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Driver fatigue detection using Raspberry-Pi

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ABSTRACT

The subject of fatigue monitoring is becoming more important in transportation and traffic management (including, for instance, the development of systems to detect and prevent driver drowsiness). People who work in offices are also susceptible to exhaustion, but there is currently no widely deployed system that is able to monitor this condition. In most cases, the driver’s eyelids will become heavy due to exhaustion after lengthy hours of driving or in the absence of mental concentration. Typically, when the driver’s concentration begins to fade, audio alert would be provided to force the drivers awake. In recent times, drowsiness is risky since it can result in an accident. Thus, a solution has been proposed to identify driver drowsiness by comparing several algorithms to find improved accuracy and execution time. Besides, this system will alert the driver with an audible warning in the event of drowsiness is detected.

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1. INTRODUCTION

Drowsiness is defined by a strong urge to sleep. It is a state in which a person has a strong urge to sleep. It has two distinct meanings: the state of not falling asleep and the chronic condition of being in that state regardless of the daily cycle. While performing duties that require constant concentration, such as driving, it is risky to do so while drowsy. If a person is sufficiently tired, they may get drowsy, which can result in a traffic accident [1]–[3]. Statistic of road accident in Malaysia from the year 2005 to 2009 provided by MIROS (Malaysia Institute of Road Safety) shows that the number of road accidents keep increasing each year [4]. Machine learning can help to lessen the likelihood of an accident occurring. An alert system, for example, can help monitor and alert the driver if drowsiness occurs [5], [6]. One of the primary issues of a traffic collision is an accident induced by drowsy driving. According to reports, fatigued driving causes a substantial number of road accidents, resulting in serious injuries and fatalities [7]–[9]. As a result, numerous studies have been conducted in the development of systems that can detect and notify a driver’s drowsiness, preventing the drivers from falling asleep and causing an accident [10]–[14].

Eye blinks and the percentage of eye closure (PERCLOS) have been proposed as measures to determine drowsiness in individuals. The PERCLOS approach suggests that fatigue can be assessed by observing the percentage of drooping eyelids [15]. To achieve this, a software library contains samples of both open and closed eyes that serve as reference points for distinguishing fully open from completely closed eyes. As a person gradually falls asleep, the eyelids tend to droop over an extended period, enabling the observation of the driver’s transition into drowsiness. The PERCLOS method employs a proportional number, considering the driver as tired when the eyes are around 80 percent closed, which is close to being entirely closed [16], [17].

Nonetheless, a drawback of this method is its limited real-time applicability, as it requires a fixed threshold value for eye opening to function accurately [18]–[20]. Similarly, the eye blink pattern detection method encounters the same issue. It necessitates the camera to be positioned at a specific angle to obtain a clear video image without interference from eyebrows or shadows obscuring the eyes.

Electroencephalography (EEG) is a technique used to measure the electrical activity of the brain. It can detect various signals like heartbeats, eye blinks, and major physical movements such as head movements. EEG involves placing sensors on the top of the head to capture brain activity in both humans and animals [21]–[23]. Cui *et al.* [24] have highlighted EEG as a highly effective approach for detecting drowsiness and exhaustion, building upon previous studies on identifying drowsiness indicators. However, the method has some limitations, mainly its sensitivity to noise near the sensors. During EEG experiments, it is essential to maintain a completely silent environment, as any external noise can interfere with the accurate measurement of brain activity. Another drawback is the impracticality of using EEG in real-world driving scenarios. Wearing a device with numerous wires on the head while driving can be inconvenient and potentially unsafe if the wires become loose due to head movement. Despite these limitations, EEG remains one of the best methods for experimental purposes and data collection in controlled settings.

