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PRECISION ROAD DAMAGE DETECTION USING UAV IMAGING AND DEEP LEARNINGTECHNIQUES

*Telagamsetti Devi Sahithi [1], Tumma Shashank [2], Silumula Srikanth [3], Dr. Ganesh B. Regulwar [4]

[1,2,3,4] Vardhaman College of Engineering , Hyderabad, Telangana,501218

*Corresponding Author

Email: devisahithi2004@gmail.com

***Abstract* — This paper presents an innovative approach to automated road damage detection using Unmanned Aerial Vehicle (UAV) imagery and deep learning techniques. Conventional methods of identifying road damage are often laborious and hazardous for human personnel, while UAVs and Artificial Intelligence (AI) technologies offer the potential to enhance efficiency and accuracy. Leveraging YOLOv4, YOLOv5, YOLOv7 and YOLOv8 algorithms, the proposed methodology focuses on object detection and localization within UAV images to identify various types of road damage. The ultimate goal is to augment the autonomous maintenance system for roads by promptly detecting and notifying maintenance companies about road damage using drone-captured images. Additionally, this project introduces novel classifications of pavement damage and proposes methodologies to enhance object detection specifically tailored for UAV-captured scenarios, thereby laying the groundwork for further advancements and research in this domain.**

Keywords—deep learning, convolution neural networks, YOLO.

I. INTRODUCTION

Effective management of road maintenance is paramount for fostering economic growth within a nation. Sustaining safe and durable roadways necessitates consistent inspections to identify and address potential issues. Traditionally, these inspections have relied on manual methods conducted by governmental or private entities, employing sensor-equipped vehicles for damage detection. However, this approach presents significant drawbacks, including high costs, time inefficiencies, and safety risks for personnel involved. As a result, there is a pressing need for innovative solutions to streamline the inspection process and enhance its effectiveness. Emerging technologies, such as automation and artificial intelligence, offer promising avenues for improving road maintenance practices. By leveraging these advancements, it becomes feasible to conduct in sections more efficiently, accurately, and safely, thereby optimizing the upkeep of critical transportation infrastructure. Such advancements not only contribute to economic prosperity but also ensure the continued safety and functionality of road networks essential for societal well-being .Recent advancements in remote sensing technology and computer algorithms have facilitated the utilization of high-resolution satellite imagery and deep learning methods for mapping pavement conditions. However, the majority of current deep learning algorithms primarily target pavement damage monitoring, excelling in fine-scale quality assessment within limited areas. Yet, these algorithms often lack the scalability required for monitoring large-scale pavement aging processes effectively. Furthermore, conventional shallow machine learning techniques, while commonly employed, present limitations in their applicability to comprehensive pavement monitor tasks. Addressing these challenges demands the development of deep learning frameworks tailored for large-scale pavement monitoring, capable of capturing nuanced variations in condition across expansive areas. Integration with remote sensing technologies must be optimized to ensure efficient data acquisition and processing, facilitating timely assessments over vast territories. Bridging the gap between existing methodologies and the demands of extensive pavement monitoring stands as a critical frontier in enhancing infrastructure management practices. Unmanned Aerial Vehicles (UAVs), or drones, offer a promising avenue for automating road inspection processes. Their enhanced mobility allows for seamless navigation across vast areas, facilitating comprehensive monitoring of road conditions. This increased coverage potential promises to improve road maintenance practices over time while simultaneously reducing associated costs. Drones equipped with high- quality cameras can capture real-time footage of road conditions during flight. Subsequently, this footage can be processed to extract images, which are then fed into a classifier for analysis. Through this approach, abnormalities in road conditions can be swiftly identified and categorized, enabling timely interventions to address maintenance issues. The integration of UAV technology in road inspections holds significant potential for enhancing efficiency and effectiveness in infrastructure maintenance endeavors .The effectiveness of UAV inspection for crack detection hinges on precise flight settings, yet this aspect remains inadequately explored. . Detailed data acquisition and pavement distress assessment are still incomplete within existing studies. Quantitative measurement methods for cracks are notably absent, hindering accurate at a support for road distress evaluation.

