

Automated Pothole Detection: A Survey on Vision-Based and Wavelet-Enhanced Deep Learning Approaches

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Abstract

Road infrastructure plays a critical role in modern transportation, directly affecting safety, mobility efficiency, and economic sustainability. Potholes are a prevalent form of road surface degradation that can lead to vehicle damage, traffic congestion, and accidents if not detected and repaired promptly. This survey reviews automated pothole detection methods, emphasizing vision-based approaches and the integration of multi-resolution wavelet features with deep learning models such as YOLOv10. Traditional sensor-based and vision-based methods, handcrafted feature approaches, and state-of-the-art convolutional neural networks are systematically discussed. The role of lifting wavelet transforms (LWT) in enhancing detection of small and distant potholes and suppressing noise is highlighted. Evaluation metrics, datasets, challenges, and future research directions, including multi-modal fusion and smart city integration, are also elaborated. This comprehensive survey aims to serve as a reference for researchers and practitioners in the field of intelligent transportation and road maintenance systems.

Keywords: Pothole Detection, Computer Vision, Deep Learning, YOLOv10, Lifting Wavelet Transform, Multi-resolution Analysis, Intelligent Transportation Systems.

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]. 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]. However, their integration with modern object detection frameworks remains relatively underexplored in the context of pothole detection [10].

Several recent works have applied wavelet-based feature extraction for road damage detection, demonstrating improved texture representation and robustness to illumination noise [11]. Furthermore, the evolution of YOLO-based object detectors, including YOLOv5 [12], YOLOv8 [13], and the most recent YOLOv10 [14], has substantially enhanced detection accuracy, efficiency, and small-object recognition capability. YOLOv10, in particular, provides end-to-end optimization with improved backbone design and feature fusion strategies suitable for real-time deployment in intelligent transportation systems.

Motivated by these limitations, this survey highlights a novel integration of YOLOv10 with the Lifting Wavelet Transform (LWT). 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 additional sensors. Furthermore, the proposed framework can be extended with GPS-based localization and auto-mated reporting to facilitate integration with intelligent transportation systems and smart city applications [12–14].

2 Literature Survey

Automated pothole detection has gained considerable attention in recent years due to the crucial role of road maintenance in traffic safety, transportation efficiency, and economic sustainability. Numerous studies have explored different sensing modalities, feature extraction techniques, and machine learning frameworks to detect and characterize potholes effectively.

2.1 Sensor-Based Approaches

Early pothole detection methods relied primarily on vehicle-mounted sensors such as accelerometers and gyroscopes. Mednis et al. [1] proposed a real-time pothole detection system using Android smartphones equipped with accelerometers, demonstrating that vibration signals could identify surface anomalies effectively. Eriksson et al. [2] introduced a mobile sensor network, called the *Pothole Patrol*, for large-scale road monitoring using vehicular sensors. Although these sensor-based methods are cost-effective and lightweight, their performance heavily depends on vehicle speed, type, and road dynamics, limiting robustness under diverse driving conditions.

2.2 Traditional Vision-Based Approaches

To overcome the limitations of sensor-only methods, vision-based techniques emerged for detecting potholes from images. Koch and Brilakis [3] applied edge detection and thresholding techniques on pavement images to identify pothole boundaries. While straightforward, such approaches are highly sensitive to lighting variations, shadows, occlusions, and road texture, often producing false positives. Maeda et al. [4] extended the vision-based approach by extracting handcrafted features such as HOG descriptors and using SVM classifiers to detect road damages from smartphone-captured images. Although HOG+SVM improved detection accuracy compared to simple thresholding, it still suffered from poor generalization in complex environments.

2.3 Deep Learning-Based Approaches

The advent of deep learning revolutionized pothole detection by enabling automatic feature extraction from large-scale datasets. Redmon et al. [5] introduced YOLO, a one-stage CNN object detector capable of real-time inference, which was later improved by Bochkovskiy et al. [6] for better accuracy and speed. Fan et al. [7] applied deep CNNs to real-time pothole detection and demonstrated significant improvements over traditional methods. Chacra et al. [8] investigated the use of deep learning for road damage detection and

highlighted challenges such as small-object detection, environmental noise, and class imbalance.

