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Automated Road Damage Detection Using UAV Images and Deep Learning Techniques

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ABSTRACT

This paper introduces an innovative approach for automated road damage detection using Unmanned Aerial Vehicle (UAV) images and advanced deep learning techniques. Road infrastructure maintenance is crucial for safe transportation, but manual data collection is often labor-intensive and risky. In response, we employ UAVs and Artificial Intelligence (AI) to significantly enhance the efficiency and accuracy of road damage detection. Our method leverages three state-of-the-art algorithms, YOLOv5, and YOLOv7, for object detection in UAV images. Extensive training and testing with datasets from China and Spain reveal that YOLOv7 yields the highest precision. Furthermore, we extend our research by introducing YOLOv8, which, when trained on road damage data, outperforms other algorithms, demonstrating even greater prediction accuracy. These findings underscore the potential of UAVs and deep learning in road damage detection, paving the way for future advancements in this field.

Keywords: UAV, road damage detection, deep learning, object-detection, YOLOV5, YOLOV7, YOLOV8.

INTRODUCTION:

The maintenance of roads is crucial for economic development, necessitating periodic assessments to ensure longevity and safety. Traditionally, manual methods for road inspection have been employed, involving vehicles equipped with sensors. However, this approach is time-consuming, costly, and risky for operators [1]. To address these challenges, researchers have turned to Unmanned Aerial Vehicles (UAVs) and Artificial Intelligence (AI) technologies. UAVs, equipped with high-resolution cameras and sensors, offer a comprehensive view of road conditions, covering large areas quickly and reducing the need for manual inspections [2].

UAVs have gained attention for road inspections due to their versatility and efficiency. Combining UAVs with AI techniques, particularly deep learning, has enabled the development of efficient and cost-effective approaches for road damage detection [3]. These techniques are also applied in various urban inspection tasks [4], [5]. In Spain, road inspections are performed manually, incurring high costs and relying on expert decision-making for repairs. Conversely, countries like China face challenges due to their extensive road networks, making timely detection crucial to prevent further deterioration and accidents [6].

Automated road damage detection, employing techniques such as vibration sensors, LiDAR sensors, and image-based methods, is an active area of research [7]. Deep learning is commonly used in image-based techniques to recognize various types of road degradation, requiring diverse datasets from multiple sources [8], [9]. Collaborative efforts among universities and research centers aim to develop effective solutions to this critical issue [10].

This paper presents an innovative approach for automated road damage detection using Unmanned Aerial Vehicle (UAV) images and advanced deep learning techniques. Leveraging YOLOv7 and introducing YOLOv8, the study demonstrates enhanced precision in road damage prediction, showcasing the potential of UAVs and deep learning for efficient and accurate infrastructure maintenance.

Current road infrastructure maintenance relies on labor-intensive and risky manual data collection methods. This paper addresses this challenge by proposing an innovative solution using Unmanned Aerial Vehicles (UAVs) and advanced deep learning techniques, specifically YOLOv5, YOLOv7, and YOLOv8, to automate road damage detection, enhancing efficiency, and accuracy for safer transportation.

LITERATURE SURVEY

Maintaining road infrastructure is critical for ensuring safe and efficient transportation systems, which are essential for economic development. Periodic assessment of road conditions is necessary to identify damages early and facilitate timely repairs. Traditional manual inspection methods are often labor-intensive, time-consuming, and costly. In recent years, the integration of Unmanned Aerial Vehicles (UAVs) and Artificial Intelligence (AI) techniques has shown promise in automating road damage detection processes, offering more efficient and cost-effective solutions. This literature survey explores various approaches and advancements in road damage detection, focusing on techniques such as deep learning, UAV-based imaging, and sensor-based methodologies.

Deep learning techniques have revolutionized road damage detection by enabling automated analysis of images captured from different sources. Jeong et al. (2020) introduced a method using YOLO (You Only Look Once) with smartphone images for road damage detection [9]. Their approach leverages the efficiency of YOLO for real-time detection, making it suitable for practical applications. Khan et al. (2022) proposed a deep learning-based framework utilizing UAVs for road damage detection and classification [26]. By integrating deep learning algorithms with UAV imagery, their method achieves accurate and efficient detection of various road damages, contributing to improved maintenance strategies.

