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Driver Drowsiness Detection using Transfer Learning and Computer Vision

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ABSTRACT

Driver drowsiness is a common causes of road accidents resulting in injuries, fatalities, property damage and crash severity, especially for vulnerable road users. This issue requires the development of an effective drowsiness detection and alert system. Web cameras provide a low-cost, real-time solution for monitoring driver alertness. However, accurately classifying eye states as open or closed is challenging, particularly when drivers wear glasses or encounter varying lighting conditions. This study proposes a method using transfer learning and computer vision to detect driver drowsiness. The method uses computer vision to identify the eye state of a driver. A dataset from the MRL Eye Dataset will be used to train the system. The webcam will be placed closely in front of the user to detect the eyes of the driver. The system is designed to deal with face areas in the video captured. The videos are converted into image frames per second to locate the eye location. When the eyes are located, the eye state will determine whether the eyes are open or closed. If the eyes are detected to be closed for more than 10 consecutive frames, the eyes are considered closed and this shows that the driver is drowsy, at which point the driver will get alerted. This system able to detect the driver's drowsiness with or without the presence of eyeglasses in both ideal and poor lighting conditions. The experimental results of this system have an accuracy of 97% and low computational complexity. Overall, this study presents a significant contribution to the field of drowsiness detection by proposing a real-time, low-cost and accurate system that can be installed in vehicles to ensure safe transportation Drowsiness.

1. Introduction

Driver drowsiness has been the main issue in road accidents resulting in significant life and property losses. According to Royal Malaysia Police statistics, there were 1,305 fatalities caused by drivers' drowsiness between 2011 and 2021 [1]. Drowsiness is the main cause of microsleep, where a driver drowses off for just a few seconds. Microsleeps are especially dangerous for drivers because of the short time it takes to make a serious mistake at the wheel. Drowsiness will cause a state of low

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alertness. If the driver dozes for 3 seconds while going 100 km per hour, the car can travel 95 metres in the wrong direction [2]. Consequently, the car will run off the road or collide with another vehicle. Driver drowsiness detection is a car technology designed to help prevent accidents caused by drowsy or fatigued drivers. It uses various sensors and monitoring approaches to assess the driver's level of alertness if signs of drowsiness are detected. According to the review by Komol *et al.,* [3], there are four approaches that have been commonly used to monitor and measure drowsiness: vehicle-based, biological-based, image-based and hybrid-based measures that combine one or more measures.

The first approach is vehicle-based measures, which predict the level of drowsiness depending on the steering wheel angle and the road lane position. According to Albadawi *et al.,* [4] and Li *et al.,* [5] measuring steering wheel angle from lane position will determine the driver's driving style. Driving requires constant control of the steering wheel to keep a car in its lane. Studies have demonstrated that after a long duration of driving and a long-distance route, the driver will experience a loss of energy or drowsiness. Therefore, by acquiring the real-time operation data of the driver's steering wheel, the drowsiness symptom of the direction angle data change is mined and the driver drowsiness level identification model is developed to recognise the driver's drowsiness level. The limitations of the Albadawi *et al.,* [4] paper is that the model has moderate results for different subjects under real driving conditions. The results obtained show that the models were dividing the drowsiness into three states: awake, fatigued and very fatigued. But, while differentiating between fatigued and very fatigued, the model was not efficient enough. According to Li *et al.,* [5], another flaw of this approach is that drivers are typically notified only in a deep drowsy state, which could be too late when the alarm occurs. In addition, this approach mostly comes with an expensive car accessory [3].

The second approach is biological-based measures, which mainly use body sensors to detect biological features such as measuring heart rate variability using a wearable electrocardiogram (ECG) [6], measuring movement of the eyes using electrooculography (EOG) [7], measuring Heart Rate Variability (pulse using photoplethysmography(PPG) [8], measuring cardiac data using a heart rate chest strap belt [9,10] and measuring brain activity using a brain-sensing headband electroencephalogram (EEG) [11]. In this approach, the driver has to use devices that can be worn and attached to the driver's arm, chest and head for data collection. The limitations of this drowsiness detection approach that monitors the driver's condition require expensive equipment that is uncomfortable to wear while driving and is unsuitable for driving. Therefore, it is easier to have a simple tool to detect drowsiness or a microsleep situation without a tool that is attached to the human body.

Previous studies have thoroughly investigated various approaches to precisely identify and reduce dangers associated with drowsiness. By exploring the changing field of sleepiness detection in this study, highlighting the critical role multimodal techniques play in improving the precision and dependability of detection systems. Early techniques for drowsiness detection generally relied on singular signals, such as EEG or eye-tracking data [12,13]. But for efficient detection, a more sophisticated knowledge is required due to the biological details of human physiology and behaviour. The limitations of unimodal approaches have been highlighted by recent breakthroughs, leading to a paradigm change in favour of multimodal strategies. This research studies the use of physiological signals for the detection of drowsiness. The authors' use of the phrase "singular and hybrid signal approaches" implies that they examine both single physiological signals and combination signals.

Multimodal fusion or techniques is used to improve the precision and consistency of drowsiness detection by investigates the combinations of many physiological signals (multimodal). Integrating information like eye tracking data, EEG and ECG can give a more complete picture of the driver's condition [12]. With data quality improvement, the model might be more capable of managing variances in individual signal quality if data from several physiological signals is integrated. Signal combination can improve the overall quality of the data utilized for drowsiness detection by minimizing the downsides of any one method.

The third approach is image-based measures, which use computer vision techniques to detect the driver's visual features such as eye features [14], mouth [15], facial expressions [16] and head movement [17]. The system uses computer vision techniques recorded by a camera or webcam to identify the visual features or drowsiness signs of the driver. This approach was more comfortable and did not require the driver to put any devices on their body during driving. The camera will be placed closely in front of the user to detect the face area of the driver in the video captured. The advantage of this approach is that it is inexpensive by using a low-cost webcam or camera on a smartphone.

