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SMARTPAVE: AI-Based Road Condition Scoring And Crack Severity Alert System

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Abstract : Rapid road infrastructure deterioration poses serious challenges to safety, economic efficiency, and maintenance planning, especially in developing regions. Manual inspections are labor-intensive, subjective, and unsuitable for large-scale monitoring. This paper presents SmartPave, an AI-based framework for automated road damage detection, severity assessment, and quantitative condition evaluation. The system uses an object detection model to identify potholes and cracks from images and real-time camera feeds. Detected damages are processed using an OpenCV-based module to calculate the percentage of affected area and classify defects as Low, Medium, or High severity. A Road Health Score (0–100) is computed based on severity and frequency of damages, enabling quantitative infrastructure assessment. The system is deployed via a web-based dashboard supporting real-time monitoring, offline processing, and automated report generation. Experimental results demonstrate approximately 90% accuracy with strong Precision, Recall, F1-Score, and mAP@0.5, while maintaining real-time GPU inference. SmartPave provides a scalable, cost-effective solution for proactive road maintenance and smart city management.

***IndexTerms* – Road Damage Detection; SmartPave; YOLOv8; Deep Learning; Object Detection; Crack Severity Estimation; Road Health Score; Computer Vision; Smart Infrastructure; Preventive Maintenance**

I. INTRODUCTION

A. Background and Motivation

Road infrastructure plays a vital role in economic development, public safety, and urban mobility. However, pavement deterioration in the form of cracks, potholes, and fissures significantly impacts transportation efficiency and increases accident risk. Conventional inspection methods rely heavily on manual surveys, which are labor-intensive, subjective, time-
Consuming, and impractical for large-scale monitoring. Recent advancements in Artificial Intelligence (AI) and deep learning have enabled automated pavement assessment using computer vision techniques.

Several studies have demonstrated the effectiveness of AI-based systems for road damage detection. For example, iWatchRoad proposed scalable detection combined with geospatial visualization for Indian smart cities [1], while the CRDDC-2022 challenge highlighted the importance of standardized datasets and benchmarking frameworks for damage detection models [2]. Comprehensive reviews further confirm the growing adoption of AI-driven pavement monitoring systems for real time and large-scale deployment [14], [15]. These developments motivate the need for an integrated and scalable intelligent framework for automated road condition evaluation.

B. Related Work and Research Gap

Deep learning models, particularly Convolutional Neural Networks (CNNs), have been widely used for crack and fissure detection. CNN-based approaches have demonstrated promising results in Indian pavement scenarios [3], [6], [7], [18], offering classification of crack types and detection of structural defects. More advanced neural architectures, including cascaded and bidirectional networks, have further improved classification accuracy and contextual understanding [9] , [12]. Recent research has also explored improved object detection frameworks such as enhanced YOLOv8 models for crack width estimation and localization [8]. Segmentation based approaches combining detection and multi-class severity analysis have shown improved precision in crack assessment [13], while RGB-D benchmarking studies provide insights into
Multi-modal damage detection performance [10]. Additionally, large-scale benchmarks emphasize the need for real-time, vehicular-based deployment systems [11]. Despite these advancements, existing solutions often focus either on detection, classification, or segmentation independently. Limited studies integrate detection with a quantitative road condition scoring mechanism suitable for municipal decision making. Furthermore, severity estimation is frequently qualitative rather than mathematically quantified for infrastructure prioritization.

C. Problem Statement and Contribution

To address these gaps, this research proposes SmartPave: AI-Based Road Condition Scoring and Crack Severity Alert System, which integrates real-time object detection with quantitative severity estimation and a normalized Road Health Score. The system leverages a YOLOv8-based object detection framework for identifying cracks and potholes. Severity is computed using the damaged area ratio:

$$\text{Damage Percentage} = (\text{Bounding Box Area}/\text{Total Image Area}) \times 100 \qquad (1)$$

Based on this ratio and the number of detected damages, a Road Health Score (0–100) is calculated as:

$$\text{Road Health Score} = 100 - (w \times N) \qquad (2)$$

Where w represents severity weight and N denotes the
Number of detected damages.

