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Performance analysis of hybrid model to detect driver drowsiness at early stage

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ABSTRACT

Vehicle accidents result in numerous fatal and non-fatal injuries that place a heavy financial burden on individuals. The risk of disability for individuals has also increased, and it is difficult for their families to survive. Driver drowsiness is one of the major causes of accidents on the roads. Various researchers have proposed a wide range of approaches, including subjective, vehicle-based, physiological and behavioral measures that help to develop driver drowsiness detection system (DDDS). Most of the studies on DDDS have been developed by utilizing only single measure that haven't yielded positive results. In this paper, a hybrid model-based DDDS is proposed that combines sensor-based physiological and behavioral measures to detect the drowsy state of the driver in an efficient way. Galvanic skin response (GSR) sensor and camera have been effectively used to detect the drowsy state of the driver. A study was carried out on ten individuals to implement and evaluate the performance of the system. The results indicate that the proposed DDDS can detect transitions from alert to a drowsy state of the driver effectively with an accuracy of 91%. The proposed system would enable drivers to use their vehicles more securely and effectively on the roads.

Keywords: Artificial intelligence, Behavioral measures, Driver drowsiness, Hybrid measures, Sensor-based physiological measures, GSR sensor.

1. INTRODUCTION

Vehicle collisions due to driver drowsiness play major contribution towards fatal and non-fatal accidents. According to National Highway Traffic Safety Administration (NHTSA) data total 91000 accidents occurred on the road due to drowsiness in 2017. This report suggested that the numbers are likely much more than the actual incidents (Horne and Baulk, 2004; Albadawi et al., 2022). Researchers have invested significant efforts towards identifying drowsy state of the drivers at early stage to avoid the road accidents. However, detecting driver drowsiness at an early stage and under different conditions remains a challenging task. Many studies have considered subjective, vehicle, physiological and behavioral parameters for drowsiness detection in vehicles. However, none of these approaches has proven useful in developing a DDDS that can be safely deployed (Sahayadhas et al., 2012). Hybrid measures incorporate elements of two or more different kinds of measures to compensate for the limitations of single measures. Finding the right equipment and technologies that can be installed in a vehicle and make the driving experience more pleasant is the first step in proposing the DDDS.

Drowsiness is a transitional state from awake to sleepy. In this physiological condition, drowsiness increases with passing time. Drowsiness makes it challenging to maintain focus and keep one's eyes open since one's head and body become unsteady. Also, one of the most noticeable signs of drowsiness is frequently yawning. As a result, drowsy drivers caused traffic mishaps. In order to avoid an accident, it is crucial to identify drowsiness and inform the driver immediately (Albadawi et al., 2022).

Drowsiness impairs a driver's ability to pay attention to the road, which makes it more

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difficult to apply the brakes or steer the car. Because of the circadian cycle, most drivers become drowsy between the hours of midnight and seven in the morning, then again drowsy between the hours of two and four in the afternoon. The typical highway driver is between the ages of 18 and 30, and they are unaccompanied (Ramzan et al., 2019; Soares et al., 2020). Past research has demonstrated that young people are susceptible to drowsiness, which can result in deadly and nonfatal injuries. Accidents on the road are a common and undesirable occurrence while travelling. It is considerably simpler to identify road accident indications such intoxicated driving, braking failure, ignoring traffic signals or rules, and reckless driving than it is to identify accidents caused by drowsy drivers (Doudou et al., 2019). Due to the absence of a vehicle failure in good road and weather circumstances, it is much more challenging to determine the accident's primary cause.

Driver drowsiness can be detected in two different ways: intrusive approach where the components are directly attached to the driver's body to gather the bio signals that is useful for drowsiness detection. In non-intrusive approach, a camera or sensors are affixed on the different vehicle areas for the drowsiness detection (Siddiqui et al., 2021). The subjective, vehicle-based and behavioral measures are examples of the non-intrusive approach, whereas physiological measures characterize the intrusive measures. In this context, "hybrid measures" refer to those that integrate elements from multiple measures for the drowsiness detection of the driver. To detect the drowsy state of the drivers, five different measures are used as depicted in Fig. 1 (Čolić et al., 2014). These measures are:

1. Subjective measures (SM)
2. Vehicle-based measures (VBM)
3. Behavioral measures (BM)
4. Sensor-based physiological measures (SBPM)
5. Hybrid measures (HM)

In order to identify driver drowsiness, subjective measures are used by involve questioning the driver in a simulated setting. Subjective reports of drowsiness while driving can be evaluated using the seven point Likert scale in Stanford Sleeping Scale (SSS) and the 9 point Likert scale in Karolinska Sleeping Scale (KSS) (Shahid et al., 2012). The Likert scale ranging from "very alert" to "very sleepy" is used in the SSS to evaluate drowsiness, while a nine-point Likert scale ranging from "very alert" to "very drowsy" is used in the KSS. One of the major drawbacks of subjective measurements is that they are often impractical and yield skewed results, making them useless in actual driving situations (Murugan et al., 2019).

In vehicle–based measures, cameras and sensors can be used in the vehicle components to record the vehicle behavior on the roads to identify the drowsy state of the driver. Standard Deviation of Lane Placement (SDLP) and Steering Wheel Movement (SWM) are the most used vehicle-based drowsiness examinations (Feng et al., 2009). To identify drowsiness in drivers, SDLP uses a camera installed to track the lane movement of the vehicle. Its dependence on road signs, illumination, and weather is its greatest weakness. SWM uses many steering wheel sensors to detect driver drowsiness. SWM is unsuitable for daily driving due to its high cost and False Positive (FP) detection (Doudou et al., 2019).

The driver's actions may be deduced from the driver's eyes, mouth and head position. A camera installed in the dashboard of the car takes a picture of the driver's face. Researchers have been able to identify drowsy driving by analysing the driver's blink rate and PERCLOS data using Machine Learning (ML) and Deep Learning (DL) algorithms. These non-intrusive behavior measures are employed in both simulated and real driving situations. Behavioral measures outperform vehicle-based measures because they are in-dependent of road conditions and have a lower FP detection rate (Ngxande and Burke, 2017).