Driver fatigue can also be detected with OpenCV. If the face is detected in this system, facial landmarks will be used to extract the eye areas. If the eye aspect ratio (EAR) reveals that the driver's eyes have been closed for a long enough period of time, an alarm will sound to rouse him up. Rather than using the standard image processing method for computing blinks, this system used a metric termed EAR. Instead, EAR is a considerably simpler technique that involves a simple computation based on the ratio of distances between the eyes' facial landmarks. With OpenCV, Python, and dlib, this system recognises eye blinks. The only hardware utilised in these systems is a USB camera (Logitech 920) and a regular laptop as it is a basic system of detecting drowsiness with an alarm.

2. METHOD

2.1. Haar cascade classifier

Haar cascade is a face recognition algorithm that may be used to identify faces in photos or real-time recordings. Arakawa [25], added edge or line detection features. To train the algorithm, a big number of positive images with faces is provided, as well as a huge number of negative images without faces. The model developed as a result of this training session is available on the OpenCV GitHub repository. The models are stored in the repository as XML files and can be accessed via OpenCV techniques. Among them are face detection, eye detection, upper and lower body detection, and license plate detection, among others.

To detect the face in an image, OpenCV's haar cascades will be employed, which boils down to finding the bounding box (x, y)-coordinates of the face in the frame. The dlib's facial landmark predictor may be used to get 68 prominent points that can be used to locate the eyes, eyebrows, nose, mouth, and jawline given the bounding box of the face. The visual representation of the 68 facial landmark coordinates from this detection approach is shown in the Figure 1.

Figure 1. Visualizing the 68 facial landmark coordinates

2.2. Dataset and features

For this algorithm, comparison, pre-prepared datasets have been used from kaggle which is drowsiness dataset by Aditta Das Nishad. The total number of images is 2,900 images consist of 726 images of closed eye, 726 images of opened eye, 723 yawn images and 725 not yawn images. Each category is divided into 2 subsets, training dataset and testing dataset with ratio 7:3. For each algorithm that will be tested, different ratio will be applied including 5:5 and 6:4 to find the average accuracy for various ratio of dataset.

2.3. Deep learning

The implementation for deep learning algorithm consists of three convolution blocks having 3 convolutional layers each. A dropout layer follows convolution block for avoiding overfitting and a maxpool layer. Lastly, three fully connected layers follow convolution layers for classification. Model training runs for a total of 50 epochs with “adam” optimizer.

2.4. Artificial neural network

By using multilayer perceptron from ANN, we trained this model with 4 hidden layers with 300, 200, 100, 70 neurons respectively. As mentione previously, we are using “adam” optimizer, 50 epochs to train the model. The database is split to train and test dataset with 7:3 ratio respectively using train_test_ split function.

2.5. Eye aspect ratio

After recognizing the driver’s face, the eye blink rate is used to calculate the driver’s sleepiness level. Using the scalar value, the EAR formula can detect the eye blink. For example, if a driver blinks their eyes more frequently, it indicates that they are drowsy. To determine the eye blink frequency, it is important to precisely detect the eyes shape. The EAR is used to assess the eye-opening state based on landmarks recognised in the image with face. The eye landmarks are recognised the computed height and width of the eye for each video frame. The EAR can be defined by (1).

$$EAR = \frac{\|p_2 - p_6\| + \|p_3 - p_5\|}{2\,\|p_1 - p_4\|} \tag{1}$$

The EAR formula is shown above, with p1 through p6 representing 2D landmark positions. As shown in Figure 2, the p2, p3, p5, and p6 are used to measure height, while the p1 and p4 are used to measure eye width in metres (m). When the eye is open, the EAR remains constant, but when the eye is closed, it rapidly goes to zero.

2.6. Threshold value and number of consecutive frames

Several critical configuration settings are established within this system, playing a pivotal role in its functionality. These settings include the threshold value for the EAR, the number of consecutive frames in which closed eyes are deemed indicative of fatigue, and the threshold value for detecting yawns. A value of 0.25 is selected for the EAR threshold, while a yawn threshold of 30 is chosen. Additionally, the system considers a total of 30 consecutive frames, which is equivalent to approximately three seconds, to identify sustained patterns. These settings collectively contribute to the precise determination of drowsiness within the system.

