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A Review on Deep Learning Techniques for EEG-Based Driver Drowsiness Detection Systems

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Driver Drowsiness is considered one of the significant causes of road accidents and fatal injuries. Due to this, creating systems that can monitor drivers and detect early drowsiness has become an important field of research and a challenging task in recent years. Several research attempts were proposed to solve this problem based on several approaches and techniques. The Electroencephalogram (EEG) is one of the most efficient and reliable method, among the physiological signals-based monitoring approaches. In this area, many Machine Learning (ML) techniques have been used to detect EEG-based driver drowsiness. However, due to the limitations of ML techniques, many researchers have shifted their focus to the use of deep learning (DL) techniques, which have demonstrated superior performance in many fields including the physiological signals classification tasks. This paper reviews and discusses numerous new research papers that have proposed and implemented driver drowsiness detection systems based on EEG and deep learning techniques. In addition, we have outlined the limitations and difficulties of the existing works and highlighted and proposed some propositions that will help future field researchers enhance and generalize the results. Based on our thorough analysis, we have determined that the latest advancements in detecting driver drowsiness have employed the convolutional neural network (CNN) technique, which has demonstrated effective performance in classifying signals. Furthermore, the primary issue encountered in all works is developing a more precise and accurate method. Nevertheless, we seek a precise system capable of swiftly identifying a state of drowsiness while using minimal spatial memory and processing resources.

Povzetek: Narejen je pregled objav za zaznavanje zaspanosti voznikov na osnovi EEG signalov z uporabo metod globokega učenja. CNN se izkaže za učinkovito metodo pri klasifikaciji signalov.

1 Introduction

A significant number of individuals face extended periods of work during the night, including security officers, truckers, and medical personnel. Consequently, operating a motor vehicle while experiencing fatigue is widespread. It is likely something that the majority of drivers have done. It is crucial to develop a method for alerting drivers when their fatigue reaches a critical level, hindering their ability to drive safely.

Drowsiness, known as fatigue, is a psychophysiological transition state between alertness and sleep. When a driver is in this state, his/her concentration and performance decrease, while his/her reaction time increases [1]. This state affects the results of some tasks requiring concentration, such as driving [2]. Driver drowsiness is the third cause of traffic accidents, and is responsible for 25% of road accidents, following high speed and alcoholism [3]. Studies have demonstrated that 24-hour sleep deprivation induces the same degree of impairment as an individual with a blood alcohol concentration of 0.10%, which exceeds the legal limit. Based the National Highway Traffic Safety Administration (NHTSA), drowsy driving has caused 100000 crashes, more than 1500 deaths, and $12.5 billion in monetary losses [4]. Nevertheless, the National Highway Traffic Safety Administration (NHTSA) acknowledges the difficulty in accurately quantifying the exact figures of accidents, injuries, or fatalities caused by drowsy driving. It recognizes that the reported statistics are lower than the actual occurrences. According to a study by the Foundation for Traffic Safety of the American Automobile Association, over 320,000 drowsy driving accidents occur annually, including 6400 crashes resulting in fatalities [56]. The statistics indicate that driver drowsiness is a real problem; therefore, it is necessary to develop a system that can detect it quickly and accurately in its early stages and alarm the driver to prevent road accidents and reduce the fatality rate. In this regard, several researchers have proposed numerous approaches to detect drowsy drivers. These approaches can be categorized into three main categories: vehicle-based, information obtained by monitoring the vehicle's movement and behavior; behavior-based, information obtained through the analysis of the driver's facial expressions and movements; and physiological signals-based obtained by attaching specialized sensors to the driver's body as summarized in Figure 1 [5]. Physiological methods are the most used because they have proven to be effective, accurate, and reliable [5, 6]. Physiological signals such as Electrocardiogram (ECG), Electrooculogram (EOG), Photoplethysmogram (PPG), Electromyogram (EMG), and Electroencephalogram (EEG) were utilized to identify drowsy drivers because, they can detect the body signals changes and compare this change to the normal state [1].

The Electroencephalogram (EEG), a record of the electrical activities of different brain regions [1], is the most widely used of the Physiological signals. It is known as the gold standard for drowsiness detection due to its low cost, usability, and dependability [6]. EEG signals are measured and captured by placing a device containing a pattern of electrodes on the scalp based on the international 10-20 system of EEG electrode placement. These signals are subdivided into several bands based on frequency. There are five well know bands: the delta band (0.5-3 Hz), the theta band (4-7 Hz), the alpha band (8- 13 Hz), the beta band (14-30 Hz), and gamma-band (greater than 30 Hz) [8].

To detect drowsiness state successfully, many researchers have proposed and implemented robust detection systems using two well-known mechanisms, Machine Learning (ML) and Deep Learning (DL). Machine Learning is a subfield of artificial intelligence. It has been used in several classification tasks [9]. Hu & Min. [10] have proposed a gradient boosting decision Tree (GBDT) to determine whether a driver is drowsy or not. They claim the accuracy reached 94%. In [11], Mu et al. used the SVM algorithm to classify a driver as tired or awake based on the forehead FP1 and FP2 electrodes. The accuracy of this approach is 85%. the following five ML techniques: the K-nearest neighbor (KNN), support vector machine (SVM), extreme learning machine (ELM), hierarchical extreme learning machine (H-ELM), and the modified hierarchical extreme learning machine algorithm with particle swarm optimization (PSO-H-ELM) have been proposed in [12] to identify the drowsiness state using EEG signals. The achieved accuracy of these algorithms is 79.31%, 79.31%, 74.08%, 81.67%, and 83.12%, respectively. Nevertheless, ML techniques have limitations, such the need for massive data and hand-crafted feature extraction as intermediary steps [3] (see Figure 2).

Deep learning is a subfield of machine learning that has been utilized in different fields, including speech recognition, computer vision, and natural language processing [13]. DL techniques have demonstrated their effectiveness in EEG task classification, especially convolutional neural network (CNN), because it does not require hand-crafted feature extraction. They can automatically detect and learn features through convolutional layers [14, 5].

This review aims to present and explain the pipeline of an EEG-Based driver drowsiness detection system using deep learning techniques. Then, analyze and discuss several new research papers that used deep learning techniques to detect and classify whether a driver is in a drowsy or awake state using EEG signals, especially those published over the past three years, by listing the extracted features, methods, classifiers, and the used datasets, and classification metrics such as accuracy, sensitivity, and precision. Finally, highlight the limitations and challenges of the reviewed papers and propose future improvements. The paper is organized as follows: The second section outlines the search strategy followed in this work. The third section describes the backgrounds and the related works cited in this literature review. The results are discussed in the fourth section. The fifth section presents the challenges and limitations of the discussed works furthermore some propositions that can be as future works. Finally, a conclusion is provided in the sixth section.