Physiological measures can identify driver drowsiness with high efficacy. Drivers now have electroencephalogram (EEG), electrocardiogram (ECG) and Electrooculography (EOG) attached to them instantly to capture important physiological data (Hasan et al., 2022). The problem with the physiological measure is that it is hard for the driver to operate the vehicle when there are a lot of intrusive components attached to their body (Doudou et al., 2018). Therefore, using this intrusive technology in real-world driving is difficult for driver. Therefore, electromyogram (EMG), photo plethysmography (PPG), and galvanic skin response (GSR) sensors can be used to capture physiological information without causing discomfort (Shahrudin and Sidek, 2020). GSR is a physiological skin conductance (SC) sensor. The literature shows that GSR sensors can identify driver drowsiness when behavioral approaches fail in certain conditions (Sharma et al., 2016).

Hybrid measures that combines the two or more measures can detect drowsiness of the driver (Bajaj et al., 2021). The overall accuracy can be increased by utilizing two or more measures instead of only one. Table 1 shows possible combination of different types of measures that can be used to detect driver drowsiness.

The combination of all three measures cannot be implemented simultaneously due to high cost and difficult to implement in real driving conditions. Vehicle-based measures have a high incidence of FP detection when paired with other measures due to their reliance on road and lane markers. In actual driving conditions, it is therefore difficult to integrate vehicle-based data with other measurements. Positive results are more common when both behavioral and physiological measures are used together. Yet it's a challenge to get drivers to wear the intrusive components based on physiological measures. It has been discovered that biological sensors can effectively replace intrusive physiological components in detecting the drowsiness of driver (Bajaj et al., 2022). Because of advances in both artificial intelligence and biological sensors, it is now possible to apply hybrid measures for early detection of driver drowsiness.

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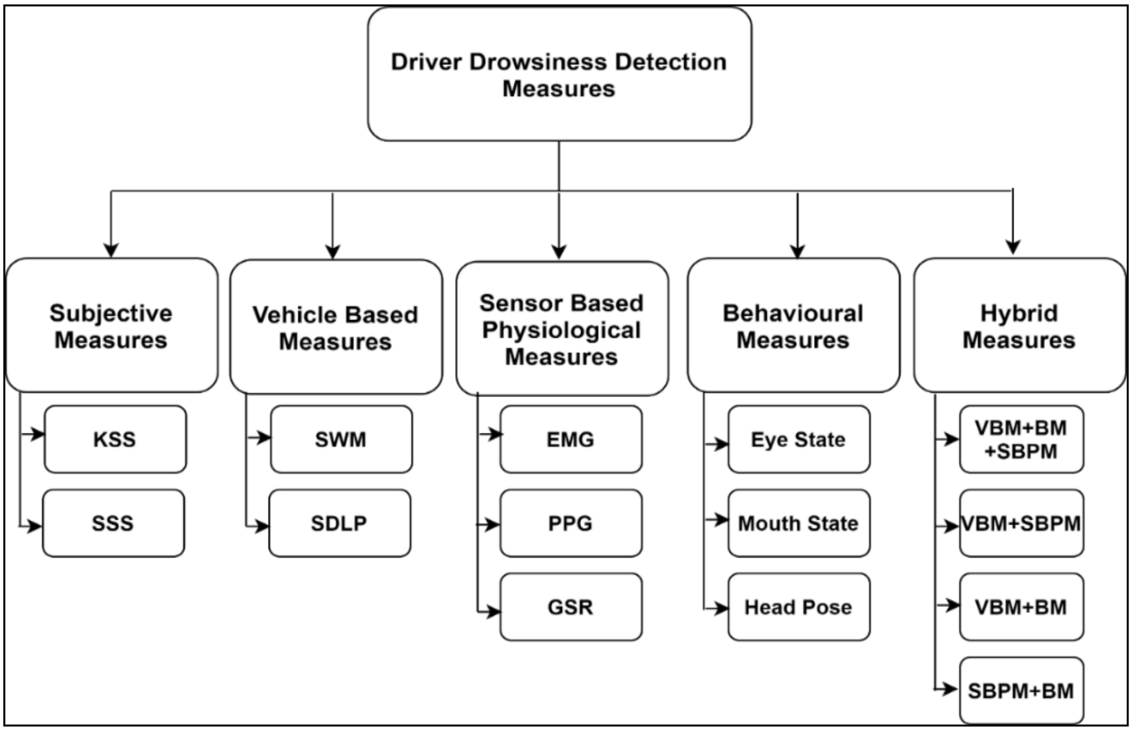

Fig. 1. Various measures and its methods for driver drowsiness detection

Table 1. Feasibility of various hybrid model for the DDDS

Reference	Hybrid measures	Accuracy	Limitation
Cheng et al., 2012	Behavioral + Vehicle-based	90%	High false detection rate
Leng et al., 2015	Vehicle-based + Physiological	93%	Intrusive and high false detection rate
Lemkaddem et al., 2018	Behavioral + Physiological	98%	Intrusive and not working effectively in low light conditions
Gwak et al., 2020	Vehicle-based + Physiological + Behavioral	81%	Expensive and difficult to implement in real driving conditions

An intelligent, cost-effective solution is necessary to detect driver drowsiness. Many efforts had been made in the past to identify driver drowsiness. Nevertheless, there is currently no fool-proof way of identifying drowsy drivers in advance. A hybrid model has been proposed by integrates behavioral and sensor based physiological measures. In order to measure the SC of the driver, a GSR sensor is used and a camera is installed on the center console of the car in order to record the driver's behavior. AI based algorithm is utilized to identify the facial features of the driver. The microcontroller is used to collect the data from the camera and GSR sensor and further calculate the drowsy state of the driver. Two types of alarms (soft and hard level) are generated based on the intensity of the drowsy state. Where, intensity is measured based upon the threshold values of SC, Percentage of Eye Closure (PERCLOS) and yawning. The performance of the DDDS based on hybrid model has been thoroughly analysed in a variety of settings, including low light, with spectacles, and with a beard. This study also explains how to put into practice and assess performance via an android based mobile application. This method is particularly useful for generating accurate models with limited data. In the near future, these systems could be implemented in vehicles for the drivers to calculate their drowsiness level, alerting them and their acquaintances as needed.