Another research is by validating and interpreting a multimodal drowsiness detection system. The implementation of explainable machine learning involves a focus on enhancing the transparency and interpretability of the model's decisions. To construct a comprehensive drowsiness detection system, the research investigates the integration of many modalities, such as physiological signals, behavioural information or facial expressions [13]. Combining these modalities yields a more comprehensive picture of the driver's condition. Using machine learning for reliability is increased when accessible machine learning methods are integrated into the drowsiness detection system. This is to make sure that the model's decisions are clear and interpreted, which facilitates the validation and reliability of the system's outputs.

According to Komol *et al.,* [3], image-based measures presented different accuracies on the drowsiness detection system, between 72.25% and 99.59%, based on the different scenarios and selected features. However, the system’s performance is acutely affected in cases where it is difficult to track facial data due to obstructions. Anyhow, most measures rely on eye features to achieve high accuracy between 85% and 99%. Thus, a drowsiness detection system that uses an image-based approach with eye features is the most suitable and reliable for assessing and monitoring a driver’s drowsiness because of its high accuracy and use of a low-cost webcam. Table 1 shows the average accuracy metric between different parameters and method used from the previous research.

There are several eye features image-based detection systems that have been introduced for drowsiness detection such as eye state recognition (closed or open) with CNN [14]], eye aspect ratio by tracking the blinking duration [28], eyelid closure analysis [30] and an optical correlator that estimates the eye’s position and state (open or closed) [31,32] as illustrated in Figure 1.

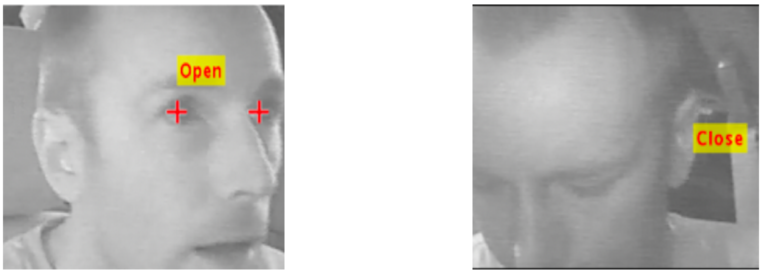
Table 1
Detailed evaluation of experimental parameters, method and average accuracy among various methods

Parameters	Method	Average Accuracy Metric
Steering Wheel [18]	RF	79%
	Binary Decision Classifier	78.01%
	SVM	63.86%
	BPNN	62.10%
EEG [19]	ANN	88.2%
ECG [20]	SVM	80.9%
Heart Rate (ECG) [21]	KNN	92%
ECG [22]	CNN	70%
Respiration (with thermal camera) [23]	SVM & KNN	SVM: 90% KNN: 83%
Facial features, Head movement [24]	3D CNN	73.9%
Driver's Posture [25]	ResNet50, MobileNetV2	ResNet50: 94.5% MobileNetV2: 98.12%
Eye State (Close/Open) [26]	Transfer Learning (VGG-16, VGG-19)	VGG-16: 95.45% VGG-19: 95%
Eyes (EAR) values [27]	SVM	94.9%
EEG Signal (Eye Signal) [28]	RF	91.18%
	SVM	82.62%
Eye & Mouth [29]	CNN & LSTM	84.85%

(a) Eye state recognition (closed or open) [14]

(b) Eye aspect ratio by tracking the blinking duration [28]

(c) Eyelid closure analysis [30]



(d) Optical correlator estimates the eye's position and state [31,32]

Fig. 1. A comparison of different eye features and their effect on accurate detection in assessing drowsiness

Among these, the eye state recognition based on CNN shows the highest accuracy among others, which is greater than 95% [3,11]. Several CNN architectures that have been trained on various datasets for drowsiness detection based on eye state recognition purposes are VGG16, VGG19, ResNet50, Inception and MobileNetV2 [14,16]. These architectures are important for improving the accuracy and performance of applications in CNN. This architecture is usually used in pre-trained models in transfer learning. Attention is needed to choose the suitable architecture for the project, such as input size, depth and robustness. The effectiveness of these architectures can vary based on the specific dataset, pre-processing techniques and training strategies used. A brief overview of the architectures is:

i. VGG16 and VGG19: VGG (Visual Geometry Group) architectures are known for their simplicity and effectiveness. They consist of multiple convolutional layers with small kernel sizes followed by max-pooling layers. VGG16 has 16 layers and VGG19 has 19 layers. While they might be computationally expensive.
ii. ResNet50: ResNet (Residual Network) is known for its skip connections or residual blocks, which help mitigate the vanishing gradient problem and enable training of very deep networks. ResNet50 is a variant with 50 layers.
iii. Inception: Inception introduced the concept of "inception modules" that use multiple filter sizes in parallel to capture features at different scales. This architecture aims to improve the utilization of computational resources and has shown strong performance. The Inception architecture, also known as GoogleNet,
iv. MobileNetV2: MobileNetV2 is designed for efficient deployment on mobile and embedded devices including classification, object detection and semantic segmentation. It employs depth wise separable convolutions to reduce the number of parameters and computational complexity while maintaining good performance.

Between these architecture models, MobileNetV2 shows the highest accuracy among others [17]. MobileNet-V2 has the advantages of being fast, lightweight and having high accuracy, which makes it suitable for training with limited datasets [17].

The existing technologies to detect driver drowsiness and fatigue are very costly systems that apply to the high-end car models. Therefore, to increase drivers' alertness levels, high accuracy and low computational complexity applications should be designed to detect driver drowsiness and fatigue in various condition. In addition, an affordable, but robust system that are relies on low-cost camera needs to process real time visual features of driver with or without glasses in various lighting condition during the day and night.

