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A YOLOv8-based approach for multi-class traffic sign detection

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Abstract

Recognizing traffic signs is a crucial task in autonomous vehicles to improve road safety. In this study, we propose a novel You Only Look Once version 8 (YOLOv8) model for identifying traffic signs. The model has been trained on the Kaggle dataset, which contains multiple traffic signs under different environments. The YOLOv8 model achieved an accuracy of 80.64% and a recall of 65.67% on test data. These metrics highlight the model's capability to recognize traffic signs. Notably, YOLOv8 brought about some notable improvements over earlier versions, such as enhanced detection in difficult situations and enhanced small-scale sign identification. The paper also explores the difficulties that arose throughout the model's training phase and provides workable solutions that were used to overcome these difficulties, improving the model's performance. The encouraging outcomes demonstrate the viability of implementing the YOLOv8-based strategy in practical traffic management systems, which is a positive advancement towards the creation of more sophisticated and dependable traffic sign recognition technology.

Keywords: YOLOv8; Multiclass Traffic Sign Detection; Deep learning; Precision; Recall

1. Introduction

Traffic signs are crucial to traffic flow, which speeds up the development of intelligent transportation systems and helps advance technologies like autopilot and assisted driving. Presently, the primary approach for detecting traffic signs involves gathering pictures using cameras placed on vehicles, followed by detection and recognition using computer vision and pattern recognition techniques. Target identification methods like Faster RCNN, YOLO, FCOS, etc. have become widely employed in traffic sign detection due to the rapid growth of deep learning technology.[1][2][3]. This study proposes a novel method for recognizing traffic signs by YOLOv8 model, which was trained on the Kaggle dataset that contains images from different environments and angles [4][5]. The YOLOv8 model showed excellent performance, these findings show the model's capability to recognize different kinds of traffic signs, which is a significant advancement over earlier models[6][7]. This YOLOv8-based traffic sign recognition technology has the potential to improve traffic management systems and make roads safer and more effective if it is successfully implemented.

2. Methods

2.1. Data collection

We used the Kaggle dataset for training the model. It contains images of different traffic signs like stop signs, speed limit signs, and traffic signals in different angles, lighting, and distances. The images of the dataset are of high quality and annotated with labels [8].

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2.2. Model architecture

YOLOv8's backbone network serves as its framework and is in charge of extracting features from the input picture. YOLOv8 uses a Darknet variation called CSPDarknet53 as its foundation.

A unique Cross-Stage Partial (CSP) connection is introduced in the CSPDarknet53 design, which improves gradient flow during training and information flow between the network's various stages.

A Path Aggregation Network (PANet) is introduced as the neck structure of YOLOv8. By facilitating information flow across various spatial resolutions, PANet helps the model successfully capture characteristics at several scales.

Each of the many detecting heads that make up the head structure is in charge of projecting bounding boxes, class probabilities, and abjectness ratings on various scales. The true breakthrough of YOLOv8 is found in its detecting head. It makes use of an altered YOLO head that has a new IoU (Intersection over Union) loss function and dynamic anchor assignment [9].

These enhancements help handle overlapping items better and forecast bounding boxes with more accuracy.

2.3. Model Training

The dataset is divided into an 80:10:10 ratio so that the training, validation, and testing sets have all class data. the model was trained using stochastic gradient descent (SGD) optimization and a learning rate of 0.0001 so that the model observes all patterns in the images. SGD was chosen because of its simplicity and its effectiveness in reducing the loss function [10].

The model was trained for 50 epochs, with a batch size of 120, and dropout regularisation at a rate of 0.15 was used to ensure that the model doesn't overfit and generalizes properly. Using these hyperparameters the YOLOV8 model was trained to detect traffic signs in real-world.

Here one epoch represents the one pass of model through the training dataset, used to measure the performance of the model. The batch size determines the number of samples from the training dataset that the model needs to learn in one forward or backward pass. Dropout sets some of the neurons to zero during training so that the model is not prone to overfitting [11]. The model is evaluated using classification evaluation metrics like precision, recall, mAP50, and mAP50-95.

3. Results and Discussion

The results of the trained YOLOV8 model show promising results for multi-class traffic sign identification. The model achieved a Precision of 80.64 %, Recall of 65.67%, mean average precision at 50% intersection over union (IoU) known as mAP50% of 77.18%, and mean average precision between 50% and 95% intersection over union (IoU) known as mAP50-95 of 64.95 %. These metrics are represented in the Table 1 for easy understanding:

Table 1 Metric values of YOLOV8

Metrics	**Score**
Precision	80.64
Recall	65.67
mAP50	77.18
mAP50-95	64.95

The precision value of the model indicates its capability to identify correctly traffic signs out of all predicted detections. This demonstrates the model's capability to minimize false positives. The recall value of the model indicates its ability to identify all relevant classes of the test dataset and avoid false negatives. The mAP50 of the model suggests better confidence and precision. The mAP50-95 provides a strict evaluation of the localization accuracy of the model for stricter IoU.

These results indicate the effectiveness of the YOLOV8 model has the capability of accurately detecting various types of traffic signs and its effectiveness in lowering both false positives and false negatives – both important for preserving road safety.

