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Smart Alert System for Drowsy Driver using Haar Cascade Classifier and Dlib Facial Landmark

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Abstract
The rise in accident rates involving vehicles such as cars and lorries in Malaysia can be attributed, in part, to driving while drowsy. Various researchers have proposed different techniques for detecting drowsiness, with behavioral-based methods gaining popularity due to their non-intrusive nature. This study focuses to develop and evaluate the accuracy of a behavioral based drowsiness detection system by studying the characteristics of drowsy drivers. The research utilizes the Haar cascade classifier algorithm, Eye Aspect Ratio (EAR) algorithm, and Dlib Facial Landmark Algorithm to effectively detect drowsiness and fatigue. By continuously monitoring the EAR values and identifying when they frequently fall below a threshold value (0.23), the system triggers an alarm sound to alert the driver. The analysis conducted showed that this study achieved a higher level of accuracy, indicating that the algorithms used were highly effective in detecting drowsiness and fatigue with almost 100% accuracy in various conditions, including different lighting conditions (day and night). Consequently, this research contributes to the development of an efficient and reliable drowsiness detection system that can potentially mitigate accidents caused by driver impairment.
Keywords: *Smart alert system; Drowsiness detetction system; Haar cascade classifier; dlib facial landmark.*

1. INTRODUCTION

Vehicles are essential for daily mobility, making it easier to travel between locations. However, operating a vehicle while fatigued or drowsy poses a significant risk, greatly increasing the likelihood of collisions and injuries [1][2]. Drowsy driving, defined as driving while feeling sleepy or exhausted, impairs a driver's ability to make decisions, react quickly, and stay alert. Falling asleep at the wheel causes drivers to lose control of the vehicle, often resulting in collisions with other vehicles or stationary objects. Therefore, monitoring driver fatigue is crucial to preventing such accidents.

Various methods, including physiological, behavioral, and vehicle-based metrics, are commonly used to monitor drowsiness [3-6]. Vehicle-based measures track factors such as lane deviations, steering wheel movements, and accelerator pedal pressure. Any changes in these metrics beyond predetermined thresholds can indicate a higher likelihood of driver drowsiness. Behavioral methods involve using cameras to capture driving behaviors, such as yawning, eye closure, blinking, and head position, with alerts triggered when signs of sleepiness are detected. Physiological measures examine the relationship between physiological signals—such as electrocardiograms (ECG), electromyograms (EMG), electrooculograms (EoG), and electroencephalograms (EEG)—and driver fatigue. While physiological methods can be effective, they are often better suited for offline applications due to concerns about detection accuracy and the need for specialized equipment, which can be uncomfortable and impractical for drivers.

Behavior-based methods have emerged as a practical option for real-time drowsiness detection due to their low latency and reasonable accuracy [3]. However, further research is needed to enhance detection accuracy, particularly when accounting for environmental factors like ambient lighting, face masks, and sunglasses. Behavioral methods are nonintrusive and cause minimal disruption to the driver, which is why we prioritized them in our study. Our proposed monitoring system accurately tracks the driver's facial features using Dlib Facial Landmark analysis, the Eye

Aspect Ratio (EAR), and the Haar Cascade Classifier algorithm. This approach offers a simple yet effective way to detect fatigue without interfering with the driving experience.

By carefully analyzing the EAR value and quickly identifying situations where the value frequently drops below the critical threshold of 0.23, our system immediately triggers an alarm to inform the driver. This timely intervention significantly reduces the likelihood of accidents, thus promoting road safety. Addressing the critical issue of drowsy driving is essential for road safety. Our study demonstrates the effectiveness of a behavioral-based real-time drowsiness detection system, which offers a practical and nonintrusive solution for monitoring driver alertness. By improving detection accuracy and ensuring timely interventions, such systems can significantly reduce the risk of accidents caused by driver fatigue. Further research into enhancing these techniques considering environmental factors will continue to improve their reliability and efficacy.

The paper follows the following structure: In Section 2, a literature review on drowsiness detection is presented, encompassing various techniques and measures. Section 3 elaborates on the methodology utilized for designing and implementing the drowsiness detection system. The framework of the proposed system is outlined in Section 4, while Section 5 delves into the performance evaluation results, including experiments and metrics. Finally, Section 6 concludes the findings and emphasizes the significance of drowsiness detection systems.

