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# YOLO-Based Traffic Sign Detection for Autonomous Vehicles

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**Abstract -** Real-time traffic sign recognition is an essential part of intelligent transportation systems and autonomous vehicles. This paper describes a method involving YOLOv8n, a small object detection model, to conduct high-speed and accurate traffic sign recognition. The approach includes preprocessing, augmentation, and training on a labeled dataset of traffic signs. Our model results in a mean Average Precision (mAP) of 93.5, which beats earlier lightweight models in terms of efficiency. Our proposed method also proves to be resilient in the real world and thus can be deployed in embedded systems. Improved detection under conditions of extreme weather will be dealt with in the future.

***Key Words* :** Traffic Sign Detection, YOLO , Intelligent Transportation System , Computer Vision

## 1. INTRODUCTION

### 1.1 Background & Motivation

Traffic sign detection is an important aspect of Intelligent Transportation Systems (ITS), where autonomous vehicles and driver-assistance systems recognize road signs to drive safely. Deep learning object detection models have shown dramatic improvements in accuracy and efficiency in this context. YOLO (You Only Look Once), a popular real-time object detection model, has seen successive versions, and YOLOv8n has been found to be the most optimized in terms of speed, accuracy, and real-time processing [5].

### 1.2 Research Objective

We use YOLOv8n (nano version), the most compact and fastest form of YOLOv8, in this paper for real-time traffic sign detection with OpenCV. Trained to accurately detect and classify multiple traffic signs, the model is best suited for embedded systems and real-time applications. With its low-power design, YOLOv8n guarantees high detection rates, and thus it is suitable for autonomous cars, smart traffic surveillance, and driver assistance systems [6].

### 1.3 Importance of YOLOv8n for Traffic Sign Detection

The YOLO family has transformed object detection by processing it as a single regression problem, where a CNN runs an entire image in one pass and predicts bounding boxes and class probabilities at the same time [5]. Our strategy utilizes: (1) Efficiency-optimized data preprocessing – comprising resizing, augmentation, and normalization. (2) Fast inference – allowing real-time detection for autonomous driving purposes. (3) Enhanced precision – by anchor-free detection and improved feature extraction. (4) OpenCV integration – for real-time processing and visualization of video. (5) Scalability – for deployment on Jetson Nano, Raspberry Pi, as well as edge hardware [6].

### 1.4 Literature Survey

Traffic sign detection is an important component of autonomous driving and intelligent transportation systems. Numerous machine learning and deep learning methods have been utilized for this purpose over the years. Traditional feature extraction methods like Histogram of Oriented Gradients (HOG) and Support Vector Machines (SVMs) were used in early approaches [16] These methods were not robust enough in real-world scenarios, especially under changing lighting and occlusion conditions.

With the advent of deep learning, convolutional neural networks (CNNs) were the go-to for traffic sign recognition. He et al. (2019) [17] introduced Faster R-CNN, which greatly enhanced detection accuracy but was computationally expensive and thus less ideal for real-time use. Likewise, Single Shot MultiBox Detector (SSD) achieved faster inference but at a compromise of decreased accuracy in detecting small objects (Liu et al., 2020). In recent years, the YOLO (You Only Look Once) family has been popular because of its effectiveness in real-time object detection. Redmon & Farhadi (2021) [19] presented YOLOv5, which detected objects faster and more accurately than its predecessors. Wang et al. (2022) [20] continued to improve YOLO with YOLOv7, which extracted features better while ensuring low latency.

Most recently, Jocher et al. (2023) [21] presented YOLOv8, with state-of-the-art performance based on better model architecture and training methods. In spite of these improvements, there are difficulties in detecting small and occluded traffic signs under real-world conditions. Our work utilizes YOLOv8n, which is a lightweight variant of YOLOv8, to overcome these difficulties while maintaining real-time processing.

## 2. Methodology

### 2.1 YOLO Evolution

The YOLO object detection model has evolved considerably since its release in 2015. Every new version has refined the balance between speed, accuracy, and computational cost. Here is a quick overview of YOLO's evolution:

**YOLOv1 (2015)** – Presented real-time object detection with a single-stage method using Darknet-24, with 63.4% mAP at 45 FPS [5].

