Advanced Road Damage Detection via UAV Imagery and Deep Learning Techniques

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ABSTRACT: This study presents a novel technique for automating the identification of street damage through the use of unmanned aerial vehicles (UAVs) and advanced deep learning algorithms. Maintaining road infrastructure is crucial for safe operation; however, manual data collection can often be labor-intensive and hazardous. We employ UAVs and artificial intelligence (AI) to significantly enhance the efficiency and precision of detecting road damage. Our method implements three sophisticated algorithms, Yolov5 and Yolov7, to identify objects in UAV images. Comprehensive training and evaluation utilizing data sets from China and Spain indicate that Yolov7 achieves the highest accuracy. Additionally, we augment our analysis with Yolov8, which surpasses previous systems in predicting road damage when trained on relevant data and demonstrates improved accuracy. These findings underscore the potential of UAVs and deep learning in the identification of road damage, paving the way for further advancements in this domain.

Key words: *UAV, road damage detection, deep learning, object-detection, YOLOV5, YOLOV7, and YOLOV8".*

1. INTRODUCTION

Maintaining highways is essential for economic development and requires ongoing assessment to ensure longevity and safety. Traditionally, manual methods have been employed for road monitoring using vehicles fitted with sensors. This approach can be challenging for operators and carries certain risks. Researchers have turned to unmanned aerial vehicles (UAVs) and artificial intelligence (AI) to address these issues. UAVs, equipped with high-resolution cameras and various sensors, can provide a comprehensive view of road conditions, thoroughly examine large areas, and lessen the need for human inspections. The interest in UAVs for road monitoring has grown due to their versatility and efficiency. By integrating UAVs with AI techniques, particularly deep learning, effective and cost-efficient approaches to detect road damage have been developed. These approaches are also applied in multiple urban inspection tasks. In Spain, road assessments are carried out manually, resulting in higher costs and reliance on expert judgment for maintenance. Conversely, countries like China face challenges due to their extensive road networks, making quick detection crucial to prevent further deterioration and accidents. Automated detection of road damage through the use of devices like vibrating sensors, Lidar sensors, and image-based algorithms is a critical area of research. Deep learning is implemented in image-based methods to identify various types of road deterioration, requiring diverse datasets from northern sources. Universities and research institutions are collaborating to devise effective solutions for this pressing issue.

This study presents a novel method for the automated detection of road damage through the use of UAV images and advanced deep learning algorithms. It utilizes Yolov7 and introduces Yolov8, showcasing improved accuracy in identifying road damage and highlighting the effectiveness of UAV technology and deep learning for precise infrastructure maintenance. Contemporary road infrastructure upkeep depends on data collection methods and hazardous manual inspections. This research addresses the issue by proposing an innovative approach that integrates UAV and sophisticated deep learning algorithms, specifically Yolov5, Yolov7, and Yolov8, to automate the identification of road damage, thereby enhancing efficiency and accuracy for safer transportation.

2. RELATED WORK

Maintaining road infrastructure is essential for ensuring safe and environmentally friendly transportation networks, which are vital for economic growth. Regular assessments of road conditions are crucial for promptly addressing issues and facilitating timely repairs. Traditional methods of manual inspections can be burdensome, time-consuming, and expensive. Recent advancements in the integration of UAVs with AI technologies have demonstrated the capability to automate the identification of road damage, offering a more efficient and cost-effective solution. This literature review explores various methods and innovations in detecting road damage, highlighting approaches that include deep learning, UAV-based imagery, and sensor-based systems. Deep learning techniques have revolutionized road damage detection by enabling automated image analysis from diverse sources. Jeong et al. (2020) presented a method utilizing Yolo (You Only Look Once) with smartphone images for road damage identification. Their approach leverages Yolo's effectiveness for real-time detection, making it suitable for practical applications. Khan et al. (2022) proposed a deep learning framework utilizing UAVs to identify and classify road damage. By integrating deep learning algorithms, the UAV images achieve precise and efficient identification of various road issues while enhancing maintenance strategies.

