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Developing a Drowsiness Detection System for Safe Driving Using YOLOv9

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ABSTRACT — Drowsiness detection systems play a crucial role in safe driving, considering the high rate of traffic accidents caused mainly by drowsiness. Several drowsiness detection systems built using the eye aspect ratio (EAR), percentage of eyelid closure (PERCLOS), and convolutional neural network (CNN) methods still have limitations in terms of accuracy and response time. This study aimed to overcome these problems by applying the You Only Look Once version 9 (YOLOv9). This method has advantages in terms of speed and accuracy because it can detect objects in real-time in one processing stage. The dataset was collected independently from several sources in a real environment inside the vehicle with various lighting and viewing angles; then, labeling, preprocessing, and modeling processes were conducted. The model performance was evaluated based on precision, recall, F1 score, and mean average precision (mAP) metrics. The best model was optimized using several optimization techniques to determine the most optimal results. The results indicate that the YOLOv9 model trained using Nesterov-accelerated adaptive moment estimation (Nadam) optimization has a better image processing speed than other models. This model yielded a precision, recall, F1 score, mAP@50, mAP@50, mAP@50-95, and processing speed of 99.4%, 99.6%, 99.5%, 99.5%, 85.5%, and 52.08 FPS, respectively. The developed model can detect drivers' drowsiness signs, such as closed eyes, yawning, abnormal head positions, and unnatural hand movements, in real time. However, this model still has limitations in detecting drivers wearing sunglasses, so further development is needed to improve its performance in these conditions.

KEYWORDS — Safe Driving, Drowsiness Detection System, YOLOv9, Real-Time Object Detection.

I. INTRODUCTION

Safe driving is one of the crucial aspects that must be considered in daily life [1], given the high rate of traffic accidents in various countries, which often result in serious injuries or even fatalities. One of the main factors causing accidents is drowsiness while driving [2]. Based on data reported by the National Highway Traffic Safety Administration, a total of 693 fatal accidents occurred in the United States in 2022 [3]. In Indonesia, a 2023 study revealed that at least 79% of respondents had experienced drowsy driving at least once, and 32% of them reported nearly being involved in a fatal accident due to drowsy driving [4]. Data from various studies indicate that 20–30% of road accidents are caused by drowsy drivers [5]. Drowsiness while driving is extremely dangerous as it significantly reduces a driver's ability to react quickly and appropriately to emergency situations on the road, such as sudden braking or unexpected vehicle direction changes. Additionally, drowsiness can cause drivers to lose focus and concentration, thereby increasing the risk of accidents.

Several factors can cause drivers to experience drowsiness while driving, significantly increasing the risk of accidents. The first factor is lack of sleep, which prevents the body from getting adequate rest. This leads to fatigue in both the brain and the body, thereby drastically reducing the ability to stay focused and alert while driving [6]. The second factor is fatigue caused by long journeys, especially when drivers travel without taking sufficient rest breaks. In such conditions, the muscles become tense, and energy is depleted, making drowsiness more likely to occur [7]. The final factor is monotonous road conditions, such as straight and long highways with minimal variation, which often cause drivers to lose concentration and feel drowsy due to the lack of visual stimulation [8]. With the advancement of technology, various efforts have been made to minimize accidents caused by drowsiness, one of which is the development of driver drowsiness detection systems [9]. Early detection of drowsiness can provide timely warnings, allowing drivers to take preventive actions, such as taking short breaks to alleviate their drowsiness. However, most existing drowsiness detection systems still face several limitations in terms of accuracy and response time. The You Look Only Once (YOLO) method is a highly popular approach in the field of computer vision, particularly for real-time object detection tasks [10].

The YOLO method offers advantages in terms of speed and accuracy [11], as it can efficiently detect objects in a single stage, compared to other detection methods that typically require multiple processing stages [12]. Previous research has developed computer vision-based systems that integrated the eye aspect ratio (EAR) and percentage of eyelid closure (PERCLOS) metrics to detect drowsiness. This system utilizes a camera to monitor the driver's eye position, triggering an alarm if the eyes remain closed beyond a predefined duration. Although this method achieved an accuracy of up to 80%, its performance is influenced by lighting conditions and it is less capable of automatically adapting to variations in EAR thresholds for different drivers, requiring manual adjustments for each user [13]. In addition, other research using the convolutional neural network (CNN) method yielded an accuracy of 93%, although the detection results were very dependent on the quality of lighting and the orientation of the camera towards the driver's face [14].

