

Real-Time Traffic Sign Recognition Using Integrated Camera Sensors and Yolov8 Algorithm

Alfiana Ramadhani ^{1,*}, Yusuf Athallah Adriyansyah ²

Email: alfianaramadhani@student.uns.ac.id

¹ Teknik Elektro, Universitas Sebelas Maret, Surakarta, Indonesia

² Department of Intelligent Computing and Analytics, Faculty of Information & Communication Technology, Universiti Teknikal Malaysia Melaka, Malaysia

* Corresponding Author

Abstract

Traffic signs are essential in maintaining smoothness and safety on the road. However, many drivers still violate them, causing various negative impacts. Traffic Sign Recognition (TSR) is a technology that detects and identifies various types of traffic signs by utilizing artificial intelligence in the domain of computer vision. TSR has been applied in various vehicle applications, such as the Advance Driver Assistance System (ADAS) and Autonomous Driving System (ADS). This system integrates camera sensors with the YOLOv8 algorithm, which has high accuracy and fast data processing. The data used were 2093 images and annotated through Roboflow. Then, data were trained through Google Collaboratory with a mAP evaluation result of 95.5%, showing that the system can detect objects accurately. The precision of the model in detecting objects was 93.5%, while its success rate was 93.3%. The testing results of the system can utilize images, videos, and cameras in real time.

Keywords: deep learning, sign, TSR, YOLOv8

I. INTRODUCTION

Traffic signs are essential in maintaining smooth and safe traffic on the highway. According to the Regulation of the Minister of Transportation of Indonesia Number 13, traffic signs are part of road equipment in the form of symbols, letters, numbers, sentences, and/or combinations that function as warnings, prohibitions, obstacles, or instructions for road users. There are more than 300 traffic signs in Indonesia based on data submitted by the Indonesian Transportation Agency. Despite the cruciality, many road users still violate traffic signs. These violations can undoubtedly increase the number of traffic accidents due to the lack of discipline by road users [1]. Violating traffic signs not only results in a fine but can also have severe consequences, both for the violators and others, such as accidents or disruption to traffic flow.

In the midst of efforts to overcome traffic sign violations, a technological innovation emerged in the form of Traffic Sign Recognition (TSR) as an effective solution to improve safety and smoothness on the highway. TSR is a technology that can detect

and identify various types of traffic signs [2]. TSR has been applied in various vehicle applications, such as Advanced Driver Assistance (ADAS) and Autonomous Driving Systems (ADS) [3]. The system utilizes integration between sensors to detect signs and inform the driver or even automatically adjust the vehicle's behavior.

In detecting various traffic signs, a method is needed for the recognition system. There are many methods, such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), color thresholding, and Convolutional Neural Networks (CNN) [4]. However, the accuracy of the image recognition is still lacking. Thus, an algorithm called You Only Look Once (YOLO) emerged as a solution with high accuracy and fast processing rate [5].

The study aims to demonstrate TSR using the integration of camera sensors with the YOLOv8 algorithm to detect traffic signs with high accuracy so that it can improve safety and smoothness on the highway. Section II of the study discusses the camera sensor and the YOLOv8 method applied to TSR. The methodology is discussed in Section III, the results

and discussion in Section IV, and finally, the conclusion is given.

II. LITERATURE REVIEW

A. Traffic Signs

Traffic signs are visual instructions and symbols placed on public roads to warn, inform, instruct, or regulate the behavior of road users, especially in dense and crowded urban areas [6]. They are made with simple visual symbolic language so drivers can easily understand and obtain information for safe driving [7].

Traffic signs are usually made of reflective materials that can be seen at night and in low-light exposures [8]. The reflective design not only improves safety but also ensures that drivers can easily recognize and understand the intended message.

Each traffic sign conveys information that is differentiated based on shape, color, and size, and is adjusted to environmental conditions. Among the many characteristics, the most prominent comparison is from the color and shape, where traffic signs can be divided into three types: prohibitory, warning, and information signs. Some of the specifications are provided [9].

1) Prohibitory Signs

Prohibitory signs are signs that serve to provide information to drivers about restrictions that must be obeyed. These signs are usually in circles and red.

