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Automated Road Damage Detection Using UAV Images and Deep Learning Techniques

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Abstract: - Automated road damage identification utilizing UAV photos and sophisticated deep learning algorithms is presented in this research as a novel methodology. While keeping roads in good repair is essential for travel safety, gathering data by hand can be a dangerous and time-consuming ordeal. Our solution is to use UAVs together with AI to make road damage identification far more efficient and accurate. To identify objects in UAV photos, our approach makes use of three cutting-edge algorithms: YOLOv5, YOLOv7, and YOLOv5. Extensive testing and training using Chinese and Spanish datasets show that YOLOv7 produces the best accuracy. In addition, we expand our study by presenting YOLOv8, an algorithm that surpasses existing algorithms and shows significantly better prediction accuracy when trained on road damage data. These results demonstrate the promise of unmanned aerial vehicles (UAVs) and deep learning for detecting road damage, which should lead to further developments in this area. Unmanned Aerial Vehicle (UAV), road damage detection, object detection, YOLOV5, YOLOV7, and YOLOV8 are index words.

Keywords: identification, YOLOv8, Unmanned Aerial Vehicle (UAV), algorithm

1. INTRODUCION

Road maintenance is essential for economic growth, therefore it's important to check them periodically to make sure they're safe and last a long time. Historically, road inspection has been conducted manually using sensor-equipped cars. On the other hand, operators run the danger of losing time, money, and energy using this method [1]. Unmanned Aerial Vehicles (UAVs) and Artificial Intelligence (AI) have become the tools of choice for academics seeking to tackle these difficulties. Unmanned Aerial Vehicles (UAVs) with high-resolution cameras and sensors can survey vast regions rapidly, eliminating the need for human inspectors to manually check roads [2].

Because of their efficiency and adaptability, UAVs have recently attracted interest for use in road inspections. We have developed efficient and cost-effective ways for road damage detection by combining UAVs with AI techniques, especially deep learning [3]. Several urban inspection jobs also make use of these strategies [4], [5]. Spanish road inspections are labor-intensive and expensive, and the country's repair decisions are based on the opinions of experts. Timely diagnosis is critical to avoid further deterioration and accidents, which poses issues for nations like China with vast road networks [6].

There is a lot of ongoing research on automated road damage detection using technologies including image-based algorithms, LiDAR sensors, and vibration sensors [7]. Recognizing different kinds of road deterioration using deep learning in image-based algorithms sometimes requires varied datasets from several sources [8], [9]. In order to address this pressing problem, academic institutions are working together to find viable solutions [10].

Automated road damage identification utilizing UAV photos and sophisticated deep learning algorithms is presented in this research as a novel methodology. The research showcases the potential of UAVs and deep learning for efficient and precise infrastructure maintenance by demonstrating greater accuracy in road damage prediction using YOLOv7 and introducing YOLOv8.

Manual data collecting techniques are currently used for road infrastructure maintenance, which is labor-intensive and dangerous. In order to automate road damage identification, improve efficiency and accuracy for

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safer transportation, this article presents a novel method that utilizes Unmanned Aerial Vehicles (UAVs) and sophisticated deep learning algorithms, particularly YOLOv5, YOLOv7, and YOLOv8.

2. LITERATURE SURVEY

Economic progress cannot occur without well-maintained transportation networks that are both safe and efficient. It is important to regularly inspect the road conditions in order to spot damage quickly and make repairs when they are needed. Manual inspections have traditionally been used, but they may be expensive, time-consuming, and labor-intensive. More efficient and cost-effective options for automating road damage detection procedures have been offered by integrating Unmanned Aerial Vehicles (UAVs) with Artificial Intelligence (AI) approaches in recent years. Deep learning, unmanned aerial vehicle (UAV) imagery, and sensor-based algorithms are some of the topics included in this literature review on road damage identification. By allowing automatic analysis of photos obtained from many sources, deep learning algorithms have transformed road damage identification. In order to identify road damage, Jeong et al. (2020) presented a system that combines smartphone photos with the YOLO (You Only Look Once) principle [9]. Their method is applicable to real-world scenarios since it takes use of YOLO's effectiveness in real-time detection. For the purpose of detecting and classifying road damage, Khan et al. (2022) suggested a system based on deep learning that makes use of UAVs [26]. Their approach detects different types of road damage efficiently and accurately by combining UAV footage with deep learning algorithms; this helps with better maintenance methods. When it comes to evaluating road damage, remote sensing technologies like crowdsensing and satellite images provide extensive coverage. After an earthquake, researchers Izadi et al. (2017) used satellite photos to develop a neuro-fuzzy method for assessing road damage [10]. To reliably detect road damage, especially in the aftermath of seismic occurrences, their approach integrates genetic algorithms with Support Vector Machine (SVM) categorization. To facilitate automated road damage identification, Arya et al. (2022) released RDD2022, a global picture dataset [13]. The use of this dataset allows for the evaluation and comparison of various detection techniques, which ultimately leads to progress in the area. The effectiveness and precision of road damage identification has been the subject of recent research into cutting-edge machine learning methods. In order to identify road damage, Shim et al. (2022) suggested an approach that combines a Generative Adversarial Network (GAN) with super-resolution and semi-supervised learning [32]. Their method improves detection performance, particularly for low-resolution photos, by combining super-resolution methods with GAN-based semi-supervised learning. Using Detectron2 and faster R-CNN, Pham et al. (2020) created a system for detecting and classifying road damage [37]. Their approach, which is built on top-notch object identification frameworks, shows great promise in detecting and categorizing different kinds of road damage.

