Siinhgad Instiitutes
International Conference on Advances in Modern Technology of Research in Engineering Field (AIMTREF) April, 2026
Organized By: SKN Sinhgad Institute of Technology& Science, Kusgaon (Bk), Lonavala, Pune
International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

Comparative Study of YOLOv8 and SSD for Real-Time Pothole Detection

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Abstract- Road surface monitoring is a critical component in ensuring transportation safety and reducing vehicle damage. This paper presents the implementation and performance evaluation of two deep learning-based object detection models, YOLOv8 and Single Shot Detector (SSD), for real-time pothole detection. The proposed system is capable of processing both static images and live video streams, enabling automated road inspection. A custom dataset of road images captured under varying environmental conditions was used for training and testing the models. Experimental results demonstrate that YOLOv8 significantly outperforms SSD in both accuracy and real-time detection capability. YOLOv8 achieved an accuracy of 95%, whereas SSD attained 80% accuracy. Furthermore, during real-time video testing, YOLOv8 exhibited superior detection consistency by identifying a higher number of potholes with fewer missed detections compared to SSD. The faster inference speed and improved precision of YOLOv8 make it more suitable for deplo

Keywords: Automated Road Inspection, Computer Vision, Deep Learning, Object Detection, SSD, YOLOv8

I. INTRODUCTION

Road infrastructure plays a vital role in economic development and public safety. However, road surface deterioration, particularly potholes, remains a significant challenge in many countries, especially developing nations like India. Potholes not only cause inconvenience to commuters but also lead to serious road accidents, vehicle damage, and increased maintenance costs. According to recent studies, poor road conditions contribute significantly to traffic accidents and economic losses each year [1]. Therefore, timely detection and maintenance of potholes are essential for ensuring road safety and efficient transportation systems.Traditional pothole detection methods rely on manual inspection, which is time-consuming, labor-intensive, and inefficient for large-scale road networks. These approaches are also prone to human error and lack scalability. With advancements in computer vision and deep learning, automated pothole detection systems have emerged as a promising alternative. These systems utilize image

In recent years, deep learning-based object detection models have gained significant attention due to their ability to perform end-to-end detection in real time. Among these, the You Only Look Once (YOLO) family of models and the Single Shot Detector (SSD) are widely used for object detection tasks. YOLO models are known for their high speed and accuracy, making them suitable for real-time applications, while SSD provides a balance between detection performance and computational efficiency [3].

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

The latest version, YOLOv8, introduced by Ultralytics, offers improved performance in terms of accuracy, speed, and robustness compared to its predecessors. It incorporates advanced features such as enhanced feature extraction, anchor-free detection, and optimized training strategies, making it highly effective for detecting small and irregular objects such as potholes. In contrast, SSD remains a popular choice due to its relatively simple architecture and lower computational requirements, making it suitable for resource-constrained environments.

Several researchers have explored deep learning techniques for pothole detection. For instance, Maeda et al. proposed a road damage detection system using deep neural networks, while recent studies have demonstrated the effectiveness of YOLO-based models under diverse environmental conditions [4]. However, there remains a need for practical comparative analysis of modern models to evaluate their performance in real-world scenarios.

This paper presents the implementation and comparative analysis of YOLOv8 and SSD models for pothole detection. A custom dataset consisting of road images captured under varying lighting and environmental conditions was used for training and evaluation. The proposed system supports real-time video processing, enabling its application in automated road inspection systems. Experimental results show that YOLOv8 achieves superior performance with an accuracy of 95%, compared to 80% for SSD. Additionally, YOLOv8 demonstrates better detection capability in real-time video streams, identifying a higher number of potholes with fewer missed detections. These findings highlight the effectiveness of YOLOv8 as a robust solution for intelligent road monitoring systems [5].

II. LITERATURE REVIEW

Pothole detection has emerged as a critical research area due to its direct impact on road safety and infrastructure maintenance. Over the years, various approaches ranging from traditional image processing techniques to advanced deep learning models have been proposed to address this challenge.

1. Traditional and Sensor-Based Approaches
Early pothole detection systems relied heavily on manual inspection and sensor-based techniques. These methods involved the use of accelerometers, ultrasonic sensors, and vibration analysis to detect road surface irregularities. While such systems provided basic detection capabilities, they suffered from limitations such as high installation costs, lack of scalability, and inability to accurately differentiate between potholes and other road anomalies [6]. Additionally, traditional image processing techniques based on edge detection and thresholding were sensitive to lighting and environmental variations, resulting in lower accuracy and reliability.