2) Warning Signs

Warning signs are signs that serve to warn drivers if there is a potential danger on the road. These signs are usually yellow.

3) Information Signs

Information signs are signs that function to help drivers in driving their vehicles, such as for navigation or providing route guidance. Usually, these signs are square and blue.

The appearance of traffic signs can vary in different countries, making them difficult for computer systems to recognize. Developing technology that can detect and recognize all types of signs worldwide is challenging. In addition, difficult conditions, such as low or obstructed light intensity, different viewing angles, bad weather, and interference from objects or humans, can affect the detection of signs, making it increasingly difficult to detect accurately.

B. Camera Sensors

A camera sensor is an electronic device that detects light and converts it into an electronic signal that a computer system can process. This sensor is an essential component in digital cameras that are used to record images and videos.

Camera sensors commonly used in autonomous vehicles and ADAS have the same function as cameras found in most smartphones. They are affordable and widely available in various sizes and features. Camera sensors are practically easy, the system is also simplistic, so it can be adjusted to various types of vehicles and is user-friendly. This type of sensor has the ability to help identify objects and distinguish them from the background. It is used to understand the surrounding environment since all information is captured by the camera sensor [10].

C. YOLOv8 as Object Detection Algorithm

YOLO (You Only Look Once) is an algorithm developed to perform real-time object detection, image classification, and instance segmentation [11]. YOLO was created by Joseph Redmon and Ali Farhadi in 2015. Basically, YOLO uses an implementation of the Convolutional Neural Network (CNN) to predict bounding boxes, labels, and confidence probabilities [12].

The YOLO algorithm continues to develop rapidly every year, set with the main goal of achieving the best object detection results. Since its first introduction, YOLO has undergone various improvements and enhancements, with its latest version being YOLOv8. YOLOv8 was released in 2020 with additional optimizations and new modules to improve accuracy and efficiency. The architecture of YOLOv8 consists of a backbone network, neck, and head, as can be seen in Figure 1.

The following are the advantages of the YOLOv8 algorithm compared to other versions and algorithms [13].

- 1) YOLOv8 performs faster and more accurately in detecting objects.
- 2) YOLOv8 has a smaller architecture size, making it more practical than the previous versions.
- 3) YOLOv8 has better feature extraction, which results in a more accurate object detection.
- 4) YOLOv8 has multi-scale capabilities that can handle objects of various sizes in an image.
- 5) YOLOv8 can detect objects in a single image, making the object detection process easier.
- 6) YOLOv8 can detect objects in large images with high accuracy compared to previous versions.

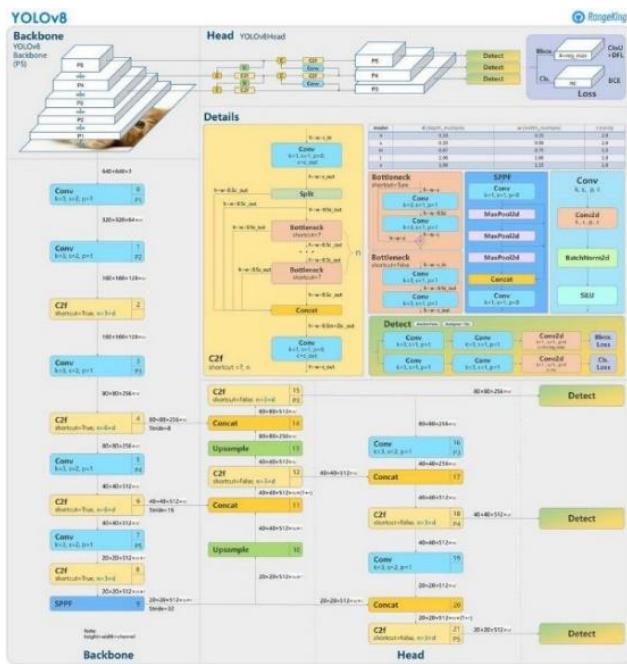


Figure 1. Architecture of YOLOv8

III. METHODS

The section discusses the research methods used in the traffic sign recognition system.

