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UAV Imagery And Deep Learning for Automated Road Damage Detection

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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.

Keywords: UAV, Road damage detection, Deep learning, Object-detection

1.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 [1], rooftops [2], vegetation [3], and urban environments [4], [5]. Currently, road condition inspections in Spain are performed manually, requiring personnel to travel along roads to identify damage points. This method incurs high costs due to the need for human labor and specific cameras and sensors for the task. The decision-making process for repairing road damages is the responsibility of an expert. In contrast, countries like China have a vast network of roads and highways, making them susceptible to surface cracks and rainwater infiltration, which can accelerate the deterioration of roads and pose risks to vehicle safety.

Without timely detection and the rapid availability of information on road defects, excessive wear on vehicles and an increased likelihood of traffic accidents can occur, leading to further financial losses. Therefore, the development of automated techniques for detecting road deterioration has become a critical area of research, with many universities and research centers collaborating to find effective solutions. Automatic road damage detection is an active area of research that aims to detect and map various types of road damage

using multiple techniques such as vibration sensors, Light Detection And Ranging (LiDAR) sensors [6], and image-based methods. These techniques are often used in combination to improve the accuracy of damage detection. Machine learning approaches, such as deep learning, are commonly used in image-based techniques to recognize various types of road degradation. These methods typically require a dataset of images, which can include top-down photographs, images captured by unmanned aerial vehicles [7], pictures obtained by mobile devices [8], [9], images obtained from satellite image platforms [10], thermal images [11], and 3D images or stereo vision of the asphalt surface [12]. Researchers have been conducting studies using a variety of datasets to train the model, incorporating additional images captured by drones, cameras mounted on cars, and satellites. To facilitate the learning process, these datasets are often annotated to identify different types of road damage, including, but not limited to potholes, cracks, and rutting. Annotating these images enables the algorithm to learn to detect and classify various types of road damage accurately. Using a large and diverse dataset, researchers can enhance the accuracy and reliability of their models, ensuring that they can effectively identify and address different types of damage on the roads.

The "UAV and Deep Learning For Automated Road Damage Detection" project aims to develop an automated system that identifies ground holes, like potholes, in real time, enhancing road safety and infrastructure management. Using deep learning models, specifically CNN-based architectures like Faster R-CNN, the system can accurately classify and localize hazardous ground surfaces in diverse conditions. This involves training on annotated datasets of various ground types to help the model recognize features unique to ground holes. The project's key challenge is achieving high accuracy across variable conditions while ensuring real-time performance, especially for applications in autonomous systems. The system is designed for seamless integration with surveillance cameras or mobile platforms, offering real-time alerts that enable proactive maintenance and improved safety. Its applications span road maintenance, smart cities, and autonomous navigation, reducing manual inspection efforts and supporting more efficient infrastructure monitoring.

2. LITERATURE SURVEY

Road damage poses a significant threat to the longevity and safety of transportation infrastructure. Timely detection of pavement damage is crucial for ensuring efficient maintenance and repair, which, in turn, enhances road safety and prolongs the lifespan of road networks. Traditionally, road inspection methods rely on manual surveys or specialized vehicles equipped with sensors. However, these methods can be expensive, labor-intensive, and difficult to scale. With the advent of advanced imaging technologies and deep learning techniques, street view images have emerged as an innovative solution for monitoring pavement damage due to their wide coverage, frequent updates, and accessibility.

This study introduces a novel dataset specifically designed for automated road damage detection: the Street View Image Dataset for Automated Road Damage Detection (SVRDD**)**. The dataset consists of 8,000 street view images collected from Baidu Maps, covering five administrative districts within Beijing City, China. These images were carefully analyzed, and over 20,000 instances of pavement damage were manually identified and annotated. The damage instances included various types of road surface defects such as cracks, potholes, and deformations.

The availability of such a dataset is essential for training and evaluating deep learning models for road damage detection. To assess the effectiveness of existing computer vision techniques in detecting pavement damage, ten well-established object detection algorithms were trained and tested using the SVRDD dataset. The evaluation results highlight the strengths and weaknesses of these algorithms in identifying different types of road damage from street view images. This comparative analysis provides valuable insights into the performance of current detection models and lays the foundation for further improvements in deep learning-based road damage assessment.