The objective of this paper is to implement the hybrid model that is the combination of behavioral measures and sensor based physiological measure and evaluate the system to check the effectiveness on the basis of different parameters. In addition, the performance analysis has been carried out with other single measure i.e. behavioral and physiological measures to compare the effectiveness of the proposed hybrid model. The contribution of this paper are as follows:

- Implementation of DDDS based on hybrid model to detect the driver drowsiness at an early stage that helps to improve the overall accuracy of the system.
- Performance analysis of the DDDS based on hybrid model and compare it with other measures.

The rest of the paper is arranged as follows: Section 2 presents the materials and methods to perform the research work on DDDS, Sections 3 and 4 explains the working of hybrid model followed by the implementation of DDDS.

Section 5 discusses the performance analysis and compare hybrid based DDDS with others individual measures and finally Section 6 presents the conclusion of the proposed DDDS.

2. MATERIALS AND METHODS

As depicted in Fig. 2, a number of scholarly articles were studied and represented by the Prisma flow diagram, which is the recommended methodology for conducting systematic reviews, in order to construct the DDDS. For the system review, numerous databases including Google Scholar, IEEE Explore and ScienceDirect were utilized to research the pertinent literature. The articles are selected from the databases using keywords such as “driver drowsiness”, “hybrid measures”, “behavioral measures” and “physiological measures”. Only English-language articles with at least two citations published in journals or conferences are shortlisted.

Using various keywords, 227 articles were discovered during the identification procedure. 139 articles remain following the eradication of duplicate and ineligible articles during the verification phase. Due to the inaccessibility of 21 articles and the exclusion of 57 articles on the basis of their abstracts, 61 articles qualify for further analysis. In the end, following the exclusion of 23 articles due to topic incompatibility, 38 articles are finally selected for this research in order to propose a DDDS.

2.1 Hybrid Measure (Behavioral and Sensor Based Physiological Measure)

To build an effective DDDS, a hybrid model has been proposed in this paper. Due to advancement in technology like AI and physiological sensors, the behavioral measures and Sensor based physiological measure can be used for the early detection the driver drowsiness.

2.1.1 Behavioral Measure

Physical characteristics of the driver, such as the eyes, mouth, and head inclination, form the basis of behavioral measures. To determine drowsy driving, ML and DL algorithms analyze PERCLOS (Ngxande and Burke, 2017). Yawning and head movement of the driver are additional indicators that can help for drowsiness detection. behavioral measures can be used in both simulated and real driving conditions due to non-intrusive characteristics. According to recent research trends, behavioral measures with latest DL based algorithms provide are provide high accuracy than vehicle-based measures.

2.1.2 Sensor Based Physiological Measures

Despite the high accuracy of physiological measures, they are intrusive. Actual driving conditions make these intrusive devices challenging to use (Sahayadhas et al., 2012). Sensor based physiological measures provides the promising results for drowsiness detection of the driver by using various physiological sensors that are compact, lightweight, and less intrusive (Akiduki et al., 2022). Galvanic Skin Response (GSR) sensor is one of the physiological sensors that can be used to detect drowsiness by collecting the driver’s physiological characteristics (Doudou et al., 2018). It has been suggested in the literature by the number of researchers that GSR sensors can be beneficial for identifying drowsiness of the drivers when behavioral measures are ineffective (Sharma et al., 2016).

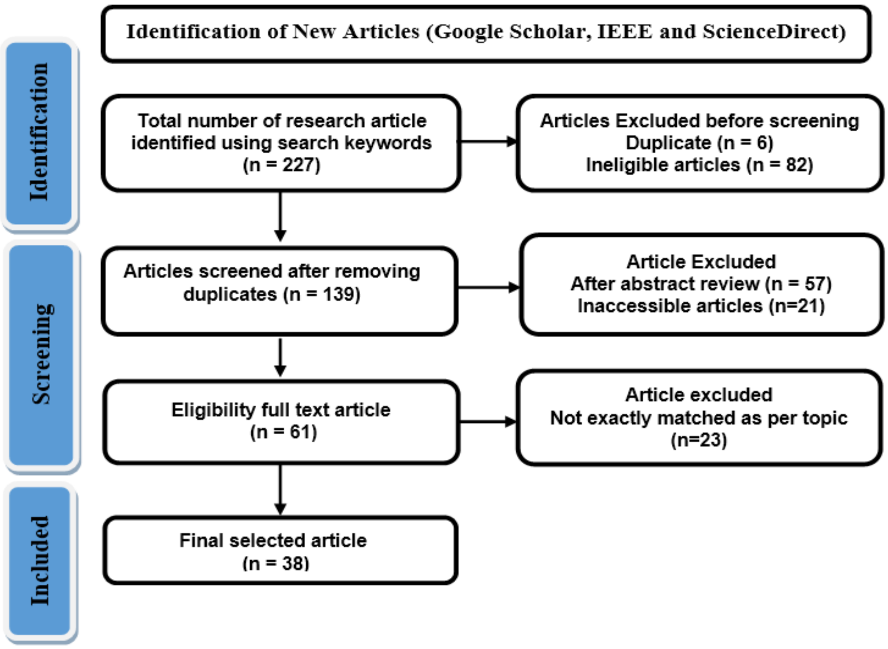

Fig. 2. Prisma flow diagram for literature review

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2.2 Components Used to Develop DDDS

To develop a DDDS, there is a need of components which are as follows:

- Raspberry Pi 3 Model B+
- GSR sensor
- Analog-to-digital converter
- Pi camera
- Cloud hosted database (Firebase)
- Other requirements (Power adopter, breadboard and jumper wires)

Raspberry Pi 3 Model B+ is a microcontroller used for various IoT based devices. it's easier to build a DDDS that relies on a microcontroller for monitoring drivers (Naidu et al., 2020). Raspberry Pi 3 Model B+ microcontroller board diagram is shown in Fig. 3.

