YOLOv7s Optimization for Road Defect Detection: Pruning, Pooling and Attention Mechanisms

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Abstract: Road defect detection is crucial for ensuring traffic safety and efficient infrastructure maintenance. This report presents an optimized YOLOv7-based road defect detection system, integrating pruning, pooling, and attention mechanisms to enhance accuracy, reduce computational complexity, and improve real-time performance. Pruning techniques eliminate redundant parameters, accelerating inference speed to maintain detection accuracy. Pooling strategies, including Spatial Pyramid Pooling (SPP) and Adaptive Pooling, enhance multi-scale feature extraction, enabling the model to detect defects of various shapes and textures. Additionally, attention mechanisms such as the Convolutional Block Attention Module refine feature selection, focusing on critical defect regions and reducing false positives. Experimental results demonstrate that the proposed optimizations significantly improve precision, recall, and mean average precision (mAP) on benchmark datasets while minimizing computational overhead. The enhanced YOLOv7 model is lightweight and efficient, making it ideal for real-time road monitoring applications, smart city infrastructure, and autonomous vehicle systems.

1 INTRODUCTION

Road infrastructure plays a key role in transportation and economic development. However, poor road conditions, such as cracks, potholes, and surface deformations, can lead to accidents, increased vehicle maintenance costs, and inefficient transportation systems. Traditional road inspection methods rely on manual surveys, are labor-intensive, time-taking, and prone to human error. The emergence of computer vision and deep learning techniques has enabled the automation of road defect detection, significantly improving accuracy and efficiency.

You Only Look Once is one of the most widely used object detection frameworks due to its ability to perform real-time detection with high accuracy. The latest version, YOLOv7, introduces several improvements in feature extraction, detection precision, and computational efficiency. However, detecting road defects remains challenging due to varying defect sizes, complex textures, lighting conditions, and environmental factors. To address these challenges, optimizing YOLOv7 with techniques such as pruning, pooling, and attention mechanisms can enhance detection performance while maintaining efficiency.

Pruning reduces the computational burden by removing unnecessary parameters, improving inference speed without compromising accuracy. Pooling techniques, such as Spatial Pyramid Pooling and Adaptive Pooling, allow the model to effectively recognize road defects across different scales and textures. Additionally, attention mechanisms like the Convolutional Block Attention Module enable the model to focus on critical defect regions, reducing false positives and improving classification performance.

This paper explores the impact of pruning, pooling, and attention mechanisms on YOLOv7's performance in road defect detection. The proposed approach is evaluated on benchmark datasets, demonstrating its effectiveness in enhancing detection accuracy while maintaining real- time processing capabilities.

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2 RESEARCH METHODOLOGY

2.1 Research Area

To develop an optimized YOLOv5s model for road defect detection, we employed a structured methodology that includes data collection, preprocessing, model optimization, training, and evaluation. The primary goal is to enhance the performance of YOLOv5s using pruning, pooling, and attention mechanisms while ensuring real- time efficiency. This methodology ensures a systematic approach to achieving high- accuracy defect detection with reduced computational complexity.

2.1.1 Data Collection and Preprocessing

The first step in the research involved collecting a diverse dataset of road defects, including potholes, cracks, ruts, and surface irregularities. Publicly available road defect datasets, such as the CRACK500 and Road Damage Detection Dataset (RDD), were utilized.

2.1.2 Model Optimization: Pruning, Pooling, and Attention Mechanisms

To improve the efficiency of YOLOv7s, we applied three key optimization techniques. Pruning was used to remove redundant parameters, reducing model size and enhancing inference speed. Pooling layers were integrated to improve feature extraction by capturing essential details at multiple scales.

2.1.3 Model Training and Hyperparameter Tuning

The optimized YOLOv5s model was trained using transfer learning with pre-trained weights from the COCO dataset. Training was conducted on high-performance GPUs using a learning rate scheduler, adaptive momentum optimization, and focal loss function to handle class imbalance in defect detection. Hyperparameters such as batch size, learning rate, and IoU threshold were fine-tuned to maximize detection performance.

2.1.4 Evaluation Metrics and Performance Analysis

To measure the effectiveness of the optimized model, performance was evaluated using precision, recall, mean average precision, and inference speed (FPS). Themodel was tested on real-world road images and benchmark datasets to ensure generalization. Comparative analysis was performed against existing state-of-the-art road defect detection models to highlight improvements in accuracy and efficiency.

