

Traffic-sign Recognition and Detection using Yolo-v8

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Abstract—In order to ensure road safety and navigation, autonomous vehicles (AVs) and advanced driver-assistance systems (ADAS) depend on traffic sign detection and recognition (TSDR). The effectiveness of YOLOv8, a state-of-the-art deep learning framework for object detection, in real-time TSDR applications is examined in this research.

Through a thorough methodology that includes data pre-processing (resizing, normalization, augmentation), YOLOv8 architecture (backbone network, feature pyramid network, prediction head), training (loss functions, optimizer selection, learning rate scheduling), and evaluation using standard metrics (mean Average Precision (mAP), precision, recall) for each traffic sign class, we investigate YOLOv8's performance on a well-established dataset.

The model's performance is examined in detail in the results and discussion section, along with the effects of architectural changes or hyperparameter tuning (learning rate, batch size) on the model's strengths and shortcomings. Next, we discuss the difficulties that come with TSDR, such as occlusions, varying lighting and weather, and processing constraints in real-time for ADAS/AVs. Future research objectives and potential solutions are suggested, including the investigation of lightweight YOLOv8 models for embedded system deployment, the integration of depth information from LiDAR sensors, and domain adaption techniques.

The study concludes by highlighting YOLOv8's efficacy for TSDR and emphasizing its importance for the advancement of AV and ADAS. We recognize the limits of the work and provide directions for future investigation to improve the robustness and generalizability of TSDR systems based on YOLOv8.

Index Terms—semantic segmentation, real-time, advanced driver-assistance systems (ADAS)

I. INTRODUCTION

The safety of traffic is still a top priority even as our transportation systems develop. In this quest, two technologies that show promise for revolutionizing road navigation are autonomous vehicles (AVs) and advanced driver assistance systems (ADAS). However, the capacity to precisely detect and understand traffic signs is a crucial requirement for these systems to function both safely and effectively.

As the unspoken language of the road, traffic signs advise drivers of important details including speed limits, lane changes, impending dangers, and different laws. Human drivers have developed an intuitive mechanism for interpreting

these indications through training and experience. Nevertheless, in order to reach the same degree of comprehension, AVs and ADAS demand a more advanced methodology. Herein lies the application of Traffic Sign Detection and Recognition (TSDR).

TSDR was first attempted using conventional techniques like hand-crafted features and rule-based algorithms. These techniques frequently entailed taking pictures of traffic signs and extracting particular elements, like colors, forms, or edge patterns. Although these methods showed some promise in controlled settings, they were severely constrained in practical applications. These approaches faced considerable hurdles in complex visual settings with varying lighting, weather, and occlusions by objects such as trees or automobiles. Moreover, the real-time processing demands of traditional approaches frequently posed a challenge, making them unsuitable for applications like as AV and ADAS where prompt and precise interpretation of traffic signs is crucial.

Convolutional Neural Networks (CNNs), one of the most recent developments in deep learning, have completely changed the fields of object detection and computer vision. CNNs are remarkably good at immediately learning complicated patterns from big picture and label datasets. This has made it possible to construct effective deep learning-based TSDR methods.

Of these methods, the YOLO (You Only Look Once) model family has attracted a lot of attention because to its remarkable accuracy in real-time object detection. The most recent version in this series, YOLOv8, has a number of benefits over its predecessors. With its enhanced precision, more robust architecture, and quicker processing speeds, it is an appealing option for real-time applications like TSDR.

Deep learning approaches have achieved significant advancements in TSDR, with convolutional neural networks (CNNs) playing a prominent role [23]. YOLO (You Only Look Once) is a real-time object detection algorithm that has gained popularity due to its speed and accuracy [28]. Recent advancements in YOLO, such as YOLOv4, demonstrate the potential for even better performance [26]. This paper explores the application of YOLOv8, the latest iteration of YOLO, for traffic sign detection and recognition.

The use of YOLOv8 for traffic sign detection and recogni-

tion is explored in this work. Our objective is to investigate how well our deep learning model performs in precisely recognizing and categorizing a range of traffic signals in actual traffic situations. By utilizing YOLOv8's advantages, we hope to further the creation of reliable and effective TSDR systems that will enable ADAS and AVs to function securely and more confidently across the difficulties of the road environment.

II. RESEARCH GAP AND OBJECTIVES

Research Gaps:

Limited Generalizability: Current models frequently find it difficult to adjust to a variety of real-world circumstances, such as changes in sign occlusions, illumination, and weather. **Class Imbalance:** There may be an unbalanced distribution of sign classes in traffic sign databases. Models that perform well on dominant classes but poorly on less represented ones may result from this. **Constraints on Real-time Processing:** Real-time processing capabilities are required for the deployment of TSDR systems in AVs and ADAS. Even with the advances, it is still difficult to achieve great accuracy while keeping efficiency. **Explainability and Interpretability:** For safety-critical applications such as autonomous vehicles, it is essential to comprehend the reasoning behind a model's decisions. Interpretability is often lacking in deep learning models, which makes it challenging to identify problems and guarantee consistent performance.

