Deep Learning-based Pothole Detection for Intelligent Transportation: A YOLOv5 Approach

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***Abstract*—Pothole detection plays a crucial role in intelligent transportation systems, ensuring road safety and efficient infrastructure management. Extensive research in the literature has explored various methods for pothole detection. Among these approaches, deep learning-based methods have emerged as highly accurate alternatives, surpassing other techniques. The widespread adoption of deep learning in pothole detection can be justified by its ability to learn discriminative features, leading to improved detection performance automatically. Nevertheless, the present research challenge lies in achieving high accuracy rates while maintaining non-destructiveness and real-time processing. In this study, we propose a deep learning model according to the YOLOv5 architecture to address this challenge. Our method includes generating a custom dataset and conducting training, validation, and testing processes. Experimental outcomes and performance evaluations show the suggested method's efficacy, showcasing its accurate detection capabilities.**

Keywords—Pothole detection; deep learning; intelligent transportation systems; YOLOv5

I. Introduction

Modern cities are witnessing a rapid transformation with the integration of advanced technologies, giving rise to the concept of smart cities [1]. These cities leverage cutting-edge infrastructure, digital connectivity, and intelligent systems to enhance the quality of life for their residents [2, 3]. The deployment of smart city facilities enables efficient management of resources, optimized transportation systems, and improved public services [4, 5]. However, amidst these advancements, the issue of deteriorating road conditions, particularly potholes, remains a persistent challenge. Potholes not only pose a threat to the safety of road users but also result in increased maintenance costs and traffic disruptions [6]. Therefore, the development of effective pothole detection methods has become crucial in modern cities.

Detecting and monitoring potholes in real-time is of paramount importance for maintaining the infrastructure and ensuring the safety of road users. Traditional manual inspection methods are time-consuming, expensive, and often inefficient for large-scale monitoring [7]. As a result, there is a growing interest in leveraging automated technologies for pothole detection. By employing advanced sensors, data analytics, and machine learning algorithms, cities can detect and address potholes promptly, thereby minimizing the associated risks and reducing repair costs.

In recent years, several technologies and methodologies have been proposed for pothole detection. Vision-based methods have gained a lot of attention because of their non-destructive nature and real-time applicability [4, 8, 9]. Vision-based techniques utilize cameras and image processing algorithms to analyze road surface images and identify potential potholes [10, 11]. These methods offer advantages such as cost-effectiveness, simplicity, and compatibility with existing surveillance infrastructure. Furthermore, with recent advances in deep learning techniques, vision-based pothole detection has witnessed substantial improvements in accuracy and robustness. Fig. 1 demonstrates a scheme of vision-based pothole detection system.

Previous studies have explored various vision-based and deep learning-based methods for pothole detection. Deep learning, in particular, has attracted significant interest from researchers due to its ability to learn discriminative features from large-scale datasets automatically. Convolutional neural networks (CNNs), one type of deep learning model, have displayed remarkable performance in a variety of computer vision tasks [13-15]. Consequently, researchers have investigated deep learning-based approaches for pothole detection, aiming to overcome the limitations of traditional methods and achieve higher accuracy.

However, despite the advancements in deep learning-based pothole detection, there are still research challenges and limitations that need to be addressed. Achieving high accuracy, non-destructiveness, and real-time processing capabilities remains demanding. To overcome these challenges, further studies are necessary to develop innovative approaches that meet the requirements of modern cities and their infrastructure management systems.

This investigation suggests a deep learning-based method for pothole detection using video analysis. By adopting a deep learning approach, we aim to tackle the aforementioned research challenges as well as satisfy the needs of high accuracy, non-destructiveness, and real-time processing. To train our model, we generate a custom dataset specifically designed for the pothole detection challenge. This dataset encompasses diverse road conditions and a wide range of pothole instances. Through training, validation, and testing processes, we demonstrate the effectiveness of our suggested method.