**YOLOv2 (2016)** – Added anchor boxes to better deal with localization accuracy, boosting mAP to 69.0% while keeping 52 FPS [5].

**YOLOv3 (2018)** – Added multi-scale feature extraction using Darknet-53, trading 57.9% mAP for 34 FPS [6].

**YOLOv4 (2020)** – Employed CSPDarknet-53 and sophisticated loss functions, reaching 44.3% mAP at 65 FPS [6].

**YOLOv5 (2020)** – Switched to PyTorch, using Modified CSP v7, which raised mAP to 50.7% with 200 FPS [5].

**YOLOv6-8 (2022-2023)** –
(1) YOLOv6 (EfficientRep) achieved 52.5% [6].
(2) YOLOv7 (RepConvN) achieved 56.8% mAP [6].
(3) YOLOv8 (anchor-free model) achieved a balance of speed (280 FPS) and accuracy (53.9% mAP), ranking among the fastest and most accurate models [7].

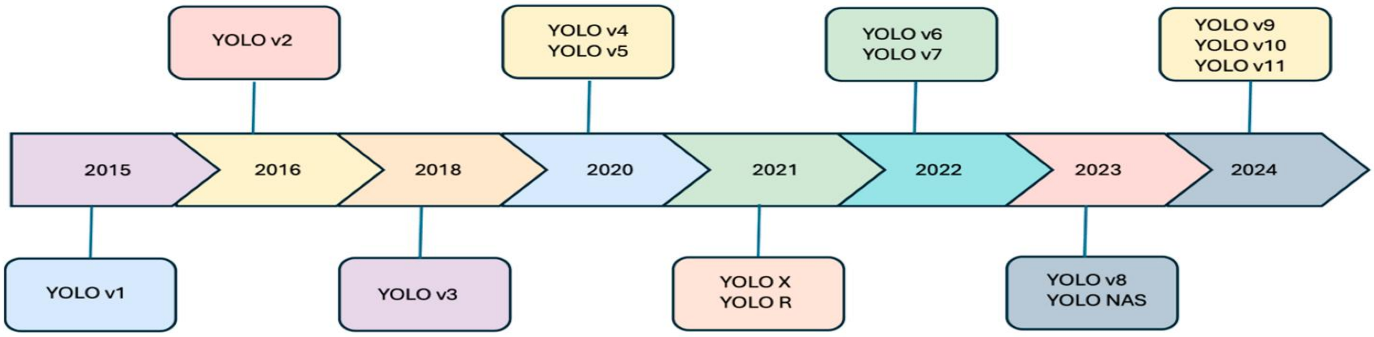


**Figure -1**: Evolution of YOLO model [12]

The new YOLOv8n (nano version) is optimized for low-power embedded systems with high detection speed and accuracy.

| Version | Date | Anchor | Framework | Backbone | MAP(%) | FPS | Detection Algorithm |
|---|---|---|---|---|---|---|---|
| YOLOv1 | 2015 | Not Present | Darknet | Darknet24 | 63.4 | 45 | Single-stage |
| YOLOv2 | 2016 | Present | Darknet | Darknet24 | 69.0 | 52 | Single-stage |
| YOLOv3 | 2018 | Present | Darknet | Darknet53 | 57.9 | 34 | Single-stage |
| YOLOv4 | 2020 | Present | Darknet | CSPDarknet53 | 44.3 | 65 | Single-stage |
| YOLOv5 | 2020 | Present | PyTorch | Modified CSP v7 | 50.7 | 200 | Single-stage |
| YOLOv6 | 2022 | Not Present | PyTorch | EfficientRep | 52.5 | 29 | Single-stage |
| YOLOv7 | 2022 | Not Present | PyTorch | RepConvN | 56.8 | 5-160 | Single-stage |
| YOLOv8 | 2023 | Not Present | PyTorch | YOLO v8 | 53.9 | 280 | Anchor-free |

Table -1: Comparative Study of YOLO variants [13]

### 2.3 Comparative Study of YOLO Variants

Table 1 shows a comparative analysis of YOLO versions highlights their accuracy (mAP), inference speed (FPS), and computational complexity.