2. Related Works

Driver drowsiness is a significant contributor to road accidents, prompting a wealth of research into advanced detection systems to mitigate associated risks. Various studies have utilized cutting-edge technologies to enhance the detection and prevention of driver fatigue.The Advanced Driver Assistance System (ADAS) module [7], employing visual information and artificial intelligence, exemplifies this effort. The system analyzes drivers' facial movements and eye closures, using the PERCLOS indicator—a measure of eyelid closure over the pupil—to detect drowsiness. Despite its potential, the module currently lacks real-time operation capabilities in autonomous vehicles. Similarly, study [8] assesses a production-ready Driver Monitoring System (DMS) in a high-fidelity driving simulator, demonstrating that integrating DMS with vehicle-based sensors significantly improves the ability to distinguish drowsiness levels, though differentiating between moderate and severe drowsiness remains a challenge.

Further innovations are explored in study [9], which merges IoT with advanced neural networks like LSTM, VGG16, InceptionV3, and DenseNet. By incorporating transfer learning and multiple drowsiness indicators, this approach achieves high accuracy under various conditions and adapts to current challenges, such as drivers wearing masks during the pandemic. However, real-world validation is still required to confirm its effectiveness. The development of drowsiness detection systems continues with Python and the Dlib model in study [10], which utilizes facial landmark coordinates and aspect ratios for detection. While achieving a high recognition accuracy on dataset videos, the system's performance in real-time is limited by variable lighting conditions. Study [11] introduces a real-time monitoring system employing OpenCV and Raspberry Pi that includes video acquisition, face detection, eye detection, and drowsiness alerts, facing similar challenges in low-light conditions.

In study [12], the results demonstrate a 20% improvement in sleepiness detection using a combination of Haar cascades and a simplified Yolo-Lite model. While the detection rate has improved, the simplified Yolo-Lite, though efficient, may lack the robustness required for diverse and uncontrolled environments. The study also recommends incorporating additional monitoring features in future iterations to enhance system performance and adaptability. Meanwhile, the authors in [13] utilize video capture with face detection to analyze head position and blinking patterns. However, the system's inability to perform well in low-light and night-vision conditions highlights a significant flaw. Further addressing driver fatigue, study [14] employs an infrared camera and hands-off detection sensors within a system that includes a Raspberry Pi, GSM/GPS module, and various sensors, demonstrating its efficacy in reducing fatigue-related accidents. However, the combination of hardware presents challenges in adapting to practical driving conditions. Study [15] offers a comprehensive monitoring system that detects drowsiness and monitors heart rate using IoT technology, capable of sending emergency messages in critical situations. Nonetheless, the reliability of IoT-based systems in areas with unstable internet connections or hardware failures remains a concern. Although the system can send emergency alerts, its effectiveness in reducing fatigue-related accidents depends on a reliable, uninterrupted data flow, which may not always be feasible in remote locations.

The introduction of a respiratory signal-based detection system in study [16] adds to the variety of approaches and presents an intriguing physiological marker for drowsiness detection. This research should be continued. The study might, however, be criticized for concentrating too much on a single physiological signal, which could restrict its applicability if a driver's sleepiness has little effect on respiratory patterns. A more comprehensive strategy that takes into account several physiological cues might increase accuracy. Another work by [17] examines the application of an advanced machine learning technique for drowsiness detection by analyzing electrocardiogram (ECG) data using a self-attention autoencoder (SA-AE). Although this model has potential, issues with accessibility and computing efficiency in real-world driving scenarios are brought up by the intricacy of ECG data and the resource-intensive nature of SA-AE.

Agarkar [18] suggests employing visual markers in a camera-based method to identify signs of tiredness and yawning. These techniques work well in controlled environments, but further research is needed before they can be widely used. Despite the difficulty of data collecting, study [19] assesses the potential of electroencephalography (EEG) due to its high accuracy in comparison to conventional approaches. Finally, a convolutional neural network (CNN) developed by genetic algorithms is discussed by Jebraeily, Sharafi, and Teshnehla [20]. This CNN exhibits greater accuracy in detecting tiredness and paves the way for further advancements in real-world driving applications. Overall, despite the fact that driver drowsiness detection technology has advanced significantly, more work is still required to address issues with real-time applications, environment adaptability, and system integration to guarantee successful deployment in driving scenarios.

