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Modern Drowsiness Detection in Deep Learning: A review

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ABSTRACT

Recent statistics show that drowsiness is now more of a factor in some car accidents than alcohol. So numerous monitoring systems have been developed to reduce, and accidents eliminate these events. Drowsiness detection systems are plentiful, but it isn't clear which one is the most effective. This review paper will address the following issues: firstly, determining the extracted features, whether behavioral-based, physiological-based, or vehicle-based, which are used to detect driver drowsiness; secondly, focusing on using deep learning to detect driver drowsiness. Finally, concluding from this study that the hybrid-based features should be used Because it gives strength in determining the drowsiness of the driver.

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1. Introduction

One of the most common contributing factors to car accidents is fatigued driving. However, all over the world, drowsiness is a leading cause of car accidents and is to blame for the deaths of tens of thousands of people yearly [1, 2]. Various studies indicate that drowsiness may be a factor in up to 20% of all traffic accidents and 50% on some roadways. According to ongoing research, driver drowsiness is the major contributor to many car accidents and is believed to be responsible for 1,200 deaths and 76,000 injuries annually [3]. Driver drowsiness detection systems have been worked on and developed by researchers worldwide to reduce such accidents and improve the safety of both the driver and the passengers [1].

The drowsiness detection systems are based on four methods: Vehicle, behaviorally, physiological, and hybrid [1, 4]. Systems based on vehicles can detect drowsiness by monitoring the driver's actions, such as changing lanes, rotating the steering wheel, increasing their speed, applying more pressure to the accelerator pedal, etc. On the other hand, behavioral-based drowsiness detection systems rely on the operator's driving behavior. To be more specific, in such systems, eye closure, yawning, and head posture are monitored through a camera to detect drowsiness. In

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addition, some Systems based on physiological signals, such as electrocardiograms (ECG) and electrooculograms (EOG), identify drowsiness by correlations between these signals [1, 4, 5]. And the final option systems are based on merged between previous methods to detect drowsiness.

Deep learning has recently attracted a lot of research. It has rapidly developed and succeeded in many domains, including speech recognition, sensor data, motion graphics, spectrographs, ECG, electronics devices, and simulated data [5, 6]. For example, convolutional neural networks (CNNs) in detecting drowsy drivers have been widely studied. Facial landmarks in images taken on mobile devices or other devices were recognized by the framework of their work and passed on to a CNN-based qualified Deep Learning model to detect drowsy driving [7, 8]. This review paper has three main categories of Drowsiness-Detection-Techniques, each with its advantages, disadvantages, and limitations. Drowsiness in drivers can be better detected by combining previous and deep learning techniques.

A paper is organized into five sections. The second section describes the general structure of the deep learning techniques in driver drowsiness. The following section shows sleepiness detection strategies are detailed. The fourth section explains the advantages and disadvantages of the four methods for detecting driver drowsiness and the deep learning methods used for classification. Finally, we discussed the study's conclusion.

2. A General Template of Deep Learning Techniques for Detecting Driver Drowsiness

Deep learning is artificial intelligence (AI) applied to forecasting, classification, and prediction tasks. Different layered models are used in deep learning, referred to as a neural network for the system [9, 10]. Figure (1) demonstrates the general template of deep learning techniques for detecting driver drowsiness.

2.1. Data Acquisition

Collecting data is the first step in any experiment. The amount and quality of data collected are critical to building an accurate model. Some researchers have found that they can use publicly available, validated, and accessed datasets to detect drowsiness in drivers. Another approach is to build a dataset from scratch [4].