To the best of our knowledge, SVRDD is the first publicly available dataset based on street view images for pavement damage detection. Unlike traditional datasets that rely on drone imagery or close-up photographs, SVRDD leverages images from widely used mapping services, making it a unique and scalable resource for road maintenance applications. This dataset can support future research in automated road inspection and facilitate the development of more advanced deep learning models. By integrating street view imagery with AI-driven analysis, SVRDD contributes to the growing field of smart infrastructure monitoring, ultimately promoting safer and more sustainable road networks.

Road infrastructure is a critical component of urban development, ensuring smooth transportation and economic growth. However, pavement damage, such as cracks, potholes, and surface deformations, can significantly impact road safety and increase maintenance costs. Traditional road inspection methods, which involve manual assessments or specialized vehicles equipped with high-resolution cameras and sensors, are often expensive, time-consuming, and difficult to scale. To address these limitations, recent advancements in artificial intelligence (AI) and computer vision have paved the way for automated road damage detection using street view images. Street view images are panoramic images captured by vehicle-mounted cameras as part of large-scale mapping efforts. These images provide a comprehensive view of urban and rural road conditions, making them valuable for infrastructure monitoring. Compared to aerial imagery (e.g., drone-based monitoring), street view images offer several advantages:

Better Visibility of Road Surfaces: Unlike aerial images, street view images capture detailed views of road damage at ground level.

Regular Updates: Mapping services update their street view imagery periodically, providing fresh data for monitoring infrastructure changes.

Large-Scale Coverage: Mapping services collect vast amounts of imagery, making it possible to analyze road conditions over entire cities and countries.

Cost-Effectiveness: Since street view images are publicly available, using them for damage detection eliminates the need for expensive dedicated survey vehicles.

To advance research in this field, a novel dataset known as the Street View Image Dataset for Automated Road Damage Detection (SVRDD) has been introduced. This dataset consists of 8,000 high-resolution street view images obtained from Baidu Maps, covering five administrative districts within Beijing City, China. The dataset was meticulously curated, with over 20,000 instances of pavement damage manually labeled and categorized.

The damage types annotated in the dataset include:

Cracks (longitudinal, transverse, and alligator cracks)

Potholes

Surface deformations and depressions

Patchwork and road wear

These diverse damage types reflect real-world road conditions and serve as an important benchmark for training deep learning models. With the availability of SVRDD, researchers can now train and evaluate deep learning models to automate pavement damage detection. To test the effectiveness of computer vision techniques, ten well-established object detection algorithms were trained and tested on the SVRDD dataset. These include: 2. YOLO (You Only Look Once) 3. SSD (Single Shot MultiBox Detector) 4. RetinaNet 5. EfficientDet Other state-of-the-art object detection networks The evaluation of these models was based on key performance metrics such as:

Precision: Measures how accurately the model identifies actual pavement damage. 2.Recall: Determines the model's ability to detect all instances of damage. 3.Mean Average Precision (MAP): A standard metric for assessing object detection accuracy. The comparative analysis of these object detection models provided several insights:

High-performing models such as YOLO and Faster R-CNN demonstrated strong accuracy in detecting road damage.

Challenges remain in detecting smaller or occluded damage instances. Occlusions from vehicles, shadows, or lighting variations can make detection difficult.

Generalization to different environments is limited. The dataset is based on Beijing roads, and model performance may vary when applied to other regions with different road conditions.

Real-time processing considerations are crucial. For deployment in smart infrastructure systems, models must achieve a balance between detection accuracy and computational efficiency.

The SVRDD dataset represents a significant advancement in the field of automated road damage detection. It introduces several key benefits:

First-of-Its-Kind Dataset: SVRDD is the first publicly available dataset utilizing street view images for pavement damage detection, setting a new benchmark for future research.

Scalability and Accessibility: Unlike datasets that require expensive dedicated equipment, SVRDD leverages widely available mapping services, making large scale damage detection feasible.

Supports AI Innovation: The dataset provides a valuable resource for researchers working on deep learning, image processing, and smart infrastructure monitoring.

Enhances Cost-Effective Maintenance: By integrating SVRDD with AI-driven analysis, municipalities can prioritize road repairs efficiently, reducing maintenance costs and improving overall road safety.