3. METHODOLOGY

In developing the proposed system, an iterative and incremental development approach has been used. The approach shown in Figure 1 allows for a flexible and adaptable technique to measure the driver’s drowsiness and state of driver.

The drowsiness detection system is developed incrementally and iteratively, steadily enhancing its capabilities, addressing issues as they arise, and ensuring proper validation. The system has three primary goals. First, it focuses on analyzing the characteristics of drowsy drivers, particularly by identifying facial and eye movements, as well as blinking patterns. This analysis forms the foundation for creating an effective drowsiness detection model. Second, the system employs OpenCV’s Facial Landmarks and Haar Cascade Classifier algorithms to build this model. These methods are used to accurately detect signs of drowsiness in video captured by a webcam. Lastly, the system aims to continuously monitor the video feed to test its detection capabilities and trigger an alarm when drowsiness is detected, thereby alerting the driver and reducing the risk of accidents.

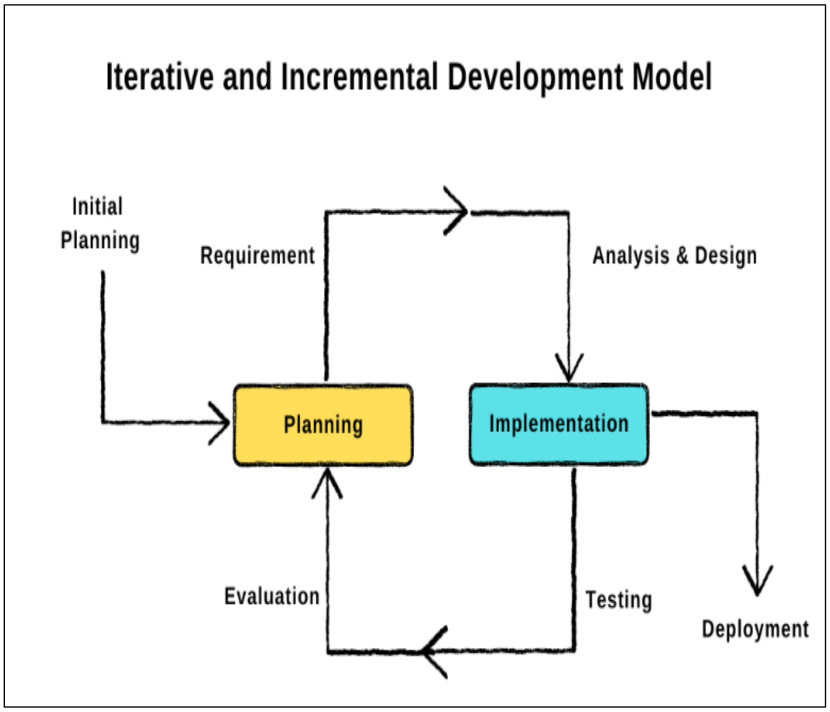

Fig. 1. Iterative and incremental development model

The development process begins with the requirements gathering phase, followed by the design and implementation phases. Key algorithms, such as the Dlib Facial Landmark Algorithm, EAR, and Haar Cascade Classifier, are integrated into the system. Extensive testing is conducted using the webcam's video stream to evaluate the system's performance. Feedback from users, experts, and stakeholders is collected, leading to iterative improvements in accuracy and functionality. The development process uses the PyCharm IDE and various software libraries, including OpenCV, NumPy, Dlib, Matplotlib, imutils, and Pygame. This gradual and iterative approach ensures the systematic development of a reliable drowsiness detection system, aimed at effectively reducing accidents caused by driver fatigue.

4. Smart Alert System for Drowsy Drivers' Framework

The system framework in this study serves as a methodical and systematic way to direct the creation and execution of a Smart Alert System for fatigued drivers. It provides a methodical approach to addressing the proposed system objectives and achieving the intended results. The framework offers a systematic and structured strategy for creating and putting into use an intelligent sleepiness detection system. In order to predicting drowsiness accurately, it combines a number of algorithms and approaches. Figure 2 shows the architecture of the system and the associated flows.

