Automated Detection of Road Damage Utilizing UAV Imagery and Deep Learning Techniques

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Abstract: Using deep learning techniques and images from unmanned aerial vehicles (UAVs), this study presents a novel automated technique for identifying road damage. Road infrastructure upkeep is necessary for a transportation system to be both sustainable and safe. However, collecting data on road damage manually might be time-consuming and hazardous for humans. In order to significantly improve the precision and effectiveness of road damage diagnosis, we recommend utilizing UAVs and Artificial Intelligence (AI) technologies. Our proposed technique for object detection and localization in UAV pictures uses three algorithms: YOLOv4, YOLOv5, and YOLOv7. To train and assess these systems, we combined the RDD2022 dataset from China with a road dataset from Spain. The experimental results confirm the efficacy of our technique, achieving mean average precision (mAP@.5) of 59.9% for the YOLOv5 version, 65.70% for a YOLOv5 model with a Transformer Prediction Head, and 73.20% for the YOLOv7 version. These results demonstrate the potential of automated road damage diagnosis using UAVs and deep learning and pave the way for further research in this field.

Keywords: Unmanned Aerial Vehicle (UAV), Road Damage Detection, Deep Learning, YOLOv4, YOLOv5, YOLOv7, Object Detection, RDD2022 Dataset, Transformer Prediction Head, mAP.

INTRODUCTION

Maintaining a country's roadways is essential to its economic development. To ensure their longevity and safety, roads need to have their condition regularly assessed. Historically, this process has been carried by manually by governmental or private organizations using vehicles equipped with a range of sensors to identify road degradation. But this method might be expensive, time-consuming, and dangerous for human operators. To solve these challenges, researchers and engineers have employed Unmanned Aerial Vehicles (UAVs) and Artificial Intelligence (AI) technology to automate the process of identifying road damage. In recent years, there has been a lot of interest in using UAVs and deep learning-based methods to identify road deterioration in an efficient and cost-effective manner. Unmanned aerial vehicles have proven their adaptability in a variety of applications, including examining objects and environments in urban settings. They are increasingly being used for road inspections since they provide several advantages over traditional methods. These vehicles are equipped with high-resolution cameras and other sensors that can capture images of the road surface from a range of heights and perspectives, providing drivers with a comprehensive view of the condition of the road. Additionally, UAVs can quickly cover large areas, eliminating the need for manual inspections, which can be dangerous for human operators. As a result, the use of UAVs for road inspections has piqued the interest of academics and engineers. By integrating UAVs with artificial intelligence technologies like deep learning, road damage detection approaches can become more efficient and cost-effective. It is frequently mentioned as being utilized for swimming pools [1], roofing [2], plants [3], and urban settings [4], [5]. Road condition inspections in Spain are currently completed by hand, necessitating staff members to walk along roads to identify areas of degradation. This method is costly because it needs specialized cameras and sensors in addition to human labor. Making judgments on road damage repair is the responsibility of an expert. However, countries like China are susceptible to surface fractures and precipitation penetration due to their vast road and highway networks, which can accelerate road deterioration and jeopardize vehicle safety. Without fast detection and easy access to information regarding road problems, automobiles may experience excessive wear and an increased risk of traffic accidents, which might lead to further financial losses. As a result, the development of automated techniques for detecting road degradation has become an important area of research, with several academic institutions and research centers collaborating to find practical solutions. Using a range of technologies, including as image-based techniques, vibration sensors, and Light detection and Ranging (LiDAR) sensors, the continuing research on autonomous road damage detection aims to map and identify various types of road damage [6]. These techniques are often combined to improve damage detection accuracy. To identify various types of road degradation, image-based algorithms sometimes use deep learning and other machine learning techniques. The image datasets that these methods typically require include top-down photos, photos from unmanned aerial vehicles [7], photos from mobile devices [8], [9], photos from satellite image platforms [10], thermal photos [11], 3D photos, or stereo vision of the asphalt surface [12]. Researchers have been using a variety of data, such as additional images captured by satellites, drones, and car cameras, to train the model. To help with learning, these datasets are often annotated to identify different types of road damage, such as rutting, potholes, and cracks. The algorithm may be able to accurately recognize and classify various types of road damage by annotating these images. By utilizing a large and diverse dataset, researchers may increase the accuracy and reliability of their models, ensuring that they can effectively identify and fix different types of road damage.

