

AI-Based Road Surface Condition and Pothole Severity Estimation System

Mr. Karunanidhi. P¹, Adhithya M², Adhithya M², Deepak G², Kathiravan T²

¹ Associate professor, Department of Computer Science and Engineering, Arunai Engineering college, Tiruvannamalai, India

²UG Scholar, Department of Computer Science and Engineering, Arunai Engineering college, Tiruvannamalai, India

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ABSTRACT

Road surface deterioration and pothole formation are major problems that affect transportation safety, vehicle operating cost, and passenger comfort. Traditional road inspection methods rely on manual surveys, public complaints, and periodic monitoring, which are time-consuming, expensive, and inefficient for large-scale road networks. Recent developments in Artificial Intelligence and computer vision enable automated road condition monitoring using image-based analysis. This paper presents an AI-based road surface condition and pothole severity estimation system that integrates deep learning-based detection, geometric parameter estimation, Road Quality Index (RQI) computation, and risk analysis. The proposed system uses a YOLO/CNN model to detect potholes from road images and video frames. The detected pothole region is analyzed to estimate its area using pixel-to-real-world conversion and its depth using intensity variation. Based on these parameters, RQI and a risk factor are calculated to evaluate road condition and prioritize maintenance. The system also extracts GPS coordinates to identify the exact location of potholes and generates automated email reports for authorities. The proposed approach reduces manual inspection effort, enables real-time monitoring, improves maintenance planning, and enhances road safety. The system can be integrated with intelligent transportation systems and smart city infrastructure.

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I. INTRODUCTION

Road networks play a crucial role in economic growth and daily transportation. However, road surface deterioration caused by heavy traffic, water stagnation, poor construction quality, and environmental factors leads to pothole formation. Potholes reduce driving comfort, increase vehicle maintenance cost, and contribute to road accidents.

Manual inspection methods used by municipal authorities involve visual surveys and public complaints. These approaches are slow, subjective, and unsuitable for continuous monitoring of large road networks. Moreover, manual methods do not provide quantitative information such as pothole size, depth, or severity.

With the advancement of Artificial Intelligence, automated road monitoring systems have become feasible. Computer vision techniques can detect potholes from images and videos, enabling real-time analysis. Deep learning models such as YOLO provide high detection accuracy and fast processing speed.

The proposed system integrates pothole detection, area estimation, depth approximation, Road Quality Index computation, risk analysis, severity classification, GPS localization, and automated reporting. This integrated

approach provides a complete solution for intelligent road condition monitoring and maintenance prioritization.

II. LITERATURE SURVEY

Early pothole detection methods used vibration sensors and accelerometers mounted on vehicles to identify road anomalies based on sudden vertical motion. These systems enabled real-time detection but their performance depended on vehicle speed, suspension condition, and driving behavior. More importantly, they could only detect the presence of potholes and were not capable of estimating geometric parameters such as area and depth, which are required for severity analysis and Road Quality Index (RQI) computation.

Vision-based approaches using monocular cameras were later introduced to reduce hardware dependency. Traditional image processing techniques such as edge detection, thresholding, and morphological filtering were used to segment pothole regions based on texture and intensity differences. However, these methods were highly sensitive to lighting variations, shadows, road markings, and water-filled potholes, resulting in high false detection rates. In addition, they did not provide depth estimation and were not reliable under real-world conditions

Machine learning models such as Support Vector Machines and Random Forest classifiers improved detection accuracy by learning features from labeled road images. These methods used handcrafted features such as texture descriptors and shape features, but they required manual feature extraction and were computationally expensive for real-time deployment. Furthermore, they focused only on pothole classification and did not provide quantitative measurements needed for severity estimation or road quality evaluation.