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3. PROPOSED METHODOLOGY

The proposed system aims to enhance road damage detection by integrating advanced deep learning models, such as transformers, with real-time edge computing capabilities. By leveraging a combination of high-resolution images and multi-modal data from sensors like accelerometers and GPS, it can provide more accurate and timely damage assessments. The system will feature adaptive learning algorithms that continuously update the model with new data, improving detection accuracy over time. Additionally, it will employ a robust user interface for real-time visualization and integration with road management systems, ensuring efficient maintenance planning and response.

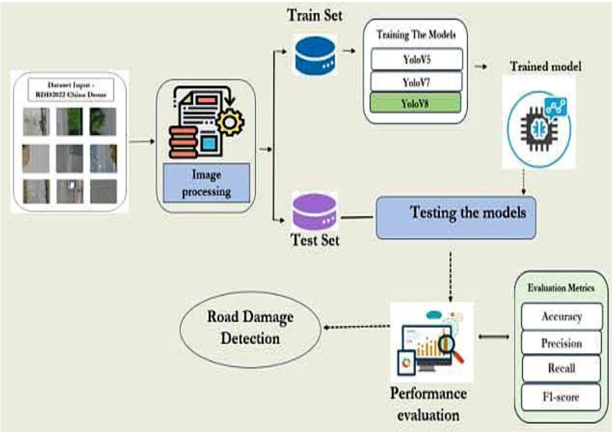

Figure 1: Proposed System.

The proposed methodology typically includes the following key components:

Step 1: Dataset Input: The input consists of RGB road images (e.g., images of roads with and without damage).The dataset is collected and prepared for processing.

Step 2: Image Processing: The images are preprocessed (e.g., resizing, normalization, augmentation) to improve model performance. The dataset is then split into train and test sets.

Step 3: Training the Models: The training dataset is fed into different YOLO models: YOLOv5, YOLOv7, and YOLOv8.The models learn to detect road damage patterns.

Step 4: Trained Model: After training, the models are stored and ready for testing.

Step 5: Testing the Models: The trained models are evaluated on the test set to check their performance.

Step 6: Performance Evaluation: The models are assessed using different evaluation metrics: i)Accuracy ii)Precision iii)Recall iv)F1-score.The best-performing model is selected.

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Step 7: Road Damage Detection: The final model is used to detect road damage in real-world images. The results help in road maintenance and infrastructure improvements.

Applications:

Unmanned Aerial Vehicle (UAV) imagery combined with deep learning techniques has revolutionized automated road damage detection by offering efficient, cost-effective, and accurate solutions. Here are the key applications of this technology:

Road Infrastructure Monitoring & Maintenance

Real-time Damage Detection & Assessment

Cost-effective & Scalable Road Inspection

Smart City & Intelligent Transportation Systems

Disaster Management & Post-disaster Road Assessment

Advantages:

Combining UAV (Unmanned Aerial Vehicle) imagery with deep learning offers a powerful solution for automated road damage detection, significantly improving efficiency, accuracy, and cost-effectiveness. Below are the key advantages:

High Accuracy & Precision: Deep learning models (e.g., YOLO, CNNs, Transformers) can detect and classify road damage with high accuracy. UAVs capture high-resolution aerial images, ensuring even small cracks or potholes are identified. Reduces human error in manual inspections.

Faster & Real-Time Road Assessment: UAVs can survey large road networks quickly, reducing the time required for inspections. Deep learning algorithms process images in real-time, allowing immediate detection and reporting. Faster response times help authorities fix damages before they worsen.

Cost-Effective Solution: Reduces the need for expensive, labour-intensive manual road inspections. UAVs can cover large areas in a single flight, lowering operational costs. Minimizes long-term repair costs by enabling proactive maintenance.

Enhanced Safety: UAVs eliminate the need for human inspectors to physically survey dangerous roads. Reduces the risk of accidents by detecting road hazards early. Ensures safer transportation for drivers and pedestrians.

Scalability & Wide Coverage: Can inspect urban roads, highways, bridges, railways, and airport runways. UAVs can be deployed in remote or hazardous areas where human inspections are difficult. Ideal for both small and large-scale infrastructure projects.

