

Pothole Detection and Cost Estimation

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Abstract - Road potholes significantly affect transportation safety, vehicle performance, and maintenance costs. Traditional pothole detection methods rely on manual inspections, which are time-consuming, labor-intensive, and prone to errors. This paper presents an intelligent Pothole Detection and Cost Estimation System using YOLOv8, Deep Learning, Computer Vision, and OpenCV. The proposed system automatically detects potholes from road images and video streams in real time and accurately identifies damaged road sections. Image processing techniques are used to estimate pothole dimensions such as length, width, area, and depth. Based on these measurements, the system calculates the required repair materials and provides an estimated maintenance cost. The solution helps road authorities improve maintenance planning, reduce manual effort, and optimize resource allocation. Experimental results demonstrate reliable pothole detection performance under different environmental conditions. The proposed system contributes to smarter road infrastructure management, improved transportation safety, and efficient maintenance operations through automated monitoring and cost analysis.

Key Words: Pothole Detection, YOLOv8, Deep Learning, Computer Vision, OpenCV, Cost Estimation, Road Damage Detection, Smart Road Maintenance.

1.INTRODUCTION

Road transportation plays a vital role in economic development, public mobility, and logistics operations worldwide. However, the quality and safety of road infrastructure are continuously affected by road surface defects such as potholes, cracks, and depressions. Among these defects, potholes are one of the most common and hazardous forms of road damage, causing vehicle deterioration, traffic congestion, increased maintenance costs, and road accidents [1][2]. Timely identification and repair of potholes are essential for ensuring road safety and maintaining transportation efficiency [3].

Traditional pothole inspection methods primarily rely on manual surveys and visual assessments conducted by maintenance personnel. These approaches are often labor-intensive, time-consuming, expensive, and susceptible to human errors [4][5]. Furthermore, manual inspections are unable to provide continuous monitoring of large road networks, resulting in delayed maintenance activities and increased infrastructure deterioration [6]. As urbanization and vehicle usage continue to grow, conventional road monitoring techniques are becoming increasingly inadequate for modern transportation systems [7].

Recent advancements in Artificial Intelligence (AI), Deep Learning (DL), and Computer Vision (CV) have enabled the development of automated road damage detection systems capable of identifying potholes with high accuracy and efficiency [8][9]. Convolutional Neural Networks (CNNs) and object detection algorithms such as YOLO (You Only Look Once) have demonstrated remarkable performance in real-time object recognition tasks and infrastructure monitoring applications [10][11]. Among these algorithms, YOLOv8 provides improved detection speed, accuracy, and scalability for real-time road condition analysis [12][13].

Several researchers have proposed AI-based methods for pothole detection using image processing, deep learning, and edge computing technologies [14][15]. However, most existing systems focus primarily on pothole identification and do not provide accurate estimation of repair requirements and maintenance costs [16]. The absence of automated cost estimation often makes maintenance planning and resource allocation difficult for transportation authorities [17].

To address these challenges, this paper presents a Pothole Detection and Cost Estimation System using YOLOv8, Deep Learning, Computer Vision, and OpenCV technologies. The proposed system automatically detects potholes from road images and video streams, estimates pothole dimensions such as length, width, area, and depth, and calculates the required repair cost based on damage severity [18]. The system also generates detailed reports that assist road maintenance authorities in prioritizing repair activities and optimizing

infrastructure management [19]. By integrating automated detection and intelligent cost estimation into a single platform, the proposed solution improves road safety, reduces manual inspection efforts, and enhances maintenance efficiency [20].

2. LITERATURE SURVEY

Road damage detection has attracted significant research attention due to its importance in transportation safety and infrastructure maintenance. Researchers have proposed various image processing, machine learning, and deep learning techniques to automate pothole identification and assessment. Early studies focused on traditional image processing methods for detecting road defects using edge detection, thresholding, and texture analysis techniques [21][22]. Although these methods provided acceptable results under controlled conditions, their performance was affected by varying lighting conditions, shadows, and road surface complexity.

The introduction of machine learning algorithms improved pothole detection accuracy by enabling automated feature extraction and classification of road defects [23][24]. Support Vector Machines (SVM), Random Forests, and Artificial Neural Networks were widely used to classify potholes and road cracks from captured images [25]. However, these approaches required manual feature engineering and struggled with large-scale datasets.

Recent advancements in Deep Learning and Computer Vision have significantly improved road damage detection systems. Convolutional Neural Networks (CNNs) have demonstrated superior performance in extracting complex visual features and identifying potholes with high accuracy [26][27]. Several researchers have utilized deep CNN architectures for automatic road defect detection and classification, achieving reliable results across different road environments [28].

