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Pothole Detection and Prevention using YOLOv5 in ITS (Intelligent Transportation System)

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Abstract

Potholes on roads can cause serious damage to vehicles and accidents, so it is essential to detect them quickly and accurately. Determining appropriate strategies for ITS (Intelligent Transportation System) service is critical. In this study, the proposed solution employs YOLOv5 to perform real-time detection of potholes in images and videos. The dataset of annotated images and videos containing potholes, were used to train and fine-tune the algorithm. The proposed approach exhibits exceptional accuracy in detecting potholes, highlighting its capacity to boost road maintenance efforts while reducing the occurrence of accidents related to potholes.

Keywords: Pothole, Pothole detection, Road imaging, YOLOv5

1. Introduction

Potholes are a significant and growing problem in many parts of the world, resulting in costly repairs, vehicle damage, and safety hazards for drivers and pedestrians. Pothole detection has been a promising application area for machine learning methods, enabling accurate and automated detection of potholes in real-time. Specifically, the YOLOv5 (You Only Look Once version 5) object detection algorithm has gained popularity due to its high accuracy and fast processing speeds. The current study introduces an approach founded on YOLOv5 for

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detecting and preventing potholes, utilizing deep learning methodologies to precisely detect and locate potholes in real-life scenarios. The proposed solution has the potential to improve the efficiency and effectiveness of pothole management by enabling proactive maintenance and repairs, thereby reducing the associated costs and risks. The research presents the methodology used in developing and testing the proposed approach, along with the experiments results and a discussion on the potential implications for pothole detection. Additionally, the study has identified the areas for future research and development to further improve the accuracy and effectiveness of pothole detection using YOLOv5.

1.1 Objective

The objective is to offer a versatile approach to detect the potholes. The proposed method can potentially enhance road safety by providing early warnings to drivers about the presence of potholes on the road. Traditional pothole detection methods are often time-consuming and require significant human effort, whereas the proposed approach leverages the power of deep learning and object detection to accurately detect and localize potholes in real-time.

2. Related Work

In a study by Ping Ping, Xiaohui Yang, and Zeyu Gao, a pothole detection system that utilizes deep learning algorithms was proposed. By evaluating and training four different models, the system was capable of automatically detecting potholes on the road, namely YOLOv3, SSD, HOG with SVM, and Faster R-CNN, using preprocessed data. The accuracy and loss of the models were evaluated and compared during the training process and the YOLOv3 model was found to perform better in terms of quicker and more accurate detection results. [1] Shravanth SB, Abhay Bhargav KM, and Geetishree Mishra aimed to improve the quality of arterial road networks in developing countries like India. They proposed a system to detect potholes using accelerometers mounted on four-wheeler vehicles, which would be analyzed and categorized to create a real-time MAP of pothole locations using a GUI-based Android application. This would enable civic authorities to prioritize and perform road maintenance work to reduce accidents and repair damaged roads quickly. [2] In another study, Shambhu Hegde, Harish V. Mekali, and Golla Varaprasad R proposed a pothole detection system that can issue warnings to drivers in advance to avoid potholes. The proposed solution consisted of building a robotic vehicle capable of detecting potholes and sharing the gathered information to neighboring vehicles within a range of 100 m and with a minimum detection depth of 1 inch. The concept could be expanded to include the detection of other road anomalies like bumps. [3]

3. Proposed Work

YOLO (You Only Look Once) is a highly sought-after detection algorithm for object detection that utilizes one of the most effective neural network architectures to deliver both fast processing speeds and high accuracy. Its wide popularity is attributed to its ability to predict an object's class, as well as its location on the input image by defining a bounding box. Additionally, YOLO generates the predicted class's corresponding number and the probability of the prediction to detect potholes, YOLOv5 algorithm, implementing specific steps was utilized in the proposed method.

