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Enhancing road safety: machine learning-based driver drowsiness detection

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ABSTRACT

Cars are a means of land transportation commonly used by humans. With cars, human activities can become more efficient and save time, especially when traveling. When driving a car, drivers must have a high level of focus and must obey the rules and prioritize safety when driving. A traffic accident is an unexpected and unintentional event involving vehicles or road users. The negative impacts of traffic accidents such as material loss, illness and death can affect the level of public health, vehicle factors and environmental factors. Of the several factors that cause accidents above, accidents are caused by humans. Accidents that occur are greatly influenced by the condition of the vehicle driver. Driver fatigue shows that sleepy drivers are the cause of road accidents. This research will develop a machine learning model to detect drowsiness in car drivers. The model will detect the driver's eyelid image and yawn condition. The data used is driver images which are collected and then processed using machine learning. The results of the study provide an overview of the level of drowsiness of car drivers.

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1. INTRODUCTION

Cars are a means of land transportation commonly used by humans (Hasan et al., 2022). With cars, human activities can become more efficient and save time, especially when traveling (Fouad, 2023). When driving a car, drivers must have a high level of focus and must obey the rules and prioritize safety when driving. However, the large number of activities carried out can increase feelings of fatigue and drowsiness, thereby causing a decrease in the driver's focus value when driving a car (Ebrahim Shaik, 2023). Traffic safety and reducing the number of traffic accidents is a crucial and urgent issue throughout the world (Hatta Fudholi et al., 2021). Every year, thousands of lives are lost and millions of people are seriously injured in road accidents (Abbas, 2020). Motorized vehicles are the primary means of transportation in almost all countries, and drivers play an important role in maintaining road safety. One of the serious threats to traffic safety is driver drowsiness (Ahmed et al., 2023).

When drowsy, drivers experience decreased alertness, increased reaction time, and a higher risk of falling asleep at the wheel. This threatens not only the driver himself, but also all other road users (Jain et al., 2021). According to the United States' National Highway Traffic Safety Administration (NHTSA), it is estimated that drowsiness is a contributing factor in approximately 100,000 crashes each year. Most of these accidents result in serious injury or even death. A traffic accident is an unexpected and unintentional event involving vehicles or road users (Albadawi et al., 2022). The negative impacts of traffic accidents such as material loss, illness and death can affect the level of public health, vehicle factors and environmental factors (Gade et al., 2022). Of the several factors that cause accidents above, accidents are caused by humans. Accidents that occur are greatly influenced by the condition of the vehicle driver. Driver fatigue shows that sleepy drivers contribute up to 20% of the causes of road accidents (Nor Shahrudin & Sidek, 2020). Drowsiness when driving is a condition that is often ignored by car drivers and is one of the causes of frequent accidents, especially when driving long distances (Phan et al., 2021).

The increasingly rapid development of technology and science makes human activities easier. One of them is by detecting the drowsiness level of motor vehicle (car) drivers. Several methods have been developed to detect driver drowsiness by conducting studies measuring eye movements (Titare et al., 2021). Research that develops a method that can detect drowsiness in drivers by measuring the length of time the eyelids close and open (Pachouly et al., 2020). Research looking at the driver's physical condition by measuring heart rate, heart rate, head movements and vehicle behavior is a determining factor in detecting driver drowsiness (Magán et al., 2022).

Therefore, detecting driver drowsiness quickly and accurately is an important step in improving road safety. Various detection technologies and systems have been introduced in recent decades, including the use of cameras, eye movement sensors, voice analysis and driver physiological data (Umut et al., 2017). However, these traditional methods often have limitations in terms of accuracy and response time (Viswapriya & Balabalaji, 2021). In recent years, machine learning has taken center stage in the development of more sophisticated driver drowsiness detection systems (Chinthalachervu et al., 2022). Machine learning algorithms, powered by abundant data and increasingly sophisticated computing capabilities, offer the potential to detect driver drowsiness more precisely and in real-time (Reddy et al., 2019). The machine learning-based drowsiness detection system uses various features, such as facial expressions, eye movements and driver activity to identify symptoms of drowsiness (Thakur et al., 2022).

This research aims to explore the development of a machine learning-based driver drowsiness detection system and evaluate its performance in real life situations. The model will detect the driver's eyelid image and yawn condition. The aim is to contribute to efforts to improve road safety by presenting innovative solutions to the problem of driver drowsiness which has long been a threat in traffic.

2. RESEARCH METHOD

The method used in developing this application is an iterative method. The iterative method is a method that combines processes in the waterfall model and iteratively in the prototype model. This model explains the stages in developing machine learning applications starting from analysis to the testing stage. The machine learning application development process goes through several stages from when the application is planned until it is used.