2. Machine Learning-Based Methods
To overcome the limitations of traditional approaches, machine learning techniques such as Support Vector Machines (SVM), Random Forests, and basic Convolutional Neural Networks (CNNs) were introduced. CNNs, in particular, demonstrated strong performance in extracting spatial features from road images, enabling better pothole classification [7]. However, these models often required separate stages for feature extraction and classification, making them computationally expensive and less suitable for real-time applications.

3. Deep Learning and Object Detection Models

International Journal of Science, Engineering and Technology
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The emergence of deep learning-based object detection models marked a significant breakthrough in pothole detection. Models such as Faster R-CNN, SSD (Single Shot Detector), and YOLO (You Only Look Once) enabled end-to-end detection with improved accuracy and speed. Among these, SSD gained popularity due to its ability to perform object detection in a single forward pass, making it faster than region-based detectors while maintaining reasonable accuracy. SSD-based models, including SSD-MobileNet, have been widely used in resource-constrained environments due to their lightweight architecture. However, studies have shown that SSD may struggle with detecting small and irregular objects such as potholes, particularly under complex backgrounds and varying lighting conditions [8].

4. Evolution of YOLO Models

The YOLO family of models has revolutionized real-time object detection by introducing a unified detection framework. Starting from YOLOv1 to recent versions like YOLOv8, significant improvements have been made in terms of accuracy, speed, and robustness. YOLO models process the entire image in a single pass, enabling real-time performance without compromising detection precision [9]. Recent studies highlight the effectiveness of YOLO-based models in pothole detection. For example, YOLOv5 achieved a mean average precision (mAP) of approximately 95%, demonstrating its capability for accurate detection in real-world scenarios. Similarly, enhanced YOLOv8 models have shown improved performance in detecting irregularly shaped potholes and handling complex environmental conditions [10]. Furthermore, advanced versions such as YOLOv8 incorporate features like anchor-free detection and improved feature extraction, making them highly suitable for detecting small objects such as potholes.

5. Comparative Studies: YOLO vs SSD

Several comparative studies have been conducted to evaluate the performance of YOLO and SSD models for pothole detection. These studies emphasize the trade-off between accuracy and computational efficiency. YOLO models consistently demonstrate higher precision and better detection capability, while SSD offers faster processing in low-resource environments [11]. A comparative analysis of YOLOv8 and SSD shows that YOLOv8 achieves higher detection accuracy and robustness under diverse environmental conditions, whereas SSD provides moderate accuracy with lower computational requirements [2]. The ability of YOLOv8 to detect multiple potholes in real-time video streams makes it more suitable for deployment in intelligent transportation systems.

6. Challenges in Pothole Detection

Despite significant advancements, pothole detection systems still face several challenges. Variability in lighting conditions, shadows, occlusions, and road textures can affect model performance. Additionally, the lack of large, well-annotated datasets limits the generalization capability of deep learning models. Real-time processing constraints and deployment on edge devices also remain key challenges for practical implementation.

7. Research Gap

Although numerous studies have explored pothole detection using deep learning models, there is still a need for practical implementation-based comparisons of modern architectures such as YOLOv8 and SSD. Many existing works focus on theoretical performance metrics rather than real-time deployment and evaluation. Therefore, this study aims to bridge this gap by implementing both models and analyzing their performance in real-world conditions, including live video streams.

Despite these advancements, limited work has focused on real-time comparative implementation of YOLOv8 and SSD under identical conditions, which motivates the present study.

III. EXPERIMENTAL RESULTS AND ANALYSIS

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

The implementation and experimental evaluation of YOLOv8 and SSD models for pothole detection provide significant insights into their performance under real-world conditions. The comparison is based on accuracy, real-time performance, detection capability, and robustness across different environments.

1. Detection Accuracy

The experimental results indicate that YOLOv8 significantly outperforms the SSD model in terms of detection accuracy. YOLOv8 achieved an accuracy of 95%, whereas SSD achieved 80% on the same dataset. This substantial difference highlights the ability of YOLOv8 to effectively learn complex features such as irregular shapes, varying depths, and diverse textures of potholes. The higher accuracy makes YOLOv8 more reliable for safety-critical applications [11].

