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Fatigue Detection System with Haar Cascade Classifier

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Abstract: Drowsy driving is one of the major contributing factors to Malaysia's rising accident statistics. Drowsiness may be caused by a few reasons including fatique. Therefore, this study proposes a design for image processing to detect fatique during driving using the Raspberry Pi 3 board. The Haar Cascade Classifier technique is used to recognize eyes and faces, while the Eye Aspect Ratio (EAR) algorithm is used to detect eyes blink (open and close) to fulfil the research's goal. The system's average EAR value ranged from 0.125 while the eyes were closed to 0.299 when the eyes were opened. This project is an upgraded version of a previous project that includes an LCD display with a touch panel and interaction between driver and system. For future improvement, a GPS can be implemented into the system so it can inform the driver the nearest Rest & Relaxation so they can go take a rest after receiving several warnings.

Keywords: Fatigue Detection System, Drowsy Driver, Haar Cascade Classifier, Eye Aspect Ratio

1. Introduction

Every year, distracted and drowsy driving results in thousands of deaths and injuries [1],[2]. Numerous research experiments using artificial intelligence have been conducted over the years to determine ways to minimize fatal accidents caused by driver distraction and drowsiness. Despite the initiative, driver monitoring systems have not gained widespread adoption because many studies rely on non-direct characteristics (e.g., steering wheel movement, lane location standard deviation), wearing intrusive equipment, or using high-performance processors. These research studies are classified according to the type of vehicle used, the type of activity observed, and the type of physiological measurements made [3].

Numerous automakers and researchers have embraced vehicle-based measurement and introduced driver monitoring systems on the basis of its real-time efficiency, non-intrusive operation, and adaptability [4],[5]. However, vehicle-based measurement is not a solution that is exclusive to distraction and drowsiness, as variations in in-vehicle data can be the result of distracted driving,

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independent driving styles, or road geometry, among other factors [3],[6]. The experiment demonstrated a situation in which the driver's driving pattern remained unaffected by drowsiness [7]. Additionally, since vehicle-based measurement usually detects drowsiness after it has progressed to the final stage, warnings to avoid an accident may be created too late [8].

When driving, the driver's physiological signs are distinctive and are closely linked to detecting distraction and drowsiness. The physiological monitoring system for drivers provides high precision and can be applied in real time [9]. Despite these advantages, commercializing the device is difficult due to the large, costly, and invasive equipment used to collect data on physiologic signals [10]. There are many wearable devices for obtaining physiological signals, such as rings, watches, and headbands, but they are not effective sources for detecting driver distraction and drowsiness. For these factors, commercialization of a driver monitoring device based on physiological measurements is challenging.

For decades, driver monitoring systems based on behavioral analysis have been suggested as a compromise and have been actively researched. The majority of research on driver monitoring systems that employ behavioral measurement has relied on hand-crafted machine learning features and classifiers. However, hand-crafted features are often low-level and inadequate for dealing with object presentation variations such as pose, lighting, and orientation [11],[12]. It is far too difficult to choose the right features and classifiers based on the characteristics of the datasets [11]. Following AlexNet's well-publicized victory at the ILSVRC2012 (IMAGENET Large Scale Visual Recognition Challenge 2012) [13], deep learning with a network for learning features has been extensively researched and has demonstrated superior classification efficiency in a variety of fields.

Nevertheless, since deep-learning algorithms use a significant amount of memory and computing, the majority of studies involving a deep-learning-based driver monitoring device make use of a high-performance CPU or GPU. Additionally, the majority of studies employ a hierarchical system that sequentially detects faces, eyes or mouths, and driver condition (distraction or drowsiness). Not only does a hierarchical structure necessitate higher CPU or GPU requirements, but the driver status is not recognized properly if the driver's face is not identified or is detected poorly. Although tracking algorithms have been used to tackle this issue, there is no one-size-fits-all solution for accurately identifying and tracking the driver's face at the moment. Face recognition and tracking may have a noticeable effect on the system's speed and accuracy.

In, Park et al [14] suggested a system without a hierarchical structure thus demonstrated that the driver's drowsiness could be detected directly from the primary image by compromising efficiency dramatically. To solve this problem, a Fatigue Detection System is purposed which enables drivers to be alerted when he falls asleep or feeling drowsy by using Raspberry Pi 3 Model B+. This is because Raspberry Pi 3 B+ has a faster processor in comparison to other versions on the market and even to previous Raspberry Pi models. The CPU features a 64-bit 1.4 GHz quad-core processor that is capable of operating at much higher clock speeds. Not just that, but it can even more efficiently and precisely regulate and track the chip's temperature.