In contrast, research utilizing the YOLOv8 method has demonstrated significant improvements. Leveraging a dataset encompassing various distracted behaviors and fatigue conditions, YOLOv8 exhibited exceptional performance with a precision of 97.5%, a recall of 92.8%, an F1 score of 95.1%, and a mean average precision (mAP) of 96.7% [15]. This system is also capable of detecting conditions in real-time with high consistency across diverse lighting scenarios. Therefore, the YOLO method is considered an ideal choice for implementing the proposed drowsiness detection system. In this study, this system was developed using YOLOv9, incorporating several versions, including YOLOv9t, YOLOv9s, YOLOv9m, YOLOv9c, and YOLOv9e, which are advanced iterations of YOLOv8. The model built using YOLOv9 was evaluated based on precision, recall, F1 score, and mAP metrics. The best model was then optimized using several optimization techniques, such as AdamW, stochastic gradient descent (SGD), Adam, Adamax, Nesterov-accelerated adaptive moment estimation (Nadam), RAdam, and RMSProp to determine the most optimal results.

The best model was implemented using Streamlit [16], making it accessible through both web and mobile platforms. The system was equipped with a warning feature in the form of an alert sound activated when the driver exhibited signs of drowsiness, such as closed eyes, yawning, abnormal head positions, and unusual hand movements. With this alert, drivers are expected to stop their vehicles promptly and take a short rest to reduce the risk of accidents. This system is anticipated to make a significant contribution to improving safe driving, particularly for private car drivers who are prone to fatigue during long-distance journeys.

II. METHODOLOGY

YOLO is one of the most popular real-time object detection methods in the field of computer vision [17]. It operates by dividing an image into a grid (small squares) and simultaneously identifying objects within the grid in a single processing step [18]. An illustration of how the YOLO method works is shown in Figure 1. This figure provides a simple illustration of how the YOLO method works. In this method, the input image is divided into a grid (e.g., 5 × 5), where each cell is responsible for detecting an object if the object's center falls within that cell. For each cell, YOLO predicts several bounding boxes that include positional coordinates (x, y), width, height, and a confidence score indicating the likelihood that the box truly encompasses an object. Additionally, YOLO generates a class probability map, representing the probability that the object within the box belongs to a specific category (e.g., dog, bicycle, or others). The predictions from the bounding boxes and class probabilities are then combined to identify the detected objects. Irrelevant boxes are eliminated using the non-maximum suppression (NMS) technique to avoid duplicate detections, resulting in more accurate final detection. By integrating detection and classification into a single stage, YOLO operates with exceptional speed and efficiency, making it ideal for real-time applications [19]. The following sections will elaborate on the steps involved in the research methodology. Below are the stages undertaken in this study.

A. GATHERING DATASET

The dataset was collected from several sources, totaling 1,400 samples. It consisted of images of drivers' faces exhibiting signs of drowsiness and awake conditions. The images were captured under various lighting conditions and from diverse angles. Figure 2 illustrates the signs of a driver in a drowsiness state, which include closed eyes, yawning, abnormal head position changes, and unusual hand movements. Meanwhile, Figure 3 depicts the signs of a driver in an awake state.