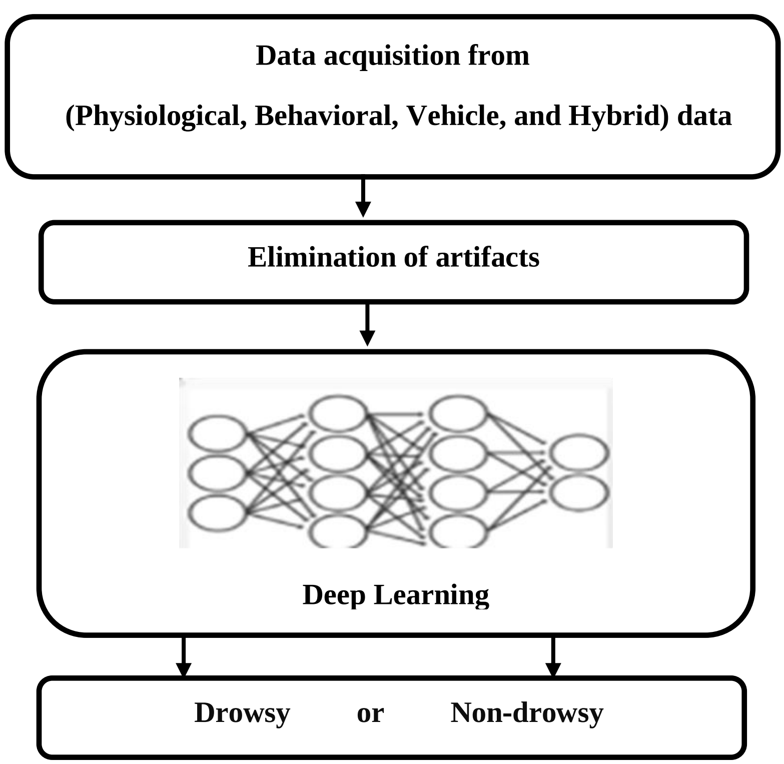

Fig (1): The general template of Deep learning techniques for Driver Drowsiness Detection.

2.2. Preparation of Training Data

Assigning paths, forming labels, and resizing our images will prepare our dataset for training [5]. The other steps are the Convolution layer (CL), Pooling layer (PL), Second CL, PL, Dense layer (DL), and finally, Logit layer (LL).

3. Literature Review

The detection of drowsiness can be broken down into four main areas: firstly, techniques based on the vehicle; secondly, techniques based on behavior; thirdly, techniques based on Physiological. And finally, hybrid techniques. Figure (2) illustrates categorizing drowsiness detection methods [11].

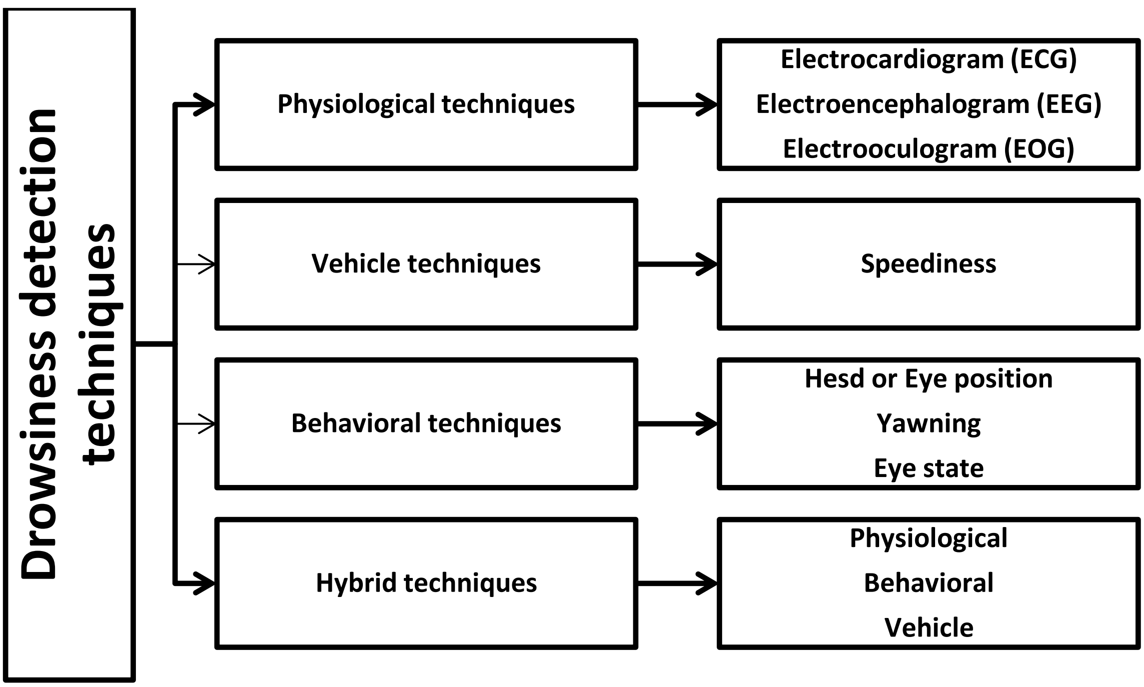

Fig (2): The overview of sleep detection techniques [11].

