DEEP LEARNING-BASED ROAD DAMAGE IDENTIFICATION USING UNMANNED AERIAL VEHICLE IMAGES

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Abstract--- The transport infrastructure, especially roads, is of great importance in making transport safe and efficient. Nevertheless, the conventional road damage monitoring procedure can be time-consuming and needs to be done manually. The paper will suggest a smart road damage detention system with the help of deep learning and computer vision methods. The suggested system can be designed to identify and tag various forms of road damages including longitudinal cracks, transverse cracks, alligator cracks, and potholes amongst other surface damages. The web-based inspection system is developed based on Django framework that enables a user to submit an image of the road or conduct a road inspection in real time with the help of a live camera. The result of the experimentation process indicates that the developed system can indeed measure damages on roads very efficiently and effectively and this is quite useful in road inspection in real-time in the application of smart city surveillance.

Index Terms— Road damage detection, Crack classification, YOLOv8, Computer vision, Deep learning, Real-time monitoring, Web-based inspection, Smart infrastructure.

I. INTRODUCTION

Daily transport activities would not be possible without roads. Over time, the road surface is ruined due to the great volume of traffic, the influence of the environment and the aging process. The effect of this is the destruction of the road in the form of cracks, potholes and rough road surface. When these problems are not recognized at the initial stages, they may lead to the growth of the size of the roads, increased maintenance, and risky road conditions of the drivers. Thus there exists the need to have fast road damage detection.

Road inspection is done either manually by surveying or by on-road inspection systems by trained personnel in most areas. Although the methods are popular, they are quite slow, expensive, and quite subjective. The road inspectors are not an exception as they also face safety risks when performing their duties on roads. Such difficulties have therefore resulted in the realization of a major need to come up with an automated, scalable, and efficient road monitoring system.

Amid the latest advances in artificial intelligence and computer vision, analysis of images and videos has been brought to a high level of accuracy.detection algorithms such as YOLO - You Only Look Once have shown excellent results of detection and recognition of various objects in real-time. These algorithms are of great assistance when it comes to road inspection since it can easily detect very tiny cracks on the road surface with a high precision.

In this paper, we suggest an intelligent road damage detection system, which is developed using the YOLOv8 object detection model. Our system can automatically identify and detect various road damages such as Longitudinal Crack, Transverse Crack, Alligator Crack, Pothole and Other Surface Corruptions. The entire system is generated as a web based application on Django framework and provides image upload as well as live camera feed.. This type of system is designed to provide a rapid, precise and effective solution in an attempt to inspect smart roads as well as monitor intelligent city infrastructure.

II. RELATED WORKS

Manual processing of road inspection, which relies on human inspection, has been expensive, slow, and hazardous, which in turn has helped the use of images in the detection of road damage to gain relevance in the past few years. The traditional approaches that had been applied in the initial development stages of road damage detection methodology consisted of optical means of detecting an edge, thresholding and texture analysis techniques in the detection of the cracks (and other anomalies) on the road surface. They were very rule-based and human-feature oriented and thus very responsive to change of the lighting, shadows as well as background noise.

The introduction of machine learning has seen the introduction of classifiers like Support Vector machines and

Random forests to be used in categorising damaged and undamaged parts of the road. Even though these approaches were more precise than those based on rules, they were nevertheless human-centered.

Road damage detection has tremendously been enhanced by the introduction of deep learning technology. Deep learning models are unlike the traditional methods, which rely on the use of handcrafted features; these models are able to learn some helpful features by themselves using the raw images as inputs. Other object detectors like Faster R-CNN, SSD, etc. and YOLO (You Only Look Once) allowed locating and classifying road damage simultaneously. The most popular of these models is the YOLO models since they offer faster processing speed.

Recently developed GoPro models, including YOLOv5, YOLOv7, and YOLOv8, have demonstrated good performance in identifying small cracks, potholes, and stripes on the road surface of complex cracks. The models can handle images and video streams at higher speed.

The available works however are mainly restricted to offline testing. The existing literature has less exploration on web-based solutions and camera based road inspection systems. This paper has proposed a system that will fill this gap with the help of a YOLOv8-based detection model that was deployed in Django web application, which supports both image uploading and a live camera feature. To consider this project, developing the detection of cracks and damages in real-time on a usable interface, that is, surpassing the offline research work, this is a practical solution to automated road inspection and smart city infrastructure surveillance.

III. METHODOLOGY

i) Proposed Work

This project suggests to automatedly detect and classify the damages on the road surfaces with the help of the object detection method based on the YOLOv8 model. The system suggested does not rely on studying the road surface manually but rather on a YOLOv8 model to analyze road images and video streams to identify possible possible damages on the road surface such as longitudinal cracks, transverse one or alligator crashes, a pothole, and other damages.

