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LEVERAGING UAV-CAPTURED IMAGES AND YOLO TO AUTOMATE ROAD DAMAGE DETECTION

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Abstract: A new way to use UAV-captured pictures and YOLO to automatically find road damage is described in this study. Maintaining the roads is important for keeping people safe, but collecting data by hand is often hard to do and dangerous. In reaction, we use unmanned aerial vehicles (UAVs) and artificial intelligence (AI) to make finding road damage much faster and more accurate. Three cutting-edge algorithms—YOLOv5, YOLOv7—are used in our way to find objects in UAV pictures. YOLOv7 gives the most accurate results after a lot of training and testing with samples from China and Spain. We also add to our study by presenting YOLOv8, which does better than other algorithms when trained on data about road damage, showing even better prediction accuracy. These results show that UAVs and DL could be useful for finding damage on roads. This opens the door for more progress in this area.
Index terms - UAV, road damage detection, DL, object-detection, YOLOV5, YOLOV7, YOLOV8.

1. INTRODUCION

Maintaining roads is important for economic growth, so they need to be checked on a regular basis to make sure they last and are safe. Traditionally, cars equipped with sensors have been used for road inspections performed by hand. This approach is time-consuming, expensive, and dangerous [1]. Researchers are using UAVs and AI to solve these issues. UAVs with high-resolution cameras and sensors provide a complete road assessment in a short period, reducing the need for manual inspection [2].
UAVs are versatile and fast, making them popular for road assessments. Unmanned aerial vehicles (UAVs) and artificial intelligence (AI), notably Deep Learning (DL), have made road damage detection fast and affordable [3]. These methods are also used for different types of city inspections [4, 5]. In Spain, road checks are done by hand, which is very expensive and means that fixes are decided by experts. China, on the other hand, has problems because it has a lot of roads, which means that problems need to be found quickly to stop them from getting worse and causing crashes [6]. Shaking sensors, LiDAR sensors, and image-based approaches are being studied for automated road damage detection [7]. Image-based Road damage detection using DL requires a broad variety of data from numerous sources [8, 9]. Universities and study groups are working together to try to find good answers to this important problem [10].

2.LITERATURE SURVEY

Maintaining road infrastructure is important for keeping transportation systems safe and working well, which is important for economic growth. Road conditions need to be checked on a regular basis so that damage can be found early and fixed quickly. Traditional checking methods that are done by hand often require a lot of work, take a long time, and cost a lot of money. In recent years, combining Unmanned Aerial Vehicles (UAVs) with Artificial Intelligence (AI) has shown promise in automating the process of finding damage on roads, making solutions faster and cheaper. Remote sensing technologies, like satellite images and crowdsensing, can be used to look at a lot of ground to figure out how bad the damage is to roads. Izadi et al. (2017) used satellite pictures to describe a neuro-fuzzy method for evaluating road damage after an earthquake [10]. Their method uses both genetic algorithms and Support Vector Machine (SVM) classification to correctly find damage to roads, especially after earthquakes. Arya et al. (2022) created RDD2022, a set of images from around the world that can be used to automatically find damage to roads [13].

3.METHODOLOGY

3.1. Proposed Work:

The suggested method is a high-tech way to keep an eye on the road surface and find damage. It will improve the way roads are inspected automatically using pictures taken by UAVs (drones or satellites) and the latest AI and artificial vision technologies. This method builds on previous work by comparing and scoring the effectiveness of three YOLO (You Only Look Once) object recognition algorithms for accurately finding damage to roads. These are YOLOv5, YOLOv7. Notably, YOLOv7 has the most accurate predictions.

3.2. System Architecture:

The automatic road damage identification system uses pictures from UAVs and DL methods. It is made up of several parts that work together. At first, UAVs with high-resolution cameras and sensors take pictures of road surfaces from different heights and angles. After that, these pictures are preprocessed to make them better and get rid of any noise or other problems. After the pictures have been cleaned up, they are put into a DL model, like a YOLO (You Only Look Once) model, which has been trained to find damage to roads.