A. System Design

The system design was carried out to establish a structured series to provide a clear picture of the form of the system being built. The main purpose of the design process is to simplify the process of reading and understanding the structure and components involved in the system [14]. As part of the system design process, a system block diagram is also presented to visualize the main components and their interconnections. Figure 2 presents the flowchart of how the system works.

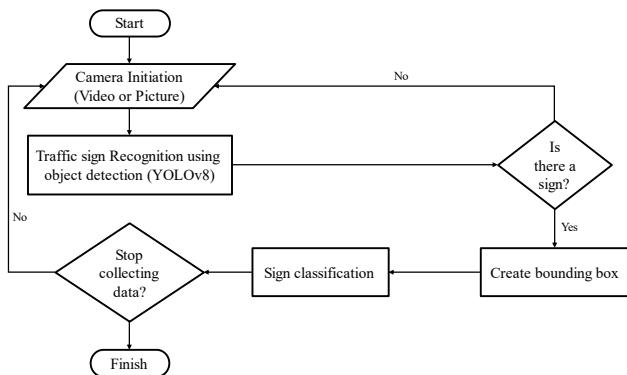


Figure 2. Flowchart of traffic sign recognition system's mechanism

B. Artificial Intelligence (AI) Project Cycle

The AI Project Cycle is a structured methodology for building AI projects [15]. This methodology consists of several stages, as described in Figure 3.



Figure 3. Methodology of AI project cycle

1) Problem Scope Definition

At this stage, identification was carried out on the scope of the problem to be solved. In this case, it is to reduce traffic violations on the highway through a traffic sign recognition system.

2) Data Acquisition

At this stage, relevant data must be collected, such as information about various traffic signs on the highway, including traffic lights, no-parking signs, no-entry signs, and many others.

3) Data Exploration

The next step was data exploration, where the data was analyzed to ensure that it met the criteria and was relevant to the problem to be solved. This process helps identify possible patterns and trends in the data and evaluate its quality and suitability for further processing.

4) Modelling

At this stage, a model that fits the problem to be solved was developed. The model can be designed using machine learning or deep learning to be used in the decision-making process, such as classifying traffic signs on the highway.

5) Evaluation

The final step was evaluation, where the model that had been created was assessed for its performance to ensure whether it had achieved the previously set targets. The evaluation was essential to ensure the effectiveness of the model in solving existing problems.

IV. RESULTS AND DISCUSSIONS

A. Data Acquisition

Data collection consists of images of various types of traffic signs on the highway. The data collection source used was Roboflow, which is a public dataset. The data type used was JPG format, with as many as 2093 images and a data size of 80 MB. A few

examples of the data collection are presented in Figure 4.

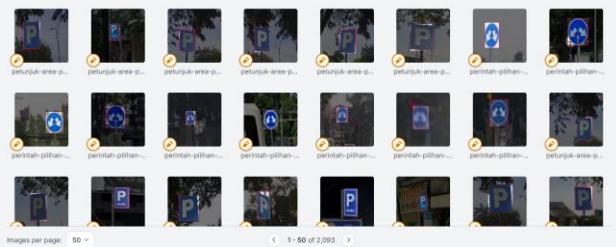


Figure 4. Dataset collection of traffic sign images

B. Data Exploration

Data exploration can be done to understand the characteristics of vehicle image data that will be used to train the model. Data exploration has several stages, namely as follows:

1) Image Resizing

All dataset images were resized to 640x640 pixels at this stage through the Roboflow website. Non-uniformity in pixel datasets can hinder the machine's ability to recognize patterns accurately. Image resizing shown in Figure 5.

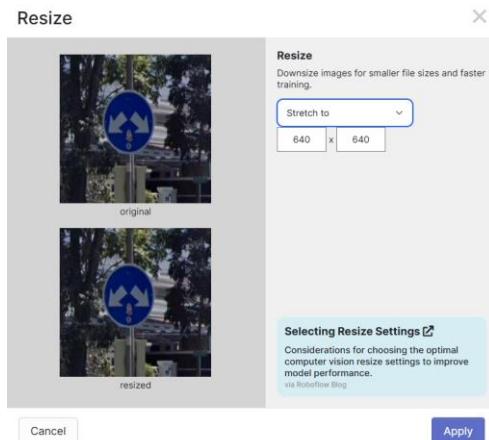


Figure 5. Image resizing

2) Image Annotation (Labeling)

Image annotation or labeling is the process of providing labels or additional information to data to help machines understand and classify the information they process. Image annotation shown in Figure 6. In this study, the dataset was divided into 21 classes, as shown in Figure 7.

