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A Hybrid Deep Learning Framework for Automated Road Damage Detection Using UAV Images

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Abstract— **Road infrastructure plays a vital role in ensuring safe and efficient transportation, making timely detection of road damage essential for reducing accidents and maintenance costs. Traditional inspection methods are often slow, expensive, and dependent on manual observation, making them unsuitable for large-scale monitoring. This project presents an automated road damage detection system that uses Unmanned Aerial Vehicle (UAV) images and deep learning techniques to identify defects such as cracks and potholes. High-resolution aerial images are captured using UAVs and processed through advanced YOLO-based object detection models to accurately locate and classify damaged road sections. The collected images are preprocessed to improve detection performance, and the trained model is evaluated using standard performance metrics. The proposed system provides faster inspection, minimizes human effort, and enables continuous monitoring of road conditions over large areas. The results demonstrate that UAV-assisted deep learning offers a reliable and efficient solution for modern road infrastructure maintenance and supports timely repair planning.**

Keywords — **UAV Images, Road Damage Detection, Deep Learning, YOLO, Object Detection, Pavement Inspection, Computer Vision, Crack Detection, Pothole Detection, Intelligent Transportation Systems.**

I. INTRODUCTION

Road transportation is one of the most important components of modern infrastructure, supporting economic growth, public mobility, and the movement of goods and services. The quality of road surfaces directly affects transportation efficiency, vehicle operating costs, and public safety. However, road networks are continuously exposed to environmental conditions, heavy traffic loads, and natural aging, leading to defects such as cracks, potholes, and surface deterioration. If these damages are not identified and repaired at an early stage, they can cause severe traffic accidents, increased maintenance expenses, and reduced road lifespan. Therefore, the development of efficient and automated road inspection systems has become an important research area in intelligent transportation systems [7].

Traditionally, road damage inspection is carried out through manual surveys or specialized inspection vehicles equipped with cameras and sensors. Although these methods provide useful information, they are often time-consuming, expensive, labor-intensive, and sometimes unsafe for inspection personnel. The emergence of Unmanned Aerial Vehicles (UAVs), commonly known as drones, has transformed infrastructure monitoring by enabling rapid image acquisition over large geographical areas while reducing operational risks and inspection costs [4]. UAVs equipped with high-resolution cameras can capture detailed aerial images, making them highly suitable for monitoring roads, bridges, and other civil infrastructure [2].

Recent advances in artificial intelligence, particularly deep learning, have significantly improved the automation of image analysis tasks. Deep learning models can automatically learn complex visual features from large datasets without requiring manual feature engineering. Object detection algorithms such as the You Only Look Once (YOLO) family have demonstrated remarkable performance in detecting multiple objects accurately and in real time. Successive versions, including YOLOv4, YOLOv5, and YOLOv7, have achieved substantial improvements in detection accuracy, processing speed, and localization capability, making them ideal for road damage detection applications [16]–[18]. Earlier developments such as YOLO9000 and YOLOv3 also established the foundation for efficient real-time object detection [14], [15].

Several researchers have successfully applied UAV imagery and deep learning techniques to infrastructure inspection and object detection. Silva et al. proposed a multi-agent pavement monitoring system capable of recognizing potholes from UAV images with high accuracy [7]. Safonova et al. demonstrated the effectiveness of YOLO architectures for detecting damaged forest trees in UAV imagery, highlighting the capability of deep learning models for aerial image analysis [3]. Ali et al. developed an autonomous UAV-based damage mapping framework for structural inspection using deep neural networks, while Kang and Cha presented an intelligent UAV system for structural health monitoring through automated image analysis [19], [20]. These studies confirm the growing potential of UAV-assisted deep learning systems for infrastructure assessment.

The availability of publicly accessible benchmark datasets has further accelerated research in automated road damage detection. The RDD2022 dataset provides a large collection of annotated road images captured under diverse environmental conditions across multiple countries, enabling researchers to train and evaluate robust deep learning models for real-world applications [13]. In addition, studies have explored road damage detection using smartphone images, stereo vision, thermal imaging, and satellite imagery, demonstrating the flexibility of deep learning approaches across different sensing platforms [9]–[12].