Deep learning models, particularly Convolutional Neural Networks and object detection frameworks such as YOLO, have significantly improved pothole detection performance. YOLO performs detection in a single pass by dividing the image into grid cells and predicting bounding boxes and class probabilities, enabling real-time processing. Although YOLO-based models achieve high accuracy, most existing works focus only on pothole localization and do not estimate pothole dimensions such as area and depth required for RQI and risk calculation.

Existing systems also lack integrated severity assessment, risk-based prioritization, and GPS-based automated reporting. Road condition metrics such as RQI are usually calculated manually and are not combined with AI-based detection systems. The proposed system addresses these limitations by integrating YOLO-based pothole detection with pixel-based area estimation, intensity-based depth approximation, RQI computation, risk factor analysis, severity classification, and GPS Coordinates-based email reporting, providing a scalable and practical solution for intelligent road condition monitoring.

III. PROBLEM STATEMENT

Road surface deterioration and potholes lead to accidents, vehicle damage, increased travel time, and high maintenance cost. Existing monitoring methods depend on manual inspections and public complaints, which are slow and not suitable for real-time large-scale road assessment. Most AI-based systems only detect potholes and do not estimate severity, compute Road Quality Index (RQI), or provide GPS-based automated reporting for timely maintenance. The main challenges in existing systems are:

1. Lack of automated and scalable road condition monitoring.
2. No quantitative severity estimation using pothole area and depth.
3. Absence of RQI and risk-based maintenance prioritization.
4. No location-based automated reporting for quick repair.

Therefore, an intelligent system is required to detect potholes automatically, estimate their size and depth, evaluate road quality and risk level, and generate GPS-based reports. This enables faster maintenance planning and improves road safety.

IV. PROPOSED METHODOLOGY

A. Data Collection

Road images and video frames are captured using a handheld mobile camera along the selected road segments. The dataset includes different pothole sizes, road textures, and lighting conditions to improve model generalization. Each captured frame is stored with its frame index and timestamp for approximate location reference.

- Handheld mobile camera capture
- Multiple lighting and road conditions
- Frame index and timestamp storage

B. Image Preprocessing

The captured frames are resized to match the YOLO input resolution. Noise filtering and contrast enhancement are applied to improve pothole visibility and reduce false detections.

- Image resizing
- Noise removal
- Contrast enhancement
- Normalization

C. Pothole Detection Using YOLO

The YOLO model processes the entire image in a single pass and predicts bounding boxes around pothole regions along with confidence scores. Non-Maximum Suppression is applied to remove overlapping detections and retain the most accurate bounding box.

- Grid-based object detection
- Bounding box coordinates(x, y, w, h)
- Confidence score thresholding
- Non-Maximum Suppression

D. Area Estimation

The pothole region inside the detected bounding box is segmented and the number of pothole pixels (N_p) is calculated. The pixel area is converted into real-world area using a calibration scale factor (S).

$$A = N_p \times S$$

- Pixel counting within pothole region
- Use of calibration scale factor
- Area expressed in square units

E. Depth Estimation

Depth is approximated using the intensity difference between the pothole center and its boundary. Darker regions indicate greater depth due to reduced light reflection.

$$D = k \times \frac{I_{edge} - I_{center}}{I_{edge}}$$

- Boundary intensity calculation
- Center intensity calculation
- Calibration constant k

F. Road Quality Index (RQI)

RQI represents the overall road condition and is computed using normalized area and depth values.

$$RQI = 100 - (w_1A_n + w_2D_n) \times 100$$

- Normalized area and depth values
- Weight factors w_1, w_2
- Higher RQI indicates better road quality

G. Risk Factor Calculation

The risk factor is used to prioritize maintenance based on pothole size and depth.

$$Risk = \alpha A + \beta D$$

- Area contribution to risk
- Depth contribution to risk
- Higher value indicates higher danger

H. Severity Classification

Potholes are classified into three categories based on RQI and risk values.