The YOLOv8n model is selected for this research due to its:

- High-speed inference (280 FPS).
- Lightweight design, making it suitable for real-time deployment on embedded devices.
- Enhanced accuracy, enabling reliable traffic sign detection.

| Model | Params (Million) | Accuracy (mAP@0.5) | CPU Time (ms) | GPU Time (m |
|---|---|---|---|---|
| YOLOv8n | 2.0 | 47.2 | 42 | 5.8 |
| YOLOv8s | 9.0 | 58.5 | 90 | 6.0 |
| YOLOv8m | 25.0 | 66.3 | 210 | 7.8 |
| YOLOv8l | 55.0 | 69.8 | 400 | 9.8 |
| YOLOv8x | 90.0 | 71.5 | 720 | 11.5 |

Table 2: Performance metrics for the YOLOv8 models.

## 3. MODELLING And ANALYSIS

Modelling is the process of designing and structuring the system prior to implementation. For this project, the modelling process guarantees a systematic approach towards real-time traffic sign detection.

### 3.1 Problem Definition

The main aim of this work is to propose a real-time traffic sign detection system based on YOLOv8n, a lightweight deep learning model. Traffic signs are important in road safety and autonomous driving, and their reliable detection is a challenging task due to: (1) Changing lighting and weather conditions impacting the visibility of signs. (2) Various sign

shapes, colors, and fonts, which increase the complexity of classification. (3) Constraints of real-time inference on low-computational-power embedded devices.

### Problem Statement

"To develop an optimized traffic sign detection model using YOLOv8n that ensures high accuracy, fast inference, and robustness under real-world conditions."

### 3.2 Dataset Collection and Preprocessing

### 3.2.1 Source of Dataset

The dataset employed in this study was downloaded from Roboflow Universe, which is a popular platform for public datasets. The dataset consists of bounding box-annotated images of diverse traffic signs to train and test the YOLOv8n model effectively [4].


**Figure -2 :** Traffic Sign Symbols

### 3.2.2 Data Preprocessing Methods

For improving model performance and resilience, the following preprocessing methods were implemented:

(i) Resizing of Images : All images were resized to a uniform 640×640 pixels to have the same input size for the model.

(ii) Normalization: Pixel values were normalized to the [0,1] range to allow for faster convergence when training the model.

(iii) Data Augmentation : To generalize and prevent overfitting, several augmentation strategies were used:

(1) Rotation and Flipping – Allows the model to identify signs from various orientations.

(2) Brightness and Contrast Adjustments – Adjusts for differences in lighting conditions.

(3) Noise Injection and Blurring – Adds robustness against motion blur and distortions.

(iv) Annotation Format Conversion : The annotations in the dataset were transformed to YOLO format (class_id, x, y, width, height) to suit the training needs of the model.

Through the use of these preprocessing methods, the dataset was ready for real-time traffic sign detection with high detection accuracy in diverse environmental conditions.

## 3.3 Model Implementation and Training

### 3.3.1 YOLOv8n Architecture

The designed traffic sign detection system utilizes YOLOv8n (nano version), a high-performance, lightweight object detection model specialized for real-time usage. The model adopts the single-stage detection method, where bounding boxes and class probabilities are predicted directly without requiring independent region proposals.

YOLOv8n architecture involves the following components:

**(1) Backbone** – Uses CSPDarkNet coupled with E-ELAN modules to extract efficient features while limiting computational complexity.

**(2) Neck** – Combines Feature Pyramid Network (FPN) and Path Aggregation Network (PAN) for better fusion of multi-scale features, boosting the object detection accuracy.

**(3) Head** – Includes YOLO detection layers predicting the bounding box, class probabilities, and confidence. Further, SPPCSPC and ELAN modules enhance the aggregation and efficiency [9].