2. Materials and Methods

This section discusses the overview of the working procedure for this project including hardware and software implementation in the fatigue detection system.

2.1 Materials

The Raspberry Pi 3 Model B and Raspberry Pi 8 Mega Pixel camera sensors are the core devices for the prototype-based image processing. The Raspberry Pi 3 model B, manufactured by the Raspberry Pi Foundation, is shown in Figure 1. The Raspberry Pi 3 Model B is Raspberry Pi's third iteration. While preserving the popular board configuration, the Raspberry Pi 3 Model B offers a more powerful 10 times quicker processor than the Raspberry Pi of the first generation. It also comes with wireless networking LAN and Bluetooth, making it the ideal solution for powerful linked designs.

Figure 1: Raspberry Pi 3 Model B+

The RPi Camera (E) shows in Figure 2 is a Raspberry Pi Camera Module that is capable of recording in low light conditions. It is compatible with all versions of the Raspberry Pi computer. It has a 5-megapixel OV5647 sensor and the highest resolution it can achieve is 1080p. The photo resistor, which serves as an ambient light detector, is built into the IR LED board, which aids in the operation of the night vision feature. On it is an adjustable resistor for controlling the ambient light threshold for toggling the infrared LED; when ambient light is lower than the threshold value, the infrared LED is on, and vice versa when ambient light is higher than the threshold value. Screw holes on the board are used for both attaching and power supply purposes.

Figure 2: 5MP Raspberry Pi Camera Night Vision

Figure 3 shows the Raspberry Pi 5 inch display. It has an 800x480 resolution and a 5inch resistive touch screen LCD with HDMI interface, which can support several mini-PCs and multiple systems at the same time. It works with a variety of systems, including Raspberry Pi, Banana Pi, and BB Black, as well as standard desktop computers.

Figure 3: Raspberry Pi 5 Inch Display

2.2 Methods

This project is purposely to detect drowsiness of a fatigue driver in the car while driving. The major goal of this project is to identify driver drowsiness, which can be accomplished in a variety of ways, including monitoring the driver's facial expression and measuring the Eye Aspect Ratio (EAR). Every person's blinking pattern is different. In terms of eye squeezing, blink duration, and speed of closing and opening the eye, the pattern varies [15]. Haar Cascade Classifiers, Shape Predictor 68 facial landmark detection, Eye Aspect Ratio (EAR) all played a role in the suggested solution. The project working flowchart is shown in Figure 4.

