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Advancement in driver drowsiness and alcohol detection system using internet of things and machine learning

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ABSTRACT

Globally traffic accidents are influenced by factors such as drowsiness and alcohol consumption. Consequently, there has been a considerable focus on the development of detection systems as part of ongoing efforts to mitigate these risks. This review paper aims to offer a comprehensive analysis of various drowsiness and alcohol detection methods. The paper particularly emphasizes drowsiness and alcohol detection methods, including those centered on sensor-based approaches, physiological-based techniques, and visual analysis of the eye and mouth state. The aim is to evaluate their method, effectiveness and highlight recent advancements within this domain. Additionally, this review paper evaluates the research gaps of these detection methods, considering factors such as precision, sensitivity, specificity, and adaptability to different environmental conditions.

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1. INTRODUCTION

In recent time, the issue of road accidents caused by driver fatigue and alcohol impairment continues to be a concern, particularly for the safety of the general public [1]–[4]. According to research conducted by the Malaysian Institute of Road Safety Research (MIROS) one of the factors leading to accidents is driver drowsiness. Fatigue related incidents account to 7.7% of car accidents 9.9% for lorries and 7.9% for buses. Additionally, a survey conducted by MIROS among truck drivers in the Klang Valley revealed that 17.7% of them experienced drowsiness while driving [5]–[9]. Data from the Transport Ministry indicates that Malaysia recorded 1,114 fatalities due to drunk driving between 2012 and 2018. Furthermore, a report from previous year highlighted those accidents involving drivers serve as a significant cause of mortality, among young individuals [10].

Driver monitoring systems have been extensively developed due to the concerning statistics and potential dangers associated with conditions like drunk driving and drowsiness [11], [12]. To mitigate risks on the road it is crucial to identify and address driver drowsiness effectively [13], [14]. Detecting drowsiness in real-time can enable interventions and alertness measures thereby preventing accidents caused by fatigued drivers [15]. Over the year's researchers have explored behavioral indicators to develop efficient systems, for detecting intoxication and drowsiness [16]–[21].

This comprehensive review aims to provide an in-depth overview of various approaches employed in driver drowsiness and intoxication detection systems, focusing specifically on sensor-based, physiological, and behavioral indicators. By reviewing, we aim to identify the research gaps in existing systems, particularly in areas like sensor fusion, real-time adaptability, and the accuracy of detecting subtle changes in driver behavior. Section 2 discusses the literature review, highlighting existing research on sensor-based, physiological detection techniques and behavioral indicators for fatigue and intoxication. Section 3 examines the research gaps, highlighting the challenges namely, sensor reliability, environmental interference, and computational limitations. Following this, section 4 summarizes the findings and offers suggestions for future research directions.

2. LITERATURE REVIEW

Over the years, researchers have made significant progress in developing techniques to detect alcohol intoxication and driver drowsiness. This literature review explores the existing studies, emphasizing the methods employed, comparisons of various systems, and their limitations. By critically evaluating these approaches, the review aims to offer a comprehensive overview of the current work, highlight areas for improvement and outline potential directions for future research.

The initial section of this review focuses on sensor-based systems for detecting driver drowsiness. These systems employ a range of sensors to monitor physiological and behavioral signs of fatigue and intoxication, aiming to deliver timely warnings in order to reduce the risk of accidents caused by impaired drivers. Among the commonly used techniques, physiological-based methods stand out, as they track key vital signs namely, heart rate, breathing rate, and electrodermal activity to evaluate the driver's fatigue level. These metrics provide real-time feedback, making them highly effective in identifying drowsiness.

In recent years, facial feature analysis, particularly focused on the driver's eye behavior, has gained a lot of attention among the researchers. Various algorithms have been developed to detect signs of fatigue by monitoring eye movements, blinking frequency, and eyelid closure (PERCLOS). These systems have proven effective in real-time applications, where continuous monitoring of eye states provides early warning signs of drowsiness. Expanding on this approach, several studies have integrated mouth-based indicators, such as yawning detection and lip movement analysis, to enhance the accuracy of drowsiness detection systems.

2.1. Existing work on driver drowsiness and alcohol detection based on sensors

A common approach in modern systems includes the usage of sensors to monitor specific environmental and physiological parameters. This method incorporates specialized sensors installed within a car to gather crucial data and detect potential signs of fatigue or intoxication. Among the frequently employed sensors are the MQ-3 alcohol sensor and the eye blink sensor, which play pivotal roles in identifying drunkenness and drowsiness, respectively, enabling timely interventions to prevent accidents. The eye blink sensor tracks the driver's eye movements, analyzing patterns that may indicates fatigue. By continuously measuring the frequency and duration of eye blinks, the sensor can gauge tiredness and issue alerts when these metrics exceed the predefined thresholds. This real-time monitoring facilitates the early detection of drowsiness, allowing the driver to take appropriate actions, such as pulling over or taking a break. Similarly, the MQ-3 alcohol sensor is designed to detect alcohol levels by analyzing the driver's breath. It measures the concentration of alcohol molecules and compares the results against the preset limits. If the detected concentration exceeds the legal threshold, the device generates an alert, warning the driver against operating the vehicle while intoxicated. By integrating these sensor-based strategies, existing systems have shown promise in mitigating the risks associated with drowsy and alcohol-impaired driving. Ongoing research continues to focus on enhancing the accuracy and reliability of these sensors, reflecting a commitment to improving their ability to monitor a broader range of physiological and environmental parameters effectively.

Kinage and Patil [22] proposed a system designed to enhance road safety through the integration of various detection mechanisms. The system comprises three primary components: alcohol detection, eye tracking, and head movement detection. MQ-3 sensor is employed for alcohol detection due to its low cost and high sensitivity to alcohol. The sensor detects ethanol in the air or human breath in order to measure the level of alcohol present. The eye tracking component uses an infrared sensor with an infrared (IR) light emitting diode (LED) and an IR photodiode. This setup measures the light reflected from the eye to calculate the blink rate, enabling the detection of driver drowsiness. For the head movement detection, the system incorporates a 3-axis detection accelerometer, ADXL330. The system detects head accelerations in various directions, which are indicated by the LED signals. The system employs both relative and absolute mapping techniques to determine the changes in the head position.