The aim of this study is to employ deep learning algorithms to overcome the limitations of the aforementioned algorithms and to develop a solution for real-time open and closed eyes detection.

This study proposes a deep learning neural network-based approach for detecting driver drowsiness. The proposed technique uses features that are learned by using CNNs to detect and recognize eye state that open or closed. This technology is used to give warning to the driver with a light alarm in the case of drowsy or fatigue to help prevent accidents. Taking advantage of deep learning techniques, this study applies deep neural networks with MobileNet-V2 for driver drowsiness detection. The significances of this study are: A CNN-based novel classification model was developed for drowsiness detection on the basis of eye state open or closed.

2. Methodology

This drowsiness detection system consists of two main states which is offline training and real-time monitoring. The offline training state consists of three main stages: Image dataset preparation, image pre-processing, feature extraction and training. While in the real-time monitoring state, also consist two main stages: system development and system testing. The flowchart of the drowsiness detection system is illustrated in Figure 2.

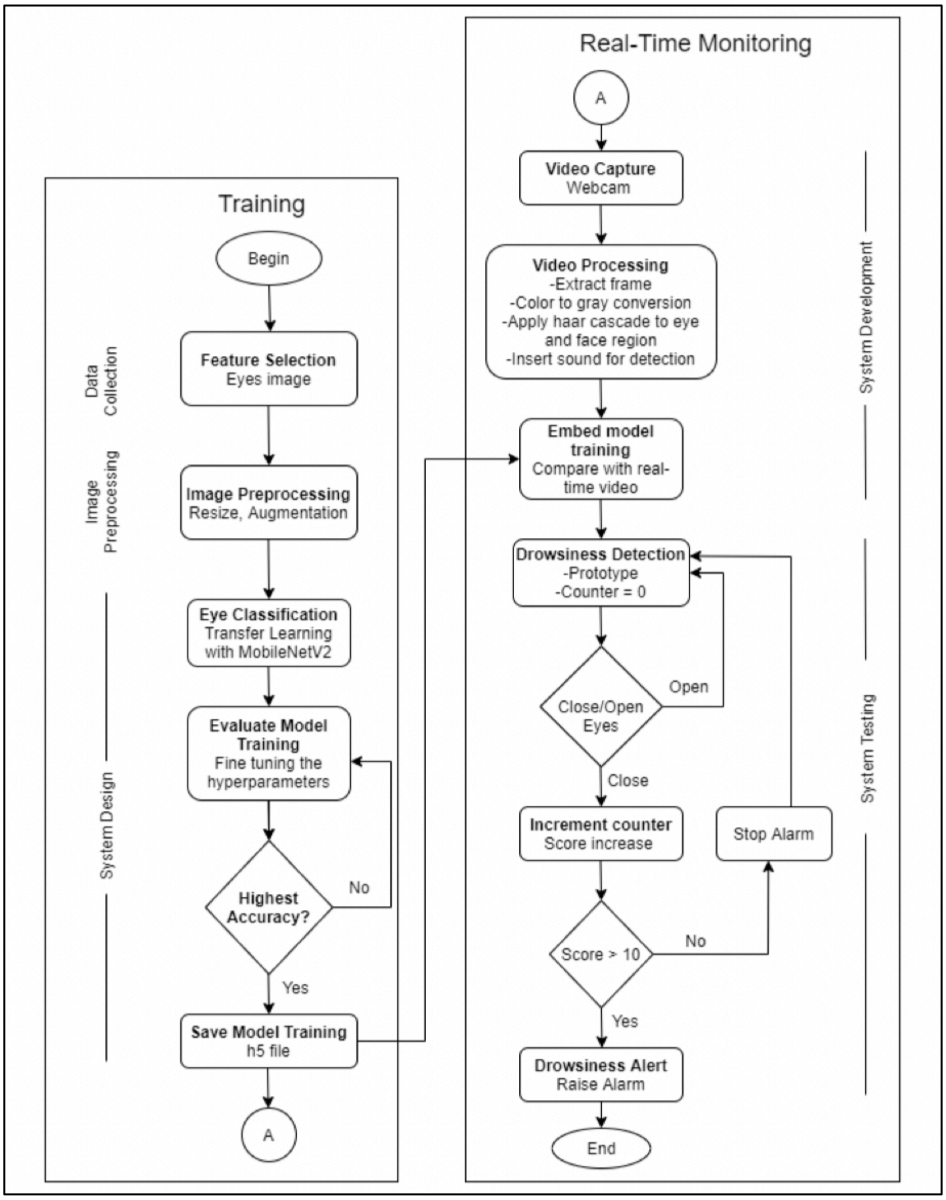


Fig. 2. An all-inclusive flowchart describing the architecture and purpose

2.1 State 1: Offline Training
2.1.1 Data collection

The dataset used in this study is from the Media Research Lab (MRL) Eye Dataset which includes infrared photographs with diverse eyes open and closed, with some wearing glasses, light intensities and resolutions as shows in Figure 3. It consists of 84,898 images over 37 folders that represent 37 different people, including 33 men and 4 women. Three separate cameras, the Intel RealSense RS 300 (640x480), IDS Imaging (1280x1024) and Aptina (752x480), were used to take these pictures. The eye state is particularly important to the goals of the system and is included in each image name, which also contains significant information. The images were separated into two folders, Close Eyes and Open Eyes. Using Python code, it analysed the image names and sorted them automatically according to the fourth index representing the eye state (0 for closed eyes, 1 for open eyes). Only 6,405 images chosen in total were 5,124 for training, 513 for validation and 1,281 for testing. Each dataset's distribution of images was calculated based on previous research done by other researchers working on related projects.

