

“Smart Road Pothole Detection using YOLOv8 and Computer Vision”

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Abstract— The Road damage such as potholes and cracks is a major concern for transportation safety and infrastructure management. Traditional methods of road inspection are manual, timeconsuming, and often inefficient, leading to delayed maintenance and increased risk of accidents. This project presents a smart and automated approach for detecting road surface damages using deep learning and computer vision techniques. The proposed system utilizes the YOLOv8 (You Only Look Once) object detection model to identify potholes and cracks from road images and video frames in real time. The model is trained on a combination of custom and publicly available datasets to ensure robustness under varying environmental conditions such as lighting, shadows, and road textures. In addition to detection, the system estimates the physical dimensions of potholes, including length and width in meters, using pixel-to-meter conversion techniques. Each detection is also associated with a confidence score, indicating the reliability of the prediction. The results demonstrate that the model achieves high accuracy and efficiency in detecting road damages, making it suitable for real-world applications. The system can assist government authorities and maintenance agencies in proactive road monitoring, prioritizing repairs, and improving overall road safety. Furthermore, the solution is scalable and can be integrated with real-time surveillance systems, mobile applications, or vehicle-mounted cameras for continuous monitoring. This project highlights the potential of deep learning-based solutions in addressing real-world infrastructure challenges and contributes toward the development of smart city systems.

1. INTRODUCTION

The Road networks are a critical component of a country's infrastructure, facilitating transportation, trade, and daily commuting. However, continuous exposure to environmental conditions such as rainfall, temperature variations, and heavy vehicular loads leads to gradual deterioration of road surfaces. This deterioration manifests in the form of potholes, cracks, and surface deformities, which significantly impact road safety and driving comfort. Potholes are among the most common and hazardous road defects, often causing accidents, traffic congestion, and vehicle damage. According to various transportation studies, poor road conditions contribute to a considerable percentage of road accidents worldwide. Therefore, timely detection and maintenance of such defects are essential for ensuring safe and efficient transportation systems.

Transportation infrastructure serves as the backbone of modern socio-economic development. However, road surfaces are subject to continuous degradation due to environmental stressors— such as freeze-thaw cycles and moisture infiltration—and mechanical loading from heavy- tonnage vehicles. Among various forms of pavement distress, potholes represent a critical failure point. Beyond increasing vehicle operational costs and fuel consumption, potholes pose a severe threat to road safety, often acting as primary catalysts for suspension damage, tire blowouts, and fatal maneuvers.

2. LITERATURE REVIEW

2.1. Study 1: YOLO-Based Pothole Detection Authors: Joseph Redmon et al. Proposed the YOLO object detection framework for real-time object detection. YOLO processes an entire image in a single pass, making it significantly faster than region-based methods. It provides a strong foundation for developing pothole detection systems.

.Limitations

Earlier YOLO versions showed lower accuracy for small or partially damaged potholes.

2.2. Study 2: Pothole Detection using Deep Learning Researchers developed convolutional neural network (CNN)-based methods for detecting potholes from road images.

Key Contributions

Achieved higher accuracy than traditional image processing. Reduced dependence on handcrafted features. Improved robustness under different road conditions.

Limitations

High computational requirements. Required large labeled datasets for training.

2.3 Study 3: YOLOv5 for Road Damage Detection

Researchers applied YOLOv5 to detect potholes and other road damages.

Key Findings: Faster inference than many CNN-based approaches. Suitable for real-time deployment. Good detection accuracy under daylight conditions.

Limitations

Reduced performance in low-light or rainy weather. Difficulty detecting very small potholes.

2.4 Study 4: YOLOv8 for Smart Road Monitoring

YOLOv8 introduced several improvements over previous YOLO versions.

YOLOv8 demonstrated excellent performance for detecting road defects in real-time traffic environments.

2.5 Study 5: Computer Vision-Based Road Inspection

Several researchers combined computer vision with edge devices and cloud platforms.

3. PROBLEM STATEMENT

Despite advancements in automated systems, several challenges remain in the domain of road damage detection:

- Manual inspection methods are inefficient and not scalable
- Many automated systems depend on additional hardware components
- Existing models often lack generalization on unseen data
- Limited focus on extracting meaningful information beyond detection

Therefore, the problem addressed in this project is: To design and develop a deep learning-based system that can accurately detect potholes and roadcracks from images, evaluate its performance on new data, and provide additional information such as size estimation, without relying on external hardware.

4. Methodology :

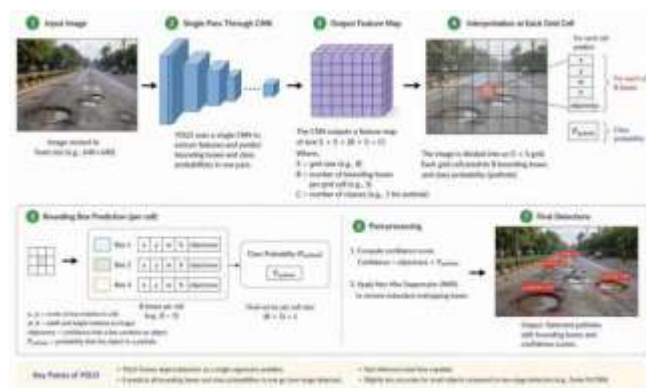


Fig 3.3: Working of YOLO Object Detection Model

Despite significant advancements, existing methodologies still have certain limitations. Traditional and image processing-based methods lack robustness and accuracy, especially under varying environmental conditions. Machine learning approaches require manual feature extraction, which limits their effectiveness. Even in deep learning-based methods, the performance of the model heavily depends on the dataset. If the dataset is not diverse enough, the model may fail to generalize well on new images.

