

Enhanced Road Safety: Real-Time Pothole Detection Using YOLOv9

Daarshini Anbalagan¹, Mohd Norzali Hj Mohd^{1*}

¹ Faculty of Electrical and Electronic Engineering

Universiti Tun Hussein Onn Malaysia, Batu Pahat, 86400, Johor, Malaysia

*Corresponding Author: norzali@uthm.edu.my

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Abstract

The goal of this research is to develop a real time pothole detection system with the advanced YOLOv9 model which outperforms previous ones, such as YOLOv5 and YOLOv8. PGI and GELAN in YOLOv9 enhance the accuracy of the detection through programmable gradient information (PGI) and the Generalized Efficient Layer Aggregation Network (GELAN), which reduce data loss and improve the performance. The methodology involves training the YOLOv9 model on a large dataset of diverse images and video streams which cover a wide range of road conditions and lighting. The results show that the YOLOv9 model has a detection accuracy over 90% with real time processing speed of up to 31.76 frames per second (FPS). This study concludes that such advanced technology can be very useful in improving road safety by enabling faster repair and more effective maintenance, which in the end can help solve some of the major challenges in infrastructure management.

1. Introduction

Potholes are a big issue in the area of road safety in Malaysia and they have caused 181 accidents including 23 fatalities between 2022 and July 2023 [1]. The existing methods of pothole detection are relatively slow and expensive and therefore lead to the delays in the repair of the potholes and the increase in the risk to the drivers. These conventional approaches are not very efficient for the purpose of pothole detection since they are not capable of making real time analysis and they are not efficient with the irregular shapes of potholes which can cause accidents and damage to vehicles [2]. But, the use of deep learning techniques, especially the YOLO (You Only Look Once) framework is a revolutionary approach to solve this problem. The latest version of YOLO, namely YOLOv9 uses convolutional neural networks to analyze images taken from vehicles in a fast and efficient manner in order to detect potholes in real time [2].

YOLOv9 when implemented on edge devices such as Raspberry Pi not only improves the accuracy of detection but also sends early warnings to drivers as well as road authorities. This innovation may well result in a marked decrease in the number of accidents and an improvement in the way in which roads are maintained. Furthermore, the social benefits are enormous because the enhancement of road safety may lead to the reduction of injuries and deaths while the economic benefits can be seen in the reduction of vehicle repair and maintenance costs [3]. Thus, Malaysia can develop high quality transportation infrastructure that contributes to the welfare of its people by properly solving the pothole problem.

Recent studies have identified the higher performance of YOLOv9 over YOLOv5 in object detection. For instance, YOLOv9 has a mean Average Precision (mAP) of 93.6%, which is significantly higher than the performance of YOLOv5, which typically achieves a mAP of around 54.4% under the same settings [4], [5]. In

contrast to YOLOv5, which includes next-generation features such as the Squeezed-and-Excitation (SE) attention mechanism, YOLOv9 enhances its architectural advancement with the inclusion of Programmable Gradient Information (PGI) and Generalized Efficient Layer Aggregation Network (GELAN). These advancements allow YOLOv9 to utilize parameters more efficiently while enhancing overall performance despite taking slightly longer training times [6]. Moreover, YOLOv9 is competitive in training speed with higher accuracy on a range of detection tasks and therefore is a suitable option for high-accuracy applications.

Traditional pothole detection methods, including manual checks, are typically ineffective and inaccurate, leading to increased repair time and safety risks. Existing technologies also cannot keep pace with changing roadway conditions, especially in high-density urban areas with complex traffic patterns and non-homogeneous weather conditions. In addition, most systems are unable to detect potholes under adverse conditions, e.g., at night or if water or debris is covering them.

This study utilizes the YOLOv9 deep learning model in real-time pothole detection from images and videos captured from vehicles using advanced computer vision methods. The system is found to work effectively under different environmental conditions, thus making it more robust and adaptable compared to traditional methods. It aims to improve road safety and allow more effective transport systems that can handle the requirements of urban areas that are congested by sending timely warnings to drivers and aid to maintenance personnel in rapid response.

The project will improve the existing pothole detection system from YOLOv5 to YOLOv9 with 90% detection rate in 50 milliseconds. It will incorporate the Coral USB Accelerator to improve speed and efficiency to provide real time detection at a frame rate of 20 frames per second or more. Pothole images identified will be saved through Firebase, which provides quick and easy access with less than 1 second of retrieval time. The system will also possess the capability of emitting a beep sound when a pothole is identified providing immediate feedback to drivers in less than 2 seconds to increase their awareness.