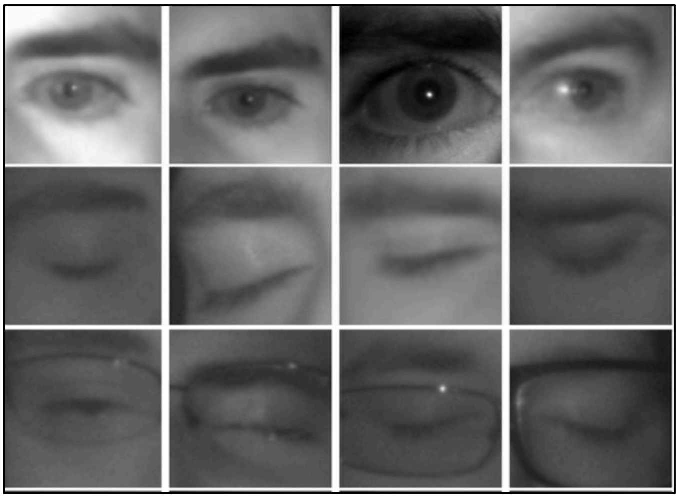


Fig. 3. Media research lab (MRL) eye dataset

2.1.2 Image pre-processing

The image then went through image pre-processing, the images being divided into training sets and testing sets. The image then went through a data augmentation process which then each of the image data will be copied into 5 more images with different angle, sizes and rotation. Next, the data standardize by:

i. Fixed image size of 224 x 224
ii. Rescale pixel values of [0-255] to [0-1]

This will improve the creation of more accurate machine learning models while reducing dependency on training data acquisition. The initial RGB coefficients images were formed in the range of 0-255, but given a typical learning rate, such values would be too high for the model to handle

Several methods have been developed to detect the face and eyes. First, the method known as Cascade Object Detector utilising Haar Cascade [1]. If a face is found, the Haar cascade classifier which segments facial landmarks was employed to extract the eye region. This will appear boundary rectangles for the detected of face and eye region as shown in Figure 4.

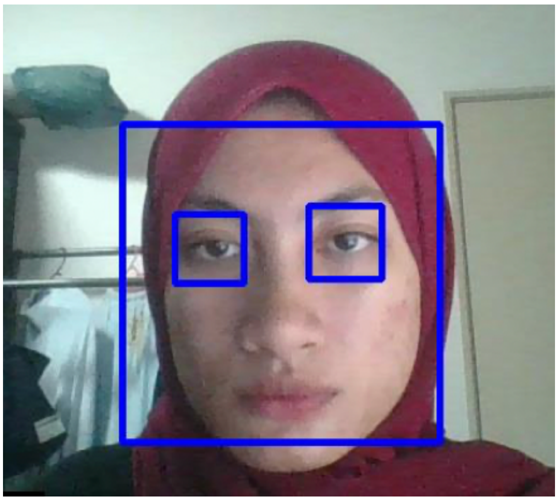


Fig. 4. An overview on how Cascade Classifier Detection works in improving recognition of face and eyes in images

2.1.3 System design

System design involves two part which are eye classification and data training. Eye classification begins with the deep learning technique called transfer learning. The training starts with the eye classification which uses the eyes image data. For data training, CNN architectures were trained based on MobileNetV2. This architecture involves building the network structures where the 1000 classes in the last layer need to be eliminated until it achieves 2 classes only (open and closed). The last layers need to be added which need to be flattened, adding a dense layer with 64 neurons and the activation function using ReLU (Rectified Linear Activation) Function. ReLU replaces negative inputs with zero, allowing positive values to pass unchanged. The choices of the value for dropout layers are important because if the value is too high, it will impact the model accuracy negatively. The common value used in this dropout layer is between 0.2-0.3. Then, the last layers need to be added with more neurons with activation functions using SoftMax. The SoftMax activation function is used in the output layer of a neural network for multi-class classification tasks. It transforms the raw output scores of the network into a probability distribution over multiple class. The output of the SoftMax function assigns a probability to each class, indicating the likelihood that the input belongs to that class. The architecture is shown in Figure 5.

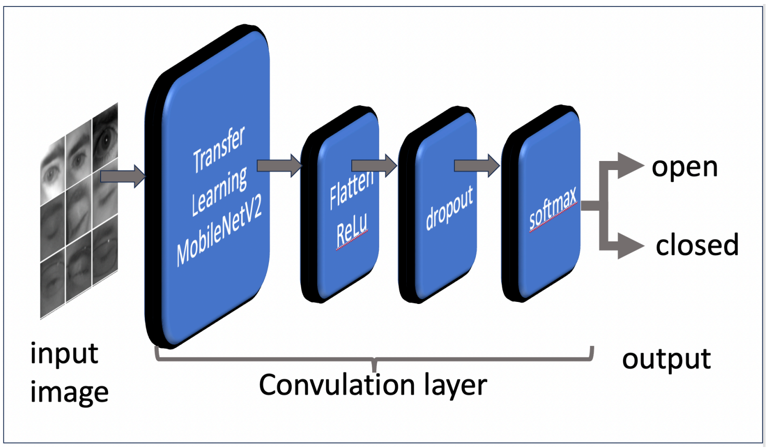


Fig. 5. The architecture and mechanisms underlying transfer learning in neural networks

2.2 State 2: Real-Time Monitoring
2.2.1 System development

In real-time monitoring, the graphical user interface (GUI) is develop as shown in Figure 6. This GUI is design using Tkinter and OpenCV cascade classifier. Tkinter is a standard python interface to use for designing and adding widgets to a system. To make the system functional, OpenCV, Tkinter, Numpy and Pygame need to be imported first. The GUI contains button menu. The main button is the Detect Drowsiness with Alarm button. This button will be used to capture driver's face using webcam.