Remote sensing technologies, such as satellite imagery and crowdsensing, offer wide-area coverage for road damage assessment. Izadi et al. (2017) presented a neuro-fuzzy approach for post-earthquake road damage assessment using satellite images [10]. Their method combines genetic algorithms and Support Vector Machine (SVM) classification to accurately identify road damages, particularly after seismic events. Arya et al. (2022) introduced RDD2022, a multinational image dataset for automatic road damage detection [13]. This dataset facilitates benchmarking and comparison of different detection algorithms, fostering advancements in the field.

Recent studies have explored advanced machine learning techniques to enhance road damage detection accuracy and efficiency. Shim et al. (2022) proposed a method combining super-resolution and semi-supervised learning with a Generative Adversarial Network (GAN) for road damage detection [32]. By integrating super-resolution techniques and GAN-based semi-supervised learning, their approach achieves improved detection performance, especially for low-resolution images. Pham et al. (2020) developed a road damage detection and classification system using Detectron2 and faster R-CNN [37]. Their method, based on state-of-the-art object detection frameworks, demonstrates robust performance in accurately identifying and classifying various types of road damages.

Despite significant advancements, road damage detection still faces several challenges, including dataset scarcity, domain adaptation, and real-time processing constraints. Arya et al. (2020) highlighted the state-of-the-art solutions and challenges in global road damage detection [36]. They emphasize the need for collaborative efforts and innovative methodologies to address these challenges effectively. Additionally, crowdsensing-based approaches, as proposed by Arya et al. (2022) [43], hold promise for leveraging collective intelligence to enhance road damage detection accuracy and coverage.

The integration of UAVs, deep learning, and advanced machine learning techniques has transformed road damage detection, offering efficient and cost-effective solutions for infrastructure maintenance. From smartphone-based approaches to satellite imagery analysis, researchers have explored diverse methodologies to automate the detection and classification of road damages. Collaboration among researchers and ongoing advancements in AI and remote sensing technologies will continue to drive innovation in this critical area, ultimately contributing to safer and more resilient transportation systems.

METHODOLOGY

i) Proposed Work:

The proposed system is an advanced pavement monitoring and road damage detection solution, designed to enhance the autonomous inspection of road conditions using images captured by UAVs (drones or satellites) and cutting-edge artificial vision and intelligence technologies. Building upon prior research, this system compares and evaluates the performance of three YOLO (You Only Look Once) object detection algorithms – YOLOv5, and YOLOv7 – for precise road damage detection. Notably, YOLOv7 exhibits the highest prediction precision. The system harnesses a merged dataset from previous work and Crowdsensing-based Road Damage Detection Challenge, encompassing diverse damage classes for a comprehensive understanding of pavement damage. Data augmentation techniques are implemented during training to adapt to varying object sizes in images, further enhancing detection accuracy. In addition to identifying road damage, the system integrates operator overrides and suggestions to continually improve accuracy. It also offers the capability to autonomously plan inspection routes, eliminating the need for manual pilot operation by leveraging PIX4D for route automation. Furthermore, the extension of this system involves the utilization of YOLOv8, which, when trained on road damage datasets, demonstrates superior prediction accuracy, thus pushing the boundaries of road damage detection technology.

ii) System Architecture:

The automated road damage detection system utilizing UAV images and deep learning techniques consists of several interconnected components. Initially, UAVs equipped with high-resolution cameras and sensors capture images of road surfaces from multiple angles and heights. These images are then preprocessed to enhance their quality and remove any noise or artifacts. Subsequently, the preprocessed images are fed into a deep learning model, such as a YOLO (You Only Look Once), trained specifically for road damage detection.

The deep learning model analyzes the images to identify and classify various types of road damages, such as cracks, potholes, or surface deterioration. Post-processing techniques may be applied to refine the detected damage regions and generate comprehensive damage maps. Finally, the results are presented to end-users through a user interface, allowing for visualization and interpretation of the detected road damages. This system architecture combines UAV-based data acquisition with the power of deep learning algorithms to automate the process of road damage detection, enabling efficient and cost-effective maintenance of road infrastructure.