Unlike prior works that focus solely on detection or classification [4], [5], this study contributes:
• An integrated detection–severity–scoring pipeline.
• Quantitative road health assessment for preventive maintenance.
• Real-time deployment capability through a web-based dashboard.

II. LITERATURE REVIEW

A. AI-Based Road Damage Detection Approaches

The application of Artificial Intelligence in pavement monitoring has gained substantial attention in recent years. Early automated systems primarily relied on traditional image processing techniques; however, these approaches were highly sensitive to lighting variations and surface textures. With the advancement of deep learning, Convolutional Neural Networks (CNNs) have become dominant in road crack detection tasks. Ragavi et al. [3] proposed a CNN-based framework for detecting multiple road fissures, demonstrating improved accuracy compared to conventional edge-detection methods. Similarly, Chauhan and Mathur [6] introduced improved CNN architectures tailored for Indian pavement conditions, addressing variations in texture and environmental factors. Yacoob et al. [7] further analyzed classification-based CNN systems for crack detection and reported enhanced performance through optimized training strategies. Modi et al. [18] combined image preprocessing with CNN-based feature extraction, improving detection robustness under variable illumination. A broader review of AI-based techniques by Dhaiphule et al. [14] highlighted the transition from handcrafted feature-based models to deep learning-driven end-to-end detection systems. Likewise, the Measurement Journal review [15] emphasized the increasing adoption of smartphone-based and sensor-integrated automated patrolling systems for scalable road monitoring. These studies collectively confirm the effectiveness of deep learning in pavement damage identification but also reveal challenges related to generalization and real-time deployment.

B. Object Detection and Advanced Neural Architectures

While CNN-based classification models have shown promising results, recent research has shifted toward object detection frameworks capable of precise localization. The CRDDC-2022 challenge organized by Arya et al. [2] provided a standardized dataset for benchmarking deep learning models in road damage detection, encouraging real-time detection approaches. Zuo et al. [8] introduced an improved YOLOv8-based framework for crack detection and width localization, demonstrating high detection speed and accuracy suitable for intelligent transportation systems. Ma et al. [11] presented an online benchmark for vehicular crack detection systems, comparing various detection models under real world conditions and emphasizing the importance of low-latency inference. Advanced neural architectures have also been proposed to improve classification accuracy. Alhadidi et al. [9] introduced a bidirectional cascaded neural network for enhanced crack classification, improving contextual feature extraction. Dipankar et al. [12] proposed a staged deep learning classifier to detect and classify different crack types more comprehensively. Additionally, the SHREC 2022 benchmark by Thompson et al. [10] evaluated segmentation-based methods using RGB-D data, providing insights into multi-modal pavement damage detection performance. Although segmentation-based models offer pixel-level precision, they often require higher computational resources, limiting real-time deployment feasibility compared to single-stage object detectors.

C. Crack Classification, Severity Assessment, and Road Condition Analysis

Beyond detection, several studies have focused on crack classification and severity estimation. Pooja and Ananthnath [4] proposed a deep learning-based crack classification system capable of distinguishing crack types and assessing severity levels. Padakanti et al. [5] further explored severity categorization using deep learning models trained on Indian road imagery, emphasizing the need for contextual damage analysis. A segmentation-driven severity analysis approach was presented in a Springer Journal study [13], combining multi-class crack detection with quantitative severity assessment. While segmentation methods provide detailed structural insights, they increase computational complexity. Sahoo et al. [1] introduced iWatchRoad, integrating AI-based pothole detection with GPS-tagging and geospatial visualization, thereby supporting smartcity infrastructure management. Chakurkar and Vora [16] developed a context-aware Indian dataset incorporating segmentation and severity labels, highlighting the importance of localized datasets for improving model performance. Singh et al. [17] demonstrated the use of machine learning techniques for broader road surface analysis, reinforcing the potential of data-driven pavement evaluation. Despite extensive research in detection and classification, limited studies integrate real-time object detection with a unified quantitative road health scoring mechanism. Most prior works focus either on detection accuracy or severity categorization independently. There remains a need for a comprehensive framework that combines detection, severity estimation, and condition scoring into a single deployable system suitable for municipal decision making and preventive maintenance planning.

