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Research Paper

USING UAV PHOTOS AND DEEP LEARNING TO AUTOMATICALLY DETECT ROAD DAMAGE

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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 could be time-consuming and hazardous for humans. Therefore, in order to significantly improve the precision and effectiveness of road damage diagnosis, we propose utilizing UAVs in conjunction with Artificial Intelligence (AI) technology. Our proposed method for object recognition 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 approach, 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 identification 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.

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1. 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 for human operators, this method may be expensive, time-consuming, and dangerous. To solve these challenges, researchers and engineers have employed Unmanned Aerial Vehicles (UAVs) and Artificial Intelligence (AI) technology to automate the process of detecting road damage. In recent years, there has been a lot of interest in the employment of UAVs and deep learning-based methods to give practical and affordable solutions for identifying road damage. 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 offer 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, because UAVs can quickly cover large areas, manual inspections—which can be dangerous for human operators—are no longer necessary. As a result, employing UAVs for road inspections has piqued the interest of engineers and academics. When UAVs are combined with artificial intelligence

techniques like deep learning, road damage detection systems can become more efficient and cost-effective. Urban inspections of urban surroundings [4], [5], greenery [3], roofs [2], and swimming pools [1] are among its frequently mentioned uses. Staff members must now walk along roads to identify areas of deterioration as part of Spain's manual road condition evaluations. This method is costly since it calls for specialized cameras and sensors in addition to human labor. Decisions about the repair of road damage are made by 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 rapid identification and quick access to information regarding road problems, cars may experience excessive wear and an increased risk of traffic accidents, which could lead to further financial losses. As a result, the development of automated techniques for detecting road deterioration has become an important area of research, with numerous academic institutions and research facilities collaborating to find practical solutions. Using a range of technologies, including as image-based methods, vibration sensors, and Light Identification and Ranging (LiDAR) sensors, the current study on autonomous road damage identification aims to map and identify various types of road damage [6]. These techniques are commonly combined to improve damage detection accuracy. To detect various types of road damage, image-based approaches commonly 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 facilitate learning, these datasets are often annotated to identify different types of road damage, such as potholes, cracks, and rutting. The algorithm may learn to accurately recognize and classify various types of road damage by annotating these images. By employing 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.

2. LITERATURE SURVEY

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

https://ieeexplore.ieee.org/document/8622327

In order to adequately repair road fractures and stop further degradation, they must be found promptly and efficiently. Most fracture detection methods now use manual inspection instead of automatic image-based identification, which adds to the process's overall expense and time commitment. In this research, we describe an automated pavement distress analysis system based on the YOLO v2 deep learning architecture. 1,813 images of roadways were used for testing, while 7,240 images captured with mobile cameras were used to train the system. 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 could 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 can be found in [11].

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

https://www.sciencedirect.com/science/article/abs/pii/S0926580521003861

Many communities and road agencies share the objective of implementing automated road damage assessment. However, they frequently 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 regard. It first assesses the suitability of the Japanese model for 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 releases its data and model for autonomous road damage diagnosis and categorization.

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

https://link.springer.com/article/10.1007/s12524-024-02075-x

Unmanned aerial vehicles (UAVs) are helpful tools for locating road cracks. Road surfaces can 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 supplanted traditional visual assessments. DL algorithms trained on large datasets are used to quickly identify high-performing road fractures. The Deep Learning Assisted Rapid Road Crack Detection and Classification (DL-RRCDC) approach uses ensemble learning and hyperparameter adjustment to increase accuracy. It employs Gaussian filtering to remove noise and a squeeze-and-excitation densely coupled network (SE-DenseNet) with the YOLOv8 detector. 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"

https://www.researchgate.net/publication/372769154_Road_Damage_Detection_Based_on_Deep_Learning