Remote survey technologies, such as satellite imagery and crowdsensing, offer extensive resources for assessing road damage. IZADI et al. (2017) presented a neuro-fuzzy approach to evaluate road damage following earthquakes through satellite images. Their method combines evolutionary algorithms with SVM classification to effectively detect road damage, particularly after seismic incidents. Arya et al. (2022) introduced RDD2022, a global dataset of images aimed at automating road damage detection. This dataset facilitates benchmarking and comparison of different detection methodologies, fostering advancement in this field.

Recent studies have explored advanced machine learning techniques to enhance the precision and efficiency of road damage identification. Shim et al. (2022) proposed a method that merges super resolution with semi-supervised learning through generative adversarial networks (GAN) to detect road damage. Their technique boosts detection performance, particularly with low-resolution images, by employing semi-supervised GAN learning. Pham et al. (2020) developed a system for detecting and classifying road damage using Detectron2 and Faster R-CNN. Their method effectively identifies and categorizes various types of road damage by utilizing top identification frames of objects.

Despite significant advancements, road damage detection still faces numerous challenges, such as limited datasets, domain adaptation issues, and constraints in real-time processing. Arya et al. (2020) highlighted key solutions and challenges in the global identification of road deterioration. They underscore the importance of collaborative efforts and innovative strategies to effectively address these issues. Crowdsensing approaches, as proposed by Arya et al. (2022), hold promise for leveraging collective intelligence to enhance the accuracy and scope of road damage detection.

The combination of UAVs, deep learning, and advanced machine learning techniques has transformed the identification of road damage and offered efficient and cost-effective methods for infrastructure maintenance. Researchers have examined various strategies, ranging from smartphone-based methods to satellite imagery, to automate the detection and classification of road damage. Ongoing collaboration between researchers and continuous advancements in AI technology and remote surveying will persist in this critical area, ultimately enhancing the safety and resilience of transportation networks.

3. METHODOLOGY

i) Proposed Work:

The proposed system is an advanced road monitoring solution designed to detect road damage, aiming to enhance self-sustaining road inspections using images captured from UAVs (drones or satellites) and cutting-edge artificial vision and intelligence technologies. This system builds upon earlier studies to assess the performance of three algorithms for object detection, specifically Yolov5 and Yolov7, to accurately identify road damage. Yolov7 demonstrates the highest prediction accuracy. The approach employs a consolidated dataset from previous research and a prompt to detect roadway damage, encompassing various forms of damage for a comprehensive understanding of road deterioration. Techniques of data augmentation are applied during training to adapt to different object sizes in images, thereby improving detection accuracy. This technology not only recognizes road deterioration but also incorporates optimization for the operator and guidelines to continuously enhance accuracy. Additionally, it provides the capability to autonomously plan inspection routes, eliminating the necessity for human piloting through the use of Pix4D to automate route navigation. Furthermore, the extension of this system includes Yolov8, which shows enhanced predictive accuracy when training on datasets of road damage, thus increasing the ability to detect roadway issues.

ii) System Architecture:

The automated system for identifying road damage utilizes UAV images and deep learning techniques, encompassing several interconnected components. Initially, UAVs equipped with cameras and high-resolution sensors capture images of road surfaces from various angles and heights. These images are then pre-processed to enhance quality and eliminate any noise or artifacts. After pre-processing, the refined images are fed into a deep learning model, specifically YOLO (You Only Look Once), which is trained to detect road damage. The deep learning algorithm analyzes the images to detect and classify different types of road damage, such as cracks, potholes, and surface deterioration. Additional processing techniques may be employed to highlight the identified damage areas and generate detailed damage maps. Finally, the compiled data is presented to end users through an interface that facilitates the visualization and understanding of road damage alternatives.