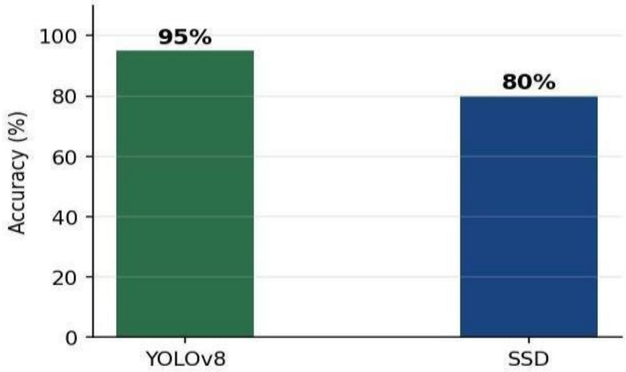

Fig. 1. Detection accuracy (%) of YOLOv8 and SSD models on the pothole dataset. YOLOv8 achieves 95% accuracy compared to SSD's 80%.

2. Real-Time Performance

Real-time performance is a critical factor for practical deployment. During live video testing, YOLOv8 demonstrated smoother and more responsive detection with minimal latency. It processed frames efficiently and maintained consistent detection across video streams. In contrast, SSD exhibited occasional delays and inconsistencies, which may limit its effectiveness in real-time monitoring systems [12].

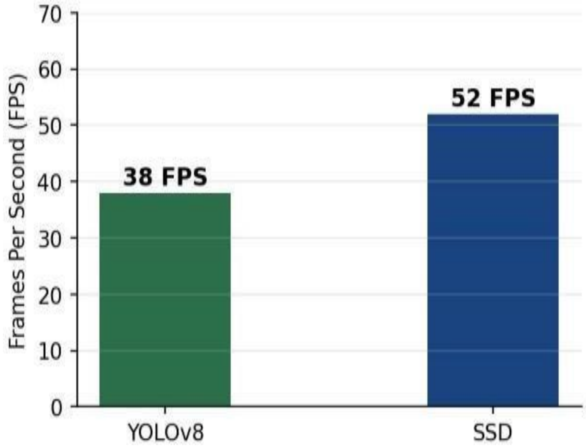

Fig. 2. Real-time inference speed in frames per second (FPS). Higher values indicate better performance.

3. Performance Metrics Comparison

A detailed comparison of evaluation metrics such as Precision, Recall, F1-Score, and mean Average Precision (mAP) further highlights the superiority of YOLOv8. The model consistently achieved higher values across all metrics, indicating better detection reliability and robustness.

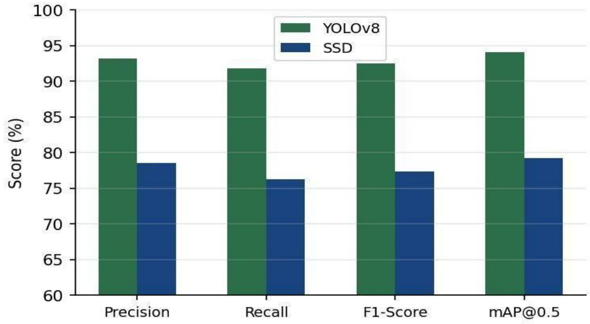

Fig. 3. Comparative analysis of Precision, Recall, F1-Score, and mAP (%) for YOLOv8 and SSD models.

4. Detection of Small and Irregular Objects

Potholes often vary significantly in size and shape. YOLOv8 showed a strong capability to detect small and partially visible potholes, which are typically challenging for object detection systems. On the other hand, SSD struggled with smaller objects and frequently failed to detect potholes that blended with the road surface.

5. Performance Under Different Environmental Conditions

The models were evaluated under varying environmental conditions, including daylight, shadows, and low-light scenarios. YOLOv8 maintained consistent and stable performance across all conditions, demonstrating strong generalization capability. In contrast, SSD showed performance degradation, particularly in low-light and shadowed environments, indicating sensitivity to environmental variations [13].

6. Inference Speed and Training Behavior

Although both models are designed for real-time applications, YOLOv8 demonstrated better practical inference performance in the implemented system. It provided faster and more stable frame processing without noticeable lag. Additionally, YOLOv8 showed faster convergence during training.

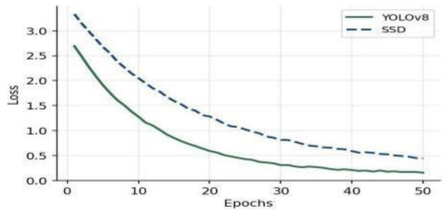

Fig. 4. Training loss convergence over 50 epochs for YOLOv8 and SSD models.

