

Autonomous Road Damage Detection using Unmanned Aerial Vehicle Images and YOLO V8 Methods

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ABSTRACT:

Using photos from Unmanned Aerial Vehicles (UAVs) and deep learning algorithms, this research provides a revolutionary automated road damage identification method. In order to provide a secure and long-lasting transportation system, road infrastructure maintenance is essential. On the other hand, gathering road damage data by hand may be dangerous and labor-intensive. Therefore, we suggest using artificial intelligence (AI) and unmanned aerial vehicles (UAVs) to greatly increase the effectiveness and precision of road damage identification. For object recognition and localisation in UAV photos, our suggested method makes use of three algorithms: YOLOv4, YOLOv5, and YOLOv7. We used a mix of a Spanish roadway dataset and the Chinese RDD2022 dataset for training and testing these methods. Our method obtains 59.9% average precision (mAP@.5) for the YOLOv5 versions, 65.70% mAP@.5 when using the YOLOv5 version using the Transformers Prediction the Head, or 73.20% mAP@.5 for that YOLOv7 version, testing results show the effectiveness of our methodology. These findings open the door for further study in this area and show the possibilities of employing deep learning and UAVs for automatic road damage identification.

INTRODUCTION

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A nation's ability to prosper economically depends on its ability to maintain all of its roadways. To maintain roads' lifespan and safety, an evaluation of their state must be done on a regular basis. Historically, road damage has been manually detected by governmental or commercial entities using different sensors installed in their cars. But using this strategy may be costly, time-consuming, and risky for human operators. Researchers and engineers are using artificial intelligence (AI) and UAVs, or unmanned aerial to automate the process of addressing these difficulties. Halil Ersin Soken was the associate editor who oversaw the manuscript's evaluation and gave it the go-ahead to be published. road damage detection ceasing. Using UAVs along with deep learning techniques to provide effective and affordable ways for road damage identification has garnered a lot of attention in recent years. Unmanned aircraft have shown to be adaptable in a range of scenarios, such as inspecting things and surroundings in cities. Due to their many benefits over conventional techniques, they are being employed for road inspections more and more. High-resolution cameras as well as other sensors installed in these cars enable them to take pictures of the road's surface from a variety of perspectives and altitudes, giving drivers a thorough understanding of the state of the road. Furthermore, since UAVs can cover a big area fast, they eliminate the need for manual checks, which may be hazardous for human operators. Consequently, academics and engineers have begun to pay close attention to the usage of UAVs in road inspections. Using UAVs in conjunction with artificial intelligence methods, such deep learning, may result in the development of effective and affordable methods for detecting road damage. Urban inspections of items like roofs, plants, and urban environs are among the things for which it is often said that it is used. Road condition checks in Spain are now carried out manually, requiring workers to walk along roads in order to locate areas of degradation. Because it requires specialized cameras and sensors as well as human work, this technology is quite expensive. Experts are responsible for making decisions about the rehabilitation of damaged roads. However, because of their extensive networks of highways and roads, nations like China are more vulnerable to surface fissures and rainfall intrusion, which

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may hasten road degradation and jeopardize driver safety. Excessive wear on cars and a higher chance of traffic accidents may happen in the absence of prompt detection and quick access to information on road faults, which can result in additional financial losses. In order to discover practical answers, several colleges and research institutions are working together to create automated approaches for detecting road degradation, which has turned into a crucial topic of study. Using a variety of approaches, including vibration sensors, Light Detection and Ranging (LiDAR) sensors, and image-based algorithms, automatic road damage detection is an active field of study that seeks to identify and map different forms of road damage. To increase the precision of damage detection, these methods are often combined. Image-based methods that identify different kinds of road deterioration often involve machine learning techniques, such as deep learning. Typically, these techniques demand for a picture dataset, which may comprise photos taken from the top down or by unmanned aerial vehicles. Images from satellite image platforms, including thermal, 3D, and stereo vision views of the asphalt surface, captured by mobile devices. To train the algorithm, researchers have been using a range of information, including extra photos taken by satellites, drones, and fixed cameras on autos. In order to aid in the process of learning, these data sets are often labeled to distinguish between various forms of road damage, such as cracks, potholes, and rutting. The system can properly identify and categorize different kinds of road damage thanks to the annotation of these photographs. Researchers may improve the precision and dependability of their models by using a sizable and varied dataset, guaranteeing that they are able to accurately recognize and handle various forms of road damage.

RELATED WORK

“A platform for swimming pool detection and legal verification using a multi-agent system and remote image sensing,”

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fires in the bush. Canberra was hit by firestorms in January 2003, which was a major natural catastrophe. Twenty years ago, there were seventy-five fatalities from the Victoria Ash Wednesday fires. Occurrences such as this have directed Australian research towards environmental and emergency management. In this research, we propose a new method for classifying small area bodies of water, namely swimming pools, using Support Vector Machines (SVM). These features serve as an important supply of water for rescue operations and are vital in the battle against bushfires in Australia's cities.

