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Comparative Analysis and Performance Enhancement of YOLO Architectures for Real-Time Road Pothole Detection in Infrastructure Surveillance.

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ABSTRACT

Potholes are among the most common road surface defects and pose significant challenges to transportation safety, vehicle maintenance, and infrastructure management. Conventional road inspection methods rely heavily on manual surveys or specialized equipment, which are often time-consuming, costly, and unsuitable for large-scale or real-time monitoring. This paper presents a comparative performance optimization study of multiple YOLO based object detection models for real-time pothole detection in road infrastructure monitoring systems. Various YOLO variants are evaluated using a dataset of road images and video frames collected under diverse environmental and lighting conditions. Detection parameters such as input resolution, confidence threshold, and non-maximum suppression are optimized to enhance accuracy and inference speed. Performance is evaluated using mAP, precision, recall, FPS, and latency. Results highlight trade-offs between accuracy and real-time performance and identify efficient configurations for deployment.

Keywords— Pothole Detection, YOLO, Deep Learning, Real-Time Monitoring, Infrastructure Systems.

INTRODUCTION

Road infrastructure is a fundamental component of modern transportation systems, directly affecting travel safety, mobility efficiency, and economic productivity. Well-maintained road networks enable reliable transportation, reduce vehicle operating costs, and support regional development. However, continuous exposure to heavy traffic loads, environmental stress, temperature fluctuations, and water infiltration gradually deteriorates road surfaces, resulting in structural defects such as potholes, cracks, and surface depressions. Among these defects, potholes are particularly hazardous because they can lead to accidents, damage vehicles, increase fuel consumption, and disrupt traffic flow. Therefore, timely detection and repair of potholes are essential for ensuring safe transportation and efficient infrastructure management.

Conventional road inspection techniques primarily rely on manual surveys or specialized vehicles equipped with sensors and measurement instruments. Although these methods can detect surface defects, they are often labor intensive, costly, and time-consuming, making them impractical for monitoring large-scale road networks. Furthermore, manual inspections are subject to human error, inconsistency, and limited coverage, while sensor based systems require expensive hardware and maintenance. These limitations restrict their effectiveness in modern smart-city environments where continuous and real-time monitoring is required.

Recent advances in artificial intelligence (AI), particularly in deep learning and computer vision, have enabled the development of automated road inspection systems capable of detecting defects directly from visual data. Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in image recognition and object detection tasks due to their ability to learn hierarchical feature representations from raw images. Such models can identify complex patterns and textures associated with road damage, making them highly suitable for infrastructure monitoring applications.

Among modern object detection frameworks, single-stage detectors such as the You Only Look Once (YOLO) family of models have gained widespread popularity because of their ability to perform detection in a single forward pass.

Unlike traditional multi-stage detectors, YOLO-based architectures simultaneously predict bounding boxes and class probabilities, enabling high speed processing with competitive accuracy. This characteristic makes them particularly suitable for real time applications such as intelligent transportation systems, autonomous vehicles, and roadside monitoring platforms.

Despite significant progress in automated pothole detection research, most existing studies focus on a single detection architecture or specific implementation scenario. Comparative analyses evaluating multiple YOLO variants under consistent experimental conditions remain limited. In addition, the trade-off between detection accuracy, computational complexity, and inference speed is often overlooked, even though it plays a crucial role in practical deployment, especially on embedded or edge devices with limited resources.

To address these challenges, this study presents a comprehensive comparative analysis of different YOLO architectures for real-time pothole detection. The proposed approach evaluates models using diverse datasets captured under varying environmental conditions and analyzes performance using standard evaluation metrics such as mean Average Precision (mAP), precision, recall, frames per second (FPS), and inference latency. By optimizing key detection parameters and systematically comparing model configurations, the research aims to identify efficient solutions that balance accuracy and speed, thereby enabling scalable, cost effective, and real-time road infrastructure monitoring systems.

LITERATURE REVIEW

[1] Patel, S., & Sharma, R. (2023): Deep Learning-Based Pothole Detection Using YOLOv5 Patel and Sharma presented a pothole detection framework based on the YOLOv5 object detection model, incorporating image preprocessing techniques to improve robustness under different lighting and weather conditions. Their experimental evaluation showed that the proposed system achieved strong detection accuracy, with high precision and recall, while maintaining real-time processing capability, demonstrating its effectiveness for automated road inspection applications.