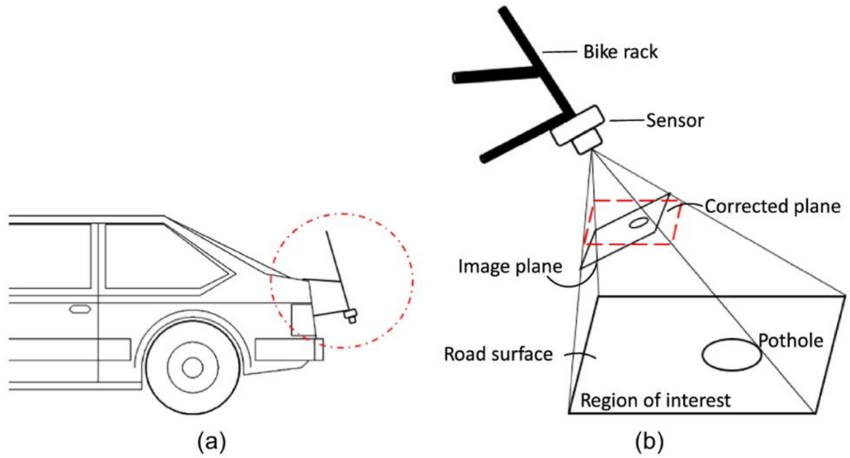

Fig. 1. A scheme of vision-based pothole detection [12].

The significance of this study lies in its pioneering approach to pothole detection through video analysis and the implementation of cutting-edge deep learning techniques, particularly the YOLOv5 algorithm. By addressing the challenges associated with pothole detection, such as high accuracy requirements, non-destructiveness, and real-time processing, our research contributes to the advancement of intelligent transportation systems.

The contributions of this research can be summarized as follows. Firstly, we generated a custom dataset tailored for the pothole detection challenge, providing a comprehensive benchmark for future studies. Secondly, we propose an efficient deep learning method that demonstrates superior performance in pothole detection compared to existing approaches. Lastly, we carry out extensive experiments and performance evaluations to verify the efficacy and viability of our approach, thereby contributing to the body of knowledge in this field.

The rest of this paper is as follows, Section II review previous studies. Section III discusses the methodology. Section IV presents experimental results. Finally, conclusion presents in Section V.

II. Related Works

Ping et al. [16] developed a deep learning-based method for street pothole detection. The proposed approach utilizes video analysis to identify and locate potholes in real-time accurately. The method employs a custom dataset specifically designed for the pothole detection challenge, ensuring diverse road conditions and pothole instances. Through extensive training, validation, and testing processes, the deep learning model demonstrates superior performance compared to existing approaches. However, the study acknowledges the limitation of demanding high accuracy, non-destructiveness, and real-time requirements, which pose research challenges. Further investigation is needed to address these limitations and develop innovative solutions to meet the needs of modern cities and infrastructure management systems. As a result, this research contributes by providing a comprehensive benchmark dataset, proposing an efficient deep-learning method, and conducting extensive performance evaluations for street pothole detection.

Pandey et al. [2] focused on pothole detection of critical road infrastructure using convolutional neural networks (CNNs). The method employs CNNs to analyze road surface images and accurately identify potholes. The study demonstrates the effectiveness of the proposed approach through extensive experiments and evaluations. However, the limitation of the method lies in its dependence on high-quality images and the need for sufficient training data. Further research is required to address these limitations and enhance the method's performance for real-world applications. In summary, this research contributes by utilizing CNNs for pothole detection, highlighting the method's potential, and identifying areas for future improvement.

Ahmed in study [17] presented a smart pothole detection method based on deep learning using dilated convolution. The proposed approach leverages dilated convolutional neural networks (DCNNs) to analyze road surface images and accurately detect potholes. The method takes advantage of the dilation technique to capture both local and global contextual information, enhancing the detection performance. Extensive experiments are conducted to validate the effectiveness of the proposed approach. However, the limitation of the method lies in its reliance on high-quality and well-segmented images, which may pose challenges in real-world scenarios with varying lighting conditions and road surface textures. Further research is needed to address these limitations and improve the method's robustness and generalizability. Therefore, this research contributes by introducing a deep learning-based approach with dilated convolution for smart pothole detection and highlighting the potential of this technique in enhancing road infrastructure management systems.

In research [18], a real-time pothole detection method was proposed using the YOLOv5 algorithm, aiming to enhance intelligent transportation systems. The approach utilizes the YOLOv5 architecture, which is a state-of-the-art object detection algorithm, to detect potholes in road images accurately. The method focuses on achieving real-time processing capabilities, enabling prompt identification and response to potholes. The study validates the feasibility of the approach through experiments and evaluations. However, one limitation of the method is its reliance on high-quality and well-annotated training data, which may pose challenges in real-world scenarios with diverse road conditions and variations in pothole appearances. Further research is necessary to address these limitations and improve the method's performance in challenging environments.