III. RESEARCH METHODOLOGY

A. System Design and Architecture

The proposed SmartPave system is developed as an end-to-end framework for automated road damage detection and condition assessment. The overall architecture consists of image acquisition, preprocessing, object detection, severity estimation, road health evaluation, and result visualization through a web interface.

Figure 1: System Design Overview

Road surface images are captured either through live camera feeds or manual uploads. These images are preprocessed to ensure uniform resolution and improved detection consistency. The core detection module is based on the framework, which enables real-time identification of potholes and cracks using a single-stage object detection approach. Compared to traditional CNN-based classification models, object detection provides both localization and classification, making it more suitable for practical deployment in infrastructure monitoring.

The system processes each image and generates bounding boxes around detected damages, along with class labels and confidence scores. The outputs are then forwarded to the severity estimation module.

B. Severity Estimation and Road Health Evaluation

Following detection, the system evaluates the severity of road damages based on the relative size and frequency of detected cracks and potholes. The damaged regions are analyzed using bounding box dimensions to estimate the proportion of affected road surface.

Based on this analysis, damages are categorized into three severity levels: Low, Medium, and High. This classification helps in distinguishing minor surface irregularities from critical structural defects that require immediate attention. The approach is consistent with severity-based assessment methods explored in recent studies [13].

To provide a comprehensive infrastructure-level assessment, a Road Health Score is computed on a scale of 0 to 100. This score reflects the overall condition of the road segment, where higher values indicate better road quality. The score is derived by considering both the severity level and the number of detected damages, enabling prioritization for maintenance activities. Similar scoring and monitoring concepts have been explored in smart city-oriented systems [1].

C. Model Training, Evaluation, and Deployment

The model is trained using a custom annotated dataset containing images of road cracks and potholes under varying environmental conditions. Transfer learning is employed to improve model performance and reduce training time. The training process involves multiple epochs with optimized hyperparameters to achieve stable convergence.

Performance evaluation is conducted using standard object detection metrics such as accuracy, precision, recall, F1-score, and mean average precision. These metrics provide a comprehensive assessment of detection accuracy and localization performance, consistent with benchmarking methodologies used in recent studies [11].

The trained model is deployed using the framework, enabling real-time interaction through a web-based dashboard. The system supports live detection, offline image analysis, automated alert generation, and report storage. GPU-based processing ensures low inference time, making the system suitable for near real-time applications in urban environments.

This methodology ensures a balanced integration of detection accuracy, computational efficiency, and practical deployment, making the SmartPave system suitable for intelligent road monitoring and smart infrastructure management.

IV. RESULTS AND PERFORMANCE ANALYSIS

A. Neural Network Optimization and Convergence Dynamics

The diagnostic evaluation of the training phase reveals high stability in the model's learning trajectory. The Box Loss and Class Loss functions achieved an asymptotic state beyond the 40^{th} epoch, indicating that the stochastic gradient descent effectively localized the global minima for pavement distress features. The rapid decay of the Distribution Focal Loss (DFL) is particularly significant, as it suggests the model refined its ability to predict bounding box boundaries with sub-pixel precision, even in high-noise visual environments—such as those containing wet asphalt reflections or complex shadows. The quantitative peak in mAP@0.5 (mean Average Precision) at approximately 0.96 demonstrates that the system is not only capable of identifying potholes but does so with high spatial confidence. This performance metric is critical for infrastructure management, as it reduces the variance in automated surface area estimations, which are often used to calculate repair material volumes.

