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A COMPREHENSIVE REVIEW ON THE DETECTION OF DRIVER DREAMINESS USING PHYSIOLOGICAL, VEHICULAR AND BEHAVIORAL APPROACHES

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Abstract— Disasters are frequently caused by drowsiness, which has significant consequences for safeguarding against deliberate coercion. Many deadly collisions could be averted if drivers who are fatigued are alerted throughout their shift. There are numerous methods for detecting drowsiness, which indicate the amount of driver fatigue and awareness when driving. Outward manifestations, such as eye shutting, yawning, eye blinking, and head movement, can be used to measure the level of fatigue. As difficult as it may sound, developing a sleepiness detection system that produces precise and trustworthy findings necessitates the application of robust algorithms. A variety of strategies have been employed to combat stress and fatigue. The present rising trend in deep learning entails an evaluation of the algorithms to see how precisely they recognise tiredness. This paper provides a comprehensive review of present work patterns, research, and development, as well as advancements in drowsiness detection. The machine divides the existing approaches into three categories: methods based on behaviour, methods based on vehicles, and methods based on physiological principles. After the examination challenges the predetermined percentage of matches, drowsiness is identified and an alert alarm is emitted to wake the driver.
Keywords — Drowsiness, Detection, ANN, CNN, SVM, LSTM, HMM, EEG, ECG, EOG, Eye tracking.

I INTRODUCTION

Laziness or drowsiness is a major contributor to pressure on health and real injuries, deaths, and other calamities. Increasing sleepiness makes driving far more hazardous. Accidents are caused by the lack of concentration caused by the casual transition from a state of vigilance to a state of relaxation. [6] Lack of sleep, worry, anxiety, and alcohol consumption are only few of the potential causes of force weariness. Each of these could result in calamity. Drowsiness may be viewed as the body's natural shift from a highly conscious state to a state of sleep. Difficulties in concentration, constant squinting, or droopy eyelids, Ruminating; disconnected/wandering thoughts, inability to recollect the most recent few kilometres travelled; failure to detect exits or visitors' symptoms and signs, frequent yawning and/or eye strain , difficulty keeping a head-up position, lane departure, following too closely, or running a shoulder rumble strip are violations are the common symptoms of drowsiness.

II REASONS FOR SLEEP DEFICIENCY

Driving is one of the most important concerns in the field of analysis. Rapid driving, yawning, stiffness, serious eyes, and sluggish reactions are all indicators of driver weariness. It is generally caused by substantial factors, such as fatigue, labour, time, and various biological factors. [5] Iatrogenic causes of drowsiness include extended work hours, drug side effects, and specific sleep disorders. Eventually, the person falls asleep due to the compounding of their lack of sleep. The approach of brain activities changes during the day. When struck times are prolonged, finally the character falls asleep. The extent of a person's health has a big bearing on whether or not they are deemed drowsy.

Fig:1 Factors causing drowsiness

2.1 Sleep Disorders

Prolonged sleep deprivation can raise the likelihood of sleep disorders. Sleep disorders can disrupt the communication between nerve cells.

[14] Sleep disorders such as narcolepsy and sleep apnoea cause excessive daytime tiredness. If the disorders are left untreated, they may cause sleep disturbances.

2.2 Alcohol Consumption

Alcohol and some drugs can also cause fatigue. It impairs the driver's ability to drive. Alcohol use may hinder one's creative and imaginative vision. Moreover, excessive drinking might cause memory loss and blackouts. [14] This appears to be pretty unstable when driving.

2.3. Continuous Driving

Constant driving without a break might impair a driver's concentration, reaction time, and running ability. [14] The driver may be tired, which may result in accidents.