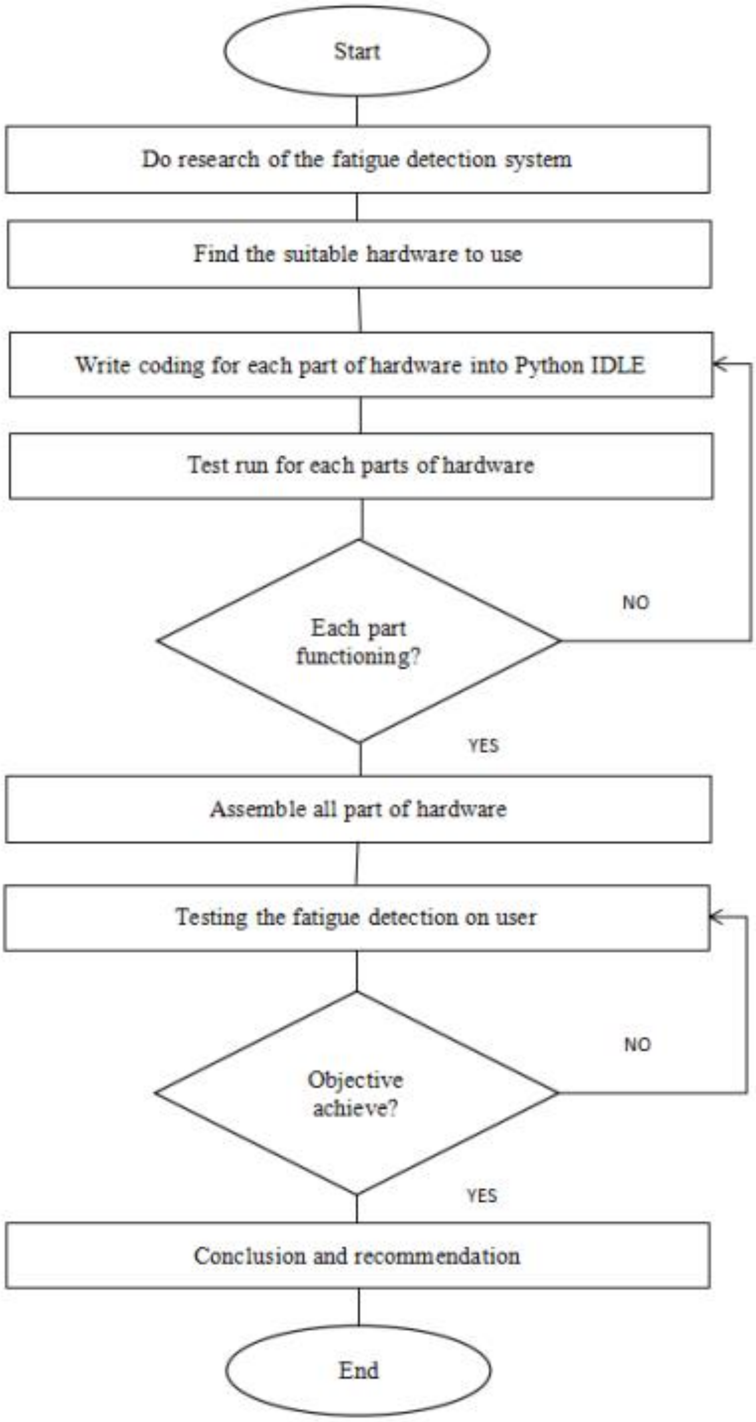


Figure 4: Project Working Flow Chart

2.3 Equations

A shape predictor is used to forecast the face and eye region in a live video broadcast. As shown in Eq.1, a measure of tiredness can be determined by computing an eye aspect ratio (the Euclidean distance between two eyes is calculated), passing these calculations to a predetermined data set, and performing facial landmark identification. The ocular landmarks for each video sequence are identified and recorded. The eye's aspect ratio (the relationship between its width and height) has been calibrated.

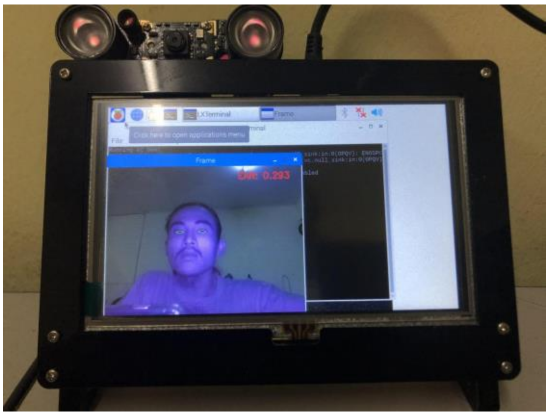
$$\text{EAR} = \frac{||p2 - p6|| + ||p3 - p5||}{2||p1 - p4||} \quad Eq.1$$

3. Results and Discussion

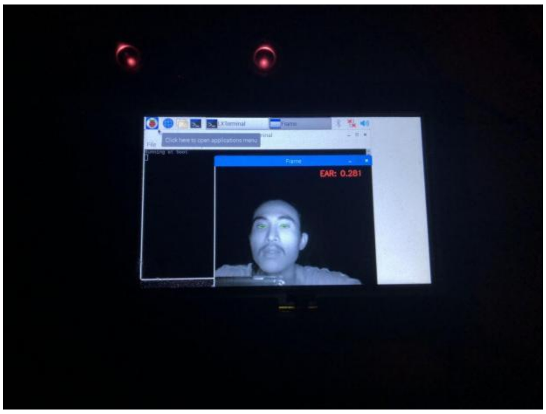
Two testing have been carried out to test the accuracy of the fatigue detection system; (1) Camera Testing, (2) EAR Testing.

3.1 Camera Testing

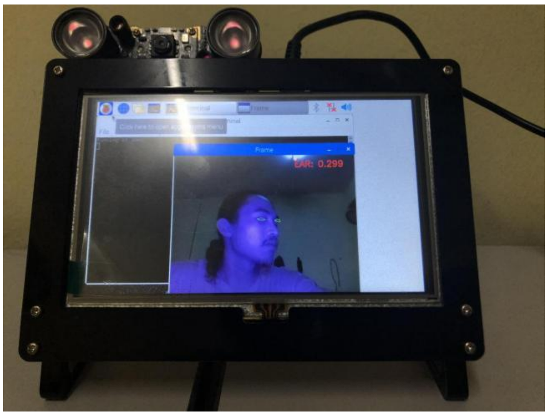
The camera has been tested in several different environment to make sure it will work efficiently as shown in Figure 5. The respond output of the alarm and the notification will pop up on the screen for user to interact when there are drowsiness detected multiple times. Table 1 shows the camera respond result according to the different environment.



