AI-based Transportation System (SALAMTAK)

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Abstract— **With the economy's recent rapid growth, road building has transitioned into a phase of coexistence between construction and maintenance. Even road upkeep has grown to be a significant component of road development. Every year, the government spends a sizable sum on road upkeep. In order to lower maintenance expenses, it is crucial to identify road issues such as cracks and potholes. The purpose of this study is to overcome the problems with traditional road problem detection's poor real-time performance and low accuracy. A method based on YOLOv8 and YOLOv5 has been developed for the detection of road problems by utilizing the benefits of deep learning networks in target detection. The technique makes use of annotated photos from a training set of about 15,000 photographs. Finally, the YOLOv8 model has proven to have remarkable performance, outperforming YOLOv5 with results of an amazing 74.8 mAP, which is still commendable. In addition, compared to conventional identification techniques, the speed of road problem detection has increased.**

Keywords— YOLOv8, YOLOv5.

I. Introduction

Due to the hazards to public safety and the associated financial costs, developing a trustworthy method for spotting cracks and potholes on roadways is essential [1]. Our ability to prevent accidents, save lives, and save maintenance costs depends on our ability to foresee these threats. By automating the detection process and improving infrastructure maintenance, modern technologies like computer vision and sensors are being used [2]. Planning for transportation, resource allocation optimization, and increased connection can all be done with the aggregated data that was acquired [8]. By funding this initiative, we can transform road maintenance, resulting in safer and more effective transport systems for all.

A. Problem

Road hazards including cracks and potholes offer serious risks to other road users and frequently cause lane deviations, decreased driving control, and an increased risk of accidents. Numerous people may be impacted by these situations, which might result in serious injuries or fatalities. Additionally, these road imperfections not only make driving less enjoyable overall but also seriously endanger drivers' safety. However, locating and fixing cracks and potholes may be a time- and resource-consuming task, particularly when working with large road networks.

B. Background Information

1) Artificial Intelligence (AI)

AI is a broad field of computer science that focuses on developing intelligent computers with the capacity to carry out functions typically associated with human intellect. This field includes the subdomains of computer vision, robotics, natural language processing, and machine learning. AI enables computers to replicate and emulate human-like intelligence by utilizing cutting-edge computing techniques, empowering them to solve complicated problems and perform jobs that were previously only possible for humans.

2) Machine Learning (ML)

ML uses statistical techniques and large datasets to train these models, allowing them to generalize from the data and perform tasks accurately. ML is a specialized area within the field of AI that is dedicated to creating algorithms and models capable of enabling computers to learn and make predictions or decisions autonomously, without the need for explicit programming.

3) Deep Learning (DL)

DL is a subset of machine learning that focuses on training artificial neural networks with numerous layers. These networks are intended to learn from complex datasets and extract hierarchical representations. Deep learning makes it easier to build complex models that can handle and analyze huge amounts of data efficiently, enabling the discovery of detailed patterns and the extraction of high-level features. Over a wide range of applications and domains, these capabilities enable precise predictions and well-informed choices.

4) Artificial Neural Network (ANN)

ANNs are computer models that take their cues from how the human brain is organized and functions.

They are widely used in the fields of artificial intelligence and machine learning to solve complex issues and generate data-driven predictions. They have shown substantial growth in popularity. ANNs are excellent at processing and analyzing massive amounts of data, which enables them to spot patterns, glean valuable insights, and generate precise forecasts. They have become indispensable instruments in numerous sectors and research fields thanks to their adaptability and versatility.

5) *Convolutional Neural Network (CNN)*

CNNs a subset of artificial neural networks designed specifically for processing grid-like input, such as images or sequential data with spatial relationships. Their use has completely changed the field of computer vision and made it possible for tasks like picture classification, object recognition, and image segmentation to significantly advance. The most popular models for extracting and learning complex features from visual data are CNNs, which use convolutional layers to identify regional patterns and hierarchies. The field of computer vision has reached new heights as a result of its unmatched performance and cutting-edge outcomes, spurring additional study and applications in a variety of industries.

C. *Paper Outline*

1) Related Works: This section reviews the research on crack and pothole identification that has already been done, highlighting various methodology, approaches, and their shortcomings.

2) System Architecture: The relationships between the major system components are shown in this section.

3) Results: Results of the project are shown in this section. contrasting the project's findings with those of other researchers.

II. RELATED WORK

A. *specific works for discovering crack on the road*

1) Safaei et al.[3] Create a system for automatically identifying and categorising cracks in 2-D and 3-D pavement photographs. The test's results, which included a precision score of 0.89, recall of 0.83, F1 score of 0.86, and crack length measuring accuracy of 80%, were deemed to be promising.

