Recent Advances in Drowsiness Detection A Systematic Review

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***Abstract*—Drowsiness detection systems are being talked about a lot lately because they have the potential to prevent accidents caused by drowsiness in different industries, especially transportation. These systems use sensors like EEG sensors and eye-tracking sensors to keep track of a person's behavior or brain functions and identify signs of drowsiness. This review paper is focused on why drowsiness detection systems are important in promoting safety on the road and other places where drowsiness can cause accidents. The paper explores different ways of detecting drowsiness, including performance-based, physiological, and behavioral methods. It also gives an overview of drowsiness detection systems, what they can be used for, and the sensors and algorithms they use to identify drowsiness. It also discusses the challenges of designing and implementing effective drowsiness detection systems, such as individual differences, data variability, and real-world scenarios. Overall, this paper provides insights into the current state of drowsiness detection technology and the potential for future research to enhance the accuracy and effectiveness of these systems. Drowsiness detection systems have the potential to save lives by preventing accidents caused by drowsiness, and this paper provides valuable information about the development and application of these systems.**

Keywords—drowsiness, industries, transportation, EEG sensors, eye-tracking sensors, behavior, signs of drowsiness, physiological, sensors, algorithms, effectiveness.

I. INTRODUCTION

Road safety is a crucial concern for public health, as it can result in injuries and deaths. The Ministry of Road Transport and Highways Research Wing stated that "The road accidents caused 1,53,972 fatalities and injured 3,84,448 individuals in 2021" [1]. Drowsiness is a major contributor to numerous car accidents annually, since a driver who is feeling sleepy may not be capable of preventing or evading collisions while driving. Accidents caused by drowsiness are more likely to result in serious injuries or death. Drowsiness refers to the condition of feeling excessively tired or sleepy during the daytime, which can cause forgetfulness and a tendency to fall asleep at inappropriate times [3]. While drowsiness may be a temporary state, its consequences can be significantly detrimental. Fatigue, which diminishes alertness and concentration, is a frequent contributor to drowsiness [4]. Driving for extended periods without sufficient rest or operating a vehicle while feeling tired can cause drivers to feel drowsy [5]. Driving while drowsy is risky and often arises when a driver has not had enough rest or due to working in shifts or untreated insomnia [2]. The main concern in these situations is the driver's diminished ability to focus, leading to delayed responses to events while driving. Fortunately, researchers have recommended various techniques for detecting early signs of drowsiness in drivers and issuing warnings to prevent potential accidents. Drivers who are feeling drowsy tend to exhibit a range of symptoms, such as frequent yawning, frequent closure of the eyes, and driving in an irregular manner [6]. Lately, a significant amount of research has been dedicated to developing methods to detect driver drowsiness [7,8]. To decrease the frequency of accidents, researchers suggest implementing several techniques to quickly identify signs of drowsiness. These methods encompass image-based techniques that use cameras to monitor facial expressions and movements, biological-based techniques that involve the use of sensors placed on the driver's body to capture bio-signals, Methods that use the vehicle as a basis for observation by tracking its movements and actions, and Hybrid techniques incorporate a combination of two or more of the categories mentioned above. Ramzan and colleagues [9] conducted a thorough investigation in 2019 that analyzed the current methods used to identify driver drowsiness and the widely used categorization techniques in this area. The DDD techniques were classified into three sets: behavioral, physiological, and vehicular factors. In addition, they evaluated the most effective supervised learning techniques for detecting sleepiness and conducted a comparative analysis to evaluate the benefits and drawbacks of the three DDD categories. Sikander and Anwar [8] conducted a thorough investigation of the latest developments in identifying drowsiness. The DDD techniques were categorized into five groups according to the exhaustion features they recognized, namely physical, vehicular, biological, subjective reporting, and hybrid. In our research, we classify DDD systems into four groups based on the techniques used to evaluate drowsiness: visual-based, biologically-oriented, automotive, and hybrid. We also summarize and present in a table the parameters, features, methods, and quality measures employed in these systems, and provide a comparison of their effectiveness and dependability. The paper also addresses present challenges in the DDD domain and future trends that integrate cellphones, edge computing, wearable gadgets, and the Internet of Things (IoT).