III TAXONOMY OF DROWSINESS DETECTION

Many respiratory technologies have been utilised to detect fatigue in recent years. Generally, three precept classifications are used to categorise fatigue detection techniques:

(i) Techniques based on physiological parameter values

(ii) Vehicle parameter-based techniques

(iii) Techniques based on behavioural parameters

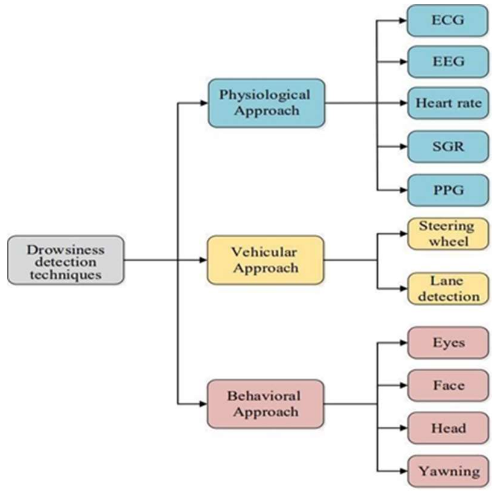

Fig: 2 Architecture of drowsiness detection technique

3.1 Mechanism for Detecting Sleepiness Based on Physiological Measurements

The term "physiological parameters-based sleepiness approaches" refers to methods for determining driver weariness based only on the physical and environmental circumstances of the driver. In addition to the body's temperature, pulse rate, response rate, and heart rate. The measurements are gathered using digital equipment that are placed to the skin to assess the road conditions. Electroencephalography (EEG), inhalation charge, electrooculography (EOG), electromyography (EMG), and electrocardiography (ECG) are examples of physiological indicators that are typically highlighted in sleepiness detection systems. [7] [8] [9].

EEG-Based fatigue Detection Electroencephalography systems such as the OpenBCI, Cyton, and Biosensing board capture brain-generated signals in a non-invasive and low- cost manner. [15] These alerts are triggered by specific types of thought stimuli as well as eye blinks, but they also contain a significant amount of noise, such as that produced by the board. Nevertheless, noise can be decreased by using approved filters. In this regard, the purpose of this painting is to demonstrate how specific types of filters can be used to reduce noise from mind signals received from encephalography devices (along with a Cyton biosensing board) that are generated when a person blinks his/her eyes and classify them into distinct types of blinks. Nonetheless, noise can be decreased using existing filters. The goal of this image is to show how, by using a specific type of filter, it is possible to smooth the noise from the mind signals received from encephalography devices (including a Cyton biosensing board) that are generated when a user blinks his or her eyes and categorise them into different types of blinks.

ECG-Based Driver Fatigue Detection

Electrodes are used in an electrocardiogram (ECG) to detect and display the tiny electric changes that occur with each heartbeat. It is employed to look at a variety of abnormal heart activities, including arrhythmias and conduction problems. The electrocardiogram is one of the most crucial diagnostic methods for identifying heart problems (ECG).

EOG-Based Driver Fatigue Detection

A far more environmentally friendly technique for eye monitoring involves electro-oculography, which is also known as applying electrodes to the face and scalp. (EOG).The EOG system was and remains one of the earliest methods for analysing eye movements [2]. It is seen to be a useful resource for human-computer communication. The electrodes of EOG prevent eyesight obstruction, which is one benefit. Electromyography In determining users' eye movements during passive and active engagement, detection uses electroencephalography (EEG) and electro- oculography, which are particularly well-suited for brain-computer interfaces.

ELECTROMYOGRAPHY

Electromyography (EMG) is the most accurate way for assessing whether or not a muscle is fatigued, as the EMG signals provide more exact information on the muscle's performance. Electromagnetic muscle impulses were recorded using both invasive and non-invasive methods. In the invasive method, a needle is inserted directly through the skin and into the muscle. This approach involves placing electrodes on the skin's surface to obtain a reading. The surface EMG signal is gaining importance in numerous domains. It is used to assess the neuromuscular system and diagnose muscle or nerve disorders [3]. Prosthesis could be controlled by means of EMG alerts. The EMG signal can also be used to detect muscular fatigue. This information could be crucial as it could prevent permanent harm to the individual [4]. When determining whether a person can maintain the appropriate degree of force for a certain task, muscle fatigue is evaluated. Often, the amplitude and frequency of an EMG signal are examined to determine if a muscle is fatigued.