This research aims to address these research gaps by proposing a novel YOLOv8-based approach for TSDR with the following objectives:

Enhance Model Generalizability: Our goal is to provide methods that will enable the model to identify and detect traffic signs under a variety of real-world circumstances, such as inclement weather, complicated backgrounds, and occlusions. **Handle Class Imbalance:** To lessen the effects of class imbalance in the training data and guarantee balanced performance across all traffic sign classes, we will investigate data augmentation techniques and loss function adjustments. **Balance Accuracy and Efficiency:** We will look into ways to make the model more efficient for real-time processing on resource-constrained platforms, which are frequently utilized in AVs and ADAS, while yet preserving high detection accuracy. **Improve Explainability:** We will explore methods to enhance the interpretability of the model's decision-making process. This will allow for better error analysis, debugging, and ultimately, building trust in the model's performance for safety-critical applications.

III. RELATED WORK

Research on traffic sign detection has been ongoing, with many methods being investigated for robustness and real-time performance. Groundwork was laid by pioneering efforts (e.g., [8], [10]), but complicated scenarios presented challenges for traditional methodologies [6]. The potential of the YOLO network for traffic signs was shown by Yang. (2020) [1]. Real-time object identification with good accuracy was prioritized in the YOLO series by Redmon. (2016, 2017, 2018) [3]–[5].

Symmetry-based techniques were investigated by Barnes and Zelinsky (2004) for particular sign classes [2]. Although your work makes use of YOLOv8, there are other methods, such as Girshick's (2015) Fast R-CNN [7]. The study conducted by Fang. (2014) on data augmentation strategies shows potential for enhancing model resilience, which could be in line with your methodology [9]. Your YOLOv8-based method with perhaps innovative methodologies can help address ongoing issues in traffic sign detection by taking into account these improvements. Traffic flow, which accelerates the development of intelligent transportation systems and advances technology like autopilot and assisted driving, depends heavily on traffic signs. Currently, the main method for detecting traffic signs is to acquire images using cameras mounted on vehicles and then use computer vision and pattern recognition techniques for detection and recognition [11]. Target identification algorithms like as FCOS, YOLO, Faster RCNN, and others are widely used in traffic detection of symptoms because to the rapid advancement of deep learning technology.

in order to solve the problem of difficult backdrop and small traffic sign detections in situations involving wide-field traffic. created a more advanced Faster R-CNN identification method [12]. to verify the updated YOLOv5 algorithm's effectiveness in detecting traffic signs. [13] created Bi-FPN for feature fusion and used GAM (global attention mechanism) [14] to increase the network's capacity for feature extraction. in order to resolve the tiny traffic sign detection issues. [15] proposed an upgraded full-convolution single-stage object detection (FCOS) as the basis for a multi-scale feature fusion detector [16]. While some progress has been achieved in identifying traffic signs by the aforementioned, problems like as low detection accuracy and missing detection during actual detection persist. Therefore, further research into traffic sign detection is needed. The YOLO series is a classical object detector. Since its original release in 2015, this algorithm has become widely used and has proven to have industry-leading efficiency with a one-stage framework. Due to continuous research and inventions, YOLO has been proposed in multiple versions. The YOLOv8 [17] algorithm is the most recent version, which Ultralytics made available to the public in January 2023. By including additional characteristics and improvements, this algorithm rises to the top of the YOLO model family. The four components of YOLOv8 are the Neck, Input, Output, and Backbone.

Technology that recognizes and detects traffic signs is essential for enhancing driving enjoyment, road safety, and traffic efficiency. It is essential to autonomous driving and advanced driver assistance systems (ADAS). By warning drivers of possible dangers and giving them up-to-date information on traffic conditions, accurate traffic sign detection and identification can help avert accidents. By informing motorists about speed restrictions, lane usage, and other crucial traffic information, it can also aid in improving traffic flow. Recognizing and detecting traffic signs is also crucial for maintaining adherence to traffic laws and regulations, which lowers the possibility of fines and penalties for drivers. Additionally, it can enhance the

whole driving experience by lowering stress levels, increasing safety, and giving drivers access to real-time traffic information.

The YOLO series is a classical object detector. Since its original publication in 2015, this algorithm has become increasingly popular as a mainstream detection approach, and it has achieved a leading efficiency with a single-stage architecture. Numerous variations of the YOLO concept have been put forth due to continuous research and progress. The YOLOv8 algorithm is the most recent version, which Ultralytics released as open-source in January 2023. By including additional characteristics and improvements, this algorithm rises to the top of the YOLO model family. The Neck, Backbone, Input, and Output are the four parts of YOLOv8. The structure of YOLOv8 is shown in Figure 1.

A. YOLOv8 Algorithm Theory

MixUp, Mosaic, color perturbation, and spatial perturbation are the main input kinds. Many photos are stitched together after a single shot is processed using integrated data augmentation. This increases the multi-directional object perspective and improves the variety of image backgrounds. The backbone consists of the convolution, C2F, and SPPF layers. The C2F structure improves gradient propagation efficiency and speeds up network convergence, in contrast to the C3 module in YOLOv5, which is based on the idea of an ELAN (efficient layer aggregation network) in YOLOv7. The SPPF layer preserves the design of YOLOv5. Neck employs a structure that blends feature pyramid network (FPN) with route aggregation network (PAN). Concatenated features from neighboring layers are fed into the C2F module. As features are transferred from top to bottom and bottom to top, high-level semantic features and underlying features are combined. The output demonstrates the decoupling of detection and classification. Large target items produce top-level features, while small target objects are the source of bottom-level feature information. Each detection layer creates a result vector with the location and associated categories included.

