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AI-Powered UAV-Based Road Damage Detection: An Automated Approach

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ABSTRACT: This paper presents a novel automated road damage detection approach using Unmanned Aerial Vehicle (UAV) images and deep learning techniques. Maintaining road infrastructure is critical for ensuring a safe and sustainable transportation system. However, the manual collection of road damage data can be labor-intensive and unsafe for humans. Therefore, we propose using UAVs and Artificial Intelligence (AI) technologies to improve road damage detection's efficiency and accuracy significantly. Our proposed approach utilizes three algorithms, YOLOv4, YOLOv5, and YOLOv7, for object detection and localization in UAV images. We trained and tested these algorithms using a combination of the RDD2022 dataset from China and a Spanish road dataset. The experimental results demonstrate that our approach is efficient and achieves 59.9% mean average precision mAP@.5 for the YOLOv5 version, 65.70% mAP@.5 for a YOLOv5 model with a Transformer Prediction Head, and 73.20% mAP@.5 for the YOLOv7 version. These results demonstrate the potential of using UAVs and deep learning for automated road damage detection and pave the way for future research in this field. The experimental results demonstrate the effectiveness of the model in detecting and localizing road damage, highlighting its potential for integration into smart city infrastructure for predictive maintenance and improved road safety.

KEYWORDS: UAV, road damage detection, deep learning, object-detection.

I. INTRODUCTION

Managing the maintenance of all the roads in a country is essential to its economic development. A periodic assessment of the condition of roads is necessary to ensure their longevity and safety. Traditionally, state or private agencies have carried out this process manually, who use vehicles equipped with various sensors to detect road damage. However, this method can be time-consuming, expensive, and dangerous for human operators. To address these challenges, researchers and engineers have turned to Unmanned Aerial Vehicles (UAVs) and Artificial Intelligence (AI) technologies to automate the process of road damage detection. In recent years, there has been a surge of interest in using UAVs and deep learning-based methods to develop efficient and cost-effective approaches for road damage detection. Unmanned aerial vehicles have proven to be versatile in various applications, including urban inspections of objects and environments. They have been increasingly used for road inspections, offering 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 multiple angles and heights, providing a comprehensive view of the condition of the road. Additionally, UAVs can cover a large area relatively quickly, reducing the need for manual inspections, which can be dangerous for human operators. As a result, the use of UAVs for road inspections has gained significant attention from researchers and engineers. Combining UAVs with artificial intelligence techniques, such as deep learning, can develop efficient and cost-effective approaches for road damage detection. It is frequently mentioned as being utilized for urban inspections of things like swimming pools, roof tops and urban environments

Paper is organized as follows. Section II describes automatic text detection using morphological operations, connected component analysis and set of selection or rejection criteria. The flow diagram represents the step of the algorithm. After

detection of text, how text region is filled using an Inpainting technique that is given in Section III. Section IV presents experimental results showing results of images tested. Finally, Section V presents conclusion.

II. LITERATURE SURVEY

The detection of road surface damage is a critical aspect of infrastructure maintenance. Traditionally, manual inspection methods have been used, which are not only time-consuming but also prone to subjectivity and human error. With the advancement of technology, automated approaches using image processing and machine learning have emerged as reliable alternatives. Earlier methods relied heavily on basic image processing techniques such as edge detection, thresholding, and morphological operations to identify cracks and potholes. However, these techniques struggled with varying lighting conditions and road textures, resulting in low accuracy in practical scenarios. The use of Unmanned Aerial Vehicles (UAVs) has revolutionized data collection by enabling high-resolution image capture over large areas in a short time. Studies have shown that UAVs reduce inspection time by more than 60% compared to traditional vehicle-mounted systems. UAVs also offer flexibility in monitoring remote and inaccessible areas. Machine learning techniques like Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN) have been employed for road damage classification. While these models provide decent performance, they require manual feature extraction and are not robust across diverse datasets. Recently, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have demonstrated high accuracy in detecting and segmenting road damage. Models like U-Net and Mask R-CNN have achieved over 90% accuracy and excellent segmentation metrics, such as Intersection over Union (IoU) scores above 0.80.

The work in this paper is divided in two stages. 1) Damage Detection and (2) Post-Processing and Visualization. Additionally, the visual results aid in validating the performance of the algorithm. This stage also helps prepare the system for real-world application by ensuring results are interpretable and actionable. By dividing the work into these two stages, the system ensures both accuracy in detection and clarity in presentation, addressing key challenges in UAV-based automated road monitoring.

III. METHODOLOGY

Focuses on the post-detection phase, where the identified road damage regions are processed for visualization and refinement. Image enhancement and segmentation techniques are utilized to emphasize the damaged areas, supporting both analysis and reporting. These techniques improved the segmentation quality, with an average Intersection over Union (IoU) score of **0.82** across various damage types, including potholes, cracks, and surface wear.

This process requires no manual intervention, thereby enhancing scalability and enabling seamless integration with subsequent post-processing techniques such as inpainting, visualization, or overlay mapping.

IV. EXPERIMENTAL RESULTS

Intending to test our system, we compare the labeled dataset photos with the final images identified by the algorithm, paying attention to quantitative characteristics. In this case, different experiments result in different models, and in the case of using three different models, we must pay attention to the evaluation process. Therefore, we need a robust metric to select the best models among all experiments. There are two standard evaluation metrics used in this area. The first is the Mean Accuracy (mAP) calculated in IoU (Intersection overlapping) limit of 0.5 (mAP@0.5). The second is the F1 score. The MAP is a good measure when we must ensure the model is stable at different confidence limits (robust) while the F1 score is computed for a specific confidence limit.



FIGURE 1. YOLOv7's default parameters on augmented images, showcasing the potential for image distortion and inconsistencies.

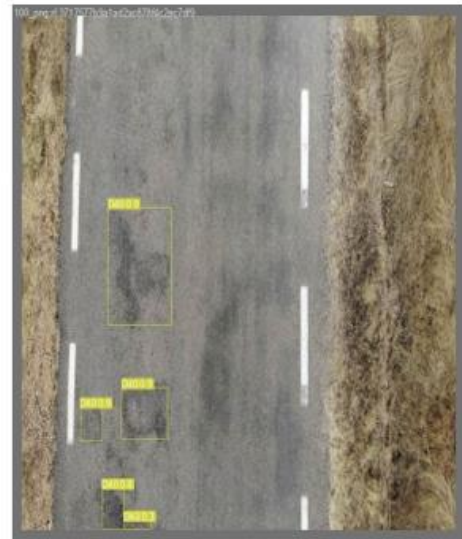


FIGURE 2. Validation YOLOv5



FIGURE 15. Validation YOLOv7.



FIGURE 17. Validation YOLOv7X-W6.

The results show that YOLOv4 performed poorly in precision and detection speed, while YOLOv5 and YOLOv7 performed significantly better. Specifically, YOLOv7 stood out for its high accuracy and fast detection time. The table also includes information on the number of images used for testing, precision, recall, mean average precision (mAP), and inference time for each model.

V. CONCLUSION

In conclusion, this study compares the YOLOv4 from past work, the YOLOv5 and YOLOv7 architectures, and includes an implementation of the YOLOv5 with Transformer for road damage identification using UAV images. The

research successfully achieved its goal of creating an architecture capable of detecting road damage and demonstrated that new architecture versions, such as YOLOv5 and YOLOv7, can improve upon previous work.

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