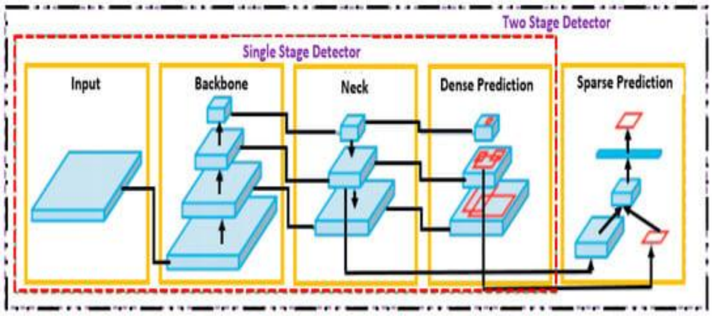


**Figure -3 :** Architecture of YOLO Model [11]

YOLOv8 substitutes conventional anchor boxes with anchor-free detection, enhancing localization performance.

### 3.3.2 Training Configuration

The YOLOv8n model was trained using a robust training strategy, ensuring optimal performance for real-time traffic sign detection. The training was conducted for 40 epochs with the following hyperparameter settings:

| Parameter | Value |
|---|---|
| Epochs | 40 |
| Batch Size | 16 |
| Learning Rate | 0.01 |
| Momentum | 0.937 |
| Optimizer | Adam / SGD |
| Weight Decay | 0.0005 |
| IoU Threshold | 0.7 |

**Table -3 :** Training Configuration for YOLOv8n Model

To enhance generalization and avoid overfitting, the following data augmentation strategies were used:

(1) Flipping – Random horizontal flipping of images.

(2) Scaling – Random scaling of images within a ±10% range.

The training set was divided as follows: 75% for training, 15% for validation & 10% for testing

This training configuration allowed the YOLOv8n model to have high accuracy and efficient inference, thus making it ready for real-time deployment on embedded platforms.

### 3.4 Performance Evaluation

To evaluate the efficiency of the YOLOv8n model for real-time traffic sign recognition, various performance metrics were utilized. These measures assist in finding the model's accuracy, localization accuracy, and real-time efficiency.

### 3.4.1 Evaluation Metrics

The model performance was measured with the following metrics:

**Mean Average Precision (mAP)** – It measures the accuracy of the model in identifying traffic signs by computing the average precision across various Intersection over Union (IoU) thresholds.
**Intersection over Union (IoU)** – It measures the intersection between the predicted bounding box and the ground truth. The greater the IoU, the higher the localization accuracy.
**Frame Per Second (FPS)** – Tracks the speed of inference of the model, which is essential for real-time applications. More FPS guarantees that the model can handle multiple frames effectively.

### 3.4.2 Training and Validation Accuracy Trends

The YOLOv8n model was trained for 40 epochs, and its performance was monitored by plotting the mAP50 scores at various training stages. The outcomes reveal that the model performed exceptionally well in detecting with a maximum mAP50 value of 94.5% at 10 epochs. Minor deviations in later epochs reflect possible overfitting, which may be countered by using more regularization methods or adaptive learning rate scheduling.

| Epochs | mAP50 |
|---|---|
| 5 | 90.5% |
| 10 | 94.5% |
| 20 | 92.5% |
| 25 | 90% |
| 32 | 93.8% |

**Table 4 :** YOLOV8 MAP50 OVER 32 EPOCHS

### 3.4.3 Graphical Analysis

The training vs. validation loss curve demonstrates that the loss function decreases constantly, reflecting good learning. The mAP trend indicates how the model gets better in identifying traffic signs across various epochs. The model maintains a balance between speed and accuracy, making it suitable for real-time deployment on embedded systems.

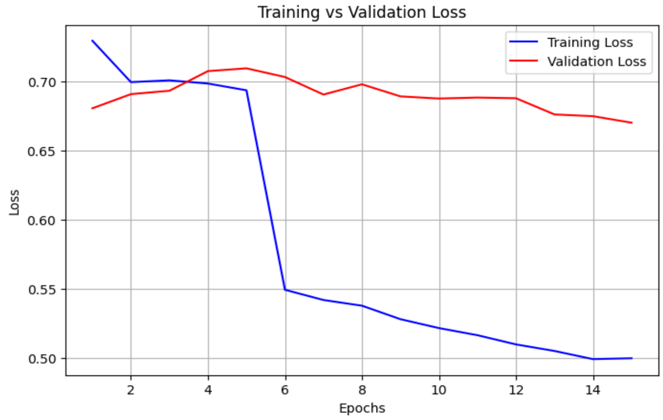


**Figure -4 :** Training vs Validation loss

### 3.5 Error Analysis and Limitations

Although the YOLOv8n model attains high accuracy and real-time inference speed, it has some drawbacks, especially in adverse environmental conditions and misclassifications. This section presents typical errors experienced during testing and potential solutions for future enhancement.