Scarcity of datasets, adaption to new domains, and limitations on processing in real-time are still major obstacles in road damage identification, despite considerable progress in the field. In their 2020 study, Arya et al. [36] outlined the current problems and best practices for detecting road degradation throughout the world. In order to successfully tackle these issues, they stress the need of teamwork and new approaches. Furthermore, crowdsensing-based methods show potential for improving road damage detection accuracy and coverage via the use of collective intelligence, as suggested by Arya et al. (2022) [43]. Road damage identification has been revolutionized by the combination of UAVs, deep learning, and sophisticated machine learning algorithms. This has provided infrastructure maintenance with efficient and cost-effective solutions. Various strategies have been investigated by researchers in an effort to automate the identification and categorization of road problems. These methodology range from smartphone-based systems to satellite data analysis. Ultimately, safer and more robust transportation networks will be the result of continued innovation in this vital sector, driven by collaboration among academics and continuous breakthroughs in AI and remote sensing technology.

3. METHODOLOGY

i) Proposed Work:

To improve the autonomous examination of road conditions, the suggested system employs state-of-the-art artificial vision and intelligence technologies in conjunction with pictures taken by UAVs (drones or satellites) to provide a sophisticated pavement monitoring and road damage identification solution. Constructed on top of previous studies, this system assesses the efficacy of three YOLO (You Only Look Once) object identification algorithms—YOLOv5, YOLOv7—in detecting exact road damage. Among these models, YOLOv7 stands out for its exceptional prediction accuracy. The system uses a combined dataset from prior research and the Crowdsensing-based Road degradation Detection Challenge to analyze pavement degradation thoroughly. This dataset encompasses varied damage classifications. During training, data augmentation methods are used to adjust to different item sizes in photos, which improves detection accuracy even more. Not only does it detect road damage, but it also incorporates operator overrides and recommendations to make accuracy improvements over time. Furthermore, it provides the option to automate inspection routes using PIX4D, doing away with the necessity for a human pilot. In addition, this approach is enhanced by including YOLOv8, a road damage recognition algorithm that reaches new heights in terms of prediction accuracy when trained on road damage datasets.

ii) Architecture of the System:Multiple parts work together to form the automatic road damage identification system that uses deep learning algorithms and photos taken by UAVs. In the beginning, unmanned aerial vehicles (UAVs) with sensors and high-resolution cameras take pictures of the road surfaces from all different angles and heights. After that, the photos undergo preprocessing to improve their quality and eliminate artifacts and noise. After that, a deep learning model that was trained to identify road damage, like YOLO (You Only Look Once), is given the preprocessed photos. Images of road degradation, including cracks, potholes, and surface deterioration, are analyzed and classified by the deep learning model. To improve the identified damage areas and create detailed damage maps, post-processing methods may be used. The findings are then made available to end-users via an interface, which allows them to see and understand the identified road damage. Automating the process of detecting road damage, this system design allows for efficient and cost-effective maintenance of road infrastructure by combining data collecting from UAVs with deep learning algorithms.

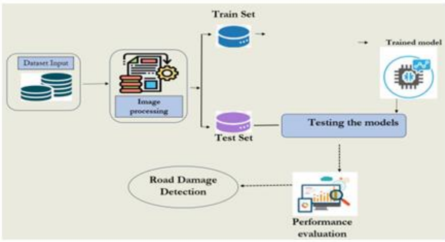
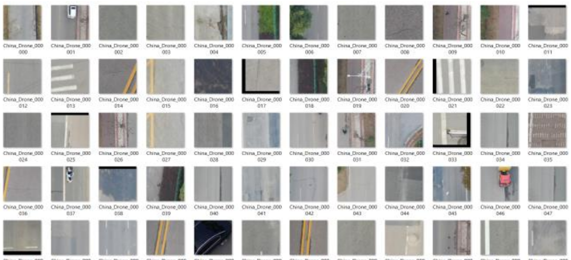


Fig 1 Proposed architecture

iii) Dataset Collection:

Images are read, resized, converted to arrays, and labelled as part of the dataset collecting process once features are extracted. The first step is to extract picture characteristics using either conventional computer vision methods or approaches based on deep learning. The next step is to get the images from the dataset, which is usually formatted as a directory structure. Resizing pictures makes ensuring their proportions are consistent, which improves the model's performance and the computer's efficiency. When photos are turned to arrays, the pixel intensities are transformed into numerical data that machine learning algorithms can work with.



