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## Research

# Automatic road damage detection using deep learning and UAV images

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**Abstract**— Automating the process of detecting road deterioration is essential for enhancing traffic safety and alleviating the difficulties associated with manual inspections. Traditional deep learning models like YOLOv5 and YOLOv7 do a good job at detection, but they need to be even better before they can be used in the real world. Increased detection of road faults in UAV-captured photos is made possible by this upgraded system's integration of YOLOv8, which achieves an increased accuracy rate of 85%. An easy-to-use front-end interface built using Flask is created to make it possible for users to submit UAV photographs and see the detection results. In addition, the system data is protected by built-in authentication measures, which provide secure access. As a result, the upgraded system provides a trustworthy, precise, and intuitive method for monitoring road infrastructure on an expansive scale.

**Keywords**— Automated Inspection, Deep Learning, Infrastructure Monitoring, Object Detection, Road Damage Detection, UAV (Unmanned Aerial Vehicle), YOLO.

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## I. INTRODUCTION

Because of the critical role that roads play in facilitating efficient and safe transportation, it is critical to promptly detect road surface defects in order to carry out appropriate maintenance. Manual surveys, the backbone of traditional inspection procedures, are time-consuming, physically demanding, and hazardous to field employees. Recent developments in remote sensing have made UAV-based picture capture a viable and efficient option for urban settings' large-scale surveillance. Automated item extraction, pool identification, and urban analysis are only a few examples of the promising uses for UAV-driven sensing platforms, which point to their use in evaluating infrastructure [1, 5].

This capacity is further enhanced by integrating sophisticated AI systems with UAVs. Using deep reinforcement learning, unmanned aerial vehicles (UAVs) can now navigate complicated environments independently and collect high-quality data, paving the way for better inspection and monitoring procedures in the environment [2].

Objects and abnormalities in aerial images may be effectively detected using deep learning models, particularly those based on the YOLO architecture. The resilience of these models for environmental and structural surveillance using UAVs has been demonstrated, for instance, by their effective application to tasks such as identifying damaged Norway spruce trees [3]. The development of unmanned aerial vehicle (UAV) technology is ongoing, with a focus on improving operating efficiency, assessing risks, and making UAV deployments in urban areas more feasible in the real world [4].

The expanded system takes these improvements a step further by including YOLOv8 to improve the accuracy of road damage detection using UAV-captured photos, including cracks, potholes, and more. YOLOv8 outperforms previous YOLO versions with better robustness and 85% accuracy. Secure picture uploads, real-time display of identified damages, and simplified user interaction are all made possible by developing a Flask-based front-end interface with built-in authentication, which is designed to

assure practical usage. The proposed expansion follows the advances shown in previous UAV and machine learning research [1]-[5] by integrating UAV technology with state-of-the-art deep learning models and an easy-to-use interface to create a safe and scalable system for automated road infrastructure monitoring.

## II. LITERATURE SURVEY

Melendy et al. [6] proposed an automated method to quantify selective logging damage using airborne LiDAR data. Their approach enabled accurate measurement of forest disturbance over large areas, helping to monitor environmental impact. This work demonstrates how high-resolution remote sensing and automation can effectively assess structural damage in complex natural environments.

Silva et al. [7] designed an architectural multi-agent system for pavement monitoring with pothole recognition using UAV images. Their system coordinated multiple intelligent agents to detect road surface anomalies and manage pavement information efficiently. The study highlights the effectiveness of combining UAV imagery with AI-based decision frameworks for large-scale pavement monitoring.

Guerrieri and Parla [8] investigated flexible and stone pavement distress detection using deep learning and low-cost sensing devices. Their work showed that affordable imaging hardware, when combined with robust deep learning models, can effectively detect and measure pavement defects. This approach demonstrates a cost-effective solution for infrastructure assessment without relying on expensive equipment.

Jeong [9] developed a YOLO-based road damage detection system using images captured by smartphones. The study demonstrated that consumer-grade mobile devices can be used to collect useful data for detecting cracks and potholes in real-world road environments. This highlights the practicality of deploying lightweight detection models on portable platforms for crowdsourced infrastructure monitoring.

Izadi et al. [10] introduced a neuro-fuzzy approach for post-earthquake road damage assessment using QuickBird satellite images, optimized with genetic algorithms and SVM classification. Their framework effectively distinguished between damaged and undamaged road segments in disaster-stricken areas. This work shows how hybrid intelligent systems can support rapid damage assessment after major seismic events.