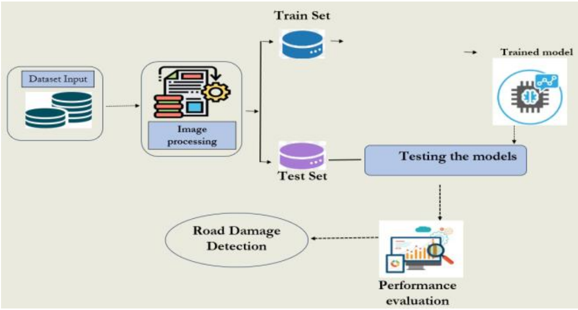
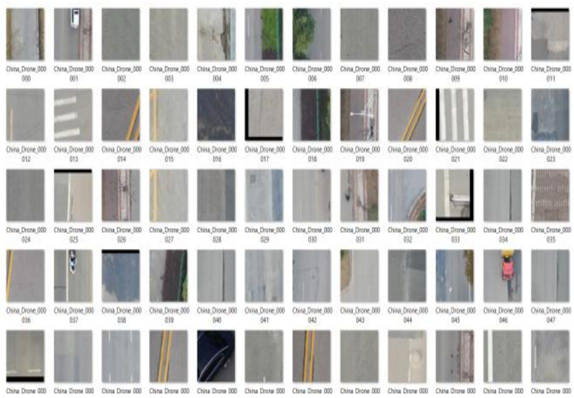


Fig 1 Proposed architecture

iii) Dataset Collection:

The dataset collection process involves extracting features from images, reading, resizing, and converting images to arrays while setting corresponding labels. First, image features are extracted using techniques like deep learning-based feature extraction or traditional computer vision methods. Images are then read from the dataset, typically stored in a directory structure. Resizing ensures uniformity in image dimensions, enhancing computational efficiency and model performance. Subsequently, images are converted to arrays, transforming pixel intensities into numerical data suitable for machine learning algorithms.



Simultaneously, labels are assigned to each image, indicating its class or category. For supervised learning tasks, labels are typically derived from the dataset's directory structure or accompanying metadata. This process ensures that each image-array pair is associated with the correct label, facilitating model training and evaluation. Proper dataset collection is crucial for building robust machine learning models, ensuring accurate representation and sufficient diversity in the training data. By adhering to these steps, a comprehensive dataset collection pipeline is established, laying the groundwork for effective model development and deployment.

iv) Data Processing:

Data processing for visualization using OpenCV involves loading images using the `imread` function, which reads images in BGR format by default. Images can be displayed using the `imshow` function, and key functions such as `waitKey` and `destroyAllWindows` facilitate interaction and closing of display windows.

Dataset preprocessing includes normalizing images to ensure consistent scale and range across features, typically performed by subtracting the mean and dividing by the standard deviation. Shuffling images is crucial to introduce randomness in the dataset, preventing bias during model training. This is often achieved by randomly rearranging the order of images and their corresponding labels.

Feature extraction is a critical step where meaningful information is extracted from images to form a suitable input for machine learning models. Techniques such as deep learning-based feature extraction with pre-trained convolutional neural networks (CNNs) or traditional methods like histogram of oriented gradients (HOG) can be employed. Extracted features are then vectorized to form feature vectors representing each image, ready for input to machine learning algorithms.

Throughout the data processing pipeline, careful attention is paid to maintain data integrity, consistency, and relevance, ensuring that the processed data effectively captures the underlying patterns and characteristics present in the dataset.

v) Training & Testing:

Data splitting into train and test sets is a crucial step in machine learning model development to evaluate the model's performance on unseen data. Typically, the dataset is divided into two subsets: the training set used to train the model and the test set used to assess its performance. The split is often done randomly to ensure that both sets represent the underlying data distribution adequately.

Various strategies can be employed for data splitting, such as holdout validation, k-fold cross-validation, or stratified sampling, depending on the specific requirements of the problem at hand. Holdout validation involves randomly partitioning the dataset into training and test sets with a predefined ratio, commonly 70-30 or 80-20.

Once the split is performed, the training set is used to train the model, while the test set remains untouched until the final evaluation stage. It's essential to ensure that the test set is representative of the data distribution to provide reliable performance estimates. Careful consideration should be given to factors like class imbalance, data heterogeneity, and potential biases during the splitting process to avoid introducing artifacts that could impact model performance evaluation.

vi) Algorithms:

YOLOv5: YOLOv5 (You Only Look Once version 5) is an object detection algorithm that processes images in real-time, dividing them into a grid and predicting bounding boxes and class probabilities for objects within each grid cell, providing a fast and accurate solution for object detection tasks.