2. Methodology

Deep learning approach to pothole detection is explained in this section. The data is gathered to train the model which is standard flow of the suggested methodology. Pothole images are taken from Kaggle and annotated with the assistance of tool like Roboflow. Image augmentation is generally required to increase the accuracy of deep models in order to create a robust classifier with training data. Images are augmented by various methods, including horizontal flip, vertical flip, and rotation, to increase the dataset. An adequate dataset is required to increase the efficiency of pothole detection models.

The YOLOv9 model is utilized as the model to identify potholes. The created dataset has been tested several times with the model. The dataset is then used to train a deep learning model to detect potholes that exist on the road surface. After training the model is saved and tested using a different image dataset. The input video stream is run by the microcontroller such as Raspberry Pi 5 Model B, which can be using a single camera like Logitech C270.

Fig.1 the image illustrates a system workflow for real-time pothole detection and data visualization. It begins with a real time video stream capturing road conditions to identify potholes. The data is recorded with the assistance of a data logger that comprises a Raspberry Pi 5, a webcam, and a Coral USB Accelerator, which is used to speed up machine learning. Using Python and the YOLO (You Only Look Once) deep learning model, the system detects potholes from the video input. Upon detection, the data is then uploaded into the cloud storage. For ease of visualization, the data is uploaded to Firebase, a cloud computing service that offers efficient storage and visualization, thus allowing users to easily analyse and access information about potholes.

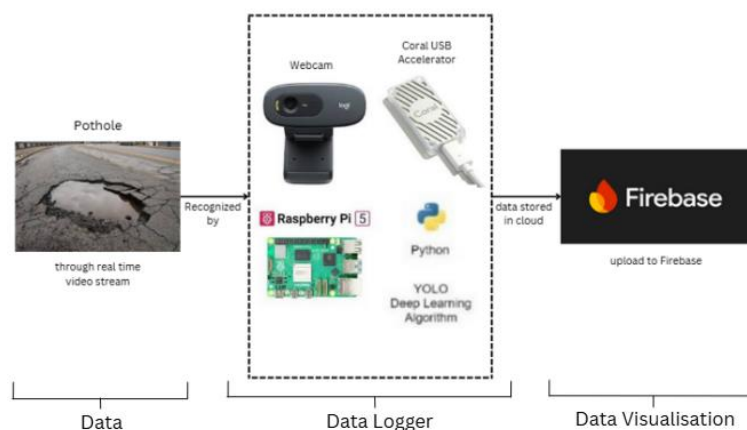


Fig. 1 System workflow

Fig. 2 illustrates the project flowchart creates an end-to-end workflow to develop a real-time pothole detection system based on the YOLOv9 model. It starts with the collection of a diverse data set of pothole images under different lighting conditions and road types, then annotating the images to label potholes with bounding boxes, which is essential for successful model training. More advanced data augmentation techniques, such as random cropping and color jittering, will be used to enhance the model's robustness. The intended transition from YOLOv5 to YOLOv9 is based on the former's superior accuracy of approximately 86.5% mean Average Precision (mAP). Training involves dividing the dataset, configuring model parameters, and utilizing the Coral USB Accelerator to speed up processing. Firebase will make it easy to store images of potholes that have been discovered, and a user-friendly interface will display the detected potholes and provide feedback through beep alerts when a detection is made. Extensive testing will guarantee the effectiveness of the system under different conditions, and further post-deployment monitoring will identify areas for further optimization, thus improving the development of intelligent transport systems that are adaptive to urban environments.

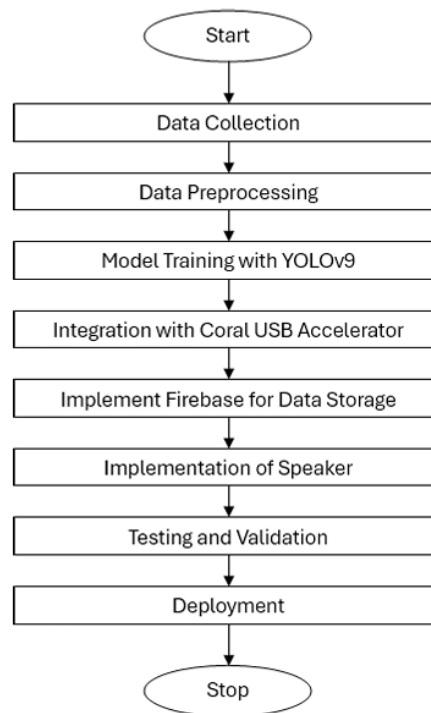


Fig. 2 Flowchart of Project

Fig.3 illustrates the flowchart explains a real time pothole detection system for automobiles. The process begins when the vehicle is driven and the system is constantly monitoring the road for pothole using camera. When the pothole is detected, the system produces a beep sound to alert the driver and takes an image of the pothole. This image detection is sent to a Firebase database where they are displayed to review or analyze further. This cycle continues until the system is stopped.

