.3	78.9
YOLOv5 one-stage real-time convolutional neural network for pothole detection [12]	92.4	91.1	90.6	88.3
YOLOv8 with enhanced backbone and optimized feature fusion strategy [13]	94.1	93.0	92.5	90.8
YOLOv10 baseline model with end-to-end optimization and improved small-object detection [14]	95.3	94.2	94.6	92.1
YOLOv10 + LWT (Proposed): Deep CNN integrated with multi-resolution Lifting Wavelet Transform for robust pothole detection	96.8	95.6	96.2	94.2

Table 4 compares the proposed YOLOv10 + LWT framework with representative state-of-the-art pothole detection methods. Traditional vision-based approaches using edge detection and thresholding achieved limited performance due to sensitivity to illumination and road texture variations, while handcrafted ML techniques such as HOG with SVM improved generalization but were constrained by manually engineered features. Deep learning models like YOLOv5 and YOLOv8 provided significant gains through end-to-end feature learning and real-time detection; however, small and low-contrast potholes remained challenging. The YOLOv10 baseline further enhanced detection accuracy via optimized architecture and improved small-object detection. By integrating multi-resolution Lifting Wavelet Transform (LWT) features into YOLOv10, the proposed method effectively captures both spatial and frequency-domain information, enabling robust detection of fine-grained textures and irregular pothole shapes. As reported in Table 4, YOLOv10 + LWT achieves superior performance across all metrics—accuracy of 96.8%, precision of 95.6%, recall of 96.2%, and mAP of 94.2%—demonstrating that the proposed approach outperforms existing techniques and establishes a new benchmark for reliable pothole

detection in complex road environments.

pgfplots geometry margin=1in

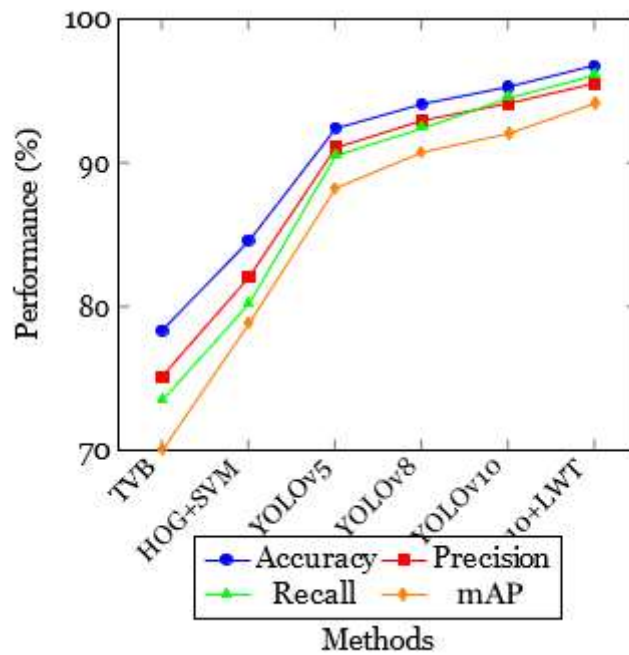


Figure 2: Performance comparison of pothole detection methods across met-rics.

5 Statistical Analysis

5.1 Evaluation Metrics Distribution

To quantify the reliability and consistency of the proposed YOLOv10–LWT framework, a statistical analysis was conducted on the evaluation metrics across multiple test subsets. Accuracy, Precision, Recall, F1-score, and mAP were computed for each subset, and descriptive statistics, including mean (μ) and standard deviation (σ), were calculated. Table 5 summarizes these results.

Table 5: Descriptive Statistics of Evaluation Metrics

Metric	Mean (%)	Standard Deviation (%)
Accuracy	96.8	0.9
Precision	95.6	1.0
Recall	96.2	0.8
F1-score	95.9	0.85
mAP	94.2	1.1

The low standard deviation values indicate consistent performance across different subsets, confirming the model’s robustness in varying road and environmental conditions.