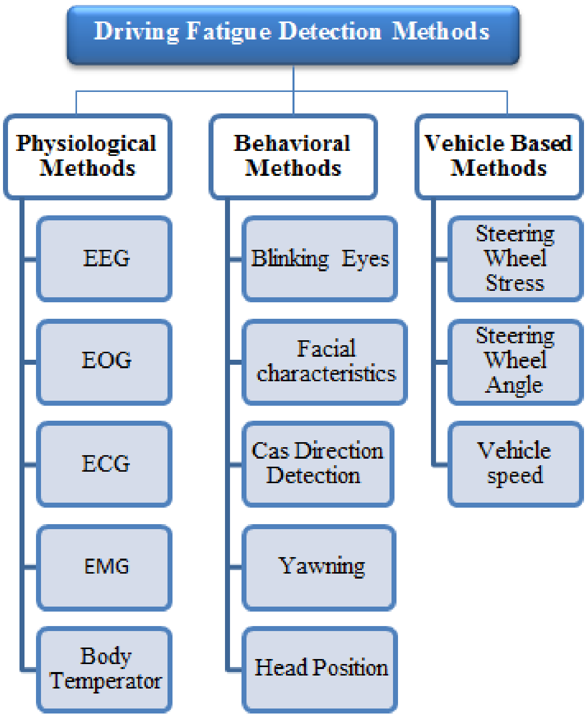

Figure 1: Drivers' fatigue detection methods [7]

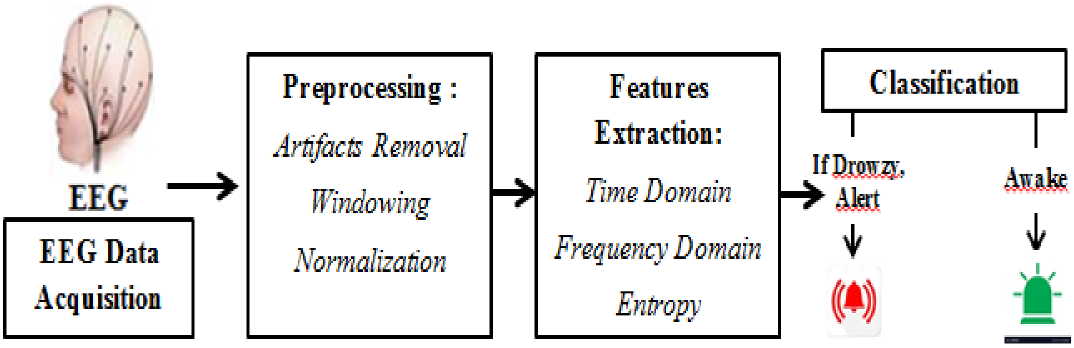

Figure 2: EEG based drowsiness detection and warning scheme [1]

2 Search strategy

The keywords used for collecting the papers are "Driver Drowsiness", "Driver fatigue" "EEG", "Electroencephalogram", "Deep Learning", "Detection", and the query used in Google scholar was "deep learning for EEG-based driver drowsiness detection system" and "deep learning for EEG-based driver fatigue detection system". Furthermore, the papers were selected based on three criteria the paper must be: written in English, either a journal article or conference article (reviews papers were excluded), and new (last three years).

Many researchers have employed deep learning techniques to detect driver drowsiness based on EEG signals. For example, Google Scholar results using this query "deep learning for EEG-based driver drowsiness detection system" have shown that from 2019 to 2022 (03/04/2023), about 5240 works were published in this context (see Figure. 3).

3 Deep learning for EEG-Based driver drowsiness

Figure 4 illustrates a general architecture of an EEG-based drowsiness detection system using deep learning techniques. The process starts by collecting EEG signals using one of the existing wearable devices placed on the scalp to acquire raw data; the obtained signals are then preprocessed to remove artifacts, normalize and prepare them for feeding into a DL model that classifies whether the individual is drowsy.

3.1 Data acquisition

The first step of an EEG-Based driver drowsiness system is acquiring and collecting Real-time EEG signals. However, because of safety concerns collecting real-time EEG is not feasible, leading many researchers to use driving simulators under several experimental protocols see Figure. 5.

After preparing the simulated environment, a wearable device, a set of electrodes placed on the scalp based on the international 10-20 system, must be used to acquire the EEG data. However, a wearable device with numerous electrodes is expensive and may be uncomfortable for the driver. Due to these limitations, some researchers have focused on identifying the most effective and informative regions that can provide more information about drivers' states using fewer electrodes [52].

3.2 EEG- based drowsiness datasets

A dataset is a collection of information on a specific subject that can be used by machine learning and deep learning methods for many purposes, such as classification and prediction. For example, there are various available online datasets on EEG-based drowsiness context.

3.2.1 Sleep -*EDF* dataset

The Sleep-EDF dataset [36] is obtained from the Physionet database [37], which contains 197 whole-night Polysomnographic (PSG) sleep recordings with EEG, EOG, chin EMG, and event markers. They were sampled at 100 Hz and 1 Hz.

3.2.2 The Original EEG data for driver fatigue detection

This dataset is generated by a 40-channel Neuroscan amplifier. It contains twelve healthy subjects and twelve drowsy subjects. The signals are obtained from a 32-channel electrode cap (30 effective channels and two reference channels), and digitized at 1000 Hz [38, 42].

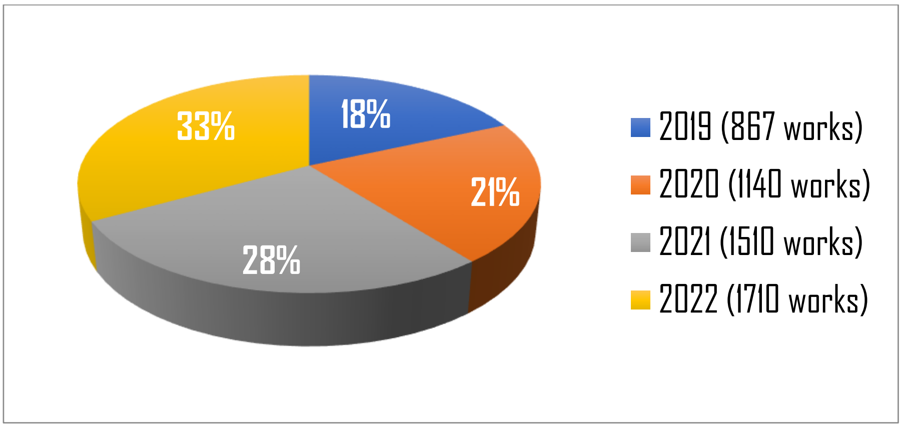

Figure 3: Number of studies using deep learning for EEG-driver drowsiness detection during 2018 -2023

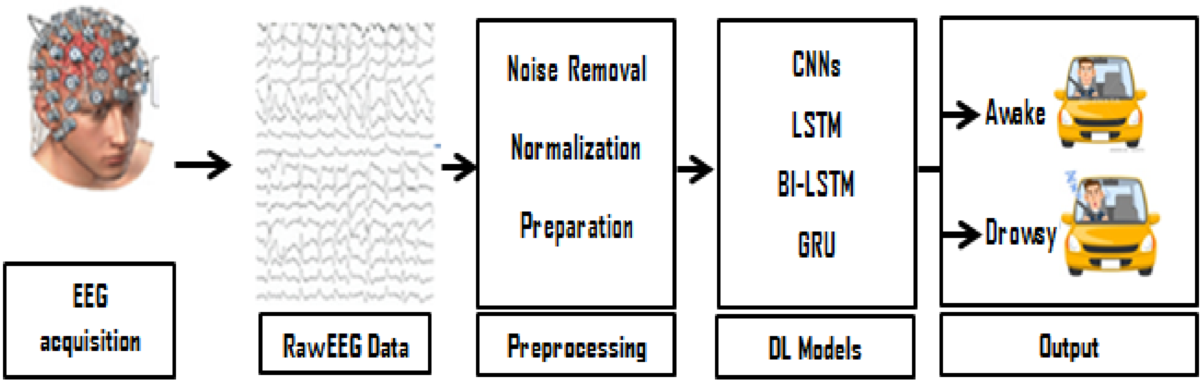

Figure 4: General architecture of a DL based EEG drowsiness detection system

Figure 5: The road scene of the driving simulator [5]

3.2.3 Multi-channel EEG recordings during a sustained-attention driving task

This dataset consists of twenty-seven subjects that participate in a 90-minute driving task from the National Chiao Tung University. The signals were acquired using a 32 Ag/AgCl electrodes EEG wired cap (two reference electrodes) and digitized at 500 Hz. The Institutional Review Broad of Taipei Veterans General Hospital, Taiwan, had approved the experimental protocol [39].