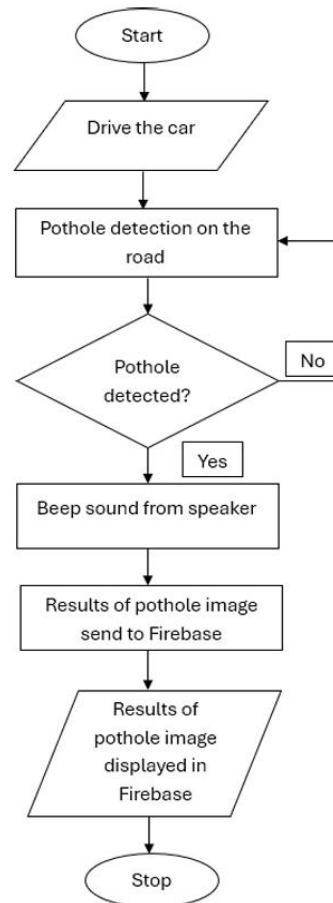


Fig. 3 Flowchart of System

2.1 Rationale for using YOLOv9 and Coral USB Accelerator

The reason why YOLOv9 and the Coral USB Accelerator were used in preference to other methods of pothole detection is that they have an increased functionality compared to other methods. YOLOv9 is the latest version of YOLO, and it includes advanced features such as Programmable Gradient Information (PGI) and the Generalized Efficient Layer Aggregation Network (GELAN) that significantly enhance detection accuracy and speed. The enhancements introduced in YOLOv9 offer improved accuracy levels and increased processing speeds, making it highly suitable for use in real-time applications in active environments where instant notifications are crucial for ensuring road safety. The model has been found to be effective in detecting different forms of road damage such as potholes in various conditions, which are often difficult for conventional approaches to effectively address.

The Coral USB Accelerator greatly improves YOLOv9 by incorporating the processing power that allows the model to execute efficiently on edge devices. This is a critical integration for real-time usage because it permits rapid pothole detection without introducing latency. Additionally, the Coral USB Accelerator is specifically created and optimized for machine learning, making it a low-cost option that adds to the overall system performance of the pothole detection.

3. Results and Discussion

This evaluation of the pothole detection model is illustrated through several performance metrics. Fig. 3(a) depicts the confusion matrix indicates that 69% of actual potholes were correctly classified, while all the background instances were accurately predicted, highlighting areas of strength and potential improvement. Fig. 3(b) shows the F1-Confidence Curve shows that the model performs best at a confidence threshold of 0.263, guiding the selection of optimal prediction thresholds. Fig. 3(c) shows the Recall-Confidence Curve shows that recall increases with growing confidence thresholds, up to a maximum of 0.92 when the threshold is at 0, demonstrating the trade-off between confidence and recall in pothole detection. Lastly, Fig. 3(d) demonstrates the Precision-Confidence Curve demonstrates that precision rises as the confidence level rises, attaining perfect precision (1.00) at a level of 0.832, which is critical to ensure highly accurate predictions for pothole detection.