This study looks at the development of a road damage detection model and its potential impacts on society and the economy. Accurate and timely identification of deteriorating road conditions could improve traffic flow, significantly reduce the incidence of auto accidents, and ultimately save lives. The adoption of this technology can also result in significant cost savings for municipal and road management organizations by optimizing the scheduling and prioritization of maintenance and repair operations. Significantly, deep learning techniques—specifically, the YOLOv7 model—have enhanced detection accuracy, reduced computational complexity, and increased overall efficacy. Several experiments were carried out for this study to compare the performance of the YOLOv5 and YOLOv7 models. The results show how effective the YOLOv7 architecture is in accurately identifying damaged areas and categorizing objects. The application of the YOLOv7 model in deep learning and computer vision has greatly improved the precision and efficacy of road damage detection models. The YOLOv7 architecture is significantly more effective in accurately identifying damaged areas and classifying objects, according to the results of a series of tests comparing the YOLOv5 and YOLOv7 models. Many techniques, including picture augmentation and hyperparameter optimization, were employed to improve accuracy. The first experiment combined rotation, image scaling, flipping, and hue saturation value configuration with YOLOv7 to reach an average accuracy of 79.75% across

all test picture categories. However, with an accuracy of 19.75%, Experiment 2 showed flaws in the Gaussian Blur method's application to YOLOv7, leading to a bias towards blurred images and a commensurate decrease in overall precision. In Experiment 3, the YOLOv5 algorithm yielded an average accuracy of 55.75% across all categories using a more thorough dataset. This was less accurate than the YOLOv7 approach used in the first experiment. In order to detect road damage, this study suggests combining the YOLOv7-trained model with a range of image augmentation approaches. The model obtained a 75% F1 score, according to the results. This technology's outstanding performance, which provides valuable information about the condition of roads and enables timely maintenance and repair interventions, justifies its use in practical applications. It is also recommended that the software utilized in this study be used to facilitate end users' adoption of the proposed approach. Further research and development may reveal the model's full potential in improving road infrastructure management and guaranteeing safer and more effective transportation networks.

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

https://asp-eurasipjournals.springeropen.com/articles/10.1186/s13634-022-00931-x#:~:text=To%20address%20these%20issues%2C%20we%20present%20a%20lightweight,a%20good%20balance%20of%20detection%20precision%20and%20speed.

In computer vision, timely and accurate completion of object identification tasks is crucial. However, complex models and long calculation durations are issues with the deep learning-based techniques now used to detect 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, to ensure reliable detection, we replace the original feature pyramid network with BiFPN, which improves the network's feature description capabilities. Additionally, during the model training phase, the localization loss is modified to Focal-EIOU in order to obtain a higher-quality anchor box. Lastly, we add many Chinese road scene samples to the well-known RDD2020 dataset and evaluate YOLO-LRDD against several 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 increases single picture identification speed by 22.3% while maintaining the same accuracy. Additionally, it is easier to implant in mobile devices because 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 detection algorithms: YOLOv4, YOLOv5, and YOLOv7. Drones or satellites take these pictures, which are then fed into algorithms to detect different kinds of road damage. In terms of prediction accuracy, YOLOv7 performs better than the other two models. The RDD2022 dataset, which is publically available, was used for both training and testing. Only 200 photos were used 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 noticeably greater because to sophisticated architecture enhancements and optimization strategies. YOLOv8 is a promising contender for future deployments in automated road damage detection systems using UAV photography, as demonstrated by the model's better detection performance after being trained on the same RDD2022 dataset.

b) System Architecture:

Data collection, preprocessing, model training, and damage detection are the four primary parts of the system design. 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. In order to recognize and categorize various forms of road damage, the models use object detection. Road damage monitoring can be done quickly, accurately, and automatically over large geographic areas because to the architecture's support for real-time processing and ability to be installed on cloud or edge devices.

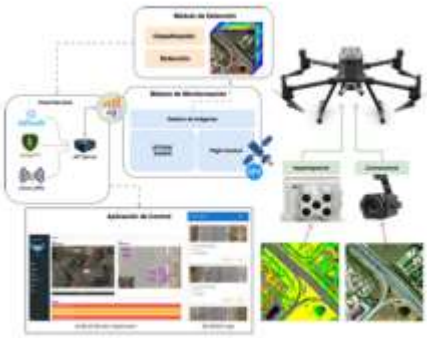


Fig4.2System Architecture

Fig1: proposed architecture

c) Modules:

i. Module for Data Loading

The road damage datasets (RDD2022 and others) must be imported into the system for additional processing by this module.

ii. Module for Data Preprocessing

To make sure photos are appropriate for deep learning model training, it cleans, resizes, and formats the data.

iv. Module for Data Splitting

To efficiently assess model performance, this module divides the dataset into training and testing sets.

iv. Module for Model Generation

The YOLOv4, YOLOv5, YOLOv7, and YOLOv8 models are constructed and trained using this module. It evaluates each algorithm's accuracy and performance.

v. Module for User Interface

User interaction, login, and registration are managed by this module. In addition to viewing road damage forecasts and outcomes, users can upload photos.

vi. Module for Prediction and Visualization

Following processing, this module uses bounding boxes and confidence scores to show discovered road damage on the uploaded photos.

e) Algorithms:

1. **YOLOv5**

YOLOv5 is a real-time object detection system that creates a grid out of incoming photos and forecasts class probabilities and bounding boxes for each grid cell. It is well-known for its quickness and precision in object recognition tasks, which makes it appropriate for identifying road damage in UAV photos.