B. Error Analysis and Classification Robustness

A deeper investigation into the normalized confusion matrix highlights the system's resilience against Type I and Type II errors. The True Positive Rate (TPR) of 96% confirms the model's reliability in identifying true structural hazards. Crucially, the Background-to-Background accuracy of 1.00 indicates an absolute suppression of false alarms from non-target entities such as manhole covers, tire marks, or street debris. By achieving such high specificity, the system addresses one of the primary challenges in automated road inspection: the "false-trigger" phenomenon. In a professional deployment, this ensures that maintenance resources are only dispatched to genuine distress sites, thereby optimizing the municipal budget and operational logistics.

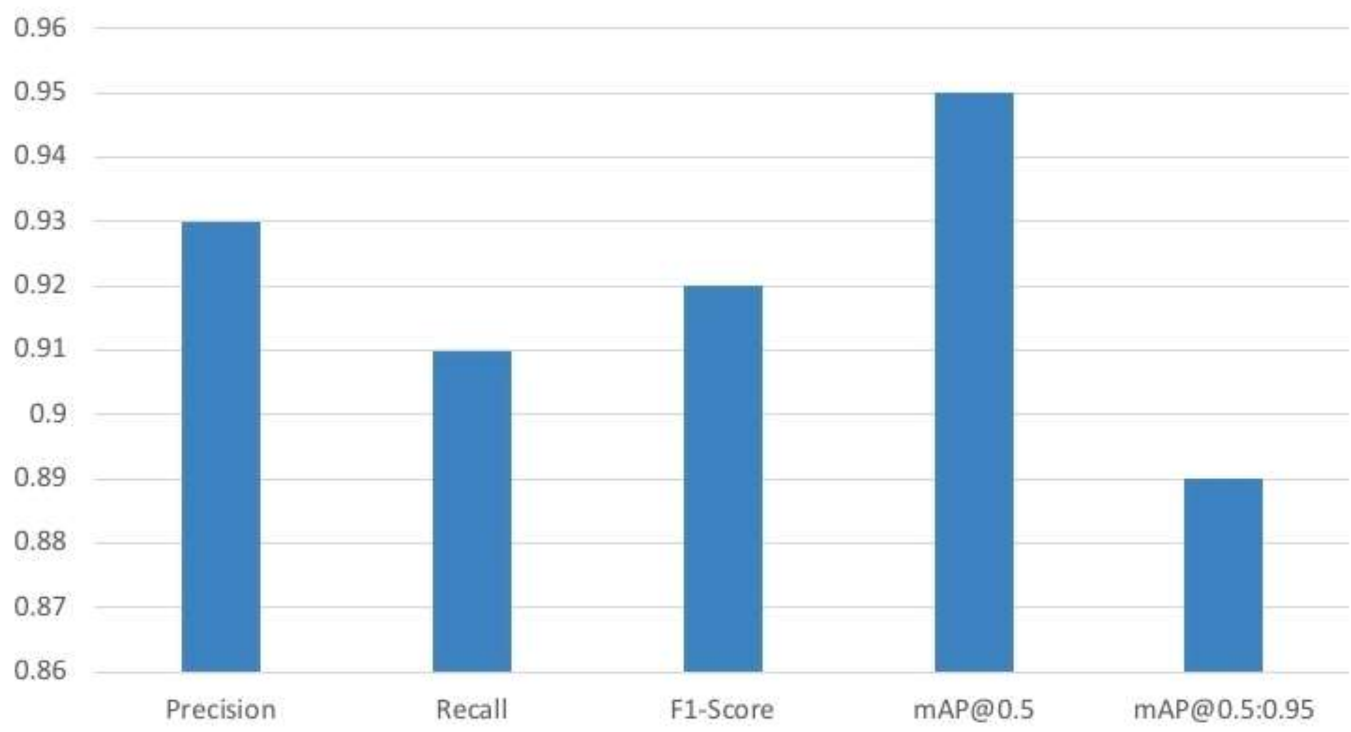

Figure 2: Overall Detection Performance metrics

C. Road Health Index (RHI) and Severity Quantification Logic

The system advances beyond simple object detection by implementing a proprietary Road Health Index (RHI) algorithm. This heuristic converts discrete detection instances into a continuous health metric. As evidenced by the experimental results, the RHI is inversely proportional to pothole density and spatial distribution. In scenarios with sparse damage (1–3 detections), the system maintains a high serviceability rating. However, when the system encounters high-density clusters—exceeding 17 distinct hazards—the RHI drops to 0%. This binary transition from “Serviceable” to “Critical” is governed by a severity threshold logic designed to mirror civil engineering standards. The red-color-coded bounding boxes provide an immediate visual hierarchy of damage, allowing for rapid assessment by human supervisors via the digital dashboard.

