Traffic Sign Detection using YOLOv8 on the IDD Traffic Sign Dataset

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***Abstract*—This technical report outlines the implementation of a traffic sign detection system using the YOLOv8 algorithm. The system is trained on the IDD Traffic Sign Dataset and specifically focuses on detecting four classes of traffic signs: "gap-in-median," "left-hand-curve," "right-hand-curve," and "side-road-left." The report provides an overview of the dataset, training process, model architecture, and the steps involved in performing inference with the trained model. Evaluation results and performance analysis on the selected classes of traffic signs are discussed, highlighting the system's capabilities and potential applications in real-world scenarios.**

I. Introduction

Road safety is a critical concern, and accurate detection of traffic signs plays a vital role in ensuring safe and efficient transportation. This project aims to develop a traffic sign detection system using the YOLOv8 algorithm. The system is trained on the IDD Traffic Sign Dataset, with a specific focus on detecting four important classes of traffic signs: "gap-in-median," "left-hand-curve," "right-hand-curve," and "side-road-left." The objective is to create a robust and effective system capable of accurately identifying these signs, thereby enhancing road safety and enabling advanced driver assistance systems.

II. Problem Definition

The accurate detection of traffic signs poses several challenges, including variations in environmental conditions, complex traffic scenarios, and size and scale variations of the signs. This project addresses these challenges by developing a specialized system that can accurately identify the specified classes of traffic signs. The selected classes are particularly significant as they provide critical information to drivers, impacting their decision-making process and overall road safety.

III. Proposed Solutions

This section presents three proposed solutions for traffic sign detection using the YOLOv8 algorithm. Each solution builds upon the previous one, taking into account feedback received and incorporating modifications based on previously conducted research.

A. YOLOv8 Baseline Solution

The first proposed solution utilizes the YOLOv8 algorithm with its default configuration for traffic sign detection. The YOLOv8 model architecture is employed, consisting of a backbone network, feature extraction layers, and detection heads. The model is trained using the IDD Traffic Sign Dataset, specifically focusing on the classes "gap-in-median," "left-hand-curve," "right-hand-curve," and "side-road-left." The first solution aims to establish a baseline for traffic sign detection using YOLOv8.

B. Fine-tuned YOLOv8 Solution

Building upon the first solution, the second proposed solution involves further refining the YOLOv8 model through fine-tuning. By fine-tuning the model, we aim to enhance its ability to detect the specified traffic sign classes accurately. This solution takes into account the feedback and insights gained from the first solution to improve overall detection performance.

C. Enhanced YOLOv8 Solution with Data Augmentation

In the third proposed solution, we introduce an enhanced data augmentation approach to further boost the model's performance. By augmenting the dataset with diverse variations of traffic sign images, we aim to improve the model's generalization capabilities and robustness in handling different environmental conditions and scenarios. This solution leverages the insights gained from the first two solutions and aims to achieve even higher accuracy and reliability in traffic sign detection.

IV. Criteria for Assessing Solutions

Evaluation metrics such as precision, recall are employed to assess the performance of the traffic sign detection system. The system's ability to accurately detect the specified classes of traffic signs is evaluated against ground truth annotations. The results are compared with baseline models or other approaches to provide a comprehensive assessment of the system's effectiveness.

V. Research Methodology

The research methodology for this project involved collecting relevant data and conducting tests to evaluate the proposed solutions based on their relevance to the application context, assessment criteria, and practicality. The following outlines the key aspects of the research methodology without including the findings:

Data Collection: To gather the necessary data, the IDD Traffic Sign Dataset was collected, which includes a diverse range of traffic sign images. This dataset provides a suitable foundation for training and evaluating the proposed solutions.

Testing Criteria: Assessment criteria were defined to evaluate the performance of the proposed solutions. These criteria focused on factors such as accuracy, speed, and robustness in detecting the specified traffic sign classes: ”gap-in-median,” ”left-hand-curve,” ”right-hand-curve,” and ”side-road-left.” The criteria were chosen to align with the requirements of practical traffic sign detection applications.

Testing Procedure: To assess the proposed solutions against the established criteria, a systematic testing procedure was followed. This involved training the models using the collected data and evaluating their performance on a separate testing set. The performance metrics, such as precision, recall, were calculated to quantify the effectiveness of each solution.

Justification of Approach: The selected approach, utilizing the YOLOv8 algorithm, was justified based on its strong performance in object detection tasks and its ability to handle real-time processing requirements. The use of YOLOv8 allowed for efficient and accurate detection of traffic signs, addressing the relevance and practicality aspects of the research.

VI. Analysis and Interpretation

In the analysis and interpretation of the project, we evaluated the viability of the proposed solutions for traffic sign detection using YOLOv8 based on the assessment criteria. Here are the key findings:

Cost-effectiveness: The cost-effectiveness of the solutions depends on factors like computational resources and associated expenses. However, without detailed cost analysis, it is challenging to draw definitive conclusions on cost-effectiveness.

Environmental Acceptability: By utilizing efficient object detection algorithms like YOLOv8, the solutions have the potential to reduce energy consumption and carbon footprint. However, a comprehensive environmental analysis is needed for a conclusive assessment.