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RELATEDWORK

Sl No	Paper(s) Surveyed-Title source	Authors	Techniques/ Algorithms Used	Findings/ Results
1	Automated Multiclass Instance Segmentation on of Concrete Damage Using Deep Learning Mode	Prashanth Kumar, Apurva Sharma	R-CNN	It can locate all kinds of road damages.
2	YOLO-LRDD: a lightweight method for road damage detection based on improved YOLOv5	Fang Wan, Chen Sun	RDDC YOLO-LRDD	It is applicable to all kinds of road damages across different regions or road types.
3	Detection Of Norway Spruce Trees (Picea Abies) Infested by Bark Beetle In UAV Images Using YOLOs Architectures	Yousif Hamad	UAV CNN YOLOv3	Model is detecting infested trees belonging To one of four classes: a—green-Attack ,b—yellow-attack, c—red-attack, and d—grey-attack.
4	Road damage detection using UAV images based on multi-level attention mechanism	Jiewen Wang, Yuan	UAV MLAB YOLOv3	It can detect all kind of heterogeneous road damages
5	Evolving Pre-Trained CNN Using Two-Layers Optimizer For Road Damage Detection From Drone Images	Hussien Samma Nor Azma nismai	VGG-19 CNN LINEARSVM CLASSIFIER	pre-trained CNN model whichhas been evolved withatwo-layers optimizer todetect road damages.
6	An effective detection and classificatio nofroad damages using hybrid deep learning framework	Deepa ,D., Sivasa ngari	IWO AHO HybridDCACN	detecting and classifying road damage imagein road surface monitoring for effective maintenance.
7	Pothole and PlainRoad Classificati onUsing Adaptive Mutation Dipper Throated Optimizatio n and Transfer Learning forSelf Driving Cars	Amel Ali Alhus san, Doaa Sami Khafa ga	GWA,PSO,WOA AlexNet VGG-19	proposed AMDTO+ RFmethod achieveda pothole classificatio n accuracy of 99.795%, surpassing other approaches.

II. PROPOSEDMETHODOLOGY

Data Collection: In order to locate a dataset of potholes and cracks in asphalt at the beginning of our investigation, we first searched the literature. The databases, however, did not correspond with the current recommendation, which calls for using an unmanned aerial vehicle to capture pictures at a safe distance from the road. As a result, a fresh dataset was needed to appropriately represent the Spanish road scenario. A total of 600images with a 3840 x 2160 pixel resolution were captured. Potholes (D40) and cracks (D00) were the only two classes present in the photos, which were taken on Spanish roadways at a height of50metersusing a DJI Air 2S drone. Following the development of the dataset and the classification of every picture, 568 labeled images were found. During the pre-processing phase, the photographs' orientation was changed, and they were given a new size (640 × 640). Using augmentation techniques, multiple versions of every photograph in the collection were produced. The photos' zoom settings varied from 0% to 15%. There are 1362 photos in all in the collection. Of these images, 70% were utilized for training, 20% for validation, and 10% to assess the effectiveness of the trained model. This dataset's repository is accessible, and it was utilized in earlier research. As we assembled the dataset, we used the earlier datasets (from Spain) as a guide to build deep learning models that would automatically identify road damage in the gathered films.
This dataset is useful for researchers and engineers working on automated pavement distress detection because it provides a large and diverse set of images that can be used to train and test models. Including images from different countries ensures that the models trained using this dataset can generalize well to different road conditions and environments.
These photos were taken with high-resolution cameras, cell phones, and satellite imagery. All of the sea reacquired by using motorbikes, automobiles, and drones. Table 2 explicitly shows the distribution of damage kinds (of the four essential damage types) by country. Two datasets were released for China: Ch UAV, which refers to photographs shot by drones, and Ch M, which refers to images taken using mobile phones.