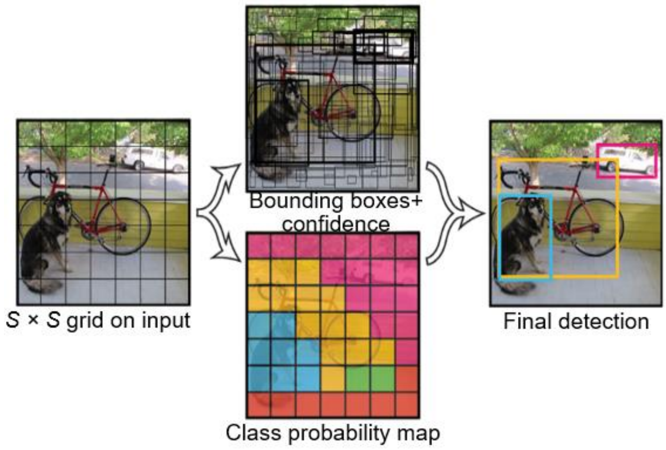

Figure 1. Model divides the image into an $S \times S$ grid, where each grid cell predicts a bounding box, a confidence score for that box, and a class probability. These predictions are encoded as a tensor with dimensions ($S \times S \times (B * 5 + C)$).

B. LABELING DATASET

Labeling is a graphical user interface (GUI)-based tool used for annotating images with bounding boxes, facilitating the creation of labeled datasets for computer vision projects [20]. In this process, the collected dataset was labeled into two main classes: drowsiness and awake condition. Figure 4 shows the results of the dataset labeling process categorized under the awake class, representing signs that the driver is not in a drowsiness state. Meanwhile, Figure 5 displays the drowsiness class, depicting signs of drowsiness in the driver.

C. PREPROCESSING DATASET

At this stage, the images were resized to 320 pixels. The YOLO algorithm was used to detect and isolate key facial areas such as the eyes, mouth, and head. This process generated bounding boxes to focus on critical regions associated with signs of drowsiness. The YOLO algorithm was applied at this initial stage to assist in the early detection of specific objects that indicate drowsiness. Consequently, in the subsequent training phase, the model could concentrate more effectively on relevant parts for classification.

D. MODELING YOLOV9

In this model development phase, the YOLOv9 algorithm was used, including its variants: YOLOv9t, YOLOv9s, YOLOv9m, YOLOv9c, and YOLOv9e [21]. Each version was trained using the same dataset and tested on test data to obtain evaluation results.

E. MODEL EVALUATION

The trained model was evaluated using metrics such as precision, recall, F1 score, mAP, and processing speed. Testing was conducted under varying lighting conditions, camera positions, and driver perspectives. The following is an explanation of each metric that was used.

1) PRECISION

Precision measures the accuracy of correct positive predictions (true positives) relative to all positive predictions

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Figure 2. Signs of drowsiness state.

Figure 3. Sign of awake state.

(true positives + false positives). It evaluates how accurately the system detects the correct objects [22]

$$P = \frac{TP}{TP+FP}. \tag{1}$$

2) RECALL

Recall measures how well the system detects all objects that should be identified by comparing the number of true positives to the total number of relevant objects (true positives + false negatives) [23].

$$R = \frac{TP}{TP+FN}. \tag{2}$$

3) F1 SCORE

The F1 score is the harmonic mean of precision and recall, providing a balance between the two [24].

$$F1 = \frac{2 \times P \times R}{P+R}. \tag{3}$$

4) MEAN AVERAGE PRECISION

The mAP is the average value of average precision (AP) for each class in the dataset, where Q represents the number of classes and $AP(q)$ is the AP for the q class. mAP evaluates the overall performance of the model across all classes [25].

$$mAP = \frac{1}{Q} \sum_{q-1}^{Q} AP(q). \tag{4}$$

F. MODEL IMPLEMENTATION

In the final stage, the model was selected based on the best metric results from the various YOLOv9 versions previously applied. The chosen model was implemented into a simple drowsiness detection system using the Streamlit. The system was equipped with an alert feature in the form of a warning alarm sound when the driver was detected to be drowsy.

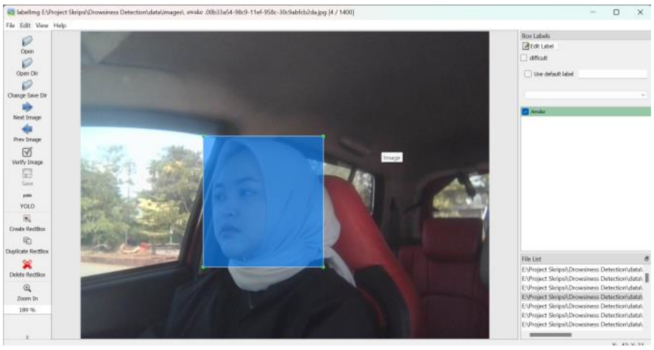

Figure 4. Labeling process results of awake.