Fig. 3. Raspberry Pi 3 Model B+ microcontroller

Grove GSR sensors are biologically grounded SC monitors. Two fingers on the same hand serve as attachment points for the sensor's two electrodes. The working of the GSR sensor by sending an electrical current through one electrode and receive the resultant signal to the other electrode. Alterations in SC are also brought on by shifts in skin moisture. SC can be used as an indicator for a person's response to exertion or stress (Grove - GSR Sensor - Seeed Wiki 2022). The GSR sensor, comprised of a micro board and two finger electrodes, is shown in Fig. 4.

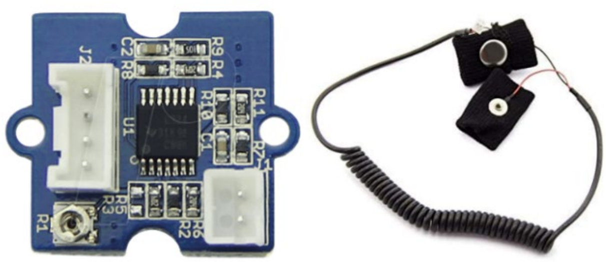


Fig. 4. GSR sensor

During drowsy state, one trend in GSR readings is that it goes down. When figuring out the GSR, the sensitivity of the skin is taken into account. The skin's resistance is proportional to its SC. Hence the following equation can be used to calculate the skin's reaction (R).

$$SC = 1/R \tag{1}$$

Micro siemens (µs) are the units of measurement for SC of the human. A healthy human having a reading between 250 to 450 µs represents the normal condition whereas, the values that ranges from 128 to 250 µs, reflects the drowsy condition of the human and can be further determine the drowsiness of the driver at the wheels.

The MCP 3008 Integrated Circuit (IC) is an electronic device that capable to convert analog signals to digital signals. It helps to converts analogue GSR values into meaningful data. Due to the fact that the Raspberry Pi 3 Model B+ lacks analogue inputs (MCP3008 | Microchip Technology 2022). Fig. 5 depicts the MCP 3008 IC.

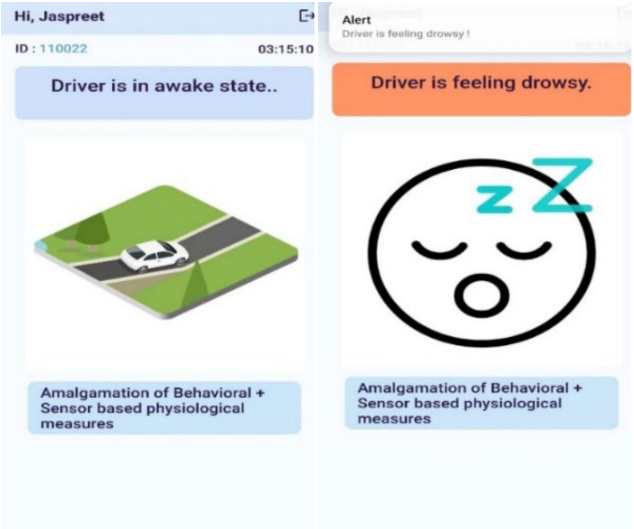
Fig. 5. MCP3008 IC

In order to get high-quality photos with your Raspberry Pi, you need an image sensor like the Raspberry Pi Camera v2. It can record HD video and stills, allowing for precise face feature detection by the driver. The minimum focus distance for this lens is around 50 centimetres. It plugs into a Raspberry Pi through one of the board's many small headers (Biswal et al., 2021). The image in Fig. 6 depicts the top of the pi camera module.

Fig. 6. Pi Camera v2 8 MP

Firebase is used to capture the driver's real-time data. Firebase is a Google tool that helps collect data from a microcontroller in the form of JavaScript object notation (JSON) and transfer it to a mobile device. It is straightforward to store and retrieve data for a mobile application. The data recorded in the firebase can be used to present the drowsiness level of the driver as text. Few screenshots are shown in the Fig. 7.

Other requirements like power bank, jumper wires and breadboard are used to develop the DDDS. The 5 volt of direct current (DC) is provided to Raspberry Pi 3 Model B+ by attaching the 20000 mah battery using USB cable. To connect MCP3008 IC, breadboard and jumper cables are also used.



(a) (b)

Fig. 7. (a) Driver in awake state; (b) Driver in drowsy state

Pi camera and GSR sensor are attached to the Raspberry Pi 3 Model B+ which is burned with Python code that help to communicate with these devices. This allows the Pi to record SC and obtain the useful data. Fig. 8 is a representation of the entirety of the hardware implementation, which comprises of a Raspberry Pi 3 Model B+ coupled to a camera and a GSR sensor through an MCP3008 integrated circuit.

2.3 Face Detection and Recognition Techniques

Face detection is essential for identifying the driver's face and extracting facial traits to assess the driver's drowsiness. Recognizing faces and obtaining their attributes requires a reliable face detection method (Karim et al., 2021; Wang et al., 2022). Facial recognition software is increasingly included in modern electronics as a means of verifying the user's identification. Several face detection methods are described here so that the best method for the proposed hybrid model can be chosen (Singh and Brisilla, 2021). The three most popular techniques for identifying faces that is used in behavioral measures. When it comes to rapid face detection, OpenCV's Haar Cascade classifier stands out as a top. Both Paul Viola and Michael Jones, in 2001, came up with the concept. OpenCV is a free and open-source computer vision toolkit that is based on ML and includes a detector and a trainer. A pre-trained classifier can identify a human face and eye from an XML source (Verma et al., 2019). Whilst this method may quickly and easily locate the object, it is unable to identify partially hidden faces. When in the face detection phase, it makes several erroneous predictions (Viola and Jones, 2001; Boyko et al., 2018)