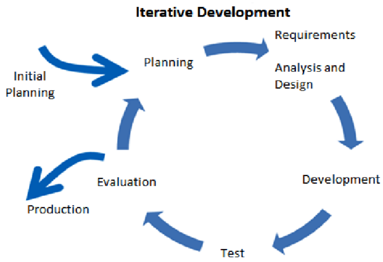


Figure 1 Iterative Method

In this research, the data used is driver image data. At this stage, after the data collection process is carried out, data pre-processing is then carried out so that the data can be processed by machine learning. Carrying out training on machine learning is the same as teaching a machine to learn patterns from input data so that the machine can automatically predict new data based on the data patterns it has learned (Basavaraj Murdeshwar et al., 2019). However, no matter how good a machine is at learning patterns from data, the data still needs to be well prepared using data processing so that it can be understood by the machine. Data Augmentation is a technique for manipulating data without losing the core or essence of the data. For data in the form of images, you can rotate, flip, crop, etc (Altameem et al., 2021).

The dataset that has been cleaned and processed is then ready for us to train with machine learning (Dipu et al., 2021). The only way to know whether our machine learning model is good or not is to test it on new cases or data that the model does not yet recognize. A better option is to divide the dataset into 2 parts, namely training data and testing data (Gwak et al., 2020).

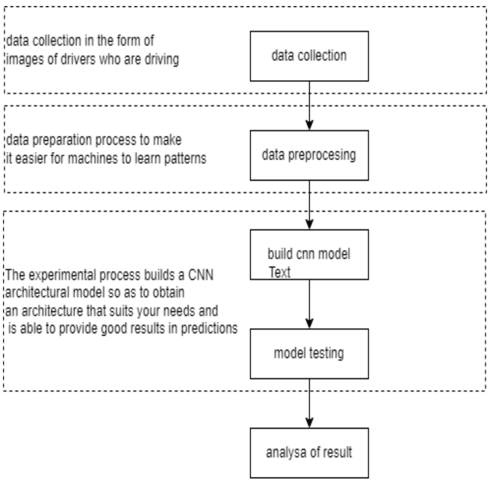


Figure 1 Research Flow

3. RESULTS AND DISCUSSIONS

In this research, the data used is facial image data. Image data is increased by image augmentation. Augmentation can take the form of image rotation and flipping the image horizontally. Before training the model, the image data is cut into the face and eyes. This research uses haarcascade developed by OpenCV as an extraction feature to obtain facial and eye images

Figure 3. Driver image data

In general, there are only 2 main parts in the architecture that will be used, namely the feature extractor in the form of several CNN layers, and the predictor in the form of a stack of FCNs (Reddy Chirra et al., 2019). The first part will process the incoming window data bundle to read the correlation information between each data point and produce a collection of abstract features that the predictor will use to predict the output.

At the feature extractor stage, the CNN layer is used. The image is convolved using a filter with a kernel whose weight has been determined. An example of image convolution can be seen in Figure 6. Then after that the process produces an output called an activation map or feature map (Padamata et al., 2020).

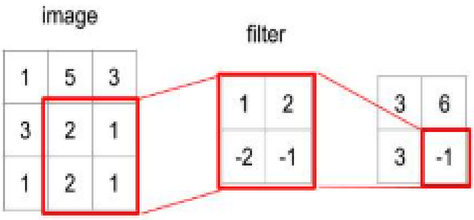


Figure 4. Convolution process

After convolution, the image has been broken down into small parts, but the resulting array is still quite large. Therefore, in the next process, downsampling is carried out, the use of which is called max pooling or average pooling. Max pooling takes the largest pixel value in each pooling kernel and average pooling takes the average pixel value based on the pooling kernel. This process aims to retrieve the most important information without reducing the number of parameters.

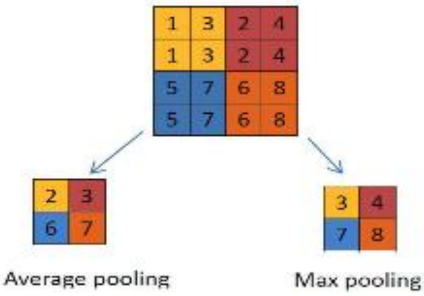


Figure 5. Downsampling process

The final process is the predictor. The predictor consists of a dense layer which is a fully connected network. An illustration of a fully connected network can be seen in Figure 9. This process begins by inputting a small array that has been downsampled into another neural network. The results of the predictor are a classification of eyes open or closed and yawning or not yawning.

After the dataset has been successfully collected, the next stage is to carry out training and testing. The only way to know whether our model is good or not is to test it on new cases or data that the model does not yet recognize. A better option is to divide the dataset into 2 parts, namely training data and testing data.