[2] Dhanush, K., Reddy, A., & Kumar, P. (2022): Automatic Road Damage Detection Using CNN This work proposed a convolutional neural network– based method for identifying road surface defects, including potholes and cracks. The study demonstrated that deep feature learning significantly outperformed conventional image processing techniques; however, increased computational complexity resulted in higher inference time, limiting the suitability of the approach for real-time deployment.

[3] Lee, J., & Kumar, R. (2023): Real-Time Pothole Detection Using YOLO and Edge Computing Lee and Kumar developed a real-time pothole detection system using a lightweight YOLOv4-tiny model optimized for edge computing platforms. The proposed framework focused on achieving an effective balance between detection accuracy and computational efficiency, enabling reliable real-time performance on resource constrained roadside and in-vehicle hardware.

[4] Gupta, A., & Verma, R. (2022): AI-Powered Road Surface Monitoring Using Drone Imagery Gupta and Verma investigated the use of drone-captured imagery combined with deep learning techniques for large-scale road surface monitoring. Their system enabled wide-area inspection and GPS-based localization of defects; however, the requirement for high-resolution images and substantial computational resources posed challenges for real-time processing.

[5] Kaur, S., Singh, P., & Thakur, R. (2021): Automated Pothole Detection Using Image Processing and Machine Learning This study explored a cost-effective pothole detection approach by integrating traditional image processing techniques with machine learning classifiers such as support vector machines. While the method demonstrated reasonable efficiency, its performance degraded under complex road textures and varying environmental conditions, limiting overall robustness.

[6] Rahman, M., & Das, S. (2022): Vision-Based Autonomous Pothole Detection Using YOLOv4 and GPS Integration Rahman and Das proposed an autonomous pothole detection framework using the YOLOv4 model combined with GPS-based geo-tagging. The system enabled accurate localization of detected potholes, supporting maintenance planning; however, the study focused on a single YOLO variant and did not analyze performance optimization across different architectures.

[7] Lakshmi, B. N., & Ramesh, K. (2023): Pothole Detection and Severity Classification Using DCNN Pothole The authors designed a deep convolutional neural network to classify potholes into different severity levels. Although the model achieved high classification accuracy, its computational complexity resulted in increased inference time, which limited its applicability in real-time road monitoring scenarios.

[8] Nguyen, L., & Chen, H. (2023): Edge AI-Based Real Time Road Anomaly Detection Framework Nguyen and Chen

introduced an edge AI–based framework utilizing lightweight deep learning models for real-time detection of road anomalies. Their findings emphasized the importance of reducing model size and inference latency to enable efficient deployment in smart city and edge computing environments.

[9] Agarwal, T., & Patel, V. (2021): Hybrid Image Processing and Machine Learning Model for Road Defect Detection This research proposed a hybrid detection framework combining image processing techniques with supervised machine learning models. While the approach achieved computational efficiency, it demonstrated limited adaptability and lower accuracy compared to deep learning–based object detection methods.

[10] Wang, X., Zhang, Y., & Liu, Q. (2022): Deep Learning-Driven Road Maintenance System for Smart Cities Wang et al. presented a deep learning–based road maintenance system designed for smart city applications, enabling automated detection and prioritization of road defects. The study highlighted the need for scalable and real-time detection solutions but did not include a comparative evaluation of different YOLO variants.

[11] Zhou, Y., & Lin, J. (2021): Road Damage Detection Using YOLOv4 and Image Segmentation Zhou and Lin combined YOLOv4 with image segmentation techniques to improve the localization accuracy of road damage detection. Although the integration enhanced detection precision, the added segmentation stage increased computational overhead, negatively affecting real-time performance.

[12] Li, F., & Huang, Y. (2020): Road Damage Detection Using Deep Transfer Learning Li and Huang applied transfer learning techniques to enhance road damage detection performance using limited training data. The results demonstrated improved generalization capability; however, the study did not focus on evaluating inference speed or real-time deployment feasibility.

[13] Bhattacharya, P., & Singh, D. (2022): Real-Time Detection of Road Damages Using YOLO This study evaluated YOLO-based detection models for identifying multiple types of road surface defects in real time conditions. The authors emphasized the importance of systematic performance benchmarking to determine suitable models for practical deployment.

[14] Park, S., & Choi, Y. (2023): Deep Learning-Based Pothole Detection from Drone Imagery Park and Choi investigated pothole detection using deep learning models applied to high-resolution drone imagery. While the proposed approach achieved high detection accuracy, processing large image sizes introduced challenges for real-time inference and scalability.

[15] Saini, A., & Kumar, N. (2024): AI-Based Automated Assessment of Road Surface Health Saini and Kumar proposed an AI-driven framework for continuous road surface health assessment using object detection models. The authors identified a lack of comparative analysis among different YOLO variants, highlighting a research gap in performance optimization for real-time road monitoring systems.