Literature Survey

Christopher N. Watling (2) The software for detecting fatigue is examined in this study utilising both a single-method and a mixed- method approach. Many physiological signals, including electroencephalography (EEG), electrooculography (EOG),and electrocardiography (ECG), are measured using this technique (ECG). As a starting point, subjective sleepiness indices were determined using the Karolinska Sleepiness Scale. Using a psychomotor vigilance test (PVT), signals were recorded, and the procedure required pre- processing, extracting, and identifying the physiological signals' most crucial functions for detecting sleepiness. Ultimately, four supervised machine learning models were created to forecast the stage of fatigue based on the user's perception of fatigue and the physiological data gathered. Each physiological measure's effects exhibit a unique pattern of overall performance, with better sensitivity but poorer specificity, and vice versa. Although the hybrid biosignal-based models have a better overall performance profile, they are still capable of minimizing the gap between the two metrics. The study's findings indicate that hybrid solutions outperform stand-alone approaches for the selected functions. This could have implications for future research.

A classification system based on a deep neural network that makes use of ECG and respiration data for a layered sleepiness detection system is provided by the author Serajeddin Ebrahimian and colleagues (3). The proposed technique uses the heart-rate signal, heart-rate variability (HRV), and power spectrum density (PSD) of the HRV as inputs. Convolutional neural networks and long- term memory (LSTM) networks are used in this methodology (CNNs). Determining a method for categorizing fatigue based on an individual's breathing and ECG signals was the main goal of this study. With upgraded models, multiple combinations of cardio-respiratory features were added. 91% of the time, the CNN-LSTM model generated accurate results for three-level classifications, and 67% of the time for five-level classifications. The sleepiness evaluations were proved to be more accurate than the majority of physiologically-based techniques in the literature. There is also the possibility that built-in, non- intrusive sensors for respiratory and ECG signals in autos may use well-known classification algorithms to identify varying levels of driver drowsiness in a manner that does not irritate the driver unduly.

In their experiment, Sadegh Arefnezhad et al. (5) utilised the percentage of eyelid closure (PERILOUS) as a measure of driver fatigue. Using EEG data, this study introduces a novel way for evaluating the immediate state of driver fatigue. Using the modelling technique, they analyse EEG data to determine which brain activities are DANGEROUS. At the interpretation step, we determine the PERILOUS degree by examining the length of time a Bayesian filtering approach has been utilised. During the interpretation step, they utilised Bayesian filtering to assess the degree of PERCLOS throughout time. The proposed framework was evaluated using a dataset consisting of 18 driving trials conducted by 13 drivers. With an average Root Mean Square Error (RMSE) of 0.117, the modelling performance in calculating PERILOUS provides dependable and repeatable findings in trials utilised for non-intrusive and accurate multilevel sleepiness categorization with minimum driver disturbance (with a PERILOUS range of 0 to 1).

Sreeza Tarafder and his coworkers (6) The author examined whether the electroencephalogram's ocular artefacts might distinguish between awake and sleeping states. The author of this work extracted 25 blink-related alternatives from a public dataset that comprised the unrefined graphical indications of 12 people using the BLINKER algorithm. The tagged and reinforced K-Nearest Neighbor (KNN) tree models were trained using the seven elite parameters. The performance of these types has also been enhanced by making them superior. EEG eye- artifact functions may differentiate between sleep and wakefulness, and ensemble-based optimised trees have the greatest rate of accuracy (91.10%) of any standard machine-learning model.

Umit Budak generally includes camera-based structures and wearable sensors to diagnose driver behaviour [7]. Electroencephalogram (or EEG) is utilised by a number of additional effective alternatives for diagnosing driver fatigue. In this article, EEG data are also used to assess fatigue, with the proposed technique consisting of three essential components. Within the basic building block, raw EEG signals are transformed into strength distribution and zerocrossing distribution functions, which are then converted into EEG spectrogram images to get spectral entropy and instantaneous frequency functions. In the second construction component, pre-trained AlexNet and VGGNet are used to immediately apply deep function extraction on EEG spectrogram images. The third component, the tunable Q-component wavelet transform (TQWT), is used to separate EEG alerts into useful sub- bands. The spectrogram images of the obtained sub-bands are then produced along with statistical data like the mean and standard deviation of the sub-band frequencies. Each building block's characteristic group is likely sent into a long- short-term memory (LSTM) network in order to classify them. The proposed technique was evaluated using a tenfold pass validation check, and the average precision was calculated accordingly. The average accuracy rating obtained was 94.31%.