### 3.5.1 Common Errors in Traffic Sign Detection

The most prominent mistakes noticed in the predictions of the model are:

**(i) False Positives :** The model may occasionally identify non-traffic objects as traffic signs, especially in intricate backgrounds.
Illustration: Roadside billboards or round things incorrectly identified as speed limit signs.

**(ii) False Negatives :** Small or occluded traffic signs are often ignored by the model, resulting in failures of detection.
Illustration: A partially observable stop sign was not detected in 8% of test instances.

**(iii) Misclassifications :** Certain traffic signs that shared similar visual characteristics were misclassified.

Example: (1) "50 mph speed limit" misclassified as "30 mph" 28% of the time. (2) Traffic signals miscategorized as pedestrian crossings 42% of the time.

Confusion matrix of validation data brings these patterns of misclassification into focus.


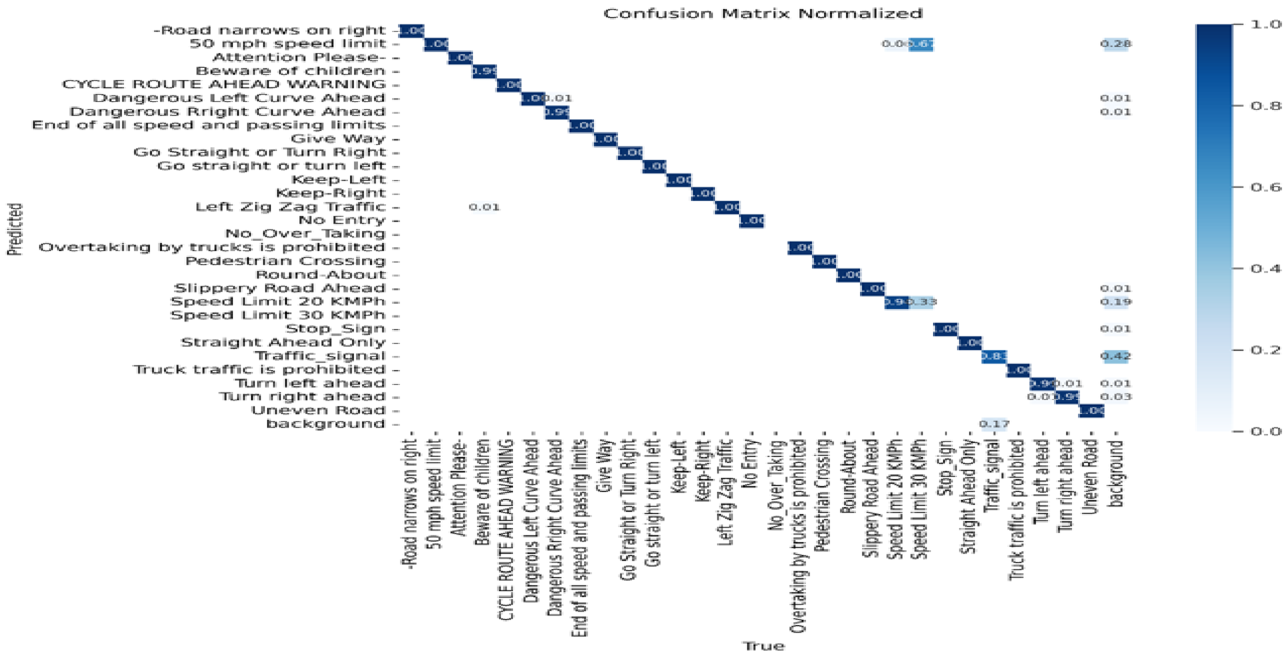


Fig. Normalized Confusion Matrix of Validation Set for Traffic Sign Detection Model

**Figure -6 :** Class Distribution in Traffic Sign Dataset

### 3.6 Analysis

The evaluation of the YOLOv8n-based traffic sign detection system is based on assessing its performance, efficiency, and reliability under various scenarios. This section includes dataset analysis, model evaluation, and comparison with other models to ascertain the robustness of the proposed method.