Jenis and Dharshini [23] proposed a system aimed at preventing accidents caused by driver drowsiness and alcohol consumption. The system employs an eye blink sensor to monitor drowsiness by tracking the driver's blink rate. If the driver's eyes remain closed for more than 5 seconds, a buzzer is activated and the speed of the vehicle is reduced using a DC motor. For alcohol detection, an MQ-3 sensor analyzes the driver’s breath for alcohol content. When alcohol is detected, an LED indicator glows, and the DC motor adjusts the vehicle’s speed according to the detected alcohol level.

Shalini *et al.* [24] devised a multifunctional system designed to detect driver drowsiness, alcohol consumption, and mobile phone usage during driving. The system utilizes sensors to monitor these parameters, comparing the sensor readings with pre-defined reference values stored in the micro-controller’s memory. If the reading exceed the set thresholds, the micro-controller triggers a warning mechanism to alert the driver. This aler system employs various methods, inlcuding liquid crystal display (LCD) display, audible alarms, and other warning signals, to avert potential accidents. The core components of the proposed system include an Arduino microcontroller, eye blink sensor, alcohol sensor, and mobile phone usage sensor.

Sreedhar *et al.* [25] developed a vehicle-based device specifically to identify instances of alcohol consumption and driver drowsiness. The system comprises several components, including a microcontroller (ATMEGA328), crystal oscillator, regulated power supply, LED indicator, alcohol sensor (MQ303A), eye blink sensor, LCD display, DC motor, and relay. The alcohol sensor, a semiconductor sensor, is highly sensitive and responds quickly to alcohol detection. The eye blink sensor uses infrared technology to monitor eye blinks, producing a high output when the eyes are closed and a low output when the eyes are open.

Manideep *et al.* [26] presented a system that uses an infrared (IR) sensor to monitor the driver's eye movements, triggering a buzzer if an abnormal blink rate is detected, prompting the driver to remain alert. The system extends its functionality by incorporating additional features, including an alcohol detector and a seat belt detector, to address multiple factors that contribute to accidents. Additionally, an accelerometer is integrated to detect vibrations and tilts, which could indicate an accident. In the event of a collision, the global position system (GPS) module is activated to send the car's latitude and longitude coordinates to pre-saved emergency contacts via the global system for mobile (GSM) system, ensuring rapid assistance. The IR sensor serves to detect eye blinks, with its output directed to an Arduino for processing. Table 1 provides a summary of driver drowsiness and alcohol detection methods based on sensors, various sensor technologies and their applications for monitoring and identifying signs of fatigue and intoxication.

Table 1. Summary of driver drowsiness and alcohol detection based on sensors

Author (s)	Year	Comparison			Limitation
		Method	Sensor	Hardware	
Kinage and Patil [22]	2019	Using sensors to detect drowsiness and alcohol consumption of the driver in real-time and alerts the driver using voice messages	MQ-3 sensor Accelerometer ADXL330 Infrared sensor	- Arduino Uno R3	– Not very accurate for monitoring the driver’s eyes when the driver wears glasses and can be affected by sunlight.
Jenis *et al.* [23]	2020	Eye blink sensor and an alcohol sensor to detect drowsiness and alcohol consumption respectively.	MQ-3 sensor Eye blink Sensor	- Arduino Uno - DC Motor - L298H Bridge - Buzzer - LED	– Slows down the car using a DC motor, which may not be effective in all situations. – Wearing the eye blink sensor frame not fit comfortably for all drivers
Shalini *et al.* [24]	2019	Monitoring driver drowsiness, alcohol consumption, and mobile phone usage using sensors.	Eye blink Sensor MQ-3 sensor Mobile Sniffer	- Atmel 89C51 - Relays - LCD Display - Buzzer - RF transmitter and receiver	– No automatic alert system to send emergency messages to family members or vehicle owners
Sreedhar *et al.* [25]	2022	To improve safety, an alcohol sensor and an eye blink sensor are used to detect alcohol consumption and fatigue, respectively. If either is found, the engine is locked through a relay.	Eye blink Sensor MQ-3 sensor	- Arduino UNO - Crystal Oscillator - LED indicator - LCD display - DC Motor - Relay - Buzzer	– Driver always need to wear the eye blink sensor frame. – It won't detect drowsiness if the driver forgets to wear the sensor or takes it off while driving
Manideep *et al.* [26]	2022	IR sensor to detect eye blinks and face detection to track the driver's eyes and MQ3 gas sensor for alcohol detection.	Eye blink Sensor MQ-3 sensor IR sensor Vibration Sensor	- Arduino UNO - GPS module - GSM module - Buzzer	– -Certain lighting conditions may prevent infrared sensors from accurately detecting blinks of the eyes. – Drivers who use glasses or other eye accessories could find that the sensor is not as accurate.

2.2. Existing work on physiological based techniques for drowsiness detection

The use of physiological-based techniques which involve monitoring and analyzing physiological signals to estimate an individual's level of alertness is also one of the promising approaches for drowsiness detection. These methods take use of the fact that some of the physiological changes within the human body which are related to drowsiness. Many research efforts have looked into physiologically based techniques as a way to diagnose and track people's levels of drowsiness. These methods use a variety of sensors, such as electroencephalogram (EEG), electrocardiogram (ECG), photoplethysmography (PPG), galvanic skin response (GSR), and electromyography (EMG), to record and analyses physiological data related to drowsiness. By analyzing these signals, researchers hope to create non-intrusive, dependable systems for identifying and warning people who may be at risk of drowsiness-related problems.