2.7. Lip distance

The objective here is to find the distance between top lip and low lip. Referring to visual facial landmark in Figure 1, the top lips consists of coordinate 51-53 and 62-64 and the mean is calculated for all 6 coordinates and labelled as top_mean. Meanwhile for low lip, the mean is calculated for coordinates 68-66 and 59-57. The distance is returned for yawning detection later.

2.8. Flow chart

The system will start by getting images input from real-time video, face, eyes, and mouth detection using haar cascade. Then the eyes and mouth are extracted and estimated for EAR calculation. After the EAR is passing certain threshold value, the system will issue warning as an alarm to remind and waking up the driver. The system will be in loop until the user quits the system as shown in Figure 2.

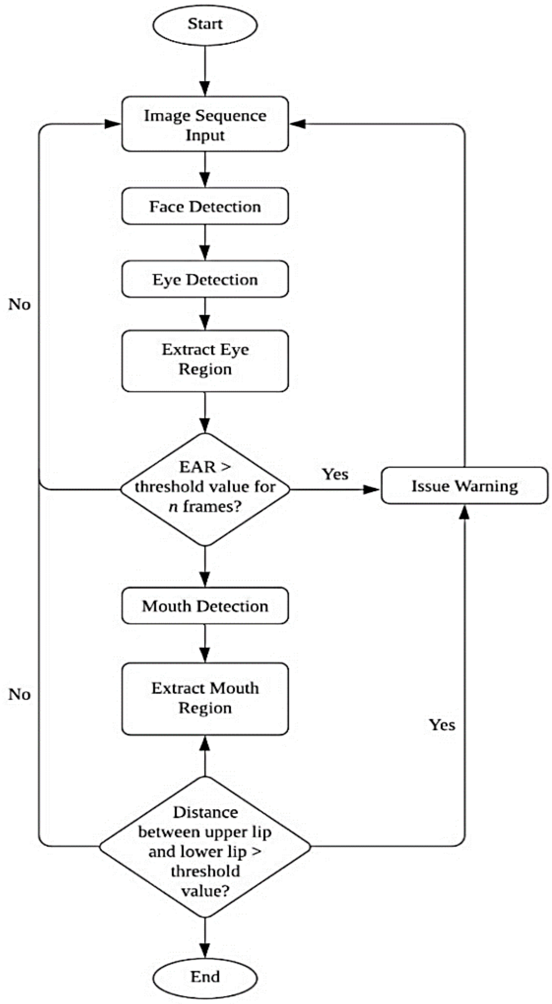


Figure 2. Flowchart

3. RESULTS AND DISCUSSION

3.1. Accuracy testing

For deep learning and ANN, both detections are set up as discussed in previous sub-section 2.3 and 2.4. Different ratio of dataset also being tested to find the average accuracy in using these two algorithms and shown in Table 1. Meanwhile for EAR, the threshold value is determined to detect fatigue. Different setup to test the accuracy is done as shown in Table 2. In all these algorithms, the driver is considered fatigue if the detection happens for 30 consecutive frames which is around 3 seconds. After comparing 3 algorithms, the algorithm to use for this project is EAR due to its consistent accuracy and faster detection by using pre trained neural network-based prediction.

Table 1. Accuracy result for deep learning and ANN

Algorithm/Ratio	7:3	5:5	6:4	Average accuracy
Deep learning	74%	73%	74%	73.67%
ANN	88%	88%	88%	88%

Table 2. Accuracy result for EAR

Setup	Test	Detect	Not detect	Accuracy
Initial	10	10	0	100
Fatigue	10	9	1	90
Wear spectacles	10	9	1	90
Dim light	10	9	1	90