2. **Yolov7**

YOLOv7 is a more sophisticated variant of the YOLO family that uses deep neural networks to improve detection speed and accuracy. It increases efficiency and real-time prediction performance in detecting different kinds of road damage by performing object detection in a single forward pass.

3. **YOLOv4**

YOLOv4 uses a deep neural network to accurately identify and categorize items in photos. It is quite successful at identifying road anomalies since it uses contemporary improvements like PANet for feature aggregation and CSPDarknet53 as a backbone network.

4. YOLOv8

The most recent iteration of the YOLO series, YOLOv8, offers improved object detection task performance. YOLOv8, which was specifically trained on road damage datasets, performs better in terms of accuracy than previous YOLO models, which makes it perfect for accurately identifying road damage in photos taken by unmanned aerial vehicles.

4. EXPERIMENTAL RESULTS

The RDD2022 dataset, which consists of UAV-captured photos of road damage, was used for the experimental evaluation. 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. YOLOv5 came in second with 59.9% and YOLOv5 with a Transformer Head with 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 detection.

Accuracy: A good measure of a test's reliability is how effectively it can distinguish between healthy and sick people. To determine the test's reliability, compare the number of true positives and negatives. The following math:

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

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

Precision: Precision is the number of affirmative cases or the classification's accuracy rate. Precision is calculated using the following formula:

Precision = TP/(TP + FP)

$$\text{Pr}\,e\,cision = \frac{TP}{(TP + FP)}$$

Recall: Machine learning recall measures a model's capacity to find all relevant examples of a class. Comparing the overall number of positive observations with the number of accurately predicted ones shows how comprehensive a model is at capturing instances of a class.

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

F1-Score: An accurate machine learning model is indicated by a high F1 score. combining precision and recall to increase model correctness. The accuracy statistic quantifies the frequency with which a model correctly predicts a dataset.

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

mAP: evaluating the Precision on Average (MAP) quality level. Both the quantity of relevant recommendations and the listing position are considered. The total of all users' or inquiries' Average Precision (AP) at K is the Mean Absolute Precision (MAP) at K.

$$\text{MAP} = \frac{1}{N} \sum_{i=1}^{N} \text{AP}_i$$

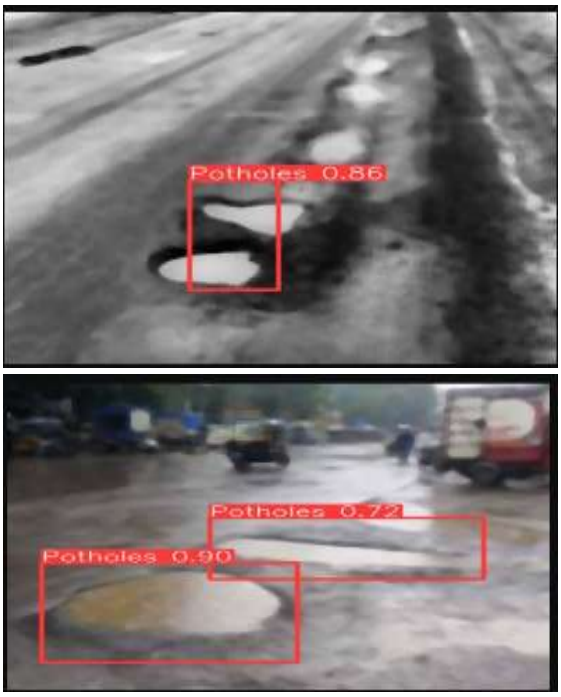


Fig.2. predicted Result

5. CONCLUSION

The efficacy of sophisticated YOLO models—YOLOv5, YOLOv7, and the improved YOLOv8—for precise and instantaneous road damage identification using UAV imagery is demonstrated in this work. 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 that is not obvious in typical RGB photos, future research can investigate combining 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 areas 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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