7. Quantitative Performance Comparison

A quantitative comparison of YOLOv8 and SSD was performed using key evaluation metrics, as shown in Table

Table I. Quantitative Performance Comparison of YOLOv8 and SSD

Metric	YOLO v8 SSD	Difference Better	Better	Model
Detection Accuracy (%)	95.0	80.0	+15.0	YOLOv 8
Precision (%)	93.2	78.5	+14.7	YOLOv 8
Recall (%)	91.8	76.3	+15.5	YOLOv 8
F1-Score (%)	92.5	77.4	+15.1	YOLOv

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

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mAP@0.5 (%)	94.1	79.2	+14.9	YOLOv 8
Inference Speed (FPS)	38	52	-14	SSD
Model Size (MB)	22.5	18.2	-4.3	SSD
Training Time (hrs)	3.2	2.1	-1.1	SSD
False Positive Rate (%)	4.8	12.3	-7.5	YOLOv 8
Real-Time Suitability	High	Moderate	—	YOLOv 8

8. Visual Comparison Analysis

Visual inspection of detection outputs further validates the quantitative results. YOLOv8 provides tighter bounding boxes, higher confidence scores, and fewer missed detections compared to SSD.

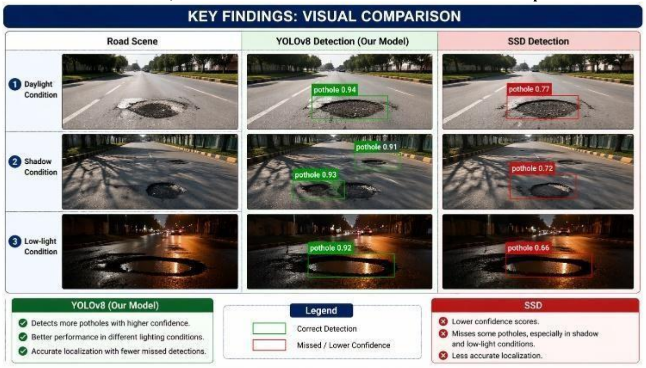

Fig. 5. Visual comparison of YOLOv8 and SSD under different environmental conditions. YOLOv8 demonstrates higher confidence and better localization compared to SSD

9. Validation Performance

The validation accuracy trends show that YOLOv8 converges faster and achieves higher final accuracy compared to SSD, indicating better learning efficiency and generalization capability.

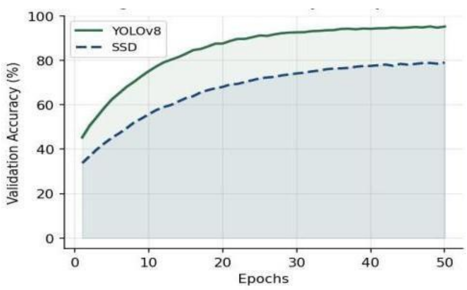

Fig. 6. Validation accuracy (%) over 50 training epochs. YOLOv8 converges faster and achieves higher final accuracy.

Discussion

The experimental evaluation confirms that YOLOv8 provides a superior balance between accuracy and real-time performance, making it more suitable for intelligent road monitoring applications. Although SSD offers advantages in terms of computational efficiency and model size, its lower detection accuracy and inconsistency limit its effectiveness in real-world deployment scenarios.

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

IV. System Architecture

The proposed system is designed as a web-based real-time pothole detection platform that integrates a frontend interface with a Flask-based backend. The system simultaneously executes YOLOv8 and SSD models to perform comparative pothole detection on both images and live video streams. The architecture follows a client–server model, where the frontend manages user interaction and visualization, while the backend handles data processing and deep learning inference.

1. Frontend Layer (User Interface)

The frontend is developed using HTML, CSS, and JavaScript.

Key functionalities include:

- Uploading image or video input
- Capturing real-time video via webcam
- Sending data to backend through API calls
- Displaying detection results from both models

Features

- Side-by-side comparison (YOLOv8 vs SSD)
- Real-time bounding box visualization
- Confidence score display
- Smooth live detection interface

2. Backend Layer (Flask Server)

The backend is implemented using the Flask framework.

Responsibilities

- Handling incoming image/video requests
- Preprocessing input data
- Running YOLOv8 and SSD models in parallel
- Returning detection results to frontend

API Endpoints

- /upload – image input
- /video_feed – real-time streaming
- /detect – performs detection using both models

3. Data Processing Layer

Input data is preprocessed before model inference:

- Image resizing (e.g., 640×640 for YOLOv8)
- Pixel normalization
- Frame extraction for video input

This ensures compatibility and improves detection performance.