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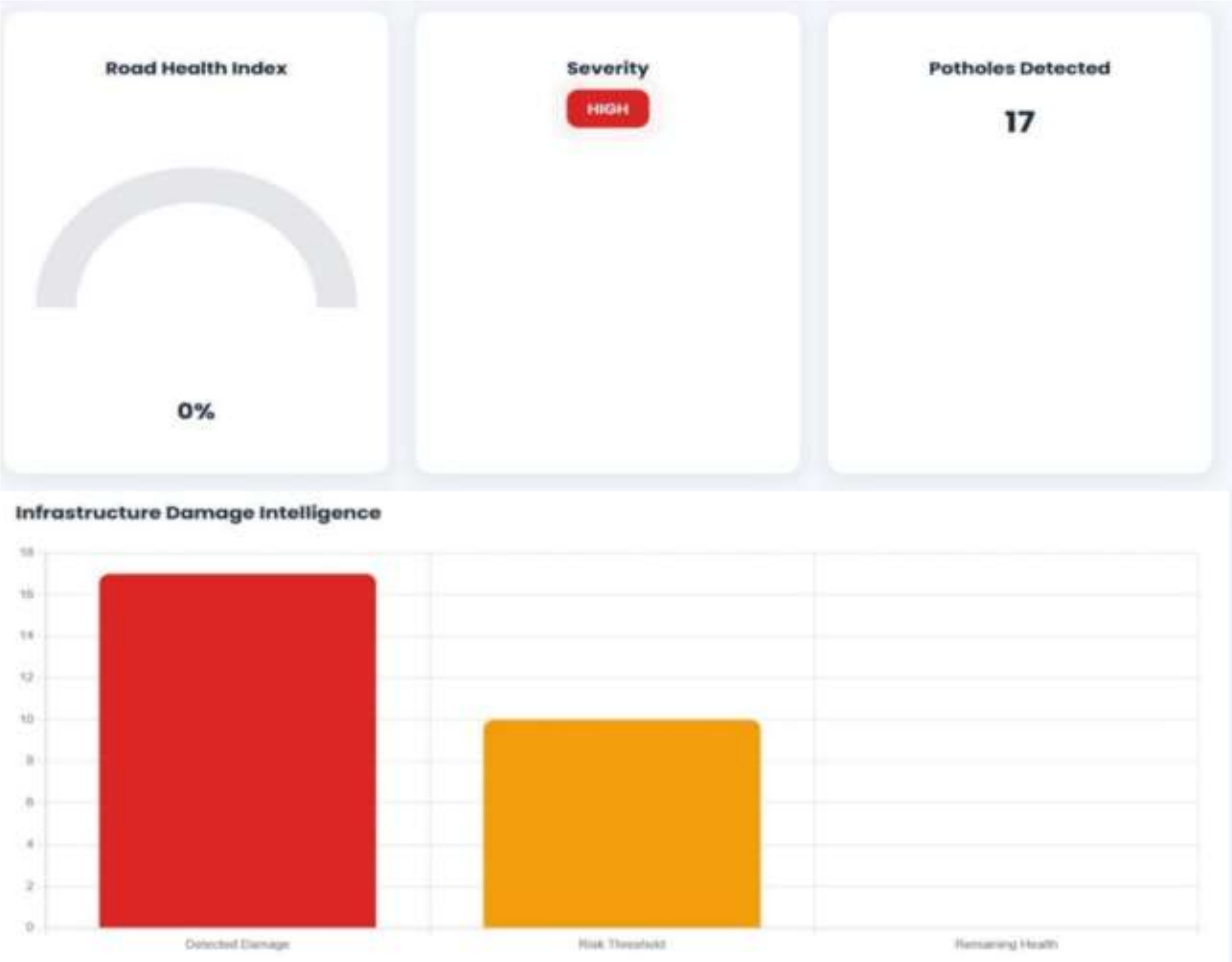