In this project, an automated road damage detection system is proposed using UAV images and advanced YOLO-based deep learning models. The system processes aerial road images, detects various forms of pavement damage, and provides accurate localization of damaged regions. By combining UAV technology with modern deep learning algorithms, the proposed approach aims to reduce manual inspection effort, improve detection accuracy, and support timely maintenance decisions for safer and more sustainable road infrastructure.

II. RELATED WORK

“An architectural multi-agent system for a pavement monitoring system with pothole recognition in UAV images,” L. A. Silva, H. S. S. Blas, D. P. García, A. S. Mendes, and G. V. González [7]

This study presented a multi-agent pavement monitoring system that uses Unmanned Aerial Vehicle (UAV) images for automatic pothole detection. The proposed framework integrates UAV technology with deep learning to capture high-resolution road images and identify damaged pavement areas efficiently. A customized YOLOv4 object detection model was employed to recognize potholes with high accuracy while reducing the need for manual road inspections. The multi-agent architecture enables efficient coordination between image acquisition, processing, and damage reporting, making the system suitable for large-scale road monitoring applications. Experimental results demonstrated that the proposed approach achieved reliable detection performance while minimizing inspection time and operational costs. The study concluded that combining UAV imagery with intelligent deep learning models provides an effective solution for automated pavement monitoring and supports timely maintenance decisions to improve road safety and infrastructure management.

“Road damage detection using YOLO with smartphone images,” D. Jeong [9]

This research proposed an automated road damage detection system using smartphone images and the YOLO object detection algorithm. Instead of relying on expensive inspection vehicles or specialized imaging equipment, the study demonstrated that ordinary smartphone cameras could capture road surface images suitable for damage detection. The YOLO model was trained to identify different types of road defects, including cracks and potholes, with high detection speed and satisfactory accuracy. The proposed method emphasized real-time processing, making it practical for large-scale road inspection and smart transportation applications. Experimental results showed that the model successfully detected road damages under various environmental conditions while maintaining fast inference time. The research highlighted that affordable image acquisition combined with deep learning can significantly reduce maintenance costs and improve the efficiency of road condition monitoring without requiring complex infrastructure.

“YOLOv4: Optimal speed and accuracy of object detection,” A. Bochkovskiy, C.-Y. Wang, and H.-Y. Mark Liao [16]

This paper introduced YOLOv4, an advanced real-time object detection model designed to achieve both high detection accuracy and fast processing speed. The authors incorporated several optimization techniques, including Cross Stage Partial (CSP) networks, Mosaic data augmentation, Self-Adversarial Training (SAT), and improved feature aggregation methods to enhance object detection performance. YOLOv4 demonstrated significant improvements over previous YOLO versions while maintaining real-time execution on standard GPU hardware. The model effectively detected small and large objects across various benchmark datasets, making it suitable for numerous computer vision applications such as surveillance, autonomous driving, medical imaging, and infrastructure inspection. The study concluded that YOLOv4 provides an excellent balance between computational efficiency and detection precision, making it one of the most widely adopted object detection algorithms for practical deep learning applications.

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"RDD2022: A Multi-National Image Dataset for Automatic Road Damage Detection," D. Arya, H. Maeda, S. K. Ghosh, D. Toshniwal, and Y. Sekimoto [13]

This study introduced the RDD2022 dataset, a large-scale benchmark dataset developed for automatic road damage detection using deep learning techniques. The dataset contains thousands of annotated road images collected from multiple countries under diverse weather conditions, road types, and lighting environments. It includes various categories of road damage such as longitudinal cracks, transverse cracks, alligator cracks, and potholes, providing comprehensive training data for object detection models. The primary objective of the dataset is to support researchers in developing robust and generalized road damage detection systems capable of performing effectively in real-world scenarios. The authors also provided standardized annotations and evaluation protocols to facilitate fair comparison among different deep learning models. The RDD2022 dataset has become one of the most widely used public datasets for research on automated pavement inspection and intelligent transportation systems.