Figure 6. Image visualization

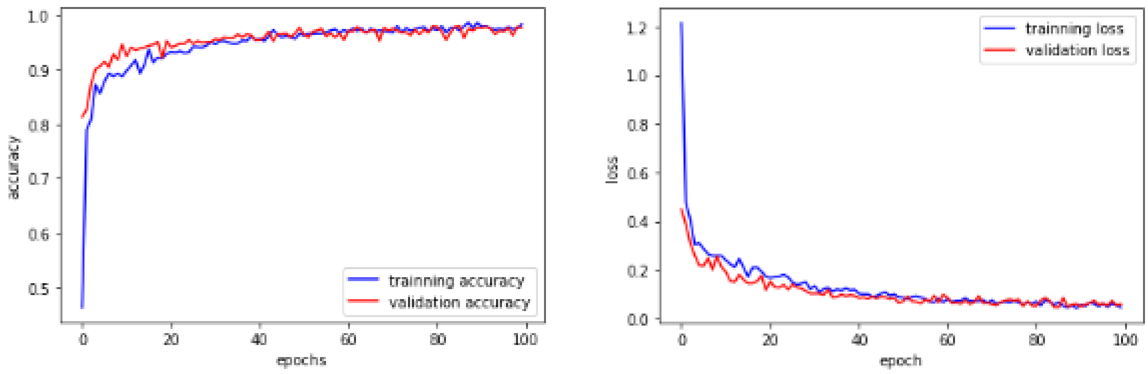
Next, the model is trained on the train set, then tested on the test set, a set of data that the model does not yet recognize. Comparing the predicted results with the actual labels in the test set is the process of evaluating model performance. By testing the model against testing data, we can see the mistakes made and correct them. Testing data is taken with a proportion of 70:30.

Table 1. Model architecture details

Process	Parameter
Convolution	Filter = 256, kernel = (3,3), Padding = 1, Shape (145,145,3), Activation = ReLU
Max Pooling 2D	Pool_size = (2,2)
Convolution	Filter = 128, kernel = (3,3), Padding = 1, Shape (71,71,256), Activation = ReLU
Max Pooling 2D	Pool_size = (2,2)
Convolution	Filter = 64, kernel = (3,3), Padding = 1, Shape (34,34,128), Activation = ReLU
Max Pooling 2D	Pool_size = (2,2)
Convolution	Filter = 32, kernel = (3,3), Padding = 1, Shape (16,16,64), Activation = ReLU
Max Pooling 2D	Pool_size = (2,2)
Flatten	
Dropout	0.5
Dense	Units = 64, Activation = ReLU
Dense	Units = 4, Activation = Softmax

Table 2. Hyperparameter data

Hyperparameter	Value
Epoch	100
Optimizer	Adam
Initial learning rate	0.001
Decay rate	0.98



(a) (b)

Figure 7. (a) accuracy graph based on epoch (b) loss graph based on epoch

In this research, the model training process was carried out with 100 epochs with an initial learning rate of 0.001. The learning rate is made to decrease as the epoch increases, the learning rate decreases by the decay rate. The hyperparameters used are shown in table 2. After the training process is carried out, the model is tested using test data.

Based on Figure 7 (a) and Figure 7 (b), it can be seen that the model can properly classify yawning, not yawning, eyes closed and eyes open. The accuracy value increases with increasing epochs, the accuracy value reaches 0.932% and the loss value decreases with increasing epochs, the loss value reaches 0.121. From the results of testing with a total of 680 images, it was found that a total of 634 images could be classified correctly. The classification results can be seen in the following confusion matrix table.

Tabel 3. Confusion Matrix

Actual Prediction	Yawning	No Yawning	Eyes Closed	Eyes open
Evaporate	48	13	2	0
Doesn't Evaporate	0	70	4	0
Closed eyes	1	2	210	4
Eyes open	0	0	20	306

After classifying yawning, not yawning, eyes closed and eyes open, the model will detect the driver's level of sleepiness. The level of driver sleepiness is divided into three parts, namely: not sleepy, sleepy and very sleepy. The driver is said to be not sleepy when his eyes are open and does not yawn, the driver is sleepy when one of the drivers yawns or his eyes are closed and the driver is very sleepy when the driver yawns and his eyes are closed. The following is an example of the results of detecting drowsiness in a driver.

It can be seen in the detection example that the model can detect the level of sleepiness based on images. There are some failures in detection, it appears that the driver is very sleepy but the model detects as a non-drowsy driver. The model's error in detecting was due to the image taking angle not capturing the front face correctly, so the model failed to detect the image.

Figure 8. Results of drowsiness detection

4. CONCLUSION

In this research, we successfully explored and applied a machine learning-based drowsiness detection system to improve road safety. The research results show that this approach is able to make a positive contribution in reducing the risk of traffic accidents due to drowsy drivers. By collecting and analyzing data from various sources, the developed machine learning model succeeded in recognizing patterns related to the driver's level of alertness, which includes a description of the car driver's level of sleepiness. Suggestions for future research are to conduct further research on factors that can influence sleepiness levels, such as weather conditions, travel time, and other environmental factors.

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