According to the study that presented by Hwang *et al.* [27], it is insufficient to distinguish between alert and drowsy driving states just based on reaction time. Significant overlaps in the distribution of reaction times between various data blocks suggested possible classification problems. The study used a hybrid strategy that combines manual video inspection with reaction time to address issue. The quickest reaction times to lane deviations were used to identify candidate warning blocks in video recordings that showed behavioral indicators of drowsiness. The necessity to avoid employing a set threshold is shown by the fact that the reaction time distribution differed significantly amongst subjects. The study employed a driving simulation setup with numerous signals being captured, including as in-ear, scapha, conventional, ECG, PPG, and GSR. Different features were retrieved from these signals after they had been processed for analysis. The results highlight the significance of integrating physiological information with video inspection in order to precisely distinguish between alert and tired driving states.

A smart offline system to identify driver drowsiness was proposed by Hossan *et al.* [28]. The EEG sensor was employed by the authors to collect driver brain signals for fatigue detection. When a driver's fatigue is identified, a buzzer alarm is utilized to notify them. Next, a semi-automatic parking mechanism with a microcontroller is used to control the oil flow and then park the car.

An EEG-based fatigue detection system with three key components was proposed by Budak *et al.* [29]. First, the instantaneous frequency and spectral entropy features are taken out of the EEG spectrogram images. To determine the energy distribution and zero-crossing distribution properties, the raw EEG signals are also examined. Second, the direct extraction of detailed features from the EEG spectrogram pictures using pre-trained AlexNet and VGG16 models. Third, a configurable Q-factor wavelet transform is used to separate the EEG signals into corresponding sub-bands. The acquired sub-bands spectrogram pictures and statistical features, such as the mean and standard deviation of the sub-bands instantaneous frequencies, are subsequently calculated by the authors. The collected feature groups are sent to an long-short term memory (LSTM) network classifier once the three components have been processed.

An offline driver drowsiness detection system was proposed by Artanto *et al*. [30] by sensing eye closure using an inexpensive (electro-myo-graphy) EMG and ESP8266 wifi module. The eyelid muscles were observed using three electrodes to calculate the eyelid closure interval and the electrical muscle activity of the skin. The skin-borne EMG electrodes were put on a spectacles frame. The system will buzz the driver when the driver's eyelid closure exceeds the threshold value. Table 2 summarizes the physiological-based techniques for drowsiness detection, highlighting the methods used to monitor vital signs such as heart rate, breathing rate, and electrodermal activity to assess driver fatigue.

2.3. Existing work on driver drowsiness monitoring using visual analysis of eye state

The development of reliable driver drowsiness monitoring systems employing visual analysis of eye condition has been the subject of numerous researches. These systems can detect and measure the degree of drowsiness in drivers by utilizing the strength of machine learning and deep learning algorithms. These algorithms can properly evaluate the driver's state of attentiveness by examining several visual indicators such eyelid motions, eye closure duration, and eye blink patterns and can then offer prompt warnings or interventions as needed. A summary of the many approaches, datasets, and performance indicators used in this study field is also intended in this section. The current research in this area has significantly advanced the accuracy and dependability of driver drowsiness monitoring systems.

Based on the proposed model by Patnaik *et al.* [31], the computer vision algorithm is used to analyse the images captured by the webcam and detect the position of the driver's face and eyelids. The Haar-cascade technology is used for effective object detection, and the histogram representation is used to analyze the image's density variation. The MQ3 sensor is used to detect alcohol consumption, and if the alcohol percentage is higher than 40%, the system will put the ignition lock on the car until the reset alcohol consumption is proposed. The webcam is used to capture frames of the driver's face and analyze them for drowsiness, and if detected, the system will alert the driver with a buzzer signal.

Table 2. Summary of physiological based techniques for drowsiness detection

Author (s)	Year	Method	Comparison Hardware	Dataset	Limitation
Hwang *et al.* [27]	2016	A hybrid approach combining manual video inspection and reaction time, along with multiple physiological signals recorded during a driving simulation setup, to accurately identify alert and drowsy states.	- PPG sensor - GSR sensor - ECG electrodes - EEG electrodes - Logitech steering wheel - Three monitors - HD video camera (Microsoft) - g®.USBAMP system (g.tec) - BIOPAC MP150 - Accelerometer - 5V pulse signal	Not Mentioned	– Driving simulation environment may not fully replicate real-world driving conditions. – Placement of in-ear EEG electrodes may have limitations compared to traditional scalp-based EEG.
Hossan *et al.* [28]	2016	EEG signals are used in a smart system to identify driver drowsiness.	MQ-3 sensor Eye blink Sensor	EEG motor movement/imagery dataset stored in PhysioNet	– External factors like noise and interference may affect the accuracy of EEG signal acquisition. – User comfort and acceptance may be an issue, as wearing an EEG headset during driving can be uncomfortable.
Budak *et al.* [29]	2019	The system detects drowsiness using EEG-based features, deep learning, and statistical analysis.	Eye blink Sensor MQ-3 sensor Mobile Sniffer	A total of 16 subjects, with an average age and weight of 43 years and 119 kg, made up the MIT/BIH Polysomnographic EEG database.	– Dataset constraints affect system performance. – Limited generalization due to dataset bias. – Real-time performance not specified for drowsiness detection.
Artanto *et al.* [30]	2017	A low-cost EMG and ESP8266 Wi-Fi module are used in a driver drowsiness detection system to detect eye closure.	Eye blink Sensor MQ-3 sensor	Not Mentioned	– The system's ability to detect drowsiness solely based on eyelid closure may be limited. – Since there is always a lag while using the internet, the monitoring cannot take place in real time.