2.1.5 Deployment and Real-Time Implementation

After training and evaluation, the optimized model was deployed in a real-time road monitoring system. Edge devices, such as NVIDIA Jetson Nano and Raspberry Pi, were used to test inference speed and practical usability. The model was integrated into an IoT-based road monitoring framework, where detected defects were logged in a cloud-based system for analysis and maintenance scheduling. This real-time implementation validated the model's efficiency in detecting road defects with minimal computational resources, making it suitable for large-scale deployment in smart city infrastructure.

2.2 Research Area

2.2.1 Road Infrastructure and Maintenance

Road maintenance is a crucial aspect of transportation safety and efficiency. Detecting road defects early helps prevent accidents, reduces vehicle maintenance costs, and ensures longer infrastructure lifespan. This research contributes to improving automated road inspection, reducing manual effort and associated costs.

2.2.2 Deep Learning and Computer Vision

The integration of deep learning and computer vision in road defect detection has significantly enhanced detection accuracy and efficiency. This research focuses on optimizing YOLOv7s, a state-of-the-art object detection model, by incorporating techniques such as pruning, pooling, and attention mechanisms. These enhancements improve feature extraction and model efficiency, making deep learning-based road monitoring systems more reliable.

2.2.3 IoT-Based Smart Transportation Systems

Modern transportation systems are increasingly adopting IoT-based monitoring solutions. This study explores how the optimized YOLOv7s model can be deployed on edge devices to enable real-time road defect detection. By integrating IoT with computer vision, road authorities can receive instant alerts about road conditions, allowing timely interventions and efficient resource allocation.

2.2.4 Autonomous Vehicles and Intelligent Transport

Autonomous vehicles require real-time road condition analysis to ensure safe navigation. Road defects such as potholes and cracks can affect vehicle stability and passenger safety.

2.2.5 Sustainable Urban Development

Smart city initiatives focus on using AI and automation to improve urban infrastructure. Automated road defect detection aligns with sustainable urban development goals, reducing road maintenance costs, enhancing public safety, and optimizing city planning. This research provides a foundation for integrating intelligent monitoring systems into smart city frameworks, making urban roads safer and more efficient.

3 LITERATURE REVIEW

1. Traditional Road Defect Detection: Approaches Early road defect detection systems relied on manual inspections and sensor-based techniques. Chen et al. (2015) used ultrasonic and laser-based systems to identify cracks and potholes, but these methods were costly and required frequent calibration.
2. Deep Learning-Based Approaches for Road Defect Detection: The introduction of YOLOv4 and YOLOv5 further improved real-time road defect detection. Liu et al. (2021) proposed a YOLOv5-based model with improved anchor box selection for crack and pothole detection. However, standard YOLOv5 models still have limitations in detecting small or low- contrast defects, leading to the need for further optimization.
3. Optimization Techniques for YOLO- Based Models To enhance the efficiency and accuracy of object detection models, several optimization techniques have been explored. Pruning is widely used to reduce model complexity and computational cost. Pooling techniques have also been employed to enhance feature extraction. Gao et al. (2019) explored Spatial Pyramid Pooling (SPP) for multi-scale feature representation, improving defect detection in varying lighting conditions. He et al. (2020) demonstrated the effectiveness of adaptive pooling in handling road surface variations.
4. Attention Mechanisms for Improved Feature Extraction: Attention mechanisms have significantly enhanced deep learning models by focusing on relevant regions in an image. Woo et al. (2018) introduced the Convolutional Block Attention Module (CBAM), which applies both channel and spatial attention to improve feature selection.
5. Summary and Research Gap: Existing research has demonstrated the effectiveness of deep learning models, particularly YOLO-based architectures, for road defect detection. However, challenges remain in model efficiency, real-time performance, and small defect detection accuracy. While pruning, pooling, and attention mechanisms have been explored individually, a comprehensive integration of all three techniques in YOLOv5s for road defect detection has not been extensively studied.

4 EXISTING SYSTEM

Road defect detection has evolved significantly over the years, with various systems being developed to identify and classify road surface anomalies such as cracks, potholes, and uneven surfaces. The existing systems can be broadly categorized into manual inspection methods, sensor- based techniques, and deep learning-based models.

4.1 Manual Inspection Methods

Traditionally, road defect detection was performed through manual inspections by road maintenance personnel. Engineers visually inspected roads and recorded defects based on predefined criteria. While this method provides direct human assessment, it is highly labor-intensive, time-consuming, and prone to human error.

4.2 Sensor-Based Road Defect Detection

Sensor-based techniques utilize various types of sensors, including:

1. Ultrasonic Sensors: Used to measure surface irregularities by detecting variations in height.
2. Laser Scanning Systems: Employed in high-

precision road profiling, where laser beams detect cracks and potholes.