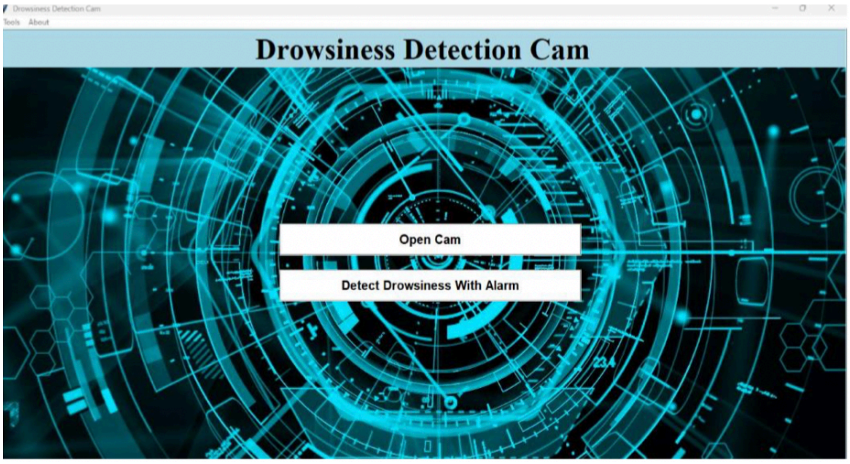


Fig. 6. An overview on Graphical User Interface (GUI) for alerting and detecting drowsiness system

Next, the system needs to be tested whether it can run properly and accuracy checking before finalizing the output. Detecting and checking any errors and webcam functionalities needs to be done for the system to ensure the required parameter needed is fulfilled and fixed. The input data for testing are video extracted from videos capturing from a webcam to detect eye open and closed by applying the proposed network models from training phase.

2.2.2 System testing

Eye detection results of open and closed eyes from face video capturing with background. The normal average duration of eye blink is 0.1s to 0.4s. It means that the eye will blink at least 2 or 3 times in one second. This is observed for a few seconds. Eye blink rates (EBR) were computed as the number of blinks per minute. As longer eye closures might indicate drowsiness or micro sleeps. To show the output text as in the left side in Figure 7, is being used to show whether the eyes are open or closed. The videos are change into image frames per second to locate the eyes positions. When the eyes are located, the eye state will determine whether the eyes are open or closed. If the eyes detected to be closed for more than 10 consecutive frames, the eyes are considered closed and this show that the driver are drowsy which then the driver will get alerted. Figure 7 below shows the system successfully running. The "Score" will also show how many times the eyes have been closed. If the "Score" > 1, then the alarm will alert the user. The alarm will only alert the user if the eyes are closed within 1 or 2 seconds. If the eyes only blinking, then the alarm will not alert the user.

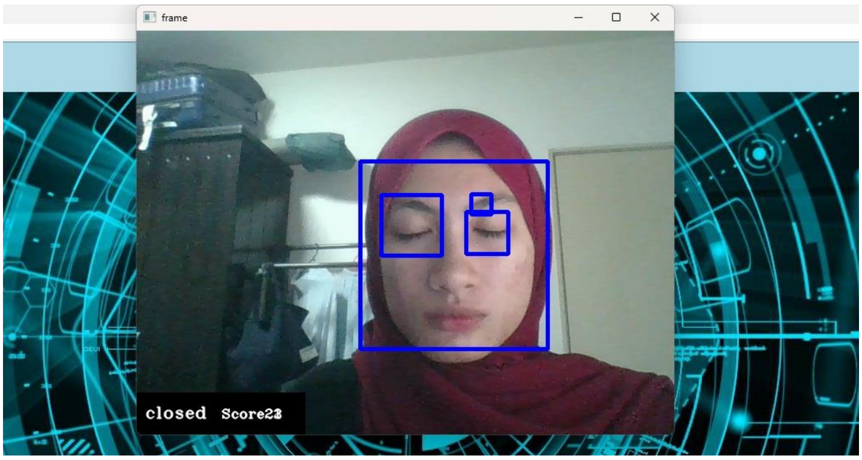


Fig. 7. Examining the eye detection outcomes, differentiating between open and closed eyes

3. Results

3.1 Tuning of Hyper-Parameters

Table 2 shows the experiment setting for the system. Various hyperparameters have been tested and modified for this system to get the best outcomes. The dataset size, train: test percentage, epoch size and batch size are specified below.

Table 2
Model performance experiment settings and hyperparameters within the framework of 5124 dataset size

Parameters	Experiment 1				Experiment 2			
Dataset size	5124							
Train: Test	80:20				70:30			
Epoch	40		50		40		50	
Batch size	8	16	8	16	8	16	8	16

Epoch is considered a hyperparameter. An epoch is the total number of iterations required to train the machine learning model using all the training data at once. It is measured in cycles. While batch size is the number of samples that are processed through a particular machine learning model before changing its internal model parameters. A batch can be seen as a for-loop making predictions while iterating through one or more samples. At the end of the batch, these predictions are then compared with the predicted output variables. By comparing the two, the error is estimated and it is then used to enhance the model.

3.2 Experiment Results

Table 3 and Table 4 are the summarization results for each experiment respectively. Based on the results in Table 3 of the two tests conducted in Experiment 1, the epoch with 40 and batch size=8 have the accuracy of 97.22% and batch size=16 have the accuracy of 97.38%. The epoch with 50 and batch size=8 have the best accuracy with 97.8%. Compared to the epoch with 50 and batch size=16 with only 97.43% accuracy. The time taken for this experiment also takes a longer time for the algorithm to train the data where it takes 1 hour and 15 minutes, but the accuracy is lower than the one with epoch=50 and batch size=8.