4. PROPOSED METHODOLOGY

The proposed system is based on the YOLOv8 object detection model, which is trained using a dataset of road images containing potholes and cracks. The model learns to identify these defects

by analyzing spatial patterns and features within the images. The overall workflow of the system involves two main phases: the training phase and the testing phase. During the training phase, the model is trained on labeled data to learn the characteristics of road damages. In the testing phase, the trained model is evaluated using new images to assess its performance and accuracy.

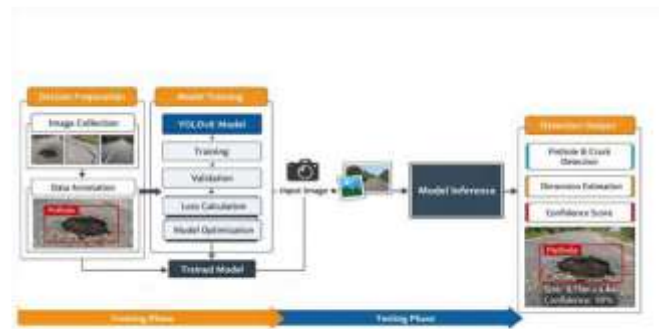


Fig 4.1: Overall Architecture of the Proposed Road Damage Detection System

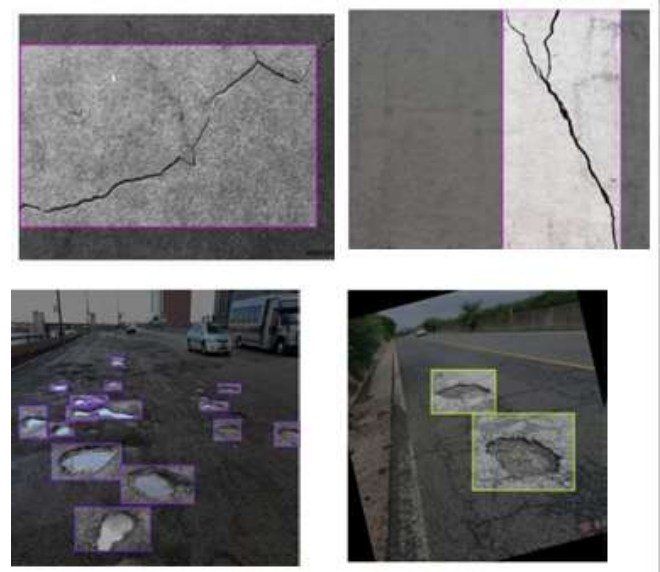


Fig 4.2: Sample Images from Dataset Showing Potholes and Cracks



Fig 4.3: Model Testing on Unseen Image

5. INPUT SCREENS



Fig 5.1 : Final Output Showing Detection, Size and Confidence



6.1 RESULTS

The model was trained using a labeled dataset of road images over multiple epochs. During training the model gradually improved its ability to detect potholes and cracks by minimizing the loss function..

6.1 Detection Results

The trained model was tested on new images to evaluate its performance. The model successfully detected potholes and cracks with bounding boxes and confidence scores.

Explanation The results demonstrate that the model can accurately identify road damages under different conditions. The bounding boxes correctly highlight the damaged regions, and the confidence score indicates the reliability of predictions.

6.2 Performance Evaluation Metrics

The performance of the model is evaluated using standard metrics such as accuracy, precision, recall, and confidence score.

Table 6.1: Performance Metrics

Metric	Value
Accuracy	80%
Precision	70%
Recall	90%
F1-Score	86%

Table 6.2: Sample Detection Confidence Scores

Image	Detected Object	Confidence Score
Image 1	Pothole	0.92
Image 2	Crack	0.88
Image 3	Pothole	0.95

Table 6.3: Dimension Estimation Results

Image	Width (m)	Height (m)
Image 1	0.76	0.49
Image 2	0.20	0.07

6. CONCLUSION:

This project presented a deep learning-based approach for detecting road surface damages such as potholes and cracks using image data. The primary objective was to design and train a model that can accurately identify road damages and evaluate its performance on unseen images without relying on external hardware systems.

The implementation of the YOLOv8 object detection mode demonstrated that deep learning techniques can effectively detect potholes and cracks with good accuracy and reliability. The model was trained using a labeled dataset of road images and successfully tested on new inputs, showing its ability to generalize beyond the training data. The results obtained from the model indicate that it can accurately identify damaged regions and provide confidence scores for each detection. Additionally, the system includes a dimension estimation feature, which provides approximate measurements of pothole size based on bounding box analysis. This adds practical value to the model by offering more than just detection.

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