3.2 Techniques for Detecting Sleepiness Based on Behavior

There are non-invasive methods for spotting fatigue, such as behavioral traits. In order to assess driver fatigue, these systems frequently employ behavioural data from the eyes, including the eye component ratio (EAR), eye blinking, and facial expressions. A tired driver's mouth can be identified by using yawning-based detection, a [1] different time of image processing technique. The level of the motive force's tiredness is assessed using the behavioral techniques listed below:

3.2.1. Method of Facial Expressions

The author [1] developed a hardware-based Drowsiness Detection system based on facial expressions as a key application of machine vision.. This technique is a component of the researchers' Finite Element Analysis, which involves a complex device that records a report on the facial features and determines whether someone is sleepy based on the findings of the report. Facial expressions are produced via horizontal projection and a dynamic template that matches the report.

3.2.2. Analysis and Extraction of Yawning

A DDT was presented by the [2] authors based solely on examination of the mouth and yawning.

Using a series of classifiers, the system locates and recognises the driver's mouth from predictor images. These photos were trained using the Support Vector Machine classifier, enabling it to conduct binary or multiclass classification and notify the driver. For their experiment, the authors chose more than a hundred common motion pictures along with twenty photographs of a yawning figure.

3.1.3Eye-Tracking Technology

Percent of Eye Closing is a technique that the authors of [3] created to track eye movement (PERCLOS). The face and eyes are recognized using a top-down model and a web camera connected to GUI software on a laptop. The camera will continue to record images until the face is identified. Using the Viola-Jones technique and Adaptive Boosting, the ocular region is extracted (Ada-Boost). S = HL, where H is the driver's height and L is the driver's eye length, is the formula used in this method to calculate the driver's fatigue level S. Each frame of the visual input is ordered according to the measured value of S. The authors of [3] developed a method termed Percent of Eye Closure to monitor eye movement (PERCLOS). The face and eyes are recognized using a web camera coupled with GUI software on a laptop and a top-down model. Unless the face is authenticated, the camera will continue to take pictures. Using the Viola-Jones technique and adaptive boosting, the ocular region is retrieved (Ada-Boost). The formula employed in this method to determine the driver's fatigue level S is S = HL, where H is the driver's height and L is the driver's eye length. The visual input is organized into frames based on the measured value of S. The alert is set off when the driver's sleepiness level is close to 0.15.

3.1.4. Method for Detecting and Monitoring Eye Blinks

A non-intrusive DDT was created by the authors

[4] using machine-based principles. The system's hardware includes a webcam that is placed in front of the driver to record head and facial movements. In order to identify and extract facial characteristics like the eyes and mouth, the Viola- Jones method and the Haar Cascade classifier are utilised. The amount of blinks per minute, which typically ranges from 12 to 19, is used to achieve this. Drowsiness is assumed if the frequency level drops below the minimum range. If the eye is closed, the attribute's value is non-zero; if the eye is open or only partially open, it is zero. This process had a 90% success rate.

Literature Survey

Drowsiness is one of the key factors that can occasionally prove fatal according to Manishi et.al. (8). Countermeasures must be done to increase driver attentiveness. There are three broad categories for drowsiness treatments: behavioural, vehicle, and physiological. Several approaches are implemented to improve the precision of experimental results. This organised review's primary objective is to investigate the various strategies applied within the behavioural parameters-based sleepiness detection system. The hybridization of these strategies can assist in overcoming the disadvantages of individual procedures, hence enhancing results. The most popular classifier, SVM, offers better accuracy and speed in most cases but is not appropriate for big datasets. Compared to CNN and HMM, HMM has a lower error rate, however CNN and HMM both take longer to train and cost more money than the SVM classifier. Future work can be undertaken with more precision. Examine yawns and other complex imagery to increase productivity.