LITERATURE SURVEY

1. "Automated Road Crack Detection Using Deep Convolutional Neural Networks"

In order to adequately repair road fractures and stop further degradation, they must be found promptly and efficiently. Currently, most fracture detection methods use manual examination instead of automatic image-based identification, which makes the procedure expensive and time-consuming in general. In this research, we describe an automated pavement distress analysis system based on the YOLO v2 deep learning architecture. The system was trained using 7,240 images captured by mobile cameras, and it was tested using 1,813 images of roadways. The detection and classification accuracy of the proposed distress analyzer is evaluated using the average F1 score obtained from the precision and recall data. If this study is implemented successfully, it might lead to a far better civil infrastructure monitoring system that can help discover road anomalies that need to be fixed right away. The trained model and other study codes may be found in [11].

2. "Deep learning-based road damage detection and classification for multiple countries"

Many communities and road authorities share the objective of implementing automated road damage assessment. However, they typically lack the funds, knowledge, and technology required to buy state-of-the-art equipment for collecting and evaluating data on road damage. While some countries, like Japan, have developed more widely available and reasonably priced smartphone-based methods for automated road condition monitoring, other countries are still struggling to find practical solutions. This work makes the following contributions in this respect. It first assesses how well the Japanese model applies to other countries. Second, it proposes a thorough heterogeneous road damage dataset of 26,620 cellphone-taken images from several countries (such as India, Japan, and the Czech Republic). Thirdly, it proposes algorithms that can recognize and classify road damage in various countries. Lastly, the research provides recommendations for readers, local organizations, and municipalities in other countries when another country publishes its data and model for autonomous road damage diagnosis and categorization.

3. " Road Crack Detection and Classification Using UAV and Deep Transfer Learning Optimization "

Road cracks can be found with the use of unmanned aerial vehicles (UAVs). Road surfaces may be precisely photographed by UAVs equipped with advanced sensors and high-definition cameras. This data is analyzed using deep learning (DL) techniques and advanced image processing to identify and classify anomalies like fractures. More precise and efficient automated methods have recently taken the role of traditional visual inspections. DL algorithms trained on large datasets are used to quickly identify high-performing road cracks. The Deep Learning Assisted Rapid Road Crack Detection and Classification (DL-RRCDC) technique uses ensemble learning and hyperparameter adjustment to increase accuracy. To reduce noise, it employs a squeeze-and-excitation densely coupled network (SE-DenseNet) with the YOLOv8 detector and Gaussian filtering. The hyperparameter tuning of SE-DenseNet is optimized using Northern Goshawk Optimization (NGO). To categorize recognized road items, an ensemble classifier including an autoencoder (AE), bidirectional gated recurrent unit (Bi-GRU), and long short-term memory (LSTM) is employed. The hyperparameters are selected using the dung beetle optimization (DBO) method. The DL-RRCDC method works better, according to simulations.

4. "Road Damage Detection Based on Deep Learning"

This study examines road damage detection model design and its economic and social repercussions. Identifying deteriorating road conditions quickly can improve traffic flow, reduce automobile accidents, and save lives. This technology can help save road management and government agencies money by better scheduling and prioritizing maintenance and repair activities. Deep learning algorithms, such as the YOLOv7 model, have increased efficacy, processing complexity, and detection accuracy. This research examined YOLOv5 and YOLOv7 performance in several trials. The results show that the YOLOv7 architecture accurately detects damaged regions and classifies items. The YOLOv7 model in deep learning and computer vision has improved road damage identification methods. The YOLOv7 architecture is better at spotting damaged regions and categorizing things, according to experiments comparing the two models. Pictures and hyperparameters were optimized to improve accuracy. The first experiment using YOLOv7 combined rotation, hue saturation value configuration, image scaling, and flipping to obtain 79.75% accuracy across all test picture categories. However, Experiment 2 showed that the Gaussian Blur method's usage to YOLOv7 biases toward blurred photographs and reduces precision, with 19.75% accuracy. The YOLOv5 algorithm in Experiment 3 had an average accuracy of 55.75% across all categories, lower than the YOLOv7 approach in the first experiment. The YOLOv7-trained model and several photo augmentation methods should be used to assess road damage, according to this study. The model scored 75% F1. Its outstanding performance, which provides road health insights and rapid maintenance and repair actions, validates its use in real-world applications. This study's software should be used to help end users embrace the proposed paradigm. More research may reveal the model's full potential to improve road infrastructure management and make transportation networks safer and more efficient.