At the same time, we give each picture a label that describes what it is. It is common practice to use the directory structure or metadata of the dataset to generate labels for supervised learning tasks. This procedure helps in training and evaluating models by associating the right label with each image-array pair. For strong machine learning models, it is essential to gather datasets in the right way, with enough variety and correct

representation. By following these steps, you may build a complete pipeline for collecting datasets, which will help you build and deploy models effectively. iv) Processing Data: When working with OpenCV data for visualization, one important step is to load photos using the 'imread' function. By default, this function reads images in BGR format. The 'imshow' function displays images, and 'waitKey' and 'destroyAllWindows' are essential methods for interacting with and shutting display windows.
As part of the dataset preparation process, pictures are normalized to make sure that all features have the same scale and range. This is usually done by taking the standard deviation and subtracting the mean. The introduction of randomization into the dataset, achieved by shuffling pictures, is essential for avoiding bias during model training. For this purpose, it is common practice to randomly rearrange the photos and labels. An essential part of training machine learning models is extracting features from pictures, which contain useful information. You may use approaches like histogram of oriented gradients (HOG) or deep learning-based convolutional neural networks (CNNs) for feature extraction. In order to prepare the extracted features for input into machine learning algorithms, they are vectorized to create feature vectors that represent each picture. Maintaining data integrity, consistency, and relevance is a top priority throughout the data processing pipeline. This guarantees that the processed data accurately represents the dataset's underlying patterns and features.
v) Training and Testing: A critical part of building a machine learning model is separating the data into a train set and a test set. This allows you to examine how well the model does on data that it has never seen before. The dataset is usually partitioned into two parts: the training set and the test set. The former is used to train the model, while the latter is employed to evaluate its performance. It is common practice to randomly divide the data such that both sets accurately reflect the distribution of the original data.
Stratified sampling, holdout validation, or k-fold cross-validation are some of the data splitting procedures that may be used, depending on the needs of the situation. Partitioning the dataset randomly into a training set and a test set according to a predetermined ratio, usually 70-30 or 80-20, is what holdout validation is all about. After the split is done, the model is trained using the training set, while the test set is kept static until the last evaluation step. For accurate performance estimations, it is critical to choose a test set that accurately represents the distribution of the data. To prevent adding artifacts that might impair the assessment of the model's performance, variables such as class imbalance, data heterogeneity, and possible biases should be carefully considered throughout the splitting process.

the sixth section, algorithms: One quick and reliable method for object recognition is YOLOv5, which stands for "You Only Look Once version 5." This algorithm divides photos into a grid and uses real-time processing to estimate the bounding boxes and class probabilities of objects inside each cell.
Because of its efficient and rapid object identification on devices with limited resources, YOLOv5 is used in this research. It is ideal for real-time road damage detection applications because of its lightweight design.
You Only Look Once version 7, or YOLOv7, is a state-of-the-art object identification system that can identify things in photos with remarkable efficiency with only one forward pass. For faster and more accurate object recognition in real time, it uses deep neural networks to forecast class probabilities and bounding boxes.
The enhanced road damage identification capabilities brought forth by YOLOv7's superior accuracy and performance compared to earlier versions are a direct result of these upgrades.
A new installment in the YOLO series, YOLOv8 stands for "You Only Look Once" and is optimized for detecting road damage. When given data on road damage, YOLOv8 performs better than competing algorithms, showing that it can make more accurate predictions. The use of deep learning for accurate infrastructure maintenance has made great strides forward with this innovation. In order to identify and categorize different kinds of road damages in large-scale datasets reliably, YOLOv8's state-of-the-art object identification algorithms are used since they promise better accuracy and scalability.

4. EXPERIMENTAL RESULTS

Accuracy: A test's accuracy is defined by how well it distinguishes between healthy and sick samples. We can determine a test's accuracy by calculating the percentage of reviewed instances with true positives and true negatives. If we express this mathematically, we get: Accuracy = TP + TN TP + TN + FP + FN.

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

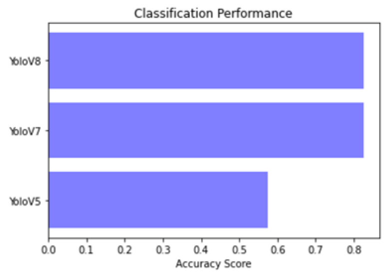


Fig 2 Accuracy comparison graph

Precision: The accuracy rate, or precision, is the percentage of true positives relative to the total number of occurrences or samples. Consequently, the following is the formula for determining the accuracy: Preciseness is TP divided by (TP plus FP), which is the sum of true positives and false positives.