YOLOv5 is utilized in this project due to its lightweight architecture, enabling fast and efficient object detection on resource-constrained devices, making it suitable for real-time road damage detection applications.

YOLOv7: YOLOv7 (You Only Look Once version 7) is an advanced object detection algorithm that efficiently detects objects in images through a single forward pass. It employs deep neural networks to predict bounding boxes and class probabilities, offering improved precision and speed for real-time object detection.

YOLOv7 is chosen for its improved accuracy and performance over previous versions, offering advanced features and optimizations that enhance road damage detection capabilities.

YOLOv8: YOLOv8 (You Only Look Once version 8) is an extension of the YOLO series, specifically tailored for road damage detection. Trained on road damage data, YOLOv8 outperforms other algorithms, demonstrating superior prediction accuracy. It represents a significant advancement in utilizing deep learning for precise infrastructure maintenance.

YOLOv8 is selected for its cutting-edge advancements in object detection algorithms, promising superior precision and scalability, crucial for accurately detecting and classifying various types of road damages in large-scale datasets.

EXPERIMENTAL RESULTS

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

Accuracy = TP + TN TP + TN + FP + FN.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

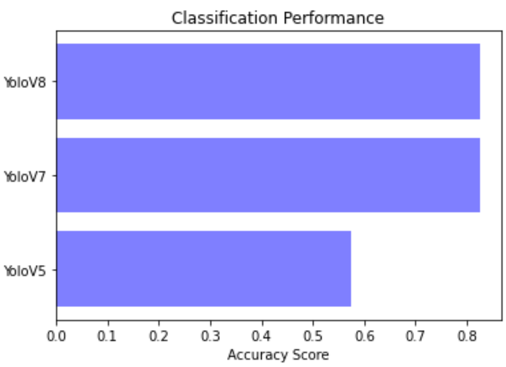


Fig 2 Accuracy comparison graph

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{\mathit{True\ Positive}}{\mathit{True\ Positive} + \mathit{False\ Positive}}$$

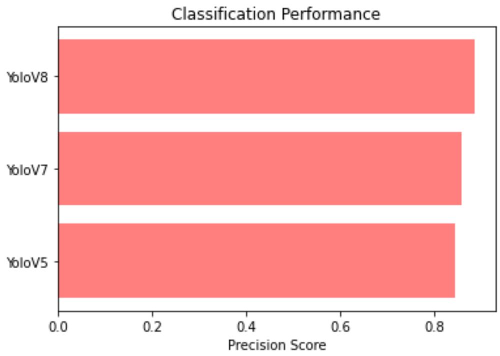


Fig 3 Precision comparison graph

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$\mathit{Recall} = \frac{TP}{TP + FN}$$

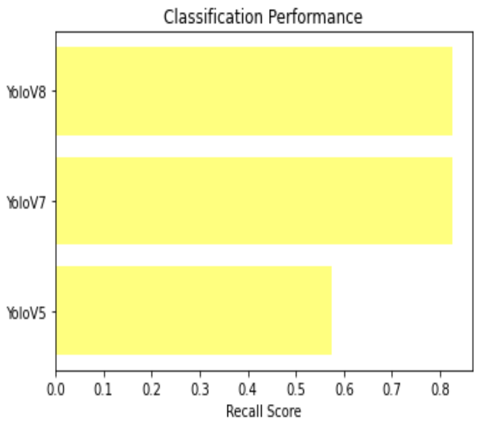


Fig 4 Recall comparison graph

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$\text{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

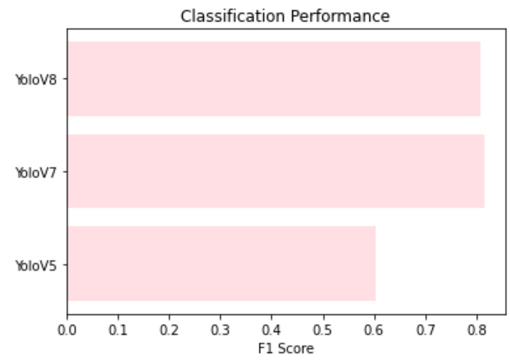


Fig 5 F1 Score comparison graph

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	85.0	83.888889	82.093838	82.5