Table 3
Results of Experiment 1 (80:20) and analysis for different epoch number and batch size

Epoch	Batch Size	Accuracy (%)	Learning Time
40	8	97.22	30 minutes
	16	97.38	50 minutes
50	8	97.8	1 hour
	16	97.43	1 hour 15 minutes

Table 4 shows the results of the two tests conducted in Experiment 2, the epoch with 40 and batch size=8 have the accuracy of 96.76% while batch size=16 have the accuracy of 97.26%. Epoch=50 with batch size=16 have the best accuracy with 98.01%. Compared to the epoch=50 with batch size=8 where it only reaches 97.68% of accuracy and the time taken for this experiment also computes at the same duration for the algorithm to train the data where it takes 1 hour, but the accuracy is lower.

Table 4
Results of Experiment 2 (70:30) and analysis for different epoch number and batch size

Epoch	Batch Size	Accuracy (%)	Learning Time
40	8	96.76	30 minutes
	16	97.26	1 hour
50	8	97.68	1 hour
	16	98.01	1 hour

Table 5 shows the summarizations of all results of experiments.

Table 5
Detailed evaluation comparing results from Experiment 1 and Experiment 2

Parameters	Experiment 1				Experiment 2			
Dataset size	5124				5124			
Train: Test	80:20				70:30			
Epoch	40		50		40		50	
Batch size	8	16	8	16	8	16	8	16
Accuracy (%)	97.22	97.38	97.8	97.43	96.76	97.26	97.68	98.01
Learning Time	30m	50m	1h	1h 15 m	30m	1h	1h	1h

*m – mins, h – hour

Experiment 1 gave the results average of 97% while Experiment 2 gave the results between 96% to 98%. The best result is from Experiment 2 with epoch=16 and batch size=8 where the accuracy is higher than the others with 98.01% accuracy. However, based on the observation, the experiment shows an average result of 97% accuracy overall with an average learning time of 1 hour.

3.3 Precision, Recall & F1-Score Results

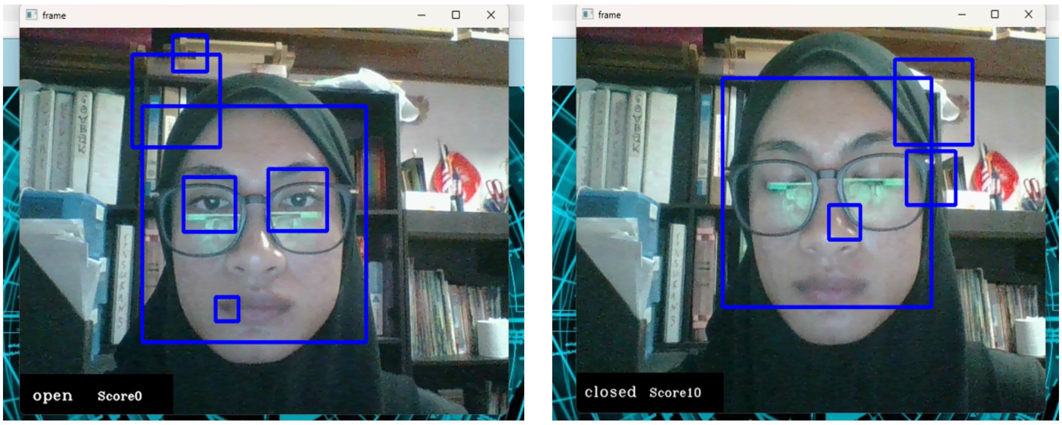
The results in Table 6 taken from the two experiments above with the highest accuracy. After assessing the drowsiness detection model, Experiment 1 shows the 'Closed Eyes' and 'Open Eyes' classes have precision values of 0.73 and 0.73 respectively. The 'Open Eyes' class had a recall of 0.29, but the 'Closed Eyes' class had a recall of 0.28. The precision and recall-balancing F1-score was computed as 0.86. While for Experiment 2, the 'Closed Eyes' and 'Open Eyes' classes have precision values of 0.75 and 0.75 respectively. The 'Open Eyes' class had a recall of 0.26, but the 'Closed Eyes' class had a recall of 0.36. The precision and recall-balancing F1-score was computed as 0.86. Together, these metrics demonstrate how well the model can detect sleepiness while reducing false positives and false negatives. Results as shown in the table below.

Table 6
Detailed results of precision, recall and F-1 score across Experiment 1 and Experiment 2

Metrics	Experiment 1	Experiment 2
Precision (Closed Eyes)	0.73	0.75
Precision (Open Eyes)	0.73	0.75
Recall (Closed Eyes)	0.28	0.36
Recall (Open Eyes)	0.29	0.26
F-1 Score	0.86	0.86

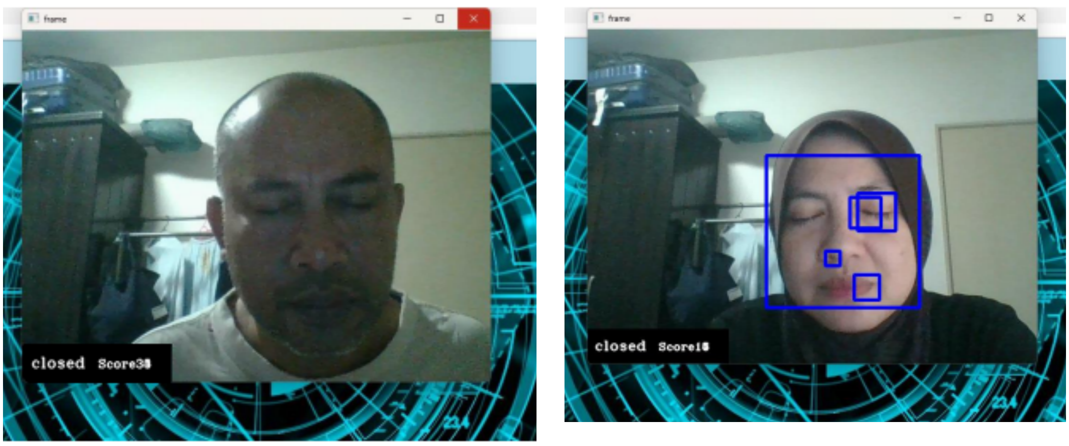
3.4 System Output

Figure 8 and Figure 9 below show the system output after it is deployed. During the experiment on User 1, User 2 and User 3, the system can detect eye state whether in the condition with or without glasses and also with more and less light condition. The system is also able to detect the eyes regardless of any gender.