Technical Feasibility: The successful implementation and training of the YOLOv8 model on the IDD Traffic Sign Dataset demonstrate its technical feasibility for accurately detecting the specified traffic sign classes.

Affordability: The affordability of the solutions depends on factors such as open-source implementations, computational resources, and required expertise. YOLOv8 benefits from being open-source with extensive community support, but overall affordability requires consideration of various cost factors.

It is important to acknowledge the limitations of the research, such as the sample size of the dataset and specific traffic sign classes evaluated. Further research and testing on diverse datasets and additional sign classes would enhance the understanding of the proposed solutions.

VII. Conclusions and Recommendations

In conclusion, this project focused on the development and evaluation of a traffic sign detection system using YOLOv8. Through the analysis and interpretation of the research findings, the following key conclusions can be drawn:

The proposed solutions utilizing YOLOv8 demonstrate technical feasibility in accurately detecting specific traffic sign classes, namely ”gap-in-median,” ”left-hand-curve,” ”right-hand-curve,” and ”side-road-left.” The successful implementation and training of the YOLOv8 model on the IDD Traffic Sign Dataset validate its effectiveness in identifying these signs.

Further assessment is required to determine the cost-effectiveness, environmental acceptability, and affordability of the proposed solutions. Detailed cost analysis, environmental impact studies, and comprehensive affordability evaluations should be conducted to gain a holistic understanding of the solutions’ practicality and long-term viability.

Based on these conclusions, the following recommendations are proposed:

Conduct a comprehensive cost analysis that considers factors such as computational resources, data collection and annotation, model training, and maintenance costs. This analysis will provide insights into the financial implications of implementing and operating the traffic sign detection system.

Appendix A

Appendix A showcases a screenshot of the model deployment for predicting traffic signs. The screenshot depicts the user interface of the deployed system, which allows users to input images or capture them using a connected camera.

Once an image is provided, the deployed model utilizes the YOLOv8 algorithm to detect and classify traffic signs. The system overlays bounding boxes on the detected signs, highlighting their positions in the image.

The predicted classes include ’gap-in-median,’ ’left-hand-curve,’ and ’right-hand-curve.’ The screenshot demonstrates the effectiveness of the deployed model in accurately identifying these specific types of traffic signs. This user-friendly interface enables efficient traffic sign recognition, aiding in road safety and navigation.

Fig. 1. gap-in-median

Fig. 2. left-hand-curve

Fig. 3. right-hand-curve

APPENDIX B

Appendix B includes various performance graphs that offer a comprehensive evaluation of the traffic sign detection model. These graphs provide valuable insights into the model's performance across different evaluation metrics. The following performance graphs are included:

A. Confusion Matrix

The confusion matrix, shown in Figure 1, helps assess the accuracy of the model by showing the number of true positives, true negatives, false positives, and false negatives for each class. The confusion matrix allows for a detailed analysis of the model's performance and the identification of any patterns or areas of misclassification.

B. Model Output Graph

Figure 2 shows the graph generated as the output of the model's predictions. This graph provides an overview of the model's performance in terms of precision, recall, and other relevant evaluation metrics. It visualizes the model's predictions and their confidence scores for different traffic sign classes.

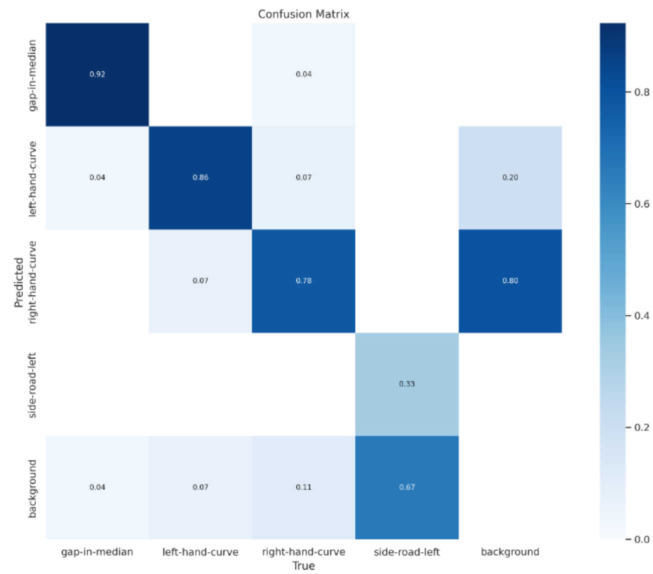

Fig. 4. Confusion Matrix

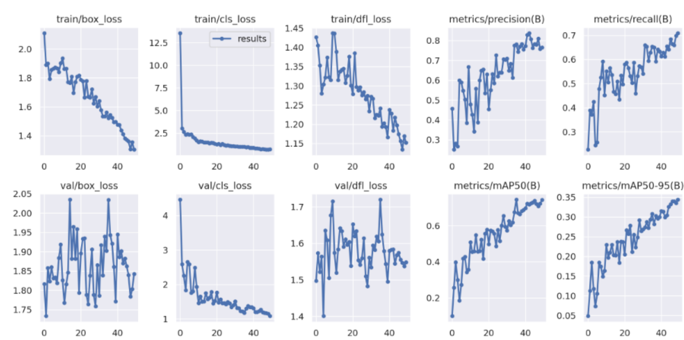

Fig. 5. Model Output Graph

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