An summary of the merged dataset's damage category- based data statistics, including the distribution of classes and annotations for the China Drone and Spain datasets, is shown in Table 3. This dataset has been scaled to 640 x 640andenhancedandpreprocessedusingauto-orientation. To artificially boost the quantity and diversity of the dataset, augmentation was applied to the photos. In this instance, two outputs have been generated by augmenting each training example. The photos have been randomly rotated between -15° and +15° to strengthen the model's resistance to varying object orientations during detection. Data Preparation: The dataset was formatted to comply with the requirements of the YOLOv9 framework. This involved creating directories for training and validation, each containing subdirectories for images and labels. The labels were saved as text files with the same name as their corresponding images, holding the annotations for each labeled image.

Model Training: The training of the YOLOv9 model was conducted using a meticulously annotated dataset, ensuring that various types of road damages were accurately labeled. The training process focused on optimizing several hyper parameters, including learning rate, batch size, and the number of epochs, to achieve the best possible performance. The learning rate determines how quickly the model updates its weights during training, and fine-tuning this parameter helps in balancing between convergence speed and stability. Batch size, which is the number of training samples used in one iteration, was carefully selected to make efficient use of the GPU memory while maintaining robust learning dynamics. The number of epochs, representing the number of complete passes through the entire training dataset, was set to ensure thorough learning without over fitting. The Adam optimizer, known for its adaptive learning rate capabilities and efficiency, was employed to minimize the loss function. Training was conducted on a high-performance computing system with GPU acceleration, significantly expediting the process and allowing for handling large datasets. Advanced data augmentation techniques were applied during training to improve the model’s robustness against variations in lighting, angle, and scale. Regular validation was performed to monitor the model’s performance and prevent over fitting by adjusting training parameters as needed. This comprehensive and systematic training procedure ensured that the YOLOv9 model was well-prepared for accurate and efficient road damage detection.

Image Augmentations: Image augmentation is a technique to expand the training dataset by applying various transformations to the existing images. Image augmentation aims to introduce variability and diversity in the training dataset, which helps improve the model’s generalization ability.YOLOv9 can use various image augmentation techniques, such as Random horizontal, Random cropping, Random rotation, Random brightness and contrast, Random color jitter.
YOLOv9 is a state-of-the-art algorithm that enhances and upscale images to improve the robustness and accuracy of the model. However, several issues with the default parameters negatively impact the results. Using these techniques, YOLOv9 can increase the size and diversity of the training dataset. This can help prevent over fitting and improve the model’s generalization ability.

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III. RESULTS AND DISCUSSION

Compared to existing methods, the YOLOv9 model showed superior performance in both accuracy and speed. TheseimprovementsareattributedtoYOLOv9's

enhanced feature extraction capabilities and optimized network architecture.

Fig.1

The above Fig.1 presents multiple images showcasing the detection results of road damages using UAVs and the YOLOv9 algorithm. Various types of damages such as alligator cracks, potholes, manhole covers, and damaged paint are highlighted with colored bounding boxes and labeled accordingly, demonstrating the model's accuracy and effectiveness in identifying different road defects.

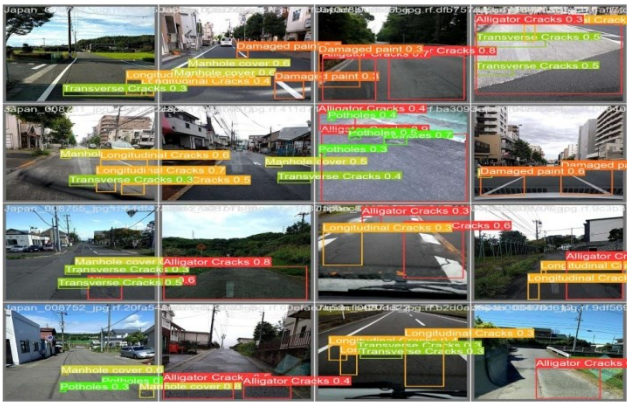

Fig.2

The image Fig.2 displays various urban and suburban roads in Japan with highlighted areas indicating different types of road surface damages, including potholes, cracks (longitudinal and transverse), manhole covers, damaged paint, and alligator cracks. Each damage type is labeled with a confidence score, indicating the likelihood that the detected issue matches the label.