Tiwari *et al.* [32] developed a system which aims to prevent accidents caused by drowsy driving. The system comprises both hardware and software components for comprehensive driver monitoring. The hardware includes essential elements such as Raspberry Pi 3, a USB Camera, temperature sensor, heart rate sensor, alcohol sensor, GPS, and a buzzer. The Raspberry Pi 3 serves as the central processing unit, orchestrating the integration of data from various sensors. These sensors collectively measure critical parameters related to the driver's health, alcohol levels, and eye condition. The USB camera is deployed to consistently observe the driver's eyes, triggering the buzzer if closed for an extended period, thus prompting immediate driver alertness. Additionally, the GPS capability enables real-time tracking of the driver's location, offering valuable insights in emergency situations. The software side involves the utilization of Python IDE and OpenCV to facilitate efficient data processing and analysis for effective monitoring.

Kaavya *et al.* [33] introduced a system employing a Raspberry Pi 3 integrated into the vehicle, along with a camera for driver monitoring, a buzzer to alert the driver in the event of detected drowsiness, a gas sensor for identifying alcohol consumption, and a vibration sensor to detect accidents. The Raspberry Pi serves as the central hub, connecting and coordinating the various sensors and the camera. An IoT module facilitates the transmission of a notification message to a server. The system employs the Haar Cascade Algorithm for facial and eye detection, utilizing image processing techniques to confirm instances of drowsiness. Upon detection of drowsiness, alcohol consumption, or an accident, a notification message is dispatched to the server, concurrently initiating a motor cutoff for safety measures.

Ashwini *et al.* [34] designed a system incorporating a Raspberry Pi 3, various sensors, a USB camera, and a buzzer, with the capability to discern driver drowsiness and concurrently monitor vital health parameters such as heartbeat and temperature. The USB camera maintains continuous surveillance of the driver's eye movements, activating the buzzer if the eyes remain closed beyond a specified duration to promptly alert the driver. The gathered data is transmitted to the server's health monitoring system, facilitating GPS-based tracking of the driver's location. In the event of an emergency, the system promptly communicates the driver's condition to their friends or relatives through an SMS notification.

Shobha *et al.* [35] introduced a system employing an Arduino chip as the primary controller, along with an MQ-3 alcohol sensor for gathering air alcohol concentration data and a webcam for ongoing surveillance of the driver's eyes. Upon the driver assuming the driving position, the system autonomously engages in alcohol detection. To identify instances of drowsiness, the system maintains continuous vigilance over the driver's eyes, and if the driver closes their eyes for a specific duration, the vehicle's braking system is activated to bring the vehicle to a stop.

Tejashwini *et al.* [36] devised a system aimed at recognizing signs of driver drowsiness and notifying the vehicle owner through various alerts such as an alarm, water sprinkler, and notifications on their Android device. The mechanism of this system centers around evaluating the eye aspect ratio (EAR) of the driver's eyes, a parameter that diminishes during periods of drowsiness. Practically, the system continuously scans the driver's face using the Pi Camera module, employing the Haar Cascade classifier to pinpoint facial landmarks. The computation of EAR, derived from these landmarks, involves a predefined threshold to signify the onset of drowsiness. Importantly, the system is engineered to function adeptly under low-light conditions, leveraging the Pi Camera module to capture images for constructing a training dataset that aids in classifier training. A cascade of classifiers is employed to filter out irrelevant background regions, ensuring the focus is directed toward face-like regions during the detection process.

Swathi *et al.* [37] engineered a comprehensive system featuring a Raspberry Pi interfaced with an array of hardware components, including an alcohol sensor, GSM module, buzzer, motor, GPS module, and a camera. The camera takes on the role of live-streaming the driver's eyes, facilitating the detection of drowsiness, while the alcohol sensor is designed to identify alcohol in the breath. The determination of the driver's drowsiness level is achieved through the calculation of the EAR. Upon surpassing a predefined threshold, the system triggers an alert with the activation of a buzzer, concurrently immobilizing the vehicle's engine. Detection of alcohol also prompts engine immobilization, coupled with the transmission of location information to authorized personnel. The system employs OpenCV and dlib libraries for image processing and facial landmark detection, underlining the integration of advanced artificial intelligence (AI) technologies in its operational framework.

Roy *et al.* [38] have introduced an advanced system designed to autonomously enhance automobile safety through a region-based automatic car system. Employing machine learning techniques, the system focuses on eye detection to identify signs of driver drowsiness. Beyond addressing driver fatigue, the system broadens its scope to detect external traffic and potential intrusions, thereby proactively preventing accidents. The preventive measures encompass monitoring not only driver drowsiness but also alcohol consumption and seat belt engagement. By integrating the internet of things (IoT) and machine learning (ML), the proposed system aspires to establish an automatic safety framework catering to both vehicle occupants and those in the surrounding environment. Sensor-generated data is systematically collected and stored in a MySQL database, facilitating administrative monitoring and intervention in the cloud when necessary. This innovative system underscores the infusion of artificial intelligence into automotive safety measures.

Hyder *et al.* [39] presented a system with four key features like real-time drowsiness detection using computer vision, alcohol consumption detection, monitoring of driver health parameters, and automatic transition to auto-driving mode if the driver is unfit. The system employs Haar features and pre-trained facial landmark detectors to analyze video streams, calculate the EAR, and trigger alerts, such as alarms and visual warnings on an LCD screen, in case of detected drowsiness. This comprehensive approach integrates various safety measures to address different aspects of driver well-being.

Mansur and Shambavi [40] proposed a system that is based on computer vision algorithms and deep learning, using a convolutional neural network (CNN). The CNN architecture has an input layer, output layer, and hidden layers, which include convolution layers with 32 and 64 nodes, and a fully connected layer with 128 nodes. Rectified linear unit (ReLU) is used as the activation function. The system is trained on a large dataset of visual images, where the patterns are extracted using a neural network. The CNN uses convolution and pooling operations to reduce the image to its basic attributes and understand and classify the image. The dataset used in the present work consists of around 7,000 images from various open-source eye image datasets, including drowsiness detection and eye state detection datasets. The system can identify the region of interest from the input image, which mainly comprises the content of eyes captured from the camera and classified into individual labels open or closed.