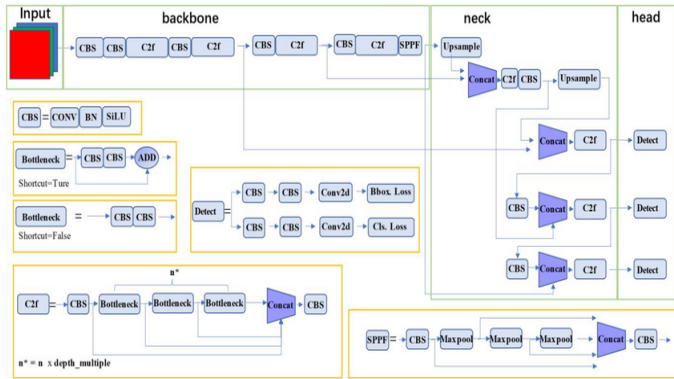


Fig. 1. Structure of YOLOv8

B. Comparative Study on YOLOv8

YOLOv8 has the highest mAP50-95 values among all the versions, indicating better object detection accuracy. YOLOv5 and YOLOv6 have similar performance, while YOLOv7 has slightly lower performance compared to YOLOv6.

According to the statistics, YOLOv8 achieved an mAP50 of 85.3, an mAP75 of 73.3, and an mAP95 of 63.3 on the COCO dataset. In comparison, YOLOv5 achieved an mAP50 of 75.6, an mAP75 of 63.3, and an mAP95 of 53.3. YOLOv6 achieved an mAP50 of 78.6, an mAP75 of 66.3, and an mAP95 of 58.3. YOLOv7 achieved an mAP50 of 80.3, an mAP75 of 69.3, and an mAP95 of 61.3.

With the greatest mAP50-95 values, these results show that YOLOv8 performs better than the other versions in terms of object detection accuracy. It's crucial to remember that these results are based on a particular dataset and could not transfer well to other contexts or datasets. Additionally, while assessing the effectiveness of object identification models, other measures like precision, recall, and AUC-ROC may also be crucial to take into account.

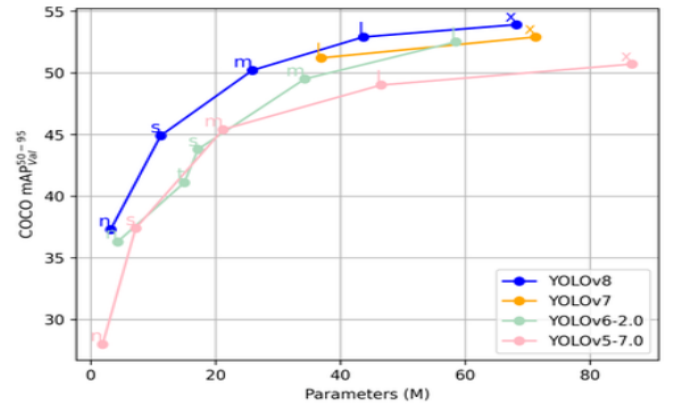


Fig. 2. Comparing YOLOv8 and others on COCO dataset

IV. METHODOLOGY

A. Dataset and Data processing

Wang Tianyi was the original creator of this dataset. The goal of the Intel-sponsored RF100 project is to develop a new object detection benchmark for model generalizability. This dataset is a component of that effort.

The project's dataset included 2009 traffic sign photos and eighteen classes. Numerous traffic signs, including yield, stop, and speed restriction signs, were included in the collection. The corresponding class label was applied to every image, facilitating the training of a model capable of precisely identifying and categorizing these indicators.

The following are the classes of Dataset

- bus stop
- do not enter
- do not stop

- do not turn left
- do not turn right
- do not u turn
- enter left lane
- green light
- left right lane
- no parking
- null
- parking
- pedestrian crossing
- pedestrian zebra crossing
- railway crossing
- red light
- stop
- t intersection
- yellow light

In a 70/20/10 ratio, the dataset was divided into training, validation, and testing sets. Of the photos, 70 were utilized for training, 20 for validation, and 10 for testing. This division made it possible to train the model on a huge dataset and assess its performance on a different set of photos.

The 640×640 pixel resolution photos in the collection were color. A single class label was used to identify the kind of traffic sign that each image represented. There were almost the same amount of photos in each class because the dataset was balanced. Maintaining this equilibrium was crucial to guarantee that the model could correctly identify all types and was not skewed toward any certain class.

