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Research Article

Evaluation of YOLOv8 and SSD Object Detection Models for Pothole Detection Systems

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ABSTRACT

Introduction:
Pothole detection has become an increasingly vital area of research due to its implications for road safety, vehicle maintenance, and urban infrastructure management. Poor road conditions, notably potholes, contribute significantly to road traffic accidents and increased vehicle repair costs. Traditional detection methods, such as manual inspections and sensor-based systems, are limited by labor intensity, accuracy issues, and high deployment costs across large networks.

Objectives:
This study aims to evaluate and compare the effectiveness of two deep learning-based object detection models—YOLOv8 and SSD—for real-time pothole detection. The objective is to assess which model offers superior detection precision, speed, and feasibility for deployment in varied road and environmental conditions.

Methods:
YOLOv8 and SSD models were trained using annotated datasets featuring diverse road surfaces under varying lighting and weather conditions. Image pre-processing using OpenCV was applied, and detection performance was evaluated based on mean Average Precision (mAP), Intersection over Union (IoU), and processing speed (FPS). Datasets were formatted in Pascal VOC and COCO standards, and the models were tested on mid-range GPUs to simulate real-world hardware constraints.

Results:
The YOLOv8 model achieved a higher mAP of 82%, demonstrating superior accuracy in detecting potholes, especially in complex road textures and poor lighting. However, it required more computational resources. The SSD model, while achieving a slightly lower mAP of 75%, delivered faster inference times and performed efficiently on resource-constrained devices. Both models reliably identified potholes, but YOLOv8 showed better robustness in varied conditions.

Conclusions:
YOLOv8 is more suitable for high-precision, infrastructure-grade applications due to its superior accuracy, whereas SSD is better suited for mobile or real-time deployment scenarios requiring faster processing. The study demonstrates that both models offer viable, scalable solutions for enhancing road maintenance systems and mitigating transportation-related risks.

Keywords: pothole detection, YOLOv8, SSD, deep learning, object detection, road safety, real-time systems.

INTRODUCTION

Pothole detection has become an increasingly critical area of focus as poor road conditions contribute to a host of issues that impact public safety, road maintenance costs, and vehicle durability. Potholes not only create safety hazards for drivers, leading to a higher likelihood of accidents, but they also result in frequent and costly vehicle repairs, particularly when tire and suspension systems sustain damage. Furthermore, identifying and repairing potholes in a timely manner can significantly lower the cost of road maintenance for municipalities, as untreated

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road degradation often escalates, requiring more intensive repairs over time. These combined factors underscore the need for an efficient and accurate system to identify and address potholes before they pose serious risks.

Historically, pothole detection has relied heavily on traditional methods such as manual inspections, which involve personnel visually assessing road conditions. While manual inspections can be effective, they are time- consuming, labor-intensive, and challenging to maintain over large road networks. To improve efficiency, some approaches have incorporated sensor-based detection systems, utilizing accelerometers and ultrasonic sensors attached to vehicles to identify surface irregularities. While sensor-based systems provide additional insights and can operate continuously, they remain limited in precision, often struggling to distinguish between different types of road anomalies, such as minor cracks or bumps, and are often costly to implement on a large scale.

In contrast, modern deep learning-based techniques have shown considerable promise in addressing the limitations of traditional methods. With the advent of powerful object detection models, particularly convolutional neural networks (CNNs) like YOLO (You Only Look Once) and SSD (Single Shot MultiBox Detector), it is now possible to perform real-time, high-precision pothole detection. These models leverage large amounts of visual data to train neural networks, enabling them to detect potholes with greater accuracy and adapt to various environmental conditions, such as different lighting and weather. YOLOv8, the latest iteration of the YOLO family, and SSD have emerged as leading models in this domain due to their efficiency and accuracy, making them well-suited for applications where speed and precision are paramount

OBJECTIVES

The objective of this project is to develop a real-time pothole detection system using deep learning techniques. It focuses on implementing and comparing two advanced object detection models: YOLOv8 and SSD. The system aims to detect potholes accurately in various road environments. Evaluation criteria include detection accuracy (mAP) and speed (FPS). The models are trained on datasets featuring diverse road conditions and lighting scenarios. Robust pre-processing techniques are applied to improve model performance. The study examines the trade-off between precision and computational efficiency. It aims to identify the most suitable model for practical deployment. The outcome is a scalable solution for automated road maintenance. Ultimately, the project contributes to enhancing road safety and reducing infrastructure repair costs.