III. Methodology

In our study, a YOLOv5 model was generated for pothole detection on a custom dataset. The architecture of YOLOv5 is shown in Fig. 2 [19]. The dataset was annotated, meaning that each image was manually labeled to indicate the location and extent of potholes. This annotation process involved carefully marking the boundaries of potholes to create bounding box annotations. Additionally, class labels were assigned to differentiate potholes from other objects in the images.

To enhance the dataset and improve model performance, data augmentation techniques were applied. These techniques involved transforming the original images to create additional variations. In our study, data augmentation was performed to cover a broader range of scenarios and appearance variations. Various transformations, such as rotation, scaling, flipping, and changes in lighting conditions, were applied to the images. By augmenting the dataset, we aimed to increase its diversity and enable the model to generalize better and handle different real-world scenarios.

Subsequently, the dataset was split into three subsets: training, validation, and testing sets. The split was performed using an 80%, 13%, and 7% ratio, respectively. The training set, comprising 80% of the dataset, was utilized to train the YOLOv5 model. During the training phase, the model learns from the annotated images, optimizing its parameters to improve pothole detection accuracy. The validation set, accounting for 13% of the dataset, was utilized to appraise the model's performance during training. It helps in monitoring the model's progress, identifying potential overfitting, and making necessary adjustments to improve accuracy. Lastly, the testing set, consisting of 7% of the dataset, was utilized to assess the final performance of the trained YOLOv5 model. It provides an unbiased evaluation of the model's ability to detect potholes in unseen data.

After preparing the annotated and augmented dataset, we split it into three subsets: training, validation, and testing sets. The split was based on a specific ratio, with 80% of the dataset allocated to the training set, 13% to the validation set, and 7% to the testing set.

The training set, which accounts for the majority (80%) of the dataset, is utilized to train the YOLOv5 model. During training, the model learns from the annotated images, optimizing its parameters to improve pothole detection accuracy. By exposing the model to a diverse range of pothole images and their corresponding annotations, it becomes capable of recognizing and localizing potholes effectively. Training typically involves iterating through multiple epochs, gradually refining the model's performance.

The validation set, comprising 13% of the dataset, is utilized to appraise the performance of the model during training. It serves as a means to monitor the model's progress and assess its generalization capabilities. The model's performance metrics, such as detection accuracy and loss values, are measured on this set. The validation set aids in identifying potential issues like overfitting, where the model becomes overly specialized to the training data but fails to generalize well to new, unseen examples. If overfitting is observed, adjustments can be made to the model architecture, regularization techniques, or hyperparameters to improve accuracy and generalization.