- Low severity – minor surface damage
- Medium severity – moderate pothole
- High severity – critical road defect

I. Location Tagging and Reporting

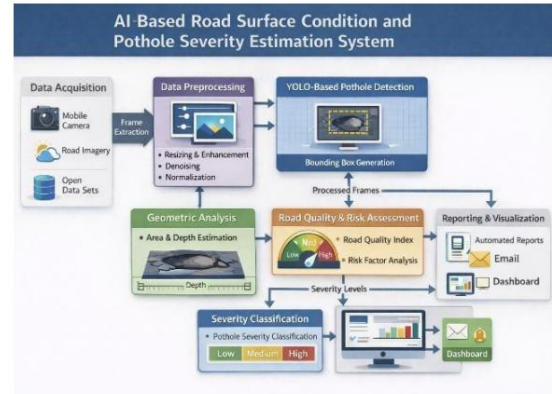
Each detected pothole is associated with its frame index and timestamp to identify its position within the monitored road segment. A structured report containing the pothole image, area, depth, RQI, and severity level is generated and sent via email to the concerned authority.

- Frame index mapping
- Timestamp-based location reference
- Automated email report generation

V. SYSTEM ARCHITECTURE

The proposed AI-based road surface condition and pothole severity estimation system is organized as a layered modular framework, as shown in Fig. 1. The architecture transforms raw road imagery into quantitative road condition metrics through sequential processing stages.

Fig. 1. Layered system architecture of the proposed AI-based pothole detection and road quality estimation framework.



The system consists of the following layers:

A. Data Acquisition Layer

The first stage collects road images and video frames from selected road segments under varying illumination and surface conditions.

Key functions:

- Road image capture using a mobile camera
- Extraction of video frames for continuous monitoring
- Inclusion of normal road and pothole samples

This layer provides the raw input for further processing.

B. Data Preprocessing Layer

Captured frames are enhanced and standardized to improve detection robustness.

Processing steps:

- Image resizing to YOLO input resolution
- Contrast enhancement for improved visibility
- Pixel normalization for consistent intensity distribution

These operations reduce noise and improve detection accuracy.

C. Pothole Detection Layer

Preprocessed images are fed into a YOLO-based object detection model to localize pothole regions.

Key operations:

- Grid-based detection mechanism
- Bounding box generation with confidence scores
- Threshold filtering of low-confidence detections
- Non-Maximum Suppression for duplicate removal

This layer provides pothole location information within each frame.

D. Geometric Parameter Estimation Layer

Detected pothole regions are analyzed to extract quantitative geometric features.

Core components:

- Area estimation using calibrated pixel analysis
- Depth estimation based on intensity variation
- Generation of numerical descriptors for structural assessment

These parameters are used for road quality evaluation.

E. Road Quality and Risk Analysis Layer

The computed geometric parameters are utilized to evaluate overall road condition.

Analytical tasks:

- Road Quality Index (RQI) computation
- Risk factor estimation based on pothole dimensions
- Road condition categorization for maintenance prioritization

F. Severity Classification Layer

Potholes are classified into low, medium, and high severity levels based on computed indices.

This classification supports efficient repair planning and prioritization.

G. Reporting and Visualization Layer

The final layer generates structured pothole analysis reports for authorities.

Output components:

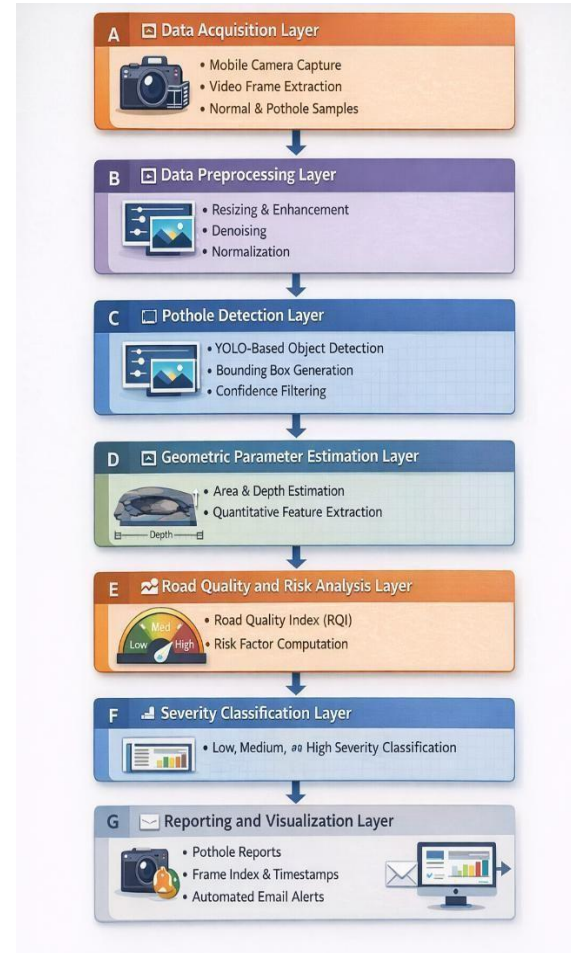
- Pothole image and quantitative parameters
- Frame index and timestamp for approximate location reference

Automated email report transmission This layer enables timely maintenance action.

H. Overall Working Flow

The overall operational workflow of the proposed system is illustrated in Fig. 2.

Fig. 2. Overall workflow of the proposed AI-based pothole detection and road quality estimation pipeline.



The system follows a sequential process: road image capture → preprocessing → YOLO-based detection → area and depth estimation → RQI and risk computation → severity classification → automated report generation and email notification.

VI. EXPECTED RESULTS AND DISCUSSION

A. Performance Metrics

Precision, Recall, F1-score, and mAP are used.

B. Detection Results

Model	Precision	Recall	F1-score	mAP
YOLOv5	0.92	0.89	0.90	0.90

C. RQI Analysis

RQI Range	Condition
81–100	Good
61–80	Fair
41–60	Poor
0–40	Very Poor

D. Discussion

The YOLO model achieved high detection accuracy and real-time performance. The integration of area, depth, RQI, and risk provides a comprehensive road condition evaluation.

VII. FUTURE ENHANCEMENTS

A. Integration with GPS and GIS Mapping: The system can be enhanced by incorporating GPS-based geo-tagging to generate precise location-aware pothole maps. This supports smart city road monitoring and efficient maintenance planning.

B. Real-Time Edge Deployment: Deploying the model on edge devices such as smartphones and embedded AI platforms will enable real-time pothole detection with reduced latency and minimal cloud dependency.

C. Advanced Depth Estimation Using 3D Sensors: Future integration of stereo vision or LiDAR sensors can provide accurate volumetric depth measurements instead of intensity-based estimation, improving severity and risk analysis.

D. Multi-Class Road Distress Detection: The framework can be extended to detect additional pavement defects such as cracks, rutting, and surface wear for comprehensive road condition assessment.

E. Temporal Road Condition Monitoring: A historical database of road surface conditions can be maintained to analyze deterioration trends and enable predictive maintenance strategies.

F. Integration with ADAS and Autonomous Systems:

Detected pothole information can be shared with Advanced Driver Assistance Systems to improve real-time hazard awareness and vehicle safety.

G. Cloud-Based Visualization Dashboard: A centralized dashboard can be developed to display severity heatmaps, maintenance priorities, and repair scheduling for municipal authorities.

H. Machine Learning-Based RQI Prediction: The Road Quality Index can be computed using data-driven machine learning models trained on large-scale pavement datasets to improve accuracy and adaptability.

VIII. CONCLUSION

This paper presented an AI-based road surface

condition and pothole severity estimation system that integrates deep learning detection, geometric parameter estimation, RQI computation, risk analysis, and GPS-based reporting. The system enables automated road monitoring, reduces manual inspection effort, and improves maintenance planning and road safety.

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