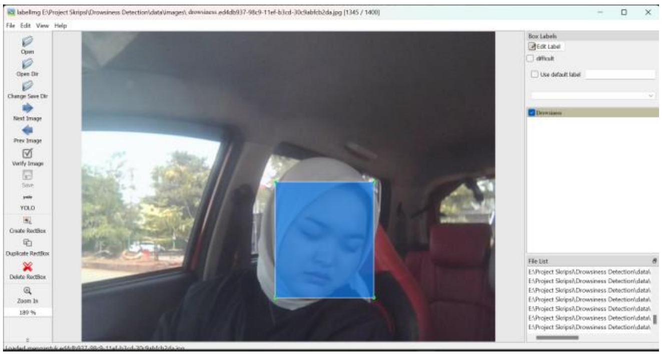

Figure 5. Labeling process results of drowsiness.

III. RESULTS AND DISCUSSION

Figure 6 illustrates the design of the drowsiness detection system developed. The drowsiness detection system developed was designed to identify signs of drowsiness in drivers, such as closed eyes, yawning, abnormal head positions, and unusual hand movements. When the system detects signs of drowsiness in the driver, it automatically emits a warning sound. Conversely, if no signs of drowsiness are detected, the system will not issue any warning. This system was designed to be implemented using the Streamlit framework, enabling the development of an interactive and user-friendly interface. The final output of this system was an application accessible via mobile devices and websites, allowing users to utilize the system without the need to purchase additional hardware. This makes it a practical and cost-effective solution for a wide range of users. In the next discussion, the results of the model evaluation, which was previously trained using the YOLOv9 method, will be explained. This evaluation includes an analysis of detection performance under various conditions, such as different lighting environments and diverse camera angles, to ensure the system's effectiveness in detecting signs of drowsiness in real-time.

A. MODEL EVALUATION

After going through several previous stages, training was carried out using the YOLOv9 algorithm for 20 epochs with AdamW optimization because, by default, the YOLO method uses this optimization: a learning rate value of 0.001667 and a momentum of 0.9. This training process was performed on a laptop with an AMD Ryzen 5 4500U with Radeon Graphics.

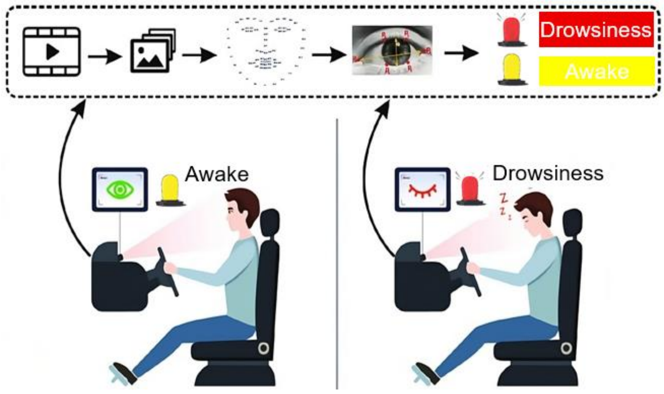

Figure 6. Design of drowsiness detection system.

The training process results are presented in Table I and Table II.

Based on the evaluation results of the YOLOv9 model presented in Table I and Table II, it can be concluded that the YOLOv9t model is the best choice for this study. This selection was based on the hardware limitations of the author's device, which was a laptop powered by an AMD Ryzen 5 4500U processor with Radeon Graphics. The YOLOv9t model demonstrated excellent detection performance, with precision, recall, and F1 score values of 99.4%, mAP@50 of 99.5%, and mAP@50-95 of 84.8%. These results indicate that YOLOv9t is capable of delivering performance comparable to more complex models while maintaining significantly better efficiency. One of its advantages is its computational efficiency, demonstrated by the lowest GFLOPs value of 6.4 and a relatively lightweight number of parameters, totaling to 1,730,214.