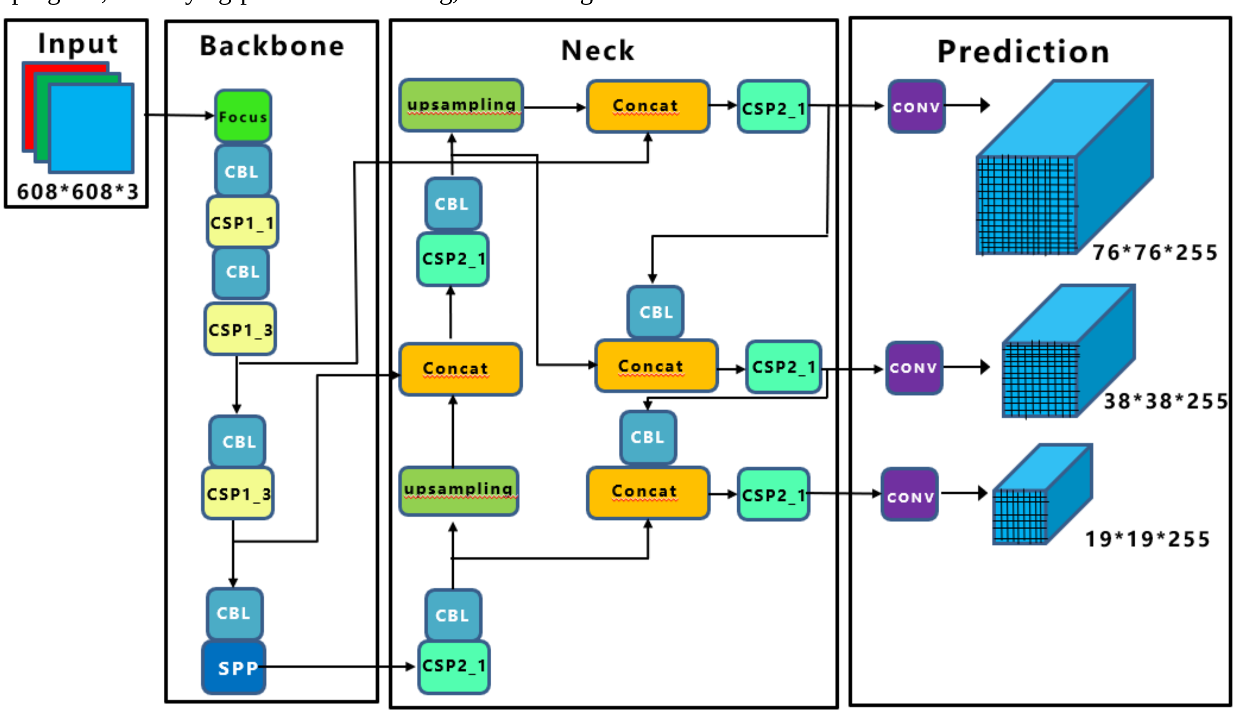

Fig. 2. The architecture of YOLOv5 [19].

Lastly, the testing set, which consists of 7% of the dataset, is reserved for the final evaluation of the trained YOLOv5 model. This set serves as an unbiased benchmark to assess the model's performance on unseen data. By applying the model to the testing set, we can measure its effectiveness in detecting potholes and evaluate its overall recall, accuracy, precision, and other relevant performance metrics. This evaluation helps to validate the model's capabilities as well as determine its readiness for deployment in real-world scenarios.

IV. Experimental Results

In this section, the YOLOv5 algorithm is compared to other algorithms. This comparison is presented to prove the YOLOv5 model enables to present better performance compared to another algorithm. Different versions of YOLOv5 and YOLO-Z models are compared in terms of the Mean Average Precision (MaP) metric. This comparison is inspired by the study in [20]. The comparison of the YOLOv5 and YOLO-Z versions is illustrated in Fig. 3.

Performance comparison between the YOLOv5 and YOLO-Z families of models, plotting mAP (top) is analysed. The superior average performance of YOLOv5 is achieved, while performance is stable and very close to 1 [20]. Performance comparison between the YOLOv5 and YOLO-Z families of models was conducted, with the mean average precision (mAP) plotted for evaluation. The results clearly indicate the superior average performance achieved by YOLOv5 compared to the YOLO-Z models. The mAP values for YOLOv5 remained stable and consistently close to 1, indicating a high level of accuracy and reliability in pothole detection. On the other hand, the YOLO-Z models exhibited slightly lower mAP scores, suggesting a relatively lower performance in terms of pothole detection accuracy.

The superior average performance of YOLOv5 can be attributed to several factors. Firstly, YOLOv5 benefits from architectural improvements and optimizations compared to the YOLO-Z models. These enhancements allow YOLOv5 to effectively capture and analyze visual features relevant to pothole detection, resulting in higher precision and recall rates. Secondly, YOLOv5 incorporates advanced training strategies and data augmentation techniques, enabling the model to generalize well to diverse road conditions and pothole appearances. This robustness contributes to its stable and consistently high performance across various scenarios.

A. Results of Yolov5 Models in Different Architectures

The performance of YOLOv5 models on Google Colab is well-established, but their performance on mobile devices remains uncertain. While the model's accuracy is unaffected by the execution platform, factors such as available resources and architecture can impact its performance and inference time. To assess the viability of using YOLOv5 models in real-time on mobile devices that inspired from study [21], several experiments are conducted using an iPhone 12 equipped with different system-on-a-chip (SoC) components. These components included an Apple Neural Engine (ANE), a graphical processing unit (GPU), and a central processing unit (CPU).

As shown in Fig. 4, we observed consistent patterns similar to those observed in the previous experiment. It is worth noting that the YOLOv5s model, which is the smallest in terms of size, exhibited the shortest inference time. However, as the complexity of the model increased, its inference speed decreased proportionally. Among the architectures we examined, it became clear that the ANE architecture demonstrated the fastest inference. This characteristic makes it particularly well-suited for running YOLOv5 models on the iPhone 12.