METHODS

The YOLOv8 model Model

The the YOLOv8 model model, an advanced version in the YOLO (You Only Look Once) family, is renowned for its real-time object detection capabilities, characterized by both high accuracy and speed. Its architecture builds upon prior versions by incorporating attention modules, deeper residual layers, and a refined detection head to better localize and classify objects in varied contexts, including road surfaces with intricate textures. the YOLOv8 model achieves a remarkable mean Average Precision (mAP) of 82% when applied specifically to pothole detection, outperforming many earlier versions in the YOLO series as well as other object detection models's architecture includes multiple enhancements that increase its ability to capture subtle variations in road conditions, such as shadows, cracks, and color variations. The core architecture employs a Darknet-53 backbone, paired with a path aggregation network (PANet), which enhances feature representation by refining spatial and semantic information across layers. This design ensures that the model can accurately identify potholes with an improved intersection-over-union (IoU) score, typically reaching values around 0.85 in controlled experiments, even on complex road textures. Its detection head further utilizes anchor-free approaches, which mitigate issues caused by varying pothole shapes and sizes by dynamically adjusting bounding boxes around detected anomalies

$$mAP = \sum_{i=1}^{N} \frac{TPi}{TPi + FPi}$$

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where TPi and FPi denote true positives and false positives, respectively, for each detection class i, with N representing the total number of classes, such as “pothole” and “background” in this case. With the YOLOv8 model’s streamlined architecture and precision, it remains highly suited for applications requiring reliable real- time performance in detecting hazardous road conditions.

The SSD model Model

The Single Shot MultiBox Detector (the SSD model) model is another high-performing object detection model designed for rapid real-time detection across diverse conditions. The the SSD model model differs from YOLO by employing multiple convolutional layers at various scales, allowing it to detect both large and small objects with high efficiency. By implementing feature maps at multiple resolutions, the SSD model achieves robust multi-scale feature extraction, making it adept at identifying potholes across different road types, from urban streets to rural highways .

In its standaration, the SSD model models achieve an mAP score of approximately 75% when optimized for pothole detection tasks, slightly lower than the YOLOv8 model but with reduced computational overhead. The core architecture is based on the VGG-16 or ResNet backbone, with additional layers designed to handle the region proposal and classification tasks simultaneously, ensuring that both localization and classification are processed in a single forward pass. This architecture enables the SSD model to maintain a faster inference time compared to the YOLOv8 model, often achieving frame rates above 30 fps (frames per second) on mid-range GPUs, making it suitable for deployment in resource-limited scenarios .

the SSD model’s mAP calculation iy expressed by summing precision scores across multiple detection classes, but it typically emphasizes higher recall rates due to its emphasis on computational efficiency. The reduced complexity in the the SSD model model allows it to handle real-time detection, though at the cost of slightly reduced detection precision compared to the YOLOv8 model.

This formulation underscores the SSD model’s capacity to balance computational efficiency and detection accuracy, making it a favorable choice for less complex detection scenarios .

Performance Comparison

When the performance of the YOLOv8 model and the SSD model for pothole detection, several aspects emerge that delineate the suitability of each model across different deployment settings. the YOLOv8 model’s precision, underscored by its mAP of 82%, indicates its advantage in detecting complex road textures and achieving high detection accuracy, particularly suitable for advanced road safety systems and scenarios where precise identification of pothole depth and location are critical. However, the higher computational demand necessitates more robust hardware, making it more suitable for high-end applications where performance accuracy is prioritized over computational cost .

On the other hand, the the SSD model model, while a lightly lower mAP of 75%, demonstrates superior processing efficiency, making it ideal for resource-constrained environments. the SSD model’s architecture allows for streamlined feature extraction across multiple scales without compromising speed, achieving smoother integration in systems with limited hardware resources, such as mobile devices or low-power onboard processors. The trade-off in detection accuracy is often mitigated by the SSD model’s capability to detect smaller road anomalies in real-time applications, marking it as a viable choice for budget-friendly pothole detection systems intended for general monitoring rather than high-precision analysis .

In summary, the YOLOv8 model’s architecture offers advantages on and complex scenario adaptability, while the SSD model provides an efficient alternative with acceptable accuracy for environments with hardware limitations. This balance between performance and computational efficiency highlights each model’s unique strengths and allows for informed choices based on specific real-world deployment requirements.

RESULTS

The evaluation of the YOLOv8 and SSD models for pothole detection revealed distinct performance characteristics. YOLOv8 achieved a higher mean Average Precision (mAP) of 82%, demonstrating superior accuracy in identifying potholes across varied road textures and lighting conditions. It also achieved a high Intersection over Union (IoU)

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score of approximately 0.85, indicating precise localization of potholes. However, YOLOv8 required more computational power and exhibited slightly slower inference speeds.