3.2.4 MIT/*BIH Polysomnographic EEG database*

The database is collected from 16 male subjects using the C3-O1, C4-A1, and O2-A1 EEG channels. The database contains 18 records, each with four files. The physiological signals were digitized at a sampling rate of 250 Hz [37, 40].

3.2.5 SE*ED-VIG dataset*

The SEED-VIG dataset is designed to investigate the vigilance estimation problem. It was collected from 23 participants and lasted approximately 2 hours. The Dataset is acquired using 18 electrode channels according to the international standard 10-20 system and down-sampled to 200 Hz. The records were labeled using the SMI eye-tracking glasses with the PERCLOS indicator [41].

Table 1: Publicly available EEG dataset for driver fatigue

Dataset	Subjects	Electrodes	Sampling frequency
Sleep-EDF [36, 37]	/	Fpz-Cz / Pz-Oz.	100 Hz
The original EEG data [38, 42]	12	32	1000 Hz
Multi-channel EEG recordings [39]	27	32	500 Hz
MIT/BIH Polysomnographic EEG [37, 40]	16	C3-O1, C4-A1, and O2-A1channels	250 Hz
SEED-VIG [41]	23	18	200 Hz

3.3 Preprocessing

EEG signal preprocessing is an essential step that can be defined as a set of signal processing steps that transform raw EEG data into a more suitable form that can be easily analyzed and handled [22]. The preprocessing involves three steps (see Figure 6): 1) removing the noise and artifacts to get closer to real neural signals, 2) normalization to scale the values of all EEG signals, and 3) signal preparation or EEG analysis. For noise removal, many methods can be used. The most popular ones are finite impulse response (FIR) and infinite impulse response (IIR) filters. There exist various techniques, such as the min-max scaling, robust scaling, standard scaling and the z-score technique that can be used during the normalization step. Finally, different time domain, frequency, and time-frequency methods are employed to prepare the signals to be fed to a DL model, such as Fourier transform techniques, Component Analysis, and Wavelet Transform [23].

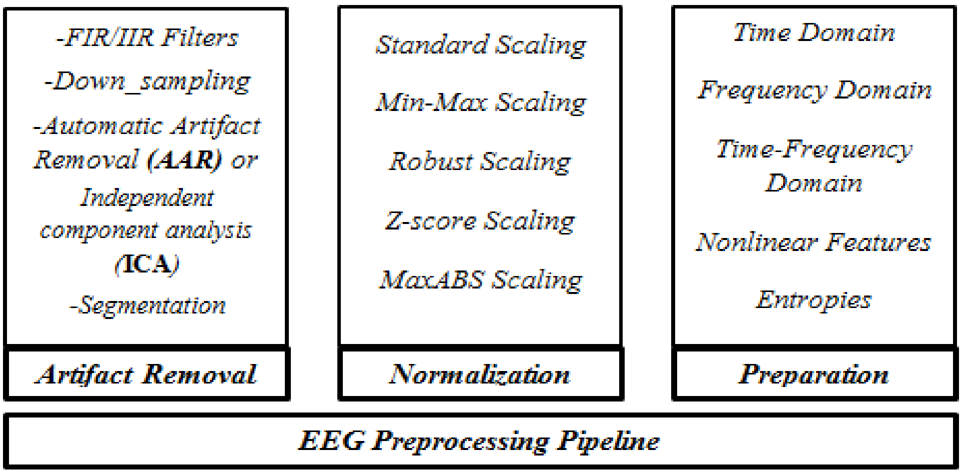

Figure 6: The EEG preprocessing pipeline

3.4 Review of deep learning techniques

Deep learning (DL) is one of the main techniques of machine learning. Deep Learning techniques are algorithms capable of emulating the human brain's actions using artificial neural networks. These artificial neural networks are constructed of tens or hundreds of neuron layers. Each layer receives and interprets information from the previous layer [24]. No human intervention is required for DL; however, a large amount of data is needed to map the given input to specific labels [25]. DL allows feeding deep neural networks DNNs with the raw data with limited or no preprocessing. In addition, in DL, the feature extraction, selection, and classification are constructed as a single pipeline [26].

DL techniques can be categorized into three main groups: deep networks for supervised learning, deep networks for unsupervised learning, and deep networks for hybrid learning. In the first category, "supervised learning", there are three main techniques Multi-Layer Perceptron (MLP), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN). In the second category, "unsupervised learning" we find the Generative Adversarial Network (GAN) and Auto Encoder (AE) and Its Variants [27].

3.4.1 Convolutional neural networks (CNN)

The Convolutional Neural Network (CNN) is one of the most popular supervised deep learning architectures that learn directly from the input without the need for handcraft feature extraction [27]. The basic CNN is like the multi-layer perceptron (MLP). It consists of many convolution layers that are followed by sub-sampling (pooling) layers that precede the last fully connected FC layers [25]. Initially, CNN was designed for image classification (two-dimensional input); but nowadays, it is also used to classify one-dimensional (1D) data such as biological signals (ECG, EMG, EEG...).

A. 2D Convolutional Neural Networks (2D-CNNs)

CNN is a deep learning model that is considered the most used, especially to deal with 2D shapes like images; therefore it is often called 2D-CNN. It is used in other fields such as natural language processing and visual recognition [27]. CNN has many different variants, such as VGG, AlexNet, GoogleNet, and ResNet. Each one of these variants has a specific architecture. They have been employed in many fields [27]. Apostolopoulos and Tzani [30] have proposed VGG19 and the MobileNet v2 to detect Covid 19 from X-ray images. In [31], M. Hussain et al. have used the Inception-v3 on both the Caltech Face dataset and the CIFAR-10 dataset.

The 2D-CNN has also been used to classify signals such as EEG signals for the diagnosis of neuronal disorders such as epilepsy and driver fatigue by transforming them into a two-dimensional spectrum (2D spectrogram) using various methods (continuous wavelet transform (CWT) [28] and Short-time Fourier transform (ST) [7]. Figure 7 presents the architecture of a 2D-CNN used to classify EEG signals into two classes “Normal” or “Seizure”.

B. 1D Convolutional Neural Networks (1D-CNNs)

Recently, a 1D-CNN is proposed to deal with 1D signal and data repositories. It demonstrated excellent performance in many fields, including biomedical data classification [29] and EEG classification [5]. 1D-CNN is a modified version of 2D CNNs that use 1D convolution operation (scalar multiplications and additions). One of its significant advantages is that in terms of computational complexity, it is lower than the 2D-CNN [29].

Figure 8 presents the architecture of 1D-CNN that can be used for EEG signals classification and seizures detection.

3.4.2 Recurrent neural networks (RNN)

Another type of DL technique, RNN, is employed mostly to deal with time-series or sequential data such as signals, text, and videos. It is used often in natural language processing and speech recognition. RNN feeds the output of the previous step as an input to the current step; that is known as a circulation behavior. It requires integral memory cells that preserve the previous outputs, whereas the integrated memory cell has three gates titled input, output, and forget gates. The main challenge of the standard recurrent neural networks is learning long data sequences because of the vanishing issues gradients. The Long short-term memory (LSTM) and Gated recurrent units (GRUs) are RNN models used to minimize those issues, and that perform well in many domains and real-world applications [26, 27].