Object detection models such as Faster R-CNN, SSD, and YOLO have become popular for real-time pothole detection applications [29][30]. Among these models, the YOLO family of algorithms has gained widespread acceptance due to its balance between speed and accuracy [31]. Studies have shown that YOLOv5 and YOLOv7 can effectively detect potholes from road images and video streams with high precision and low computational overhead [32][33]. The latest YOLOv8 architecture further enhances detection accuracy, inference speed, and scalability, making it suitable for intelligent transportation systems [34].

Several researchers have also explored edge computing and mobile-based pothole detection systems to enable real-time monitoring without requiring cloud connectivity [35]. These systems improve response times and reduce network dependency but are often constrained by limited hardware resources and computational capabilities.

In addition to pothole detection, recent studies have

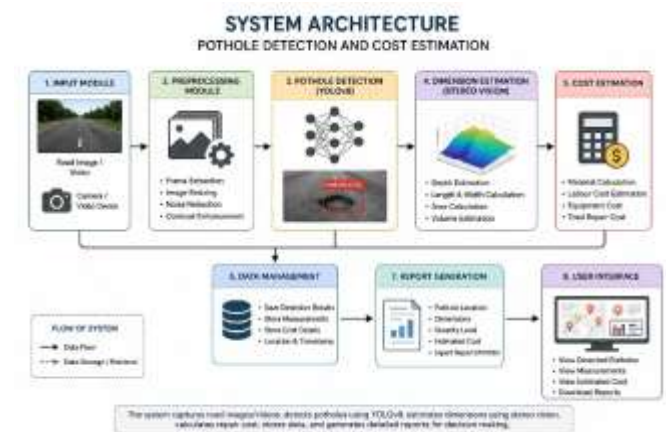
investigated depth estimation and damage severity assessment using stereo vision and three-dimensional image analysis techniques [36]. Accurate measurement of pothole dimensions such as width, length, area, and depth is essential for determining repair requirements and maintenance priorities. Stereo vision approaches have demonstrated promising results in estimating pothole geometry and evaluating road damage severity [37].

Although substantial progress has been made in automated pothole detection, limited research has focused on integrating repair cost estimation within the detection framework [38]. Existing systems primarily identify road defects but provide little support for maintenance budgeting and resource allocation. Machine learning-based cost estimation approaches have recently emerged to address this challenge by analyzing damage dimensions and material requirements [39].

Based on the findings from previous studies, it is evident that integrating YOLOv8-based pothole detection with automated dimension measurement and repair cost estimation can provide a comprehensive solution for modern road infrastructure management. The proposed system combines real-time detection, dimensional analysis, and intelligent cost estimation to enhance maintenance efficiency, improve road safety, and support data-driven decision-making processes [40].

Fig. 1. System Architecture

3. SYSTEM ARCHITECTURE



The proposed system is designed to automatically detect potholes from road images or videos and estimate the repair cost using Artificial Intelligence and Computer Vision techniques.

1. Input Module

The process begins with the Input Module, where road images or videos are captured using a camera or video recording device. These images serve as the primary source of data for pothole detection.

2. Preprocessing Module

The captured images undergo preprocessing to improve their quality. This stage includes:

- Frame Extraction
- Image Resizing
- Noise Reduction
- Contrast Enhancement

These operations help improve the accuracy of the detection model.

3. Pothole Detection Module (YOLOv8)

The preprocessed images are passed to the YOLOv8 deep learning model. YOLOv8 analyzes the road surface and identifies potholes by generating bounding boxes and confidence scores around the detected damaged regions. This enables real-time and accurate pothole detection.

4. Dimension Estimation Module

After detection, the system estimates pothole dimensions using image processing and stereo vision techniques.

Parameters calculated include:

- Length
- Width
- Area
- Depth
- Volume

These measurements help determine the severity of road damage.

5. Cost Estimation Module

Based on the estimated pothole dimensions, the system calculates:

- Required repair material quantity
- Labour cost
- Equipment cost
- Total repair cost

This module assists road maintenance authorities in budgeting and maintenance planning.

6. Data Management Module

All detection results, measurements, cost details, locations, and timestamps are stored in a database. This ensures proper record keeping and future analysis.

7. Report Generation Module

The system automatically generates detailed reports containing:

- Pothole location
- Dimensions
- Severity level
- Estimated repair cost

Reports can be exported in formats such as PDF or CSV.