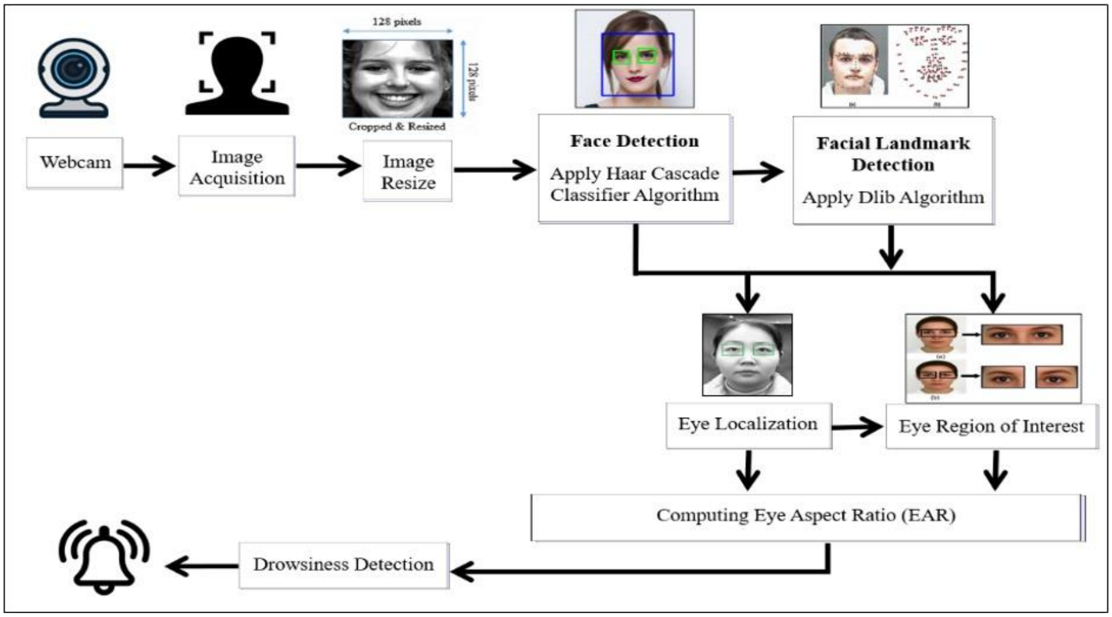

Fig. 2. Framework of the system.

To capture input images for the classifier, the system first utilizes a webcam. This image acquisition process involves recording live footage of the driver's eyes through the webcam. Once captured, OpenCV is used to resize the images to a standard format suitable for further analysis. The system then applies the Haar Cascade Classifier Algorithm to detect faces and eyes. This feature-based object detection method is trained on both positive and negative images to ensure accurate detection. Due to its real-time processing capabilities, the Haar Cascade Classifier is well-suited for this system, which requires continuous, real-time camera capture for effective monitoring.

The next step involves the implementation of the Facial Landmark Detection using the Dlib Algorithm. This algorithm utilizes a pre-trained face detector based on a modification of the standard histogram of oriented gradients. It detects the landmarks of the eyes and computes the EAR, which is used to determine the activity of the eyes. The Eye Region of Interest (ROI) is then extracted through image cropping to focus on the area near the eyes, where the system concentrates its analysis. The EAR calculation is based on a formula, and a constant value indicates an open eye, while a rapid decrease towards zero indicates a blink. The EAR formula as stated below, where P stands for the position at the face as in (1) [15].

Finally, if drowsiness is detected by the system, it triggers an alarm to alert the driver. The alarm

$$EAR = \frac{\|P_2 - P_6\| + \|P_3 - P_5\|}{2\|P_1 - P_4\|} \quad (1)$$

serves as a warning to prevent potential accidents caused by driver drowsiness.

5. RESULT AND DISCUSSION

This section presents the results and discussion of the study. The primary focus of the findings is to determine the accuracy of three key components: the Haar cascade classifier algorithm, the Dlib facial landmarks algorithm, and the EAR algorithm.

