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Research Article

A Hybrid Deep Neural Network Approach to Recognize Driving Fatigue Based on EEG Signals

Mohammed Alghanim,[1] Hani Attar ,[2] Khosro Rezaee ,[3] Mohamadreza Khosravi ,[4,5] Ahmed Solyman ,[6] and Mohammad A. Kanan[7]

[1] *Faculty of Information Technology, Zarqa University, Zarqa, Jordan*
[2] *Faculty of Engineering, Zarqa University, Zarqa, Jordan*
[3] *Department of Biomedical Engineering, Meybod University, Meybod, Iran*
[4] *School of Medicine, Shiraz University of Medical Sciences, Shiraz, Iran*
[5] *Shandong Provincial University Laboratory for Protected Horticulture, Weifang University of Science and Technology, Weifang, Shandong, China*
[6] *School of Computing, Engineering and Built Environment, Glasgow Caledonian University, Glasgow, UK*
[7] *College of Engineering, University of Business and Technology, Jeddah, Saudi Arabia*

Correspondence should be addressed to Mohamadreza Khosravi; m.khosravi@wfust.edu.cn

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Electroencephalography (EEG) data serve as a reliable method for fatigue detection due to their intuitive representation of drivers' mental processes. However, existing research on feature generation has overlooked the effective and automated aspects of this process. The challenge of extracting features from unpredictable and complex EEG signals has led to the frequent use of deep learning models for signal classification. Unfortunately, these models often neglect generalizability to novel subjects. To address these concerns, this study proposes the utilization of a modified deep convolutional neural network, specifically the Inception-dilated ResNet architecture. Trained on spectrograms derived from segmented EEG data, the network undergoes analysis in both temporal and spatial-frequency dimensions. The primary focus is on accurately detecting and classifying fatigue. The inherent variability of EEG signals between individuals, coupled with limited samples during fatigue states, presents challenges in fatigue detection through brain signals. Therefore, a detailed structural analysis of fatigue episodes is crucial. Experimental results demonstrate the proposed methodology's ability to distinguish between alertness and sleepiness, achieving average accuracy rates of 98.87% and 82.73% on Figshare and SEED-VIG datasets, respectively, surpassing contemporary methodologies. Additionally, the study examines frequency bands' relative significance to further explore participants' inclinations in states of alertness and fatigue. This research paves the way for deeper exploration into the underlying factors contributing to mental fatigue.

1. Introduction

Despite globally acknowledging driving fatigue as a major factor in fatal accidents, the intricate neural mechanisms behind it remain largely unknown, impeding the development of advanced automated detection techniques [1]. The advancement of methodologies for detecting mental fatigue holds diverse applications, particularly in critical sectors where sustaining attention is paramount, such as in security and transportation [2]. EEG data are commonly employed by several research organizations to provide insights into drivers' cognitive processes [3, 4]. Nevertheless, there are challenges in assessing a driver's cognitive condition. EEG signals pose challenges for data analysis across several dimensions [5]. Analyzing the application of attributes acquired by the model across diverse themes presents an additional challenging endeavor. The duration of sleep, level of mental activity, and the existence of unidentified external interference factors all contribute to the variability observed in EEG signals among different persons [2].

Traditional detection methods often include human feature extraction and depend on preexisting information [6]. In the context of identifying fatigue, handcrafted feature extraction methods generally take into account a limited number of parameters [7]. Nevertheless, deep learning models have the potential to provide a holistic approach for integrating learning across the whole process [8]. Deep learning models are extensively employed in current scholarly investigations, mostly in the capacity of classification algorithms. Further research is necessary to explore the impact of different environments on learned ability development.

The majority of current models are unsuccessful in uncovering the essential interchannel relationships that are known to enhance EEG-based classification [9]. This study introduces a modified Inception-dilated ResNet architecture for brain fatigue detection. Using windowed signals with overlapping circumstances, the proposed approach addresses challenges like overcoming nonstationary conditions and improving accuracy, as well as overcoming the nonstationary condition of EEG signals [10, 11]. In this assignment, we employ a modified ResNet architecture that incorporates a dilated convolutional layer, along with an Inception module. This study aims to conduct a comprehensive evaluation of the research literature produced in recent years, with the objective of analyzing and comparing various methodologies. Furthermore, we will present a feasible framework for fatigue detection via physiological indicators. Researchers are contemplating the utilization of advanced technologies, such as deep neural networks, as an alternative to traditional machine learning methods, in order to address the complex challenges encountered during the development of driver fatigue diagnostic systems. The absence of an efficient model for recognizing symptoms of weariness and stress can be attributed to several problems. These include the inability to accurately predict model outputs. They also include the complexity of extracting and selecting critical qualities and the overall difficulty in achieving high classification accuracy. Numerous other categories have been suggested within this particular domain, yet it is a necessity to acknowledge that each proposal possesses inherent limits.