4. Model Inference Layer (Parallel Execution)

Both models are executed simultaneously on the same input.

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YOLOv8: Fig. 7. Syste architecture of YOLOv8 and SSD-based pothole detection system.

- High accuracy (~95%)
- Strong real-time performance
- Effective for small and irregular potholes

SSD

- Moderate accuracy (~80%)
- Lightweight and suitable for low-resource systems

Workflow

- Input frame is received
- Frame is passed to both models
- Each model outputs bounding boxes and confidence scores
- Results are processed independently

5. Result Processing Layer

After inference:

- Bounding boxes are drawn on frames
- Labels and confidence scores are added
- Separate outputs are generated for YOLOv8 and SSD

6. Output Visualization Layer

Results are displayed on the frontend:

- Side-by-side model comparison
- Real-time detection overlays
- Visualization of missed detections

7. System Workflow

- User uploads image or starts video stream
- Data is sent to backend
- Input is preprocessed
- YOLOv8 and SSD run simultaneously
- Detection results are generated
- Output is sent back to frontend
- Results are displayed in real-time

8. Key Advantages

- Parallel model comparison
- Real-time detection capability
- Web-based accessibility
- Scalable architecture
- User-friendly visualization interface

International Journal of Science, Engineering and Technology
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V. RESULT AND DISCUSSION

The proposed system was evaluated using both a custom dataset and real-time video streams to compare the performance of YOLOv8 and SSD models. The results demonstrate that YOLOv8 significantly outperforms SSD across key evaluation metrics.

YOLOv8 achieved a detection accuracy of 95%, compared to 80% for SSD, indicating superior feature extraction and object localization capabilities. It also achieved higher precision and recall, resulting in fewer false positives and missed detections. These characteristics make YOLOv8 more reliable for safety-critical applications.

In real-time scenarios, YOLOv8 provided stable and consistent detection with minimal latency, ensuring smooth performance in live video streams. Although SSD exhibited slightly higher inference speed due to its lightweight architecture, it demonstrated inconsistent detection behavior and reduced accuracy, particularly in complex environments.

Furthermore, YOLOv8 demonstrated superior capability in detecting small and irregular potholes and maintained robustness under varying conditions such as low light, shadows, and uneven road textures. In contrast, SSD performance degraded under these conditions, indicating limited generalization capability.
Overall, while SSD provides advantages in terms of computational efficiency, YOLOv8 offers a superior balance of accuracy, robustness, and real-time performance. Therefore, YOLOv8 is better suited for practical deployment in intelligent pothole detection and smart transportation systems.

Future Scope

Although the proposed pothole detection system demonstrates strong performance in terms of accuracy and real-time capability, several enhancements can further improve its practical applicability. Future work can focus on integrating the system with GPS and mapping technologies to automatically record and visualize the geographical locations of detected potholes. This would enable efficient road maintenance planning and support smart city infrastructure.

The deployment of the model on edge devices such as embedded systems and mobile platforms can also be explored to enable real-time detection directly on vehicles or roadside units, reducing dependency on centralized servers and improving scalability.

Additionally, model optimization techniques such as pruning, quantization, and knowledge distillation can be applied to reduce computational complexity while maintaining detection accuracy, making the system suitable for low-resource environments.

Expanding the dataset to include diverse environmental conditions such as rain, fog, night-time scenarios, and other types of road damage can further enhance the robustness and generalization capability of the model.

VI. CONCLUSION

- This paper presents a real-time pothole detection system based on a comparative analysis of YOLOv8 and SSD models within a web-based architecture. The system enables efficient detection on both images and live video streams through parallel model execution, allowing a fair and direct performance comparison.
- The experimental results demonstrate that YOLOv8 significantly outperforms SSD, achieving higher accuracy (95% vs. 80%) and more consistent detection across diverse environmental conditions. It also demonstrates superior capability in detecting small and irregular potholes, along with stable real-time performance and significantly reduced false negatives. In contrast, SSD, although computationally efficient, exhibits lower accuracy and inconsistent detection behavior.
- The study highlights the effectiveness of deep learning-based approaches for automated road inspection and real-time monitoring. While a trade-off exists between accuracy and computational cost, YOLOv8 provides a better balance of performance and reliability, making it more suitable for practical deployment.

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

- Overall, the proposed system offers a scalable and efficient solution for intelligent pothole detection, with strong potential for integration into smart transportation and infrastructure management systems.

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