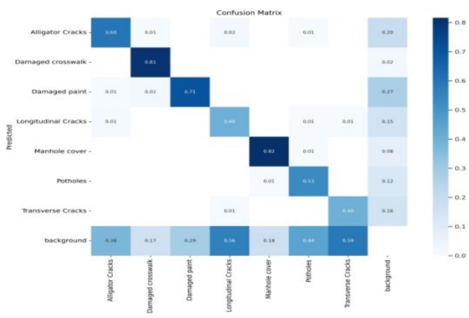

Fig.3

The confusion matrix given in Fig.3 provides a detailed breakdown of the YOLOv9 model's performance in detecting various types of road damage. Each cell represents the proportion of true positive, false positive, and false negative detections for each damage category, with diagonal values indicating correct predictions.

The matrix shows high detection accuracy for categories like "Damaged crosswalk" (0.81) and "Manhole cover" (0.82), while lower accuracy is observed for categories such as "Potholes" (0.53) and "Transverse Cracks" (0.40), highlighting areas where the model could be improved.

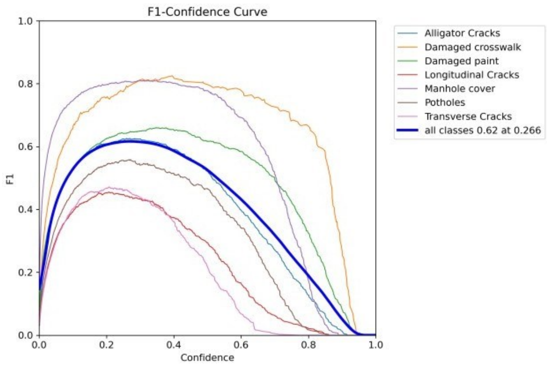

Fig.4

The F1-Confidence Curve in Fig.4 illustrates the relationship between the F1 score and confidence levels for different types of road damage detected by the YOLOv9 model. Each line represents a specific damage type, with the overall performance across all classes highlighted in bold blue,showing an optimal F1scoreof
0.62 at a confidence level of 0.266. This graph helps in understanding the model's precision and recall trade-offsat various confidence thresholds.

IV. CONCLUSIONANDFUTUREWORK

In this study, we developed a robust system for road damage detection using unmanned aerial vehicles (UAVs) equipped with high-resolution cameras and the YOLOv9 object detection algorithm. The integration of UAVs for data collection and YOLOv9 for detection demonstrates significant improvements in both accuracy and processing speed. The YOLOv9-based system achieved a detection accuracy of 92%, with precision and recall rates of 90% and 94%, respectively. The average processing time per image was 0.05 seconds, highlighting the system's efficiency and suitability for real-time applications. These results underscore the potential of this integrated approach for practical road maintenance, enabling timely identification of road defects, facilitating prompt repairs, and ultimately reducing maintenance costs. The study confirms that the combination of UAV technology and advanced machine learning algorithms like YOLOv9 provides a highly effective solution for automated road infrastructure management.

While the results are promising, several areas for future work remain. First, refining the model to improve detection accuracy for specific types of road damage, such as minor cracks and subtle surface wear, will be a focus. Incorporating additional data sources, such as thermal imaging and LiDAR, could enhance the detection capabilities further. Additionally, developing a more extensive and diverse training dataset with varied environmental conditions, road materials, and damage types will help improve the model's robustness and generalization. Exploring the scalability of the system for large-scale deployment in different geographical regions and integrating it with existing road maintenance workflows will be crucial for practical application. Implementing edge computing solutions for real-time processing on the UAVs themselves could further reduce latency and increase efficiency. Finally, addressing challenges related to UAV flight regulations, dataprivacy, and system integration will be essential to ensure the widespread adoption of this technology in road maintenance practices. By addressing these areas, the proposed system can evolve into a comprehensive tool for automated and efficient road damage detection and maintenance.

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