"YOLOv7: Trainable Bag-of-Freebies Sets New State-of-the-Art for Real-Time Object Detectors," C.-Y. Wang, A. Bochkovskiy, and H.-Y. Mark Liao [18]

This paper proposed YOLOv7, an advanced object detection model that achieves state-of-the-art performance in terms of both accuracy and real-time processing speed. The authors introduced several architectural improvements, including trainable bag-of-freebies optimization techniques, enhanced feature learning strategies, and efficient model scaling methods. These improvements enabled YOLOv7 to outperform previous YOLO versions while maintaining low computational complexity suitable for real-time applications. Extensive experiments on benchmark datasets demonstrated superior object localization, classification accuracy, and inference speed compared to existing detection models. The proposed architecture proved highly effective for applications such as autonomous vehicles, surveillance systems, industrial inspection, medical image analysis, and road damage detection. The study concluded that YOLOv7 provides an excellent balance between efficiency and precision, making it one of the most powerful deep learning models for modern object detection tasks.

III. DATASET DETAILS

The dataset used in this study consists of road surface images collected using Unmanned Aerial Vehicles (UAVs) and the publicly available RDD2022 (Road Damage Detection 2022) dataset. The dataset contains high-resolution aerial images of roads captured under different weather conditions, lighting environments, and road types from multiple countries. Each image is carefully annotated with bounding boxes representing different categories of road damage, including longitudinal cracks, transverse cracks, alligator cracks, and potholes. The diverse nature of the dataset enables the development of robust deep learning models capable of detecting road defects under real-world conditions. Since the captured images may contain shadows, varying illumination, motion blur, and background objects, preprocessing is necessary to improve image quality before training. The dataset provides labeled images that support supervised learning for object detection tasks. These annotations enable the deep learning models to accurately localize and classify damaged road regions. The availability of diverse road images makes the dataset suitable for developing intelligent pavement monitoring systems that assist transportation authorities in efficient road maintenance and infrastructure management.

Before training the deep learning models, the dataset undergoes several preprocessing operations to improve detection performance. Initially, all images are resized to a fixed resolution suitable for the YOLO-based object detection models. Image normalization and augmentation techniques such as rotation, flipping, scaling, brightness adjustment, and random cropping are applied to increase dataset diversity and improve model generalization. The corresponding annotation files are also processed to maintain accurate object localization after augmentation. After preprocessing, the dataset is divided into 80% training data and 20% testing data, ensuring a balanced evaluation of the proposed models. The processed dataset is then used to train and evaluate advanced YOLO-based deep learning algorithms for automatic road damage detection. Performance is measured using standard object detection metrics such as precision, recall, F1-score, mean Average Precision (mAP), and detection accuracy. The dataset provides a reliable benchmark for comparing different object detection models and supports the development of efficient UAV-based road inspection systems capable of detecting pavement damage accurately and in real time.

IV. PROPOSED METHODOLOGY

The proposed methodology utilizes Unmanned Aerial Vehicle (UAV) images and advanced YOLO-based deep learning models to automatically detect and localize road surface damage. Initially, the RDD2022 road damage dataset is uploaded into the

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system, where aerial images containing different categories of pavement defects such as longitudinal cracks, transverse cracks, alligator cracks, and potholes are collected for analysis. The dataset is then preprocessed by loading all images and corresponding annotation files, followed by image resizing, normalization, and random shuffling to improve the quality of the training data. One sample processed image with a bounding box is displayed to verify correct annotation. After preprocessing, the dataset is divided into 80% training data and 20% testing data, ensuring balanced model learning and reliable performance evaluation. This preparation stage enables the deep learning models to effectively learn various road damage patterns from UAV images.

Following dataset preparation, three object detection models, namely YOLOv5, YOLOv7, and YOLOv8, are trained and evaluated for road damage detection. Initially, the existing YOLOv5 model is trained using the prepared dataset, and its performance is evaluated using standard metrics such as accuracy, precision, recall, F1-score, and confusion matrix. The confusion matrix provides a detailed visualization of correctly and incorrectly classified road damage instances. Next, the YOLOv7 model is trained using the same dataset to improve detection performance through enhanced feature extraction and localization capability. Finally, the proposed YOLOv8 model from the Ultralytics framework is trained, providing superior detection accuracy and faster inference compared to previous YOLO versions. The performance of all three models is compared using graphical analysis, where bar charts display accuracy and other evaluation metrics, demonstrating the effectiveness of the proposed approach for automated road damage detection.