This makes YOLOv9t an energy-efficient model that minimizes computational requirements, making it highly suitable for deployment on devices with limited specifications. Additionally, the inference speed of this model reached 52.08 FPS, making it highly suitable for real-time inference applications, especially on hardware with limited computing power, such as laptops. Thus, the YOLOv9t model provides an optimal balance between detection performance and computational efficiency, making it the ideal choice for use in the system to be developed. In the next phase, this study focused on implementing the YOLOv9t model into a system designed to support real-time drowsiness detection. Figure 7 presents the training and validation performance of the YOLOv9t model. Based on the results of the YOLOv9t model training and validation graphs using AdamW optimization shown in Figure 7, the loss trend, both in training and validation, consistently decreases as the number of epochs increases. This indicates that the YOLOv9t model is progressively improving its learning capability and gradually minimizing prediction errors. In the evaluation metric graphs, such as precision, recall, mAP@0.5, and mAP@0.5-0.95, a steady increase was observed, approaching maximum values. This demonstrates that the model possesses excellent object detection capabilities, both in terms of accuracy and generalization to validation data. However, during the initial stages of training, the validation metrics, including precision, recall, mAP@0.5, and mAP@0.5-0.95, exhibited slight fluctuations. These fluctuations are natural and reflect the model's adaptation process to complex data patterns before eventually achieving stable convergence. Overall, the graphs indicate that the YOLOv9t model used in this study has demonstrated optimal performance, achieving a balance between high accuracy and good generalization capability. This suggests that the model can be further implemented in a real-time drowsiness detection system.

TABLE I
COMPARISON OF DIFFERENT YOLOV9 MODEL

Model	Precision	Recall	F1	mAP@50
YOLOv9t	99.4	99.4	99.4	99.5
YOLOv9s	99.6	99.4	99.5	99.5
YOLOv9m	99.6	99.5	99.6	99.5
YOLOv9c	99.4	99.5	99.4	99.5
YOLOv9e	99.2	99.5	99.3	99.4

TABLE II
ADVANCED COMPARISON OF DIFFERENT YOLOV9 MODEL

Model	mAP50-95	GFLOPs	Parameters	FPS
YOLOv9t	84.8	6.4	1,730,214	52.08
YOLOv9s	85.2	22.1	6,194,422	17.73
YOLOv9m	85.5	60.0	16,576,438	7.41
YOLOv9c	84.8	82.7	21,146,966	7.33
YOLOv9e	85.5	169.5	53,204,118	2.96

In the next stage, improvements and performance enhancements were conducted by comparing the evaluation results of the YOLOv9t model, which previously used the AdamW optimization algorithm, with several other optimization algorithms, such as SGD, Adam, Adamax, Nadam, Radam, and RMSProp. This comparison aimed to identify the best optimization method that can further enhance the model's accuracy and efficiency in the drowsiness detection process.

The evaluation results shown in Table III indicate that the optimization techniques used in training the YOLOv9 model significantly impact its performance, particularly in terms of convergence speed and generalization ability. Based on the evaluation results, optimizers such as AdamW, Adam, Adamax, Nadam, and RAdam demonstrated superior performance compared to other optimizers like SGD and RMSProp. This is due to the ability of Adam and its variants to automatically adapt the learning rate based on the first moment (mean) and second moment (variance) of the gradients. This adaptation enables more stable and faster parameter updates, allowing the model to achieve convergence efficiently, even within a limited number of epochs as in this training process.

In contrast, optimizers like SGD, which rely solely on direct gradients without incorporating momentum or adaptive learning rate mechanisms, tend to require more epochs to reach optimal results, making their performance less adequate for this dataset. While RMSProp is designed to handle unstable gradients, it exhibited lower generalization ability in this model, which could be attributed to suboptimal hyperparameter tuning or its dependence on specific data conditions. On the other hand, Adam and its variants excelled due to their stability, adaptability, and effectiveness in managing complex gradients, making them the most suitable choice for training the YOLOv9 model on an object detection dataset with two main classes: drowsy and awake. The following discussion focuses on using the YOLOv9t model with the Nadam optimizer. Table III shows that Nadam achieves slightly better accuracy compared