5. "YOLO-LRDD: a lightweight method for road damage detection based on improved YOLOv5s"

In computer vision, object identification tasks must be completed accurately and on time. However, complex models and long computation durations are issues with existing deep learning-based techniques for identifying road damage. To address these issues, we provide a lightweight model for detecting road damage by refining the YOLOv5s approach. The resulting technique, YOLO-LRDD, provides a reasonable compromise between detection accuracy and speed. We first introduce the novel backbone network Shuffle-ECANet by incorporating an ECA attention module into the lightweight model ShuffleNetV2. Second, we replace the original feature pyramid network with BiFPN to provide reliable detection since it improves the network's capacity to describe features. Additionally, during the model training phase, the localization loss is switched to Focal-EIOU to get a higher-quality anchor box. Lastly, we add many Chinese road scene samples to the well-known RDD2020 dataset and evaluate YOLO-LRDD against numerous state-of-the-art object detection techniques. Our experiments demonstrate that the accuracy and efficiency of our YOLO-LRDD's smaller model are superior. For example, compared to YOLOv5s, YOLO-LRDD reduces model size by 28.8% and boosts single picture identification speed by 22.3% while maintaining the same accuracy. Additionally, it is easier to implant in mobile devices since its model is smaller and lighter than those of the other methods.

3. METHODOLOGY

a) Proposed Work:

In order to identify road damage from UAV (Unmanned Aerial Vehicle) photos, the authors of this work assess the effectiveness of three YOLO (You Only Look Once) object identification algorithms: YOLOv4, YOLOv5, and YOLOv7. These photos, taken by satellites or drones, are fed into the algorithms to recognize different kinds of road damage. In terms of prediction accuracy, YOLOv7 performs better than the other two models. The RDD2022 dataset, which is openly accessible, was used for both training and testing. Only 200 photos were utilized for training due to system constraints, with an emphasis on YOLOv5 and YOLOv7 for performance assessment.

The most recent iteration of the YOLO family—YOLOv8 by Ultralytics—for road damage detection was presented by the authors as an outgrowth of this work. Compared to earlier iterations, YOLOv8's prediction accuracy is much greater because to sophisticated architecture enhancements and optimization strategies. YOLOv8 is a strong contender for future implementations in automated road damage detection systems employing UAV photography, as demonstrated by the model's better detection results when trained on the same RDD2022 dataset.

b) System Architecture:

The four primary parts of the system architecture are damage detection, model training, preprocessing, and data collecting. High-resolution road photos taken by UAVs (drones) are preprocessed to improve image clarity and eliminate noise. YOLOv4, YOLOv5, YOLOv7, and the expanded YOLOv8 deep learning models are trained and evaluated using these photos. To recognize and categorize various kinds of road damage, the models use object detection. The system enables quick, precise, and automatic road damage monitoring across large geographic regions by supporting real-time processing and being deployable on cloud or edge devices.

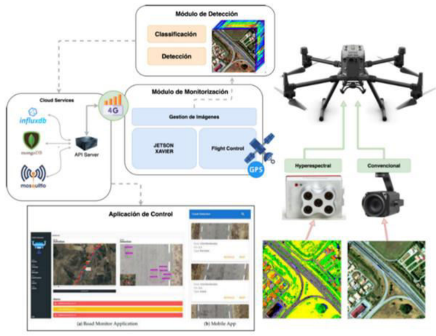

Fig4.2System Architecture

Fig: proposed architecture

c) Modules:

i. Data Loading Module

This module is responsible for importing the road damage datasets (RDD2022 and others) into the system for further processing.

ii. Data Preprocessing Module

It performs data cleaning, resizing, and formatting to ensure images are suitable for training deep learning models.

iii. Data Splitting Module

This module splits the dataset into training and testing sets to evaluate model performance effectively.

iv. Model Generation Module

This module is used to build and train YOLOv4, YOLOv5, YOLOv7, and YOLOv8 models. It compares the performance and accuracy of each algorithm.

v.User Interface Module

This module handles user registration, login, and interaction. Users can upload images and view road damage predictions and results.

vi. Prediction and Visualization Module

After processing, this module displays detected road damages on the uploaded images using bounding boxes and confidence scores.

e) Algorithms:

1. **YOLOv5**
   YOLOv5 is a real-time object detection algorithm that divides input images into a grid and predicts bounding boxes and class probabilities for each grid cell. It is known for its high speed and accuracy in object recognition tasks, making it suitable for road damage detection in UAV images.