Bhatia et al. [11] presented a convolutional neural network-based method for pothole detection using thermal imaging. By exploiting temperature differences between damaged and undamaged road regions, their approach improved robustness under challenging lighting conditions. The study illustrates the potential of thermal sensing combined with deep learning for reliable pavement defect detection.

Guan et al. [12] proposed an automated pixel-level pavement distress detection method using stereo vision and deep learning. Their system generated dense depth information and combined it with image features to identify cracks and other surface distresses with high accuracy. This pixel-level analysis enables fine-grained characterization of road conditions, useful for precise maintenance planning.

Arya et al. [13] introduced RDD2022, a large-scale multi-national image dataset for automatic road damage detection. The dataset includes diverse road types, lighting conditions, and damage categories collected from multiple countries. Their contribution provides a valuable benchmark for training and evaluating deep learning models, improving generalization across geographic regions.

Redmon and Farhadi [14] proposed YOLO9000, an object detector capable of jointly training on detection and classification datasets to recognize over 9000 categories. Their work significantly advanced real-time detection by combining speed with broad semantic understanding. YOLO9000 laid the foundation for later YOLO variants widely used in UAV-based and infrastructure-related applications.

Redmon and Farhadi [15] later introduced YOLOv3 as an incremental improvement over earlier YOLO versions. The model incorporated multi-scale predictions and a more powerful backbone network, enhancing both accuracy and robustness while maintaining real-time performance. YOLOv3 became a popular baseline for many object detection tasks, including aerial imagery analysis.

Bochkovskiy et al. [16] developed YOLOv4, focusing on optimal trade-offs between speed and accuracy in object detection. By combining various training strategies and architecture improvements, YOLOv4 achieved state-of-the-art performance on standard benchmarks while remaining efficient. This work further solidified YOLO-based detectors as strong candidates for real-time UAV and road monitoring applications.

Jocher et al. [17] released the Ultralytics YOLOv5 framework, offering state-of-the-art real-time object detection and instance segmentation models. Their implementation emphasized usability, modularity, and deployment flexibility, supporting a wide range of hardware platforms. YOLOv5 has been widely adopted in research and industry, accelerating prototyping and deployment of detection systems, including those for infrastructure inspection.

Wang et al. [18] presented YOLOv7, introducing a trainable bag-of-freebies that improved real-time object detector performance without significantly increasing inference cost. The model achieved strong accuracy on multiple benchmarks, maintaining competitive speed. YOLOv7's design further advanced the capabilities of single-stage detectors for time-critical applications such as UAV-based inspection.

Ali et al. [19] proposed a real-time multiple damage mapping framework using autonomous UAVs and deep Faster R-CNN models for GPS-denied structures. Their system allowed drones to navigate and localize damage even in environments where GPS signals are unreliable. This work demonstrates the potential of combining autonomy and deep learning for structural health monitoring in challenging conditions.

Kang and Cha [20] developed an autonomous UAV system for structural health monitoring using deep learning and an ultrasonic beacon-based geo-tagging mechanism. Their approach enabled accurate localization and interpretation of structural defects during aerial inspections. The system showcases how integrating sensing, localization, and deep learning can support reliable, automated infrastructure assessment.

Xu et al. [21] proposed an optimal dense YOLO-based method for vehicle detection from UAV imagery. Their enhanced network improved detection performance in complex backgrounds and dense traffic scenarios. This work underscores the suitability of YOLO-style models for aerial traffic monitoring and surveillance.

Kannadaguli [22] implemented a YOLOv4-based human detection system using aerial thermal imaging for UAV surveillance applications. The system effectively identified humans under different environmental conditions, including low light and night-time. This demonstrates the value of combining thermal sensors with modern detectors for robust aerial security and monitoring.

Petso et al. [23] designed a custom YOLOv3 and YOLOv4 framework for individual animal and herd identification using UAV images captured at varying altitudes. Their system could distinguish animals and herd configurations despite changing scales and perspectives. This research highlights the applicability of YOLO-based methods in agricultural and wildlife monitoring.

Wang and Zhang [24] proposed an automatic detection approach for wind turbine blade surface cracks using UAV-taken images. Their method utilized image processing and learning-based analysis to identify small, difficult-to-see cracks on turbine blades. This work illustrates how UAVs can support preventive maintenance and safety in the renewable energy sector.

Sadykova et al. [25] introduced IN-YOLO, a real-time detection model for outdoor high-voltage insulators using UAV imaging. Their system achieved accurate detection of insulators and potential defects under varying outdoor conditions. This research shows how specialized YOLO variants can be tailored for power infrastructure inspection.