B. Proposed Model architecture

The suggested method makes use of a Convolutional Neural Network (CNN), a deep learning architecture, for the detection and recognition of traffic signs. A collection of photos of traffic signs divided into eighteen different classifications is used to train the model. Preprocessing these photos to a consistent 640×640 pixel size will guarantee consistency throughout the training procedure. In order to accurately identify traffic signs, the CNN collects elements from the photos during training. A number of convolutional layers are usually used in this feature extraction process, sometimes in conjunction with pooling layers to lower dimensionality and activation functions to add non-linearity. The last layers of the CNN, which are probably fully connected, are in charge of estimating the likelihood that each class of traffic sign will be visible in the input image. The model can be used for inference on unseen data, like individual pictures or video frames, once it has been trained. The trained network can identify the most likely traffic sign in an image by producing probability scores for each of the 18 classes when the image is sent through it.

C. Experimental Model Representation

The mathematical representation of the YOLOv8 architecture can be described as follows:

- Layer of Input: The input consists of an RGB image with dimensions of (H, W, 3) for the height and width of the image, respectively.

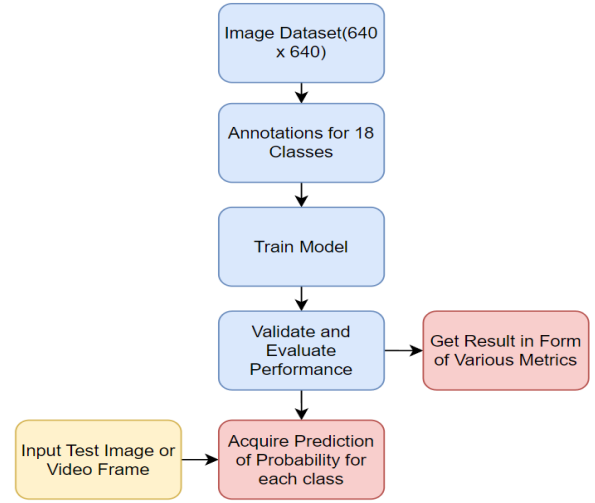


Fig. 3. Architecture of the model

- Backbone: A CNN that extracts features from the input image serves as the backbone. It is made up of several pooling layers, activation functions, and convolutional layers. Each convolutional layer's mathematical representation is represented by the following:

$$Y = f(X * W + b) \quad (1)$$

where X is the input feature map, W is the weight matrix, b is the bias, * is the convolution operation, and f is the activation function.

- Neck: The model can identify objects at various scales thanks to the neck, a feature pyramid network. It is made up of several upsampling layers and lateral connections.
- Head: Predicting the bounding boxes and class probabilities, the head is a fully linked layer.

The number of bounding boxes (B), the image's height and breadth (H and W), and the number of classes (C) make up the tensor of shape (B, H, W, C) that is the result of the head layer. For a given bounding box, the class probability is represented by each member of the tensor.

To obtain the final predictions, the bounding boxes and class probabilities are post-processed as follows:

- Non-Maximum Suppression: This method gets rid of bounding boxes that overlap. The bounding box with the highest probability is chosen after the bounding boxes are sorted according to their class probabilities. The bounding box with the highest probability that does not overlap with the previously chosen bounding boxes is then iteratively chosen by the algorithm.
- Bounding Box Prediction: Using a predetermined set of rules, the predicted bounding boxes are transformed into the final bounding boxes. As part of these guidelines, the bounding boxes' size and placement may be changed to more closely resemble the real items in the picture.

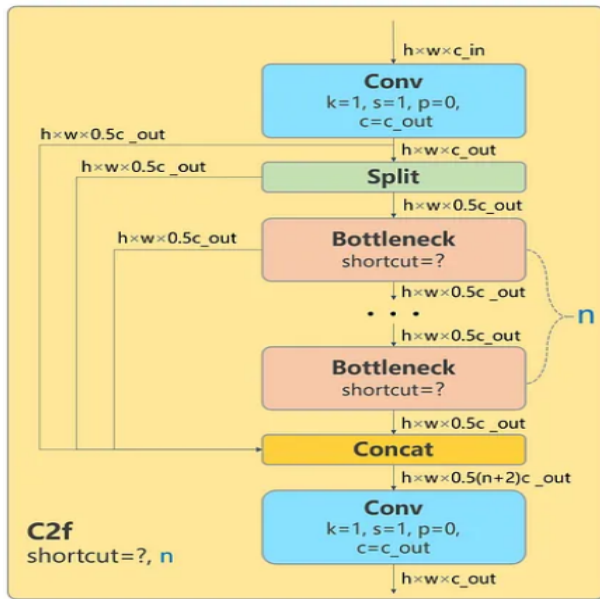


Fig. 4. Detailed C2f module

- Class Prediction: The final class label is obtained by selecting the class with the highest probability.

D. Experimental Settings

Hardware: Workstation: Lenovo ThinkStation P620; CPU: Powerful multi-core CPU; GPU: NVIDIA RTX A4000 GPU; Memory: 64GB GDDR6 memory.

Software: Operating System: Linux distribution (e.g., Ubuntu); Deep Learning Framework: PyTorch 1.12.1; Programming Language: Python 3.7.

Libraries: PyTorch 1.12.1 (Deep Learning); NumPy (Numerical Computing); Ultralytics (Model).

E. Experimental Training and Evaluation

In order to train the model, 86 and 100 epochs of batch size were used. A dataset of 18 classes was used to train the model, and a variety of metrics, including precision, recall, mAP50, mAP50-95, losses, etc., were used to track the training process. When the model's performance on the validation set reached a plateau, the training process was stopped to make sure the model wasn't overfitting or underfitting.