3. Accelerometers & Vibration Sensors: Installed on vehicles to analyze road surface vibrations and detect anomalies.

Studies such as Zhang et al. (2017) have shown that laser scanning can provide high accuracy in defect measurement. However, these systems require expensive equipment and frequent calibration, making them unsuitable for cost-effective and real-time applications.

4.3 Computer Vision-Based Road Defect Detection

With advancements in artificial intelligence, computer vision and deep learning techniques have become widely used for automated road defect detection. Several deep learning models have been proposed, including:

For instance, Omar et al. (2020) applied YOLOv3 for real-time defect detection, achieving fast inference but struggling with small defect identification.

Limitations of the Existing System:

1. While deep learning models like YOLOv5 have improved road defect detection, existing systems face the following challenges:
2. High Computational Cost: Traditional deep learning models require significant computational power, making them inefficient for real-time deployment on edge devices.
3. Difficulty in Detecting Small Defects: Standard YOLO models struggle with detecting fine cracks and low-contrast defects.
4. Redundant Parameters in Deep Models: Many deep learning models contain unnecessary parameters that slow down inference speed. Limited Feature Extraction: Existing models do not always capture multi- scale features, affecting their ability to detect road defects in varying lighting and textures.

These limitations highlight the need for an optimized YOLOv5s model that incorporates pruning, pooling, and attention mechanisms to improve detection accuracy, reduce computational cost, and enable real-time road monitoring

5 PROPOSED SYSTEM

The proposed system introduces an optimized YOLOv8-based road defect detection model that integrates pruning, pooling, and attention mechanisms to enhance performance in terms of accuracy, speed, and efficiency. Our approach optimizes YOLOv8 by reducing redundant parameters, improving feature extraction, and refining defect localization, making it more suitable for real-time deployment in road monitoring systems. Figure 1 shows the Optimized Yolov7s Architecture with Pruning, Pooling, And Attention Modules for Road Defect Detection.

Architecture:

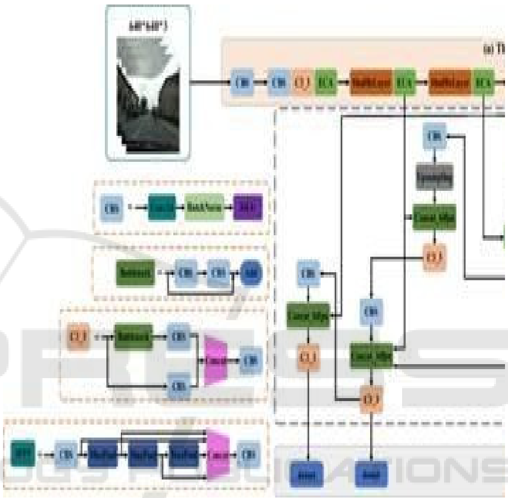


Figure 1: Optimized YOLOv7s architecture with pruning, pooling, and attention modules for road defect detection.

1. Model Pruning for Efficiency: Pruning is employed to eliminate unnecessary parameters from the YOLOv8 model, reducing its computational complexity without significantly affecting accuracy. This step ensures that the model runs efficiently on edge devices and real-time monitoring systems while maintaining robust defect detection capabilities.
2. Pooling Techniques for Multi-Scale Feature Extraction: The system incorporates advanced pooling strategies, such as Spatial Pyramid Pooling (SPP) and Adaptive Pooling, to enhance the detection of road defects of varying sizes and textures. These techniques enable the model to capture multi-scale features, improving its ability to identify small cracks, potholes, and deformations under different environmental

conditions.