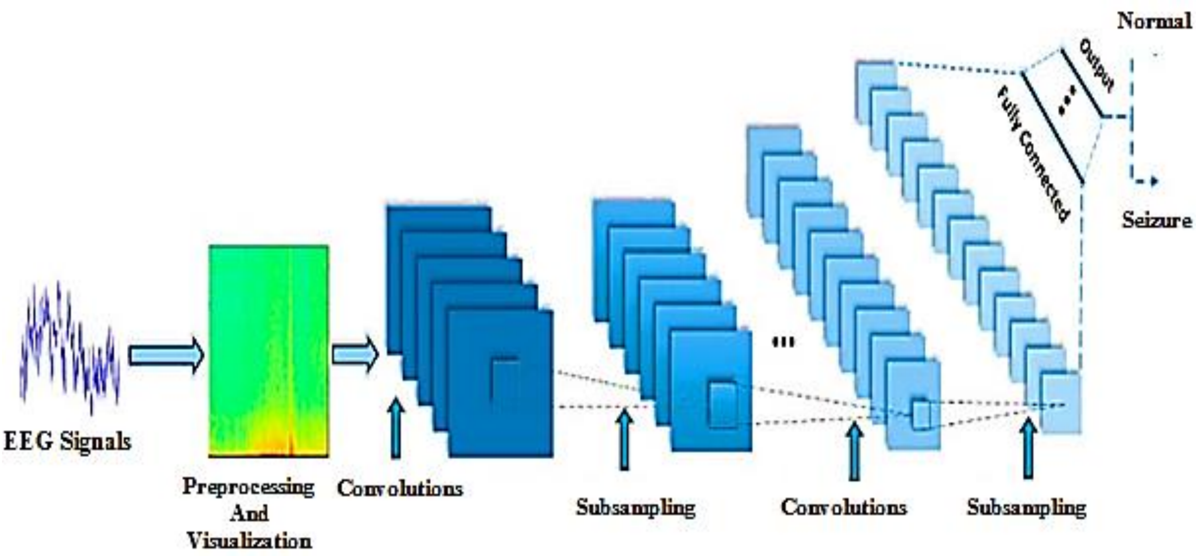

Figure 7: A typical 2D-CNN for EEG classification [23]

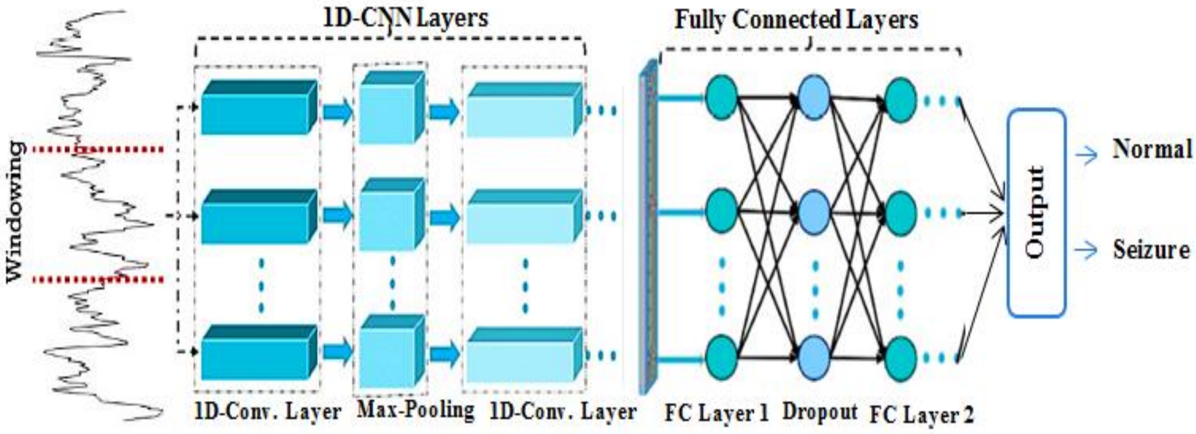

Figure 8: A typical 1D-CNN that can be used for EEG classification [23]

A. *Long short-term memory (LSTM)*

The Long Short-Term Memory (LSTM) is an enhanced version of the Recurrent Neural Network (RNN) that addresses the gradient vanishing problem and long-term temporal dependencies. The LSTM layer is distinguished by memory blocks, which are hidden units [32]. Each memory block consists of recurrently connected memory cells, with each cell containing weights and three gates, "the input, forget, and output gates," which are the distinguishing feature of LSTM models (see Figure. 9) [33, 34].

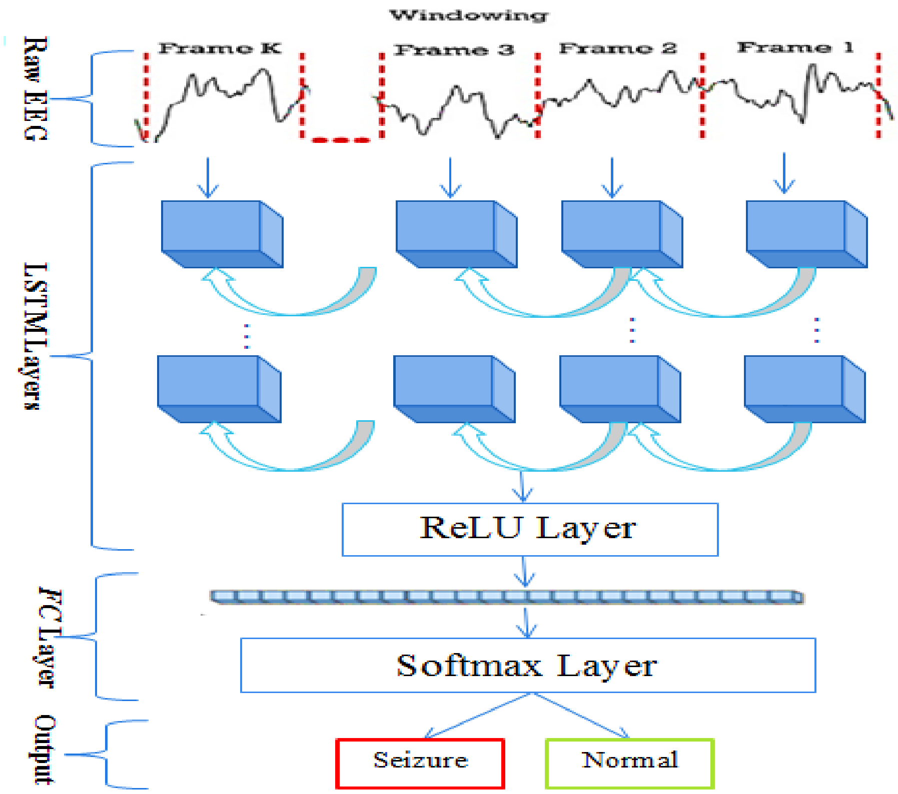

Figure 9: A typical LSTM that can be used for EEG classification

B. Gated recurrent units (GRUs)

A Gated Recurrent Unit (GRU) is another popular variant of the recurrent network. It is considered a simpler version of LSTM. GRU includes gating units that modulate the flow of information inside the unit without any separate memory cells. However, instead of three gates, the GRU has only two: the reset gate and the update gate [35].

3.5 EEG-Based driver drowsiness systems

In this Section we review and analyze some recent EEG-Based drowsiness detection schemes. Tables 2 and 4 summarized the reviewed works.

Houshmand et al. [5] designed three CNNs to detect driver drowsiness in the early stage based on single-channel signal and EEG alpha spindles. The first one is a 1D CNN with three convolution layers, three max-pooling layers, and two fully connected layers. The second one is a 2D CNN with four convolution layers, four max-pooling layers, one fully connected layer, and one flattens layer. The third one is identical to the second but with different parameter values (number of filters and nodes). The activation function of the three models is dropout. The fed data to the models are raw EEG data for 1D CNN, power spectrum analysis EEG data for the second CNN, and the CWT of EEG epochs for the third model. The P4 channel is determined to have the highest feature weight for drowsiness classification based on the neighborhood components analysis technique. The best results are obtained by CWT-CNN as follows: accuracy 94%, recall 95%, precision 91%, and F1-score 93%.