5.1. Face and Eyes Detection

The face and eye detection in this system were implemented using the Haar cascade classifier algorithm and the Dlib Facial Landmark. To evaluate the performance of these algorithms under

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various conditions, experiments were conducted with different lighting conditions (Light and Dark), subject's face postures and positions, and subjects wearing spectacles. Six drivers were recruited for the study, and 30 frames of each driver were captured. Table 1 presents the data collected for drivers in different conditions. The results show that the Haar cascade classifier algorithm integrated with Dlib Facial Landmark successfully detects drivers in different lighting conditions and when drivers wear spectacles, achieving an average accuracy of 100% for these conditions. However, when a driver is in the right or left position, the algorithm is capable of detecting the face and eyes, but sometimes struggles to accurately locate the eye positions. Despite this limitation, the average system's accuracy remains above 95% for such scenarios. Furthermore, the algorithm demonstrates its ability to detect a driver's face rotation of around 60 to 90 degrees, but the average system's accuracy drops to 77.95% under these conditions. To summarize, the combined Haar cascade classifier and Dlib Facial Landmark algorithm show promising accuracy for various conditions, except for detecting eye positions in right and left positions and face rotation at extreme angles. These findings provide valuable insights into the system's performance and limitations, which can guide further improvements and optimizations.

Table 1. Data taken when subject in various conditions

Subject	Number of frames	Accuracy (Light) (%)	Accuracy (Dark) (%)	Accuracy (60-90 degrees) (%)	Accuracy (wears spectacle) (%)	Accuracy (right position) (%)	Accuracy (left position) (%)
1	30	100	100	81.48	100	100	100
2	30	100	100	82.22	100	96.67	98.89
3	30	100	100	76.46	100	94.32	90.11
4	30	100	100	71.96	100	95.67	99.35
5	30	100	100	72.59	100	88.86	87.89
6	30	100	100	83.00	100	97.86	99.60
Average		100	100	77.95	100	95.56	95.97

5.1. Eye Aspect Ratio Analysis

The system utilizes the EAR algorithm for drowsiness detection. To establish the suitable threshold value for identifying drowsiness, the system analyzed the EAR values obtained from six drivers, ranging from the maximum value when their eyes were closed to the minimum value when their eyes were open. Based on this analysis, the system determined that the optimal threshold value for detecting drowsiness is set at 0.23.

- **Awake State**

Figure 3 illustrates the Eye Aspect Ratio (EAR) values over 100 consecutive video frames, representing the condition when the driver is awake. The graph shows that for the majority of the frames, the EAR values remain consistently above the drowsiness threshold of 0.23, ranging mostly between 0.25 and 0.31. This pattern suggests that the driver's eyes are open for longer periods, which is typical of an alert or attentive state. Although there are occasional brief dips below the threshold, these occur infrequently and are spread far apart. For example, one such dip appears around frame 60, but the overall EAR values quickly recover and remain stable afterward. In total, the EAR falls below the threshold only six times throughout the 100-frame duration, which the system interprets as normal blinking rather than a sign of fatigue. This minimal occurrence of low EAR values indicates that the driver is not experiencing drowsiness. Based on this analysis, the system confidently classifies the driver as awake and displays an "AWAKE STATE" message as in Figure 4. The consistency and stability of the EAR pattern in this graph provide strong evidence of the driver's alertness.