“Deep reinforcement learning for drone navigation using sensor data,”

Drones and other mobile robots are useful for data collecting, monitoring, and surveillance in environments, infrastructure, and structures. It's common knowledge that precise and comprehensive monitoring is essential for spotting issues early on and stopping them from becoming worse. This highlights the need for adaptable, self-governing, and potent mobile robots capable of making decisions. These systems must possess the capacity to learn by combining information from many sources. They were task specific up until recently. Our research presents a general navigation algorithm that guides the drone to the issue location by using information from its sensors. Finding issues quickly and precisely is essential in dangerous and safety-critical circumstances. We construct our generic and adaptive navigation system using long short-term recall neural networks, incremental curriculum learning, and the proximal policy optimization deep reinforcement learning method. To show its accuracy and effectiveness, we compare several configurations using a heuristic method. We conclude by discussing how the drone's safety may be guaranteed by evaluating how securely our navigation system would operate in actual situations.

“Detection of Norway spruce trees (*Picea abies*) infested by bark beetle in UAV images using YOLOs architectures,”

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Coniferous woods have suffered greatly in recent years due to widespread outbreaks caused by the European pine bark beetle (*Ips typographus*, L.). Identifying damaged trees in the early stages of infection is crucial for the timely avoidance of bark beetle spread, which is the primary solution to this issue. Thankfully, there is a great deal of promise for resolving such problems when high-resolution unmanned aerial vehicle, or UAV, footage is combined with contemporary detection methods. The objective of this study is to locate infected trees in UAV photos by evaluating and comparing three You Just Look Once (YOLO) neural network architectures: YOLOv2, YOLOv3, and YOLOv4. In order to increase the models' ability for generalization, we used a pre-processing balanced contrast improvement method (BCET) and created a fresh dataset for both training and testing. Our tests demonstrate that using the BCET pre-processing gives YOLOv4 very excellent results. With a mean average accuracy of up to 95%, YOLOv4 produced the best test results when compared to other YOLO models. The increase in accuracy for model YOLOv2, YOLOv3, and YOLOv4 was 65.0%, 7.22%, and 3.19%, respectively, as a consequence of using artificial data augmentation.

“Drones to manage the urban environment: Risks, rewards, alternatives,”

In addition to facilitating the gathering of air, liquid, and solid samples for subsequent examination in a lab setting, airborne surveillance may identify changes in vegetation, heat, visual perception, and atmospheric conditions over time. While studying urban environments using drones has a lot of promise, there are legitimate worries about privacy, safety, and security. With no danger to safety and a reduced perceived risk to security and privacy, ground-based surveillance (Internet of Things) may realize many of these potentials. Higher height drones are probably going to be approved for security reasons before being used for environmental reasons, while low-altitude drones could be restricted to certain geographically and altitudinally specified geographic locations. Although the technology is developing quickly, military drone safety

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records are still inadequate for civilian use. It's unclear yet if society will prioritize drone safety above that of traffic or shark attacks.

“Automated method for measuring the extent of selective logging damage with airborne LiDAR data,”

In addition to affecting the forest microclimate and longer-term modifications to subsidence, soil or nutrient cycling, or fire vulnerability, selective logging also affects the global carbon cycle. The techniques and equipment we use to precisely determine the volume and characteristics of logging activity will determine how well we are able to measure these effects. Measurements of these characteristics using LiDAR have great potential. Using commercial aerial LiDAR data as input, we propose here a collection of algorithms for automatic identification and mapping of key logging characteristics, such as roads/decks, skid tracks, and gaps. In 2014, commercial LiDAR data from two concessions for logging in Kalimantan, Indonesia were subjected to an automated system. Shortly after logging was finished, measurements regarding the logging features were taken in the field and compared to the algorithm findings. When accounting for GPS position inaccuracy, the computerized algorithm-mapped road/deck or skid track features exhibit high levels of agreement with field-measured data, ranging from 69% to 99%. The algorithm's worst performance was seen with gaps, which are by their very nature changeable because of the unpredictability of tree fall as opposed to the linear or regular features that are produced mechanically. Overall, the automated approach works well and shows a lot of promise as an applicable tool that can effectively and precisely capture the impacts of selected logging, maybe even differentiating between reduced impact and standard logging.