The author in [7] proposed a driver fatigue detection system based on a single channel EEG and transfer learning. The system works as follows: the acquired EEG raw data is passed through a preprocessing pipeline, and then the processed data is transformed into a two-dimensional spectrum using the Short-time Fourier Transform (STFT). After that, the resulting spectrum is then fed to a modified AlexNet CNN model employing transfer learning to determine whether the driver is drowsy or alert. The author applied transfer learning using fine-tuning to the original AlexNet by replacing the final classification layer with another layer and reducing the last fully connected layer nodes number to 5. To find the best channel, the author compared the accuracy obtained by the AlexNet CNN of seven different channels (FP1, FP2, T3, T4, O1, O2, and Oz). The FP1 and T3 channels achieved the best accuracy of 90% and 91%, respectively.

Cheng et al. [18] have developed an EEG-based prediction system to estimate the drowsiness level of drivers. They use a raw EEG signal without utilizing any artifact removal methods. The 256-point fast Fourier transform (FFT) is used to transform the time-series EEG data into the frequency domain (an image-like feature map). In the final stage, the EEG images are passed into a CNN to classify them into two classes “Drowsy” or “Awake”. The used CNN is a basic CNN with two convolutional layers, two max-pooling layers, and one fully connected layer. Three training data sets are evaluated using a leave-one-subject-out cross-validation strategy during the training phase. The proposed work outperforms the SVM classifier in both balanced (69.18 %) and imbalanced (71.15 %) data.

Guarda et al. [44] used convolutional neural networks (CNNs) to classify whether a driver is in a drowsy state or not based on EEG spectrograms. The proposed method is applied to the ULg Multimodality Drowsiness Database, where only the Fz and Pz channels are used to train the model. First, the raw EEG signals is transformed into spectrograms that have been converted into a gray-scale format. After the preprocessing and the generation of the gray-scale spectrograms, six sets of spectrograms are obtained. The proposed CNN has three convolutional layers, three pooling layers, and one fully connected layer. The input data are one or two 96*96 images (depending on how many EEG sensors are used). The proposed model achieved an accuracy of 86.74% with Fz-Pz channels and 13 seconds signals which is the best compared to the other sets. The model outperformed SVM, NN, and RF in all metrics.

Gao et al. [48] proposed a recurrence network-based convolutional neural network (RN-CNN) method to detect driver drowsiness using EEG signals. First, they collected EEG signals from 10 subjects and 30 channels using a simulated driving experiment and pre-processed the obtained signals. Then they used a recurrence network (RN), a complex network method that transforms raw EEG into a mutual information matrix of 30*30. Finally, they fed the mutual information matrix into CNN architecture to extract features and classify the driver state. The used CNN has two convolutional layers, two fully connected layers, and a softmax layer. The proposed approach achieved an accuracy of 92.25%. To evaluate the performance of the RN-CNN, the authors compared its result with other state-of-art works such as FT-CNN, PSD-SVM, CSP-SVM, and others. RN-CNN outperformed all the considered protocols.

Chaabene et al. [3] proposed an EEG-based CNN Driver Drowsiness system. Data acquisition and model analysis are the two primary procedures of the proposed architecture. The data acquisition step is divided into two-part: data collection using the Emotiv EPOC+ headset to record 14 channels and preprocessing. Data preparation to remove noise and artifacts, data annotation, and data augmentation to prevent overfitting and improve accuracy are parts of the preprocessing step. In the second step, "model analysis" a CNN with four convolution layers, one max-pooling layer, and two fully connected layers, is implemented. Two experiments were conducted to evaluate the system's performance using two classes (Drowsy/Awake); the first was conducted without data augmentation, with 2, 4, 7, and 14 channels, and the best accuracy (79.43%) is achieved with 14 channels. However, data augmentation is used in the second experiment to reach 90.14% accuracy using seven channels.

Balam et al. [6] have proposed CNN architecture for automated Driver Drowsiness detection based on a Single-Channel EEG signal. The used data are raw EEG signals from the physionet Pz-Oz dataset. To determine the best CNN model. The authors evaluated the performance of numerous CNN models with different kernel sizes, varying numbers of hidden layers, and multiple sets of filters. The proposed model is created by combining the best two evaluated CNN (CNN [4HL, 9F, 3KS], CNN [3HL, 3F, 5KS]). For the evaluation of the model's performance, three different training strategies were utilized: subject-wise, cross-subject-wise, and combined-subjects-wise validations. The results indicate that the highest accuracy 94%) was achieved with combined subjects. A comparative study is conducted between the proposed model and other models that utilized the same dataset, and the results demonstrated that the employed CNN achieved the highest accuracy of 94.87%. However, the results were close.

Ding et al. [15] have implemented a Deep Learning architecture on a mobile device that uses a single-channel EEG signal to Detect Driver Drowsiness. Their study aims to get high accuracy with a small model size and predict latency compared to the existing models. The components of the proposed architecture are an EEG signal collector, a trained model integrated into a Smartphone to predict the state of the driver then alert him/her, a cloud database that serves as a backend, and a web page that contains a remote monitor to observe the real-time condition and historical record from the backend. The employed model is a Cascaded CNN with an attention mechanism layer; it is made of three blocks: Dimension Reduced Level, Feature Extract Level, and Full Connect Level. In terms of accuracy and recall, the proposed model was compared to other deep learning and machine learning architectures. The latter outperformed the others with an accuracy of 97.26% and a recall of 96.56%. In addition, the model size (1.61 MB) and latency (26s/epoch) are more suitable for a real-time mobile system.

The authors in [16] developed a system capable of detecting vehicle driver drowsiness using a wearable EEG device and CNN. The proposed system consists of a wearable device to acquire EEG signals, a preprocessing step to remove artifacts and improve the information's quality, a trained model based on CNN for signal classification, and, as a final step, an early warning strategy to restore the driver attention. Two models were used for the classification step: a CNN with an Inception module containing five convolutional layers, two pooling layers, three Inception modules, and three fully connected layers, and the Modified AlexNet model that includes eight convolutional layers, four pooling layers, and three fully-connected layers. The obtained accuracy of the inception model is 95.69%, which is greater than the accuracy obtained by the modified AlexNet model (94.68%).

A novel framework entitled EEG-based spatial-temporal CNN (ESTCNN) developed by Gao et al. [14] to detect driver fatigue from EEG signals. The ESTCNN contains two main procedures: a Core Block to deal with the information on the temporal dimension and a dense layer to fuse the spatial features among the electrodes.

The authors implemented a CNN with 14 layers: three core blocks (where each block contains three convolution layers and one max-pooling layer), two dense layers, and a softmax layer. To validate the performance of the proposed framework, the ESTCNN was trained on ten cross-validations for each subject with an average accuracy of 97.37%. In addition, a comparative study of three studies and five competitive models was conducted, and the proposed model demonstrated the highest accuracy of 97.37%.

To solve the drawbacks of the current functional brain network methods (ignore some features of the original EEG signals) and the preprocessing methods (filter out the most noises from signals), Lin et al. [17] proposed three-part architecture for identifying driver drowsiness based on EEG signals. The first part, called front-end CNN is responsible for denoising the raw EEG signal. The second part contains a brain network construction method used to increase the connectivity of EEG channels on a fixed functional brain network with less redundancy. The last part, called the back-end graph neural network, is the fatigue driving recognition model. The proposed framework achieved the highest recognition accuracy of 98.98% compared to commonly used classifiers. In addition, it demonstrated the ability to maintain an accuracy greater than 95% when many channels are affected by noise.

Ko et al. [43] proposed an EEG-based driver drowsiness detection system using differential entropy (DE) with a novel deep convolutional neural network named VIGNet. The raw EEG data features were extracted using the DE method, a conventional machine learning-based method for feature extraction. The extracted features are the inputs to a CNN model with three convolutional layers designed to extract deep and hierarchical features and a dense layer that maps the extracted features to the decision layer. Experiments were conducted on the publicly accessible SEED-VIG dataset. The accuracy of the VIGNet model was 96 %, outperforming the accuracy of the SVM and ESTCNN models.