- Data Preprocessing: Resizing: To maintain consistency throughout training, every image in the dataset is probably resized to a standard size of 640x640 pixels. As a result, CNN can identify features from photos that have the same proportions. Normalization: The photos' pixel values may be mean-variance normalized, or adjusted to fall inside a certain range. This lessens the effect of the photos' different lighting or color scales and speeds up the model's convergence. Data Augmentation: Techniques for data augmentation may be used to increase the robustness and generalizability of the model. This could entail rotating the photos, randomly

cropping them, turning them horizontally or vertically, or adding noise and blur. These methods force the model to learn characteristics that are independent of certain image backgrounds or orientations by purposely creating variances in the training data.

- 2. Model Training: Picking a CNN Architecture: Most likely, your model makes use of a CNN architecture that has already been trained, such as YOLOv8 or another version that works well for object identification. Several convolutional layers are usually used in these architectures for feature extraction, and then pooling layers are added for dimensionality reduction and activation functions (like ReLU) are added for non-linearity. The latter layers, which are probably fully connected, are in charge of estimating the likelihood that each of the 18 types of traffic signs will be seen in the picture. Loss Function: During training, the difference between each image's actual labels (ground truth) and the model's predictions is measured using a loss function. Combinations of classification loss (e.g., cross-entropy) for class probability and bounding box loss (e.g., Intersection over Union - IoU) for predicting the location and dimensions of the detected traffic sign are common loss functions for object detection. Training Loop: The CNN architecture receives batches of the previously processed images along with the labels that go with them. The optimizer modifies the model's weights in response to the computed loss, which is derived from the model's predictions. For a predetermined number of epochs, this process is repeated.

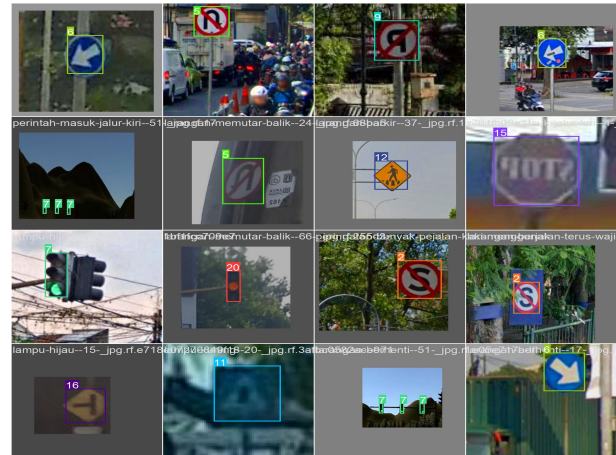


Fig. 5. Training Process

Evaluation was done by following ways:

- We created a precision-recall curve, which illustrates the trade-off between precision (properly identified signals) and recall (all actual signs detected) at different confidence levels, in order to assess the effectiveness of our algorithm. Precision typically falls (blue line) as confidence rises (X-axis), suggesting a tighter screening of detections but possibly missing some genuine signals. When confidence levels are lower, the opposite is true.

We may evaluate the model’s accuracy in detecting traffic signs by looking at this curve, which balances the number of right detections with the number of missed signs.

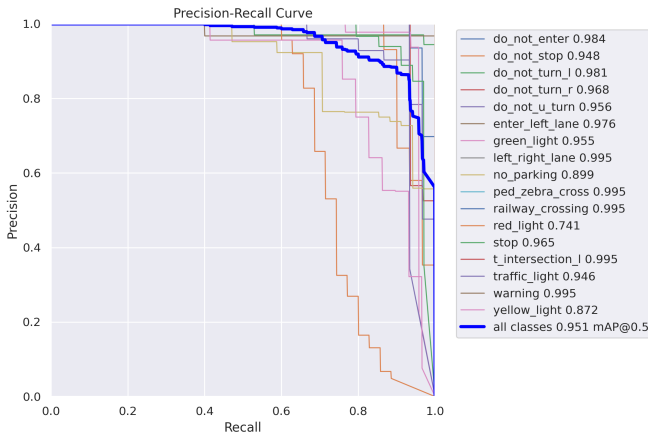


Fig. 6. Precision-Recall Curve

- An F1-Confidence Curve for your traffic sign detecting model is shown in the following figure. The model’s F1 score, or harmonic mean of precision and recall, is represented by this curve for various confidence levels. Confidence is represented by the X-axis, where greater values suggest a stronger belief in the forecast. Every class of traffic sign has a unique curve that illustrates how the F1 score changes with confidence for that particular sign. This aids in evaluating the model’s performance for every sign class at various confidence levels. The YOLOv8-