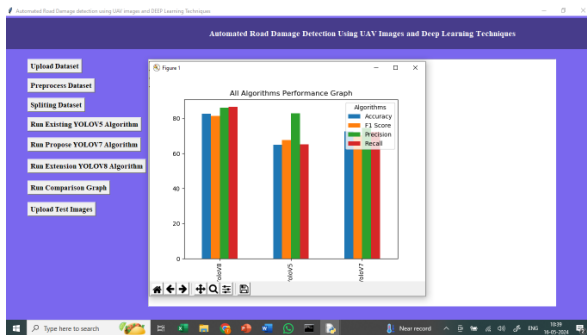
METHODOLOGY

1. **Upload Dataset:**We are able to upload datasets to the application using this module.
2. **Preprocess Dataset:**This module splits the dataset into testing and training groups and shuffle and normalizes it.

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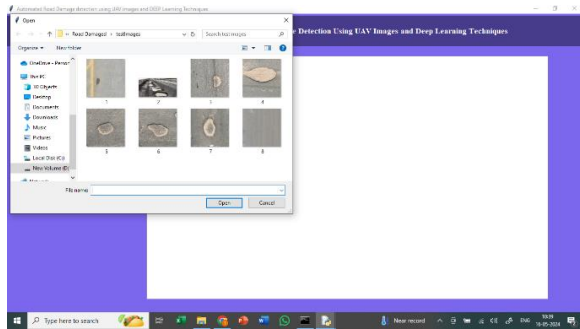
3. **Run YOLOV5 Algorithm:**This module yielded 65% accuracy for the YOLOv5 model and YOLOv5, with additional metrics shown in the confusion matrix above.
4. **Run YOLOV7 Algorithm:**YOLOv7 received 82% accuracy from this module's training, and it was also able to see a confusion matrix graph and other metrics.
5. **Run Extension YOLOV8 Algorithm:** After running the aforementioned block using this module for YOLOv8 training from the Ultralytics package, YOLOv8 achieved an accuracy of 85%, surpassing that of any other method.
6. **Run Comparison Graph:**By using The x-axis shows the names of the algorithms, while the y-axis shows accuracy along with additional metrics as various colored bars. This module compares all of the methods.
7. **Upload Test Images:**This module allows you to submit photographs of damaged roads from the test images folder.

8. RESULT AND DISCUSSION

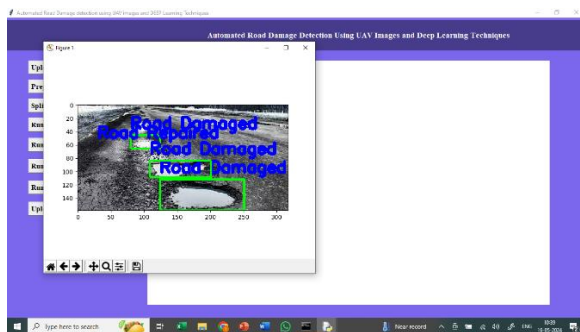


In above graph displaying comparison between all algorithms where x-axis represents algorithm names and y-axis represents accuracy and other metrics in different colour bars.

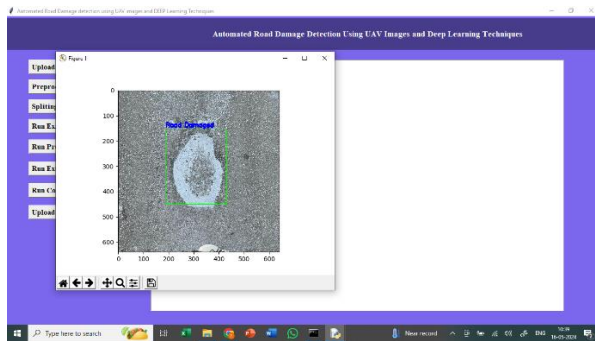
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In above screen uploading road damaged image from test images folder.



In above screen with bounding boxes damage road detected from given test input images



In above screen we can see other tested images

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CONCLUSION

YOLOv5 and YOLOv7 designs are compared with the YOLOv4 from earlier research, and an implementation of YOLOv5 using Transformer for damage to roads diagnosis utilizing UAV photos is included in this study's conclusion. In addition to proving that subsequent architectural versions, such as YOLOv5 & YOLOv7, can outperform earlier work, the study effectively met its aim of developing architecture that can identify road damage. Creating a UAV picture database specifically designed for YOLO version training was a major contribution of this work, which was improved by combining it with the RDD2022 data. In particular, for Spanish or Chinese highways, this enhanced the identification of road damage specimens and reduced the disparity in class for certain types of damage, such as potholes and crocodile cracks. The results of this investigation provide a significant addition to the discipline and open up new avenues for study in this subject. As can be seen in the section devoted to results, our execution used YOLOv4 to reach a mAP.5 of 26.8%, YOLOv5 to achieve 59.9%, YOLOv7 to get 73.20%, and the implemented Transformer to achieve 65.7%. Our work still needs to be improved upon. To improve even more, future studies may investigate other picture formats, including multispectral photos and LIDAR sensor data. Using embedded computers, the merging of such data may be able to provide superior outcomes. Furthermore, using fixed-wing UAVs is another way to tackle this topic.

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