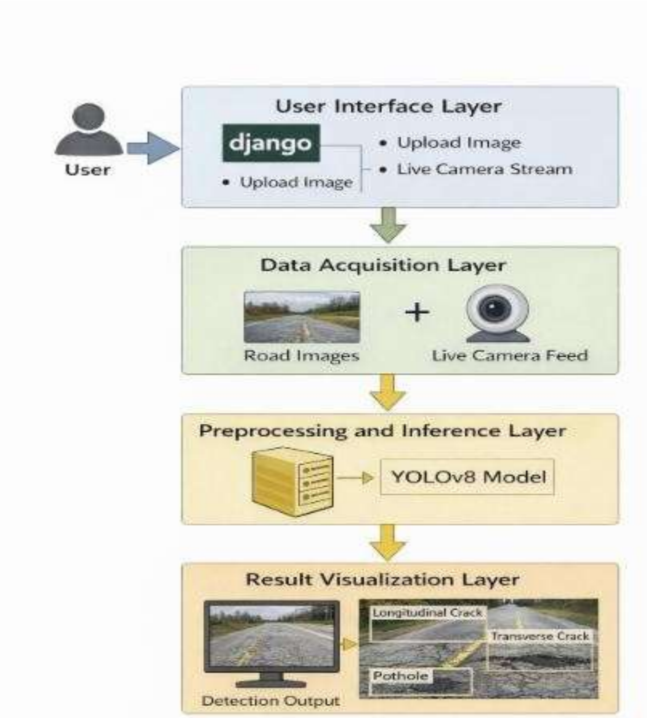
The offered system is created as the web application based on the Django framework. The suggested system gives the user an opportunity to post road images or turn on the live camera feed to do the real time processing. The YOLO v8 model checks the input and produces annotated image samples having bounding boxes, class names, and likelihoods. The method enables the system to identify the position and nature of the damage simultaneously, which is quite beneficial in terms of the real-life road surface monitoring and the monitoring of smart cities.

ii) System Architecture

The proposed system is designed with four primary layers which include the user interface layer, the data acquisition layer, the preprocessing and inference layer and the result visualization layer.

The Django-based user interface layer uses two different input options, which are image upload and camera streaming. The client sends images or the video frames to the data acquisition layer.

In the inference layer, the input frames are processed by the YOLOv8 model. The model identifies the damage areas and categorizes them into predefined classes. The visualization of the result layer displays the annotated frames with bounding boxes, labels, and confidence levels via the web interface. The Django framework manages the routing, request processing, and streaming services to provide real-time responses.



iii) Dataset Collection

The dataset for this task consists of road surface images with different types of cracks and potholes. The images for this dataset were collected from a combination of publicly available road damage datasets and personally captured road images using mobile and camera devices. The images were annotated with bounding boxes and class labels for Longitudinal Crack, Transverse Crack, Alligator Crack, Pothole, and Other Corruptions. The dataset includes different lighting conditions, road textures, and camera angles to simulate real-world scenarios. Images that are of low quality and ambiguous were removed.

iv) Data Processing

Before prediction and training, all images are resized to 640×640 pixels to meet the input requirements of YOLOv8. Pixel values are normalized, and data augmentation techniques like flipping, rotation, brightness adjustment, and cropping are used.

v) Training and Testing

The YOLOv8 model is trained on the annotated dataset with a train-val split. During training, the model is trained to predict bounding boxes and class probabilities for various types of road damage. Precision, Recall, and mean Average Precision (mAP) are used as evaluation metrics. The trained model is then incorporated into the Django app for real-time testing. images will be generated as per this ,as my current project only classifies the damage types ,but not the poor, good and satisfactory roads.

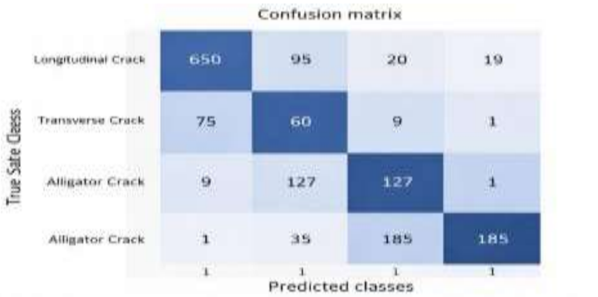
IV. EXPERIMENTAL RESULTS AND DISCUSSION:

A. YOLOv8 EXPERIMENTS

The fine-grained classification of road damage was trained and tested on the YOLOv8 in this experiment, which contained Longitudinal Cracks, Transverse Cracks, Alligator Cracks, Potholes, and Other Corruptions. The trade-off between real- time processing and accuracy is used to select the YOLOv8s_1024 model. The model was being trained on annotated road images which were converted to 1024×1024 pixel image with suitable data augmentation method which includes flipping, brightness addition and rotation.