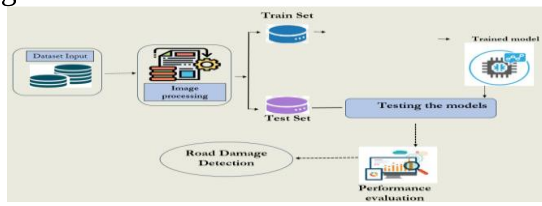
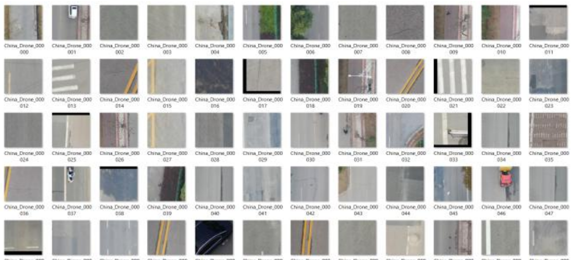


Fig 1 Proposed architecture

3.3. Dataset Collection:

In order to collect a dataset, features must be extracted from pictures, which are then read, resized, and turned into groups with names applied. First, picture features are taken out using methods such as standard computer vision methods or feature extraction based on DL.



At the same time, labels are put on each picture that show what class or group it belongs to.

3.4. Data Processing:

When using OpenCV to process data for display, the "imread" method is used to load pictures. By default, this reads images in BGR format. The "imshow" function can show images, and key

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functions like "wait Key" and "destroyAllWindows" make it easier to work with the program and close display windows.

3.5. Training & Testing:

Creating train and test sets of data is an important part of building a ML model because it lets you see how well the model works with data it hasn't seen before. The dataset usually has two parts: a training set to teach the model new things and a test set to evaluate its performance. The split is usually random to ensure that both sets match the original data distribution.

3.6. Algorithms:

YOLOv5: YOLOv5 (You Only Look Once version 5) is an object recognition method that works on images in real time, breaking them up into a grid and guessing the edges and likely classes of objects in each grid cell. It is a quick and accurate way to find objects.

YOLOv7: YOLOv7, which stands for "You Only Look Once version 7," is a sophisticated object detection method that finds things in images quickly with just one forward pass. Deep neural networks are used to predict bounding boxes and class possibilities. This makes real-time object recognition more accurate and faster.

YOLOv8: You Only Look Once version 8 (YOLOv8) is an addition to the YOLO line that is designed to find damage on the road. When trained on data about road damage, YOLOv8 does better than other algorithms, showing that it can make more accurate predictions. This is a big step forward in using DL for accurate care of infrastructure.

4.EXPERIMENTAL RESULTS

Accuracy: The capacity of a test to accurately identify weak and strong instances is known as accuracy. We should record the small percentage of true positive and true negative results in thoroughly reviewed instances in order to measure the exactness of a test. This might be expressed mathematically as:

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

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

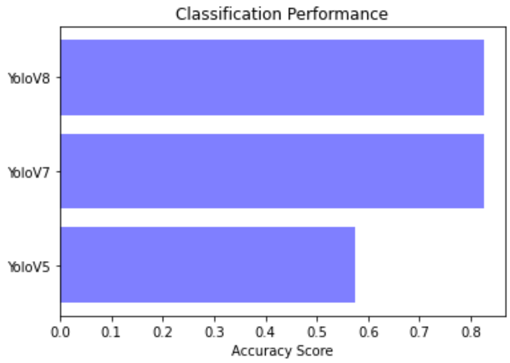

Fig 2 Accuracy comparison graph

Precision: Precision quantifies the percentage of correctly classified samples or occurrences among the positives. Consequently, the accuracy may be determined by using the following formula:

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

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

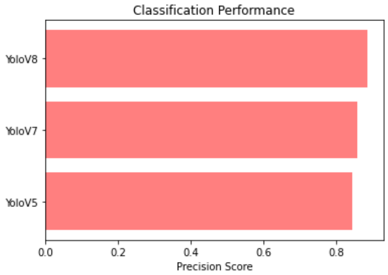

Fig 3 Precision comparison graph

Recall: A ML statistic called recall evaluates a model's ability to identify all relevant samples inside a given class. The ratio of correctly expected positive perceptions to actual positives provides information about a model's ability to identify examples of a certain class.

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

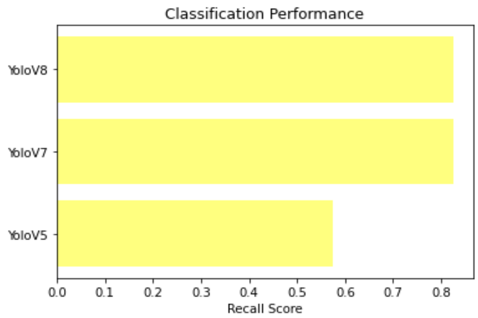

Fig 4 Recall comparison graph

F1-Score: The F1 score is a metric used in ML assessments to evaluate a model's accuracy. It combines review ratings and model precision. The accuracy measurement calculates the frequency with which a model predicts correctly throughout the whole dataset.