3.1. The vehicular features-based techniques

Numerous techniques have been proposed to improve approaches for detecting drowsiness. This section aims to overview the various methods and approaches used to detect drowsiness. The first method was previously employed based on driving patterns, depending on vehicle characteristics, road environment, and driving abilities [12]. Disturbances in either lateral or lane position, or changes in steering wheel movement, should be recorded to derive the driver's driving pattern. In addition, the steering wheel needs to be micro-adjusted while driving to keep the vehicle in its lane [2, 13]. The sensors in the steering wheel allow for the extraction of these kinds of features. Sensors monitor and measure steering movements to determine a driver's steering behavior. Approximate entropy (AP), steering-wheel angle (SWA), speed (SWV), and steering-wheel direction (SWD) are examples of this kind of feature [11, 13]. The authors in [14] use a mix of convolutional neural networks (CNN) and recurrent neural networks (RNN) with five different vehicle-based measurements (yawing rate (YR), steering wheel angle (SWA), steering wheel velocity (SWV), lateral deviation (LD), and lateral acceleration (LA)). They utilize gated recurrent unit layers and long-short term memory (LSTM) layers. Accuracy was obtained at 96.0% with (CNN-LSTM). The authors in [15] propose an ensemble network model of multiple convolution neural networks (MCNN) with two vehicle-based measures (steering wheel (SW) and pedal pressure (PP)). Accuracy was obtained of 94.2% in the detection of drowsy driving. The work in [16] applies two methods: firstly, machine learning (Logistic Regression, SVM, and Random Forest); secondly, deep learning (MLP and RNN (LSTM)) with multiple vehicle-based measures (timestamp (T), altitude (A), the accuracy of the vehicle's geolocation (AVG), bearing of degrees the direction of the vehicle (BDDV), speed GPS, speedOBD, vinNumber, rounds per minute (RPM), real throttle (RT), intake temp (IT), engine temp (ET), fuel type F(T), engine runtime (ER), pending trouble (PT), and car plate(CP)). In deep learning, an accuracy was obtained of

99.9% in detecting drowsy. The authors [17] propose Long Short Term Memory Fully Convolutional Network (LTSM-FCN) with multiple vehicle-based features (speed (S), acceleration (A), car position relative to the lane center (CPRLC), time of impact to ahead vehicle (TIAV), car angle relative to lane curvature (CARLC), and road width (RW)) where the accuracy was obtained of 95.8% in detecting drowsy. As shown in Table 1, the Vehicular Feature-based Technique is summarized in this section. It's more reliable to use techniques that employ this type of feature. But there are some drawbacks. First, it is unreliable because the geometric characteristics of roads affect their benefits, which are non-intrusive [11].

Table 1- A brief overview of vehicle-based methods

Ref	Year	Vehicle Features	Method of deep learning	Result of an accuracy
[14]	2020	YR, SWA, SWV, LD, LA	CNN-LSTM	96.0%
[15]	2021	SW and PP	MCNN	94.2%
[16]	2020	T, A, AVG, BDDV, speed GPS, speedOBD, vinNumber, RPM, RT, IT, ET, FT, ER, PT, and CP	MLP and RNN (LSTM)	99.9%
[17]	2019	S, A, CPRLC, TIAV, CARLC, and RW	LTSM-FCN	95.8%

3.2. The physiological features-based techniques

The physical characteristics of the driver are the base of Physiological techniques. In addition to the body's temperature, this method represents features such as the (heart, pulse, breath, and respiratory) rates. Numerous previous studies have used these features to detect sleepiness in drivers [11, 18].

The author process EEG signals recorded over a spatial-temporal series [18] using a convolutional neural network and interpretation approach (CNNIT). The accuracy rate for the technique in detecting drowsiness was 78.35%. While in [19], the authors proposed a technique in a deep learning architecture consisting of convolutional neural networks (CNN) and recurrent neural networks (RNN). Using the features of Electrocardiograms (ECG) and electroencephalography (EEG) pulse, it achieved an accuracy of 97%. To detect drowsiness in [8], the researchers used the physiological features extracted from electroencephalogram (EEG) signals. These features were processed using a convolutional neural network (CNN) with Long Short-Term Memory (LSTM). 41.44% is the accuracy rate in the CNN-LSTM. The researcher in [20] has suggested a novel deep learning architecture built on a convolutional neural network (CNN) to detect drowsiness automatically from a single-channel EEG signal. The results show an accuracy of 94.87%. In [21], the researchers proposed a convolutional neural network (CNN) and electroencephalography (EEG) for physiological characteristics. This method got an accuracy of about 85%. For eye state recognition (open or closed) from electroencephalography (EEG), the authors in [6] proposed three architectures: convolution neural network (CNN), gated recurrent unit (GRU), and long short-term memory (LSTM). The proposed method achieved an accuracy rate of 99.86%. EEG-Conv and EEG-Conv-R, two deep learning-based models for predicting a driver's mental state, were described by the author in [22]. Drunk drivers' mental states can be classified using an advanced 5-layer convolutional neural network, which outperforms conventional methods like SVM and LSTM. Accuracy was obtained of 91.788%, 92.682%, 88.070%, and 85.132% respectively. Table 2 illustrates a brief overview of physiological-based methods.