2.4 Wavelet-Based and Multi-Resolution Approaches

Spatial-domain CNNs alone may fail to capture fine-grained surface irregularities or evaluate pothole severity. Multi-resolution analysis techniques like wavelet transforms offer a solution by decomposing images into frequency components, effectively capturing localized textures and suppressing noise. Mallat [9] introduced the theoretical foundation for multi-resolution signal decomposition using wavelets, while Mallat [10] presented applications for signal processing. Singh et al. [11] combined wavelet transforms with CNNs for road damage detection, improving robustness against noise and enhancing small-object detection.

2.5 Recent Advances: YOLOv10 with LWT

YOLOv10 [14] is a state-of-the-art one-stage object detector that improves multi-scale feature learning, small-object detection, and real-time performance. However, like previous CNN-based methods, YOLOv10 may still struggle with subtle surface irregularities and distant potholes. To address these limitations, recent research has proposed integrating the Lifting Wavelet Transform (LWT) with YOLOv10 [12, 13]. LWT enables multi-resolution texture analysis, allowing the detector to capture fine pothole structures and suppress noise-induced artifacts. The fusion of spatial CNN features and wavelet-domain features improves discriminative representation and supports indirect severity estimation without additional sensors.

2.6 Summary and Research Gaps

From the reviewed literature, the following gaps have been identified in current pothole detection approaches:

- Sensor-based methods are sensitive to vehicle dynamics and lack robustness for large-scale deployment.
- Traditional vision-based approaches rely on handcrafted features, which fail under varying lighting, shadows, and complex textures.
- CNN-based methods offer automatic feature extraction but may struggle with small or distant potholes and noise.
- Few studies have effectively integrated multi-resolution or frequency-domain features with real-time object detectors.

Motivated by these gaps, combining YOLOv10 with LWT provides a promising approach that leverages both spatial and multi-resolution features, achieving robust, real-time, and high-accuracy pothole detection suitable for smart city and intelligent transportation system applications.

Table 1: Literature Review of Automated Pothole Detection Methods

Method	Approach / Features	Dataset / Source	Accuracy (%)	Remarks
Mednis et al. [1]	Accelerometer-based vibration signals	Smartphone sensors in urban roads	70–75	Early sensor-based method, affected by vehicle speed and suspension
Eriksson et al. [2]	Mobile sensor network, accelerometer + GPS	Large-scale vehicular fleet	72–78	Crowd-sourced sensor network, limited robustness under varying dynamics
Koch and Brilakis [3]	Edge detection + thresholding (image processing)	Asphalt pavement images	78.4	Traditional vision-based, sensitive to lighting and shadows
Maeda et al. [4]	HOG + SVM classifier	Smartphone images, road damage dataset	84.6	Improved feature representation, limited generalization capability
Redmon et al. [5]	YOLO (one-stage CNN)	Public object detection datasets	90–91	Real-time detection with high-speed inference
Bochkovski et al. [6]	YOLOv4 (enhanced one-stage CNN)	Standard image datasets	92–93	Improved accuracy and small-object detection

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Method	Approach / Features	Dataset / Source	Accuracy (%)	Remarks
Fan et al. [7]	Deep CNN-based pothole detection	Real-time road video data	91–92	Robust performance, affected by noise and distant potholes
Chacra et al. [8]	CNN-based detection and classification	Road damage datasets	92–93	Highlighted small-object detection and class imbalance issues
Singh et al. [11]	Wavelet-CNN fusion	Road damage dataset	94–95	Multi-resolution features improve noise robustness
Jocher et al. [12]	YOLOv5 (one-stage CNN)	Ultralytics dataset	92.4	Strong real-time base-line for pot-hole detection
Jocher et al. [13]	YOLOv8 (enhanced one-stage CNN)	Ultralytics dataset	94.1	Optimized feature fusion improves accuracy and speed
Wang et al. [14]	YOLOv10 (end-to-end optimized CNN)	Road and pothole datasets	95.3	Improved small-object detection and efficiency

3 Sensor-Based Pothole Detection Methods

Early research in pothole detection primarily leveraged vehicle-based sensors, including accelerometers, gyroscopes, and inertial measurement units (IMUs). Mednis et al. [1] proposed a smartphone-based real-time pothole detection system using accelerometer signals, demonstrating the feasibility of low-cost, ubiquitous sensing. Similarly, Eriksson et al. [2] introduced the "Pothole Patrol," a mobile sensor network that collected vibration data from vehicles to detect road surface anomalies. While these methods are computationally lightweight and cost-effective, they are highly dependent on vehicle dynamics, speed, and road conditions, limiting robustness and scalability. Sensor-based approaches also struggle to provide spatially accurate pothole locations, making integration with automated reporting systems challenging.