II. Literature Review

Saito and co-authors [16] introduced a DDD system that operates by examining the movements of a driver's eyelids, driver’s wheel etc... DDD intervenes by partially taking over control of the vehicle when it deviates from its lane, allowing the driver to reposition it. If the driver fails to regain control within a certain time frame, it assumes that the driver is incapacitated and takes control of the car to park it safely. During the system's operation, data were mainly collected, and the driver's status was determined using mathematical algorithms and fixation patterns. The study reported achieving up to 100% accuracy in controlling the vehicle under specific driving conditions.

Dasgupta and others [17] developed a driver drowsiness detection and warning system that uses smartphones and incorporates audio cues and PERCLOS to identify drowsiness. They created their dataset, called the Invedrifac dataset [18], and used three levels of validation to evaluate their system. In the first level, the system calculates PERCLOS features from the front camera of mobile. If the PERCLOS value exceeds a certain threshold, it proceeds to Phase 2, where the driver is prompted to say their full name. In case the first two stages are identified by the system as an indication that the driver is falling asleep, The driver is asked to touch the screen of the mobile within a time frame of 10 seconds. If the driver fails to do so, an alert is activated. This approach use a linear SVM classifier and achieved an accuracy of 93.33%.

Li and co-authors [19] proposed a method to detect drowsiness in real-time using data amassed from a receptor installed on the driver’s wheel during fourteen hours and forty-eight minutes of actual driving. The method comprises of obtaining rough estimates of entropy characteristics from time series data of SWAs by utilizing a set sliding window size and transforming the characteristics into linear form through an adaptive piecewise linear fitting technique, with a particular level of deviation. The linear feature series is analyzed by the system to calculate the warping distance and this information is used to assess the driver's alertness level. After that, a binary categorizer is used to classify the driver's state as either "drowsy" or "attentive". According to the system's experimental results, the accuracy of detecting the "drowsy" state was 84.85%, while the accuracy of detecting the "attentive" state was 78.01%.

McDonald and other [20] suggested a new method for detecting drowsiness, which involved utilizing SWA data and RF algorithms to evaluate orbit deviations. The study found that this method that uses images to find drowsiness was more accurate than the PERCLOS method. The image-based measure achieved an accuracy of 79% and detected drowsiness six seconds earlier than PERCLOS, which only had an accuracy of 55%. The University of Iowa carried out a National Advanced Driving Simulator research that involved 72 individuals, and the algorithm was evaluated using this data [21]. The adapted evaluator appraisal of drowsiness scale was utilized to measure drowsiness from the raw simulator data when lane departure occurred. The video's characteristics were withdrawn by utilizing FaceLab's eye recognition software, which operates in a manner similar to PERCLOS and a group of decision trees that utilized randomly chosen trait were used to train the RF algorithm.

Leng and others [22] created a portable device that uses both motion and biomedical sensors to identify when a driver is feeling sleepy, and they also developed a mobile application to go with it. To achieve precise outcomes, the device makes use of information from both the driver's biological signals and measurements taken from the vehicle. This device includes a bracelet that has two sensors, an electrodermal activity sensor and a photoplethysmogram sensor, which can detect PPG signals, along with a motion sensor that can detect the movement of the driver's wheel. The accelerometer and gyroscope of the device record linear acceleration and angular velocity, and the system then processes and analyzes the data collected from these sensors. Five characteristics are obtained from the unprocessed biological information, which consist of pulse, breathing, stress level, adaptation chronograph, and heart rate variability. An SVM algorithm uses the motion data in addition to these five characteristics to identify if the driver is feeling drowsy. The device has the ability to identify when the driver is feeling sleepy and will notify them through visual and vibration alerts. The accuracy rate of this device is quite impressive, with a score of 98.3%.