Prof. Prasad Reddy P.V.G.D et al. one of the main factors contributing to fatal road injuries is drowsy driving. (9). As a result, detecting driver weariness and indicating mileage is an active research field. The majority of the typical strategies found are either physiological or behaviorally based entirely techniques for sleepiness detection. It is established that some systems necessitate expensive sensors, whereas others are obtrusive to the driving force, distracting the rider. As a result, a real-time driver sleepiness detection device with low cost and high accuracy is critical. This study provides exceptional traditional strategies that have been used in sleepiness detection for over a decade. This study investigates amazing gadgets for learning strategies in sleepiness detection. Physiological measurements necessitate more expensive sensors, and car-based completely systems will not be dependable owing to their practical constraints. The data obtained by using cameras to detect minute changes in the driver's facial expressions are far inferior to those obtained by using behavioural metrics to create a green sleepiness detection device. The primary functioning principle is to detect abnormalities in the driving pattern. Using dimensionality reduction algorithms, extract the discriminative features.

Venkata Ram Reddy Chirra et al [17] identify driver weariness as one of the major contributing factors to crashes today. Intelligent/smart cameras are being developed to detect driver drowsiness as computer vision technology improves, alerting drivers and reducing accidents driven by tired driving. The study introduces a novel method for identifying driver weariness while operating a motor vehicle that is based on deep learning. In this paper, face images are analysed to identify the face and extract the eye region using the Viola-Jones face identification method. A stacked deep convolution neural network is used to extract features from the dynamically identified key frame in camera sequences during the learning phase. A SoftMax layer in the CNN classifier can tell if a motorist is awake or asleep. This device alerts the driver if they fall asleep behind the wheel. With 96.42% accuracy, the suggested method outperforms traditional CNN for a given dataset. The suggested Staked Deep CNN overcomes traditional CNN restrictions, including pose accuracy in regression.

The technique for identifying driver weariness disclosed in this article makes use of a design that can identify the driver's drowsiness. The proposed architecture consists of four deep learning models, AlexNet, VGG-FaceNet, FlowImageNet, and ResNet, that can recognise driver weariness from RGB videos of drivers. These models also assess four different implementation options, such as head movements, facial expressions, activity features, and hand gestures. Many backgrounds and settings, including indoor, outdoor, daylight, and evening, are replicated using the AlexNet model. Using the VGG-FaceNet method, facial attributes such as gender and ethnicity may be extracted. ResNet is employed for hand motions, whereas Flow ImageNet is utilised for behavioural features and head movements. The outcomes of hand gesture detection are exact and reliable. These models divide these characteristics into four categories: not sleepy, sleepiness accompanied by eye blinking, yawning, and nodding. The ensemble technique uses the outputs of these models to obtain a result by feeding it into a SoftMax classifier and receiving a positive (drowsy) or negative response. This method had an accuracy rate of roughly 85%.

3.3 Vehicular parameters-based techniques Methods for detecting

tiredness based on vehicular metrics, such as lane-changing behavior, accelerator action, vehicle speed variation, steering wheel tilt, and grip force, are included in vehicle-based approaches. The tactics are designed to monitor and record driving behaviours in order to detect poor driving performance due to fatigue. Because these measurement values are influenced by external factors such as road conditions and weather [7], we can't rely on vehicle movement alone to assess driver fatigue. Various vehicular manoeuvring strategies are described.

3.3.1. System for Real-Time Lane Detection

The author [5] described a technique for identifying weariness in dim lighting. The device works in the following order: Initially, the gadget determines lanes based solely on Though transform. In the second phase, the device uses the Viola Jones Algorithm to scan the driver's eyes. The images are segmented using the Segmentation technique, followed by the OSU Threshold method.

3.3.2. Investigation of the steering wheel angular velocity time series

The authors of [6] developed a system for identifying tiredness based on a time series examination of the angular velocity of a car's steering wheel. The detection feature for computing the steering wheel's angular velocity, which may be utilised for time series analysis, is the type of steering wheel behaviour and a detection window. In actual use, the new approach performs better than the old ones and offers many benefits. [7] has created a real-time online detection method for detecting driver weariness under actual driving conditions using steering wheel angles (SWA). This system's accuracy was 78.01%.