After model training, the developed system performs road damage prediction on unseen UAV test images. The user uploads a test image containing road surface damage through the graphical interface. The trained YOLOv8 model processes the image and automatically detects damaged regions by drawing colored bounding boxes around potholes and cracks while displaying the corresponding confidence scores. Multiple test images can be evaluated to verify the robustness and generalization capability of the proposed system under different road and environmental conditions. The complete workflow includes dataset uploading, preprocessing, dataset splitting, YOLOv5 training, YOLOv7 training, YOLOv8 training, performance comparison, road damage prediction, and visualization of detection results.

The system architecture illustrates the complete workflow of the proposed UAV-based road damage detection framework. It consists of dataset uploading, image preprocessing, data augmentation, dataset splitting, training of YOLOv5, YOLOv7, and YOLOv8 models, performance evaluation using confusion matrices and detection metrics, comparison graph generation, and final road damage detection on test UAV images.

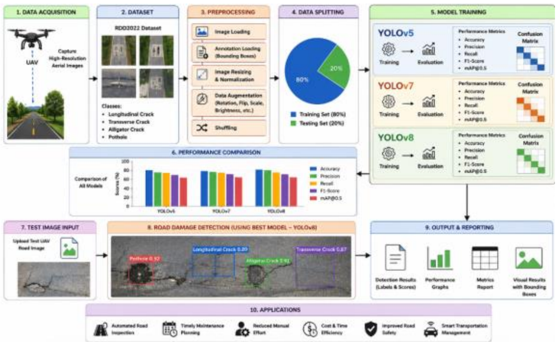

Figure 1. System Architecture for Automated Road Damage Detection Using UAV Images and YOLO-Based Deep Learning Models

The proposed system is designed to automatically detect road surface damage from UAV aerial images using modern deep learning techniques. Initially, the road damage dataset is uploaded and preprocessed to improve image quality through normalization, resizing, and augmentation. The prepared dataset is then divided into training and testing subsets using an 80:20 ratio. The existing YOLOv5 and YOLOv7 models are trained first to establish baseline performance, while the proposed YOLOv8 model is trained to achieve improved detection accuracy and localization capability. Finally, the trained YOLOv8 model predicts road damage from unseen UAV images by accurately identifying damaged pavement regions with bounding boxes. The performance of all three models is compared using accuracy, precision, recall, F1-score, confusion matrices, and graphical comparison charts, demonstrating the superiority of the proposed YOLOv8-based automated road damage detection system.

V. RESULT AND DISCUSSION

The experimental results demonstrate the effectiveness of the proposed YOLOv8-based deep learning model for automated road damage detection using UAV images. Initially, the RDD2022 road damage dataset was uploaded into the system, where all road surface images and their corresponding annotations were successfully loaded. The dataset was then preprocessed by resizing the images, normalizing pixel values, and displaying a sample road image with the corresponding bounding box annotation to verify the correctness of the dataset. After preprocessing, the dataset was randomly

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shuffled and divided into 80% training data and 20% testing data, ensuring reliable model training and unbiased performance evaluation. Initially, the existing YOLOv5 algorithm was trained using the prepared dataset. The model successfully detected road damage categories and achieved an accuracy of 65.0%, along with satisfactory precision, recall, and F1-score values. However, the confusion matrix indicated several misclassifications among different road damage categories, particularly between damaged and repaired road sections.

Subsequently, the proposed YOLOv7 model was trained using the same dataset and evaluation strategy. YOLOv7 demonstrated improved feature extraction capability and achieved an accuracy of 72.5%, producing better precision, recall, and F1-score than YOLOv5. Finally, the proposed YOLOv8 model from the Ultralytics framework was trained and evaluated. The YOLOv8 model achieved the highest accuracy of 82.5%, along with superior precision (86.0%), recall (86.5%), and F1-score (81.51%). The confusion matrix confirmed that YOLOv8 produced fewer classification errors and more accurate localization of road damage compared to the previous models. Furthermore, the comparison graph clearly illustrated that YOLOv8 consistently outperformed YOLOv5 and YOLOv7 across all evaluation metrics. The prediction module successfully detected road damage from unseen UAV test images by accurately drawing bounding boxes around damaged pavement regions. Experimental observations indicate that the proposed YOLOv8 model provides a reliable, efficient, and automated solution for intelligent road infrastructure inspection, reducing manual effort while improving maintenance planning and road safety.