Table 2- A brief overview of physiological-based methods

Ref	Year	physiological features	Method of deep learning	Result of an accuracy
[22]	2018	EEG signal	EEG-Conv,	91.788%,

			EEG-Conv-R, SVM, LSTM	92.682%, 88.070%, 85.132%
[19]	2021	(ECG, EEG) signals	CNN+RNN	97.00%
[8]	2021	EEG signal	CNN-LSTM	41.44%
[20]	2021	EEG signal	CNN-LSTM	94.87%
[21]	2021	EEG signal	CNN	85.00%.
[6]	2021	EEG signal	CNN+GRU+LSTM	99.86%
[18]	2022	EEG signal	CNNIT	78.35%

3.3. The behavioral features-based techniques

Image processing is used to recognize drivers' behavioral aspects acquired by the camera attached to the car, which is then used to follow the driver's behaviors and notify them. This method is typified by features relating to the eyes, lips, and head [11, 23].

The research [24] implemented a deep convolution neural network to extract features from the eye. It used the Viola-Jones face detection algorithm to extract the eye area from the face images, using a Soft-Max layer classifier in CNN to identify whether the driver was sleeping or not. And it had an accuracy of 96.42%. While the research [25] proposed a model focused on computer vision fields using a 3D-deep convolutionary neural network (3D-DCNN) and a fully linked neural network, it got an accuracy of 92.4%. [26] provided a method for real-time detection of driver drowsiness based on facial, eye, and mouth aspects in the multi-feature information fusion methods using a mixture of CNN and LSTM. In trials, the proposed approach achieved an accuracy rate of 84.85%. The authors of [27] proposed and implemented a mechanism for early detection and notification of drowsiness in the HM-LSTM network, LSTM network, fully connected layers, and Human judgment based on Videos of the yawn, eye, and head movements that were extracted. There was the accuracy of 65%, 61%, 57%, and 58%, respectively. Using eye and mouth characteristics, the research [28] implemented a multi-tasking Convolutional Neural Network model. Besides, this model achieved 98.81%. The research [29] proposed an approach to apply a Recurrent Neural Network (RNN) over a driver's face. This model obtained an accuracy of 92%. A convolution neural network (CNN) based on head movement, mouth, and eye blink has been developed [30] to detect driver distraction and drowsiness. This approach was able to obtain a 69% success rate.

Regarding predicting if a driver is asleep or awake, two CNNs are shown in [31]. There are three convolutional layers and one fully-connected layer in one of the CNNs, while the other is based on the AlexNet architecture and uses transfer learning techniques. The CNN built achieved a better result with an accuracy of 96%. In [32], the eyes, brow, and mouth features were retrieved and sent into the suggested 2-stream DNN and CNN (LeNet) to identify drowsiness. The methods achieved an accuracy of 63% and 92%, respectively. While the authors in [33], To detect fatigue, have combined convolutional neural networks (CNN) and long short-term memory (LSTM); and extracted the features from their videos (eyelid opening, mouth, head movement). The model achieved an accuracy of 54.71%. In work in [34], to evaluate drowsiness driver detection on the UTA-RLDD dataset, the authors compared a CNN and an LSTM. Eye aspect ratio (EAR), mouth aspect ratio (MAR), Mouth over eye aspect ratio (MOEAR), and pupil circularity (PC) were extracted using the Dlib's face detector landmarks. The accuracy in the two methods achieved about 72% and 64%, respectively. In [35], the author proposed a convolutional neural network (AlexNet) based on a publicly available dataset for driver distraction recognition with more distraction postures than alternatives. The proposed method achieved a 90% accuracy rate.

Because of its advantages, this technology is non-intrusive. Moreover, it is simple to use, and its limitations are influenced by the lighting circumstances [36, 37]. Table 3 represents an overview of the behavioral-based method.