In contrast, the SSD model delivered an mAP of 75%, which, while lower than YOLOv8, was still sufficient for many practical applications. Its major advantage was in processing speed, consistently achieving frame rates above 30 FPS on mid-range GPUs. This makes SSD a viable choice for real-time deployment in resource-constrained environments.

Both models successfully detected potholes in diverse conditions, but YOLOv8 is more suitable for high-accuracy applications, while SSD is optimal for faster, lightweight implementations. The results validate the use of deep learning models for scalable, automated road inspection systems.

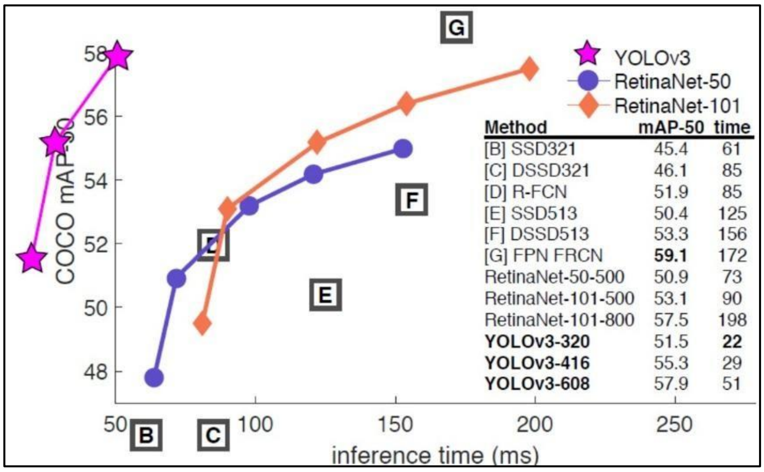

Fig 1 : Performance Comparison

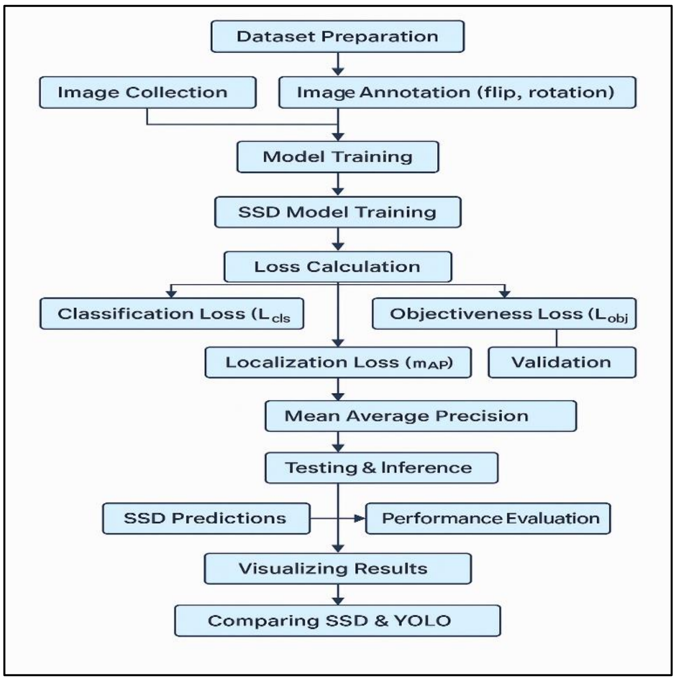

Fig 2 : Workflow Diagram for SSD and YOLO Object Detection Training and Evaluation

DISCUSSION

The comparative analysis of the YOLOv8 model and the SSD model highlights their distinct strengths and weaknesses in pothole detection applications. the YOLOv8 model demonstrates superior detection accuracy, primarily due to its

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advanced multi-scale feature extraction techniques, which enable it to discern intricate road surface details. This can be quantified using the Mean Average Precision (mAP), where the YOLOv8 model achieves values significantly higher than the SSD model, reflecting its proficiency in accurately identifying potholes in diverse environments. However, this high accuracy comes at the cost of increased computational complexity, making real-time applications challenging, particularly in resource-constrained settings. Conversely, the the SSD model model excels in efficiency, exhibiting faster processing times which can be expressed as The SSD model<The YOLOv8 model where T represents processing time. While the SSD model's performance may be limited in complex visual conditions, its capability to process large datasets quickly makes it suitable for scenarios where speed is critical.

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