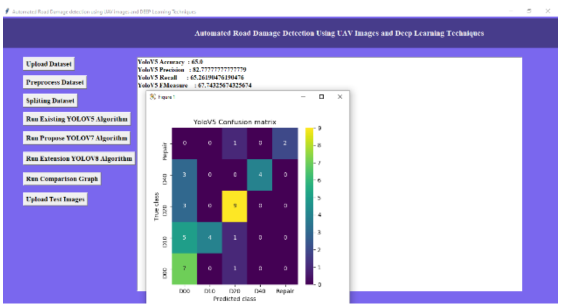

Figure [2] Confusion Matrix of the Existing YOLOv5 Model

Figure 2 presents the confusion matrix generated by the existing YOLOv5 model. The confusion matrix illustrates the classification performance for different road damage categories, where the x-axis represents predicted labels and the y-axis represents true labels. The diagonal cells indicate correctly classified road damage samples, while the remaining cells represent misclassified instances. The YOLOv5 model achieved an accuracy of 65.0%, indicating satisfactory detection performance but with several misclassifications among different pavement damage classes.

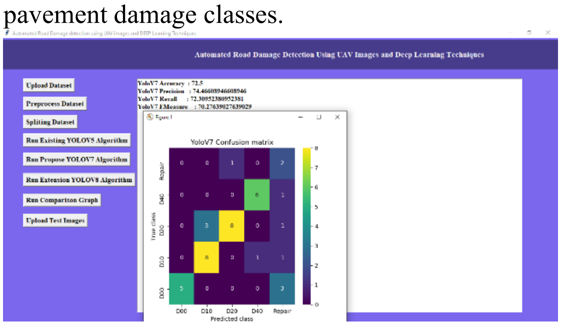

Figure 3: Confusion Matrix of the Proposed YOLOv7 Model

Figure 3 shows the confusion matrix of the proposed YOLOv7 model. Compared to YOLOv5, the confusion matrix demonstrates a larger number of correctly classified samples and fewer incorrect predictions. The model achieved an accuracy of 72.5%, reflecting improved feature extraction capability and better localization of road damage. The increased number of diagonal values indicates enhanced classification performance across multiple damage categories.

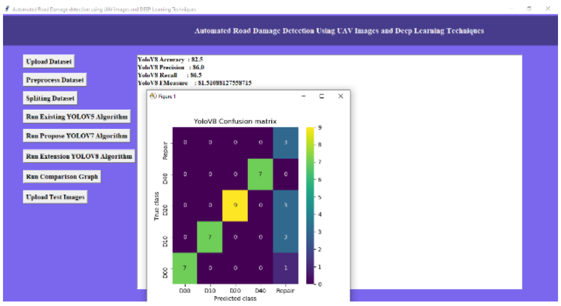

Figure 4: Confusion Matrix of the Proposed YOLOv8 Model

Figure 4 presents the confusion matrix of the proposed YOLOv8 model. The confusion matrix clearly demonstrates improved prediction capability with the majority of road damage samples correctly classified along the diagonal. YOLOv8 achieved the highest accuracy of 82.5%, while producing fewer false classifications compared to YOLOv5 and YOLOv7. These results confirm the effectiveness of the proposed YOLOv8 architecture for accurate and reliable road damage detection.