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

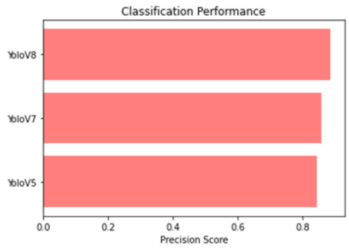


Fig 3 Precision comparison graph

Recall: The capacity of a model to detect all significant occurrences of a given class is measured by recall, a statistic in machine learning. The completeness of a model in capturing instances of a particular class is shown by the ratio of properly predicted positive observations to the total actual positives.

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

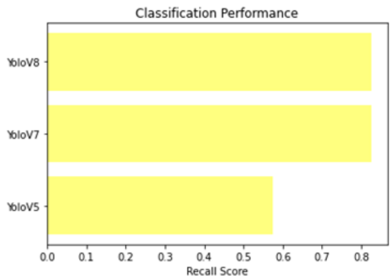


Fig 4 Recall comparison graph

F1-Score: One way to evaluate a model's performance in machine learning is via its F1 score. This method integrates a model's recall and accuracy scores. A model's accuracy may be measured by counting the number of times it correctly predicted something throughout the whole dataset.

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

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

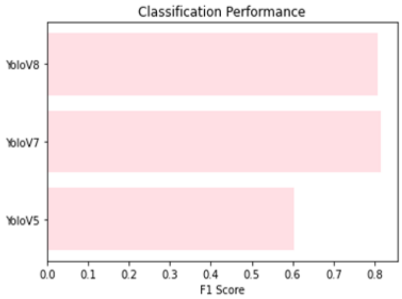


Fig 5 F1 Score comparison graph

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

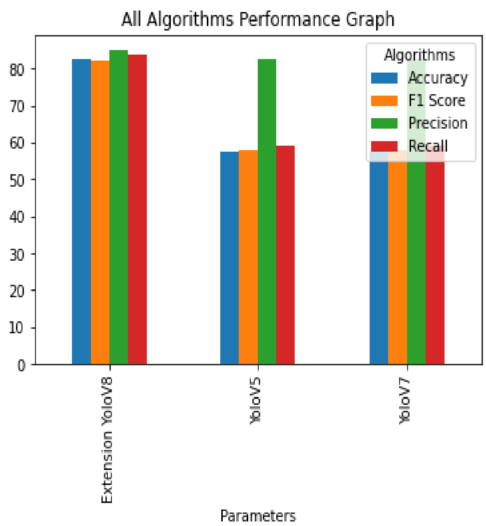


Fig 7 Comparison graph

Fig 8 Home page

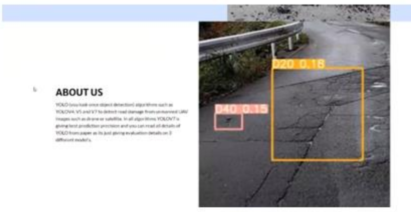


Fig 9 About page

Fig 10 Signup page

Fig 11 Signin page

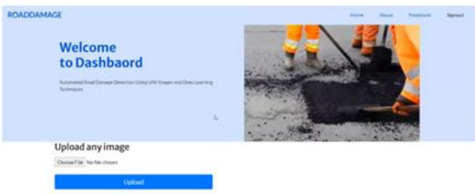


Fig 12 Main page

Fig 13 Upload input image

Fig 14 Predict result

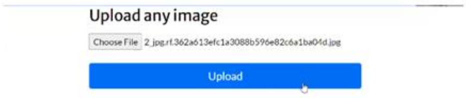


Fig 15 Upload another input

Fig 16 Prediction result

5. CONCLUSION

Finally, by comparing and applying sophisticated YOLO designs like YOLOv5, YOLOv7, and introducing YOLOv8 with Transformer for more accurate road damage recognition, this work has brought substantial progress to the field of road damage detection utilizing UAV photos. The findings show that accuracy has improved, with YOLOv8 reaching a remarkable 85%. The creation of a specialized UAV picture database for training YOLO models, which was enhanced by integrating it with the RDD2022 dataset, is a noteworthy accomplishment of this study. Thanks to this extensive dataset, road damage recognition has been much improved, particularly for roads in Spain and China, and problems with class imbalance have been reduced. There is yet opportunity for improvement, even if the results are encouraging.

6. FUTURE SCOPE

In order to increase the detection accuracy, future study may look at merging data from LIDAR sensors with multispectral photos. Another possible option is to investigate unmanned aerial vehicles (UAVs) with fixed wings. Road infrastructure maintenance and safety may be advanced thanks to this study, which lays the groundwork for future research into improving road damage detection performance and efficiency by combining varied picture types and alternative UAV platforms.

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