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Microsleep detection on drowsy-driver using convolutional neural networks (CNN)

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Abstract. In a sleepy state, we may often not realize that we often fall asleep while moving; this event is known as microsleep when an individual microsleep for 4 seconds at a speed of 100 km / h, the individual is driving as far as 111 meters in an unconscious state. According to data from the Ditlantas Polda Metro Jaya, there were 7,565 accident cases during 2020, with 1,565 seriously injured people and 559 deaths. 61% were caused by human error, including sleepiness, unfocused, and fatigue, 9% due to vehicle factors, and 30% due to infrastructure and environmental factors. Microsleep detection methods through eye blinks have been developed, including using eye aspect ratio, namely manual thresholding by setting the minimum second of eye closing/blinking using the Support Vector Machine and Convolutional Neural Network (Vanilla) methods. In this study, the best model for detecting microsleep was ResNet50, with an accuracy of 99%. This system is implemented with a haar cascade classifier to detect closing eyes as a sign of microsleep. The existence of this research is expected to help reduce and even prevent accidents caused by microsleep based on the blink of a person's eye.

Keywords: *Microsleep, Convolutional Neural Network, eye aspect ratio*

1. Introduction

We may often not realize that we often fall asleep while moving; this event is known as microsleep may often not realize that we often fall asleep while moving; this event is known as microsleep. It is defined as episodes of behavioural sleep patterns and cessation of response to stimuli and attention lapses that can interfere with detecting and responding to stimuli at a critical event [1]. So, it is not surprising that microsleep is synonymous with poor driver performance. According to Rivera and Salas (2013), drowsy drivers alone have an elevenfold contribution to severe accidents and damage to short sleep durations ranging from 1-30 seconds [2]. When an individual microsleeps for 4 seconds at a speed of 100 km / h, the individual is driving as far as 111 meters in an unconscious state, the factors that cause microsleep are the amount of time spent making activities, the amount of sleep at night, the air temperature, the sound that affects concentration, the amount of light at the time of the incident, to oxygen levels in the brain [3].

Based on the information above, it can be concluded that microsleep is a dangerous phenomenon in driving. According to data from the Traffic Directorate of the Polda Metro Jaya, there were 7,565 accident cases during 2020, with 1,565 seriously injured and 559 people dying. 61% of accidents were caused by human error, including sleepiness, unfocused, and fatigue, 9% due to vehicle factors, and

30% due to infrastructure and environmental factors. The three factors of the accident were contributed mainly by human error, one of which was caused by disturbances caused by microsleep.

Microsleep detection techniques through eye blinks have been developed, including using eye aspect ratio, namely manual thresholding by setting the minimum second of eye closing/blinking using the Support Vector Machine and Convolutional Neural Network (Vanilla) methods [4] [5]. The previous research detected blinking as a sign of microsleep by developing Vanilla CNN and obtaining an accuracy of 83.7%, thus encouraging similar research to be carried out by developing other implementations of CNN architecture. The previous research detected blinking as a sign of microsleep by developing Vanilla CNN and obtaining an accuracy of 83.7%, thus encouraging similar research to be carried out by developing other implementations of CNN architecture. Before being more specific on detecting sleepy eyes as a sign of microsleep in drivers, facial emotion recognition was carried out by Ding, W., Xu, et al. in 2016. The research was tested using a video-based approach that implements deep learning methods and managed to get high precision better than 88% [6]. Detection of sleepy eyes is then carried out by optimizing the hardware-implemented using the Internet of Things to detect the presence of microsleep in motorists focused on the classification of emotions (facial expressions). In 2017, Lee, Song, Song, & Park [7] classified the driver's emotions through a multi-modal sensor that combines a near-infrared light camera and a thermal camera. The classification is carried out by implementing the Convolutional Neural Network (CNN) and getting an accuracy of 99% for detecting the rider's emotions. The development of artificial intelligence began to narrow its research focusing on detecting sleepy eyes (not through facial expressions or emotions); in 2017, a model was developed to predict sleepy drivers using an artificial neural network (ANN) method. ANN was trained on 16 datasets to detect microsleep from the blink of an eye by taking up to 5 minutes with an accuracy of only 70-80% [8].