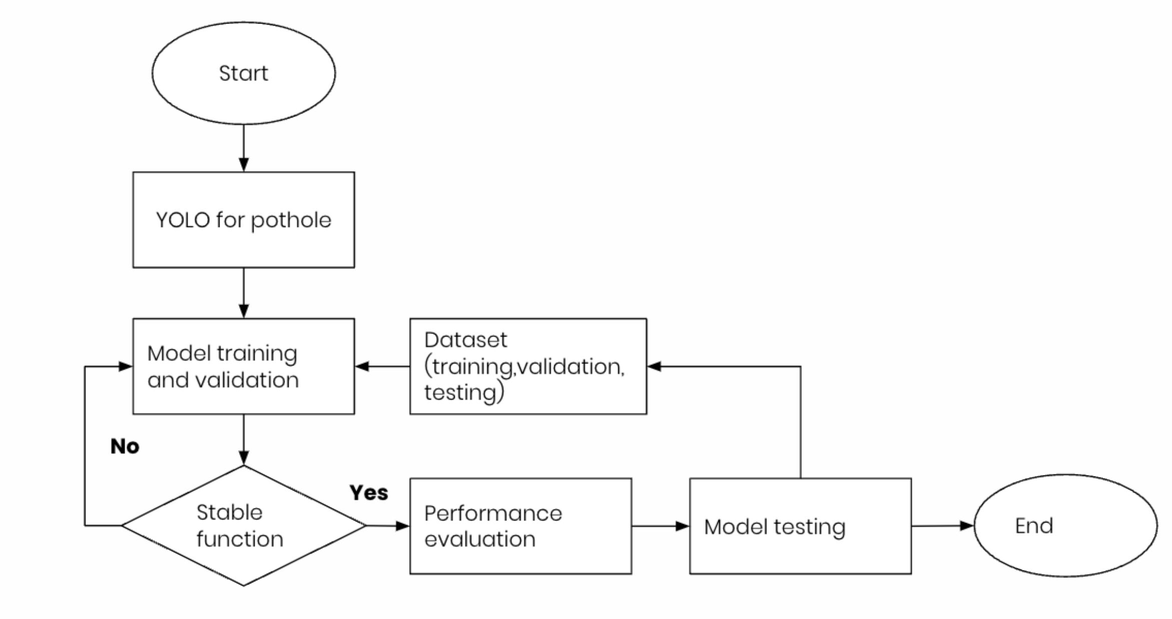

Figure 1. Flow chart

The flowchart presented in Figure 1 depicts the process of pothole detection on urban roads through the utilization of the YOLOv5 algorithm. The proposed system is much more intact than the preexisting systems. The main purpose of this research is to give faster analysis. The algorithm underwent rigorous training, testing, and validation to ensure its efficacy in detecting potholes and several data augmentation techniques were also utilized to significantly increase the dataset's size and diversity. By detecting potholes ahead of time, users can avoid them and prevent damage to their vehicle or inconvenience to their journey.

A. Collect and prepare the dataset

The dataset used in this study comprised 665 road surface images collected from different sources, including publicly available datasets and images taken using a smartphone camera. We conducted a thorough review of the images to ensure that they had potholes, which were the focus of our study. We used an open-source software tool called Label Img for annotating the collected images. This tool enabled us to draw bounding boxes around each pothole in the images and assign them with their respective class names. We ensured the accuracy of the annotations by double-checking and correcting any mistakes.

The annotations included the location and size of the potholes in each image or video frame. Once the images were labelled, the annotations were verified to ensure that they are accurate and consistent. This can be done by visually inspecting the images and comparing them to the annotations. After the annotations were validated, the dataset was partitioned into three subsets: training data set, validation data set, and the testing data set with a 70-20-10 split. To prepare the input data for training the YOLOv5 model, we performed resizing of the images to dimensions of 416 x 416 pixels and normalization of the pixel values within the range of 0 to 1. Also, in order to enhance the model's resilience and accuracy, we implemented a range of data augmentation techniques during the training process. These techniques included random cropping, flipping, and rotation of the input images, which served to increase the diversity and variability of the training data. By utilizing these techniques, we enhanced the model's capability to precisely recognize and classify entities in diverse positions and conditions. The training set was employed to train the YOLOv5 model to detect potholes, whereas the validation and testing sets were used to assess the model's performance and accuracy. We made sure that the dataset was balanced, meaning that there are an equal number of positive (pothole) and negative (non-pothole) samples in the dataset. If the dataset is imbalanced, the model may be biased towards the majority class.