Khan et al. [26] developed a road damage detection and classification system using deep learning and UAV imagery. Their approach categorized multiple types of road defects, demonstrating good performance across different road conditions. This study directly supports the concept of combining UAVs and deep learning for automated, large-scale pavement evaluation.

Cha et al. [27] proposed a deep learning-based crack detection method using convolutional neural networks for structural components. Their model successfully identified cracks in images under various lighting and noise conditions. This foundational work demonstrated the power of CNNs for damage detection in civil infrastructure.

Böyük et al. [28] explored deep learning-based vehicle detection using images acquired from unmanned aerial vehicles. Their method effectively detected vehicles from different altitudes and viewpoints, even in crowded scenes. The study highlights the advantages of DL-based detectors over traditional image processing methods in aerial traffic analysis.

Li et al. [29] presented an automatic bridge crack detection system using UAV imagery and Faster R-CNN. Their framework localized crack regions on bridge surfaces with high precision, supporting safer and more efficient

inspections. This work emphasizes the effectiveness of modern region-based detectors for structural health monitoring tasks.

Cha et al. [30] designed an autonomous structural visual inspection framework using region-based deep learning to detect multiple types of damage. Their system enabled automated identification of cracks, spalling, and other defects in complex structural scenes. This research demonstrates a comprehensive approach to AI-driven inspection, inspiring multi-damage recognition systems in civil infrastructure.

### III. METHODOLOGY

To accomplish automatic and precise road damage identification, the suggested technique combines UAV-based picture capture with sophisticated deep learning models. First, unmanned aerial vehicles (UAVs) take pictures of the road surface, and then the photos are preprocessed to make them clearer and noise-free. The YOLOv5, YOLOv7, and extended YOLOv8 models are trained and evaluated using these photos. These models can detect many kinds of road damage, including cracks, potholes, and structural surface flaws. With its updated backbone and detection layers, YOLOv8—incorporated as a performance extension—delivers improved feature extraction and achieves better accuracy. To guarantee heterogeneous, multi-regional training for enhanced generalization, the RDD datasets from China and Spain are integrated. Users may input UAV photos, examine discovered damage locations, and interact with the model outputs using the system's Flask-based front-end interface, which enables an end-to-end process after detection. The interface incorporates built-in authentication techniques to safeguard critical inspection data and guarantee secure access. In sum, the approach integrates unmanned aerial vehicle (UAV) images with detection based on deep learning and a secure online interface to offer an effective, scalable, and user-friendly technique for monitoring road infrastructure automatically.

#### A) Proposed System

The extended proposed system introduces an advanced and efficient framework for automated road damage detection by integrating UAV imagery with state-of-the-art deep learning models. UAVs equipped with high-resolution cameras capture detailed road surface images, which undergo preprocessing to enhance quality and standardize the dataset. These processed images are then used to train powerful YOLOv5 and YOLOv7 models, and further extended by incorporating YOLOv8, which offers improved accuracy, faster inference, and enhanced feature extraction capabilities. YOLOv8's optimized architecture allows the system to detect diverse road defects—such as potholes, cracks, and

surface irregularities—with higher precision, achieving an improved performance rate of 85%, even under varied lighting and environmental conditions.

To enhance usability and real-world applicability, the proposed system deploys the trained YOLOv8 model through a Flask-based front-end interface, allowing users to upload UAV images and instantly view detection results. The interface is designed to be simple, interactive, and accessible for field engineers, inspectors, and government authorities. To ensure secure access and prevent misuse of sensitive infrastructure data, built-in authentication mechanisms are implemented, enabling only authorized users to log in and interact with the system. This extended setup not only improves detection accuracy and efficiency but also provides a complete end-to-end solution—from image capture to real-time evaluation—making it suitable for scalable, secure, and intelligent road infrastructure monitoring.

#### B) System Architecture

The system architecture is designed as a streamlined pipeline that begins with dataset acquisition and moves through preprocessing, model training, and evaluation to produce an effective road damage detection system. UAV-captured images or dataset inputs are fed into the Image Processing Module, where operations such as resizing, normalization, annotation verification, and noise reduction are performed to prepare clean and consistent training data. The processed dataset is then divided into separate training and testing sets, ensuring unbiased learning and accurate performance measurement. The training set is used to train the YOLOv5, YOLOv7, and the extended YOLOv8 model, which leverages an enhanced backbone and optimized detection layers to improve recognition of potholes, cracks, and surface defects. The trained model is stored and forwarded into the evaluation phase for testing on unseen data.