The development of computer vision and machine learning provides developments for other detection methods that are carried out by detecting the presence of microsleep through real-time video by measuring the ratio of the eyes opening and closing when blinking. The Support Vector Machine (SVM) method was developed by Maior et al. l in 2020 [4]. The dataset used is obtained from DROZY – a public database for human drowsiness with a test accuracy of 94.44%. The system's weakness is that no warning is given to wake the driver. This system only develops a model to detect sleepy eyes through aspect ratio calculations. This research is expected to help reduce and even prevent accidents caused by microsleep based on the blink of a person's eye combined with deep learning implementation.

2. Proposed Method

This study aims to detect microsleep in motorists, which is detected early through the blink of an eye classified by the deep learning method. The initial stage is image acquisition by collecting datasets of eye images that are closed or not closed through various sources. The next stage is to carry out the dataset training process on several built CNN models, such as Vanilla CNN and ResNet50. From these several models, the training process and real-time testing were carried out on closed and opened eyes. The evaluation was carried out for each CNN model tested to determine which model was the best in detecting microsleep in motorists through the blink of an eye. Proposed methodology in microsleep detection is a follow:

Fig. 1. Steps in Methodology

2.1. Data Acquisition

A dataset was collected for the training process to determine the best CNN model in detecting closed and opened eyes, which are signs of microsleep. Datasets are collected from various sources to support

the accuracy of the method. Eye-close and open datasets were collected from UMass Amherst (13233 images) [9], Nanjing University (2423 images) [10], as well as multiple eye-opening and closing datasets from Kaggle (2900 images). The dataset is used in the CNN models training to detect microsleep based on close and open eyes.
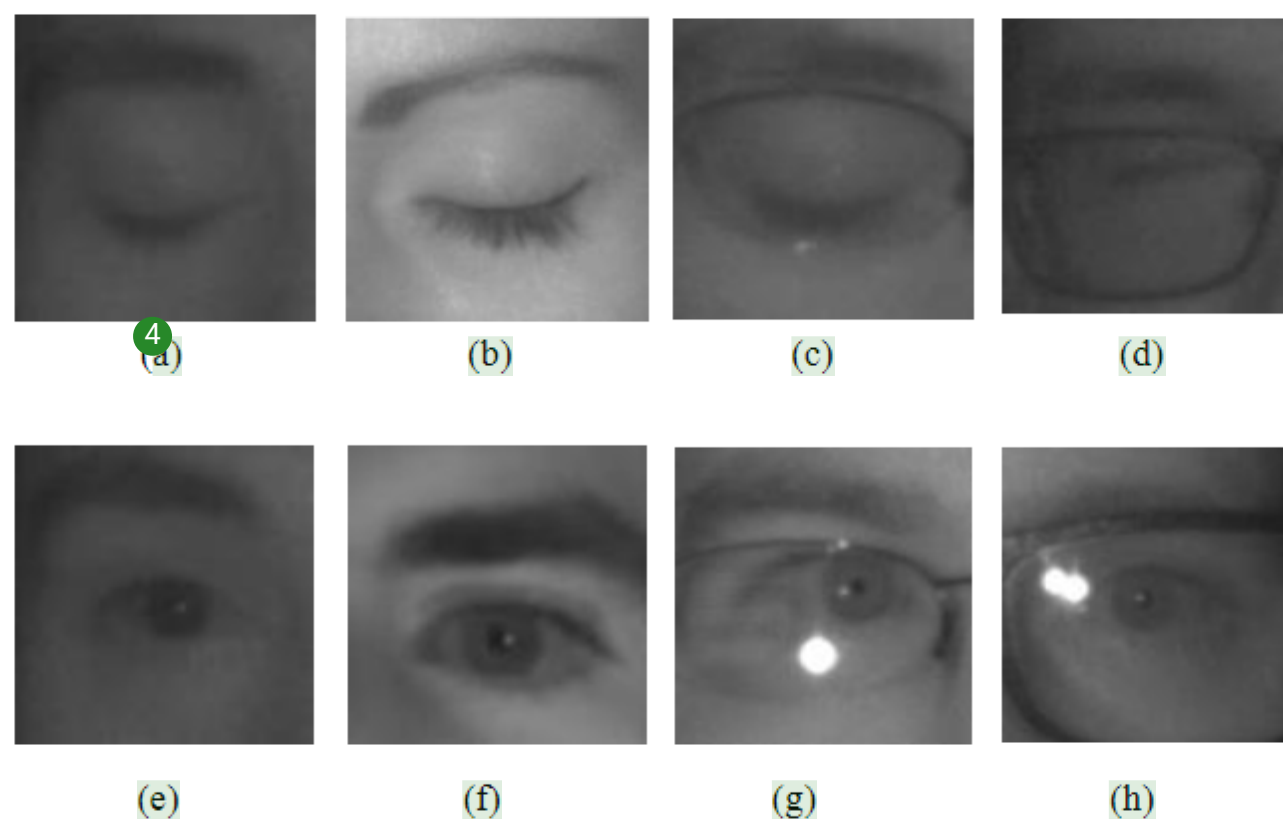

| (a) | (b) | (c) | (d) |
| (e) | (f) | (g) | (h) |

Fig. 2. From left to right sample of close and open dataset; (a)-(d) Various sample of close eyes and (e)-(h) Various sample of open eyes