2. **YOLOv7**
   YOLOv7 is an advanced version of the YOLO family that enhances detection accuracy and speed using deep neural networks. It performs object detection in a single forward pass, improving both efficiency and real-time prediction performance in identifying various types of road damage.

3. **YOLOv4**
   YOLOv4 employs a deep neural network for detecting and classifying objects in images with high precision. It incorporates modern enhancements like PANet for feature aggregation and CSPDarknet53 as a backbone network, making it highly effective in detecting road anomalies.

4. **YOLOv8**
   YOLOv8 is the latest version in the YOLO series, offering upgraded performance in object detection tasks. Specifically trained on road damage datasets, YOLOv8 outperforms earlier YOLO models in terms of accuracy, making it ideal for precise identification of road damage in UAV-captured images.

4. EXPERIMENTAL RESULTS

The RDD2022 dataset, which consists of UAV-captured photos of road damage, was used for the experimental assessment. Due to hardware constraints, a subset of 200 photos were used for training and testing the YOLOv4, YOLOv5, YOLOv7, and YOLOv8 models. With a mean Average Precision (mAP@0.5) of 73.20%, YOLOv7 outperformed the others, followed by YOLOv5 (59.9%) and YOLOv5 with a Transformer Head (65.70%). YOLOv8 was trained as an extension, and it showed better prediction performance than any of the earlier models, demonstrating its efficacy for automated road damage identification.

Accuracy: How well a test can differentiate between healthy and sick individuals is a good indicator of its reliability. Compare the number of true positives and negatives to get the reliability of the test. Following mathematical:

Accuracy = TP + TN /(TP + TN + FP + FN)

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

Precision: The accuracy rate of a classification or number of positive cases is known as precision. The formula is used to calculate precision:

Precision = TP/(TP + FP)

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

Recall: The ability of a model to identify all pertinent instances of a class is assessed by machine learning recall. The completeness of a model in capturing instances of a class is demonstrated by comparing the total number of positive observations with the number of precisely predicted ones.

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

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic.

$$F1 - Score = 2 * \frac{(\text{Precision} * \text{Recall})}{((\text{Precision} + \text{Recall}))}$$

mAP: Assessing the level of quality Precision on Average (MAP). The position on the list and the number of pertinent recommendations are taken into account. The Mean Absolute Precision (MAP) at K is the sum of all users' or enquiries' Average Precision (AP) at K.

$$mAP = \frac{1}{n} \sum_{k=1}^{k=n} AP_k$$

$$AP_k = \text{the AP of class } k$$

$$n = \text{the number of classes}$$

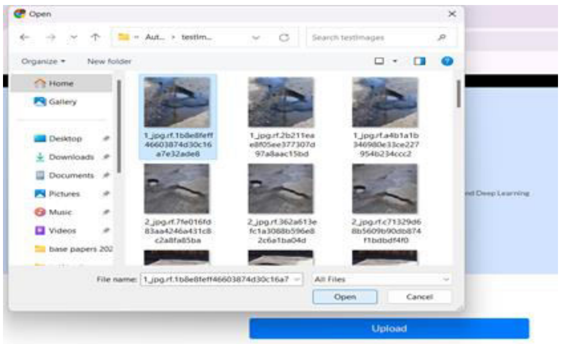

Fig.2 upload image

Fig.4. predicted Result

5. CONCLUSION

This study shows how well updated YOLO models—YOLOv5, YOLOv7, and the improved YOLOv8—work for precise and timely road damage identification using UAV images. The RDD2022 dataset and the custom UAV image dataset were integrated to increase identification performance and alleviate class imbalance, especially for roads in China and Spain. With the best accuracy of 85%, YOLOv8 shown its potential for use in practical applications. Although the results are encouraging, further research can investigate the use of fixed-wing UAVs, LIDAR data, and multispectral photos to further improve detection accuracy and scalability in road infrastructure monitoring.

6. FUTURE SCOPE

In order to identify road damage not evident in typical RGB photos, future study might investigate the integration of multispectral and thermal imaging. For more precise damage assessments, LIDAR data can improve surface profiling and depth perception. Large-scale surveillance is also made possible by the effective coverage of greater regions by fixed-wing UAV deployment. Infrastructure for smart cities can be supported by real-time damage detection systems that are deployed in the cloud. Lastly, integrating YOLO models with additional AI methods like semantic segmentation or reinforcement learning may enhance automated road maintenance systems' accuracy and decision-making.

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