Table 3- A brief overview of behavioral-based methods

Ref	Year	Behaviors features	Method of deep learning	Result of an accuracy
[24]	2018	Eye state	CNN with Soft-Max layer classifier	96.42%
[25]	2018	Face recognition	3D-DCNN and fully connected neural network	92.4%
[26]	2019	facial, eye, and mouth	CNN and LSTM	84.85%
[27]	2019	yawn, eye, and head movements	HM-LSTM network, LSTM network, fully connected layers, Human judgment	65%, 61%, 57%, 58%
[35]	2019	Face, Hand, Skin	CNN(AlexNet)	90%
[28]	2020	Eye and mouth	CNN	98.81%
[29]	2020	Face	RNN based on 3D Convolutional Networks	92%
[30]	2020	Head movement, mouth and eye blinks	CNN	69%
[31]	2020	video	CNN (AlexNet)	96%
[32]	2021	Eyes, eyebrow, and mouth	2-stream DNN CNN (LeNet)	63%, 92%
[33]	2021	eyelid opening, mouth, head movement	CNN and LSTM	54.71%.
[34]	2022	EAR, MAR, MOEAR, and PC	CNN LSTM	72% 64%

3.4. The hybrid feature-based techniques

Several researchers have proposed combining two or more characteristics to diagnose driver drowsiness better and improve the model's overall accuracy. For example, the research [39] employed a multi-cam stream technique to incorporate visual and non-visual highlights and (mCNN). To evaluate pulse inconstancy (HRV) was used electrocardiography (ECG) sensors, where accuracy achieved 93.4%. Another work [38] integrates visual and non-visual elements, such as ECG sensors and PERCLOS. As a result, driver drowsiness was detected using hybrid features and a convolutional neural network (CNN) with a deep belief network (DBN), with an accuracy of 94.5%.

4. Analysis of the Discussion

Datasets are essential for model training and prediction. To determine driver weariness, cameras, sensors, other cars, and roadside infrastructure must be used. Reliable sleepiness detection requires high-quality data. Unfortunately, real-world sleepy driving data collection is dangerous. Most studies employ driving simulators, which mimic road tests and analyze behavioral, physiological, and vehicle performance [5, 11]. The driver's drowsiness detection classifies on base three methods as follows [18, 39, 40]:

- Driver's physiological features:

It's reliable, sensitive, and has high interference. Testing needs expensive detectors, and this method requires the driver to wear and touch the instrument. It may make a driver uncomfortable, affecting driving and line of sight. These features won't help drivers drive safely and may cause accidents. Such techniques are impractical for driving.

- Driver's behavioral features:

Non-intrusive detection and obvious, direct fatigue indicators are advantages of the technology. It's driver-friendly and won't interfere with eyes, mouth, etc.; These approaches are accurate, fast, low-cost, and real-time. The fatigue detection algorithm based on driver behavior is becoming more mature and faster as computer vision technology advances. This method is the most popular and commonly utilized since it is more applicable than the other two.

- Driver's vehicular features:

Speed, steering wheel angle, and vehicle lateral distance are important features. Where combining road conditions and vehicle driving status data analyzes driver fatigue. The simple parameters of algorithm detection, road conditions, driving environment, automobile models, driver differences, and driving habits affect its reliability. For example, Lane line detection only works on standardized roads with lane lines, which reduces accuracy on routes without them. However, this method's detection effect isn't significant because it only considers driving.

- Hybrid techniques of the driver:

Multi-feature fatigue detection combines driver behavior, face information, vehicle operating parameters, and physiological parameters to determine a drowsiness state. This method is more accurate but requires additional sensors and other equipment, which raises the cost and failure rate. In addition, due to increased information processing, system operation costs rise, and real-time performance suffers compared to alternative algorithms.

Using different classifiers to train the data affects the system's efficiency and accuracy. The papers reviewed used deep learning methods. Deep Learning (DL) algorithms in sleepiness detection systems, LSTM, and CNN networks are preferred. Few works employ LSTM to mine time and memory. Its network is deep and computationally demanding but easy to install. CNN-based works are accurate. CNN maximizes local visual information but requires a big sample size, slow depth, and high quality.

One of the weaknesses that researchers can consider is their reliance on one method (behavioral-based, physiological-based, or vehicle-based). If this method fails, it will lead to the failure to detect the state of drowsiness and thus, trying to use more than one method and merging them, called hybrid methods, gives strength to detect drowsiness of the driver.

5. Conclusion

Deep learning techniques, in particular, are the focus of this review study, which tries to throw light on previous studies on driver sleepiness. Driver detection based on physiological factors is intrusive but has high accuracy, while techniques based on vehicular are inaccurate, complex, and expensive. Driver detection based on behavioral factors is simple and expensive, although it's affected by illumination, seating posture, spectacles, etc. Comparative analysis indicated that no technique could function alone and be accurate. These methods have limitations, and the researchers must weigh their accuracy, reliability, real-time performance, and ease of use. Also, from the analytical study, it was noted that Deep learning techniques such as CNN gave a very high-resolution result, and it takes too much time to train the data. Finally, it was noted that combining previous techniques could help improve drowsiness detection techniques.

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