Shamini *et al.* [41] developed a system that implemented the continuous monitoring of a driver's eyes and facial expressions to detect signs of drowsiness. With the help of webcam which is installed in dashboard and image-based processing, the system utilizes the EAR method to determine the status of the driver's eyes whether it is open or closed. Once the system has been detecting drowsiness, the system activates an alert using an alarm or buzzer. Then it will effectively be notifying both the driver and passengers. The important matter is the system is adept at functioning under diverse lighting conditions and it is also designed to accommodate drivers wearing spectacles.

Siwach *et al.* [42] developed a system using a camera to capture video frames, processed through facial detection and landmark algorithms to predict driver drowsiness. Facial detection employs Haar cascade frontal face detection, while landmark detection uses regression trees. The eye aspect ratio is assessed, and if consistently low for seven frames, an alarm alerts the driver. The encoded video is sent to a server, decoded, and analyzed with machine learning for drowsiness prediction. Integrating live streaming and video encoding, the system efficiently transmits data over the internet, offering a robust approach to drowsiness detection in drivers.

Singh *et al.* [43] proposed a system using facial feature detection and EAR analysis to determine the driver drowsiness. By using a pre-trained dataset of 3 million facial images and real-time data from a camera recording at 30 frames per second, the system undergoes a step-by-step process. First, the system initiates with image pre-processing and then proceeds to identify facial features, particularly focusing on the eyes, and calculates the EAR. If the EAR value is below the predetermined threshold of 0.25, the algorithm triggers an alarm, serving as an immediate alert to the driver.

Samadder *et al.* [44] introduced a system leveraging machine learning and deep learning techniques to identify signs of driver drowsiness and issue alerts to prevent potential accidents. The proposed system incorporates fundamental libraries such as OpenCV, Imutils, Dlib, and MySQL Connector within its programming framework. Utilizing a night vision camera, the system captures high-definition video footage of the driver's face. Subsequent analysis focuses on detecting eye blinks and evaluating the driver's visual and cognitive states. The determination of drowsiness relies on the EAR threshold value. When the EAR falls below a specified range, indicating closed eyes, an alert is triggered through a buzzer, and the relevant data is transmitted to a database.

Reddy *et al.* [45] presented a system which uses a camera placed in a Raspberry Pi to capture the driver's sleep mode with the help of image processing technology, and sensors are used for driver monitoring to avoid drunk driving. The system also has a gas sensor to detect alcohol in the driver's breath. If the system detects that the driver is in a sleeping condition based on eye closure, it captures the driver's image and location and sends it to a server using an IoT module. If the driver is found to be drunk or drowsy, the motor continuously rotates, but if the system detects the driver's sleeping condition or drunk driving, it sends an alert to the server and cuts off the motor. Table 3 (see in appendix) presents a summary of driver drowsiness monitoring techniques that employ visual analysis of eye state, detailing methods for assessing fatigue through eye movements, blinking patterns, and eyelid behavior.

2.4. Existing work on driver drowsiness monitoring using visual analysis of eye and mouth state

An extensive corpus of previous research has concentrated on using visual analysis of mouth and eye state to identify indicators of driver drowsiness. These systems accurately identify and track particular facial cues connected to fatigue, like eyelid closing and mouth yawning, using highly developed machine learning and deep learning algorithms. These algorithms can continually monitor driver behaviour and deliver prompt alarms or actions when indicators of fatigue are found by examining real-time video feeds obtained from in-vehicle cameras. Researchers have compiled and utilized large-scale datasets that icnlude diverse examples of driver facial expressions along with corresponding drowsiness labels to train and assess these algorithms. The integration of machine learning and deep learning techniques with visual analysis of eye and mouth states holds significant promise for developing effective driver drowsiness monitoring systems.

Patel *et al.* [46] proposed a system utilizes a deep learning approach for monitoring driver drowsiness through computer vision. The system employs a camera to capture the driver's facial expressions, classifying drowsiness into three categories: normal, yawn, and drowsy. Designed to be compact, the system can be implemented on a handheld microcontroller with an embedded camera while maintaining acceptable accuracy. It uses the Haar cascade algorithm for face detection, based on the Viola-Jones method, along with the Dlib library, which leverages CNN for image processing. If drowsiness is detected based on a set threshold, an email alert is sent to the relevant person or organization associated with the driver.

Varghese *et al.* [47] developed a system that utilizes visual features of the driver, such as eye and mouth positions, captured by an infrared night vision camera mounted on the dashboard of the vehicle. The system is divided into several modules, including data acquisition, pre-processing, face detection, and facial landmark marking. The key features for detecting drowsiness are the EAR, mouth aspect ratio (MAR), mouth aspect ratio over eye aspect ratio (MOE), and pupil circularity (PUC), which are calculated from the 2-D images extracted from the video. A support vector machine (SVM) classifier is used to classify the driver's state into drowsy or alert, achieving an impressive F1-score of 0.98.

Charniya and Nair [48] presented a system integrates visual features such as eye and face detection, along with yawn detection using OpenCV and Emgu with Visual Studio 2013. The algorithm for eye state detection tracks the eye state, head position, and yawning, and then uses a SVM classifier to categorize the driver as alert or non-alert. The head position is tracked using the Kalman-based tracking method, while yawn detection is performed using a back-projection theory. For alcohol detection, the system uses an alcohol sensor to detect whether the driver is intoxicated. If the driver is found to be drunk or drowsy, the system triggers an alarm using a buzzer and vibrator to alert the driver. If the alert occurs more than three times within a specified period, then the engine is turned off with LED turning 'ON' as an emergency indicator.

Yu *et al.* [49] proposed a condition-adaptive representation learning framework for driver drowsiness detection, which consists of four models designed to extract scene-specific characteristics. By focusing on these specific features, the framework performs better than existing drowsiness detection methods, according to trial data. However, the proposed framework requires the installation of a high-performance GPU computing unit in the vehicle, potentially increasing the car's cost and weight. Additionally, to effectively learn representations that cover various driving conditions, the method demands a large number of training samples that are labeled with both scene settings and drowsiness states. The suggested framework is also an offline method. Therefore, it cannot guarantee that it will be able to identify tiredness in drivers of completely different types who are not represented in the training sets.