In recent years, convolutional neural networks that can do deep learning have gained significant prominence [12–14]. Moreover, the hybrid models such as Inception and ResNet architectures surpass traditional neural networks in widespread use for decision-making purposes [15]. Deep network models learn nonlinear changes. Due to the limited allocation of cost towards fatigue studies, researchers have resorted to pretrained networks that can be easily fine-tuned with minimal exertion. Hence, this study analyzes a multitude of brain signals to identify driver weariness through the utilization of dilated deep transfer learning-inspired methodologies.

This research contributes the following:

(1) A scalable approach was developed for evaluating driver fatigue by employing a stretched ResNet and Inception module. In this particular methodology, sleepy driving analysis involves the segmentation and examination of EEG data. Our research endeavors are centered around the advancement of techniques aimed at decreasing spectrogram file sizes, enhancing processing speeds, and determining the most suitable frame length for signal extraction.

(2) Furthermore, the utilization of the model's discoveries pertaining to the cerebral regions of diverse individuals enables us to conduct a comparative analysis of these regions. In this study, we examine the significance of several frequency ranges in the detection of sleepiness by using an effective channel selection method.

(3) The model was evaluated on the Figshare and SEED-VIG datasets, revealing a substantial improvement over the existing gold standard. This methodology utilizes a limited set of channels that may be readily adjusted and examined to detect human fatigue.

The remainder of this paper is organized as follows. In Section 2, we examine what has already been written about this topic. The structure of our proposed model is discussed in Section 3. Section 4 presents the results and data from the experiments. In Section 5, the findings are thoroughly analyzed and discussed. The last section of the paper wraps up the paper.

2. Related Work

Fatigue detection strategies encompass a diverse array of approaches, falling into four primary categories: physical feature identification methods [1], vehicle trajectory assessment methods [16], physiological signal assessment methods [17], and subjective evaluation methods [18]. Physiological signals, among which EEG stands out prominently, offer an effective and intuitive means to depict drivers' cognitive states, showcasing a heightened level of reliability. Consequently, these signals are deemed particularly suitable for in-depth investigations into fatigue detection, where EEG is frequently utilized to assess brain fatigue by depicting and analyzing cerebral activity [19–21].

The landscape of fatigue detection has witnessed substantial advancements, especially with the notable progress in brain-computer interfaces (BCIs) [22–24]. This progress has led to an upsurge in research utilizing EEG to discern indicators of exhaustion. Traditional machine learning methodologies involve the classification and preprocessing of EEG data using statistical methods [25]. Wu et al. [26] introduced the concept of employing the Hilbert transform to derive instantaneous spectral entropy features, offering a method to identify distinctive attributes from EEG data. Deng et al. [27] delved into an analysis to ascertain the power spectral density across various frequency bands, using these data to formulate four distinct fatigue criteria. Moreover, the exploration of deep self-encoder networks to glean insights into signal properties was proposed, complemented by a logic regression classifier to classify these features. Chaudhuri and Routray [28] applied electrophysiological source imaging approaches using EEG data alongside the support vector machine (SVM) algorithm to delineate different levels of weariness.

The research landscape has also seen innovations in predictive modeling. Zhang et al. [29] introduced a convolutional autoencoder and CNN architecture for predicting transcription factor binding sites. Ansari et al. [30] put forth an enhanced ReLU-BiLSTM network designed to monitor a driver's physiological fatigue state, incorporating an evaluation of the driver's head position for refinement. Du et al. [31] introduced an attention-based LSTM network with a domain discriminator to acquire knowledge of spatial features across multiple electrodes. Paulo et al. [32] harnessed a single-layer CNN to decode the spatiotemporal patterns in EEG data. Xu et al. [33] proposed a CNN integrated with an attention mechanism capable of simultaneous identity and fatigue detection.