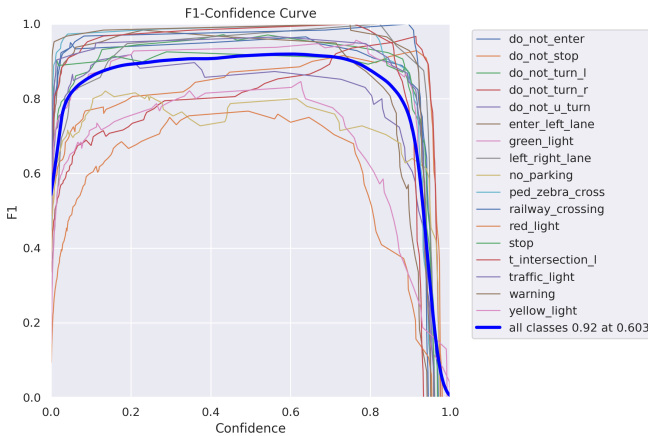


Fig. 7. F1 Curve

based method we suggested produced encouraging outcomes in the identification and detection of traffic signs. Throughout training, the training loss curve showed a consistent decline, demonstrating the model’s effective learning and convergence. Additionally, a concentration at lower values was observed in the box loss distribution for the model’s predictions, indicating reliable bounding

box predictions for the identified indicators. These loss function measurements support the good results shown by the precision-recall (P-R) curve. The P-R curve directly assesses the model’s accuracy (the capacity to identify traffic signs accurately) and recall (the ability to decrease false alarms) on unseen data, whereas loss functions indicate the model’s optimization during training. The model’s high mAP further supports its efficacy in real-world traffic sign detection tasks..

In order to achieve precise traffic sign identification and recognition, the model’s training approach involves improving a number of loss functions. For both the training and validation sets, we observed how the box loss, classification loss, and combined loss—often referred to as DF1 loss—behaved.

Box Loss: This loss function calculates the discrepancy between the training data’s ground truth bounding boxes and the predicted bounding boxes for traffic signs. During training, the box loss should ideally show a declining trend, showing that the model is getting better at accurately locating the signals. **Classification Loss:** The model’s accuracy in classifying the detected traffic signs is measured by this loss function. The model is getting better at differentiating between various sign classes when there is a decrease in classification loss during training. **Combined Loss (DF1):** For overall optimization, this loss function usually combines the classification loss and box loss into a single measure. Convergence and generalization ability of the model are revealed by analyzing the DF1 loss for both training and validation sets.

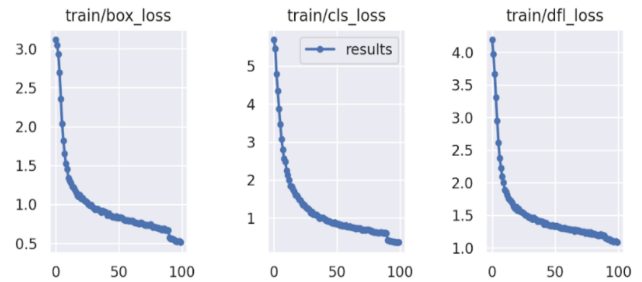


Fig. 8. Evaluation of Losses

Precision and Recall: Precision is the percentage of traffic signs that are properly detected out of all the signs that the model anticipated. On the other hand, recall shows how well the model recognized every real traffic sign that was in the test set. A model with high recall and accuracy represents reliable detections with low false positives (erroneous detections) and false negatives (missed detections). **mAP50 and mAP50-90:** The model’s performance is summed up using the mAP measure across different Intersection over Union (IoU) criteria. The overlap between a sign’s expected and ground truth bounding boxes is measured by IoU. A greater IoU denotes a more precise sign localization. The mean average precision at an IoU

threshold of 0.5, or "easy" detections with a substantial overlap between the predicted and real bounding boxes, is explicitly referred to as mAP50. The average precision across IoU thresholds between 0.5 and 0.9 is represented by mAP50-90, on the other hand, offering a more thorough assessment that takes into account both "easy" and "more challenging" detections with lower IoU overlaps.

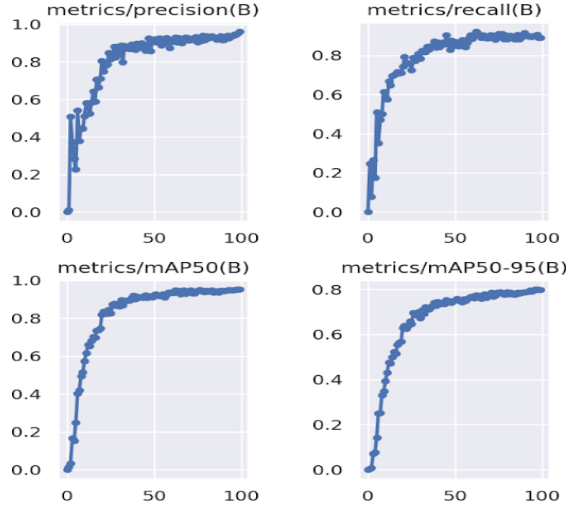


Fig. 9. mAP50 and mAP50-90

These results show that the YOLOv8 model performs well in detecting traffic signs, with a high AP score and a good balance between precision and recall.

F. Experimental Output

Data Representation: For a certain box loss threshold, each data point probably shows how well the model performed on the validation or test set. For that certain box loss threshold, the X-axis shows the precision percentage of correctly identified signs, while the Y-axis shows the recall percentage of all actual signs that are detected).