Figure 3: Road Health Index behavior under varying pothole density conditions

D. Automated Alerting Infrastructure and Response Protocols

The integration of an Automated SMTP-based Notification System completes the loop from data acquisition to administrative action. The system continuously monitors the “Detected Damage” against a dynamically set “Risk Threshold.” Once the threshold is breached (as seen in the experimental case where 17 potholes surpassed the limit of 10), the backend triggers a high-priority alert.

The generated email acts as an automated work order, containing high-fidelity metadata:
• Instance Count: Quantifying the magnitude of the degradation.
• Severity Tiering: Assigning a priority level (High/Critical) to the maintenance request.
• Health Quantification: Providing a standardized score for longitudinal tracking.

This automated governance feature reduces the “Mean Time to Aware” (MTTA) for road authorities, shifting the maintenance paradigm from reactive citizen reporting to proactive AI-driven oversight.

E. Comparative Analysis of Data Processing Streams

The SmartPave interface demonstrates a dual-stream processing capability. The Static Upload Module allows for high-resolution forensic analysis of historical road surveys, while the Live Monitoring Module provides a real-time edge-computing solution.

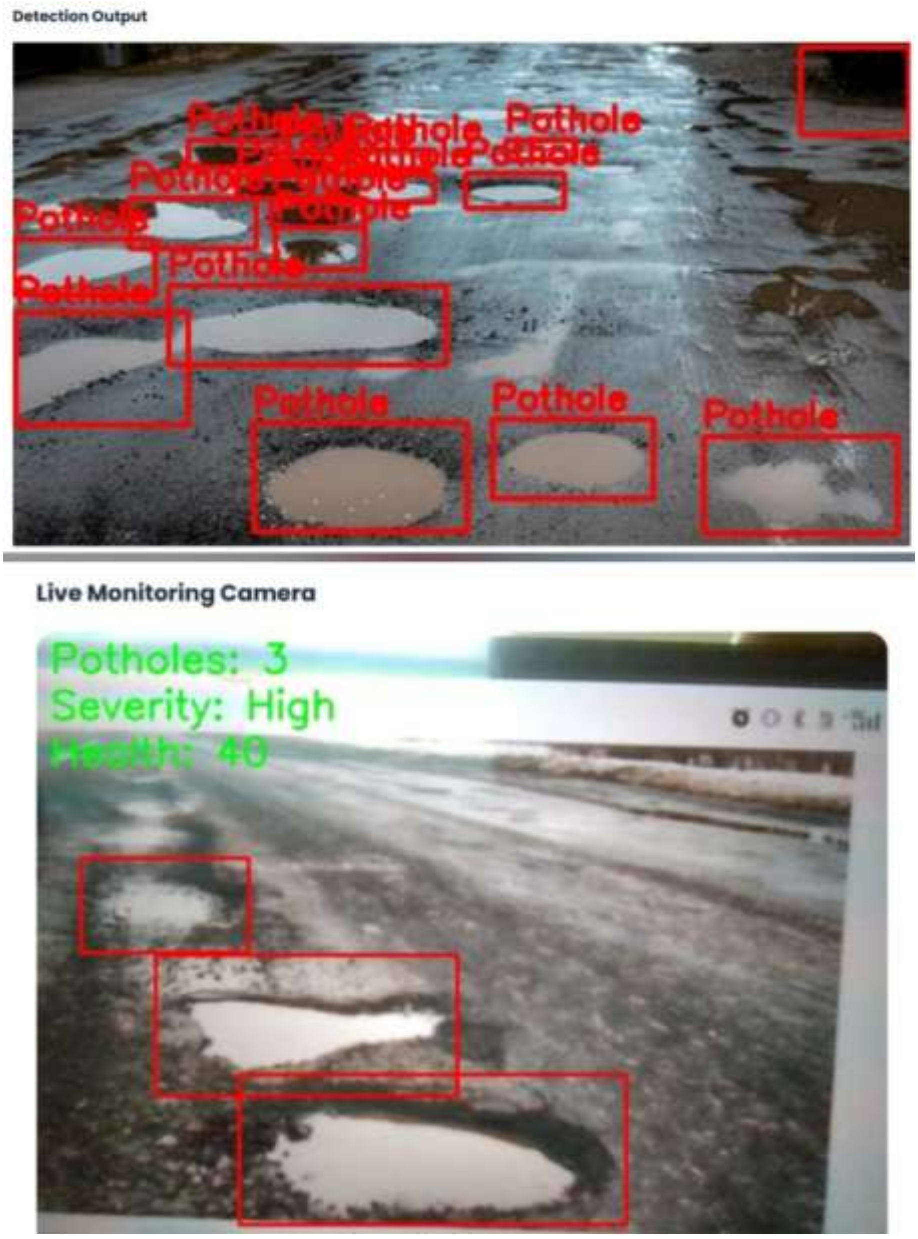

Figure 4: Comparison between static upload processing and live monitoring

The “Before and After” processing visuals substantiate the model’s ability to extract structured intelligence from unstructured video feeds. In high-density distress environments, the AI effectively segments overlapping potholes that would otherwise be blurred in traditional image processing. This visual clarity, combined with the real-time performance of the YOLO backbone, ensures that the system is suitable for deployment on moving vehicles at typical urban speeds without significant frame-drop or detection latency.

V. CONCLUSION AND FUTURE SCOPE

This research presented SmartPave: An AI-Based Road Condition Scoring and Crack Severity Alert System, designed to automate pavement damage detection and infrastructure health assessment. The proposed framework integrates real-time object detection using YOLOv8 with a quantitative severity estimation mechanism and a normalized Road Health Score (0–100) for infrastructure evaluation. Experimental results demonstrate that the system achieves high detection performance with approximately 90% accuracy