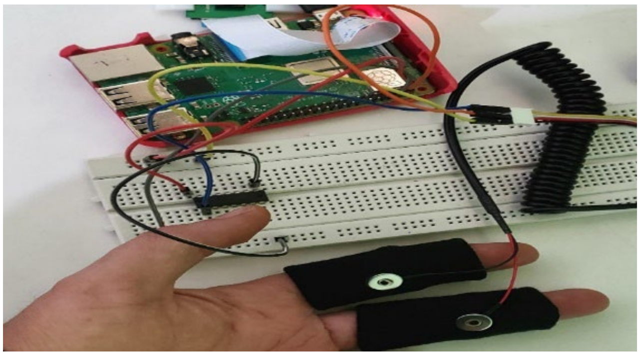


Fig. 8. Setup of the DDDS with all hardware components

Another open-source package used to put ML algorithms into practice is Davis King library (Dlib). It's useful for recognizing people's faces in still images and moving footage. Linear Support Vector Machine (SVM) + Histogram of Oriented Gradients (HOG) and Convolutional Neural Network (CNN) based face identification methods are included in the Dlib package (Jadhav et al., 2021). One common method for detecting human faces is Dlib HOG, which is both simple and reliable. The system incorporates state-of-the-art face recognition technology with a ML method based on support vector machines. It's a lightweight, fast model that doesn't require any special gear to run. However, the very precise Dlib CNN face identification algorithm is used for this purpose (Eye Blink Detection with OpenCV, Python, and Dlib - PyImageSearch 2017). Dlib outperforms OpenCV Haar Cascade in terms of accuracy, but its processing complexity prevents it from being used in real time.

Multi-task cascaded convolutional neural network (MTCNN) is one of the most widely used and reliable facial recognition systems available. Face and feature detection in photographs is performed via a MTCNN (Shi et al., 2020). Faces and facial characteristics can be accurately identified by a DL algorithm. In its whole, the MTCNN principle can be explained as follows:s

P-NET: Several frames has been generated by MTCNN that thoroughly examine entire image that is captured by the camera, from top left to bottom right of the image.

R-NET: The succeeding CNN layer, which takes P-Net data as input, discards the vast majority of frames in which a face is not present.

O-NET: In this stage, the results are more targeted than those of R-Net. Once a face has been identified in an image or video, this step determines where to find the facial land-marks.

The act of recognizing distinctive facial traits, known as facial landmark identification, can help keep tabs on driver drowsiness. Two eye locations, one nose location, and two mouth locations can all be identified with MTCNN. It is via the identification of these indicators that an effective method of drowsiness detection can be developed.

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MTCNN outperforms OpenCV's Haar Cascade and Dlib in terms of accuracy. MTCNN is capable of identifying both frontal and profile facial features in photographs. MTCNN framework takes more time to train the face recognition system as compare to OpenCV and Dlib face detection techniques. Based on the results of the study, MTCNN has been determined to be the best method for implementing face detection (Zhang et al., 2020; Yongcun and Jianqiu, 2021).

2.4 Dataset

Drowsiness detection methods have made extensive use of the secondary dataset from National Tsing Hua University (NTHU). For the NTHU-DDD dataset, 36 participants of diverse racial and ethnic backgrounds were shot day and night while yawning, blinking slowly, dozing off, and/or sporting corrective glasses. The NTHU-DDD library features model films of drivers of various racial and ethnic backgrounds. Scenes filmed while the individuals were drowsy and awake are included in the sample. Several lighting conditions were used to shoot these videos. This dataset has more accuracy than others used to train the driver drowsiness system (Weng et al., 2017).

2.5 Data Collections

Ten individuals, ranging in age from 22 to 50, were tested by using the GSR sensor and camera to see how well they could detect drowsy driving. One simulated driving system meant fewer people to test with. In order to test the validity of the drowsiness scale, several night-shift security guards participated in an experiment. It took almost two weeks to complete the test with five individuals selected in first week and other five individuals selected in second week due to lack of resources.

3. WORKING OF HYBRID MODEL

The DDDS based on hybrid model combines two types of measures: behavioral measures with sensor based physiological measures into a single framework (Bajaj et al., 2023). The overall structure of the system is shown in Fig. 9. There are three stages to this approach.

- Data acquisition
- Feature extraction
- Classification

3.1 Data Acquisition

The first step in creating a system for recognizing driver drowsiness signs is collecting relevant data. The pi camera captures footage for the purposes of facial recognition. A dashboard camera records the driver's face. A video recording is then spliced into still images. NTHU's pre-trained dataset is used for facial recognition. A GSR sensor is placed on the fingertips of drivers in order to monitor their SC. With a Raspberry-Pi microcontroller, the combination of GSR sensor and pi camera can effectively identify the SC and features of driver's face respectively in real time (Malathi et al., 2018). The next step involves analysing the driver's bioelectrical signals for traces of drowsiness.

3.2 Features Extraction

Facial features are extracted from the collected data using the MTCNN algorithm in the second stage. Locating a face