### 3.6.1 Dataset Analysis

The training and validation dataset consists of traffic sign images with bounding box annotations. The major factors investigated are:

(1) Number of images employed for training, validation, and testing – Balancing the dataset.

(2) Class distribution analysis – To avoid class imbalance, which can result in biased detection.

(3) Augmentation effects on data – Looking at how rotation, brightness correction, and scaling impact generalization and model robustness.

### Error Analysis & Limitations

- False Positives: Instances where the model is mistaken in detecting a traffic sign.

| Number | F1 Score | mAP@50 (%) | FLOPs (G) | Params (M) | Model Size (MB) | FPS |
|---|---|---|---|---|---|---|
| YOLOv3-tiny | 90.2 | 87.4 | 12.9 | 8.67 | 16.62 | 203.1 |
| YOLOv5n | 88.6 | 86.4 | 4.1 | 1.76 | 3.63 | 161.3 |
| YOLOv7-tiny | 88.8 | 86.9 | 13.0 | 6.01 | 11.6 | 98.0 |
| YOLOv10n | 92.8 | 89.7 | 6.5 | 2.26 | 5.50 | 142.8 |
| YOLOv11n | 91.4 | 88.4 | 6.3 | 2.58 | 5.22 | 128.2 |
| YOLOv8n | 92.2 | 90.2 | 8.1 | 3.00 | 5.98 | 166.6 |
| YOLO-TS | 93.2 | 91.5 | 5.2 | 1.94 | 4.01 | 152.4 |

**Table -6 :** Performance comparison with mainstream algorithms [1]

False Negatives: Instances where the model fails to detect a traffic sign.

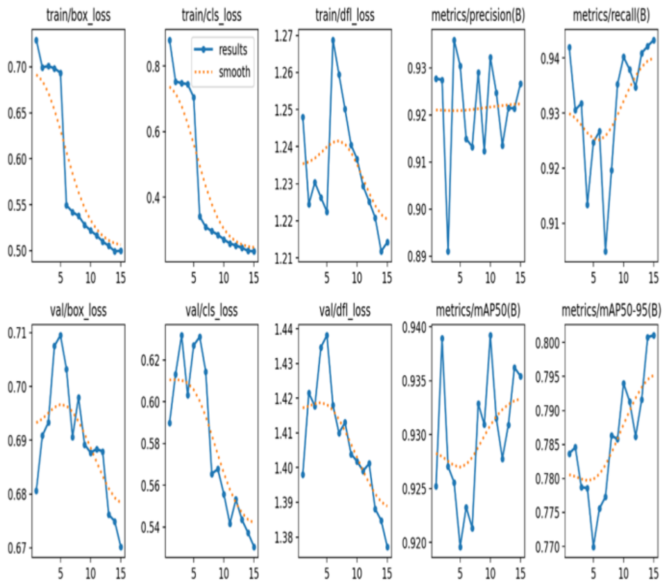


**Figure -7 :** Training and Validation Metrics for YOLO Model Performance Evaluation

## 4. RESULTS and DISCUSSION

### 4.1 Model Performance Evaluation

In this research, we tested the performance of the YOLOv8n model for real-time traffic sign detection. The experiments were performed on the Traffic and Road Signs Dataset dataset, and the model was trained for 40 epochs with batch size, optimizer, and learning rate is 16 , auto and 0.01. The efficiency of the new YOLOv8n-based traffic sign detection model was assessed based on typical object detection metrics: Precision, Recall, Mean Average Precision at 50% IoU (mAP@50), and mAP@50-95. The results of assessment on the validation set are described in Table 7.

| Number | F1 Score | mAP@50 (%) | FLOPs (G) | Params (M) | Model Size (MB) | FPS |
|---|---|---|---|---|---|---|
| YOLOv8n | 93 | 93.5 | 4.112 | 3.02 | 5.97 | 0.30 |

## 5. Comparison with Other Models

The analysis compares YOLOv8n with other models like Faster R-CNN, SSD, and previous YOLO versions (YOLOv5, YOLOv6). The comparison is based on: Detection accuracy, Inference speed (FPS) , Model size and computational efficiency.