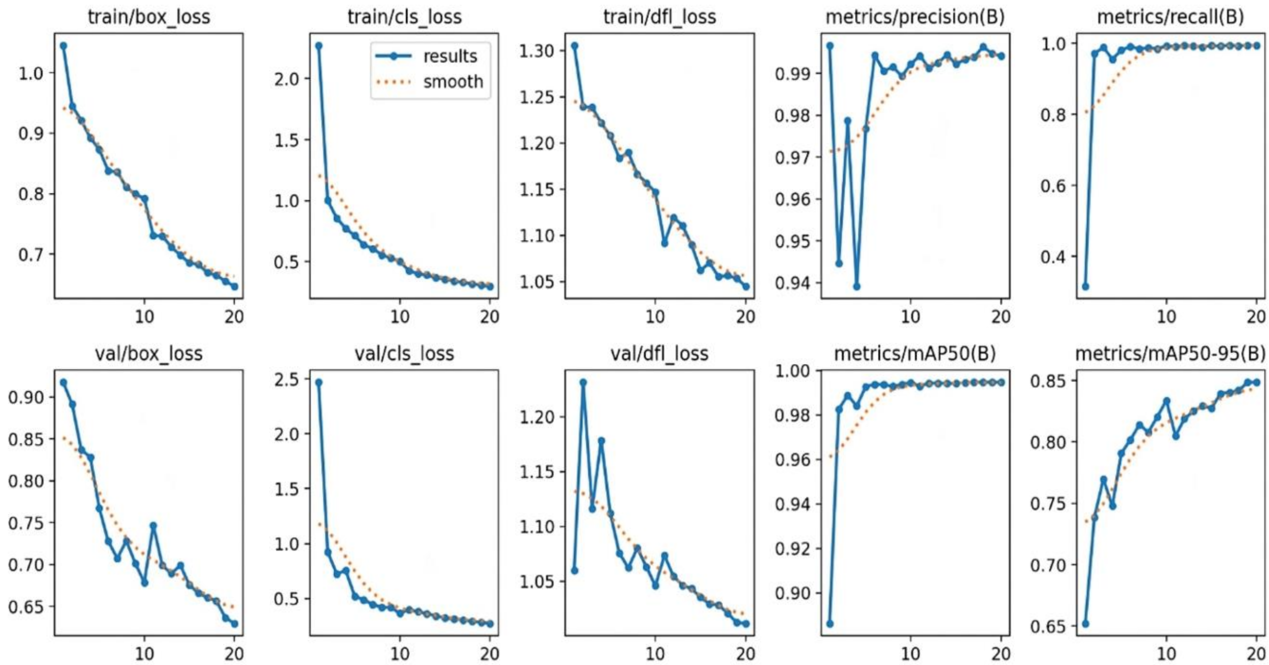

Figure 7. Training and validation performance of the YOLOv9t model with AdamW optimization.

TABLE III
COMPARISON OF YOLOV9T WITH DIFFERENT OPTIMIZERS

Opt	Precision	Recall	F1	mAP @0.5	mAP @0.5-0:0.9
AdamW	99.4	99.4	99.4	99.5	84.8
SGD	99.4	99.4	99.4	99.4	83.6
Adam	99.6	99.4	99.5	99.5	85.4
Adamax	99.5	99.5	99.5	99.5	85.4
NAdam	99.4	99.6	99.5	99.5	85.5
RAdam	99.6	99.4	99.5	99.5	84.3
RMSProp	98.8	98.1	98.5	99.4	82.5

to other Adam-derived optimizers. Figure 8 illustrates the training and validation performance of the YOLOv9t model using the Nadam optimizer.

The evaluation results of the YOLOv9t model with Nadam optimization (Figure 8) demonstrate improved performance compared to the results shown in Figure 7, which employed AdamW optimization. This is due to the advantage of Nadam optimization producing better performance than AdamW since it combines Nesterov momentum with Adam, allowing the model to see future gradient estimates before parameter updates. This accelerates convergence and improves training stability. While AdamW focuses more on regularization with weight decay to reduce overfitting, Nadam is superior in optimization exploration because Nesterov momentum helps avoid local traps. As a result, Nadam showed a higher mAP@0.5-0.9 value (85.5) than AdamW (84.8), indicating more accurate detection and better generalization in various object difficulty levels. However, in both optimization graphs, there are still fluctuations in the early stages of training. In the following discussion, this model will be implemented using Streamlit for further testing.