(a) (b)

Fig. 8. Examining women with glasses (a) Open eyes (b) Closed eyes



(a) (b)

Fig. 9. (a) Closed eyes (without glasses, less light, man) (b) Closed Eyes (without glasses, light, woman)

4. Conclusions

This study presents an approach for drowsiness detection, where an improve method is proposed in the eyes detection to recognize eye open and closed. MobileNetV2 is used for efficient deployment on mobile devices, which makes it well-suited for situation where computational resources are limited. It achieves a good balance between accuracy and model size, which is important for real-time applications in drowsiness detection. For the experiments, a data was created from real-time videos. The results were obtained from 2 experiments performed and showed an exceptionally high accuracy in drowsiness detection using the architectures based on the CNNs, with average result of 97% accuracy with an average learning time of 1 hour. The results suggest that the proposed approach is a good alternative for the implementation of the drowsiness detection system to improve road traffic safety by reducing the risk of accidents caused by drivers who may be experiencing reduced concentration. Driver drowsiness detection that are reliable and precise are crucial to avoid road accidents and increase road traffic safety.

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References

[1] Cheah, C. F. “Don’t be a victim of microsleep”, *New Straits Times*. (2022).
[2] Felson, Sabrina. “What to Know About Microsleep”, *WebMD*. (2023).
[3] Komol, Md Mostafizur Rahman, Md Mahmudul Hasan, Mohammed Elhenawy, Shamsunnahar Yasmin, Mahmoud Masoud and Andry Rakotonirainy. "Crash severity analysis of vulnerable road users using machine learning." *PLoS one* 16, no. 8 (2021): e0255828. https://doi.org/10.1371/journal.pone.0255828
[4] Albadawi, Yaman, Maen Takruri and Mohammed Awad. "A review of recent developments in driver drowsiness detection systems." *Sensors* 22, no. 5 (2022): 2069. https://doi.org/10.3390/s22052069
[5] Li, Zuojin, Qing Yang, Shengfu Chen, Wei Zhou, Liukui Chen and Lei Song. "A fuzzy recurrent neural network for driver fatigue detection based on steering-wheel angle sensor data." *International Journal of Distributed Sensor Networks* 15, no. 9 (2019): 1550147719872452. https://doi.org/10.1177/1550147719872452
[6] Lu, Jianchao, Xi Zheng, Lihong Tang, Tianyi Zhang, Quan Z. Sheng, Chen Wang, Jiong Jin, Shui Yu and Wanlei Zhou. "Can steering wheel detect your driving fatigue?." *IEEE Transactions on Vehicular Technology* 70, no. 6 (2021): 5537-5550. https://doi.org/10.1109/TVT.2021.3072936
[7] Kundinger, Thomas, Nikoletta Sofra and Andreas Riener. "Assessment of the potential of wrist-worn wearable sensors for driver drowsiness detection." *Sensors* 20, no. 4 (2020): 1029. https://doi.org/10.3390/s20041029
[8] Watling, Christopher N., Md Mahmudul Hasan and Grégoire S. Larue. "Sensitivity and specificity of the driver sleepiness detection methods using physiological signals: A systematic review." *Accident Analysis & Prevention* 150 (2021): 105900. https://doi.org/10.1016/j.aap.2020.105900
[9] Amidei andrea, Piero G. Fallica, Sabrina Conoci and Paolo Pavan. "Validating Photoplethysmography (PPG) data for driver drowsiness detection." In *2021 IEEE International Workshop on Metrology for Automotive (MetroAutomotive)*, pp. 147-151. IEEE, 2021. https://doi.org/10.1109/MetroAutomotive50197.2021.9502865
[10] Lee, Jae-Cheon and Hao Liu. "Development of a real-time driver health detection system using a smart steering wheel." *International Journal of Prognostics and Health Management* 9, no. 3 (2018). https://doi.org/10.36001/ijphm.2018.v9i3.2747
[11] Lu, Ke, Anna Sjörs Dahlman, Johan Karlsson and Stefan Candefjord. "Detecting driver fatigue using heart rate variability: A systematic review." *Accident Analysis & Prevention* 178 (2022): 106830. https://doi.org/10.1016/j.aap.2022.106830
[12] Hasan, Md Mahmudul, Christopher N. Watling and Grégoire S. Larue. "Physiological signal-based drowsiness detection using machine learning: Singular and hybrid signal approaches." *Journal of safety research* 80 (2022): 215-225. https://doi.org/10.1016/j.jsr.2021.12.001
[13] Hasan, Md Mahmudul, Christopher N. Watling and Grégoire S. Larue. "Validation and interpretation of a multimodal drowsiness detection system using explainable machine learning." *Computer Methods and Programs in Biomedicine* 243 (2024): 107925. https://doi.org/10.1016/j.cmpb.2023.107925

[14] Florez, Ruben, Facundo Palomino-Quispe, Roger Jesus Coaquira-Castillo, Julio Cesar Herrera-Levano, Thuanne Paixão and Ana Beatriz Alvarez. "A cnn-based approach for driver drowsiness detection by real-time eye state identification." *Applied Sciences* 13, no. 13 (2023): 7849. https://doi.org/10.3390/app13137849