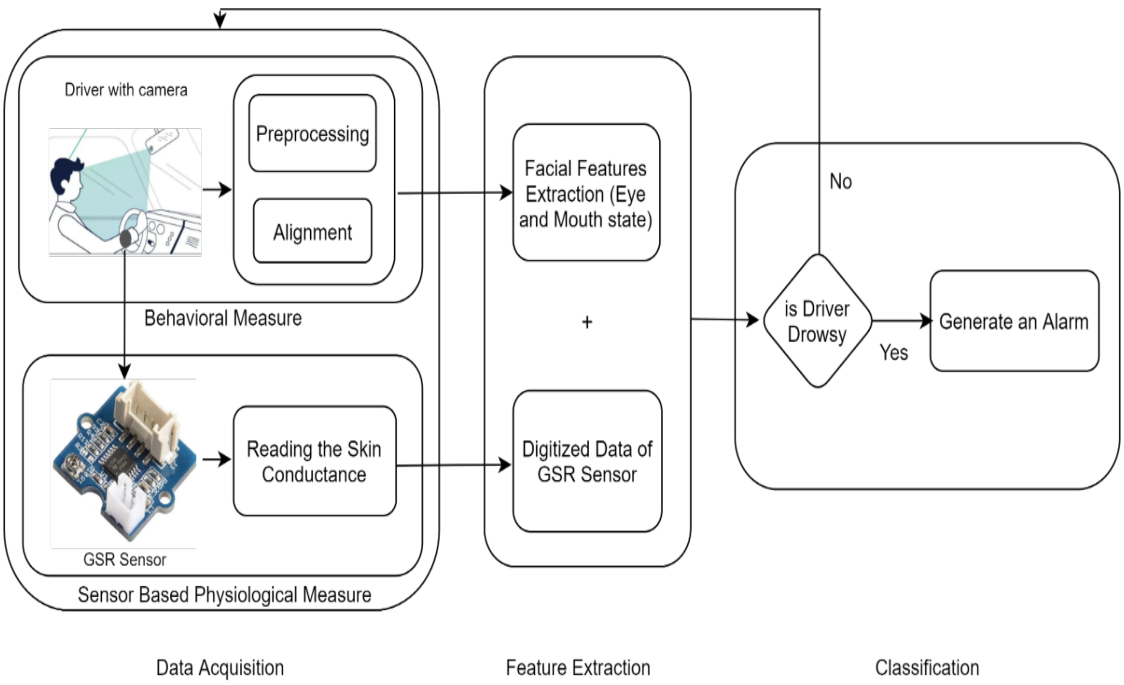

Fig. 9. Block diagram of DDDS using Hybrid Model

in a picture by using landmarks is a breeze using MTCNN (Liu et al., 2021). Based on this information, the driver's drowsiness will be rated. Information gathered by the GSR sensor is converted, sent, and categorized digitally. Eye detection with PERCLOS and mouth detection with Frequency of Mouth (FOM) Movements are used to identify if a driver is drowsy.

The ratio of open to closed eyelids can be analyzed using the PERCLOS method of sleepiness detection. Here is the equation:

$$P = EC/TOCL \times 100 \quad (2)$$

P represents the PERCLOS. At any given time, EC indicates that the subject's eyes are closed, while TOCL denotes the count of closed and open eye frames. The FOM is the fraction of open squares to the percentage of total squares that are not in use. The FOM method of calculation is similar to the PERCLOS method.

$$F = MO/TMCO \times 100 \quad (3)$$

The F represents the FOM. The number of open mouth images (MO) is the first variable, and the sum of closed and open mouth images (TMCO) is the second variable (Savaş and Becerikli, 2020).

3.3 Classification

In the final phase, a combination of behavioral and physiological sensor measures is used to assign a classification to the DDDS. Several ML and DL-based classifiers can be combined to determine the driver's level of fatigue (Kumari and Kumar, 2017). SVM, convolutional neural networks and hierarchical graphical models are only some of the classifiers that have been put to use in this investigation. Classification methods like SVM are utilized to determine the driver's current state of health. In the event that the classifier concludes that the user is not fatigued, the procedure will start over. When the classifier determines that the driver is experiencing drowsiness, one of two things happens: either an alarm is sounded to wake up the driver, or the procedure is reset to the beginning (Shahrudin and Sidek, 2020).

4. IMPLEMENTATION OF DDDS USING HYBRID MODEL

To propose DDDS, a hybrid model that is the combination of behavioral measures in which a camera is placed in the driver's line of sight on the dashboard to capture facial features and sensor based physiological measure in which a sensor is used to measure SC by placing it on fingertips of the driver. The collected GSR values and facial features data is further transferred to the microcontroller that evaluates the drowsy state of the driver. After evaluation the final result is further transferred in the JSON format to the firebase. The real-time data is converted into the text form and display the result in the mobile via application. The architecture of the DDDS is shown in Fig. 10.

5. RESULTS AND DISCUSSION

Sensor-based physiological measures and behavioral measures evaluated individually and in the combination of both measures. In sensor-based physiological measurements, the driver's SC is measured with a GSR sensor and then transmitted to the microcontroller. The driver's level of drowsiness was calculated using a threshold of 128 to 250 µs of SC and a python programme that employed a classifier technique (de Naurois et al., 2019). The pi camera, mounted on the dashboard in front of the driver, has captured the driver's face features for use in behavioral measurements. The driver's drowsiness is measured using PERCLOS and FOM parameters.

Ten individual's GSR values are shown in Table 2. Users' SC readings are shown in real time as they operate the car in a simulated environment. This number represents the cumulative effect of driving when under the influence of fatigue or stress. The sensor records GSR values over the course of the experiment, and the system shows the skin's response to the experiment every second. Individuals' skin reactions change throughout time. Within the first few minutes when the drivers are on, there is just a slight fluctuation in the skin response levels. However, after 15 min, there is a shift in GSR value indicative of extremely low dermal activity, which may lead to drowsiness. Individual 2's GSR value was the highest at 348.2 s, while Individual 6's GSR value was the lowest at 113.4. Table 2 also includes the average of all participants to determine the current GSR values of the driver.

Individuals 1, 3, 6, 7 and 9's GSR values are within the drowsy state's range, whereas Individuals 2, 4, 5, 8 and 10's GSR values are within the awake state's range. The driver's GSR value drops while they're feeling drowsy. Hence, the restrictions in a scenario where the camera is not functioning well are mitigated by detecting drowsiness using GSR measurements.

In order to monitor the behavioral measures, the training set, validation set, and test set of the NTHU dataset are utilized in this study. When simultaneously identifying the mouth and pupils of a photographed subject, the NTHU-DDD can be used in the multitask architecture. Detecting drowsiness with MTCNN on the NTHU-DDD dataset, four distinct facial landmarks are identified. This algorithm can tell if the user's eyes are open or closed, even if they are wearing glasses. Using PERCLOS and FOM computations, the exact locations of the driver's lips and eyes in the video can be identified (Savaş and Becerikli, 2020). The user's closed eye region will change color from blue to red.