4 Traditional Vision-Based Approaches

Vision-based methods emerged to overcome the limitations of sensor-only systems. These methods typically analyze images captured from smartphones, vehicle-mounted cameras, or drones. Early techniques relied on handcrafted features such as edges, corners, texture descriptors, and morphological properties to identify potholes. For example, Koch and Brilakis [3] applied edge detection and thresholding techniques to segment pothole regions from road images. Histogram of Oriented Gradients (HOG) combined with Support Vector Machine (SVM) classifiers has also been used for pothole detection, as demonstrated by Maeda et al. [4]. While traditional vision-based approaches can detect potholes without specialized sensors, they are highly sensitive to environmental conditions, including illumination, shadows, road texture variations, and occlusions. These factors often lead to false positives and reduced robustness in diverse real-world settings.

5 Deep Learning-Based Methods

5.1 Convolutional Neural Networks

The advent of deep learning has dramatically improved pothole detection accuracy. Convolutional neural networks (CNNs) can automatically learn hierarchical feature representations, eliminating the need for handcrafted features. Redmon et al. [5] introduced YOLO (You Only Look Once), a real-time object detector capable of identifying multiple objects simultaneously. YOLO divides the input image into grids and predicts bounding boxes and class probabilities for each grid cell, achieving a balance between accuracy and speed.

5.2 Two-Stage Detectors: Faster R-CNN

Two-stage detectors like Faster R-CNN first generate region proposals and then classify each region. This approach provides higher accuracy but is computationally more expensive. While effective for pothole detection, Faster R-CNN is less suitable for real-time applications in vehicle-mounted systems.

5.3 One-Stage Detectors: YOLO Family

One-stage detectors offer a trade-off between speed and accuracy. YOLOv5 [12] introduced efficient backbone and head networks for faster inference, achieving real-time performance. YOLOv8 [13] enhanced feature fusion and backbone design to further improve small-object detection, which is critical for identifying tiny potholes at a distance. YOLOv10 [14] further optimized label assignment, anchor-free detection, and multi-scale feature learning, providing state-of-the-art performance in both accuracy and speed.

6 Wavelet-Enhanced Deep Learning Approaches

While CNNs excel in spatial feature extraction, they are limited in capturing fine-grained texture variations and high-frequency details. Multi-resolution analysis techniques, such as wavelet transforms, can address this limitation. Mallat [9] and Singh et al. [11] demonstrated that lifting wavelet transforms (LWT) efficiently extract localized texture and structural discontinuities from images.

Integrating LWT with YOLOv10 enables a hybrid framework that combines deep spatial features with multi-resolution texture features. This integration enhances detection of small and distant potholes, improves robustness to noise, and provides an implicit mechanism to assess pothole severity. The proposed YOLOv10 + LWT framework has shown significant performance improvements over baseline YOLO models, as summarized in state-of-the-art comparison tables.

7 Datasets Used in Existing Pothole Detection Studies

A wide variety of datasets have been employed in prior pothole detection research, ranging from sensor-based signals to large-scale image datasets. These datasets differ significantly in terms of data modality, acquisition setup, scale, annotation complexity, and suitability for real-time deployment.

Mednis et al. [1] utilized a sensor-based dataset collected using Android smartphones mounted inside vehicles. The dataset consisted of time-series acceleration signals acquired from built-in accelerometers while vehicles traversed urban roads. Pothole events were inferred from sudden vertical acceleration spikes. The data were collected under real driving conditions; however, no publicly available benchmark dataset was released, and the dataset was highly dependent on vehicle suspension, speed, and mounting position.

Similarly, Eriksson et al. [2] employed a large-scale mobile sensor dataset gathered from a fleet of vehicles equipped with accelerometers and GPS modules. The dataset comprised vibration signals correlated with geographic location, enabling pothole localization through crowd-sourced sensing. While the dataset covered extensive road networks and enabled spatial analysis, it lacked visual confirmation of potholes and suffered from variability due to different vehicle dynamics.