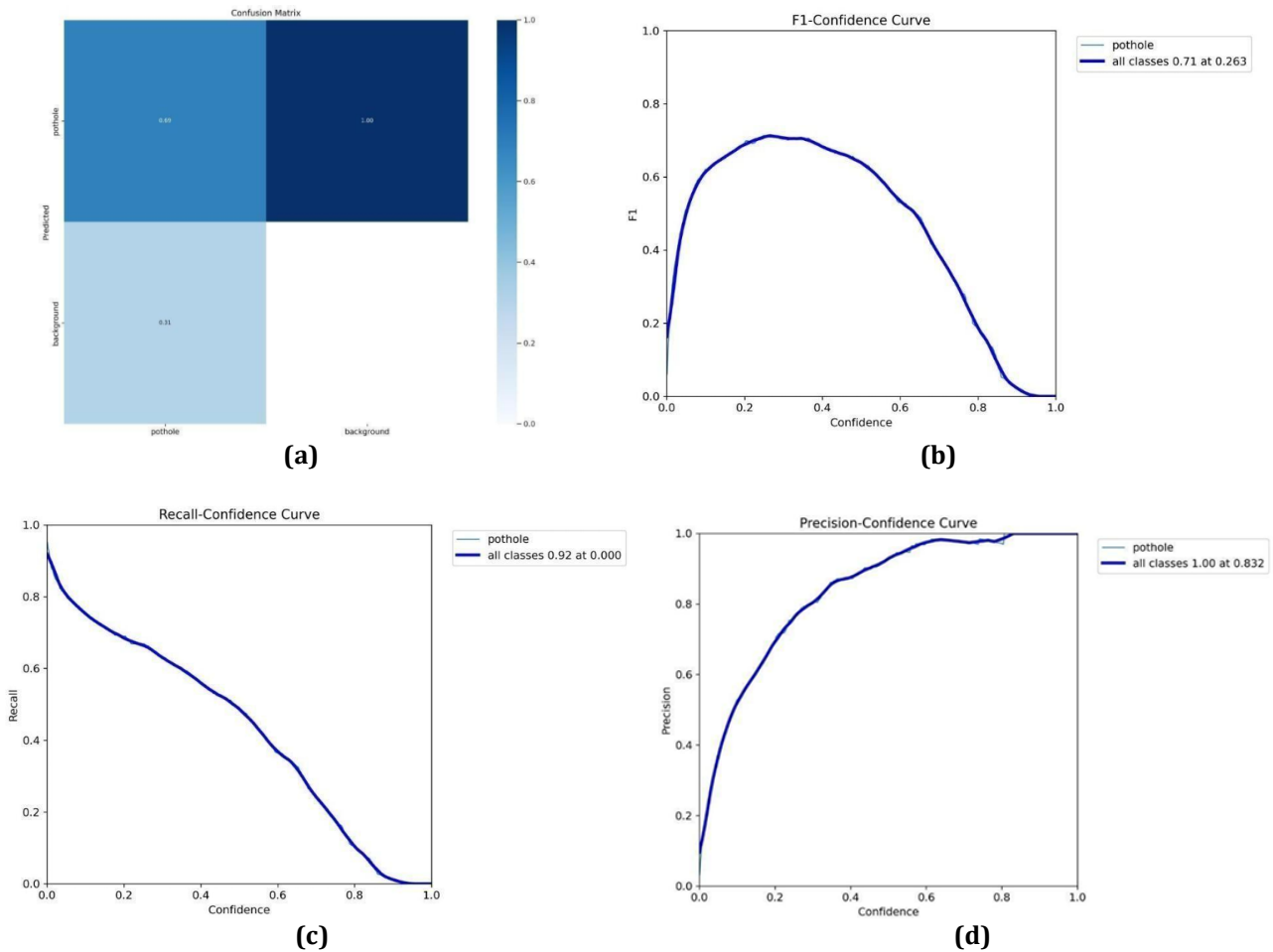


Fig. 3 Output of Implementing YOLOv9 (a) Confusion Matrix; (b) F1-Confidence Curve; (c) Recall-Confidence Curve; (d) Precision-Confidence Curve

Fig. 4 depicts the bar graph comparison of performance of various YOLO models based on means Average Precision (mAP) and inference time highlighting the improvements achieved in YOLOv9. The mAP comparison reveals that YOLOv9 greatly outperforms its previous versions, achieving a mAP of 72.8% the highest among all versions. This is a significant improvement over earlier models like YOLOv2 (40%) and YOLOv4 (43.5%) highlighting the continuous efficiency and accuracy of the YOLO framework.

In the aspect of inference time, YOLOv9 performs better with a quick processing time of 23 milliseconds, which is also on par with top-performing models such as YOLOv5 at 23.4 ms and YOLOv6 at 23 ms. Compared to older models such as YOLOv3 and YOLOv7, they both record slower inference times of 51 ms and 32 ms respectively, which can impede their application in real-time scenarios.