2) In their study, Mingxin Nie and Cheng Wang [4] addressed the issues with standard pavement crack detection's real-time performance and accuracy. They suggested a method based on YOLOv3 for detecting pavement cracks by utilising the advantages provided by deep learning networks in target detection. The scientists trained a YOLOv3 network model using manually labelled photos that they had collected. Then cracks were found and verified using the established model. Their research yielded results that showed a noteworthy 88% accuracy in crack detection.

3) Vishal Mandal, Lan Uong, and Yaw Adu-Gyamfi's research [5] focused on using the YOLO v2 deep learning system for road distress analysis. In order to train the system, the researchers compiled a dataset of 7,240 photos taken with mobile cameras. In addition, a different set of 1,813 road photos was used for testing. By analysing the detection and classification accuracy, which was quantified using the average F1 score generated from precision and recall values, the effectiveness of the suggested distress analyzer was assessed.

B. *specific works for discovering potholes on the road*

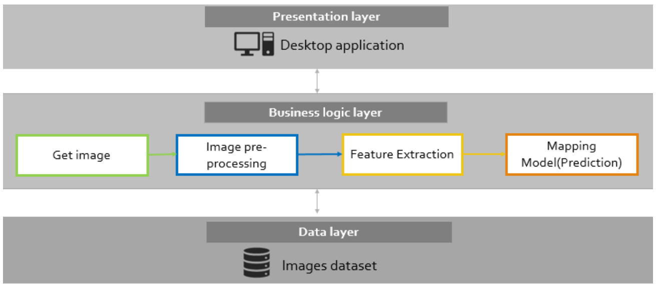
1) Bhavan Kumar S B et al.[6] Application of YOLO V5 and evaluation of its performance on a dataset of photos, including potholes in various road conditions and variations in lighting, as well as on real-time video captured from a moving car, are the objectives of this work. Additionally, it has a 91% detection accuracy rate.

2) Bhanu Prakash K Y, Sankhya N Nayak .[7] This study aims to use the YOLO v2 technology, which operates more quickly than traditional detection methods. No matter how large, how high-quality, or how colourful an image was, the system took an average of 23 seconds to process it. Even with negative tests, this functions properly. It was noted during validation that the system is functioning reasonably well, with 89.41% accuracy, 95.55% precision, 91.42% recall, and a 93.43% F1-score.

3) Mohd Oma et al.[8] The objective of this study is to apply the YOLOv4 algorithm. A dataset of around 200 photos is trained for the identification of potholes, and the average IoU of 38.38% is reached, with precision values of 0.58, recall values of 0.37, and TP and FP values of 58 and 42 respectively.

III. SYSTEM ARCHITECTURE AND METHODOLOGY

A. *System Architecture*



B. *Methodology*

1) Data layer

Gathering and storing data from various sources.

2) Business logic layer

At this stage, learning model takes place by get or load image from stored dataset and apply preprocessing such as (Convert the road images to annotated images by manually labeling the cracks and potholes with bounding boxes, Resize the annotated images to a standardized resolution to ensure consistency, Apply data augmentation techniques, such as flipping the images, adding noise to simulate different conditions, and rotating the bounding boxes to introduce variations in orientation) and after that will be extract the important feature and then apply the model detection such as training data preparation(split the preprocessed dataset into training, validation, and testing sets, Assign appropriate labels to the annotated images to indicate the presence and location of cracks and potholes) model training(Train the YOLO v8 model using the annotated images from the training set, consisting of approximately 15,000 images) and model evaluation(Evaluate the trained model using the annotated images from the validation set, which contains 332 images and Test the trained model on the testing set, which contains 178 images).

3) Presetation layer

At this stage, deployment the model on desktop application and used by user.

IV. Results

A. Description of Dataset

Data consists of two types of images cracks and potholes.

	Cracks	Potholes	Total	With augmentation
Number of images	**4029**	**1593**	**5622**	**15846**

Augmentation steps is Flip (horizontal, vertical), Noise (up to 5 % of pixels) and Bounding Box (90° Rotate: Clockwise, Counter-Clockwise).
Data is divided into 15336 training, 332 validation, 178 testing.

B. Data Collection Methdology

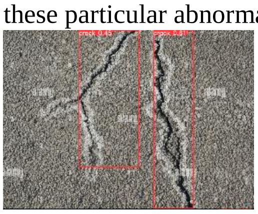
By deciding which anomalies on the road can be detected, ideas, and tools, we first established the project's scope. Then, we collected the dataset using the Kaggle platform and the Dell dataset, which is utilized as the knowledge foundation for training the detection model and improving conventional methods for detecting anomalies by using deep learning such as YOLOv8. The dataset is useful for investigations that cover various anomalies while driving.