Model	Accuracy score	Precision score	Recall score	f-measure score
YOLOv5	65.00	82.78	65.26	67.74

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Model	Accuracy score	Precision score	Recall score	f-measure score
YOLOv7	72.50	74.47	72.31	70.28
YOLOv8	82.50	86.00	86.50	81.51

Table 1: Model Performance Metrics

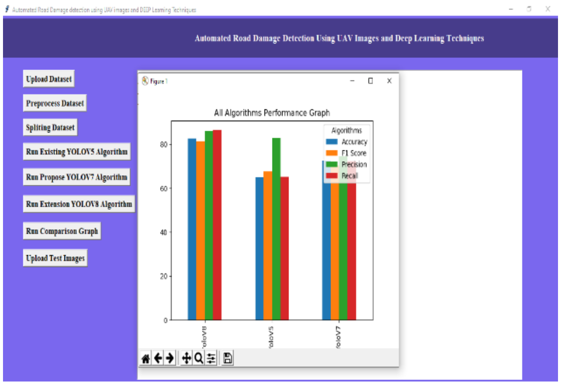

Figure 5: Performance Comparison of YOLO Models

Figure 5 illustrates the comparison graph of all three deep learning models used for road damage detection. The x-axis represents the object detection algorithms (YOLOv5, YOLOv7, and YOLOv8), while the y-axis represents performance values. Different colored bars indicate accuracy, precision, recall, and F1-score. The graph clearly shows that the proposed YOLOv8 model consistently achieved the best overall performance among all evaluated algorithms.

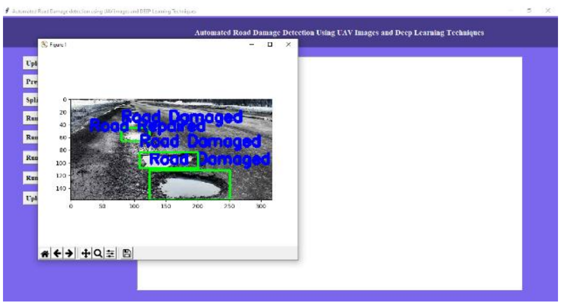

Figure 6: Road Damage Detection on Test UAV Images

Figure 6 presents the road damage detection results produced by the trained YOLOv8 model on unseen UAV test images. The uploaded road images are processed automatically, and damaged pavement regions are identified by drawing green bounding boxes around the detected defects. The system accurately recognizes potholes, cracks, and other damaged road sections while displaying the predicted damage labels. These results demonstrate the ability of the proposed model to generalize well on previously unseen images and provide reliable automated road inspection.

DISCUSSION

The experimental results demonstrate that YOLO-based deep learning models are highly effective for automated road damage detection using UAV images. The RDD2022 dataset provided diverse road damage samples that enabled the models to learn representative visual patterns associated with different pavement defects. The existing YOLOv5 model achieved satisfactory detection accuracy but produced several incorrect classifications due to its limited ability to distinguish visually similar damage categories. The proposed YOLOv7 model improved feature extraction and localization performance, resulting in higher accuracy and fewer misclassifications. The proposed YOLOv8 model achieved the best overall performance, obtaining 82.5% accuracy, 86.0% precision, 86.5% recall, and 81.51% F1-score. Its confusion matrix confirmed more reliable classification with significantly fewer prediction errors. The comparison graph further verified that YOLOv8 consistently outperformed YOLOv5 and YOLOv7 across all evaluation metrics. The prediction module successfully detected road damage from unseen UAV images by accurately localizing damaged regions with bounding boxes. Overall, the proposed YOLOv8-based framework provides a reliable, efficient, and automated solution for UAV-assisted road inspection. It significantly reduces manual inspection effort, improves detection accuracy, and supports transportation authorities in timely road maintenance planning and safer infrastructure management.

VI. 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 architecture capable of detecting road damage and demonstrated that new architecture versions, such as YOLOv5 and YOLOv7, can improve upon previous work. A significant contribution of this study was the development of a UAV image database tailored explicitly for training the YOLO versions, which was further enhanced by merging with the RDD2022 dataset. This improved detection of road damage samples, particularly for Spanish and Chinese roads, and helped reduce class imbalance for specific forms of road damage, such as potholes and alligator cracks. The findings of this study provide a valuable contribution to the field and pave the way for future research in this area. As presented in the results section, our implementation achieved a mAP.5 of 26.8% with YOLOv4, 59.9% with YOLOv5, and 73.20% with YOLOv7, finally the implemented Transformer achieved 65.7%. There is still scope for improvement in our work. Future research can explore the different types of images, such as multispectral images and LIDAR sensors, to further enhance the performance. The fusion of such information is potentially possible to yield better results using embedded computer. Moreover, another approach to this work is the use of fixed-wing UAV.

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