B. MODEL IMPLEMENTATION

At this stage, the YOLOv9t model, trained using the Nadam optimization algorithm, was selected for implementation into the system by utilizing the Streamlit framework. The Streamlit framework was employed due to its open-source nature and the ease it provides for building interactive and intuitive web applications. Streamlit is specifically designed to support data science and machine learning needs, with the ability to create engaging and informative user interfaces with just a few lines of Python code. One of its key advantages is its capability to support data visualization, machine learning model exploration, and the presentation of analysis results in a format that can be easily understood by both technical and non-technical users. By leveraging Streamlit, the process of delivering analytical results becomes more efficient and effective [26].

In the context of this drowsiness detection system, Streamlit is an ideal choice as it enables the integration of complex machine learning models with a simple yet functional user interface. This makes it easier for end-users to utilize the system without needing to understand the technical details of the model's implementation. Furthermore, Streamlit also supports development flexibility, such as customizing the interface or adding additional features according to user needs. Based on these advantages, this framework was chosen as a core component in system development.

Figure 9 shows the implementation results of the YOLOv9t model using Nadam optimization. The results demonstrate that the model is highly capable of detecting signs of drowsiness and wakefulness with excellent performance. The model exhibited consistent accuracy across various tests, including in environments with varying lighting conditions. Each prediction generated a confidence score with an average of approximately 0.88. This score is considered very good, as a confidence score closer to 1 indicates higher certainty in the model's predictions. The high confidence score indicates that the model can deliver reliable predictions in real-world scenarios. The model also demonstrated a very high image processing speed of 52.08 FPS. With its ability to consistently detect both drowsiness and awake signs under various lighting conditions, the model

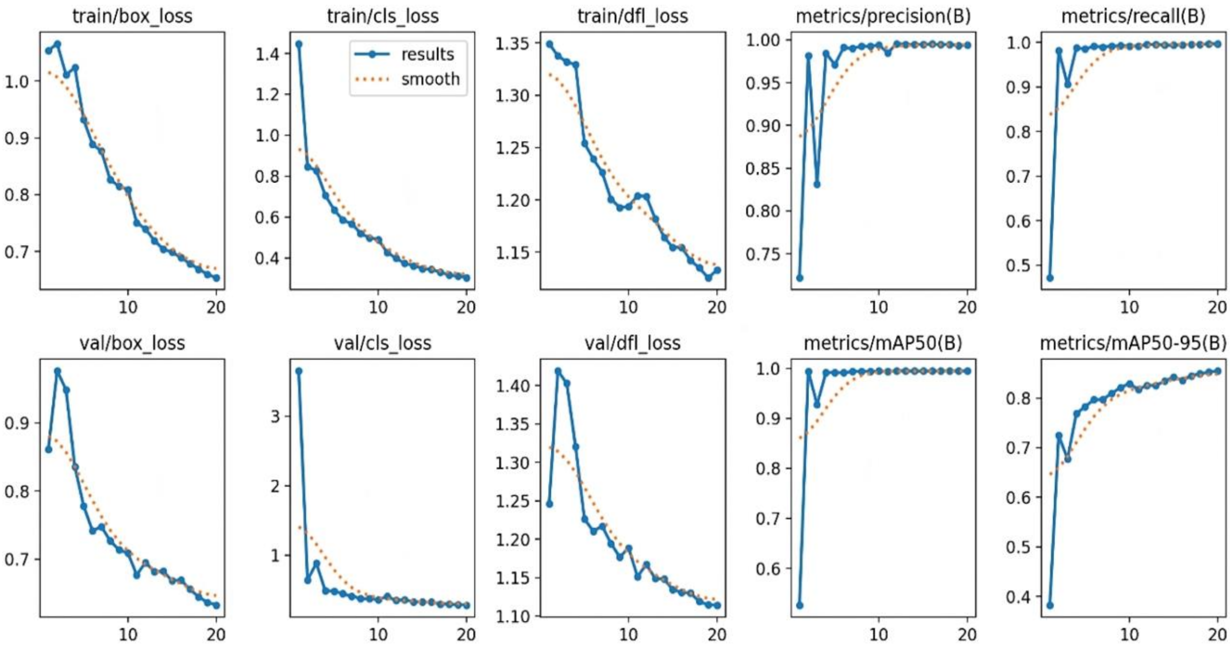

Figure 8. Training and validation performance of the YOLOv9t model with Nadam optimization.