OBJECTIVES

The primary aim is to analyze and optimize YOLO variants for real-time pothole detection. The specific objectives include the development of an automated pothole detection system, comparison of the accuracy and speed of YOLO variants, optimization of detection parameters, analysis of performance metrics, analysis of feasibility of deployment, and suggestions for scalable infrastructure monitoring.

The specific objectives of this research are as follows:

1. To develop a deep learning-based framework for automated pothole detection using YOLO object detection models.
2. To compare the performance of various YOLO variants in terms of accuracy, computational complexity, and speed in a controlled experiment setting.
3. To optimize key parameters of the model, such as the resolution of the input image, confidence levels, and non maximum suppression values.
4. To analyze the performance of the system in terms of standard metrics such as mean Average Precision (mAP), precision, recall, frames per second (FPS), and inference time.
5. To analyze the trade-off between accuracy and speed for real-time systems.
6. To analyze the feasibility of deployment of trained models on resource-constrained and edge computing devices.
7. To develop a severity classification system for the detected potholes based on spatial or visual features.
8. To develop geo-tagging or localization support for mapping the detected potholes in monitoring systems.

METHODOLOGY

The proposed system follows a layered architecture consisting of data acquisition, processing, and storage layers. Road data is captured from cameras and video streams, optionally integrated with GPS for localization. Frames are preprocessed and analyzed using YOLO detection models to generate bounding boxes and confidence scores. Detected potholes are classified by severity based on spatial analysis and stored in a centralized database for visualization and reporting.

Challenges and Limitations

When it comes to real-world implementation of automated pothole detection systems, there are some practical issues that may impact the overall performance and reliability of the system. For instance, differences in environmental factors such as light intensity, shadows, rain, fog, and reflections may have a significant impact on the quality of the image, thereby affecting the overall performance and reliability of the system. In addition, differences in road materials, textures, and markings may result in false positives or false negatives, especially if the training data does not cover such variations. Another significant limitation of the current detection system is the trade-off between model complexity and computational complexity. Although more complex models are capable of achieving higher accuracy, they also require more processing power and energy.

RESULTS

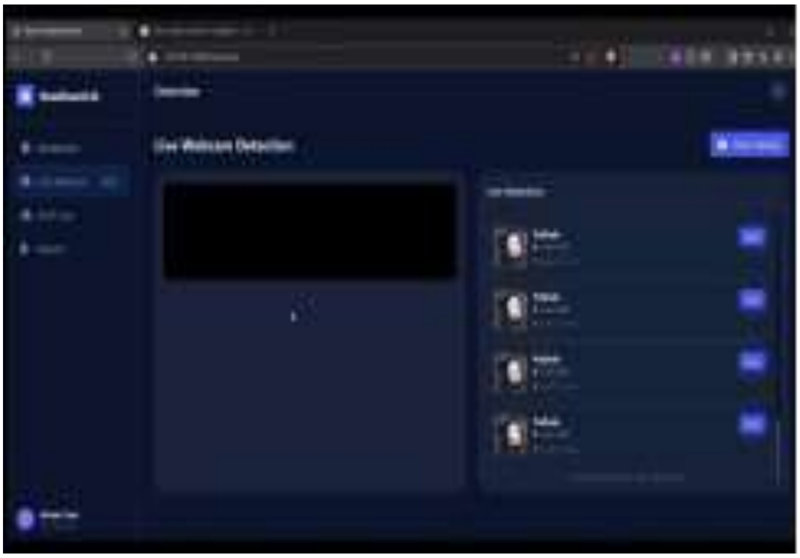

Fig 1: Live webcam-based pothole detection interface

Experimental evaluation demonstrates that optimized YOLO models can detect potholes in real time with high reliability. The system provides confidence scores, severity levels, and geographic coordinates for each detection, enabling automated monitoring and maintenance prioritization.