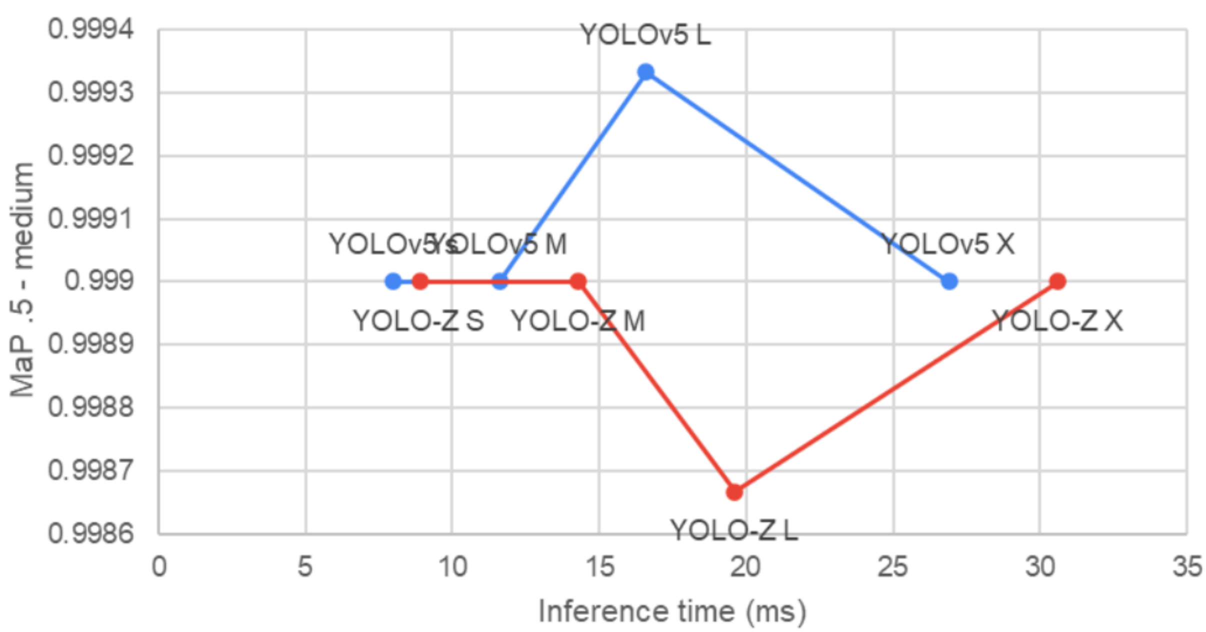

Fig. 3. Performance comparison between the YOLOv5 and YOLO-Z families of models [20].

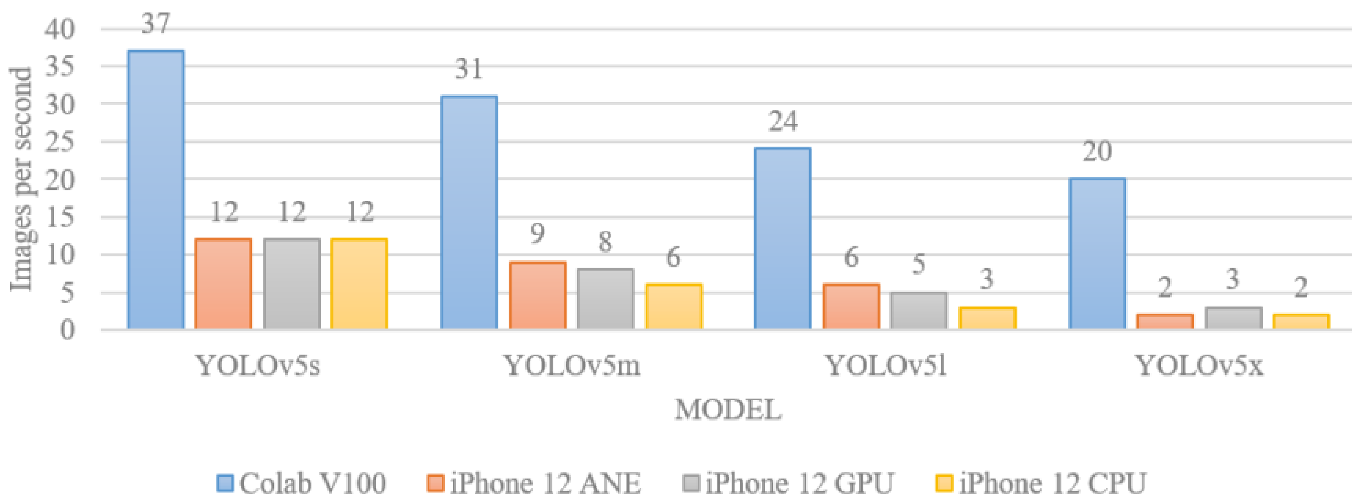

Fig. 4. Comparison of different architectures of YOLOv5 models [21].