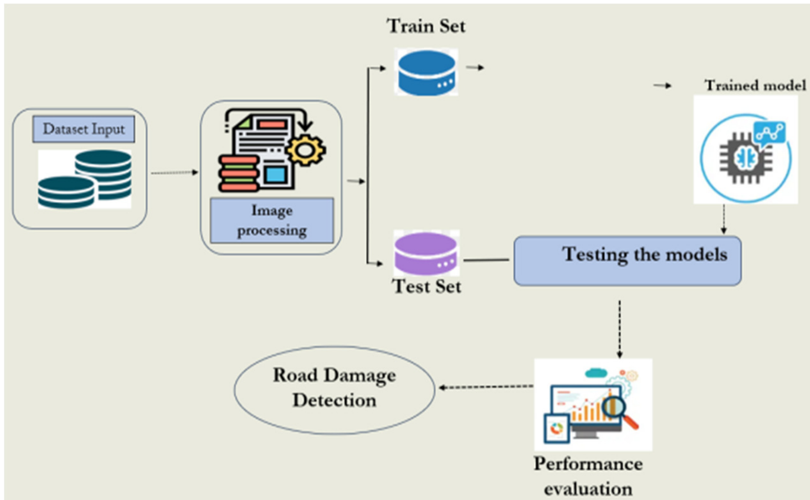


Fig. 1 Proposed architecture

iii) Dataset Collection:

The method for collecting data sets involves extracting features from images, interpreting, modifying, and transforming the images while assigning appropriate labels. Initially, images are gathered using techniques such as deep feature extraction through learning or traditional computer vision methods. The images are typically sourced from a collection that is often structured in a directory format. Ensuring uniformity in image dimensions improves calculation efficiency and model performance. The images are subsequently converted into fields, translating pixel intensity into numerical values that are suitable for machine learning algorithms.

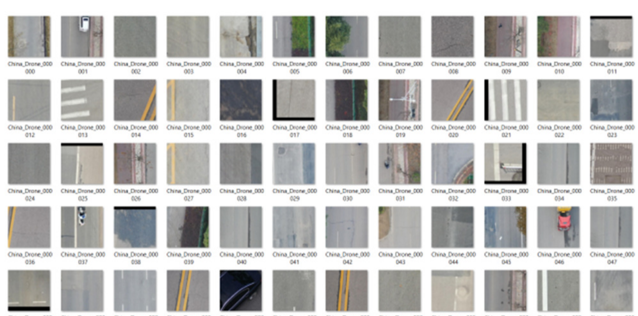


Fig. 2 Dataset collection

Simultaneously, each image is accompanied by tags that denote its style or classification. In supervised learning tasks, labels are commonly derived from the agency of the dataset listing or related metadata. This approach ensures that every image pairing is matched with the correct label, thereby enhancing the training and evaluation of the model. A careful compilation of datasets is crucial for building robust machine learning models, which guarantees accurate representation and sufficient diversity in the training data. Adhering to these steps will lead to a comprehensive collection of datasets that form the foundation for the effective development and implementation of the model.

iv) Data Processing:

Processing records for visualization using OpenCV starts with importing the library, which utilizes `IMREAD` to read images in BGR format by default. Images can be displayed with the `imshow` function, while basic operations like `waitKey` and `destroyAllWindows` allow for user interaction and window management. Training the dataset involves normalizing images to maintain a consistent size and range across features, typically achieved by subtracting the mean and dividing by the standard deviation. To ensure variability within the dataset, random shuffling of images is crucial, which helps to minimize distortion during model training. This is usually done by randomly altering the order of images and their corresponding labels.