Chen et al. [47] have used in this study a convolutional neural network (ConvNets) to detect driver drowsiness using raw Multi-Channel EEG signals without using any extraction or selection methods. The proposed architecture consists of 12 layers: five convolutional layers, three max-pooling layers, one mean-pooling layer to extract discriminative features, and three fully-connected layers that optimize the classification process (end-to-end manner). In addition, the authors used a data augmentation strategy to prevent overfitting. To evaluate the used model, the authors used 10- fold cross-validation. based on the obtained, ConvNets performed well compared to other state-of-the-art systems, achieving an accuracy of 97.02 % and a precision of 96.74 %.

Zeng et al. [49] used two classification models, the EEG convolutional (EEGConv) and the EEG convolutional residual (EEG-Conv-R), to classify drivers' mental states using raw EEG signals. Data were collected from ten subjects using 16 channels. The EEGConv architecture contains eight layers: the input layer, three convolutional layers, a pooling layer, an LRN (Local Response Normalization) layer, a fully connected layer, and the output layer. The EEG-Conv-R architecture combines the EEG-Conv with two residual blocks. The two models' evaluation was tested using intra- and inter-subject. EEGConv and EEG-Conv-R achieved greater accuracy than LSTM and SVM models, with 91.788 and 92.682 % accuracy using intra-subjects and 82.95 % and 84.38% accuracy using inter-subjects, respectively. However, the EEG-Conv-R converges faster than the EEGConv.

Table 2: Summarized studies of driver drowsiness detection based-EEG using CNNs

Authors	***Techniques***	***Type of channels***	***Classification Results***
Chaabene et al [3]	• 7 channels. • 7 Layer CNN Model. • Data augmentation.	Multi-Channel	<u>Best classification accuracy:</u> ***90.41%***
Balam et al [6]	• Pz-Oz. • Combination of two CNN models. • Subject-wise, cross-subject-wise, and combined-subjects-wise validations.	Single-Channel	<u>Best classification accuracy:</u> ***combined subjects validation at 94%.***
Ding et al [15]	• Dimension Reduced Level, Feature Extract Level, and Full Connect Level. • 15 Layer Cascaded CNN with an attention mechanism layer.	Single-Channel	<u>Best classification accuracy and Recall:</u> ***97.26% and 96.56% respectively.***

Zhu et al [16]	• CNN with an Inception module. • Modified AlexNet.	Multi-Channel	*Best classification accuracy :* ***95.69% with Inception and 94.68% with AlexNet.***
Lin et al [17]	• Front-end CNN for denoising the raw EEG signal. • Brain network construction method. • Back-end graph neural network.	Multi-Channel	*Best classification accuracy :* ***98.98%***
Gao et al [14]	• EEG-based spatial–temporal CNN (ESTCNN). • 3 Core Blocks, two Dense layers, and a Softmax layer. • Ten cross-validations.	Multi-Channel	*Best classification accuracy :* ***97.37%***
Ko et al [43]	• SEED-VIG dataset. • DE method. • VIGNet Deep Learning Model.	Multi-Channel	*Best classification accuracy :* ***96%***
Zeng et al [49]	• Ten subjects and 16 channels. • The EEGConv and EEG-Conv-R architectures. • Intra- and inter-subject evaluation methods.	Multi-Channel	*Best classification accuracy :* ***91.78% for EEG-Conv and 92.68% EEG-Conv-R*** **using intra-subjects**
Chen et al [47]	• ConvNets with 12 Layers. • Data augmentation strategy. • The 10- fold cross-validation.	Multi-Channel	*Best classification accuracy and precision:* ***97.02% and 96.74 %.***
Houshmand et al [5]	• 1D CNN and two 2D CNN with different parameters. • Dropout activation function. • Raw EEG data, power spectrum analysis EEG data CWT of EEG epochs. • The P4 channel	Single-Channel	*Best classification scores:* ***accuracy 94%, recall 95%, precision 91%, and F1-score 93% with CWT-CNN.***
Shalash [7]	• AlexNet CNN model • Short-time Fourier Transform (STFT). • a modified AlexNet CNN model. • seven different channels (FP1, FP2, T3, T4, O1, O2, and Oz).	Single-Channel	*Best classification accuracy:* ***91% with The T3 channel.***
Guarda et al [44]	• CNN • ULg Multimodality Drowsiness Database. • Fz and Pz channels. • Gray-scale EEG spectrograms. • Seven Layers CNN.	Single-Channel	*Best classification accuracy :* ***86.74%***
Cheng et al	• Raw EEG signal.	Multi-	

[18]	• 256-point FFT. • Basic CNN model. • Leave-One-Subject-Out Cross-Validation.	Channel	<u>Best classification accuracy :</u> ***71.15%***
Gao et al [48]	• RN-CNN. • 10 subjects and 30 channels.	Multi-Channel	<u>Best classification accuracy :</u> ***92.25%***

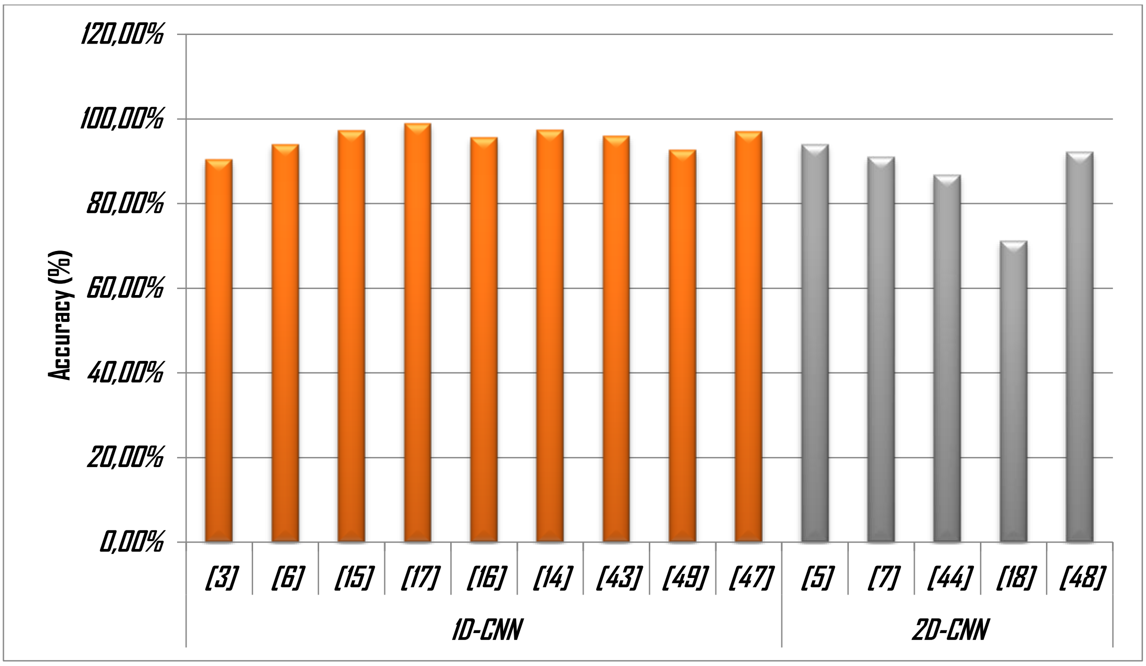

Figure 10: The obtained accuracy (%) by various study using 1D-CNN and 2D-CNN

Budak et al. [19] developed a hybrid model for detecting drowsiness using EEG signals. The developed model utilizes the majority ensemble model to combine three distinct models. Three different groups of features are extracted. The first block extracts frequency, energy, entropy, and rate distribution. The second block extracts Statistical features. In the third block, deep features are extracted from EEG spectrogram images using AlexNet and VGG16. The features extracted from each block are fed into an LSTM network classification model. The result is three different models fused by the majority ensemble model to form the primary model. The authors used the MIT-BIH Polysomnographic database and ten-fold cross-validation to evaluate the performance of the constructed primary model. The obtained average accuracy is 94.31%.