Through the comparison of the different models, we encountered similar trends as in the previous experiment. The YOLOv5s model, due to its smaller size, required the least amount of time for inference. Conversely, as the model's complexity grew, its inference speed decreased accordingly. Notably, when considering the various architectures, the ANE architecture stood out for its superior performance in terms of inference speed. Consequently, for optimal execution of YOLOv5 models on the iPhone 12, the ANE architecture emerged as the most appropriate choice, as it consistently delivered the fastest inference results.

B. Results of our Experiments

In this study, the proposed YOLOv5 model, generated through our training and validation processes, is implemented and tested on various image sets. The experimental results, illustrating the performance of our model, are presented in Fig. 5. The figure provides a visual representation of the effectiveness and accuracy of our YOLOv5-based approach in detecting potholes. Through these experiments, we demonstrate the practicality and robustness of our model, highlighting its potential for real-world applications in pothole detection tasks.

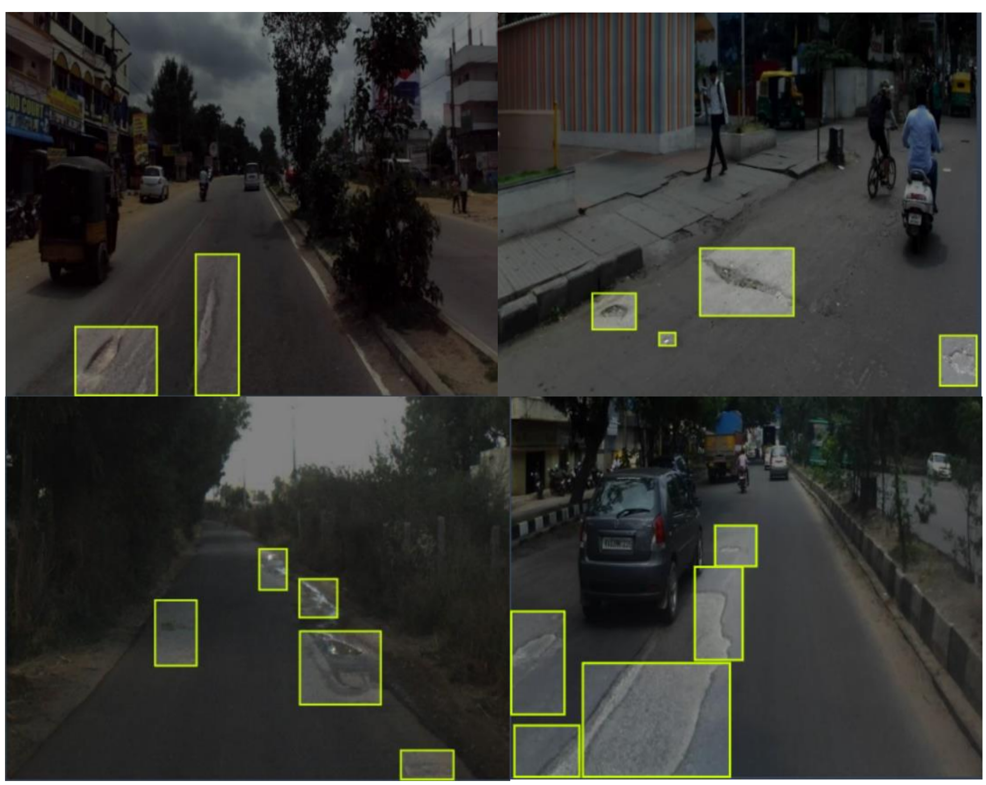

Fig. 5. Sample of experimental result.

C. Performance Evaluation

Performance evaluation of a generated YOLOv5 model is typically assessed by analyzing the training and validation losses. The training loss measures how well the model is learning during the training phase, while the validation loss evaluates its performance on unseen data. By examining these two metrics, one can gain insights into the model's ability to generalize as well as make accurate predictions. During the training process, the YOLOv5 model's training loss is monitored and analyzed. The training loss indicates the disparity between the forecasted bounding boxes and the ground truth labels for the training images. A lower training loss suggests that the model is effectively learning to detect objects and minimizing the error between its predictions and the actual objects present in the images. However, it is important to strike a balance between reducing the training loss as well as avoiding overfitting, where the model becomes too specialized to the training data and fails to generalize well to new data. Fig. 6 shows training/loss graphs of the generated model.