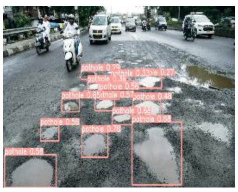
C. Experiments Conducted

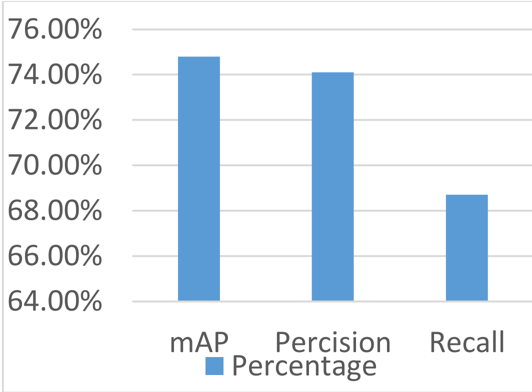
Our YOLO v8 model performed above and beyond expectations, outperforming YOLO v5 with a surprising 74.8 mAP, which was still an admirable result. These outcomes were seen specifically when photos with a single crack or pothole were detected. This demonstrates our YOLO v8 model's better accuracy and precision in locating these particular abnormalities.

D. Findings

In the detection of photos with cracks and potholes, our YOLO v8 model achieved a surprising 74.8 mAP, demonstrating excellent performance. This demonstrates our YOLO v8 model's better accuracy and precision in locating these particular abnormalities.







V. Conclusion and Future Work

A. Conclusion

In this evaluation, the effectiveness of YOLO v8 and v5 was compared using a dataset made up of 5,622 photos focusing on cracks and potholes that were collected from two different sources. Roboflow platform was used to apply augmentation techniques in order to improve the dataset, producing a total of 15,846 photos. When compared to YOLO v5, YOLO v8 performed better, with a mean average precision (mAP) of 74.8 as opposed to 71.9. Notably, YOLO v8 demonstrated improved crack and pothole detecting abilities, catching occurrences that YOLO v5 had previously missed. A desktop application was created utilizing the Tkinter toolkit to enable real-time detection and analysis functionality for both saved photographs and films. This facilitates practical usage. Future Work

1) Fine-tuning and optimization: Look at methods for optimising and tuning the YOLO v8 model further. To further improve the model's performance and accuracy in detecting cracks and potholes, this may entail modifying hyperparameters, investigating various network designs, or using cutting-edge optimisation algorithms.

2) Data collection: Think about adding more photographs from various sources to the current dataset. The model's generalization abilities can be enhanced by expanding the quantity and diversity of the dataset, which will help it perform better in real-world scenarios with a greater variety of crack and pothole variations.

3) Road anomaly detection: By increasing the dataset and training the model appropriately, you can increase the model's ability to recognise different road anomalies, such as bumps, ruts, and uneven surfaces. Through a thorough evaluation of the state of the roads made possible by this improved detection capacity, effective road maintenance and safety measures are made possible.

4) Installed camera on car deployment: Use car-mounted cameras with the crack and pothole detection model to spot unusual road conditions in real-time and warn drivers to them for increased safety.

5) On-road camera deployment: Integrate roadside cameras with the crack and pothole detection model to monitor road conditions in real-time and provide prompt identification and alarms for cracks and potholes. While the data gathered aids in future investigation and analysis of road abnormalities, the proactive method ensures prompt maintenance and promotes safer roads.

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REFERENCES

[1] Safaei, N., Smadi, O., Masoud, A. et al. An Automatic Image Processing Algorithm Based on Crack Pixel Density for Pavement Crack Detection and Classification. Int. J. Pavement Res. Technol. January 2022.

[2] Mingxin Nie, Cheng Wang. Pavement Crack Detection based on yolo v3. IEEE. 28-30 November 2019.

[3] Vishal Mandal, Lan Uong, Yaw Adu-Gyamfi. Automated Road Crack Detection Using Deep Convolutional Neural Networks. IEEE. 24 January 2019.

[4] Bhavan Kumar S B et al. Real-time Pothole Detection using YOLOv5 Algorithm: A Feasible Approach for Intelligent Transportation Systems. IEEE. 05 April 2023.

[5] Bhanu Prakash K Y, Sankhya N Nayak. ROAD POTHOLE DETECTION USING YOLOv2 MODEL. IRJMETS . 08/August-2020.

[6] Mohd Oma et al. Detection of Roads Potholes using YOLOv4. IEEE. 26 May 2021.

[7] Sang-Yum Lee et al, "Prediction and detection of potholes in urban roads: Machine learning and deep learning based image segmentation approaches", Developments in the Built Environment, 13 March 2023.

[8] Esma Dilek and Murat Dener, " Computer Vision Applications in Intelligent Transportation Systems: A Survey", MDPI, 8 March 2023.