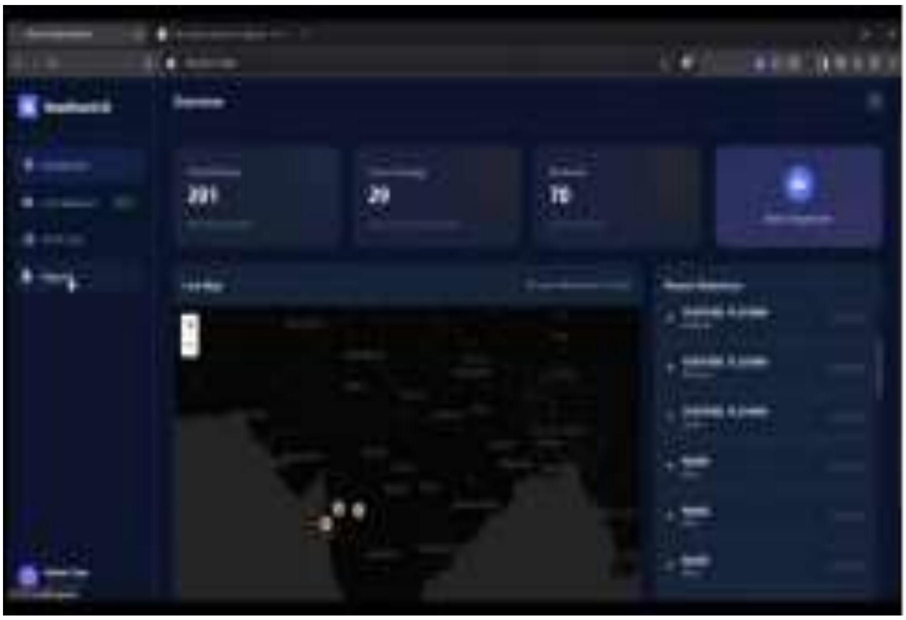

Fig 2: Dashboard view of real-time pothole monitoring system

Fig 3: Sample Output of Real-Time Pothole Detection System

The figure illustrates a representative sample output generated by the proposed real-time pothole detection framework utilizing optimized YOLO variants. It presents automatically detected potholes together with their corresponding severity levels, confidence scores, geographical coordinates, and timestamp information, thereby providing a comprehensive visualization of detection results. Each detected pothole instance is visually highlighted through cropped road-surface image segments extracted from live camera feeds or recorded video streams, enabling clear identification of defect regions within the scene. This visual representation enhances interpretability and assists in verifying detection accuracy under diverse environmental conditions.

The system categorizes potholes into multiple severity classes, such as Minor and Moderate, using an area-based spatial analysis derived from detected bounding box dimensions. This severity estimation mechanism allows authorities to prioritize maintenance operations efficiently by distinguishing critical defects that require immediate attention from less severe surface irregularities. In addition, the confidence score associated with each detection reflects the prediction reliability of the model, providing an indicator of detection certainty and enabling informed decision-making when filtering or validating results.

To further enhance usability, geo-tagging information— including latitude and longitude coordinates—is integrated with every detected instance to ensure precise localization of road defects. This spatial metadata supports region-wise assessment, facilitates mapping based visualization, and enables authorities to monitor infrastructure conditions across different geographic areas. The integration of detection results with mapping platforms also assists in route planning, maintenance scheduling, and long-term infrastructure analysis.

The generated report demonstrates the system's ability to perform automated real-time detection, severity estimation, localization, and structured reporting without requiring manual intervention. Such capabilities highlight the practical applicability of the proposed framework for large-scale deployment in intelligent transportation environments. Overall, the results validate the effectiveness, scalability, and reliability of the system as a smart infrastructure monitoring solution capable of supporting data-driven decision-making for road maintainance authorities.

CONCLUSION

The comparative optimization analysis of YOLO variants for real-time pothole detection in this study has shown that the optimization of parameters such as input resolution, confidence thresholds, and non-maximum suppression parameters can play an important role in improving system performance while maintaining the capability to process in real-time. The selection of suitable model architectures based on application requirements, especially in dynamic road environments, is also important, as indicated by the findings of this study. The proposed framework is therefore scalable, adaptable, and cost-effective for intelligent transportation systems and automated infrastructure monitoring.

Moreover, the designed system has a great potential for implementation in practical scenarios because of its modular design, which can be easily integrated with real time data sources, geo-localization modules, and monitoring systems. The system, which combines automated detection, severity evaluation, and reporting, allows data-driven decision-making for maintenance authorities, reducing manual inspection and improving response time for road repairs. Automation of the process not only improves efficiency but also helps in enhancing road safety and mitigating risks of damage to vehicles.

Future research could be oriented towards enhancing the robustness of the proposed models in extreme weather conditions like heavy rainfall, low lighting, and motion blur. Other areas of improvement could be the incorporation of depth sensing or stereo vision to enhance the accuracy of severity estimation, the optimization of the proposed models for embedded systems, and the augmentation of the training dataset to include various types of roads and geographical locations. Such developments would further enhance the reliability of the systems and help in the widespread implementation of intelligent monitoring systems for smart transportation infrastructure.

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