In addressing the ambiguity present in the literature, Dang et al. [19] introduced a multilayer brain network sensitive to rhythm, effectively identifying tiredness by incorporating the intricate relationship between frequency bands and channels into its analysis. Recent research by Wang et al. [21] brought forth dynamic graph convolutional networks (GCNs) integrated with attention-based multiscale CNN to explore the nuanced relationship between channels and spatiotemporal parameters in weariness detection and categorization. Additionally, Fan et al. [20] shed light on the use of forehead EEG for investigating weariness and distraction through meticulous feature selection.

Sheikhvand et al. [34] proposed a comprehensive two-stage automated method for measuring driver weariness utilizing compressed sensing theory and deep neural networks. This method, primarily focusing on EEG data analysis, initially employs compressed sensing theory to reduce data dimensions and subsequently employs a deep CNN for automated feature selection, extraction, and classification. The proposed network architecture, featuring three Long Short-Term Memory (LSTM) layers and seven convolutional layers, reported an impressive 95% accuracy in their study.

Dogan et al. [35] meticulously evaluated a dataset designed for fatigue identification using EEG readings. Their approach involved multilevel feature extraction through wavelet packet decomposition using 16 mother wavelet functions to create frequency subbands. The suggested framework demonstrated commendable classification accuracy of 99.90% and 82.08% based on the 10-fold and leave-one-subject-out techniques, respectively.

Ghadami et al. [36] delved into the analysis of pretrained neural networks' effectiveness in automatically predicting sleepiness from single-channel EEG spectrograms using the PhysioNet sleep-EDF dataset. They developed a 1D-CNN to leverage the time-domain properties of EEG data, achieving enhanced prediction accuracy. Their findings highlighted that the stacking-average fusion method significantly improved cross-subject data accuracy by an impressive 90.73%.

In the study conducted by Wang et al. [37], the investigation focused on evaluating the efficacy of network features and critical connections in the detection of driving fatigue. EEG data were collected twice from twenty participants during simulated driving. The findings revealed a reorganization of the brain network towards decreased efficiency during fatigue across all frequency bands. Discriminative connections were predominantly associated with frontal brain regions, specifically showing heightened connections from the frontal pole to parietal or occipital regions. The utilization of discriminating connection features in the Beta Band (β) resulted in an impressive classification accuracy of 96.76%.

Wang et al. [38] introduced a fusion entropy analysis method, incorporating spectral entropy, approximate entropy, and sample entropy to assess the time series complexity of EEG signals along with electrooculography (EOG). The study demonstrated that this fusion entropy analysis, integrating EOG and EEG, provides a promising alternative for detecting driving fatigue, achieving an impressive average accuracy rate of $99.1 \pm 1.2\%$.

Gao et al. [39] introduced a new multidimensional hybrid structure based on space-frequency and time domains for fatigue detection. Their model consisted of a Gaussian time domain network and a pure convolutional spatial-frequency domain structure. The experimental results in their research demonstrated that the proposed method effectively discriminates between alert and fatigue states, achieving accuracy rates of 85.16% and 81.48% in self-generated and SEED-VIG datasets, respectively.

Ardabili et al. [40] presented a methodology for the automated identification of driver fatigue through EEG signals, employing graph convolutional networks. Their approach involved creating a multiclass system for detecting driver fatigue, utilizing deep learning networks to analyze EEG signals. They established a standard driving simulator and compiled a dataset by recording EEG signals from 20 participants, categorized into five distinct fatigue classes. Their system achieved a maximum accuracy of 99% across four different practical scenarios. It is important to note that the dataset they utilized was specifically tailored to their analysis.

In comparison to previous works, our model possesses distinct features and advantages that set it apart from other approaches. In this approach, a hybrid deep neural network named "Inception-Dilated ResNet" is employed. This network combines features from two renowned architectures, Inception and ResNet, leading to significant improvements in fatigue detection. This selection enhances accuracy and efficiency in analyzing EEG signals. For training this network, derivative spectrograms derived from EEG data are used to amalgamate information in both temporal and spatial dimensions. This novel approach enhances the interpretability of EEG data, reducing complexity and preprocessing associated with feature extraction from these signals. Moreover, this capability allows for a more precise and comprehensive analysis of the structure of fatigue episodes.