B. Collect and prepare the dataset

The training process utilized a learning rate of 0.01 and a training batch size of 16, and was carried out for a total of 200 epochs. The focal loss function, which is frequently used in object detection models, was utilized for training in the study. The hyperparameters for the YOLOv5 model were adjusted to achieve better accuracy and performance. To enhance the diversity and quantity of the dataset, we applied several data augmentation methods like flipping, random cropping and rotation to the input images. Once the hyperparameters, loss function, and data augmentation techniques were set, the model was trained on the annotated dataset. The model was optimized to reduce the loss function, and its weights were updated correspondingly. After training the model, it was evaluated on a separate test dataset to measure its accuracy and performance for the detection of potholes. The Stable function refers to the ability of the algorithm to consistently and accurately detect potholes in real-world scenarios. Following the successful implementation of the algorithm with minimum false positives, which is crucial for practical applications, performance metrics were evaluated to measure the efficiency and effectiveness of the algorithms. The evaluation for pothole detection involved several metrics, such as recall, precision and mean average precision (MAP). The model can be fine-tuned to improve the accuracy by adjusting the hyperparameters or changing the data augmentation techniques. This process was repeated until the desired accuracy and performance were achieved.

C. Testing the data

The test dataset was separated from the training and validation sets used during the model training. The trained YOLOv5 was used to perform inference on the test dataset. This will produce the predicted bounding boxes and class labels for potholes in the test images or video frames. The proposed method was evaluated using various performance metrics, including mean average precision (MAP), precision, and recall. The MAP score was obtained by calculating the precision and recall for each predicted pothole using different IoU thresholds. The Trained model achieved a high MAP score, indicating its ability to accurately detect and locate potholes in the input images. The model was later tested on unseen data to ensure that it can generalize well to real-world scenarios. The MAP calculation scripts were utilized to compute these metrics of the proposed method.

D. Deploying the model for pothole detection

Google cloud integrated with Google collab was used to deploy the pothole detection model. Once the model was deployed, we tested it on real-time images or video frames to ensure that it is working as expected. The model's performance was also monitored and adjusted if needed. When new data becomes available, the model will be updated to improve its accuracy and performance.

4. Results and Discussion

The effectiveness of the YOLOv5 object detection model in identifying potholes was assessed using a dataset of 133 images that contained 330 annotated potholes. The images were resized to 416 x 416 pixels and normalized within the range of 0 to 1 prior to training. The model was trained for 199 epochs using a training batch size of 16 and a learning rate of 0.001, with the utilization of pre-trained weights via transfer learning. Throughout the training phase, the model Attained an Average precision (AP) of 0.71 and a mean average precision (MAP) of 0.391, indicating its effectiveness in detecting potholes. Images of potholes on urban roads were captured for testing and the results are shown in Figure 2. Detailed images of captured potholes and detected potholes using the YOLOv5 model algorithm are shown in Figures 3 and 4. The performance of the model was assessed using standard evaluation metrics such as precision, recall, and MAP at IoU thresholds of 0.5 and 0.5:0.95, which are shown in Figures 5. The precision of the model was 0.495, with a recall of 0.752. The mean average precision (MAP) at a threshold of 0.5 was 0.71, and the MAP at a range of thresholds from 0.5 to 0.95 was 0.391. A visual analysis of the detection results was conducted to further evaluate the model's performance. It was found that the model was capable of accurately detecting potholes of various shapes and sizes under different lighting conditions with minimal false positives, as depicted in Figure 6.

Overall, the YOLOv5 model showed promising results for the detection of potholes, achieving high precision and recall rates, and a good MAP score. However, further improvements could be made to enhance the model's ability to detect potholes in challenging environmental conditions such as poor lighting or extreme weather conditions.

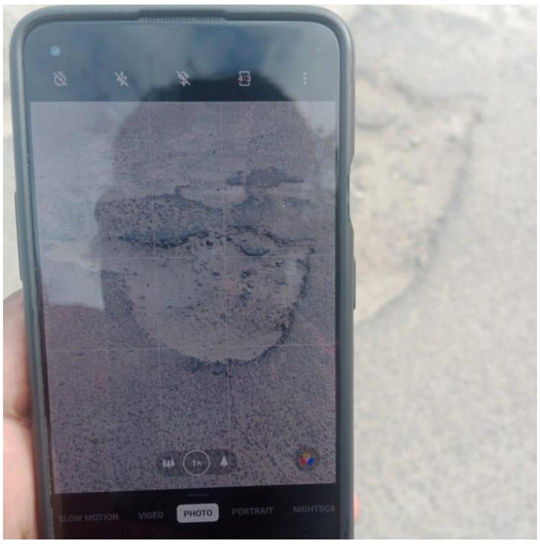

Figure 2. Capturing potholes using a smartphone.