Fig 6 Comparison Table

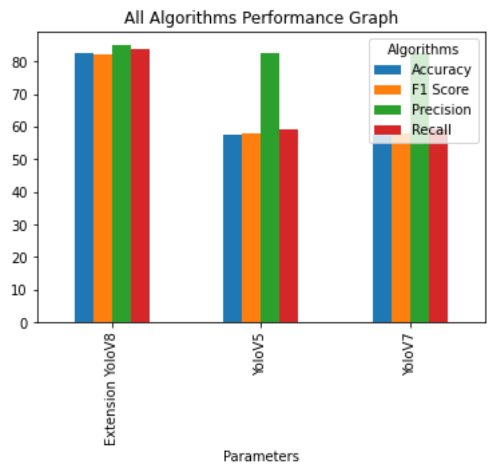


Fig 7 Comparison graph

Fig 8 Home page

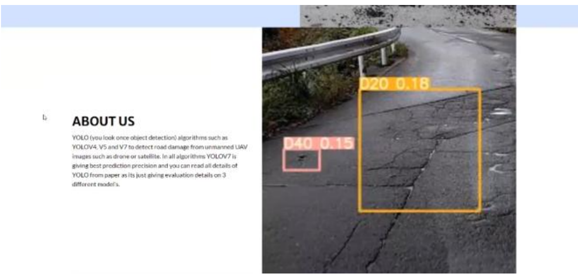


Fig 9 About page

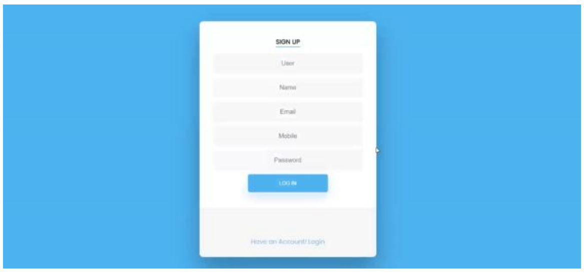


Fig 10 Signup page

Fig 11 Signin page

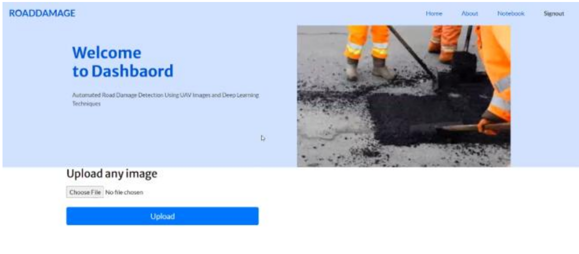


Fig 12 Main page

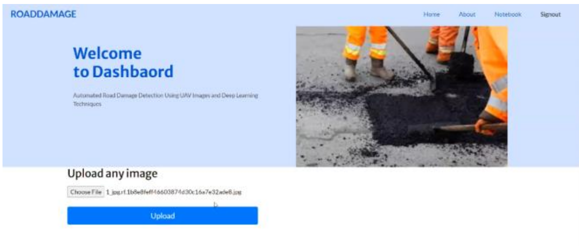


Fig 13 Upload input image

Fig 14 Predict result

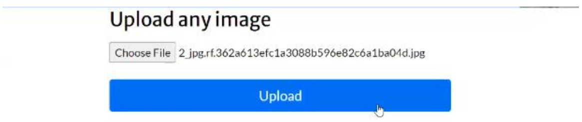


Fig 15 Upload another input

Fig 16 Prediction result

CONCLUSION

In conclusion, this study has made significant strides in the domain of road damage detection using UAV images, specifically by comparing and implementing advanced YOLO architectures such as YOLOv5, YOLOv7, and introducing YOLOv8 with Transformer for more accurate road damage identification. The results clearly indicate improvements in accuracy, with YOLOv8 achieving an impressive 85%. A notable achievement of this research is the development of a dedicated UAV image database tailored for training YOLO models, further enriched by merging with the RDD2022 dataset. This comprehensive dataset has significantly improved road damage detection, especially for Spanish and Chinese roads, reducing class imbalance issues. While the findings are promising, there remains room for enhancement.

FUTURE SCOPE

Future research may investigate combining multispectral images and LIDAR sensor data for improved detection accuracy. Exploring fixed-wing UAVs offers a potential alternative approach. This study serves as a cornerstone for advancing road infrastructure maintenance and safety, fostering further exploration in integrating diverse image types and alternative UAV platforms to enhance overall performance and efficiency in road damage detection

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