Literature Survey

A F M Saifuddin Saif et al (16) — The detection of driver drowsiness remains an unresolved scientific problem that must be addressed if traffic accidents are to be decreased. The majority of these solutions fall short in terms of precision and real-time performance, are expensive, difficult to implement, and have a high computational cost and poor frame rate. This research suggests a powerful strategy for identifying driver weariness based on head position estimation and pupil detection that involves first removing the face region. Due to flaws such as light reflection and shadow, the face region could not be extracted from any frame, hence the proposed method utilised a frame aggregation mechanism. A facial landmark's estimation is discussed in each regression. The proposed approach employs deep convolutional neural networks (DCNN) for accurate pupil detection and learning nonlinear data patterns. By using normalization during the training phase to stabilize the distributions of internal activations, the constraints of varying illumination, blurring, and reflections for robust pupil identification are handled in this context, reducing the impact of parameter initialization on the overall method. Throughout evaluation was conducted for the proposed research, which produced results that were better than those of earlier studies with an accuracy rate of 98.97% and a frame rate of 35 fps. The experimental findings show that the suggested methodology works.

Jiangfan Chen et al (11) The authors proposed a system for detecting drowsy driving based on a convolution neural network (CNN) and electroencephalographic sensors (EEG). The suggested system consists of three components: EEG data collection, sleepiness detection, and an early warning mechanism. In the drowsy and alert driving simulation scenarios, EEG signals are monitored and collected via a brain-computer interface (BCI). Using the Inception module and a modified version of the AlexNet module, neural networks are trained to identify EEG signals. Last but not least, the early warning strategy module will turn on and sound an alert if it determines that the driver is drowsy. The approach was tested using driving EEG data from simulated drowsy driving scenarios. The neural network using the Inception module obtained 95.59 percent classification accuracy using data from a one- second time window, while the modified AlexNet module only managed 94.68%. The simulation and test results highlight the effectiveness of the suggested approach for drowsy driving detection to increase vehicle safety.

According to Sajjad Samiee and others, this research delivers a ground-breaking non-intrusive sleepiness detection method based on deep neural networks and vehicle-based observations (12). The proposed approach combines convolutional neural networks (CNN) and recurrent neural networks (RNN) (RNN).The five essential vehicle-based metrics are used as network inputs: steering wheel angle, steering velocity, yawing rate, and lateral acceleration from the road centreline. Drowsiness is classified into three groups. RNN layers in the deep network structure include long-short term memory (LSTM) and gated recurrent unit (GRU). The effectiveness of the suggested method is assessed using experimental data gathered from 44 sessions in a fixed-base driving simulator simulating arduous night time highway travels. The findings show that the built-in deep networks perform better in classification accuracy than common classifiers like support vector machines and k-nearest neighbors. A combination of CNN and LSTM yielded the highest accuracy of 96.0%. (CNN- LSTM). Other signal sources, including unobtrusively acquired physiological signs, should be included in future study, and the system should be tested in real-world settings.

Author	Year	Method	Parameters	Metric	Classifier	Accuracy
Christopher N. Watling etal [2]	Dec 2021	Physiological Measures	Heart Rate, Pulse Rate, Brain Activity	EOG, ECG,EEG	Artificial Neural Network (ANN)	96.9%
Serajeddin Ebrahimianet al [3]	Aug 2022			ECG, Respiratory signals, HRV	CNN, LSTM	91%
S adegh Arefnezhad,et al [5]	Feb 2022			EEG Signals, PERILOUS	Bayesian filtering method	81%
Sreeza Tarafder et al [6]	June 2022			Electroencephalogram ocular artefacts	SVM, K- Nearest Neighbour, optimized ensemble-boosted trees	91.10%
Umit Budaket al [7]	Sep 2019			EEG signals	Tunable Q-factor wavelet transform, Artificial Neural Network	94.31%
Manishi etal [8]	Oct 2020	Behavioral Measures	Blinking the ratio of close to far eyes, Head	EEG, ECG	SVM Classifier	92%
D. Venkata Subbaiah	March 2019			EEG, EOG, ECG	SVM, CNN, HMM	95%
				FlowImageNet, ResNet	Soft Max classifier	85%