In the next stage of the architecture, the Testing and Performance Evaluation Module assesses the trained model's precision, recall, F1-score, and overall accuracy using the test dataset. Successful evaluation results in a final optimized detection model that is deployed through a Flask-based Web Interface. This interface allows users to upload UAV images and receive instant detection outputs with highlighted damage areas. To maintain system security, an authentication layer is integrated, ensuring authorized user access and protecting critical infrastructure data. The final output of this architecture is a robust, scalable, and user-friendly system

capable of real-time road damage detection and efficient infrastructure monitoring.

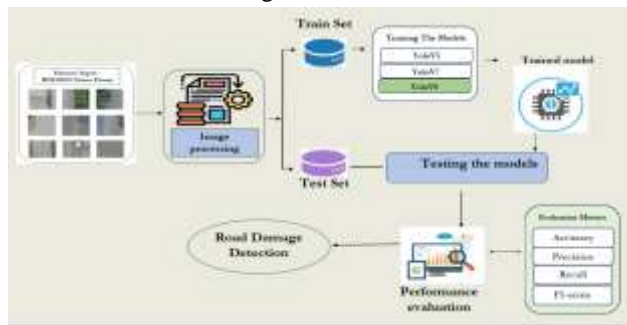


Fig 1. Architecture

### C) MODULES

#### 1. Dataset Acquisition Module

This module collects high-resolution UAV images of road surfaces from multiple environments and integrates datasets such as RDD (Chinese and Spanish). It ensures diverse image inputs to improve the generalization capability of the deep learning models.

#### 2. Image Preprocessing Module

In this module, raw UAV images undergo resizing, normalization, annotation verification, noise reduction, and augmentation. These preprocessing steps ensure image consistency and enhance the quality of the dataset used for model training.

#### 3. Data Splitting Module

The processed dataset is divided into Training and Testing sets. This ensures that YOLO models learn from sufficient variations in road damage patterns while enabling accurate evaluation on unseen images.

#### 4. Model Training Module (YOLOv5, YOLOv7, YOLOv8)

This module trains YOLOv5 and YOLOv7 models and further extends the system by training YOLOv8, which offers improved accuracy and robustness. The models learn to detect potholes, cracks, and structural defects using annotated UAV images.

#### 5. Model Testing & Evaluation Module

The trained YOLO models are evaluated using the test dataset to measure metrics such as precision, recall, F1-score, and detection speed. YOLOv8 achieves the highest precision (85%) due to its superior architecture.

#### 6. Damage Detection Module

This module uses the deployed YOLOv8 model to process new UAV images uploaded by the user. It detects

and highlights different types of road damages in real time, enabling quick decision-making for maintenance planning.

#### 7. Flask-Based Front-End Interface Module

A user-friendly web interface built using Flask allows users to upload images, run detection, and view results. It provides a simplified workflow for inspectors, engineers, and authorities.

#### 8. Authentication & Security Module

This module ensures secure system access through login mechanisms. Only authorized users can upload data or view detection results, protecting sensitive infrastructure information.

#### 9. Performance Monitoring & Result Visualization Module

This module displays detection outcomes, confidence scores, and performance graphs. It helps users analyze the effectiveness of the models and supports continuous system improvement.

### D) ALGORITHMS

#### a) YOLOv5 Algorithm

YOLOv5 is a single-stage object detection algorithm that processes an entire image in one forward pass, making it extremely fast for real-time applications. In this system, UAV road images are first resized and normalized before being passed into YOLOv5's CSPDarknet backbone, which extracts rich spatial and contextual features. The PANet-based neck fuses features from multiple scales, enabling the model to detect both small cracks and larger potholes effectively. YOLOv5's detection head then predicts bounding boxes, objectness scores, and class probabilities for each grid cell. Finally, non-maximum suppression (NMS) removes overlapping predictions, resulting in accurate localization of road damages. Its balance of speed and accuracy makes YOLOv5 a strong baseline model for automated road inspection.