*2.2.	Training and Testing CNNs Model*

The proposed CNN models in this study are Vanilla CNN and ResNet50. The Vanilla CNN model proposed in this study consists of 2 convolution sequences and a max-pooling layer which functions specifically as feature extraction. The convolution layer consists of 32 filters measuring 3x3 and 3 x 64 filters measuring 3x3. This architecture is based on a literature study conducted [11] [12] and from Keras documentation dog and cat classification [13], so to get good results, the researcher provides a max-pooling layer measuring 2x2 in each convolution layer. The last layer is fully-connected with a softmax activation function and binary cross-entropy as a loss function due to the binary classification for closing and opening eyes.
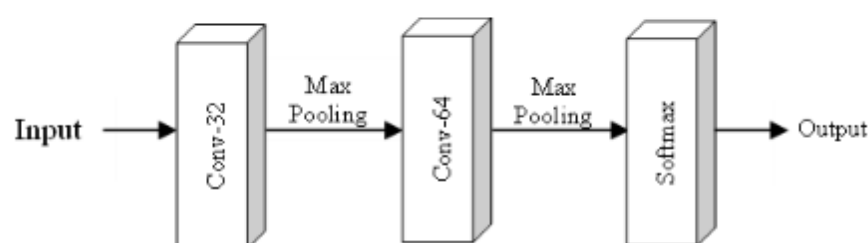

Fig. 3. Illustration of Vanilla CNN Model in this Study

As for the ResNet50 model, the model developed in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) was used by Kaiming He et al [14]. The ResNet50 architecture itself has 152 layers of high complexity, which are fine-tuned at the dense end according to the number of classes to be classified. The following is illustrated for the architecture on ResNet50 [15].
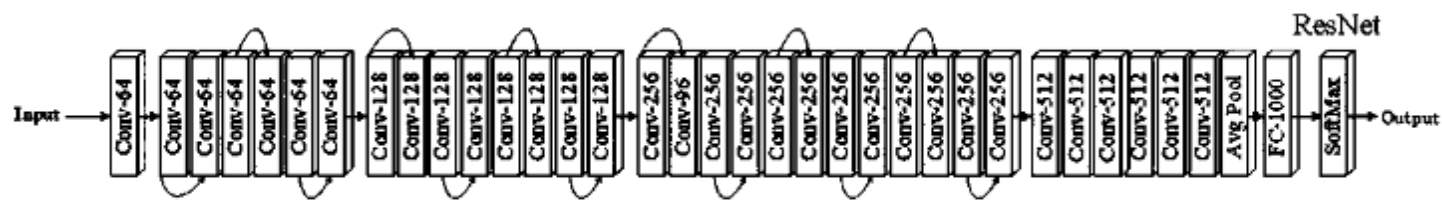
Fig. 4. Illustration of ResNet50 Model [15]

2.3.   Model Evaluation

The performance evaluation compares the CNN models, which give the best accuracy values after 5 epoch. The accuracy value shows the size of the ratio of the model in classifying correctly compared to the total number of classifications. The model with the best performance evaluation will be implemented in the microsleep detection system for sleepy eyes. The accuracy performance is given by:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

True positives (TP): Predicted positive and are actually positive.
False positives (FP): Predicted positive and are actually negative.
True negatives (TN): Predicted negative and are actually negative.
False negatives (FN): Predicted negative and are actually positive.

2.4.   Real Time Testing with Best Model

Based on the performance evaluation results obtained based on experiments, the model with the best performance will be implemented in detecting microsleep. The system is built by using the weight of the best model, which then detects sleepy eyes based on image processing training on eyes closed and eyes open. A threshold value is determined as a score for calculating the time eyes close, which will activate the alarm as a sign of microsleep.