Gupta *et al.* [50] propose a system designed for detecting driver drowsiness utilizing facial recognition, EAR, and MAR. The system employs techniques such as histogram oriented gradient (HOG) for face detection, SVM for classification, and predefined threshold values to identify yawning and closed eyes. Notably, the system integrates a dynamic threshold that progressively decreases over time to enhance sensitivity to drowsiness. Through experimental analysis, the proposed system demonstrates a substantial accuracy rate of 90% in effectively detecting instances of drowsiness. Table 4 provides a summary of driver drowsiness monitoring methods that utilize visual analysis of eye and mouth states, highlighting the method, dataset, algorithm and effectiveness in detecting signs of fatigue through facial indicators.

Table 4. Summary of driver drowsiness monitoring using visual analysis of eye and mouth state

Author (s)	Year	Comparison					Limitation
		Method	Dataset	Camera model	Algorithm	Accuracy	
Patel *et al.* [46]	2022	Detecting driver drowsiness utilizes computer vision techniques, specifically Haar cascade and CNN algorithms	https://ibug.doc.ic.ac.uk/resources/facial-point-annotations/	Web camera (720p & 30fps)	Haar cascade classifier and CNN	96%	– Incorporate additional specialties in the future to improve its predictive capabilities
Varghese *et al.* [47]	2021	Visual characteristics, such as the positions of the eye and mouth, can be collected by an infrared night vision camera and analyzed with a SVM classifier to detect fatigue.	Not mentioned	Infrared night vision camera	HOG and linear SVM	86%	– Can only store a limited amount of sensor data in microcontroller – Absence of a database system
Charniya and Nair [48]	2017	Visual features for drowsiness detection and an alcohol sensor for drunk state detection, with an SVM classifier and Kalman-based tracking method.	Not mentioned	Web camera	SVM and Haar cascade classifier	Not mentioned	– Storage limitations may occur due to the growing size of the database – The system should be designed to alert the driver relative to the level of drowsiness detected.
Yu *et al.* [49]	2019	A vision-based algorithm to detect driver drowsiness using features learned using 3D 3D-CNN.	https://cv.cs.nthu.edu.tw/php/callforpaper/datasets/DDD/	Camera and an active infrared sensor	3D-CNN	76.2	– Framework requires high-performance GPU on vehicle. – Designed for offline use, may not detect diverse, untrained drowsy states.
Gupta *et al.* [50]	2018	A combination of face detection, face recognition, and driver state monitoring.	https://ibug.doc.ic.ac.uk/resources/300-VW/	RGB camera	HOG and SVM	90	– Limited dataset diversity

3. RESEARCH GAPS

Driver drowsiness detection systems commonly use eye blink sensors to track the driver's level of alertness. These sensors might not be able to precisely identify eye blinks in some lighting circumstances. For instance, poor lighting or intense sunlight can obstruct the sensor's ability to precisely detect eye movements. Additionally, eye blink sensors may not work properly for drivers who wear eyeglasses or other eye accessories. These sensors frequently rely on detecting subtle changes in the eyelid's position or movement. The sensor's ability to see the eyelid can be obstructed by glasses or other eye accessories, resulting in unreliable or irregular results. Particularly for drivers who rely on vision assistance, this restriction could affect the accuracy of the drowsiness detection system. In addition, certain systems that rely solely on the driver wearing an eye blink sensor frame, as illustrated in Figure 1, exhibit limitations that may impact their effectiveness in detecting drowsiness.

Figure 1. Eye blink sensor with frame

Basically, the systems presume that the driver will always remember to wear it and keep it on throughout the journey. The device would not be able to effectively detect the driver's drowsiness if the driver forgets to wear the sensor or take it off while driving. Additionally, not all drivers may find the sensor comfortable to wear, potentially causing discomfort or distraction during the drive. This could lead to drivers choosing not to wear the sensor or removing it during the journey. In the context of drowsiness detection, physiologically based approaches namely, EEG, ECG, PPG, GSR, and EMG have shown significant promise in accurately identifying drowsiness. However, these methods face several challenges and limitations that must be addressed. One primary concern is the user comfort and acceptability. The sensors used in these techniques often require direct contact with the skin to detect the physiological signals effectively. For instance, ECG sensors must be placed near the skin to monitor the heart's electrical activity, as shown in the Figure 2.

Figure 2. Physiological signals sensors for fatigue and drowsiness detection

This can be uncomfortable for the driver, especially in hot and humid environments where sweating may affect the accuracy of the sensors. Additionally, elements like sweating or movement could create errors and reduce the precision of the measurements. For instance, excessive sweating or driver movement can result in errors or false readings from the ECG sensors. Similarly, EEG sensors, which require electrodes to be placed on the scalp, may cause irritation and discomfort during prolonged use. Moreover, the accuracy of physiological sensors can be influenced by medical conditions. Drivers with arrhythmia or other heart-related issues may exhibit abnormal electrical heart activity, complicating the detection of drowsiness using ECG data alone. Likewise, neurological conditions or medications can affect EEG signals, potentially leading to false positives or negatives in drowsiness detection. Another limitation is that these systems are often better suited for controlled laboratory environments than real-world driving scenarios. While driving simulators are valuable for testing and refining sensor performance, they may not fully capture the complexities of real-world conditions. Factors such as traffic patterns, road imperfections, and adverse weather can significantly impact drowsiness levels but are difficult to replicate in a lab setting. Long-term monitoring in real-world scenarios also presents challenges. Sensors like ECGs require regular maintenance and calibration to ensure accurate readings, which can be both time-consuming and inconvenient. Additionally, the need for wearable devices or wired connections attached to the body can be uncomfortable for drivers and may interfere with sensor performance. These challenges highlight the need for continued research and innovation to improve the practicality, comfort, and reliability of physiological sensors in detecting driver drowsiness.