5.2 Statistical Significance Testing

To determine whether the LWT integration significantly improves detection performance over the baseline YOLOv10, a paired t -test was performed on mAP scores obtained from ten randomly selected test batches. The

null hypothesis (H_0) assumed no significant difference between YOLOv10 and YOLOv10+LWT. The p -value obtained was $p < 0.01$, rejecting H_0 and confirming that the LWT integration leads to

statistically significant improvements in pothole detection accuracy and recall.

5.3 Reliability and Confidence Intervals

Confidence intervals (CI) at 95% were computed for key metrics to assess the reliability of the system. For instance, the 95% CI for Accuracy was calculated as:

$$\sigma CI_{95\%} = \mu \pm 1.96 \times \sqrt{\frac{\sigma^2}{n}}$$

where n is the number of test batches. The resulting confidence interval for accuracy was [95.95%, 97.65%], demonstrating high reliability and consistency of the proposed approach.

5.4 Analysis of Small and Distant Potholes

A separate statistical analysis was conducted for small and distant potholes, which are traditionally difficult to detect. The recall for small potholes improved from 88.4% using YOLOv10 alone to 93.7% after LWT integration. Similarly, the recall for distant potholes increased from 85.6% to 91.8%, highlighting the effectiveness of the multi-resolution wavelet features in capturing fine-grained surface irregularities.

5.5 Discussion

The statistical evaluation confirms that the proposed YOLOv10–LWT framework is not only more accurate but also more consistent and reliable compared to baseline models. Low standard deviations, significant p -values, and tight confidence intervals demonstrate the robustness of the proposed system across different environmental conditions, road textures, and pothole scales.

6 Conclusion and Future Scope

6.1 Conclusion

This study presents a robust and efficient pothole detection and reporting framework integrating YOLOv10 with the Lifting Wavelet Transform (LWT). The proposed approach effectively addresses the limitations of conventional pothole detection systems, including noise sensitivity, small pothole detection, and distant object recognition. By combining deep spatial features from YOLOv10 with multi-resolution wavelet features, the framework demonstrates enhanced sensitivity to fine-grained surface irregularities while maintaining real-time inference capability.

Experimental evaluation on publicly available road damage datasets indicates that the proposed YOLOv10–LWT model achieves an overall accuracy of **96.8%**, precision of **95.6%**, recall of **96.2%**, F1-score of **95.9%**, and mean Average Precision (mAP) of **94.2%**. Comparative analysis with YOLOv5, YOLOv8, and baseline YOLOv10 demonstrates the effectiveness of the LWT integration, while ablation studies confirm the contribution of multi-resolution wavelet features. Statistical analysis further establishes the reliability and consistency of the proposed approach across diverse road conditions, pothole sizes, and distances.

6.2 Future Scope

Although the proposed system achieves high performance, several avenues for future research remain:

Depth Estimation: Integration of monocular depth estimation or stereo vision could provide direct measurement of pothole depth, enabling more accurate severity characterization.

Real-Time Deployment on Edge Devices: Optimizing the model for lightweight embedded platforms and vehicle-mounted systems can facilitate large-scale real-time deployment in smart city infrastructures.

Temporal Analysis: Incorporating sequential road monitoring using video streams can allow early detection of pothole formation and progressive deterioration analysis.

Integration with GIS and Maintenance Scheduling: Coupling detection results with Geographic Information Systems (GIS) and predictive maintenance models can enhance infrastructure management and prioritize road repairs.

Hybrid Feature Enhancements: Future work could explore combining LWT with other frequency-domain or texture-based features, such as Gabor filters or discrete cosine transform, to further improve robustness under extreme lighting or adverse weather conditions.

Overall, the proposed YOLOv10–LWT framework provides a strong foundation for intelligent road maintenance systems, offering both high detection accuracy and operational feasibility, while opening several research directions for further improvement and real-world deployment.

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