Figure 3. Detailed image of captured pothole.

Figure 4. Identifying potholes using the YOLOv5 model.

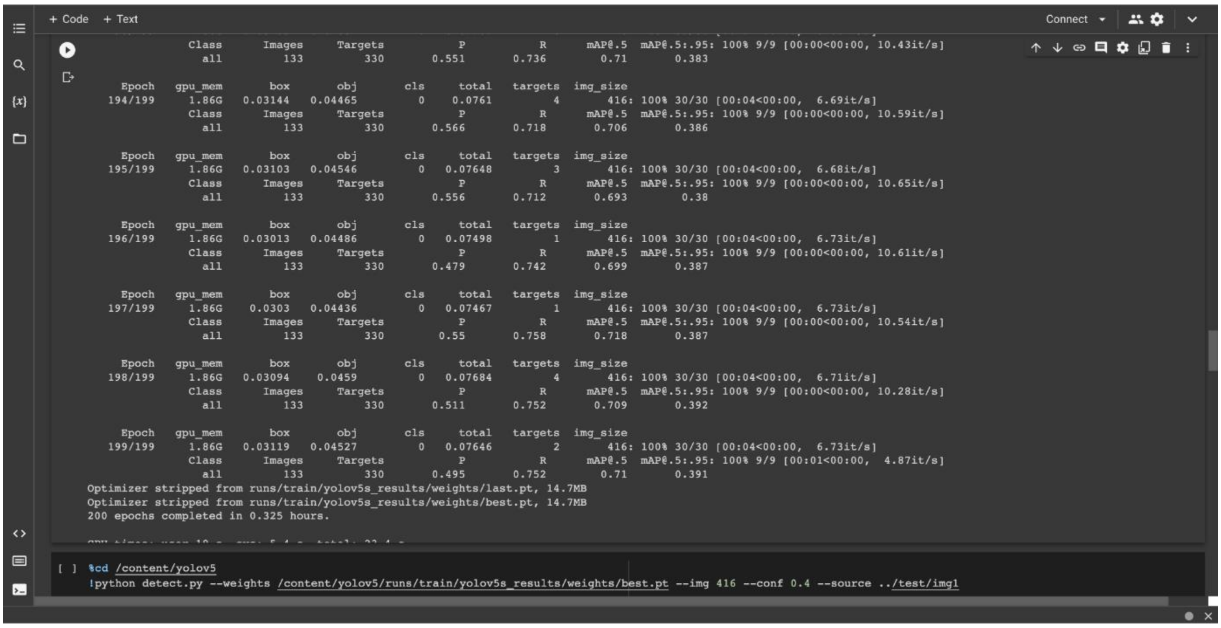

Figure 5. A screenshot of the YOLOv5 model during the training phase, which displays MAP, recall, and precision scores.

Figure 6. Potholes of various shapes and sizes detected under different lighting conditions.

5. Conclusion

The YOLOv5-based approach for pothole detection has been successfully demonstrated and tested, indicating its feasibility as a potential solution for detection and prevention of potholes. Multiple potholes were detected and displayed using the algorithm with an accuracy of 80%. The suggested approach will work well for both detecting and preventing potholes to ensure the lifecycle of a vehicle. The use of YOLOv5 for pothole detection and prevention has shown promising results in addressing the growing concern of deteriorating road conditions and associated safety hazards. Through the development and testing of the proposed approach, the effectiveness of using YOLOv5 for accurately detecting and localizing potholes in real-world scenarios is demonstrated. The proposed solution has the potential to be integrated into existing road maintenance systems for effective and efficient pothole management. By leveraging real-time data and implementing preventive measures, such as timely repairs and regular maintenance, the risks associated with potholes can be reduced and the overall safety and usability of our road infrastructure can be improved. However, there is still room for further improvements in terms of accuracy and performance, and future research can explore the use of more advanced machine learning techniques and data augmentation methods.

In terms of future research, there are several avenues for further investigation and development of pothole detection and prevention using YOLOv5. Firstly, incorporating other data sources such as weather and traffic data could offer supplementary information on the origins and consequences of potholes, allowing for more proactive measures to be taken. Another area for future research is the development of preventive measures for pothole management. By predicting where potholes are likely to form, this can proactively perform road maintenance and repairs, thus reducing the likelihood of potholes forming and improving the longevity of the road infrastructure.

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