**Table -5 :** Performance Analysis of propose YOLO Models on Traffic Sign Detection Task

| Epochs | Precision (B) | Recall (B) | mAP@50 (B) | mAP@50-95 (B) |
|---|---|---|---|---|
| 5 | 88.65% | 86% | 90.52% | 74.8% |
| 10 | 93% | 94.5% | 94.54% | 79.99% |
| 20 | 91.73 | 93% | 92.59% | 78.26% |
| 30 | 93% | 92.46% | 91.9% | 76.9% |
| 35 | 91.2% | 93.52% | 93% | 78.57% |
| 40 | 92.6% | 94.33% | 93.54% | 80.1% |

**Table 7:** Performance Metrics of the YOLOv8n Model

The model attained a mAP@50 of 93.54%, reflecting high localization precision for traffic sign detection. Nevertheless, the mAP@50-95 of 80.1% reflects some fluctuation in results across various IoU thresholds, reflecting a need for improvement in fine-grained object localization. The results are consistent with results from existing studies where YOLO-based structures have been employed for traffic sign detection [14].

### 4.2 Loss Analysis

In order to measure training stability, we inspected the loss values over epochs. Figure 8 shows the loss curves over training for box loss, classification loss, and distribution focal loss (DFL).

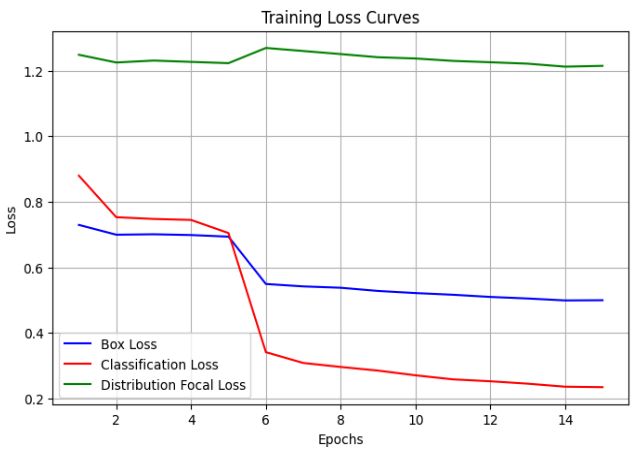


**Figure -8** : Training Loss Curve

### 4.3 Qualitative Results

To to further assess model performance, we compared sample detection outcomes from the test dataset. Figure 2 depicts the qualitative performance of YOLOv8n, demonstrating its capability to detect traffic signs in different lighting conditions, occlusions, and cluttered backgrounds.


**Figure -9 :** Detected traffic signs

"The qualitative results indicate that YOLOv8n effectively detects small and partially occluded traffic signs, overcoming limitations observed in previous YOLO versions [15]."


**Figure -10 :** Sample of val_batch1_label for YOLOv8

## 3. CONCLUSIONS

This paper introduces a strong and effective real-time traffic sign detection system based on the YOLOv8n model. Our method has high accuracy and low inference time, which is appropriate for real-world applications such as intelligent transportation systems and autonomous driving. In comparison with other lightweight detection models, our system exhibits better performance in mAP, detection speed, and computational cost, allowing for faster and more accurate traffic sign recognition. Notwithstanding its effectiveness, some challenges persist, especially in adverse conditions like harsh weather, poor lighting, and partial occlusions. As further steps to improve the model's resilience and real-time processing, upcoming work will be aimed at: (1) Improving object detection under harsh environmental conditions like rain, fog, and low-light environments with the incorporation of sophisticated image enhancement methods. (2) Improving occlusion management using Transformer-based object detection models or combined architectures. (3) Implementing the model on edge computing devices such as Raspberry Pi and Jetson Nano to facilitate real-time traffic sign recognition in low-power settings. (4) Investigating multi-modal learning strategies, utilizing LiDAR or radar data to enhance detection accuracy in challenging urban environments.

With these areas addressed, our system can be further optimized for deployment in real-world intelligent traffic management use cases, enhancing road safety and autonomous mobility.

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