3) Data Separation

The resized and labeled dataset was then divided into three groups: 1) train data with a percentage of 66%, 2) valid data with a percentage of 23%, and 3) test data with a percentage of 11%. The dataset was

separated through the Roboflow website, which aims to facilitate the training process and minimize overfitting and underfitting. Data separation shown in Figure 8.

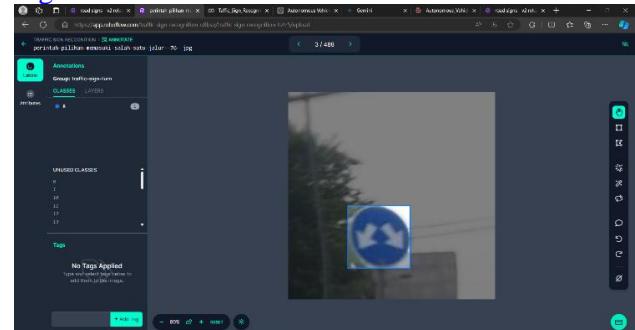


Figure 6. Image annotation

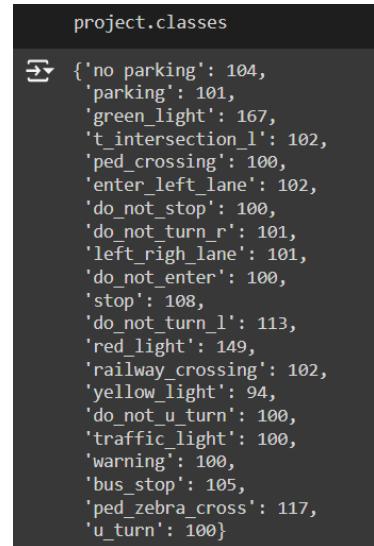


Figure 7. Classes in the dataset

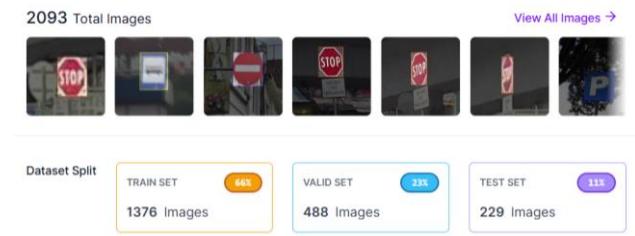


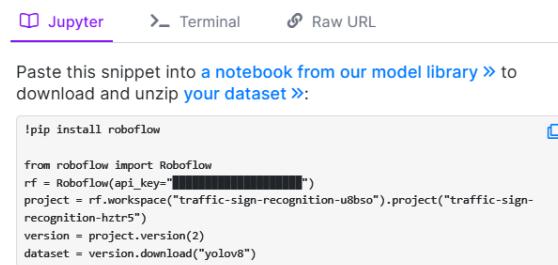
Figure 8. Data separation

C. Modelling

The modeling stage was carried out using the YOLOv8 model, which was configured via the Roboflow website. It was carried out to train the dataset that had been processed previously (pre-processing). Modeling was performed via Google Collaboratory in Python programming language. First, the dataset collected from Roboflow was imported via the source code in Figure 9 and was

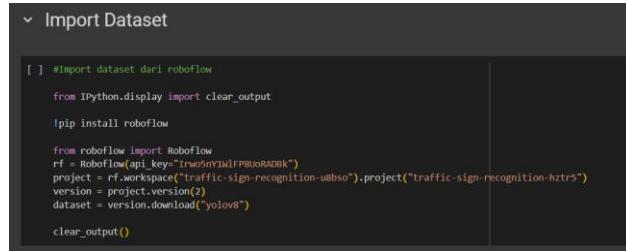
copied to the Google Collaboratory. After the dataset was imported, a training dataset of 100 epochs was performed. An epoch is a full cycle through the entire dataset used to train the model. As the number of epochs applied to the training increases, the performance of the model can be improved; however, the computation time also increases. In this study, 100 epochs of training dataset took 1 hour and 54 minutes. Dataset import process in google collaboratory shown in [Figure 10](#). Dataset training process shown in [Figure 11](#). Result of the training process shown in [Figure 12](#).