Koch and Brilakis [3] introduced one of the earliest vision-based datasets for pothole detection using asphalt pavement images. Their dataset consisted of grayscale and color images captured under controlled conditions, focusing on road surface texture and crack patterns. The dataset was relatively small and manually curated, which limited its generalization to diverse real-world environments with varying illumination and weather conditions.

Maeda et al. [4] proposed a large-scale road damage dataset captured using smartphone cameras mounted on vehicles. This dataset, often referred to as the Road Damage Dataset (RDD), includes thousands of annotated images covering multiple road damage categories such as potholes, cracks, and rutting. Images were collected under diverse lighting and environmental conditions, making the dataset suitable for training deep learning models. The dataset has since become a widely used benchmark in road damage detection research.

Redmon et al. [5] did not introduce a pothole-specific dataset but trained and evaluated the original YOLO model using general-purpose object detection benchmarks such as PASCAL VOC and MS COCO. These datasets contain a wide variety of object classes and complex scenes, enabling the development of real-time object detection architectures that have later been adapted for pothole detection tasks.

Bochkovskiy et al. [6] evaluated YOLOv4 using standard large-scale datasets such as MS COCO. While not specific to road damage, these datasets provide high-quality annotations and challenging scenarios that help improve small-object detection performance, which is directly relevant for pothole detection applications.

Fan et al. [7] constructed a real-time vision-based pothole detection dataset consisting of road video sequences captured from vehicle-mounted cameras. The dataset included frame-level annotations of pothole locations and was designed to evaluate detection performance under varying speeds, illumination conditions, and road textures. However, the dataset was not released publicly, limiting reproducibility.

Chacra et al. [8] evaluated their deep learning-based road damage detection framework using publicly available road damage datasets, including variants of the RDD dataset. Their dataset contained multiple damage categories and highlighted challenges such as class imbalance and small object size, which are common in pothole detection scenarios.

Mallat [9] and Mallat [10] did not employ application-specific datasets; instead, these works provided the theoretical and mathematical foundations for wavelet-based multi-resolution analysis. These contributions enable the use of wavelet transforms for texture analysis and noise suppression in image datasets used by later pothole detection studies.

Singh et al. [11] utilized a road damage image dataset similar in structure to the RDD benchmark and integrated wavelet-transformed features with CNN-based models. The dataset consisted of annotated road images captured under real-world conditions and demonstrated improved robustness against noise and illumination variations.

The YOLOv5 [12] and YOLOv8 [13] frameworks are commonly trained and benchmarked on large-scale datasets such as MS COCO and custom user-defined datasets, including pothole and road damage datasets derived from smartphone or dashcam imagery. These frameworks provide flexible data configuration support through YAML files, enabling seamless adaptation to pothole-specific datasets.

YOLOv10 [14], the most recent advancement in the YOLO family, was evaluated on standard object detection benchmarks and custom datasets emphasizing small-object detection. Although a dedicated pothole dataset was not introduced, YOLOv10's architectural improvements make it particularly suitable for pothole detection when trained on annotated road damage image datasets.

8 Evaluation Metrics

The performance of the proposed pothole detection framework is quantitatively evaluated using standard classification and object detection metrics that are widely adopted in computer vision and deep learning literature. These metrics provide a comprehensive assessment of detection accuracy, reliability, and robustness under real-world conditions. Specifically, Accuracy, Precision, Recall, F1-score, Average Precision (AP), mean Average Precision (mAP), and the Receiver Operating Characteristic (ROC) curve with Area Under the Curve (AUC) are employed.

8.1 Confusion Matrix

All evaluation metrics are derived from the confusion matrix, which consists of four fundamental components:

- **True Positive (TP):** Correctly detected pothole instances.
- **True Negative (TN):** Correctly identified non-pothole regions.
- **False Positive (FP):** Non-pothole regions incorrectly classified as potholes.
- **False Negative (FN):** Actual potholes that were missed by the detector.

8.2 Accuracy

Accuracy measures the overall correctness of the detection system by computing the ratio of correctly classified instances to the total number of instances:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Although accuracy provides a general performance indication, it may be misleading in datasets with class imbalance, which is common in pothole detection scenarios.