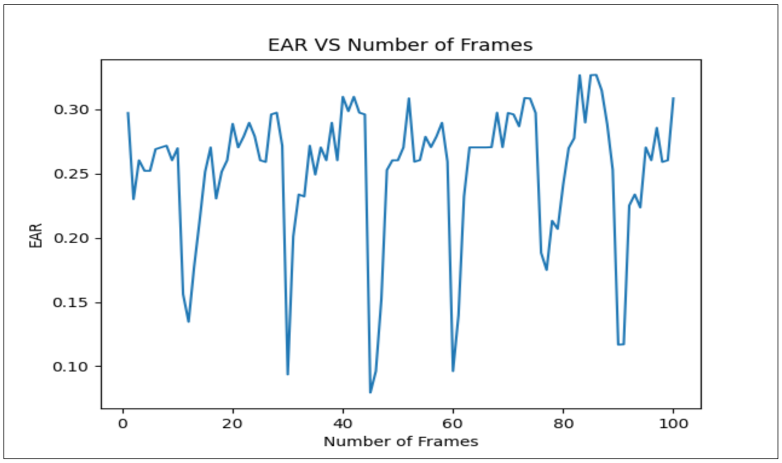

Fig. 3. EAR value in the awake condition

Fig. 4. The result when driver in awake state

- **Drowsy State**

Figure 5 presents the Eye Aspect Ratio (EAR) values plotted over 100 consecutive video frames, illustrating a drowsy driving condition. During the first 21 frames, the EAR values remain consistently low, fluctuating between 0.06 and 0.13, which is well below the designated drowsiness threshold of 0.23. This sustained decrease in EAR clearly indicates that the driver's eyes are frequently closed or only partially open, which is a key behavioral sign of drowsiness. After this period, the EAR briefly rises above the threshold, reaching values as high as 0.28 around frames 30 to 40. This suggests a short moment of regained alertness. However, sharp drops in EAR appear again around frames 45 to 55 and between frames 75 to 90, indicating repeated signs of drowsy behavior or short sleep episodes. While the EAR values do recover at times, they remain unstable and continue to fluctuate, reflecting the driver's struggle to stay awake. These repeated drops below the threshold over time enable the system to accurately identify the driver as drowsy and activate an alert by notifying the driver. Overall, the graph supports the system's ability to make effective real-time decisions by tracking EAR patterns across time rather than relying on individual measurements.

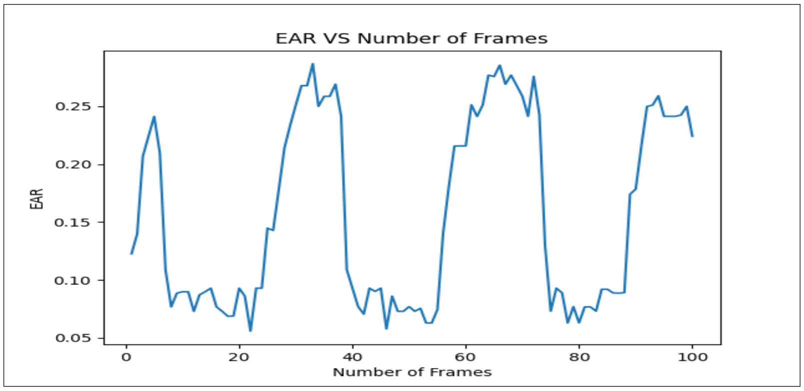

Fig. 5. EAR value in the drowsy condition

6. CONCLUSION

This study presents a behavioral-based drowsiness detection system developed using the Haar Cascade Classifier algorithm, Eye Aspect Ratio (EAR), and Dlib Facial Landmark Algorithm. The system has shown strong potential in accurately identifying signs of driver drowsiness and fatigue, achieving an impressive 100 percent detection rate under various conditions, including both bright and low-light environments. By integrating these algorithms, the system can continuously monitor the driver's facial features and analyze EAR values in real time. When the EAR consistently falls below the threshold of 0.23, an alert sound is triggered to warn the driver, helping to reduce the risk of accidents caused by fatigue or lack of focus.

The results highlight the system's value as an efficient and non-intrusive tool for improving road safety. By observing key behavioral indicators such as blinking patterns and eye movement, the system offers a practical and lightweight solution to address the serious problem of drowsy driving. The combination of these computer vision techniques works well in real-time detection, making the system a strong candidate for further development and real-world use.

Future research should aim to test the system in actual driving environments and involve a wider range of drivers. It would also be beneficial to include more detailed performance measurements, such as precision, recall, F1-score, and how quickly the system responds. Expanding the dataset and evaluating the system more thoroughly will be important steps toward making it more reliable and ready for practical use. Overall, this research shows how intelligent systems like this can play a valuable role in keeping drivers safe and reducing risks on the road.

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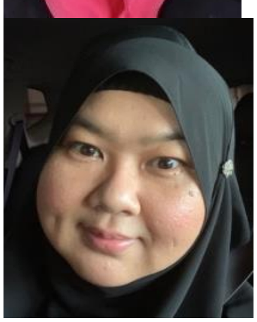

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