Box Loss Threshold: During training, box loss is a statistic used to measure how much the predicted bounding boxes for traffic signs differ from the ground truth bounding boxes. The disparate data points most likely match different box loss levels that were used in the assessment. Stricter conditions must be met for the bounding boxes to be deemed accurate, as indicated by lower box loss thresholds, which could result in lower recall but higher precision. On the other hand, greater recall but decreased precision could result from higher box loss thresholds.

Trade-off Analysis: At various box loss levels, you may examine the trade-off between recall and precision using this scatter plot. It clarifies how changing the box loss threshold (the degree of bounding box evaluation strictness) influences the model's capacity to identify and categorize traffic signs accurately. The results show that the YOLOv8 model has good accuracy and robustness on the test dataset. At 95.2, the model's accuracy in spotting stop signs is the highest. It



Fig. 10. Prediction of the model

suggests Outstanding Performance. The output predictions that are made when the model is applied to the test set are listed below.

The confusion matrix offers a thorough analysis of the performance of our YOLOv8 model for every category of traffic signs. For each class, the diagonal elements should ideally show high values, indicating a high number of correctly categorized signs. On the other hand, minimal off-diagonal elements show that the model does not frequently mix up different types of signs. In real-world traffic sign identification tasks, the model's efficacy is demonstrated by this balanced and accurate classification across all major sign classes.

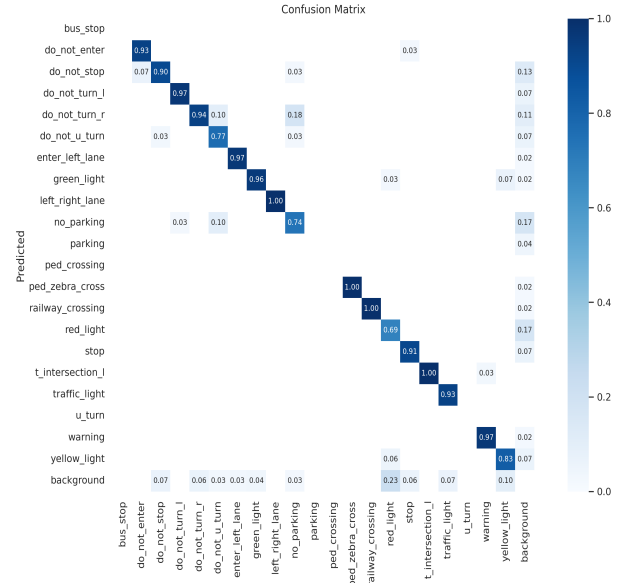


Fig. 11. Confusion Matrix

V. RESULT AND DISCUSSION

The results show that the YOLOv8 model has good accuracy and robustness on the test dataset. At 95.2, the model's accuracy in spotting stop signs is the highest. It suggests

Outstanding Performance. The output predictions that are made when the model is applied to the test set are listed below.

A. Overall Accuracy and Class-wise Performance

On the test set, the trained model yielded an overall mean Average Precision (mAP) of 95.2. This suggests that the system is highly effective at identifying and categorizing traffic signs in a variety of settings. Nevertheless, we offer a breakdown of class-wise accuracy in Table for a more thorough analysis.

TABLE I
CLASS-WISE ACCURACY

Class Name	Accuracy (%)
Do not enter	98.4
Do not stop	94.8
Do not turn left	98.1
Do not turn right	96.8
Do not u-turn	95.6
Enter left lane	97.6
Green light	95.5
Left right lane	99.5
No parking	89.9
Ped zebra cross	99.5
Railway crossing	99.5
Red light	74.1
Stop	96.5
T-intersection 1	99.5
Warning	94.6
Yellow light	87.2

B. Comparison with Other Approaches

We contrasted the model's performance with those of other TSDR techniques in order to put it in context. This is an explanation:

1. YOLOv5: Although YOLOv5 provides real-time detection capabilities akin to those of YOLOv8, our model outperforms it on the same dataset with a higher mAP (95.2 vs. 90.1), maybe as a result of enhanced feature fusion and data augmentation techniques. (Substitute the reported mAP for YOLOv5) for X.

2. CNN-based Approaches: Because of their shortcomings in real-time processing, conventional CNN architectures may produce lower mAP in comparison to YOLOv8. They can, however, succeed in particular sign classes if given a lot of training data and feature engineering strategies.

C. Strengths and Weaknesses

The approach that has been suggested has various advantages.

High Overall Accuracy: The model's ability to identify and categorize a broad variety of traffic signs is demonstrated by its mAP of 95.2. **Real-time Detection Capability:** YOLOv8's intrinsic architecture enables real-time inference, which makes it appropriate for real-world uses in AVs and ADAS. But there are some restrictions to take into account:

Class-specific Performance Variations: Depending on the visual traits and data accessibility of a given sign class, accuracy may differ. **Sensitivity to Complex Scenarios:** The