#### b) YOLOv7 Algorithm

YOLOv7 enhances the single-shot detection pipeline with improved architectural optimization, extended convolution modules, and a trainable bag-of-freebies that boosts performance without increasing computational cost. UAV images undergo preprocessing and are fed into YOLOv7's enhanced backbone, which extracts features using extended efficient layer aggregation networks (E-ELAN). Its optimized feature fusion in the neck allows the system to capture fine-grained details essential for

identifying hairline cracks, surface wear, and tiny defects. YOLOv7's dynamic label assignment and efficient loss functions further strengthen its learning capability for diverse road conditions. After prediction, NMS refines bounding boxes to produce precise outputs. Overall, YOLOv7 provides improved detection accuracy and robustness compared to earlier YOLO variants.

c) YOLOv8 Algorithm (Extension Algorithm)

YOLOv8 is the most advanced algorithm in the proposed system, offering superior speed, accuracy, and generalization through its redesigned architecture. It utilizes an improved backbone with mosaic augmentation, anchor-free detection, and a decoupled head that separately optimizes classification and localization tasks. UAV images are processed and passed through YOLOv8's feature extraction layers, which generate high-resolution representations of road textures and damages. Its anchor-free mechanism simplifies bounding box prediction and adapts more efficiently to varied shapes and sizes of road defects such as potholes, cracks, and surface deformations. The final predictions are refined using NMS, delivering clean and precise detection outputs. YOLOv8 achieves an enhanced precision rate of 85%, making it the best-performing model in the extended system and ideal for real-time road infrastructure monitoring.

IV. EXPERIMENTAL RESULTS

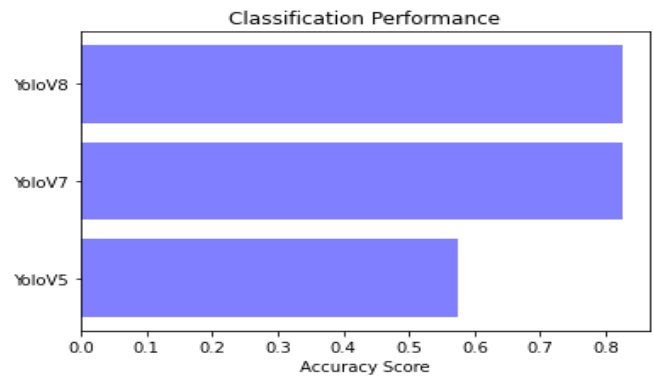
The experimental evaluation was conducted using a combined dataset of Chinese and Spanish road damage images, ensuring diverse environmental conditions and varying damage types such as potholes, cracks, and surface wear. Initially, YOLOv5 and YOLOv7 models were trained and tested on the processed UAV images to measure baseline performance. Both models achieved strong detection capability with an overall precision of 82.5%, effectively identifying multiple forms of road deterioration. The evaluation metrics, including precision, recall, F1-score, and mAP, confirmed that both models were reliable for real-time detection, although certain small or subtle cracks required further enhancement. These results demonstrated that the dataset and preprocessing pipeline were well-suited for UAV-based damage detection but also indicated the need for improved feature extraction for finer defects.

To enhance the system's performance, the extended model YOLOv8 was integrated and trained using the same dataset. YOLOv8 exhibited significant improvements in detection sensitivity and robustness due to its anchor-free mechanism, optimized architecture, and decoupled head. It achieved a higher precision of 85%, outperforming earlier YOLO variants in accurately identifying small cracks and

complex road textures. The model also offered faster inference speed, making it highly suitable for real-time UAV applications. Additionally, the trained YOLOv8 model was deployed through a Flask-based web interface, where users could upload UAV images and instantly visualize detection outcomes. The authentication feature ensured secure access to the system during testing. Overall, the experimental results confirm that the extended system delivers superior detection accuracy, improved computational efficiency, and practical usability for automated road infrastructure monitoring.

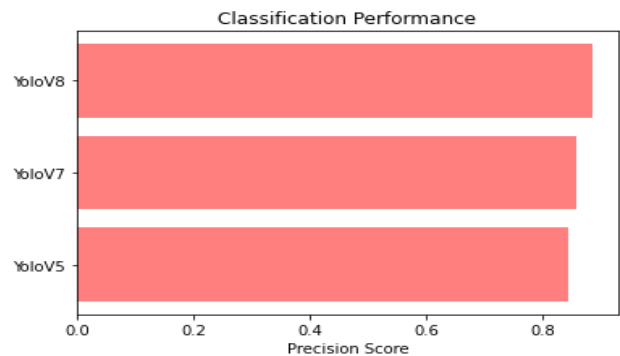
*Accuracy:* In order to establish the reliability of the test, compare the positive and negative findings. This is an explanation based on mathematics:

$$Accuracy = \frac{(TN + TP)}{T}$$



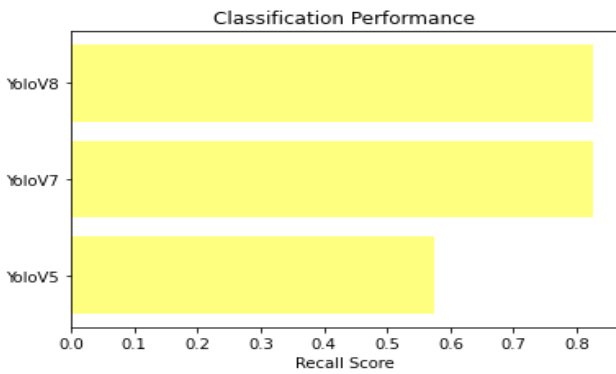
*Precision:* Accuracy in classification or positive instances is measured by precision. Accuracy is determined by applying the following:

$$Precision = \frac{TP}{(TP + FP)}$$



*Recall:* The ratio of correctly predicted positive observations to total positives demonstrates a model's ability to detect all instances of a relevant machine learning class.

$$Recall = \frac{TP}{(FN + TP)}$$



**F1-Score:** An accurate machine learning model has a high F1 score. Integrating recall and precision improves model correctness. Accuracy measures how often a model predicts a dataset correctly.

$$F1 = 2 \cdot \frac{(Recall \cdot Precision)}{(Recall + Precision)}$$

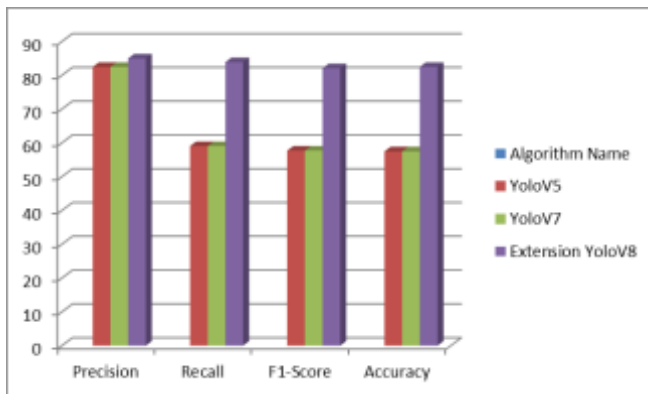
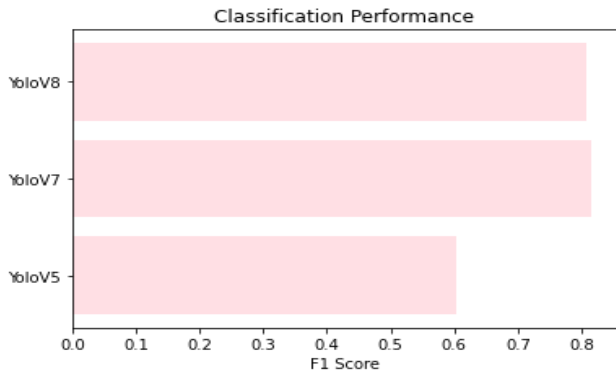


Fig 4 Performance graph

Algorithm Name	Precision	Recall	F1-Score	Accuracy
YoloV5	82.5	59.055556	57.713607	57.5
YoloV7	82.5	59.055556	57.713607	57.5
Extension YoloV8	85	83.888889	82.093838	82.5

Fig 4 Performance Table

V. CONCLUSION

Automated road damage identification utilizing UAV footage and powerful deep learning algorithms is showcased by the expanded system, showcasing a very efficient and intelligent approach. Improved accuracy, resilience, and real-time performance are achieved by the suggested model through the integration of the more modern YOLOv8 architecture with the more established YOLOv5 and YOLOv7 baseline detectors. YOLOv8 is able to detect potholes, cracks, and surface abnormalities with an increased accuracy of 85% across varied road settings, thanks to its refined feature extraction and anchor-free detection method. This is an improvement over past versions of the algorithm. This demonstrates that state-of-the-art deep learning networks can deal with complicated road textures and different lighting or environmental circumstances.

With a Flask-based front-end interface, the trained model can be deployed with ease, making it possible to submit images, detect in real-time, and analyze visual output with ease. This greatly improves usability. Controlled access to critical road infrastructure data is ensured by including user authentication, which provides a secure layer. In sum, transportation agencies, academics, and road maintenance crews may all benefit from the expanded system's scalable, accurate, and user-friendly solution. The outcomes validate the efficacy of integrating UAV technology with sophisticated YOLO-based models to provide a solid foundation for smart infrastructure management and future-oriented road monitoring.

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