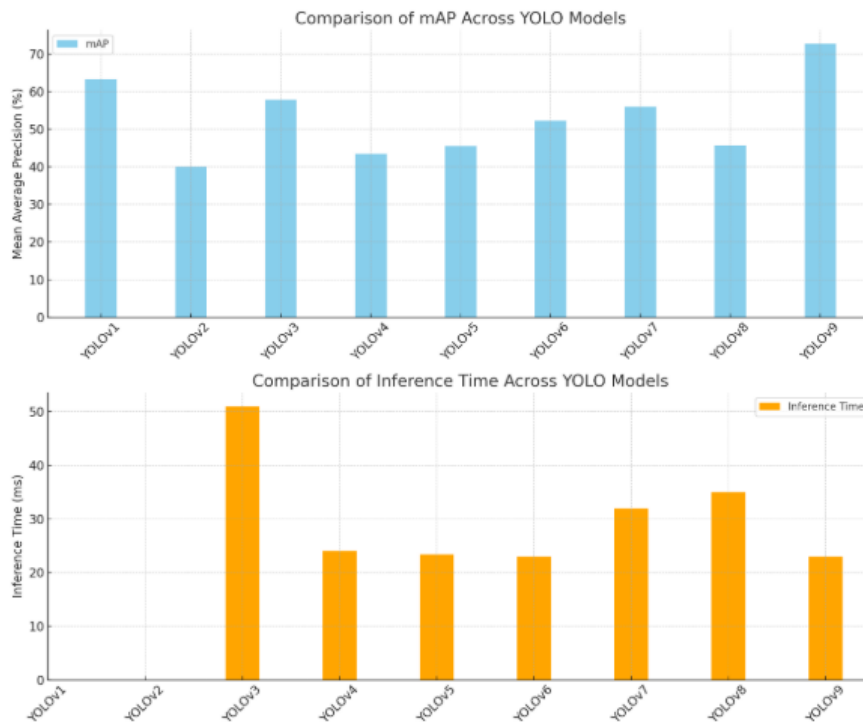


Fig. 4 Comparison of mAP and Inference Time Across YOLO Models

3.1 Limitations and Area of Improvement in Current Model

The existing pothole detection model has a number of drawbacks that can be resolved to improve its reliability and efficiency. One of the key challenges involves the responsiveness of the model to different environmental conditions. It is challenged in unfavorable meteorological conditions, for example, rain or fog, and during nighttime when lighting is poor. Different road surfaces, for instance, gravel or trash, can cause false positive readings or undetected potholes. Another limitation comes from the impact of fast motion, leading to motion blur and affecting detection accuracy. Moreover, the processing limitations of the Raspberry Pi 5 limit the ability of the system to handle complex scenarios in real time. The model also does not handle edge cases such as overlapping road obstacles or blurred patterns that can be mistaken for potholes, and its dataset is not diverse enough to allow accurate generalization to unseen road scenes.

To address such problems, various improvements can be implemented. Improving YOLOv9 through careful tuning of its hyperparameters and use of advanced pre-processing techniques could make it more efficient in different environmental conditions. The transition to even higher-class hardware like the Jetson Orin Nano would also improve real-time processing capabilities. Adding more varied road types, weather, and illumination conditions to the dataset, along with more advanced data augmentation methods, can make the model more robust. Integrating sensor fusion technologies, such as LiDAR or ultrasonic sensors, can make the detection process more accurate in adverse conditions. Inserting sound, visual, or vibration-based alerts into the feedback mechanism can also make it easier to distinguish between shallow and deep potholes.

4. Conclusion

In summary, this pothole detection project presents a successful and efficient real-time road condition evaluation system that significantly enhances road safety and maintenance activities. Through the utilization of YOLOv9's cutting-edge object recognition feature, the system successfully identifies potholes and sends real-time alerts through an easily accessible live web interface. The use of Firebase offers the potential for organized storage and easy retrieval of detection information, which is critical for further analysis and informed decision-making for road maintenance. The project efficiently combines real-time processing, notification of alerts, and data handling, thus offering a useful solution that enhances real-time response to road dangers as well as contributes to long-term infrastructure planning.

Future studies can investigate the potential ensemble of ensemble learning methods, as embodied by the ensemble of YOLOv9 and Mask R-CNN, to improve detection resilience in challenging environments. Furthermore, the increase in the dataset size to cover more diverse environmental conditions, supplemented with high-level features for nighttime detection, would significantly enhance the robustness of the system. In summary, efficient

implementation of the system can reduce accident rates, minimize car repair costs, and enhance overall safety for pedestrians and drivers alike, thus emphasizing its significant role in ensuring the public road's safety.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

*The authors confirm contribution to the paper as follows: **design and development:** Daarshini Anbalagan; **data collection:** Daarshini Anbalagan; **analysis and interpretation of results:** Daarshini Anbalagan; **draft manuscript preparation:** Daarshini Anbalagan, Mohd Norzali Hj Mohd. All authors reviewed the results and approved the final version of the manuscript. This research was supported by Ministry of Higher Education (MOHE) through Fundamental Research Grant Scheme (FRGS/1/2024/ICT02/UTHM/02/4) Vot K506 and Universiti Tun Hussein Onn Malaysia through GPPS Vot Q068.*

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