3. Result and Analysis

The experiments were performed on the processor Intel® Core™ i5-8265U @1,8GHz CPU and 8GB memory running under Windows 11 OS. Implementation using Python and Keras library with a Tensorflow backend in Google Colab supported by a single 12GB NVIDIA Tesla K80 GPU. The model implementation also uses other libraries such as NumPy, sklearn, matplotlib, and pandas.

Preprocessing was applied to resize the dataset to 224x224. Vanilla CNN also set the same size and hyperparameters in the training process. The results for the training carried out for each model are as follows.

3.1.   Training in Vanilla CNN and ResNet50

In training conducted with Vanilla CNN, the accuracy is described in Table 1 below.

Tabel 1. Accuracy Vanilla CNN and ResNet50

Epoch	Accuracy	
	Vanilla CNN	ResNet50
1	0.9017	0.9738
2	0.9839	0.9921
3	0.9875	0.9932
4	0.9907	0.9955
5	0.9921	0.9954
Average	**0.97118**	**0.99**

Based on the training carried out in experiments with both CNN models, it was found that the performance of ResNet50 was better with an accuracy value of 0.99 (99%). The explanation of the training results based on the accuracy and loss graph is presented in the image below.
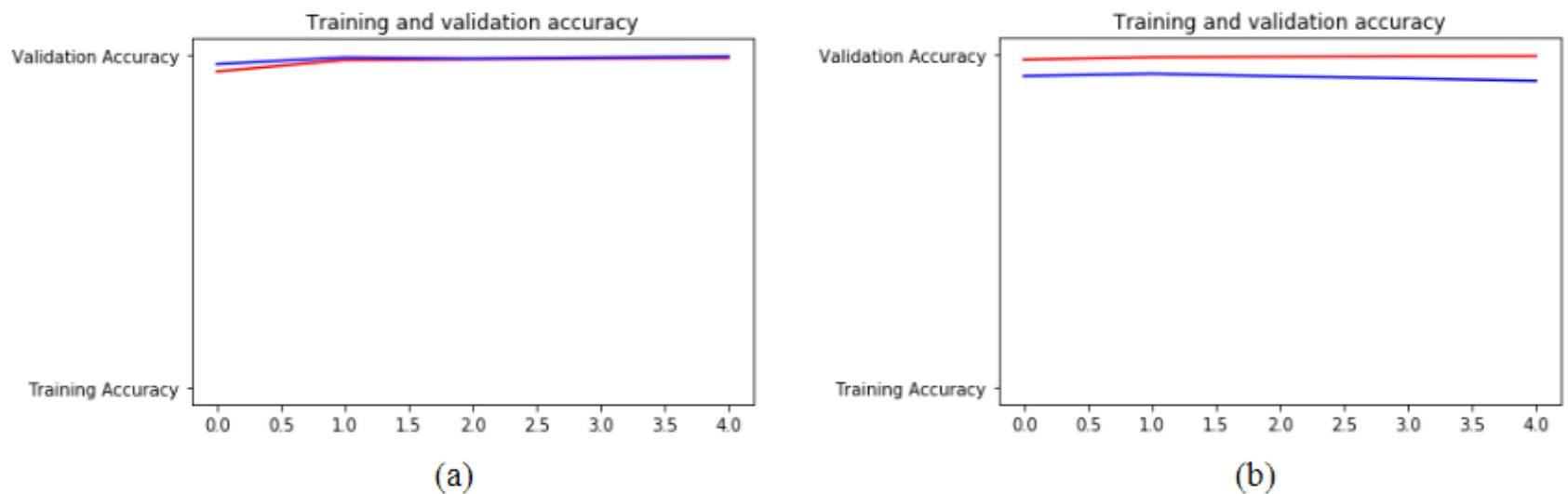

Fig. 5. From left to right. Training and validation accuracy; (a) Vanilla CNN; (b) ResNet50