Drowsy drivers continue to exhibit variations in eye state, yawning, and other behavioral reactions and biological

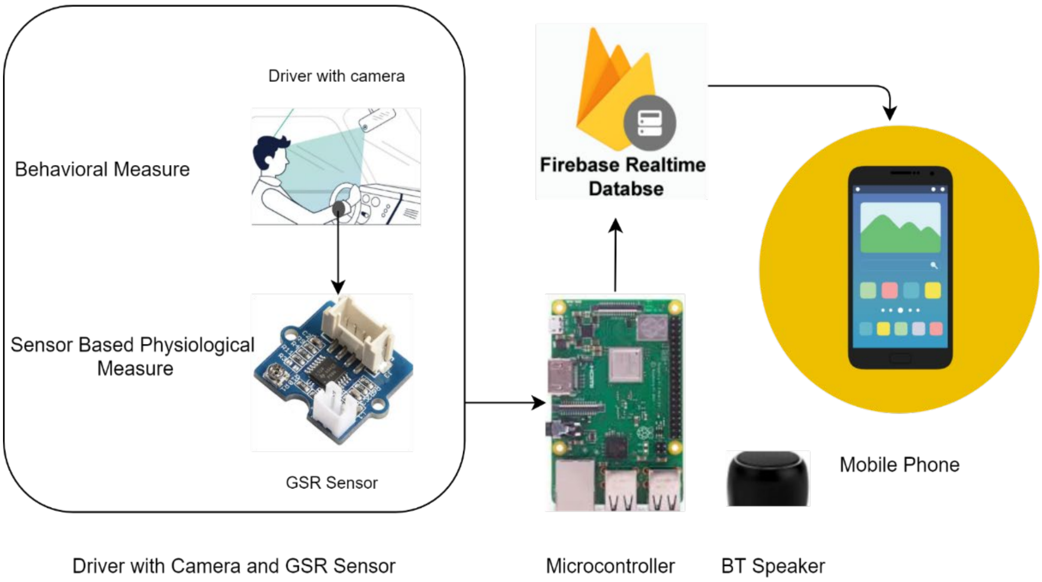

Fig. 10. Architecture of DDDS

Table 2. GSR values of the ten individuals

Individuals \ Duration	5	10	15	20	25	30	Average	Status
i1	181.81	164.87	134.34	130.95	133.82	125.21	145.17	Drowsy
i2	257.42	229.85	215.49	207.89	193.55	199.38	217.26	Drowsy
i3	199.23	203.13	172.82	144.51	167.26	174.17	176.85	Drowsy
i4	286.88	295.23	298.34	282.18	249.76	237.34	274.96	Non drowsy
i5	348.20	319.35	315.41	297.13	293.77	288.82	310.45	Non drowsy
i6	171.32	152.45	138.32	127.65	120.13	113.40	137.21	Drowsy
i7	238.12	248.50	259.30	265.40	271.34	268.12	258.46	Non drowsy
i8	317.77	312.32	304.76	296.32	289.43	281.32	300.32	Non drowsy
i9	203.66	199.12	183.45	170.19	168.33	162.78	181.26	Drowsy
i10	345.44	331.29	327.54	322.66	317.23	304.22	324.73	Non drowsy

*The individuals are abbreviated as i1–i10

signs. Driver drowsiness can be evaluated using calculations of PERCLOS and FOM. Normal driving results in PERCLOS levels below the threshold since the time eyes are open is significantly longer than the time they are closed (0.24). Closure takes more time than opening does when the driver is drowsy. The mouth also stays open for a few seconds after a yawn (5 s). When the driver's PERCLOS is 0.24 or higher and FOM is 0.16 or higher, it is assumed that they are too drowsy to safely operate a vehicle. If the driver's PERCLOS is greater than 0.24 and their FOM is less than 0.16, they are less drowsy on the road, and if they are both less than 0.24 and less than 0.16, they are awake and alert. The average PERCLOS and FOM values for the sample of ten individuals are shown in Table 3.

The effectiveness of hybrid model based DDDS for drowsiness detection of the driver was evaluated using ten individuals spanning in age from 22 to 50. Parameters like PERCLOS, FOM, and GSR levels were used to create a simulated environment in which to conduct the experiment (McDonald et al., 2018). When combined with GSR data, PERCLOS and FOM levels could indicate whether or not a person was awake and alert. Drowsiness is detected when the driver's PERCLOS is above 0.24, FOM is above 0.16, and SC is below 250. When the PERCLOS is greater than 0.24, FOM is greater than 0.16, and the SC is greater than 250, the individual is awake but not drowsy. The mean of PERCLOS, FOM and GSR values for all ten individuals are shown in Table 4 and Table 5 revealed the accuracy of proposed DDDS by calculate the driver's drowsiness level on various parameters. The facial feature detection is done by MTCNN.

To accomplish a 91% accuracy rate while significantly reducing the FP detection rate, 70% of the available dataset is used for training and 30% for testing during model training (split ratio) (Kundinger et al., 2021). Validity of the model is assured by the following equation:

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

FP represents the individual is in drowsy state, but in actual, the individual was normal. False Negative (FN) represents the individual is in normal state, but in actual, the individual was drowsy. True Positive (TP) represents the individual is in drowsy state and truly individual was drowsy. True Negative (TN) represents the individual is in normal state and truly individual was normal (Chen et al., 2021).

Table 3. PERCLOS and FOM mean values of ten individuals

Individuals \ Parameters	PERCLOS	FOM	Status
i1	0.37	0.23	Drowsy
i2	0.22	0.11	Non drowsy
i3	0.26	0.17	Drowsy
i4	0.20	0.13	Non drowsy
i5	0.11	0.08	Non drowsy
i6	0.44	0.21	Drowsy
i7	0.19	0.15	Non drowsy
i8	0.10	0.12	Non drowsy
i9	0.32	0.28	Drowsy
i10	0.08	0.05	Non drowsy

Two different kinds of alarms have been generated to detect drowsiness of the driver. When the driver's GSR values fall between 128 to 250 µs and other behavioral parameters are within the normal range, a soft level alarm is triggered. In contrast, the hard level alarm is generated when PERCLOS, Yawning, and GSR values surpass the threshold values.