Feature extraction is a vital process where meaningful data is extracted from images to provide suitable input for machine learning models. Techniques such as extracting deep learning features using pre-trained convolutional neural networks (CNN) or traditional methods like histogram of oriented gradients (HOG) can be employed. The extracted features are then organized into feature vectors that represent each image prepared to be fed into machine learning algorithms. Throughout the data processing pipeline, meticulous care is taken to maintain data integrity, consistency, and relevance, ensuring that the processed data accurately reflects the fundamental characteristics and properties of the dataset.

v) Training & Testing:

The distribution of data into training and test sets is a crucial aspect of machine learning models for evaluating their overall performance on new data. The data set is typically split into subsets: a training set for model training and a test set for performance evaluation. This division is usually done randomly to ensure that both subsets represent the underlying data distribution.

Various data distribution techniques may be employed, such as holdout, k-fold cross-validation, or stratified sampling, depending on the specific requirements of the problem. The validation process entails randomly splitting the dataset into training and test sets according to the desired ratio, commonly 70-30 or 80-20. Once the split is made, the training set is utilized to train the model, while the test set remains untouched until the final evaluation phase.

It is essential to ensure that the test set accurately represents the data distribution to provide a reliable performance assessment. Careful attention must be given to factors such as class imbalance, data heterogeneity, and potential biases during the distribution process to avoid creating artifacts that could skew the evaluation of the model's performance.

vi) Algorithms:

“YOLOv5: YOLOv5 (You Only Look Once version 5)” is an object detection algorithm that operates by processing images in real time. It divides the image into a grid and calculates the probabilities of objects and their locations (bounding boxes) within each grid cell, providing a fast and accurate means of detecting objects. This project will utilize YOLOv5 due to its lightweight architecture, allowing for object detection on devices with limited resources, which is particularly useful for identifying road damage.

“YOLOv7: YOLOv7 (You Only Look Once version 7)” is an object detection algorithm that predicts the location of objects in an image through a single forward pass. It employs a deep neural network to generate predictions for bounding boxes and class probabilities, ensuring enhanced speed and accuracy in real-time object detection. YOLOv7 was chosen for its superior accuracy and efficiency compared to previous versions, along with innovative features that facilitate the detection of road damage.

“YOLOv8: YOLOv8 (You Only Look Once model 8)” is the latest advancement in YOLO's research efforts, specifically designed to detect road damage. A dataset focused on road damage has been utilized to train the YOLOv8 algorithm, demonstrating a higher accuracy than other algorithms. The data indicates that its predictions are more reliable compared to alternative methods. This represents a significant enhancement in utilizing deep learning for precise infrastructure maintenance. YOLOv8 has been selected for its cutting-edge advancements in object detection models, featuring high precision and scalability, which are key for effectively identifying and classifying various types of road damage across large datasets.

4. EXPERIMENTAL RESULTS

Accuracy: An effective test must distinguish clearly between healthy and sick individuals, which is an indication of its accuracy. The accuracy of a test can be assessed by calculating the ratio of correctly identified positive cases to true negatives. We can also represent this mathematically:

$$\text{"Accuracy"} = \frac{\text{"TP + TN"}}{\text{"TP + FP + TN + FN"}} (1)$$

Precision: Precision measures the proportion of correctly identified positive cases or samples. The calculation of precision is determined by the following components:

$$\text{"Precision"} = \frac{\text{"True Positive"}}{\text{"True Positive + False Positive"}} (2)$$

Recall: ML recall evaluates a model's ability to identify all relevant instances of a class. It shows a model's effectiveness in capturing instances of a class by comparing correctly predicted high-quality observations to the total number of positives.

$$\text{"Recall"} = \frac{\text{"TP"}}{\text{"TP + FN"}} (3)$$

F1-Score: The effectiveness of a machine learning model is evaluated using the F1 score. This score combines the precision and recall metrics of the model. The accuracy metric measures how often the model makes correct predictions within the dataset.