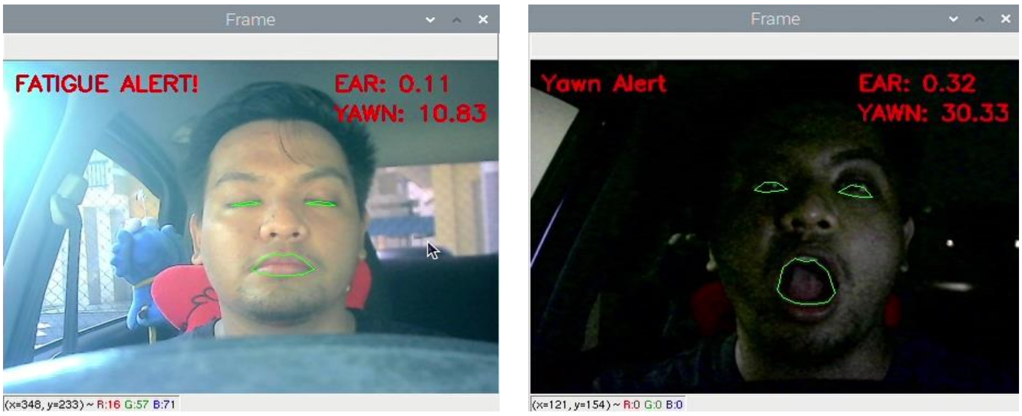
3.2. Eyes detection analysis
3.2.1. Awake state

The system works on the principle that the driver is awake if the EAR value is not frequently under 0.25. When the system determines that the driver is awake, no sound alerts are triggered. The system will only display the EAR and Yawn values on the display, as shown in Figure 3. This feature serves as an indication that the driver is awake and not showing any signs of fatigue.

Figure 3. Awake state (day)

3.2.2. Fatigue state

When the user's eyes are closed for more than 3 seconds, which is equivalent to 30 consecutive frames, a decrease in the EAR value under 0.25 indicates that the driver is experiencing fatigue. As a result, an alarm is triggered and a fatigue alert is displayed on the frame, as shown in Figure 4. Figure 4(a) shows fatigue detection during the day, while Figure 4(b) shows fatigue detection at night. This mechanism effectively signals the onset of drowsiness by triggering appropriate alerts and visual warnings.



(a) (b)

Figure 4. Fatigue state in; (a) midday and (b) night

3.3. Mouth detection analysis
3.3.1. Not yawn state

If the recorded value remains under the threshold, the system interprets it as an absence of speech or yawning. This approach allows the system to distinguish between moments of speech or yawning and other periods, improving its accuracy in detecting such activities. By using this threshold-based criterion, as shown in Figure 5, the system can effectively distinguish between instances of driver engagement in conversation or yawning and periods of non-engagement.

Figure 5. Driver not yawning state (day)

3.3.2. Yawn state

Whenever the user yawns, the threshold value increases above 30.00, triggering a yawn alert. This is visually depicted in Figure 6. Figure 6(a) shows a yawn alert occurring during daytime, while Figure 6(b) shows a yawn alert occurring at night. This threshold-based allows the system to effectively detect yawning, which can be a sign of fatigue. The distinction between daytime and nighttime yawn alerts improves the system’s adaptability to different lighting conditions, enabling it to provide accurate and context-aware responses to the user’s behavior.

(a) (b)

Figure 6. Shows a yawn alert occurring during; (a) daytime and (b) night

4. CONCLUSION

In summary, a driver fatigue detection system based on an embedded device has been successfully created with unique features and is operating well. There are various modifications that can be made to the system in the future to improve it. With instance, the webcam camera can be swapped out for a night vision camera. This is to ensure that detection is possible during night-time driving even when there is no light surrounding the driver. Apart from that, sensors such as a liquor sensor and a pulse sensor can be used to differentiate between the driver’s booze consumption and heartbeat rate in order to improve physiological-measure analysis. Alternatively, the system can integrate the suggested system with widely utilized applications such as Uber and Grab. When integrated, the system has the potential to significantly reduce the amount of fatalities and injuries caused by these drivers’ sleepy conditions. Finally, the system can be modified to accommodate new types of users, such as bike riders, as well as different domains, such as railways and aeroplanes.

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