4. EXPERIMENTAL ANALYSIS

Figure 1 shows a collection of original images that are taken in low-light conditions or have poor lighting quality. These images serve as the input to the proposed image enhancement model. These images are the input images that the model will process in order to improve their visibility and quality. The purpose of this figure is to provide a visual representation of the types of images that the model is designed to enhance.

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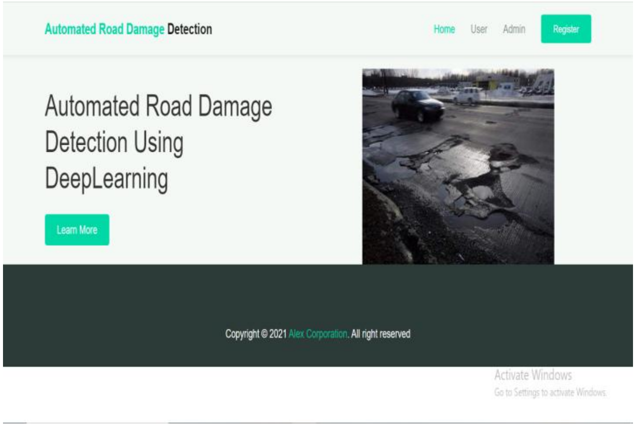

Figure 2: Home page

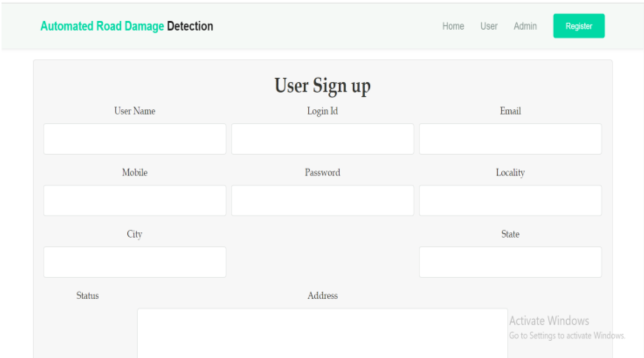

Figure 3: User Registration Page

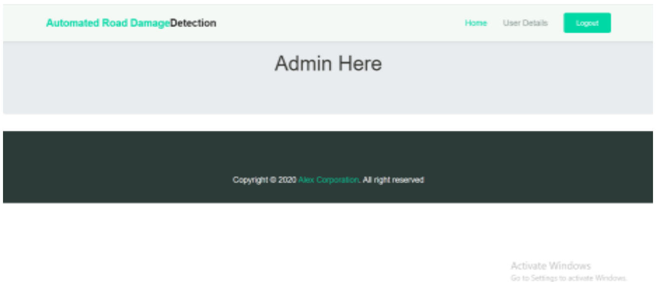

Figure 4: Admin Home

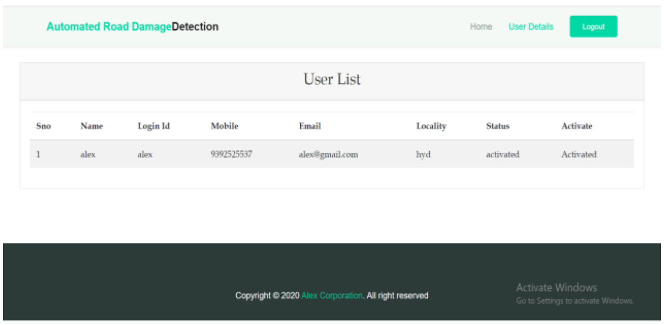

Figure 5: Activate User

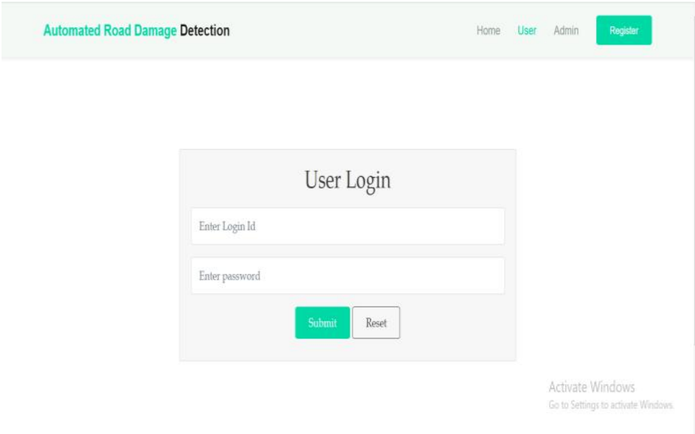

Figure 6: User Login Page

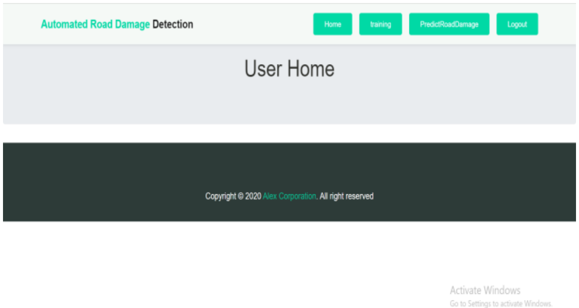

Figure 7: User Home Page

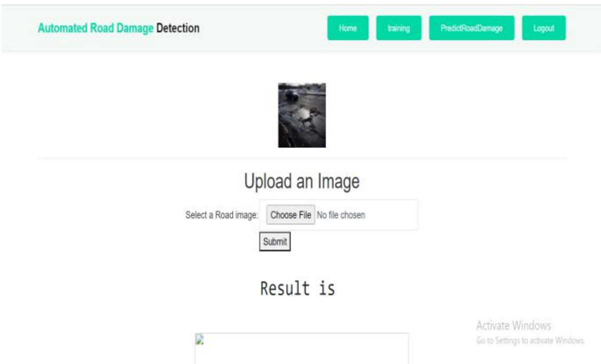

Figure 8: Prediction Page

Figure 9: Prediction

5. 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. 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.

To further improve the accuracy, efficiency, and robustness of automatic road damage detection systems, several advanced techniques and technologies can be integrated. These enhancements can help in detecting various types of road damage more precisely, enabling proactive maintenance and reducing infrastructure degradation.

Integration of Advanced Deep Learning Models Deep learning has revolutionized image-based detection systems, and incorporating state-of-the-art architectures can significantly enhance road damage detection. Transformers: Vision Transformers (ViTs) have demonstrated superior performance in image recognition tasks by capturing long-range dependencies in images. Unlike traditional CNNs, ViTs process the entire image holistically, making them effective for identifying complex road damage patterns. Generative Adversarial Networks (GANs): GANs can be used for data augmentation, generating synthetic road damage images to improve model generalization. They can also help in refining detection accuracy by enhancing low-quality images taken in poor lighting or weather conditions.