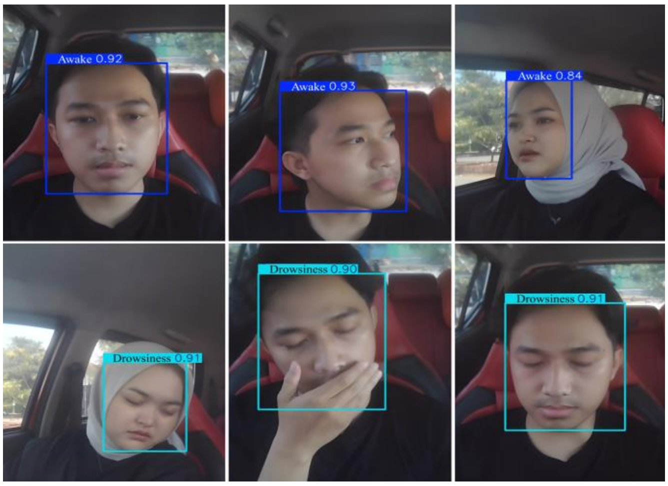

Figure 9. Implementation of the YOLOv9t model with Nadam optimization.

showcases superior performance. However, this model still has limitations in detecting drivers wearing sunglasses, so further development is needed to improve its performance in these conditions.

IV. CONCLUSION

The research results indicate that the YOLOv9t model trained using Nadam optimization demonstrates its ability to operate efficiently and accurately on hardware with limited computational power. Based on the evaluation results, this model has proven to be an optimal choice due to its excellent balance between performance and efficiency. The model achieved high detection metrics, with a precision of 99.4%, a recall of 99.6%, an F1 score and mAP@50 values of 99.5%, and a mAP@50-95 value of 85.5%, the lowest GFLOPs of 6.4, and the lightest parameter count of 1,730,214. Its inference speed of 52.08 FPS further underscores its suitability for real-time applications. During testing, the model demonstrated strong performance in detecting signs of drowsiness and wakefulness under various lighting conditions.

However, the results of both training and validation performance graphs on the model still have the same problem, namely that there are still fluctuations in the early stages of training, indicating room for hyperparameter adjustment. A more diverse dataset, the application of appropriate data augmentation, and a longer training process are necessary to get better model performance. In addition, this model still has limitations in detecting drivers wearing sunglasses, so further development is required to improve its performance in these conditions. Overall, this study focuses on the importance of a balance between accuracy, computational efficiency, and performance, especially for applications on devices with limited resources. Further research can be focused on optimizing the generalization of the model that has been created.

CONFLICTS OF INTEREST

The authors declare that there are no conflicts of interest in conducting this research or in the preparation of this paper.

AUTHORS' CONTRIBUTIONS

Conceptualization, Fernando Candra Yulianto, Wiwit Agus Triyanto, and Syafiul Muzid; methodology, Fernando Candra Yulianto and Wiwit Agus Triyanto; software, Fernando Candra Yulianto and Syafiul Muzid; validation, Fernando Candra Yulianto; formal analysis, Wiwit Agus Triyanto and Syafiul Muzid; investigation, Fernando Candra Yulianto; resources, Fernando Candra Yulianto; data curation, Fernando Candra Yulianto; writing—original draft preparation, Fernando Candra Yulianto; writing—reviewing and editing, Fernando Candra Yulianto, Wiwit Agus Triyanto, and Syafiul Muzid; visualization, Fernando Candra Yulianto; supervision, Wiwit Agus Triyanto and Syafiul Muzid; project administration, Wiwit Agus Triyanto.

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