3. Methodology

Figure 1 visually represents the essential stages of our methodology, encompassing three key procedures: feature extraction, windowing, and classification. In this framework, feature extraction involves the process of capturing and highlighting relevant patterns and characteristics from the raw data. Following feature extraction, the windowing step partitions the data into distinct segments, facilitating a more granular analysis. Finally, the classification phase employs advanced algorithms to categorize the segmented data into predefined classes, enabling accurate and efficient decision making. The interconnected nature of these three procedures forms the backbone of our approach, offering a comprehensive solution for data analysis and pattern recognition.

3.1. Windowing Procedure. In our work, we use the windowing procedure to overcome the challenge of nonstationarity in EEG signals. Due to the limited dataset size, we also arranged several methods to augment the EEG data. In addition to creating spectrogram images, geometric transformations were performed. A variety of transformations were used, including horizontal or vertical rotation, random clipping, rotation augmentation, translation to move the images left, right, up, and down, and noise injection. In terms of accuracy, there was no significant improvement. In our study, we investigated why augmentation did not result in satisfactory improvements in accuracy. This is due to two factors: the signal frequency changes in the spectrogram images did not allow relevant information to enter the model, and the model was not able to learn well. The second reason is related to biased data. If the original dataset is biased, the augmented data from it will also be biased. Therefore, it is essential to determine the appropriate data augmentation technique. The issue of computational complexity raised during the training stage, however, also caused the augmentation and improvement of a few tenths of percent in the most time-consuming model. When the model was trained, a significant improvement in convergence towards the optimum did not happen. More time and epochs were needed to train the model well.

3.2. Spectrogram Image. One way to use deep learning for fatigue detection is by analyzing the spectrogram image of the EEG signal. A spectrogram is a visual representation of the frequency content of a signal over time. By converting the EEG signal into a spectrogram image, it becomes possible to analyze the frequency content of the signal over time. Deep learning algorithms can be trained on these spectrogram images to detect patterns that are indicative of fatigue. For example, certain frequency bands may be more prominent during periods of fatigue than during periods of alertness. By analyzing these patterns, deep learning algorithms can accurately detect when an individual is experiencing fatigue.

A spectrogram is created by constructing it with the Short-Time Fourier Transform (STFT) algorithm with data that have been windowed. The moving window function $g(t)$ causes a shift in the signal $x(t)$ at the time τ, which shifts the signal $g(t)$. At each discrete time τ, the $x(t)$ data that are included within the window are transformed through a finite-time Fourier transform. The use of a Fourier transform following an expansion or contraction of the window along the time axis by a factor of τ is one option that can be used. As a consequence of the alternating procedure, the signal coming from outside the window is analyzed as if it were dynamic. The Fourier transform of the full signal is computed. STFT is used to deliver a signal in the time window to a two-dimensional time-frequency display. Here, changes in the frequency content of the signal may be viewed in real time, and the STFT method is utilized to do this. Other types of STFT include the following:

$$STFT(\tau, f) = \int x(t) g(t-\tau) e^{-2j\pi f t} dt. \tag{1}$$

In the case of a frequency-time plane with a constant window size, the frequency-time separation is consistent everywhere along the whole frequency-time plane regardless of $g(t)$. If the signal contains high-frequency as well as low-frequency components, then selecting the appropriate window size for the STFT method will be difficult. The same is true for the number of windows, which might change depending on accuracy.

With the utilization of the pretraining network, the framed signals are able to be converted into a signal power spectrum (a signal power drawing based on the frequency and time components). The rectangular window displays the power (or energy) of a signal in terms of the frequency at which it is received. Two examples of spectrograms of EEG signals from fatigue and alertness are shown in Figure 2.

3.3. Feature Learning. In order to extract visual information, NNs use filters called convolutions. When deciding which characteristics of an image to extract, the size of the features is taken into account. When the Inception modules were available, those building networks had no choice but to select a certain size for their filters. Convolutional neural architecture uses recurrent connections instead of concatenating filters to produce the outputs it is capable of. The Inception-ResNetV2 architecture uses existing connections to modify the Inception architecture. ResNet's architecture, however, makes it much easier to distinguish between class properties. When the feature mapping is thin to save processing time, the layers that came before it may lose some of the characteristics that made them unique. It has been speculated that this format will reduce work while simultaneously improving accuracy [41].