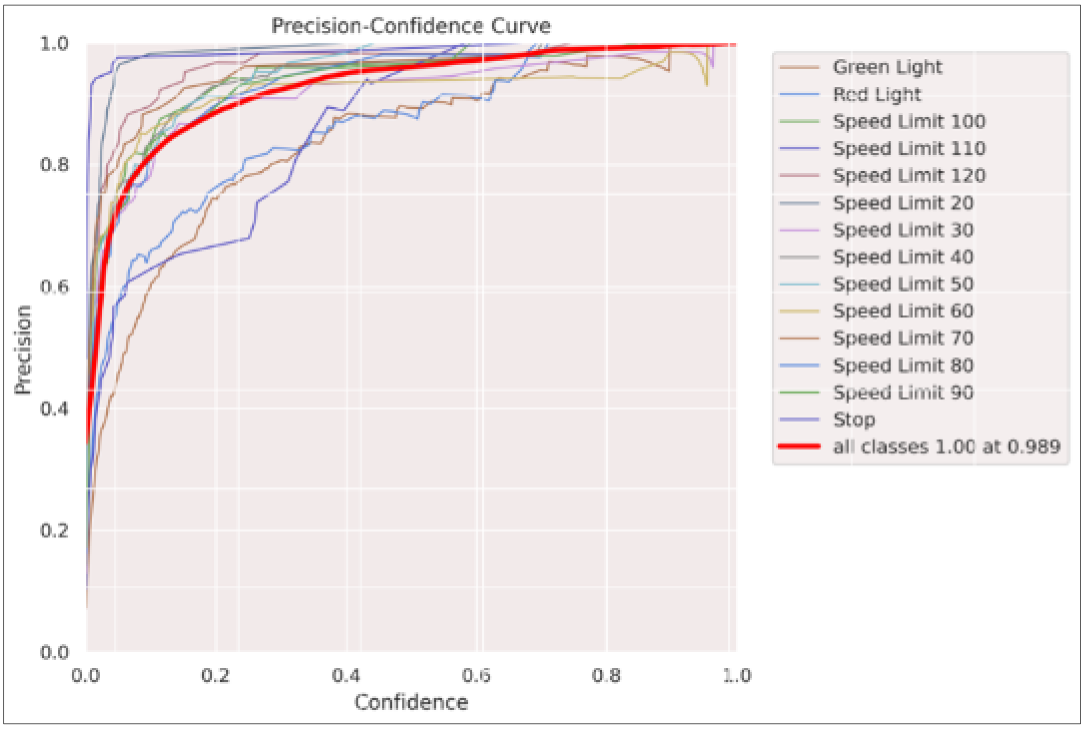

Figure 1 Precision Curve

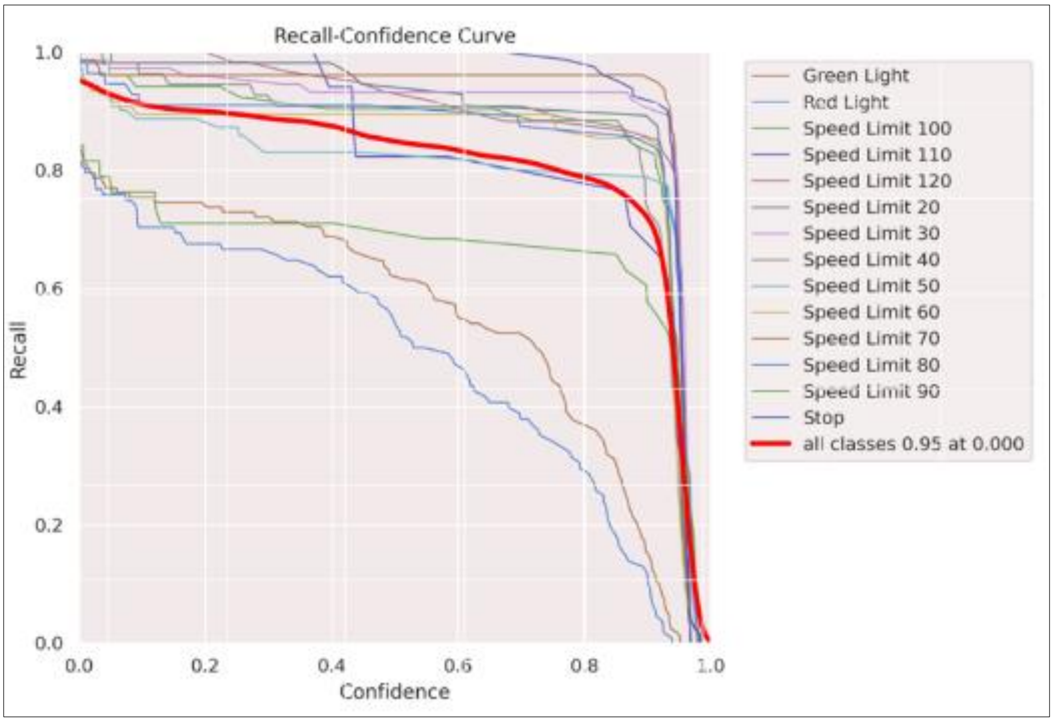

Figure 2 Recall Curve

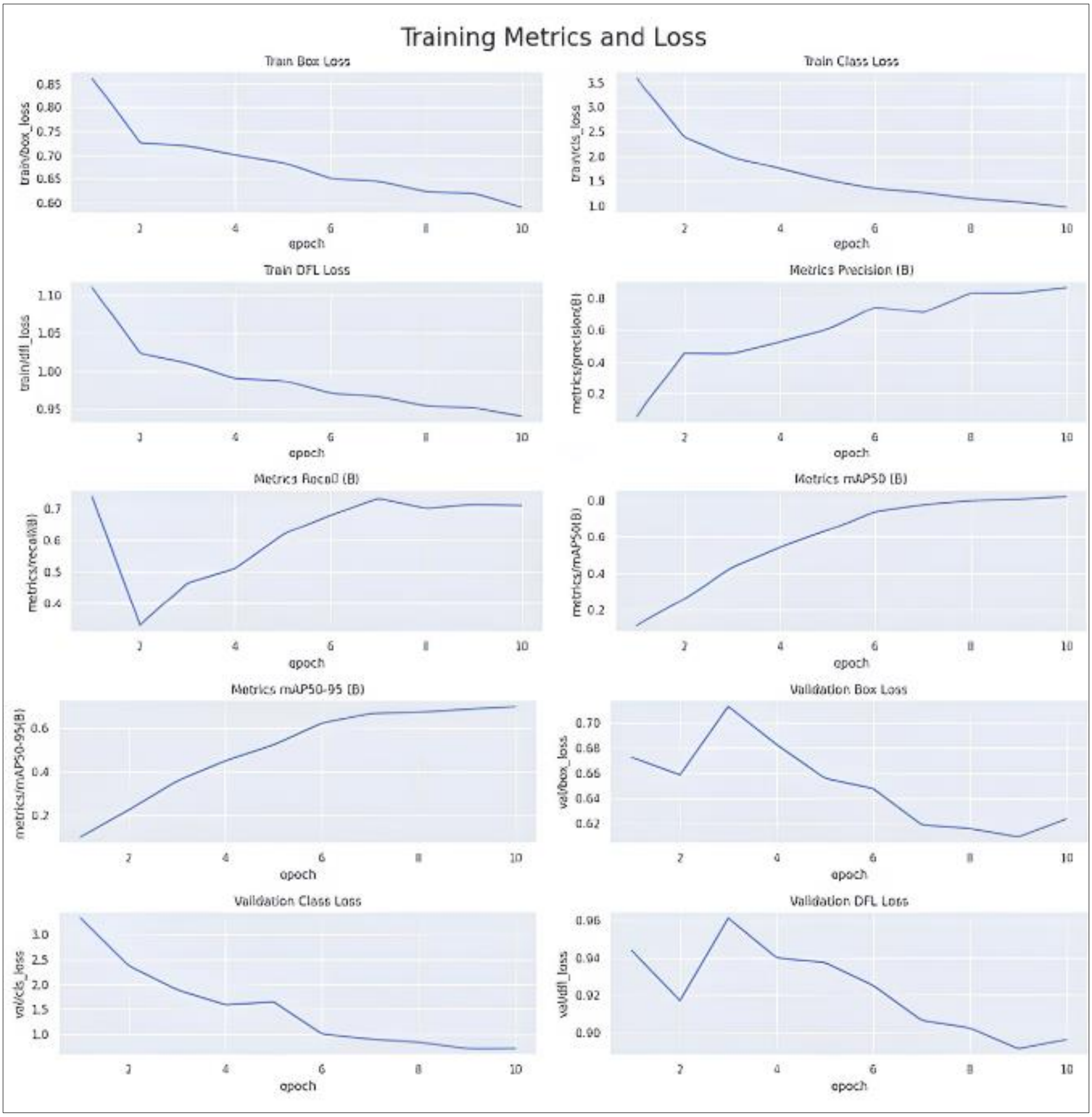

Figure 3 Loss Over Epochs

Figure 1 and Figure 2 indicate the model capability in identifying different traffic signs. The loss over epochs provides insights into the model's training process and models predicting capability is displayed in figure 4.

Figure 4 YOLOv8 Predicted Images

4. Conclusion

In conclusion, this study proposes a YOLOV8-based multi-class traffic sign detection and its effectiveness in identifying various types of signs under different conditions. The promising results of the model's performance indicate the model’s reliability and effectiveness in real-world situations. By using deep learning techniques, the proposed method provides a significant advancement in traffic sign identification technology, paving the way for more efficient and secure transportation systems. The study's findings will be important for the development of next traffic management systems and will help the ongoing efforts to increase road safety and efficiency through technological innovation.

Compliance with ethical standard

Acknowledgement

We are appreciative of the people who made the dataset accessible to the public so that this study could be conducted.

Disclosure of Conflict of Interest

No conflicts of interest are disclosed by the authors.

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