When using sensors for alcohol detection systems, it is crucial to address the limitations associated with the MQ-3 sensor. A significant drawback is that many existing systems evaluate the sensor's performance using simulated or artificially produced alcohol concentrations. While convenient, this method can yield misleading results as it does not accurately represent real-world conditions. A more reliable approach would involve testing the sensor on individuals who have consumed alcohol to assess its effectiveness in practical scenarios. Furthermore, assessing the MQ-3 sensor solely based on alcohol or ethanol concentrations overlooks other factors that can influence its accuracy. Environmental conditions such as temperature, humidity, and air quality may affect the sensor's performance. Neglecting these variables during testing could result in inaccurate alcohol detection. To enhance the reliability and accuracy of MQ-3 sensor-based alcohol detection systems, it is essential to conduct extensive testing involving real-life scenarios. This testing should include trials with actual individuals and account for a wide range of environmental factors to ensure robust and dependable performance.

Driver drowsiness detection plays a critical role in improving road safety. However, many current systems have a notable limitation: they rely solely on the EAR, often neglecting other important variables such as the MAR and Euler angles. This exclusive dependence on EAR can undermine the accuracy and comprehensiveness of fatigue detection. EAR, which measures eye openness, is a proven and reliable indicator of drowsiness. However, it provides only a partial understanding of the driver’s condition. MAR, which measures the width of the mouth, can complement EAR by offering additional insights. Since drowsiness often impacts both eye and mouth movements, combining EAR and MAR could yield a more holistic assessment of the driver’s state. Furthermore, Euler angles, which provide information about head orientation, add another critical layer of analysis. Movements such as head nods or tilts are common signs of drowsiness and can significantly enhance the accuracy of detection systems. Neglecting MAR and Euler angles could reduce the precision of monitoring systems, thereby diminishing their overall effectiveness. To address these shortcomings, it is essential to integrate MAR and Euler angles alongside EAR to develop more robust and reliable driver drowsiness detection systems. Table 5 summarizes the key research gaps in current driver drowsiness and alcohol detection systems, highlighting areas where existing technologies face limitations and opportunities for further enhancement.

Table 5. Identified research gaps in driver drowsiness and alcohol detection systems

Research Gap	Description	Impact
Lighting conditions	Eye blink sensors may struggle to detect blinks accurately in poor lighting or intense sunlight.	Inaccurate drowsiness detection due to obstructed sensor visibility.
Eyewear interference	Sensors may have difficulty detecting blinks if the driver wears eyeglasses or other accessories.	Reduced reliability and accuracy of drowsiness detection for drivers with vision aids.
Sensor Adherence and Comfort	Drivers may forget to wear or remove sensors during driving, and some sensors may be uncomfortable.	Inconsistent drowsiness monitoring and potential driver distraction or discomfort.
Physiological sensor discomfort	ECG, EEG, and other physiological sensors may be uncomfortable and affect accuracy due to sweating or movement.	Discomfort and possible inaccuracies in sensor readings during long-term use.
Medical conditions impact	ECG and EEG sensor accuracy can be affected by medical conditions like arrhythmia or neurological disorders.	Potential for false positives or negatives in drowsiness detection.
Simulation vs. real-world testing	Laboratory settings may not fully replicate real-world driving conditions, affecting sensor performance assessment.	Sensor effectiveness might not accurately reflect real-world scenarios.
Maintenance and calibration	Physiological sensors require regular maintenance and calibration, which may be challenging during long drives.	Possible issues with continuous monitoring and sensor accuracy.
Environmental factors for alcohol detection	MQ-3 sensor testing often uses simulated alcohol concentrations, which may not reflect real-life conditions.	Potential inaccuracies in detecting alcohol consumption due to unconsidered environmental factors.
Inclusion of additional metrics	Current drowsiness detection systems often rely solely on EAR, neglecting MAR and Euler angles.	Reduced accuracy in detecting driver drowsiness due to incomplete assessment of drowsiness indicators.

4. CONCLUSION

In conclusion, significant advancements have been made in the detection of intoxicated and drowsy driving in recent years. Researches have explored various methods, including sensor-based systems, physiological monitoring, and visual analysis of eye and mouth state, to develop effective and precise detection mechanisms. These systems have demonstrated promising results in mitigating the risks associated with drunk and drowsy driving. Sensor-based systems have proven useful in identifying signs of intoxication and fatigue. However, there face limitations, including reduced performance under certain lighting conditions, challenges with drivers wearing glasses, and the discomfort of requiring to wear sensors throughout a journey. Enhancing the accuracy and reliability of these sensors remains a key area for further research. Physiological-based techniques, which rely on monitoring physiological signals linked to drowsiness, also hold potential. Yet, the challenges persists, including issues related to user comfort, acceptance, and the impacts of external factors like sweat or movement. Further research is needed to assess the effectiveness and feasibility of these methods in real-world driving scenarios over extended periods. Visual analysis techniques leveraging machine learning and deep learning algorithms namely, monitoring eye blink patterns, eyelid movements, mouth yawning, and Euler angles, offer a robust approach for detect driver drowsiness. The integration of multiple indicators improves the perfomance of these systems. Advances in large-scale datasets have further improved the accuracy of the system. Despite these developments, challenges and research gaps remain. Addressing sensor limitations, conducting practical and long-term testing, and mitigating environmental effects are crucial to improving the reliability of these systems. The incorporation of diverse indicators and the development of comprehensive algorithms will further enhance the robustness and dependability of drowsiness detection system.

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AUTHOR CONTRIBUTIONS STATEMENT

Conceptualization, AS, and SY; methodology, AS, and SY; formal analysis, AS, JNM, and AA; investigation, SFAR, MFAA, and KR; writing—original draft preparation, AS, JNM, and KR; writing—review and editing, SY, SFAR, MFAA, and AA; supervision, SY. All authors have read and agreed to the published version of the manuscript.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article.