The accuracy rate of the DDDS using hybrid model can be calculated by using the following formula. It is the ratio of correct warning divided by the total generated warning.

$$A_R = \frac{CGA}{TGA} \tag{5}$$

Where A_R represents accuracy Rate, C_{GA} represents correct generated alarm and T_{GA} represents total generated alarm. Overall 91% has been achieved using the hybrid model. The proposed DDDS accuracy rate is 91% and it is successfully detecting the drowsy state of the driver.

The DDDS's parametric measures are compared to those of other methods for detecting drowsy drivers. The suggested DDDS is compared to the state-of-the-art studies in Table 6. Behavioral measures performed better than sensor-based physiological measures, but it is impracticable to rely solely on them due to their high rate of FP detection and incapacity to function in low-light conditions. Parametric metrics derived from physiological sensors are quite encouraging. The system's detection of driver drowsiness is only 76% accurate, and it plays only a supporting role overall.

Table 6 depicted that the proposed DDDS performs better than the other measures. The camera and GSR sensor work together to record the driver's facial expressions, eye movements, and other behavioral cues, as well as sensor-based physiological data like SC level. This combination helps to detect the drowsy state of the driver effectively in all conditions with a low FP detection rate.

6. CONCLUSION

In this paper, it has been concluded that none of the four distinct measures, taken separately, can ensure accuracy, as each measure has limitations in different contexts and is ineffective in detecting drowsiness. These limitations can be eliminated by combining two or more measures to detect driver drowsiness and making the system work under all conditions. Therefore, the hybrid measure, which combines a sensor-based physiological measure (less intrusive) with a behavioral measure (non-intrusive), can be utilised to effectively overcome the existing limitations. The driver's facial features are extracted using a camera as a behavioral measure and skin resistance is measured through GSR sensor as physiological measure to investigate the transition from alert to drowsy state. As an outcome the overall accuracy has been improved by reducing the FP detection rate.

This model considers a driver to be drowsy when PERCLOS > 0.24, FOM > 0.16 and SC < 250. When PERCLOS > 0.24, FOM > 0.16 and SC > 250, the person is less sleepy, and PERCLOS < 0.24, FOM > 0.16 and SC > 250 shows the normal state of the driver. The mean value of PERCLOS and FOM are utilized in conjunction with SC to identify the driver's current condition. Results are compared

Table 4. PERCLOS, FOM and GSR value of ten individuals

Individuals \ Parameters	PERCLOS	FOM	SC	Status
i1	0.37	0.23	145.17	Drowsy
i2	0.22	0.11	217.26	Non drowsy
i3	0.26	0.17	176.85	Drowsy
i4	0.20	0.13	274.96	Non drowsy
i5	0.11	0.08	311.45	Non drowsy
i6	0.44	0.21	137.21	Drowsy
i7	0.19	0.15	258.46	Non drowsy
i8	0.10	0.12	300.32	Non drowsy
i9	0.32	0.28	181.26	Drowsy
i10	0.08	0.05	324.73	Non drowsy

Table 5. Accuracy rate of proposed DDDS

Sub-jects	Duration	PERCLOS			Yawning			SC			Generate alarm soft level	Correct generate alarm soft level	Generate alarm hard level	Correct generate alarm hard level	Accuracy	Average accuracy
		Mean (>.24)	TP	FP & FN	Mean (>.16)	TP	FP & FN	Mean	TP	FP & FN						
i1	30	0.37	26	2	0.23	4	1	145.17	1	0	0	0	28	26	92.8	91%
i2	30	0.22	13	2	0.11	1	0	217.30	0	2	9	7	6	4	73.3	
i3	30	0.26	17	1	0.17	2	0	176.85	1	0	0	0	18	17	94.4	
i4	30	0.20	12	1	0.13	1	0	274.96	1	0	13	12	0	0	92.3	
i5	30	0.11	2	0	0.08	1	0	310.45	0	0	2	2	0	0	100	
i6	30	0.44	31	2	0.21	5	1	137.21	1	0	0	0	33	31	93.9	
i7	30	0.19	14	3	0.15	1	0	258.46	1	1	16	13	2	1	77.7	
i8	30	0.10	6	0	0.12	1	0	300.32	1	0	6	6	0	0	100	
i9	30	0.32	22	3	0.28	6	1	181.26	1	0	0	0	25	22	88.0	
i10	30	0.08	2	0	0.05	0	0	324.73	0	0	2	2	0	0	100	

Table 6. Evaluation of proposed DDDS based on hybrid model with other measures

Reference	Measures	Devices/ Sensors	DDD methods	Accuracy	Limitations
Boyko et al. (2018)	Behavioral	Camera	PERCLOS and yawning	Close to 100%	Only work in certain conditions
Kundinger et al. (2021)	Sensor-based physiological	GSR	SC	76%	Low accuracy
Proposed DDDS	Behavioral + Sensor-based physiological	Camera + GSR	PERCLOS, yawning and GSR data	91%	Need large number of individuals for more investigation

with the threshold values of PERCLOS, FOM and SC of the body, e.g., 0.24, 0.16 and 250 µs, respectively. Additionally, the proposed hybrid model is also cost-effective and easy to implement. In future development phase, less intrusive sensors, such as pulse rate sensors and respiration based sensors can yield more encouraging outcomes (Karim et al., 2017; Dhiman et al., 2022; Lilhore et al., 2022). The device has the ability to alert the driver to take a break and relax if it notices indicators of drowsiness (Shrivastava et al., 2022). This can help prevent accidents and save lives by spotting driver drowsiness at early stage.

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