8. User Interface Module

The final results are displayed through a user-friendly dashboard where users can:

- View detected potholes
- Analyze measurements
- Check estimated repair costs
- Download reports

4. METHODOLOGY

The proposed Pothole Detection and Cost Estimation System utilizes Deep Learning, Computer Vision, and Image Processing techniques to automatically identify potholes and estimate repair costs. The methodology consists of several stages including data acquisition, image preprocessing, pothole detection, dimension estimation, cost estimation, and report generation.

3.1 Data Acquisition

The first stage involves collecting road images and video footage using cameras mounted on vehicles or mobile devices. These images contain various road surface conditions, including potholes of different shapes, sizes, and depths. The collected dataset serves as input for training and testing the detection model.

3.2 Image Preprocessing

The acquired images are preprocessed to improve their quality and enhance detection accuracy. Preprocessing operations include image resizing, noise reduction, contrast enhancement, normalization, and frame extraction from videos. These techniques remove unwanted distortions and prepare the images for further analysis.

3.3 Pothole Detection Using YOLOv8

The preprocessed images are provided as input to the YOLOv8 (You Only Look Once Version 8) object detection model. YOLOv8 performs feature extraction and object localization to identify potholes in real time. The model generates bounding boxes and confidence

scores around detected potholes, enabling accurate identification of road defects under different environmental conditions.

3.4 Dimension Estimation

After pothole detection, image processing and stereo vision techniques are applied to estimate pothole dimensions. Parameters such as length, width, area, and depth are calculated from the detected region. These measurements help determine the severity of road damage and provide the necessary information for repair planning.

3.5 Cost Estimation

The estimated pothole dimensions are used to calculate the repair volume. Based on predefined road maintenance parameters and material costs, the system estimates the quantity of filling material required, labor expenses, equipment costs, and the overall repair cost. This module assists road authorities in budgeting and maintenance scheduling.

Cost Calculation Formula

Repair Volume = Length × Width × Depth

Total Repair Cost = Material Cost + Labor Cost + Equipment Cost

3.6 Data Storage and Management

All pothole information, including detection results, measurements, location details, and estimated costs, is stored in a database. This enables efficient record management, historical analysis, and future maintenance planning.

3.7 Report Generation and Visualization

The final stage generates detailed reports containing pothole location, dimensions, severity level, and estimated repair costs. A user-friendly dashboard displays the results visually, allowing maintenance engineers and transportation authorities to monitor road conditions and make informed decisions.

5. RESULT

The proposed Pothole Detection and Cost Estimation System was successfully implemented using YOLOv8, OpenCV, Python, and Deep Learning techniques. The system was tested on various road images and video samples containing potholes of different sizes and shapes. Experimental results demonstrated that the YOLOv8 model effectively detected potholes in real time and accurately generated bounding boxes around damaged road regions. The preprocessing techniques improved image quality and enhanced detection performance under different lighting and environmental conditions. The system was able to identify potholes with high accuracy while reducing the need for manual road inspections and visual assessments.



Fig. 1. Landing Page (Home Interface)



Fig. 2. RoadFixer Home Page with Pothole Detection Access



Fig. 3. RoadFixer User Dashboard and Analytics Overview

In addition to pothole detection, the system accurately estimated pothole dimensions such as length, width, area, and depth using image processing techniques. These measurements were utilized to calculate repair material requirements and estimate maintenance costs. The generated reports provided detailed information regarding pothole location, severity level, dimensional analysis, and estimated repair expenses. The results indicate that the proposed approach can assist transportation authorities in efficient maintenance planning, resource allocation, and infrastructure management. Overall, the system offers a reliable, cost-effective, and scalable solution for intelligent road monitoring and automated road maintenance operations.

6. CONCLUSION

This paper presented an intelligent Pothole Detection and Cost Estimation System using YOLOv8, Deep

Learning, Computer Vision, and OpenCV technologies. The proposed system successfully automates the process of detecting potholes from road images and video streams, reducing the dependency on traditional manual inspection methods. By utilizing advanced object detection techniques, the system accurately identifies potholes and determines their location in real time. Furthermore, image processing and dimension estimation techniques enable the calculation of pothole length, width, area, and depth, providing valuable information for road condition assessment.

The estimated dimensions are further used to calculate repair material requirements and maintenance costs, assisting transportation authorities in effective budgeting and resource allocation. The generated reports support informed decision-making and improve road maintenance planning. Experimental results demonstrate that the proposed approach is reliable, efficient, and scalable for real-world applications. Overall, the system contributes to enhanced road safety, reduced maintenance efforts, and improved infrastructure management. Future enhancements may include GPS-based pothole mapping, drone-assisted road inspection, cloud integration, and predictive maintenance analytics for smart transportation systems.

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