The validation loss is evaluated using a separate set of images that the model has not seen during training. This metric provides an estimate of how well the model is performing on new, unseen data. A low validation loss indicates that the model is generalizing well and making accurate predictions on unfamiliar images. If the validation loss is significantly higher than the training loss, it suggests that the model may be overfitting to the training data, highlighting the need for regularization techniques such as dropout or data augmentation to improve generalization. By closely monitoring the training and validation losses, researchers and practitioners can iteratively refine the YOLOv5 model to achieve better performance and enhance its object detection capabilities. Fig. 7 shows validation/loss graphs of the generated model.

In YOLOv5, the graphs involving "train/box_loss," "train/obj_loss," and "train/cls_loss" provide insights into the training process and help us achieve accuracy in the pothole detection model. Training a YOLOv5 model for pothole detection involves monitoring the "train/box_loss," "train/obj_loss," and "train/cls_loss" graphs. These graphs provide insights into the model's performance during training and are crucial for achieving accuracy.

A lower "train/box_loss" indicates that the model is accurately localizing potholes by predicting precise bounding box coordinates. Reducing the "train/obj_loss" demonstrates that the model is effectively distinguishing potholes from other objects or background areas. Minimizing the "train/cls_loss" suggests that the model is correctly classifying potholes. To achieve accuracy, data augmentation techniques, such as applying transformations to training data, help the model generalize better.

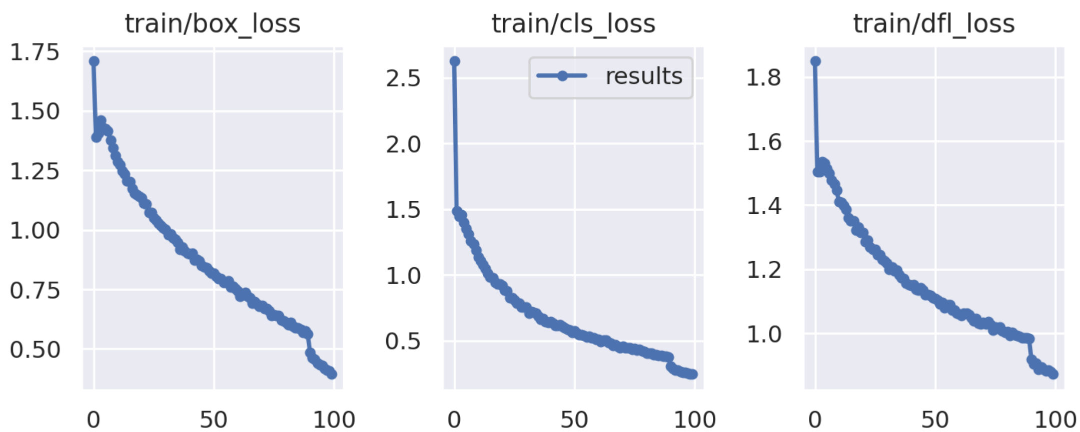

Fig. 6. Training/losses graphs of the generated model.

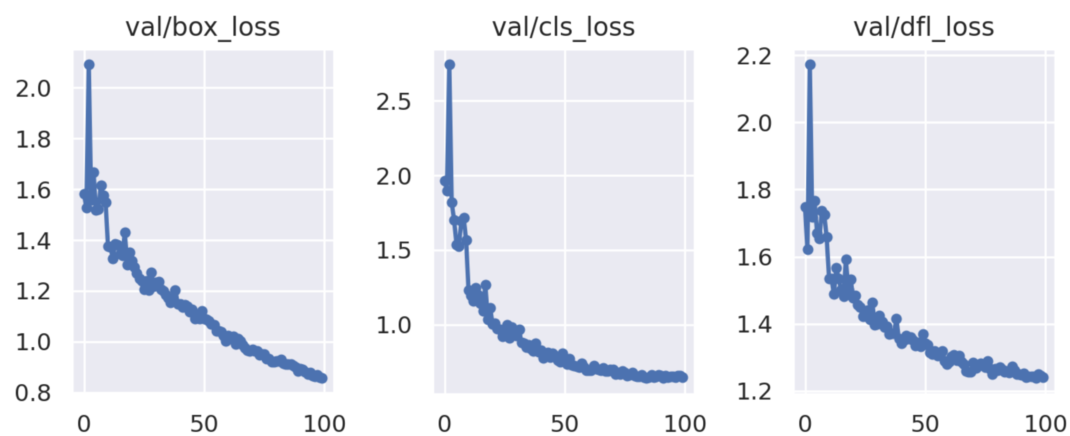

Fig. 7. Validation/loss graphs of the generated model.