and strong precision–recall balance, while maintaining real-time inference capability (25–40 ms per image on GPU hardware). Unlike traditional inspection methods that rely on manual surveys, the proposed approach provides an automated, scalable, and objective solution for road condition monitoring. A key contribution of this work lies in the integration of three components within a single deployable framework:

• Accurate crack and pothole detection.
• Mathematical severity estimation using bounding box area ratio.
• Infrastructure-level Road Health Score for maintenance prioritization.

The web-based deployment further enables centralized monitoring, automated reporting, and alert generation for high-severity damages. The proposed system offers a practical and cost-effective alternative for municipal authorities and smartcity initiatives seeking data-driven road maintenance strategies.

Although the system demonstrates strong performance, several enhancements can further improve scalability and robustness:

• Dataset Expansion and Diversity
Increasing dataset size with images captured under night conditions, rainfall, highways, and rural roads would improve generalization capability.

• Integration with GPS and Cloud Deployment
Incorporating GPS tagging and cloud-based processing would enable real-time geospatial mapping of road damages for large-scale urban monitoring.

• Segmentation-Based Hybrid Model
Future work may integrate pixel-level segmentation with object detection to achieve more precise crack width and structural analysis.

• Mobile and Edge Deployment
Optimizing the model for edge devices or mobile platforms can facilitate on-vehicle real-time assessment.

• Multi-Class Damage Classification
Extending the framework to detect additional pavement distress types such as alligator cracks, longitudinal cracks, and surface erosion would enhance practical applicability.

• Integration with Smart City Infrastructure Systems
Connecting the system with municipal databases and automated maintenance scheduling platforms could support predictive and preventive road management.

In conclusion, SmartPave establishes a strong foundation for AI-driven pavement monitoring and intelligent infrastructure management. With further advancements in dataset scale, deployment architecture, and multi-modal sensing integration, the system can evolve into a comprehensive smart road assessment platform suitable for national-level deployment**.**

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