(a)



(b)



(c)

(d)

Figure 5: Camera testing with different environment (a) Bright (b) Dark (c) Abnormal movement (d) Multiple faces detections

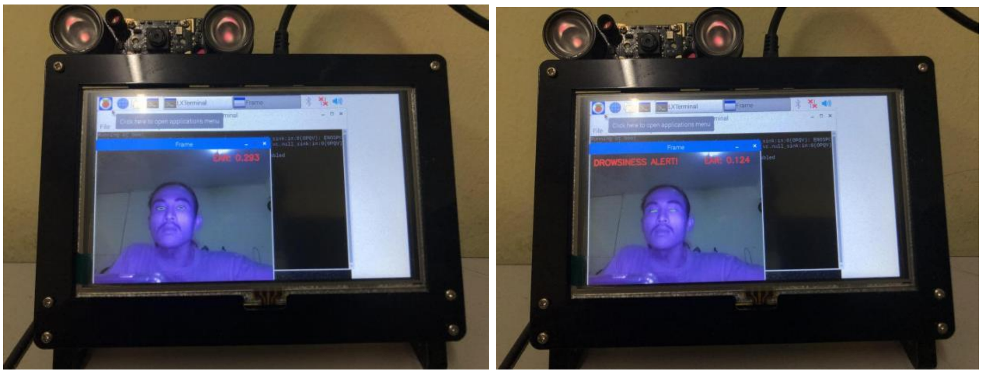
Table 1: Camera test results

Item	Environment	Camera Respond
1	Bright	Detecting Face
2	Dark	Detecting Face
3	Abnormal movement	Not Detecting Face
4	Multiple face Detection	Detecting Face

From the Table 1, during bright environment, camera was showing a good respond without any falsity. This result proving that this system can be used in bright day or facing a light reflection of car from opposite direction. As for dark environment, it also showing no problem since this project have also implemented infrared to support environment with less light such as in a tunnel or during night. Unfortunately for abnormal movement respond, the camera has no problem detecting eyes position but the system having hard time to tell either the driver is closing his or her eyes. Lastly, for multiple faces detection, the system has no problem in detecting multiple face and working for both of the face no matter which person showing drowsiness symptom.

3.2 EAR Testing

The driver's tiredness can be determined by measuring the driver's Eye Aspect Ratio (EAR). The ratio of the eyes can be different for each and every individual. One is calculated for the condition of the eyes being opened, and another is calculated for the state of the eyes being closed. Figure 6 shows the example of EAR testing result for EAR open and EAR close.



(a) (b)

Figure 6: EAR testing result (a) EAR open (b) EAR close

The pace at which the eyes close is measured every 0.3 seconds, and if the value exceeds a previously established threshold value, the raspberry pi 3 receives an alert signal from an alarm linked to the GPIO pins of the Pi 3 board, which is subsequently turned off. When a person closes his or her eyes for a period of time greater than a predetermined threshold range, an alert signal is generated to awaken the driver from his or her sleepy state as shown in Figure 6(b). Table 2 shows the average value of EAR testing for open and close conditions.

Table 2: Average value of EAR testing result

Test	EAR Open	EAR Close
1	0.293	0.124
2	0.312	0.127
3	0.303	0.119
4	0.288	0.131
5	0.297	0.122
Average	0.299	0.125

Table 3 shows the values of alarm time respond for 5 times of testing. The average value of alarm respond time is 0.031s.

Table 3: Values of alarm time respond

Test	Alarm Time Respond
1	0.029s
2	0.035s
3	0.032s
4	0.027s
5	0.031s
Average	0.031s

4. Conclusion

Driver drowsiness detection is primarily intended to keep the driver awake while driving in order to avoid an accident caused by sleepy driving. The alert signal is created by the embedded device and is sent to the driver to wake him/her up from his/her sleepy state. To calculate the tiredness of the driver in real time, the Pi is utilized in conjunction with the Raspbian camera. It is possible to quantify fatigue by recognizing the eyes and face using the Haar Cascade Classifier, particularly facial landmarks, which may be recognized using a shape predictor, and by calculating the Euclidean distance between the eyes. It will be easier to calculate drowsiness levels if there is accurate eye detection and faces in every frame. In order to accurately evaluate tiredness, frequent detection of eye blinking and head tilting must be performed. An audible warning will be issued to the driver when he/she hits the maximum threshold, causing him/her to awaken from their sleep condition.

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