Mehreen and co-authors [23] introduced a non-invasive, lightweight headband for detecting driver drowsiness, replacing the need for cameras and interferometric sensors in traditional DDD. Their introduced system employs accelerometers, gyroscopes, and EEG electrodes to capture signals and extract behavioral and biological characteristics of the driver. The researchers collected data from a driving simulator using 50 volunteers under both drowsy and alert conditions. A feature vector was created using head movement tracking, blinks, and diverse signals to achieve more precise and resilient outcomes. The authors applied the inverse feature selection method to the feature vectors across various classifiers. In the research, it was discovered that the Linear Support Vector Machine (SVM) had the highest efficacy as a classifier. Its accuracy was recorded at 86.5% without variable selection and 92% after variable selection.

Wijnands and co-authors [24] presented a new approach to detect driver drowsiness that uses a 3D-CNN with depth-wise separable convolutions to predict real-time activity from video. They conducted experiments using the NTHUDDD dataset [25]. One of the significant benefits of this method is that it automatically identifies intrinsic properties without relying on a predefined set of properties. If sufficient data tags are present, it becomes feasible to record intrinsic variables including the closure of eyelids, positioning of lips, scowling, elevation of the eyebrows, wrinkling of the nose, and elevation of the jawline. The experiments were carried out under various conditions, such as different lighting and face shield conditions, as well as with subjects wearing or not wearing eyeglasses and sunglasses. While the accuracy of the approach varied based on the chosen variable and situations, the accuracy ultimately reported was 73.9%.

Kiashari and colleagues [26] created a non-intrusive method for identifying drowsiness in drivers by analyzing their respiratory signals through thermal imaging of their face. To test their system, they conducted an experiment with a thermal imaging camera that captured an image of the driver's face while using a driving simulator. After taking thermal images of the participants, they used two computer programs (support vector machine and k-nearest neighbor) to find out the average and variation of their breathing rate and inhaling/exhaling time. While both predictive models could percive drowsiness, SVM proved to be more effective with a 90% accuracy rate, 85% specificity rate, 92% sensitivity rate, and an overall accuracy of 91%.

Celecia et al. [27] presented an accurate and cost-effective drowsiness detection system that employs an infrared emitter and camera for image capture. The system runs on a Raspberry Pi 3 Model B and uses several measurements such as PERCLOS [28], eye closure duration, and mean open time from the subject's eyes and mouth. The authors used a 300 W dataset [29] to train the device and utilized a series of regression tree algorithms sequentially, to assess the status of each feature. To estimate the driver's level of drowsiness, the Mamdani fuzzy inference system was used based on input from the three feature states. The output of the device categorizes the level of drowsiness as 'low normal', 'medium drowsy', or 'high severe'. According to the authors, their device solves the problem of incomplete drowsiness detection in images by using various measures of drowsiness. It performs well in various lighting conditions and achieves an accuracy of 95.5%.

Alioua et al. [30] proposed a dependable and non-intrusive approach for real-time drowsiness detection to minimize the incidence of road incidents. Their method uses image processing technique to study how the eyes and mouth of the driver move, to find out if the driver is drowsy. They captured a series of images using a webcam, and a face detector Support Vector Machine (SVM) was utilized to identify the driver's face area. They focused on the eyes and mouth parts of the face. They used a method called the circular Hough transform to find the iris which indicates if the eyes were open or closed. They also measured how much the mouth was open to check its state. The eye and mouth states were combined to determine whether the driver was drowsy. The proposed system is resilient and attains an accuracy of 94% and kappa statistics of 86%