Real-Time Processing with Edge Computing Traditional road damage detection systems often rely on cloud-based processing, which can introduce latency and dependency on stable network connections. Implementing real-time processing using edge computing can significantly reduce response time and enhance on-site analysis. Edge AI devices (e.g., NVIDIA Jetson, Google Coral) can process images directly from vehicle-mounted cameras, eliminating the need for cloud-based computations. Faster response and decision-making allow authorities to take immediate action, such as alerting maintenance teams to critical damages. Reduced bandwidth usage by processing data locally instead of transmitting large amounts of image data to centralized servers.

Multi-Modal Data Integration Enhancing road damage detection by incorporating multiple data sources can improve robustness and accuracy. Sensor Data Fusion: Combining camera images with accelerometer, LiDAR, or GPS data can help differentiate real road damage from shadows, puddles, or surface irregularities. Vehicle-based Sensors: Smart vehicles equipped with vibration sensors can provide additional insights into road surface quality, detecting potholes and cracks even when visual data is unclear. Crowdsourced Data: Integrating data from multiple vehicles or drone imagery can enhance coverage and provide a more comprehensive road damage assessment.

Continuous Learning and Model Adaptation Machine learning models need continuous updates to adapt to changing road conditions and new damage patterns. Implementing self-learning mechanisms can ensure long term effectiveness.

Automated Model Retraining: Using feedback loops where new images and labeled data are continuously fed into the model for improved accuracy.

Active Learning Approaches: Allowing the model to request human intervention for ambiguous cases, reducing errors in automated detection.

Federated Learning: Enabling decentralized training across multiple edge devices without sharing raw data, ensuring privacy while improving the model collectively.

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