Lee et al. [45] employed a deep neural network with four LSTM layers to classify driver drowsiness based on EEG signals and identify the optimal electrodes. They utilize three classification classes: awakeness, drowsiness, and sleep. In this experiment, 18 EEG channels were used and categorized into eleven groups based on Frontopolar (FP), Dorsolateral Prefrontal Cortex (DLPFC), and Premotor Cortex (PMC). The results indicate that the most accurate group was the FP &DLPFC group, which utilized nearly all channels. Its accuracy was 82.8 %. In this study, the authors observed that the accuracy of awakeness was greater than that of drowsiness across all channel sets, leading them to conclude that the proposed model classified drowsiness data as sleep more frequently than awakeness.

Khessiba et al. [32] proposed two deep learning architectures for detecting drowsiness states in drivers using single-channel EEG signals (Pz-Oz). The proposed models are the 1D-UNet model, designed only with deep 1D-CNN layers, and 1D-UNet-long short-term memory (1D-UNet-LSTM). They were applied to spectral band energy features captured with FFT. The performance of the proposed models is better than other shallow and deep architectures such as the Learning Vector Quantization LVQ, MLP, LSTM, and 1D-CNN-LSTM. The obtained accuracies are 79.3% and 79.4% for 1D-UNet and 1D-UNet-LSTM, respectively, using the ReLU activation function. However, when the SPOCU is used as the activation function, the accuracies are 82% for 1D-UNet and 84% for 1D-UNet-LSTM. The authors implemented the proposed DL models on the RPi 3 device to obtain a real-world evaluation of the proposed drowsiness system. The results indicate that the proposed system slightly increases execution time while maintaining high performance.

Turkoglu et al. [46] proposed a novel hybrid model consisting of deep rhythm features and an LSTM network for EEG-based driver drowsiness detection. The STFT method converts raw EEG signals into time-frequency EEG images. First, five different rhythm images are extracted from the EEG images and fed to CNN pre-trained models ResNet 18, ResNet 50, and ResNet 101 to extract deep features. Next, the extracted features are fed into LSTM layers connected and followed by a fully connected layer, softmax layer, and classification layer to classify whether a driver is in drowsiness or awake state. Two experiments were applied to evaluate the performance of the proposed scheme. The first step involves feeding the EEG images to the features extraction phase without extracting the rhythms images. In this phase, the ResNet 18, ResNet 50, and ResNet 101 were used as feature extractors, while the CNN and SVM were used as classifiers. According to the results, ResNet 18+CNN achieved the highest accuracy of 84.78 %. The second experiment consists of evaluating the proposed rhythm-based-deep features and LSTM networks by changing each time the features extractor. The best result was 97.92% obtained from the three-way concatenation of the ResNet18, ResNet50, and ResNet101 models.

Jeong et al. [50] developed Deep Spatio-Temporal Convolutional Bidirectional LSTM Network (DSTCLN) model to classify pilots' mental states from EEG signals. Based on KSS values, the authors utilized two classes (awakeness, drowsiness) and five classes known as drowsiness classes (very alert (VA), fairly alert (FA), neither alert nor sleepy (NAS), sleepy but making no effort to stay awake (SNEA), and very sleepy (VS)). The data is preprocessed after collecting EEG signals from a simulation environment using 30 EEG channels. The authors used five convolutional blocks of a Spatio-Temporal CNN to extract high-level Spatio-temporal features. The extracted features were fed into a Bi-LSTM with four Bi-LSTM layers, and a dropout layer was used to reflect the temporal information of time-series data using. The classification layer consists of three fully connected layers and a softmax layer. The deep model achieved an accuracy of 87% for 2-class and 69% for 5-class. Comparing the proposed model to other conventional techniques revealed that the DSTCLN achieved the best classification performance.

Michielli et al. [51] developed a novel cascaded RNN architecture based on long short-term memory (LSTM) for classifying sleep stages based on Single-Channel EEG signals. They proposed two RNNs-based LSTM models common in the three first steps: data acquisition, signal preprocessing, and feature extraction. Fifty-five features were extracted (time domain and frequency domain). In the selection process, which reduces the computation cost and selects the most relevant features, the minimum redundancy maximum relevance (mRMR) was utilized in the first model. In contrast, the Dimensionality reduction (PCA) has been used in the second model. In the classification step, the first model inputs are the outputs of the mRMR to classify 4-class, and the second network uses the outputs of the PCA method to classify 2-class; finally, the two models were connected using a cascaded architecture to classify five sleep stages. The cascaded RNN architecture achieved an average accuracy of 86.7%.

Table 3: Summarized studies of driver drowsiness detection based-EEG using RNNs

Authors	***Techniques***	***Type of channels***	***Classification Results***
Budak et al [19]	• Hybrid model. • Majority ensemble model. • Three groups of features. • EEG spectrograms • LSTM network model. • MIT-BIH database. • Ten-fold cross-validation.	Multi-Channel	<u>*Best classification accuracy:*</u> ***94.31%***
Lee et al [45]	• Identify the optimal electrodes.	Multi-Channel	<u>*Best classification*</u>

	• Three classification classes. • 18 EEG channels. • LSTM network model.		*<u>accuracy:</u>* ***82.8%***
Khessiba et al [32]	• Pz-Oz Channel. • 1D-UNet-LSTM. • Spectral band energy features captured with FFT. • RPi 3 device for a real-world evaluation.	Single-Channel	*<u>Best classification accuracy:</u>* ***84%***
Turkoglu et al [46]	• STFT time-frequency EEG images. • ResNet 18, ResNet 50, and ResNet 101 as extractors. • LSTM classification model. • ResNet+LSTM model.	Multi-Channel	*<u>Best classification accuracy:</u>* ***97.92%***
Jeong et al [50]	• 30 EEG channels. • Spatio-Temporal CNN. • Bi-LSTM model. • DSTCLN	Multi-Channel	*<u>Best classification accuracy:</u>* ***87% (2-class) 69% (5-class)***
Michielli et al [51]	• Cascaded RNN • Fifty-five features. • (mRMR) and (PCA).	Single-Channel	86.7%

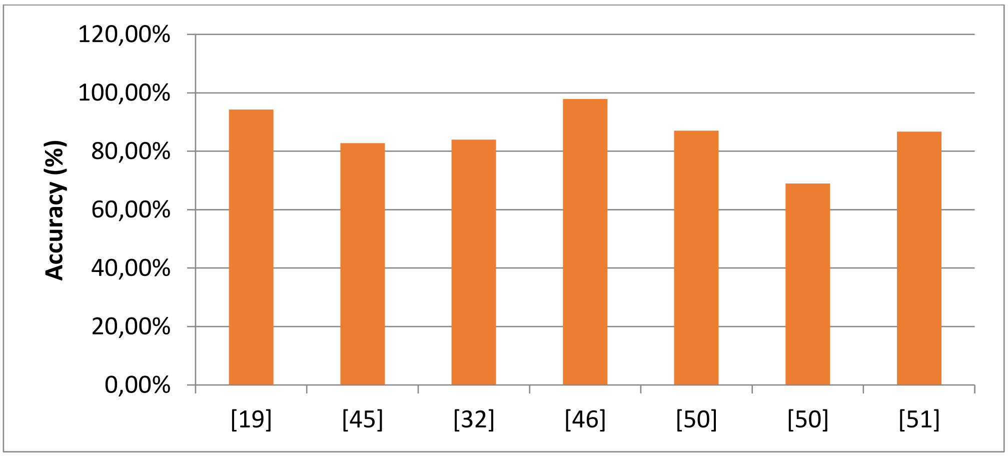

Figure 11: The obtained accuracy (%) by various study using RNNs

4 Discussion

Detecting drowsiness has been and remains an essential task because it affects the performance and throughput of persons and can lead to various negative outcomes, such as car accidents and crashes. EEG signals are the gold standard for monitoring drowsiness. In the past, many researchers have focused their studies on which brain regions are most informative in detecting drowsiness (see [1]). Most studies found that frontal, parietal, and occipital regions are the most informative [1]. In addition, some researchers oriented their research on which are the informative electrodes to reduce electrodes numbers. Researchers recently adopted artificial intelligence techniques to classify whether a driver is in a drowsy or awake state such as machine learning methods, which gave good results [10, 53, 54, and 55]. However, they required features extraction (hand-crafted extraction) and features selection (optional) steps that influence the results. Due to the existing of many methods and techniques in this area, they also need a massive amount of data. According to these limitations in the last years, most studies have used deep learning techniques such as CNN and its variants, RNNs, and its variants to detect drowsiness based on EEG signals. DL techniques have shown notable results in processing biomedical signals.