TABLE I. Various Drowsiness Detection Systems

Ref.	Author	Description	Parameter & Extracted Feature	Classification Method	Quality Metric
16	Saito and colleagues.	The system can identify when the driver is becoming drowsy and provides assistance to help them avoid drifting off the road. It allows the driver a short time to regain control, but if they don't, the system will take over and park the car safely.	The characteristics of images and vehicles were measured, such as their position on the side, angle of rotation, velocity, steering angle, force applied by the driver, and the degree of eyelid openness.	A set of mathematical procedures or algorithms outlined according to the research hypothesis.	Created their own collection of data, and achieved 100% precision in assuming control of the vehicle under specific driving circumstances.
17	Dasgupta and colleagues.	A smartphone was employed for DDD, using a three-step verification process for detecting drowsiness. Once drowsiness is confirmed, an alarm will be activated.	Features based on images, along with information obtained from voice and touch inputs, PERCLOS (percentage of eyelid closure over the pupil), vocal cues, and touch responses.	Linear SVM	They created their own dataset named 'Invedrifac' and achieved an accuracy rate of 93.33%.
19	Li and colleagues.	A system that operates in real-time utilized a posterior probabilistic model based on SVM to identify and categorize drowsiness into three levels.	A headband with Bluetooth capability for EEG and a smartwatch available for purchase were used to measure the ratio of relative EEG power in terms of power percentages.	SVM-based posterior probabilistic model	They created their own collection of data and achieved the following levels of accuracy: • 91.92% for detecting drowsiness • 91.25% for detecting alertness • 83.78% for giving a warning.
20	McDonald and colleagues.	hey used SWA as input data and compared it to PERCLOS. They trained the Random Forest (RF) algorithm by using a series of decision trees with a randomly selected trait.	Steering wheel SWA	Random Forest	They created their own set of data and achieved the following accuracy levels: • 79% for the RF-steering model • 55% for PERCLOS.
22	Leng and colleagues.	First, the sensors collected data. Then, the features were taken from the data and given to the SVM algorithm. Finally, if the algorithm	The researchers looked at things like heart rate, stress level, and respiratory rate. They also considered the adjustment counter and other features	SVM	They created their own set of data and achieved an accuracy level of 98.3%.

		detects that the driver is drowsy, an alarm on their watch notifies them.	related to biology and the vehicle.		
23	Mehreen and colleagues.	The system has a wearable headband that is non-invasive and has three sensors. It analyzes head movements, blinks, and spectral signals. The features are then sent to a feature selection block and classified using different methods.	The researchers examined two types of characteristics: biological and behavioral. They analyzed the frequency and manner of eyeblinks and also the angle and size of head movements.	They used the backward feature selection method. After that, they employed different classifiers.	They made their own dataset and achieved the following levels of accuracy, sensitivity, and precision: • Linear SVM: 86.5% accuracy, 88% sensitivity, and 84.6% precision. • Linear SVM with feature selection: 92% accuracy, 88% sensitivity, and 95.6% precision.
24	Wijnands and colleagues.	They used real-time facial video and activity prediction to execute DDD with a depth-wise separable 3D CNN. This approach had a significant benefit because it determined the important features automatically, rather than relying on a predetermined set of features.	The system looks at the face and head movements. It decides important features like closed eyes, mouth position, raised chin or eyebrows, furrowed brow, and nose wrinkles without saying them directly.	3D CNN	NTHUDDD dataset. Achieved an accuracy rate of 73.9%.
26	Kiashari and colleagues.	They used thermal imaging of the face to study the driver's breathing patterns and link them with drowsiness.	Thermal imaging technology is used to measure breath. It determines the average and variation of the breathing rate. It also measures the ratio of time spent inhaling versus exhaling.	SVM and KNN	A new set of thermal images was made. The results were as follows: SVM classifier had 90% accuracy, 92% sensitivity, and 91% precision. KNN classifier had 83% accuracy, 82% sensitivity, and 90% precision.
27	Celecia and colleagues.	The sequence uses regression tree algorithms to set parameter conditions. The Mamdani fuzzy inference system then uses these parameters to determine the driver's state.	They evaluate three things: how long the eyes stay closed (PERCLOS), the length of time the eyes are shut, and the average duration of mouth opening.	Mamdani fuzzy inference system	They used a 300-W dataset. They achieved an accuracy of 95.5% and a precision of 93.3%.
30	Alioua and colleagues.	Two methods are used to evaluate the driver's state: checking if the mouth is open and detecting the iris using the circular Hough transform method.	The duration of time during which the eyes are closed and the mouth is open.	Circular Hough transform	They made a dataset of their own. They obtained an accuracy of 94%.

III. DROWSINESS SIGN AND INDICATOR:

A driver doesn't typically become drowsy without exhibiting some indications beforehand. Some of the most common signs are [6,11]:

- Struggling to stay alert,
- Yawning or gaping too much,
- Blinking rapidly,
- Trouble keeping eyelid open,
- Driving out of your lane,
- Delayed response when noticing incoming vehicles,
- Sudden changes in the vehicle's speed.