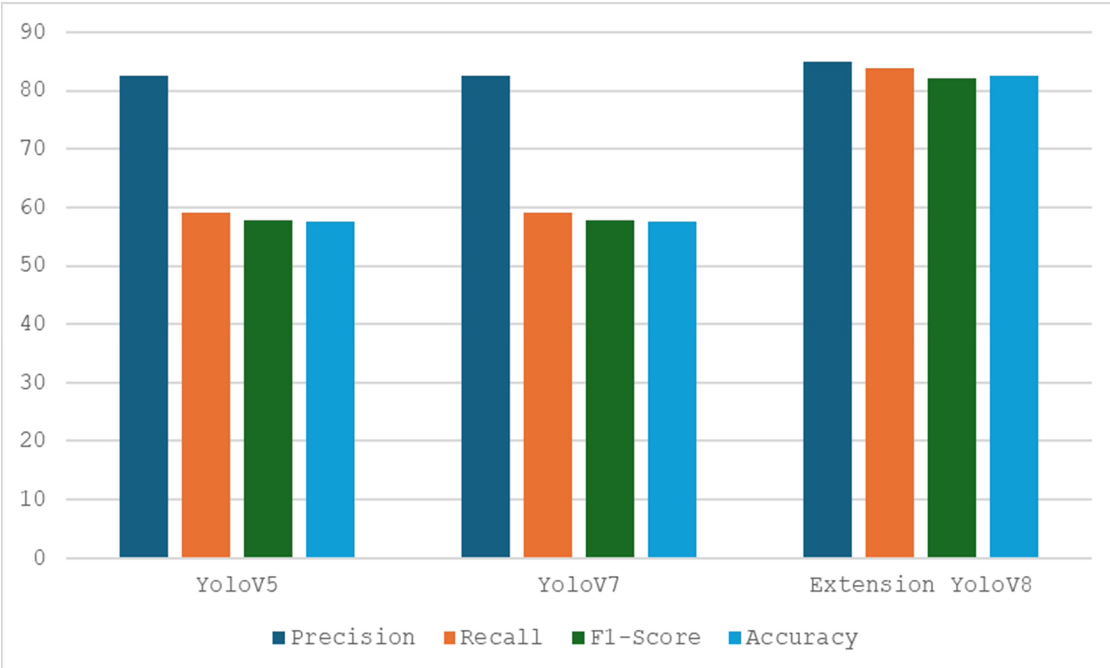
$$\text{"F1 Score"} = \text{"2"} * \frac{\text{"Recall X Precision"}}{\text{"Recall + Precision"}} * \text{"100"} (4)$$

Table (1) evaluates the “performance metrics - Accuracy, Precision, Recall, and F1 Score” for each approach. YoloV8 consistently outperforms all other algorithms on every metric. The tables offer a comparative analysis of the metrics for the other methods.

“***Table.1*** **Performance Evaluation Table”**

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**

"Graph.1 **Comparison Graph"**



In Graph (1), accuracy is depicted in blue, precision in orange, recall in green, and F1-Score in sky blue. When compared to the other models, YoloV8 outperforms all in every metric, achieving the highest scores. The results illustrated in the graphs above visually convey these findings.