Your Download Code



```
!pip install roboflow
from roboflow import Roboflow
rf = Roboflow(api_key="REDACTED")
project = rf.workspace("traffic-sign-recognition-u8bs0").project("traffic-sign-recognition-hzr5")
version = project.version(2)
dataset = version.download("yolov8")
```

Figure 9. Source code from the roboflow website

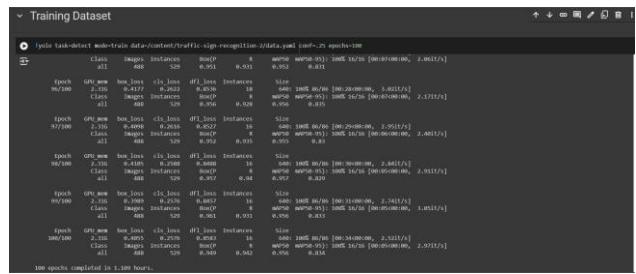


```
[ ] #Import dataset dari roboflow
from IPython.display import clear_output
!pip install roboflow

from roboflow import Roboflow
rf = Roboflow(api_key="REDACTED")
project = rf.workspace("traffic-sign-recognition-u8bs0").project("traffic-sign-recognition-hzr5")
version = project.version(2)
dataset = version.download("yolov8")

clear_output()
```

Figure 10. Dataset import process in google collaboratory



```
[ ] (pytorch) 100 epochs completed in 1.109 hours.
Optimizer stripped from runs/detect/train/weights/last.pt, 6.3MB
Optimizer stripped from runs/detect/train/weights/best.pt, 6.3MB
```

Figure 11. Dataset training process

A complete training process resulted in weights files stored in Google Drive, specifically in the following path folder.

100 epochs completed in 1.109 hours.
Optimizer stripped from runs/detect/train/weights/last.pt, 6.3MB
Optimizer stripped from runs/detect/train/weights/best.pt, 6.3MB

Figure 12. Result of the training process

D. Evaluation

Model evaluation was done by comparing the model prediction results with the actual results.

Metric evaluation was used to evaluate the model by observing its accuracy, precision, and success rate. The method was to input data in the form of JPG files to Google Collaboratory. Then, the program read the image and displayed the level of accuracy of image detection.

The evaluation stage in the study was carried out using the confusion matrix and the following loss and mAP graph.

Confusion matrix is a table used to measure the performance of a classification model. It consists of four main elements, namely True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN). TP is the number of data predicted as a positive outcome and is actually positive; FP is the number of data predicted as a positive outcome but is actually negative. TN is the number of data predicted as negative and is truly a negative outcome, while FN is the number of data predicted as negative but is actually a positive outcome. The four elements are found in four cells in the table, each representing one combination of predicted and actual values. The value in each cell represents the number of data with the same actual and predicted values. For instance, the TP cell in [Figure 13](#), specifically in both green_light row and column, shows that 41 data are actual green traffic lights correctly predicted by the model. Accuracy for each class shown in [Figure 14](#). Precision of the model shown in [Figure 15](#). Success rate of model [Figure 16](#). Comparison of model's precision and success shown in [Figure 17](#).

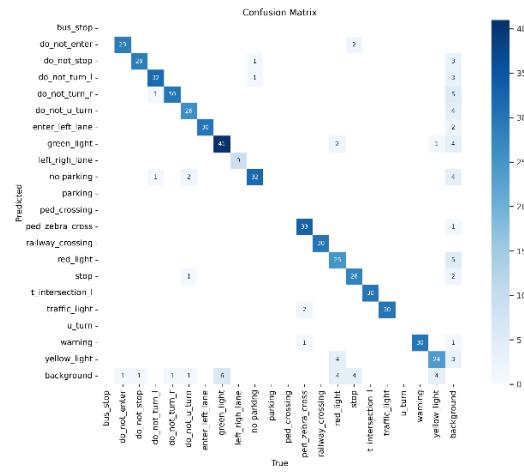


Figure 13. Evaluation results: confusion matrix

[Figure 18](#) presents two graphs: the loss graph and the mAP50 graph. The loss graph shows the loss values generated by the model during the training process. A smaller loss value indicates that the model is getting better at learning [16]. The mAP50 graph shows the mAP50 values generated by the model

during the evaluation process. The mAP50 graph is a measure of the performance of an object detection model that measures the accuracy and precision of the model at different object scales [17]. A higher mAP50 value indicates that the model is getting better at detecting objects.