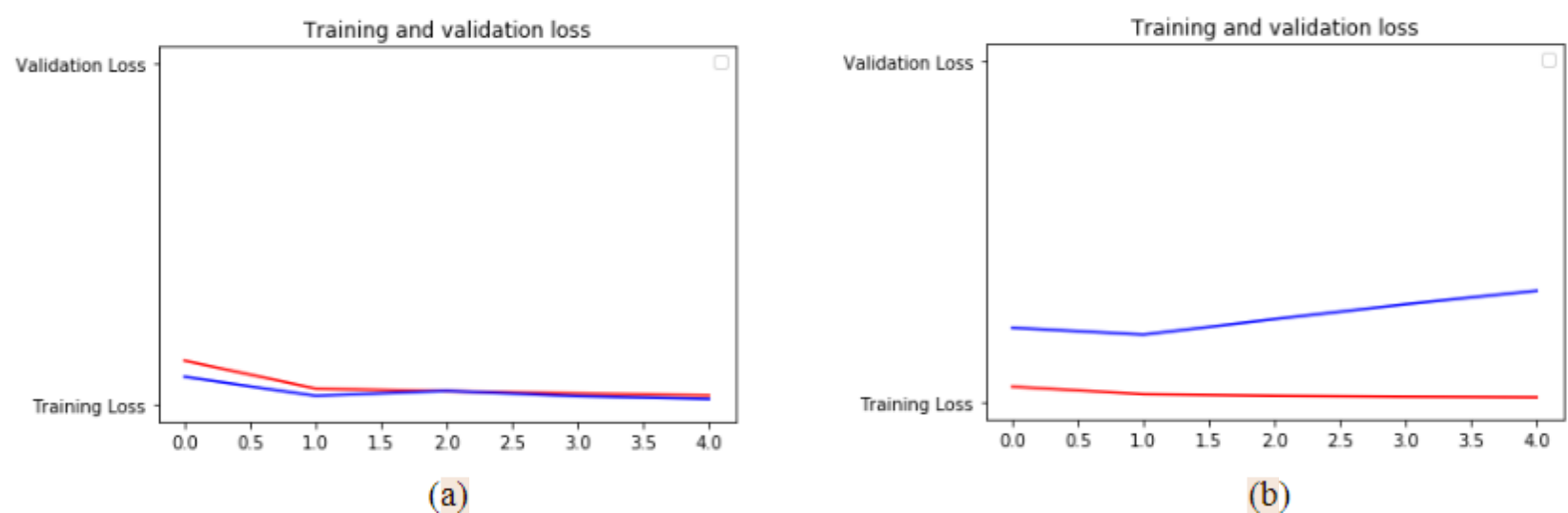Then the visualization of the loss function can be explained in the graph below.

Fig. 6. From left to right. Training and validation loss; (a) Vanilla CNN; (b) ResNet50

The model used in the implementation of sleepy eyes detection is ResNet50. ResNet50 has high accuracy due to the storage (residue) during the training process, making it more precise in classification.

3.2.   Implementation in Microsleep Detection

The implementation of microsleep detection on drowsiness eyes is carried out with a combination of the ResNet50 model and the Haar Cascade Classifier, which is also set to wait for closing the eyes so that a warning will appear the object is sleepy. The waiting time is used as a score indicating the presence of microsleep. The score sets if the rider closes his eyes for more than 2 seconds, then a warning notification will sound. The following figures are the results of the implementation of the system.
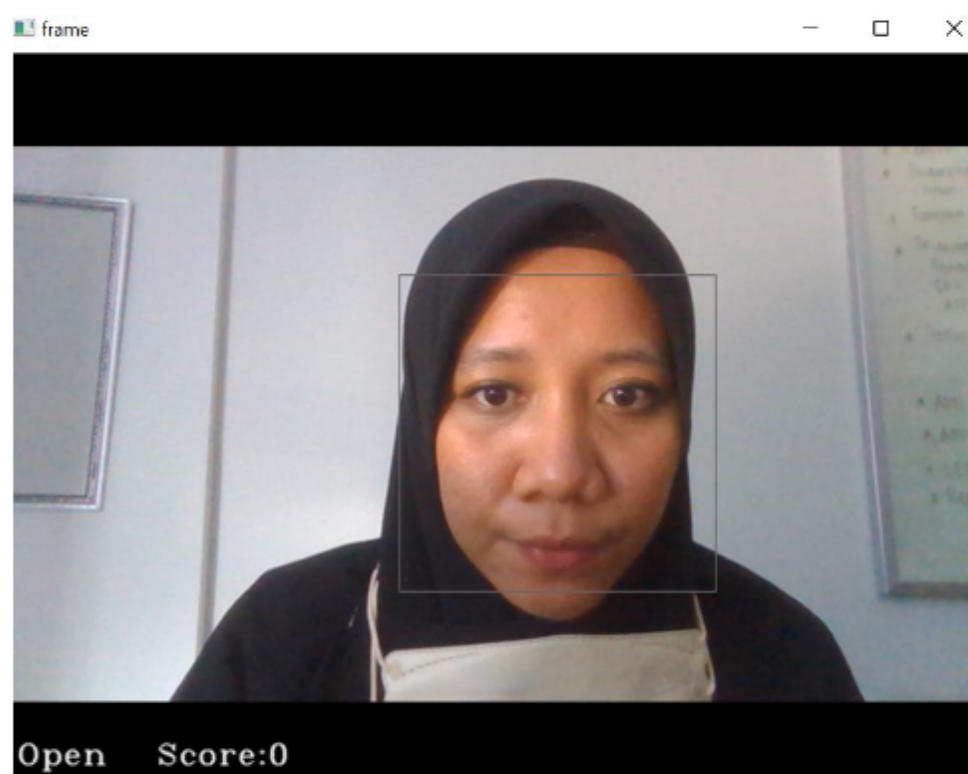
Fig. 7. Implementation system when eyes open