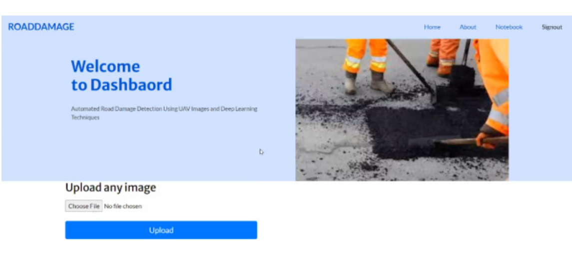


Fig.3 Home page

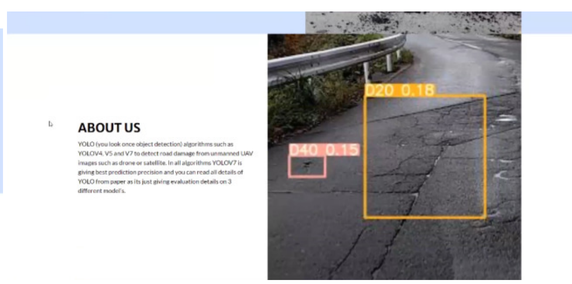


Fig.4 about page

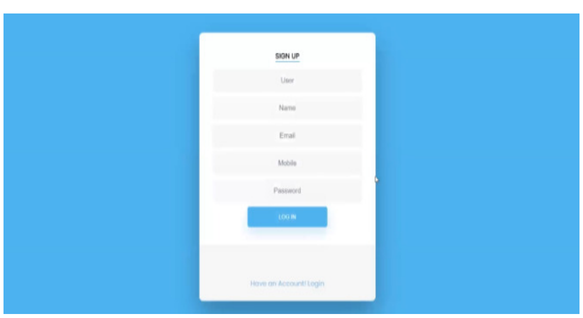


Fig.5 Signup page

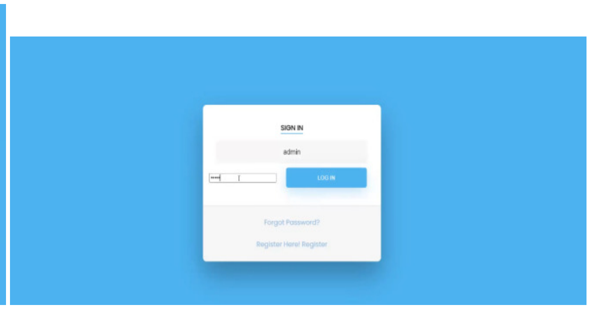


Fig.6 Signin page

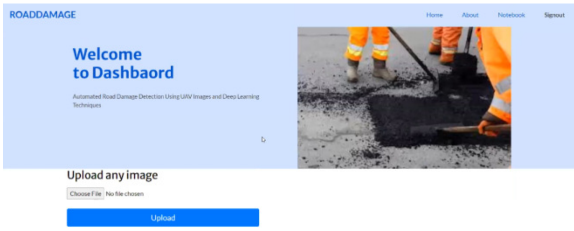


Fig.7 Main page

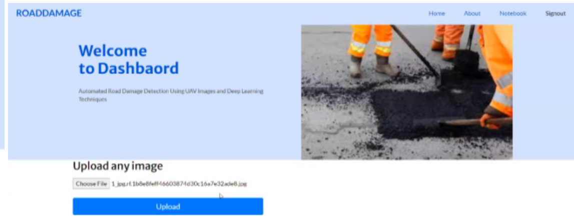


Fig. 8 Upload input image

Fig .9 Predict result

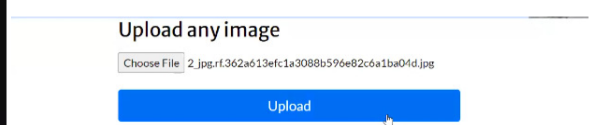


Fig.10 Upload another input

Fig.11 Prediction result

5. CONCLUSION

This work has significantly enhanced the detection of road damage through the use of UAV images by evaluating and applying advanced YOLO architectures, including Yolov5, Yolov7, and the newly introduced Yolov8, which demonstrates improved accuracy in assessing road damage. The results clearly indicate a significant increase in accuracy, with Yolov8 achieving an impressive 85% accuracy rate. This study created a specialized database of UAV images for YOLO training, enhanced by its integration with the RDD2022 data set. This comprehensive data set has greatly improved road damage detection, particularly for highways in Spain and China, which has alleviated challenges in educational settings. While the outcomes are promising, there is still room for further improvement.

6. FUTURE SCOPE

Future studies could examine how to enhance detection accuracy by integrating multispectral images with sensor data. Investigating the use of fixed-wing UAVs presents a promising strategic opportunity. This research is crucial for improving the upkeep and safety of road infrastructure, as well as for fostering further examination of the combination of different types of images and various UAV platforms to maximize the effectiveness and efficiency of road damage identification.

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