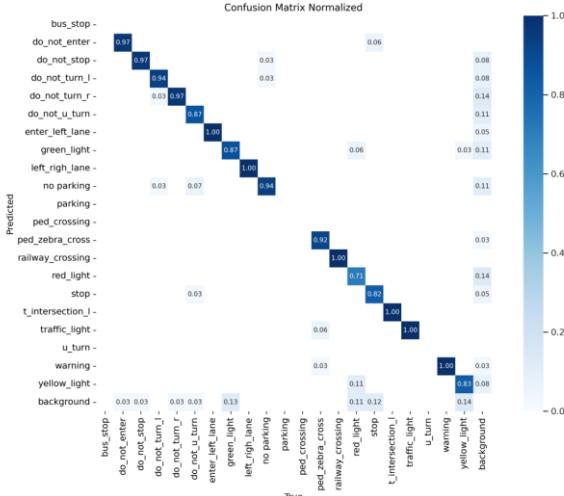


Figure 14. Accuracy for each class

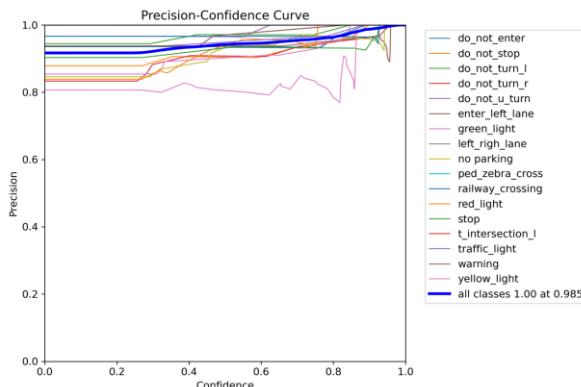


Figure 15. 0.935 precision of the model

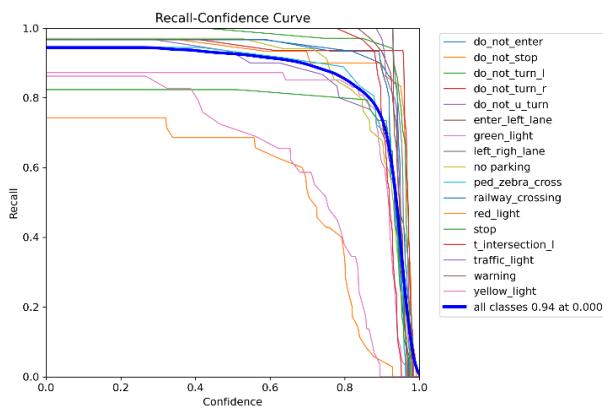


Figure 16. 0.933 success rate of model

The loss in both graphs shows that the model experienced a decrease in loss during the training

process. This prevalence shows that the model improved at learning during the training process. The mAP50 values in both graphs show that the model achieved a fairly high mAP50 value on the training data and validation data. This shows that the model performed well in detecting traffic signs. Final result of the model's evaluation shown in Figure 19. Testing results with images as inputs shown in Figure 20.