When the eyes open, there is a notification on the screen "Open" with a score of 0, so the alarm is not active. At that time, the driver who implemented the system was without microsleep detected. If the eyes are closed for more than 2 seconds, the score will show the value set to activate the alarm.
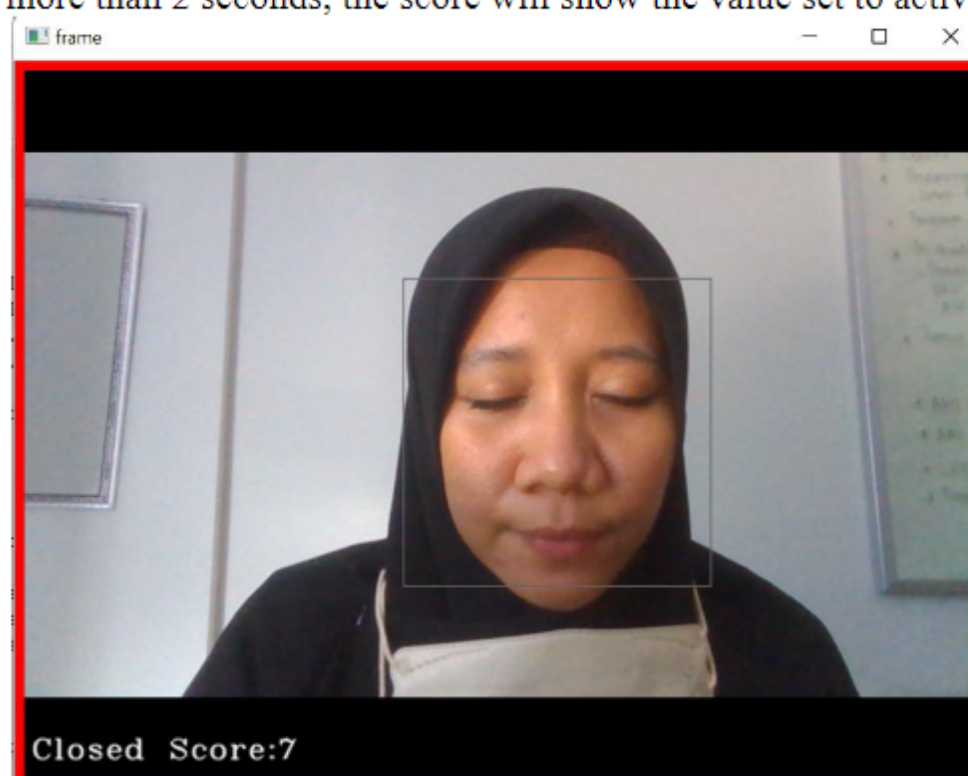

Fig. 8. Implementation system when eyes close

When the eyes are closed for more than 2 seconds, the score in the system display will increase. This more considerable value will activate the alarm so that drivers who experience microsleep will be surprised and prevent traffic accidents. The score is the ResNet50 model, classifying closed and open eyes.

4. Conclusions and Future Work

Closing eyes for a moment is one of the signs of microsleep that drivers often do not notice. In this study, microsleep detection through closed eyes is a method that can be used to prevent a drowsy-driving accident.

This study proposed several CNN models, namely Vanilla CNN and ResNet50, where the closed-eye classification model is ResNet50. The ResNet architecture saves residuals during the eye-close and eye-opening training process, making it more accurate. From the training results conducted before the detection system's implementation, an accuracy of 99% was obtained. The system can detect drowsiness by giving a warning in an active alarm if the eyes are closed for more than 2 seconds.

We will combine this computer vision system with signal processing in future works. Heart rate signal is also early detection of drowsy drivers and can identify microsleep well [16] [17].

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