Venkata Rami ReddyChirr et al [17]	Sep 2019		noddingand yawning	EOG	Stacked deep convolution neural network	96.42%
A F M Saifuddin Saif et al	June 2020	Vehicular Measures	Steering wheel, lane changing pattern	EOG	Deep Convolutional Neural Network	98.97%
Jiangfan Chen et al	April 2021			EEG	Neural Network Alex Net	95.59%
Sajjad Samiee et al	July 2020			steering wheel angle, yaw rate, lateral acceleration, and turning velocity	CNN &LSTM	96%
Azhar Quddus et al	June 2021			EEG Signals	R-LSTM C-LSTM	95-97%

Table : 1 Comparison of Drowsiness Detection Methods

According to Azhar Quddus and others, a variety of methods can be used to spot drowsy driving, including electroencephalogram (EEG), eye movement, and vehicle driving dynamics (13). EEG is the most precise method, but it is also the most time- and space-consuming. Yet, even if it is quite easy to learn car driving characteristics, it is not particularly precise. The method based on eye

movement is particularly intriguing for finding a middle ground between these two extremes. On the other hand, eye movement-based systems frequently need the use of eye-tracking equipment, which consists of a high-speed camera with a complex algorithm for gathering eye movement- related features like blinking, eye closure, saccades, etc. So, it is challenging to implement eye-tracking-based sleepiness detection as a workable solution, especially on an embedded platform. The authors of this study suggest that rather than investing in a costly eye-tracking device, eye photos taken with a camera should be used. To detect fatigue, the Recurrent Neural Network (RNN) tracks eye-related movements. Compared to standard RNNs, RNNs with Long Short Term Memory (LSTM) provide a number of advantages. In order to replicate eye movements, this technique uses a variety of LSTM cells. We employed both the conventional 1-D LSTM (R-LSTM) and the convolutional LSTM (C-LSTM), which allows for the direct utilisation of 2-D images. Data from the 38 participants in a driving simulation was divided into 48 by 48-square-inch sections. Using power spectrum analysis of multichannel electroencephalogram (EEG) data that was simultaneously recorded, individuals' attention was rated independently, and binary labels of alert and drowsy (baseline) were established. The outcomes demonstrate how successful the suggested system is. In comparison to the r- LSTM-based method, which had an accuracy of roughly 82%, the C-LSTM-based approach's accuracy was between 95% and 97% higher. By contrast, it is demonstrated that the proposed LSTM method outperforms a previously published eye-tracking-based method by a wide margin.

V CONCLUSION

Due to their utility and the need to ensure driver safety, fatigue detection systems will be a primary focus of energy research. This survey's primary objective is to rank recent studies pertaining to sleepiness detection. Many sleepiness detection technologies are utilised to detect fatigue. Physiological, vehicular, and behavioural methods are utilised to determine driver fatigue. Identified and assessed the most recent fatigue detection systems on the basis of their methodology, metrics, accuracy, pros, and cons. Although the review shows that physiological measurements are more reliable than other measurements, this method's main drawback is that it is more invasive. The behavioural measurements are unobtrusive and user-friendly, but their accuracy is impacted by the driving environment. Further features are required for reliable vehicle localization and information tracking. Physiological techniques such as EOG, ECG, and EEG data, as well as classifiers such as ANN, CNN, CNN, SVM, and LSTM, are utilised to detect driver weariness. When compared to other classifiers, the DCNN and CNN have the highest accuracy but are the most expensive. SVM is the most prevalent classifier for identifying driver fatigue and notifying the driver.

Abbreviation

1. EEG – Electroencephalogram
2. ECG – Electrocardiogram
3. EOG – Electrooculography
4. ANN – Artificial Neural Network
5. CNN – Convolutional Neural Network
6. LSTM – Long short-term memory
7. HRV - Heart rate variability
8. HMM – Hidden Markov Model
9. SVM – Support Vector Machine 10 GRU - Gated Recurrent Unit

11 PERCLOS – Present Eye Closure

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