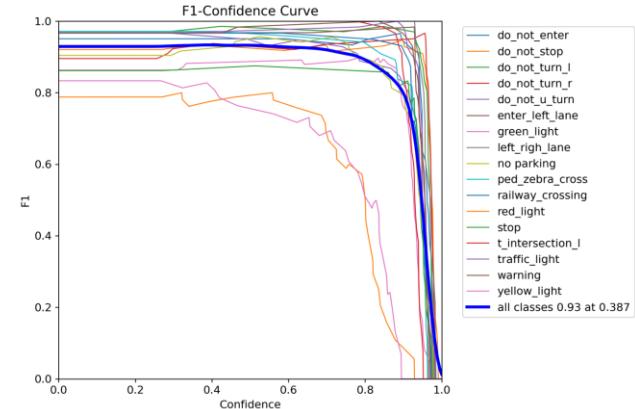


Figure 17. Comparison of model's precision and success

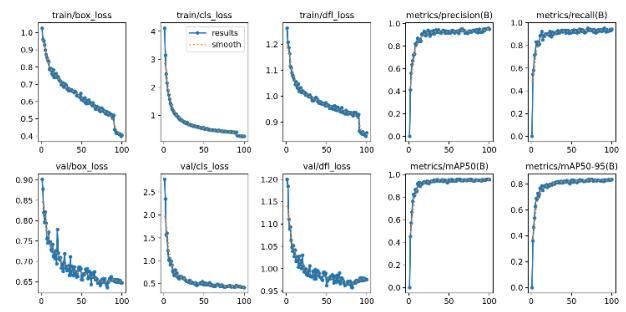


Figure 18. Loss and mAP50 graphs



Figure 19. Final result of the model's evaluation



Figure 20. Testing results with images as inputs

The evaluation results in this study show that the model trained using YOLOv8 has an mAP value of 95.5%, a precision rate of 93.5%, and a success rate of 93.3%. After being evaluated, the system was tested through direct input of images, videos, or cameras. The following are the system testing results. Testing results with videos as inputs shown in [Figure 21](#). Testing results with camera sensor's outputs as system inputs shown in [Figure 22](#).

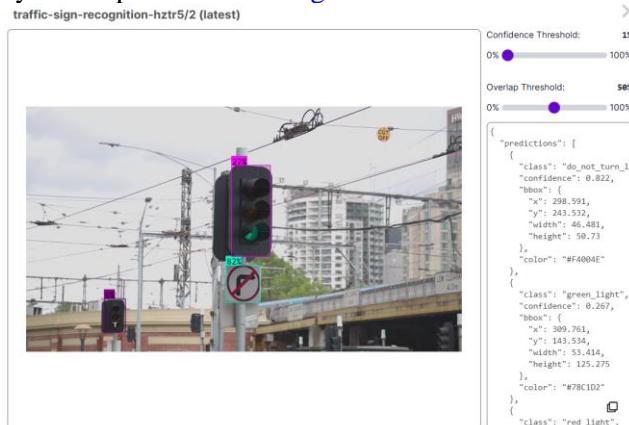


Figure 21. Testing results with videos as inputs

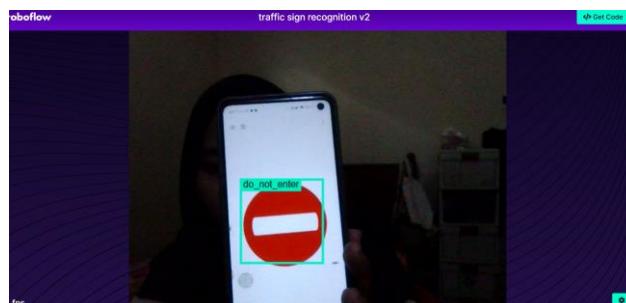


Figure 22. Testing results with camera sensor's outputs as system inputs

Based on the testing results, it was discovered that the model can predict or detect traffic signs well.

V. CONCLUSIONS

According to the real-time testing results of the traffic sign recognition system using the integration of camera sensors and the YOLOv8 algorithm developed, it functions as desired in detecting traffic signs on the highway, which was evidenced by the mAP results of 95.5%. The level of precision and success of the YOLOv8 model in training traffic sign data also received reasonably high values, which were 93.5% and 93.3%, respectively. In addition, the system successfully detected traffic signs in both image and video formats and through cameras operating in real-time.

Based on the conclusion, several suggestions can be considered, such as increasing the number of

datasets and using the latest version of YOLO. In addition, the study was only limited to simulation, so further research is needed to build a physical mechanism that can be seen in its application. Moreover, further research in optimizing traffic sign detection on autonomous vehicles is also necessary.

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