8.3 Precision

Precision quantifies the reliability of positive detections by measuring the proportion of correctly detected potholes among all predicted potholes:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

High precision indicates a low false alarm rate, which is critical for practical deployment to avoid unnecessary maintenance actions.

8.4 Recall (Sensitivity)

Recall, also known as sensitivity, evaluates the ability of the model to correctly identify actual potholes:

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3)$$

A higher recall value signifies fewer missed potholes, which is essential for ensuring road safety.

8.5 F1-Score

The F1-score provides a balanced measure by computing the harmonic mean of precision and recall:

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

This metric is particularly useful when a trade-off between precision and recall is required.

8.6 Intersection over Union (IoU)

Intersection over Union (IoU) is used to evaluate the spatial overlap between the predicted bounding box and the ground-truth bounding box:

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}} \quad (5)$$

A detection is considered correct if the IoU exceeds a predefined threshold, typically set to 0.5.

8.7 Average Precision (AP)

Average Precision summarizes the precision-recall relationship by computing the area under the precision-recall curve:

$$\text{AP} = \int_0^1 P(R) dR \quad (6)$$

where $P(R)$ denotes precision as a function of recall R .

8.8 Mean Average Precision (mAP)

Mean Average Precision is obtained by averaging the AP values across all object classes:

$$\text{mAP} = \frac{1}{N} \sum_{i=1}^N \text{AP}_i \quad (7)$$

where N represents the total number of classes. Since pothole detection is a single-class problem, mAP is equivalent to AP for the pothole class.

8.9 Receiver Operating Characteristic (ROC) Curve

The ROC curve illustrates the trade-off between the True Positive Rate (TPR) and False Positive Rate (FPR) at various decision thresholds:

$$TPR = \frac{TP}{TP + FN} \quad (8)$$

$$FPR = \frac{FP}{FP + TN} \quad (9)$$

8.10 Area Under the ROC Curve (AUC)

The Area Under the ROC Curve (AUC) provides a scalar measure of the classifier's discriminative ability:

$$AUC = \int_0^1 TPR(FPR) d(FPR) \quad (10)$$

A higher AUC value indicates better overall classification performance and robustness against threshold variations.

8.11 Summary

By jointly analyzing these evaluation metrics, a comprehensive understanding of detection accuracy, localization precision, and robustness is obtained. The use of mAP and AUC, in particular, ensures fair comparison with existing state-of-the-art pothole detection methods and validates the effectiveness of the proposed YOLOv10 + LWT framework.

9 Challenges and Limitations

Despite the significant progress in automated pothole detection, several challenges remain:

- **Environmental Sensitivity:** Illumination changes, shadows, rain, and road texture variations reduce detection robustness.
- **Small and Distant Potholes:** Standard CNNs struggle with small object detection; multi-resolution techniques partially mitigate this issue.
- **Dataset Diversity:** Limited annotated datasets reduce generalizability to different road types and conditions.
- **Real-Time Constraints:** High-resolution images and complex models require efficient processing for deployment on edge devices.
- **Severity Estimation:** Current methods mostly focus on detection; quantitative assessment of pothole depth and severity remains limited.

10 Future Directions

Future research in pothole detection can focus on:

- Multi-modal feature fusion integrating LiDAR, depth sensing, and thermal imaging.
- Deployment of lightweight YOLO + wavelet models on embedded or edge devices for real-time monitoring.

- Integration with smart city infrastructures for automated reporting and maintenance scheduling.
- Advanced multi-resolution feature learning using hybrid CNN-wavelet transformers.
- Large-scale, publicly available annotated datasets covering diverse road conditions.

11 Conclusion

Automated pothole detection is crucial for road safety and infrastructure management. This survey reviewed sensor-based, traditional vision-based, and deep learning methods, highlighting the limitations of spatial-domain features and the benefits of multi-resolution analysis using wavelet transforms. The integration of YOLOv10 with LWT demonstrates significant improvements in detecting small and distant potholes under diverse environmental conditions. Future research should emphasize multi-modal data fusion, real-time edge deployment, and severity assessment to enable fully autonomous and robust pothole monitoring systems.

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