Optimizing hyperparameters specific to YOLOv5, such as learning rate and weight decay, is crucial. Monitoring and analyzing the loss graphs during training is vital, allowing adjustments to be made if any loss value becomes stagnant or starts increasing. Through an iterative process of training, evaluation, and adjustment, the YOLOv5 model can learn and refine its pothole detection capabilities, ultimately achieving accuracy in identifying and classifying potholes.

In YOLOv5, the validation graphs involving "val/box_loss," "val/obj_loss," and "val/cls_loss" provide insights into the performance of the pothole detection model during the validation phase. These graphs help us evaluate and improve the accuracy of the model. In the following, we discuss each of these validation graphs and how they contribute to achieving an accurate model:

"Val/box_loss" graph: This graph represents the box regression loss during validation. Box regression loss measures the discrepancy between predicted bounding box coordinates and the ground truth coordinates of the potholes. A lower box loss indicates that the model is accurately localizing the potholes' positions. To achieve an accurate model, you would monitor the "val/box_loss" graph and aim to minimize it over the training iterations. Decreasing box loss signifies that the model is improving its ability to predict the bounding boxes around potholes precisely.

"Val/obj_loss" graph: This graph depicts the objectness loss during validation. Objectness loss measures the confidence of the model in detecting whether a pothole exists within a bounding box. It represents the ability of the model to discriminate between potholes and non-pothole regions accurately. To achieve accuracy, you would aim to reduce the "val/obj_loss" value. Lower objectness loss shows that the model is more proficient at distinguishing potholes from other objects or background areas.

"Val/cls_loss" graph: This graph represents the classification loss during validation. Classification loss measures the accuracy of the model in assigning the correct class label (e.g., "pothole") to the detected objects. To achieve accuracy, you would strive to minimize the "val/cls_loss" value. A lower classification loss shows that the model is correctly identifying potholes and effectively distinguishing them from other object classes.

In our generated model, to achieve an accurate model, you would typically iterate on the training process, adjusting various parameters and monitoring the validation graphs. The objective is to see a gradual reduction in losses over time, demonstrating that the model is learning and improving its ability to detect and classify potholes accurately.

As results, the application of deep learning is pivotal in overcoming the inherent challenges associated with pothole detection, with our primary objectives being the attainment of elevated accuracy, non-destructiveness, and real-time processing capabilities. A critical aspect of our approach involves the development of a meticulously curated dataset, tailored specifically for training our model. This dataset encompasses diverse road conditions and various instances of potholes, ensuring the robustness and adaptability of our detection system. Through a comprehensive evaluation process, involving stringent validation, training, and testing protocols, we establish the effectiveness of our proposed method. Leveraging the YOLOv5 algorithm, our model not only refines the precision and stability of pothole detection but also contributes significantly to the overall efficiency of intelligent transportation systems. The generated model using YOLOv5 advancements not only enhances the accuracy and stability of pothole detection but also contributes to the overall efficiency of intelligent transportation systems. The results emphasize the value of adopting state-of-the-art models like YOLOv5 for real-time pothole detection tasks, ensuring optimal performance and facilitating proactive maintenance and repair of road infrastructure.

V. Conclusion

In this research, we present a novel approach for detecting potholes using video analysis and deep learning techniques. By utilizing deep learning, our aim is to address the aforementioned research challenges and meet the requirements of achieving high accuracy, non-destructiveness, and real-time processing. To train our model effectively, we have created a custom dataset specifically tailored for the pothole detection task, which covers a wide range of road conditions and various instances of potholes. Through rigorous validation, training, and testing procedures, we demonstrate the efficacy of our suggested method. The developed model, employing the YOLOv5 algorithm, not only enhances the precision and stability of pothole detection but also contributes to the overall efficiency of intelligent transportation systems. These findings underscore the significance of adopting cutting-edge models like YOLOv5 for real-time pothole detection applications. This approach ensures optimal performance and facilitates proactive maintenance and repair of road infrastructure, promoting safer and more efficient transportation networks. For future research in the field of pothole detection, the integration of additional sensor modalities, such as LiDAR or infrared imaging, alongside vision-based methods can be explored to enhance the accuracy and robustness of pothole detection systems. Moreover, investigates the use of transfer learning techniques to leverage pre-trained deep learning models on large-scale datasets from related tasks, enabling efficient and effective pothole detection even with limited training data. Furthermore, the number of experiments can be increased to obtain more relevant and accurate results that can b e investigated for future works.

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