In literature related to DDD, various words are utilized to state this condition. The term "drowsiness" is commonly used, and it can be used interchangeably with the term "fatigue" [12]. However, they refer to two distinct but related concepts. Fatigue is a feeling of physical or mental tiredness or weakness, typically caused by prolonged exertion, illness, or lack of sleep [13,14]. On the other hand, drowsiness is a feeling of sleepiness or the need to sleep [2,3]. Although fatigue can contribute to drowsiness, they are not always directly related. It is possible to feel fatigued without feeling sleepy, or to feel drowsy even when not physically tired.

Fatigue and drowsiness can be caused by numerous factors like

- Lack of sleep,
- chronic stress,
- poor diet or nutrition,
- physical exertion,
- illness,
- medications,
- sleep disorders like sleep apnea and hypopnea.

IV. DROWSINESS METHOD AND APPROACHES

Drowsiness measurement is the process of assessing an individual's level of sleepiness or fatigue. There are various methods for measuring drowsiness, ranging from subjective self-reporting to objective measures of physiological and behavioral changes.

Some common methods for measuring drowsiness include:

- Subjective scales: These are self-reported scales, such as the Karolinska Sleepiness Scale, which ask individuals to rate their level of sleepiness on a scale from 1 to 9 as shown in figure 1 [15]. Shahid and his colleagues have defined KSS as a tool to measure how tired a person feels at a specific time of the day [16].

Scale	Degree of Alertness/Sleepiness
1	Subject extremely alert
2	Very alert
3	Alert
4	Fairly alert
5	Neither alert nor in sleep mode
6	Few signs of sleepiness
7	Sleepy, no effort to keep alert
8	Sleepy, noticeable effort to keep alert
9	Extremely sleepy, great effort to keep alert, fighting with sleepines

Fig. 1. KSS Rating

- Objective physiological measures: These measures include changes in heart rate, respiration, eye movements, and brain activity. For example, electroencephalography (EEG) can be used to measure brain activity and detect changes in sleep patterns.
- Performance measures: These measures assess an individual's cognitive and behavioral performance, such as reaction time or driving performance.
- Behavioral measures: These measures assess an individual's behavioral changes associated with drowsiness, such as yawning or drooping eyelids.
- Activity monitoring: These measures monitor an individual's physical activity, such as the number of steps taken or the amount of movement during a task.

V. DROWSINESS DETECTION PROCEDURE

Researchers have analyzed how drivers responded and drove to figure out the different stages of drowsiness. In this section, four commonly used measures for detecting driver drowsiness will be listed. Figure 2 shows some of the measurements nowadays is used to classify different levels of driver drowsiness.

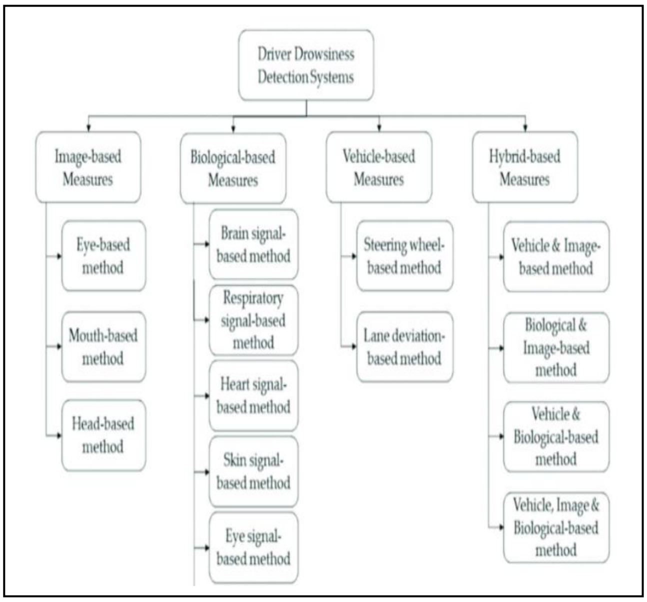

Fig. 2. Approaches to measuring driver drowsiness

The overall block diagram and data flow of a driver drowsiness detection system are shown in Figure 3. The system can use whichever of the four methods mentioned.