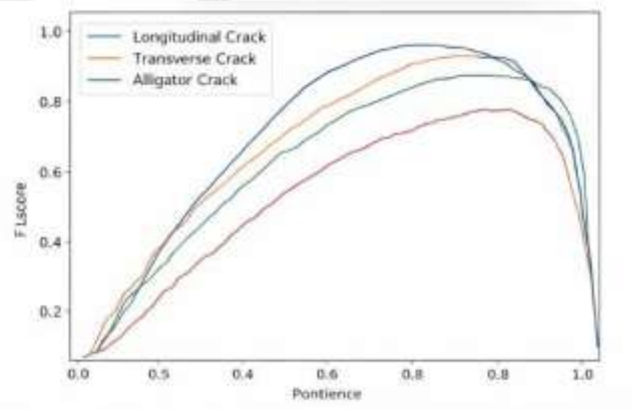
The confusion matrix of the YOLOv8 model is presented in figure (a). Most of the forms of damage are well identified as indicated in the diagonal elements. There is some vague mixing between the classes with similar visual impression, like Alligator Cracks and Transverse Cracks.

Figure (b) demonstrates the F1-Confidence curves per-class. Potholes were the highest in F1-score indicating high detection reliability, whereas Alligator Cracks had slightly lower F1-scores due to complicated surface texture and partial coverage.



(a) Confusion matrix for the YOLOv8" road damage detection

The per-class F1-Confidence curves are shown in Figure (b). Potholes had the highest F1-score, which reflects high detection reliability, while Alligator Cracks had slightly lower F1-scores because of complex surface textures and partial occlusions.



(b) F1-confidence curves for different road damage classes using YOLOv8.

The detection performance verifies that YOLOv8 achieves a considerable enhancement over the previous YOLO models employed in the previous studies. Compared with the YOLOv5 and YOLOv7 models presented in the previous studies, YOLOv8 has a better localization capability for small and slender cracks, greater robustness to varying lighting conditions, and a higher recall of potholes and longitudinal cracks.

B. Results of YOLOv8-Based Road Damage Detection

The proposed system is designed for real-time road surface defect detection and classification using the YOLOv8 object detection algorithm. The system examines each input image or real-time camera feed to detect road cracks and potholes, and the algorithm returns bounding boxes, class predictions, and confidence levels for each detected road defect.

The YOLOv8 algorithm allows for micro-level road surface examination. The algorithm is capable of precisely detecting various road damage types, such as longitudinal cracks, transverse cracks, alligator cracks, potholes, and other forms of road surface damage. The real-time analysis of the road surface allows for quick road condition assessment.

Figure shows the output examples of the system, where the identified road damages are marked with bounding boxes and their corresponding confidence levels. The output examples show that the system is capable of accurately identifying and categorizing the road damages based on the lighting conditions, angles, and textures of the roads.

The YOLOv8 framework enables detailed micro-level inspection of the road surface. It can accurately locate and identify multiple types of damages, including longitudinal cracks, transverse cracks, alligator cracks, potholes, and other surface corruptions.

C. Live Camera Evaluation

The YOLOv8 detector was also tested on live webcam feeds to mimic real-time road inspection. The process was able to run at about 12 FPS without any issues with detection and annotation. The bounding boxes, classes, and confidence scores were displayed in real-time, proving the applicability of the proposed system in real-world road inspection applications.

Figure shows sample frames from the live camera test, with accurate detection of various road defects.

V. CONCLUSION AND FUTURE WORKS:

In summary, this research work proposes a hybrid deep learning architecture that integrates a CNN model for global road condition classification with YOLOv8 for detailed road crack and pothole detection. The proposed architecture is capable of effectively evaluating global road conditions while simultaneously and accurately detecting various road defects in real-time, with a classification accuracy of 90% for CNN classification and an average F1-score of 77% with mAP@0.5 of 79% for YOLOv8 detection. The proposed architecture is therefore highly useful and applicable for real-time automated road condition monitoring and maintenance. Future improvements for automated road damage detection from images may include the incorporation of more advanced deep learning models, such as transformers or GANs, for improved detection accuracy and support for various road damage types. Real-time processing functionality with edge computing may be incorporated to facilitate real-time analysis and response. The incorporation of multi-modal data, such as the combination of visual images and sensor data (for example, accelerometers or GPS), could be considered to enhance the robustness of the system. Moreover, the continuous learning feature could be added to enhance the performance and adaptability of the model over time.

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