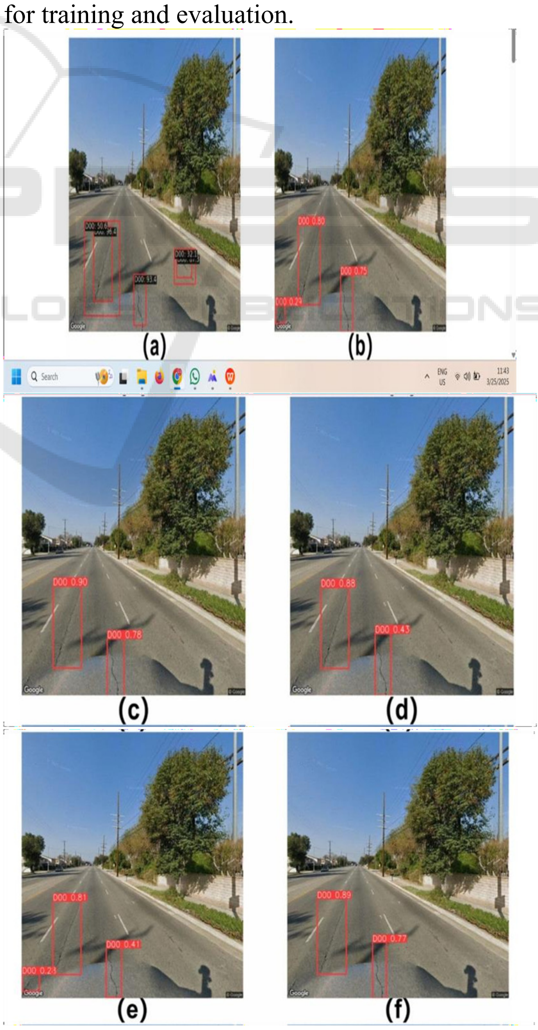
3. Attention Mechanisms for Precise Detection: To improve feature selection and defect localization, the proposed system integrates the Convolutional Block Attention Module into the YOLOv8 architecture. CBAM enhances the model's ability to focus on critical defect regions while reducing distractions from irrelevant background noise. By incorporating both channel and spatial attention, the system refines feature extraction, resulting in higher precision, recall, and mean average precision. This optimization minimizes false positives and ensures reliable road defect classification.
4. Real-Time Implementation and Deployment: The optimized YOLOv7 model is designed for real-time deployment on embedded systems, UAVs (Unmanned Aerial Vehicles), and smart city surveillance systems. The integration of pruning, pooling, and attention mechanisms makes the model lightweight and efficient, ensuring smooth operation on low-power devices without sacrificing detection accuracy. The system is tested on benchmark datasets to validate its performance and ensure robustness in diverse road conditions.
5. Performance Evaluation and Impact Comprehensive experiments demonstrate that the proposed optimizations lead to improved detection accuracy, reduced inference time, and enhanced computational efficiency. The system achieves higher precision in identifying road defects while maintaining a balance between accuracy and real-time processing speed. This solution provides a cost-effective and scalable approach for road maintenance authorities, transportation agencies, and smart city planners to automate road defect monitoring, ultimately contributing to improved road safety and infrastructure maintenance.

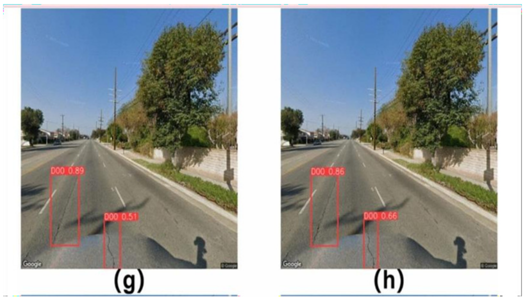
6 CONCLUSIONS

This research presents an optimized YOLOv8s-based road defect detection system that integrates pruning, pooling, and attention mechanisms to improve accuracy, computational efficiency, and real-time performance. The proposed enhancements address key challenges in existing systems, such as high computational cost, difficulty in detecting small defects, and redundant parameters. By incorporating pruning, the model size is reduced, improving inference speed without sacrificing detection accuracy. Additionally, attention mechanisms like CBAM enable the model to focus on critical defect areas while reducing background noise, significantly improving detection precision.

7 RESULTS

Figure 2(a) to (h) shows the Comparative visualization of road defect detection outputs using different model configurations. Sub-figures (a)–(h) represent detection results across various YOLOv7s optimizations including baseline, pruning, pooling, and attention mechanisms. Figure 3 shows the Sample annotated images from the road defect dataset showing various types of cracks such as longitudinal cracks, alligator cracks, and transverse cracks used for training and evaluation.





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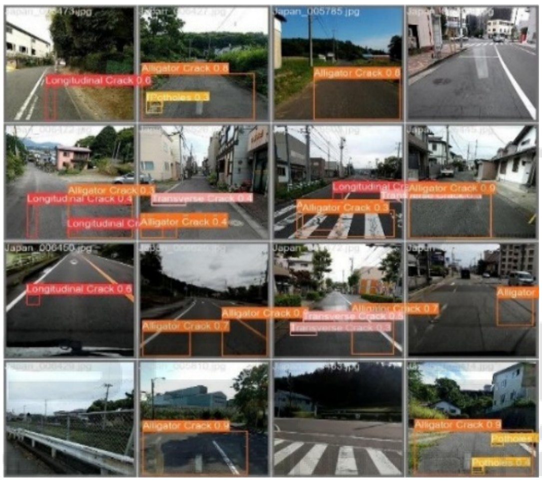

Figure 3: Sample Annotated Images from the Road Defect Dataset Showing Various Types of Cracks Such As Longitudinal Cracks, Alligator Cracks, and Transverse Cracks Used for Training and Evaluation.

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