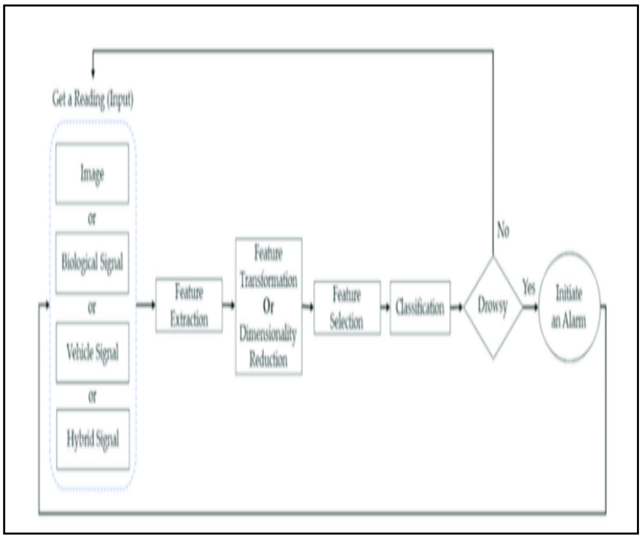

Fig. 3. Data Flow in Systems for Detecting Driver Drowsiness.

Initially, a device that senses things is used to gather information. Then, important parts are extracted from the signals to make it easier for the system to process and obtain useful information. Feature selection algorithms like backward selection or wrapper feature selection methods are used to choose the characteristics that have the strongest association with drowsiness. After that, a model is created using machine learning or deep learning to identify if the driver is drowsy. During testing, the trained model is used to detect the level of drowsiness in the driver and give a warning or take action if necessary, such as sounding an alarm or suggesting the driver take a break.

VI. Emerging Developments and Innovations in Drowsiness Detection Technologies

Drowsiness detection systems are becoming increasingly important in various industries, including transportation, healthcare, and manufacturing, to prevent accidents caused by drowsy individuals. Here are some future trends that are likely to shape the development of drowsiness detection systems:

- Artificial Intelligence (AI): AI will have a significant impact on the advancement of drowsiness detection systems. Machine learning algorithms will be utilized to examine data collected from various sensors, allowing for the identification of patterns and the prediction of drowsiness in individuals.

- Wearable Technology: Smartwatches and fitness trackers, which are wearable gadgets, are gaining popularity and can be utilized to track important cues such as heart rate and body temperature. These readings can then be employed to identify drowsiness.

- Eye-Tracking Technology: Eye-tracking technology can detect changes in eye movement, such as blinking frequency and duration, to determine whether an individual is drowsy.

- Non-Invasive Sensors: Non-invasive sensors such as cameras and microphones will be used to monitor physiological and behavioral changes in individuals to detect drowsiness.

- Integration with Autonomous Vehicles: With the increasing popularity of autonomous vehicles, drowsiness detection systems will be incorporated into them to guarantee the safety of passengers and other individuals using the roadways.

- Real-time Monitoring: Drowsiness detection systems will increasingly provide real-time monitoring of individuals to alert them when they are at risk of falling asleep or becoming drowsy.

- Personalization: Drowsiness detection systems will become more personalized to each individual's needs, taking into account their sleep patterns, work schedules, and other factors that may affect their drowsiness levels.

Overall, the future of drowsiness detection systems is promising, with advances in technology and research providing new opportunities for improving the safety and well-being of individuals in various industries.

VII. Conclusion

In summary, it is crucial to have systems that can detect drowsiness in order to prevent accidents caused by tired people. With the help of technological advancements such as wearable devices, non-invasive sensors, and artificial intelligence, these systems are becoming more advanced and precise in detecting drowsiness. By combining these systems with real-time monitoring and autonomous vehicles, safety can be further improved in various fields like transportation and healthcare. To make these systems more effective, it is necessary to develop personalized drowsiness detection systems that cater to individual requirements and circumstances. While there is still room for improvement, the future of drowsiness detection systems looks promising, and they will continue to play a crucial role in ensuring the safety and well-being of people.

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