[15] Bajaj, Srinidhi, Leena Panchal, Saloni Patil, Krutika Sanas, Harshita Bhatt and Swapnali Dhakane. "A real-time driver drowsiness detection using OpenCV, DLib." In *ICT Analysis and Applications: Proceedings of ICT4SD 2022*, pp. 639-649. Singapore: Springer Nature Singapore, 2022. https://doi.org/10.1007/978-981-19-5224-1_64

[16] Jabbar, Rateb, Mohammed Shinoy, Mohamed Kharbeche, Khalifa Al-Khalifa, Moez Krichen and Kamel Barkaoui. "Driver drowsiness detection model using convolutional neural networks techniques for android application." In *2020 IEEE International Conference on Informatics, IoT and Enabling Technologies (ICIoT)*, pp. 237-242. IEEE, 2020. https://doi.org/10.1109/ICIoT48696.2020.9089484

[17] Phan, Anh-Cang, Ngoc-Hoang-Quyen Nguyen, Thanh-Ngoan Trieu and Thuong-Cang Phan. "An efficient approach for detecting driver drowsiness based on deep learning." *Applied Sciences* 11, no. 18 (2021): 8441. https://doi.org/10.3390/app11188441

[18] Li, Zuojin, Shengbo Eben Li, Renjie Li, Bo Cheng and Jinliang Shi. "Online detection of driver fatigue using steering wheel angles for real driving conditions." *Sensors* 17, no. 3 (2017): 495. https://doi.org/10.3390/s17030495

[19] Saghafi, Abolfazl, Chris P. Tsokos, Mahdi Goudarzi and Hamidreza Farhidzadeh. "Random eye state change detection in real-time using EEG signals." *Expert Systems with Applications* 72 (2017): 42-48. https://doi.org/10.1016/j.eswa.2016.12.010

[20] Awais, Muhammad, Nasreen Badruddin and Micheal Drieberg. "A hybrid approach to detect driver drowsiness utilizing physiological signals to improve system performance and wearability." *Sensors* 17, no. 9 (2017): 1991. https://doi.org/10.3390/s17091991

[21] Kundinger, Thomas, Nikoletta Sofra and Andreas Riener. "Assessment of the potential of wrist-worn wearable sensors for driver drowsiness detection." *Sensors* 20, no. 4 (2020): 1029. https://doi.org/10.3390/s20041029

[22] Lee, Hyeonjeong, Jaewon Lee and Miyoung Shin. "Using wearable ECG/PPG sensors for driver drowsiness detection based on distinguishable pattern of recurrence plots." *Electronics* 8, no. 2 (2019): 192. https://doi.org/10.3390/electronics8020192

[23] Lee, Hyeonjeong and Jaewon Lee. "Using Wearable ECG/PPG Sensors for Driver Drowsiness Detection Based on Distinguishable Pattern of Recurrence Plots." *Electronics* 8, no. 2 (2019): 192. https://doi.org/10.3390/electronics8020192

[24] Kiashari, Serajeddin Ebrahimian Hadi, Ali Nahvi, Hamidreza Bakhoda, Amirhossein Homayounfard and Masoumeh Tashakori. "Evaluation of driver drowsiness using respiration analysis by thermal imaging on a driving simulator." *Multimedia Tools and Applications* 79 (2020): 17793-17815. https://doi.org/10.1007/s11042-020-08696-x

[25] Kiashari, Serajeddin Ebrahimian Hadi, Ali Nahvi, Hamidreza Bakhoda, Amirhossein Homayounfard and Masoumeh Tashakori. "Evaluation of driver drowsiness using respiration analysis by thermal imaging on a driving simulator." *Multimedia Tools and Applications* 79, no. 25-26 (2020): 17793-17815. https://doi.org/10.1007/s11042-020-08696-x

[26] Hossain, Md Uzzol, Md Ataur Rahman, Md Manowarul Islam, Arnisha Akhter, Md Ashraf Uddin and Bikash Kumar Paul. "Automatic driver distraction detection using deep convolutional neural networks." *Intelligent Systems with Applications* 14 (2022): 200075. https://doi.org/10.1016/j.iswa.2022.200075

[27] Hashemi, Maryam, Alireza Mirrashid and Aliasghar Beheshti Shirazi. "Driver safety development: Real-time driver drowsiness detection system based on convolutional neural network." *SN Computer Science* 1, no. 5 (2020): 289. https://doi.org/10.1007/s42979-020-00306-9

[28] Maior, Caio Bezerra Souto, Márcio José das Chagas Moura, João Mateus Marques Santana and Isis Didier Lins. "Real-time classification for autonomous drowsiness detection using eye aspect ratio." *Expert Systems with Applications* 158 (2020): 113505. https://doi.org/10.1016/j.eswa.2020.113505

[29] Zandi, Ali Shahidi, Azhar Quddus, Laura Prest and Felix JE Comeau. "Non-intrusive detection of drowsy driving based on eye tracking data." *Transportation research record* 2673, no. 6 (2019): 247-257. https://doi.org/10.1177/0361198119847985

[30] Guo, Jing-Ming and Herleeyandi Markoni. "Driver drowsiness detection using hybrid convolutional neural network and long short-term memory." *Multimedia tools and applications* 78 (2019): 29059-29087. https://doi.org/10.1007/s11042-018-6378-6

[31] Tayab Khan, Muhammad, Hafeez Anwar, Farman Ullah, Ata Ur Rehman, Rehmat Ullah, Asif Iqbal, Bok-Hee Lee and Kyung Sup Kwak. "Smart Real-Time Video Surveillance Platform for Drowsiness Detection Based on Eyelid Closure." *Wireless communications and mobile computing* 2019, no. 1 (2019): 2036818. https://doi.org/10.1155/2019/2036818

[32] Ouabida, Elhoussaine, Abdelaziz Essadike and Abdenbi Bouzid. "Optical correlator based algorithm for driver drowsiness detection." *Optik* 204 (2020): 164102. https://doi.org/10.1016/j.ijleo.2019.164102