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APPENDIX

Table 3. Summary of driver drowsiness monitoring using visual analysis of eye state

Author (s)	Year	Comparison					Limitation
		Method	Dataset	Camera model	Algorithm	Accuracy	
Patnaik *et al.* [31]	2020	Computer vision and sensor technologies to detect the driver's face position, eyelid movement, alcohol consumption, and drowsiness, and alerts the driver.	Not mentioned	USB Webcam 3.0	Haar cascade classifier	Not mentioned	- No automatic emergency message system if MQ-3 sensor detects alcohol consumption.
Tiwari *et al.* [32]	2019	Detecting eyes state of driver, liquor focus on the breath temperature and pulse rate sensor to drowsiness, alcohol detection and Health Monitoring.	Not mentioned	EO USB Camera	Not mentioned	Not mentioned	- Accuracy in drowsiness detection is limited. - MAR and Euler angles are not used to identify yawning and head tilt. - Only focused on the region of interest (ROI) around the eyes.
Kaavya *et al.* [33]	2019	The Haar cascade algorithm is used for face and eye detection and MQ-3 sensor to detect alcohol consumption.	Not mentioned	USB Camera	Haar cascade classifier	Not mentioned	- Not considering MAR and Euler angles may lead to lower accuracy.
Ashwini *et al.* [34]	2020	OpenCV and Python library for detecting driver drowsiness. MQ-7 to check the alcoholic state of the driver.	Not mentioned	USB Camera	Not mentioned	Not mentioned	- MQ-7 sensor to detect alcohol which is designed to detect carbon monoxide. - Not using an appropriate sensor for alcohol detection.
Shobha *et al.* [35]	2022	Drowsiness detection using Haar cascade classifier for face detection, Perclos algorithm for eye detection, and eye closure time for drowsiness detection.	https://cv.cs.nthu.edu.tw/php/callforpaper/datasets/DDD/	Not mentioned	Haar cascade classifier	Not mentioned	- Not extract mouth features to detect if the driver is becoming drowsy by analyzing yawning behaviour
Tejashwini *et al.* [36]	2020	Drowsiness detection based on the EAR and detects facial landmarks using the Haar cascade classifier.	https://ibug.doc.ic.ac.uk/resources/300-VW/	Pi Camera module with 1080p30, 720p60, and VGA90 video mode	Haar cascade classifier	Not mentioned	- Predict a driver's fatigue level in advance by analysing the sleep patterns that can create a highly accurate drowsy detection system
Swathi *et al.* [37]	2020	Detects drowsiness and alcohol consumption by analysing the driver's eyes and breath and locks the engine while sending an alert message to authorised personnel.	https://www.kaggle.com/datasets/kasikrit/att-database-of-faces	USB camera	Haar cascade classifier	Not mentioned	- The lack of a database limits the system's ability to store and analyse sensor data.

Table 3. Summary of driver drowsiness monitoring using visual analysis of eye state (*continue*)

Author (s)	Year	Comparison					Limitation
		Method	Dataset	Camera model	Algorithm	Accuracy	
Roy *et al.* [38]	2019	Sensors and machine learning are utilised for drowsiness detection, alcohol detection, and seat belt reminders to enhance automobile safety, with data stored in a MySQL database and monitored in the cloud.	Not mentioned	Not mentioned	Not mentioned	Not mentioned	- Only uses EAR for drowsiness detection
Hyder *et al.* [39]	2020	Haar features and pre-trained facial landmark detectors to extract the driver's eyes and determine the EAR to detect drowsiness and breathalyser for alcohol detection.	Not Mentioned	Night vision camera module	Haar cascade classifier	90%	- EAR alone may not be sufficient for detecting driver fatigue
Mansur and Shambavi [40]	2021	Uses a CNN based on computer vision algorithms and deep learning to detect drowsiness by classifying eye images as open or closed.	http://mrl.cs.vsb.cz/eyedataset	Raspberry Pi Camera Board v1.3 (5MP, 1080p)	CNN and Haar cascade classifier	95% to 96%	- Upgrade to the YOLO algorithm for improved efficiency. - Utilise the C++ OpenCV library to improve speed. - Possible upgrades to the dataset to improve accuracy.
Shamini *et al.* [41]	2022	Image-based processing techniques to monitor the driver's eyes and facial movements and determine if the driver are in a drowsy state.	Not mentioned	Web camera	Not Mentioned	Not Mentioned	- Addition of features such as yawning, blink rate, and car condition monitoring. - The scope of the system has a significant impact on state accuracy.
Siwach *et al.* [42]	2022	Utilised facial detection and landmark detection algorithms to predict drowsiness based on eye aspect ratio and sends the encoded video stream to a server for machine learning-based analysis.	https://ibug.doc.ic.ac.uk/resources/300-W_IMAVIS/	Not Mentioned	AdaBoost and Haar cascade classifier	89%	- Addition of MAR and Euler angles for more precise fatigue identification - Consideration of eye closure length, eye movement, and head posture for more accurate detection
Singh *et al.* [43]	2022	Facial feature detection and EAR are used to determine drowsiness.	http://vintage.winklerbros.net/facescrub.html	Web camera	Dlib facial feature detection algorithms and Haar cascade classifier	85.2%	- Only takes into account the eye movements
Samadder *et al.* [44]	2022	Machine learning and deep learning techniques to detect driver drowsiness by analysing high-definition video of the driver's face and using the EAR threshold value to trigger an alert.	http://vlm1.uta.edu/~athitsos/projects/drowsiness/	OV5647-based camera module (5MP)	Not Mentioned	97%	-Not be accurate in all situations -Only uses EAR for drowsiness detection
Reddy *et al.* [45]	2019	Detecting driver drowsiness utilises computer vision techniques, specifically Haar cascade	Not mentioned	Pi camera module	Haar cascade classifier	Not mentioned	- Combining the driver's sleep pattern with the pattern of eye closures for more accurate detection

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