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

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

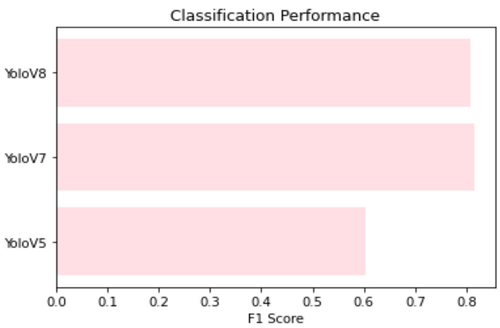

Fig 5 F1 Score comparison graph

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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

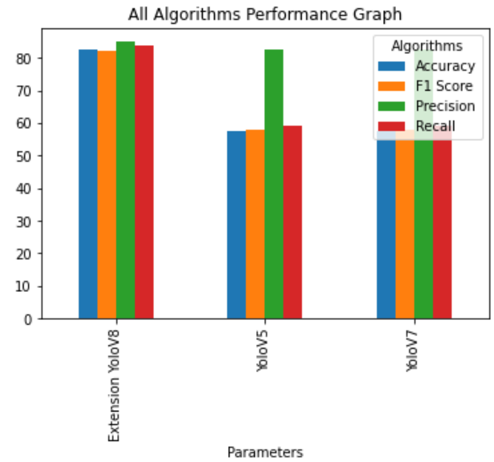

Fig 7 Comparison graph

Fig 8 Home page

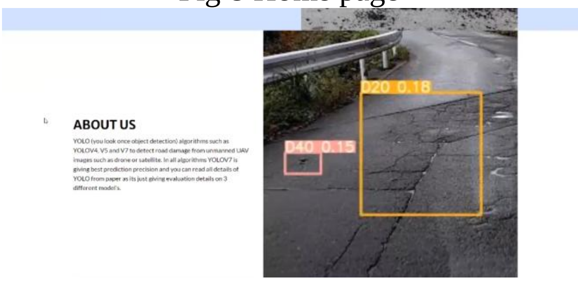

Fig 9 About page

Fig 10 Signup page

Fig 11 Signin page

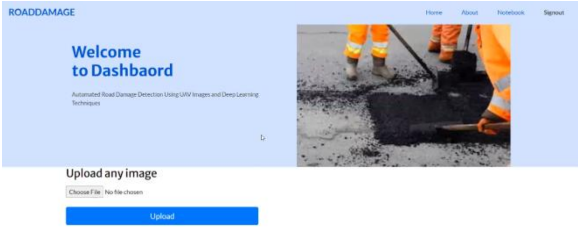

Fig 12 Main page

Fig 13 Upload input image

Fig 14 Predict result

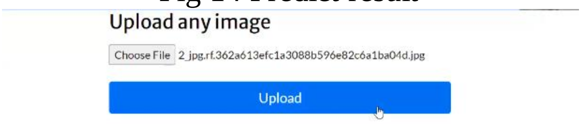

Fig 15 Upload another input

Fig 16 Prediction result

5.CONCLUSION

In conclusion, this study made a lot of progress in the field of using UAV pictures to find damage on roads. Specifically, it compared and used advanced YOLO designs like YOLOv5, YOLOv7, and YOLOv8 with Transformer to find road damage more accurately. The results clearly show that precision is getting better, with YOLOv8 getting an amazing 85%. One important result of this study is the creation of a UAV picture database specifically designed for training YOLO models. This database was made even better by combining it with the RDD2022 dataset. This large collection has made it much easier to find damage to roads, especially on Spanish and Chinese roads, which has helped fix problems with class imbalance. Even though the results are good, they can still be better.

6.FUTURE SCOPE

Researchers may look into mixing multispectral pictures and LIDAR sensor data in the future to find ways to make recognition more accurate. One possible option is to look into fixed-wing UAVs. This study is a key step toward better road infrastructure care and safety. It encourages more research into how to use different picture types and different UAV platforms to make road damage recognition more effective and efficient overall.

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