Our analysis shows that the most recent driver drowsiness-based deep learning works have used the convolutional neural network (CNN). The latter showed efficient performances in signals classification. The results in Table 2 have proved this where all the obtained accuracies exceed 90% except on [18], which was 71.15%, which is a good result considering the use of raw EEG signal without using any artifact removal methods. RNN networks also have been used as they perform well in time-series and sequential data; the results shown in Table 3 demonstrate that they are good candidates for this aim, where the highest accuracy was 97.92 % [46] and the lowest was 82.8% [45]. However, it isn't easy to compare the reviewed works due to the use of different datasets, types of channels, types of inputs, and classification model architectures. If we take the [3] and [16] works, both have used multi-channel EEG signals and EEG signals as data and CNN as a classifier. Still, they have got different results because they used different CNN architectures where the model of [3] contains four convolutional layers, one max-pooling layer, and two fully connected layers. However, in [16], it contains five convolutional layers, two pooling layers, three Inception modules, and three fully connected layers.

In addition, we have observed that in recent years, researchers in the driver drowsiness-based EEG field have shifted their focus toward using Single-Channel EEG recordings rather than Multi-Channel [6, 15, 5, 32, 51, and 7]. The main reason for this redirection is that the Multi-Channel EEG signals require a larger storage capacity and high computing time and are more expensive than single-channel records. We cannot compare the obtained results in terms of single or multi-channel. Each work employs different wearable devices, preprocessing techniques, and models. However we can say that single-channel research papers have yielded prominent results (see Tables 2 and 3). Perhaps in the future, they will be more accurate.

Another point to discuss is that in some works, instead of using EEG as signals, the authors have used some methods such as the continuous wavelet transform (CWT) [5] and Short-time Fourier Transform (STFT) [7]; to convert EEG signals to time-frequency domain images (2D spectrogram). The 2D spectrograms are then fed to CNN model that demonstrated high image classification and pattern detection performance. For example, in [5], three models were developed 1D CNN with raw EEG data, 2D CNN with power spectrum analysis EEG data and CWT-CNN with 2D spectrogram; the highest accuracy was 91% obtained by CWT-CNN. The results of [5] and [7] are encouraging, and we believe that using power preprocessing methods and the CNN model with spectrogram images will be much better.

After reading many papers on driver drowsiness detection and especially on deep learning for EEG-based driver drowsiness detection, we have noticed that all works' main problem is developing a higher accuracy system. However, we need an accurate system that can detect a drowsy state in a short time and requires small spatial memory and few computational resources. A short time because the early detection helps to avoid accidents. Memory space and computational resources must be reduced because the device where the model is integrated will be in the vehicle, which is usually a smartphone. A smartphone with an enormous capacity costs a lot.

5 Challenges and future works

In conclusion, EEG sensors are useful for detecting weariness and drowsiness using DL techniques. However, various challenges and constraints persist today, impeding the development of real-world applications. The first one is the lack of data. Most of the studies have used a few participants (50 participants or less), which can influence the results of the proposed models. As it is common knowledge, DL models require enormous data for training. In addition, the datasets should be diversified so that the models can be general, efficient, and robust. The second challenge is comparing model performance with other states of the art, as in most papers, to validate that the proposed model is better than others. However, this comparison is not reliable and unfair, as each study uses different datasets collected under different experimental conditions, the number of electrodes, sampling frequency, and the number of participants. Therefore, to obtain a fair comparison, it is recommended that all models utilize the same dataset, which is challenging due to the use of private datasets.

The third challenge is the need for powerful preprocessing methods and techniques to remove artifacts and unwanted signals from the original EEG signals without information loss. The raw EEG signal (original) is affected by various noises, such as eye blinking and muscle noises, which decrease its quality and, as a result, affect the detection model's performance. So, a preprocessing step is required to clean the signals and improve their quality.

Deep layer models with massive data may give high performance and accuracy but require high computational resources. Therefore, the last challenge is the need for powerful hardware to implement, train, and store Deep-layer models with massive data.

The fifth challenge is that most researchers typically use virtual or simulated environments to conduct their studies and develop their final system outcomes. Nevertheless, it is important to note that these results may not accurately reflect actual driving conditions, which impacts the system's reported accuracy.

The sixth challenge is that the driver may be uncomfortable because of the equipment and sensors attached to his body. In addition, even minor motion can introduce noise into the extracted signals, diminishing their precision.

For future studies, we recommend:

- Using data augmentation techniques and strategies to overcome the lack of data, improve accuracy, and achieve an acceptable generalization.

- Use available online datasets to make a reliable comparison of models, and choose the most powerful one for detecting drowsiness instead of using private datasets.
- Combine the EEG with other physiological signals such as EOG to get more accurate and efficient results.
- Implementing deeper models (with more layers) to automatically learn and extract the most prominent EEG features.
- The use of single-channel EEG signals that require low storage capacity, low computing time, and cost less than the multi-channel record, with CNN, to achieve prominent results.
- Use the cloud to avoid the necessity of powerful hardware to train it with massive data.
- Verify the accuracy of the system's findings by conducting an actual driving situation.
- After determining that the driver is experiencing drowsiness, the system should promptly notify the driver or any close traffic patrol about their possible loss of focus by generating noise or causing the steering wheel or seat to vibrate. The system may additionally prompt the driver to pause and rest, particularly if they have been driving for a prolonged duration, or enable a smooth transition to autonomous driving mode.
- Utilizing sensors to monitor the road ahead and detect probable collisions to prevent accidents caused by proximity with other cars. Once the system detects an impending accident, it can autonomously engage the brakes or issue visual and auditory alerts. This action mitigates the impact's severity or entirely averts the collision.

6 Conclusion

This paper has reviewed novel research papers on detecting driver drowsiness or fatigue using EEG and deep learning techniques such as CNNs and RNNs models. Efficient results were obtained from both DL instances, where the higher accuracy is 98.98%, and the low accuracy is 71.15% without using any artifacts removals, which is an acceptable score. In addition, we have discussed the reasons for utilizing single-channel EEG signals rather than multi-channel EEG signals in certain works and the reasons for using 2D spectrogram EEG images rather than EEG signals. At last, we have focused on some limitations of the proposed systems. For example, the importance of considering the time, accuracy, and costs (reducing the spatial memory and computational resources), the lack of data, and others are mentioned as challenges.

Declarations

Conflict of interest
The author declares that they have no conflict of interest.

Data availability statement
Data sharing is not applicable to this article as no new data were created or analyzed in this study.

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by [Imene Latreche], [Sihem Slatnia], [Okba Kazar], [Saad Harous] and [Ezedin Barka]. The first draft of the manuscript was written by [Imene Latreche] and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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