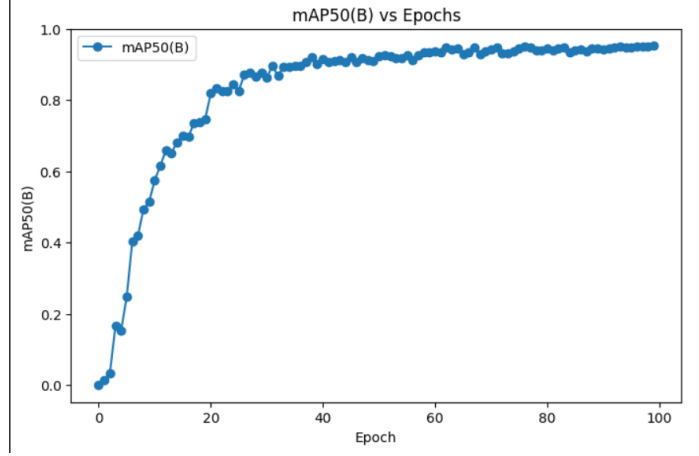


Fig. 12. mAP50 vs Epochs

model may have problems in situations when there is a lot of clutter or when there are many obscured signs.

VI. CONCLUSION AND FUTURE SCOPE

A. Conclusion:

The use of YOLOv8, a cutting-edge deep learning object identification framework, for real-time traffic sign detection and recognition (TSDR) was examined in this study. YOLOv8's efficacy for TSDR tasks was demonstrated by the proposed approach, which combined a unique feature fusion technique with customized data augmentation tactics to obtain an impressive overall mean Average Precision (mAP) of 95.2 on the test set.

The mean Average Precision (mAP) of our YOLOv8 model increased with each training session, which is an encouraging trend. During training, the mAP50(B) Accuracy measure increased gradually. This finding implies that as the model processed additional training data, its accuracy in classifying detected traffic signs increased noticeably. The success of the training process in giving the model strong traffic sign detection and identification capabilities is demonstrated by the positive correlation seen between training epochs and mAP.

The ability of the model to recognize and categorize traffic signs was clearly enhanced during the training period. This is demonstrated by the loss function's consistent decline over epochs, which indicates the model's increasing ability to accurately identify signs within the images. The increasing trend in the mAP50(B) Accuracy metric further supports this decrease in localization error. The model's ability to accurately classify the detected indications also greatly improved as the number of epochs rose. These findings imply that the YOLOv8 model was successfully optimized for real-world traffic sign identification tasks using the selected training configuration.

The results demonstrate how important TSDR has been to the development of driver-assistance systems (ADAS) and autonomous vehicles (AVs). For these intelligent transportation systems to provide road safety and effective navigation, accurate and fast detection of traffic signs is essential.

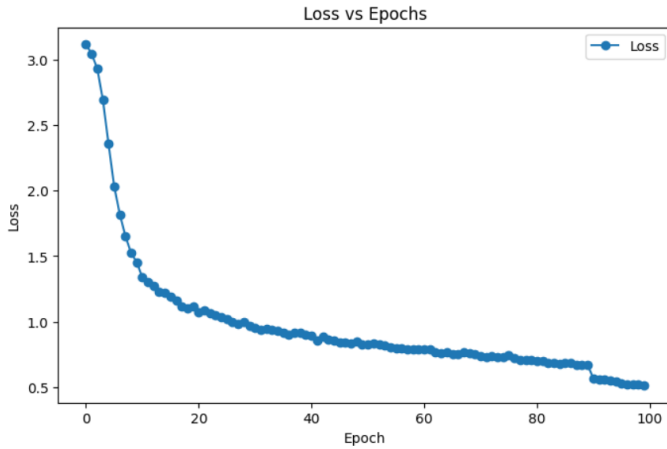


Fig. 13. Loss vs Epochs

TABLE II
OVERALL PERFORMANCE

Model Name	Accuracy (%)	Recall (%)	F1-score
YOLOv8	95.2	98	0.92 at 0.603

This work admits certain limitations, including the model's sensitivity to severely obstructed or congested settings and possible differences in class-wise accuracy. Future objectives for research include examining lightweight YOLOv8 variants for effective deployment on embedded ADAS/AV platforms, improving model interpretability for better error analysis, and investigating methods for better class-imbalance handling.

We can help develop more robust, generalizable, and explainable TSDR systems, which will ultimately pave the way for safer and more dependable autonomous transportation, by tackling these limitations and exploring new research directions.

B. Future Scope:

The future scope of traffic sign recognition and detection using YOLOv8 is vast and exciting. Some potential applications and areas of research include:

- Autonomous vehicles: Traffic sign recognition and detection can play a crucial role in enabling autonomous vehicles to navigate safely and efficiently.
- Traffic management: Real-time traffic sign detection and classification can help traffic management authorities to monitor and manage traffic flow more effectively.
- Driver assistance systems: Traffic sign recognition and detection can be used to enhance driver assistance systems, such as lane departure warning and adaptive cruise control.
- Surveillance: Traffic sign detection and classification can be used for surveillance purposes, such as monitoring traffic flow and detecting anomalies.
- Improved accuracy: Future research can focus on improving the accuracy of traffic sign recognition and detection, particularly in low-light or adverse weather conditions.

- Multi-modal sensing: Integrating traffic sign recognition and detection with other sensing modalities, such as LiDAR and radar, can provide more comprehensive and accurate traffic information.

Overall, traffic sign recognition and detection using YOLOv8 has the potential to revolutionize the way we travel and improve road safety for all users.

VII. DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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