The Inception family of architectures provides the basis for Inception-ResNetV2, which replaces the filter join procedure in Inception with residual connections. A filter expansion layer employing 1×1 convolution without activation comes in after each Inception block. This additional layer

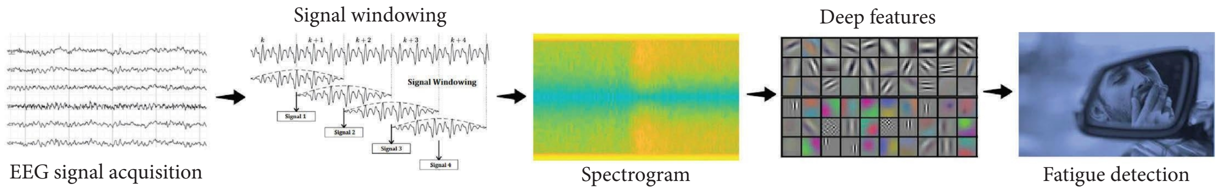
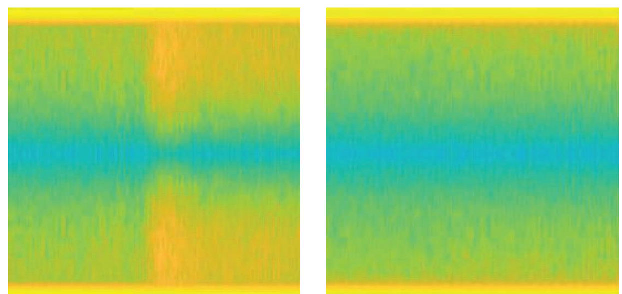


Figure 1: The suggested approach's implementation phases.



Fatigue (a)

Awareness (b)

Figure 2: The figure shows two examples of EEG spectrograms of fatigue (a) and alertness (b).

makes the filter bank as deep as the input [41]. A filter expansion layer, i.e., 1×1 convolution without activation, is required to counterbalance the dimension reduction caused by the Inception block. By using this layer, the filter bank's dimensions are expanded to match the input depth before it is added. As part of ResNet, there have been two less significant releases: version 1 and version 2. In both subversions, the A, B, and C modules, as well as the reduction blocks, are arranged in the same way. Hyperparameters are the only things that can be altered. It is possible to pinpoint the optimal value for a hyperparameter's setting using a variety of approaches. Therefore, the remaining connections represent the absolute peak of the first module's operational complexity. A residual must have the same input and output dimensions in order to be successfully integrated into a function. There are eleven different convolutions in the first convolution, and these convolutions are proportional to the depths (depths increase after each convolution). In Figures 3 and 4, we see the hybrid ResNet/Inception architecture that includes the conventional convolutional layer, the average pooling layer, the maximum pooling layer, the concatenation layer, the dropout layer, the fully connected layer, and the Softmax layer.

ReLU can also be defined more explicitly as follows [42]:

$$f(\Omega) = \max_{\text{function}}(0, \Omega), \tag{2}$$

where Ω is the input. When there are no gradients, the process of training a network is slowed down to a crawl. LReLU stands for "leaky rectified linear activation," and its formula looks like this:

$$f(\Omega) = \left[\beta \times \min_{\text{function}}(0, \Omega)\right] + \max_{\text{function}}(0, \Omega), \tag{3}$$

where β, a leakiness metric, is employed.

4. Experimental Results

For the purpose of our investigation, we looked through a database of brain signals that was stored on the Figshare repository [43] and SEED-VIG [44]. For the purpose of this experiment, a brain helmet fitted with 32 electrodes was utilized to collect EEG data. A driving simulator that was manufactured by Beijing-China Joint Training Equipment Co., Ltd., was used to test the levels of brain activity. A brain helmet and a ZY-31D automobile (see Figure 5) were employed for this particular simulated driving experience. The environment in which the data were gathered is depicted in Figure 5.

Every dataset includes a fixed simulator with displays and a software training system specifically designed for driving simulations. A computer, software for acquiring and preprocessing EEG data, and software for analyzing the data are all included in the package, as shown in Figure 6. All participants meet the requirements for representative sampling. Assuring accuracy of the results was the well-being of all test subjects throughout the study. No drugs, tea, coffee, or alcohol were consumed before the measurements of fatigue were conducted. In addition to providing a detailed explanation of the experimental process, the lab assistant also gave the participants ample time to get familiar with their surroundings.

A standard EEG typically lasts several minutes, during which laboratory staff collect data using software for a few minutes afterward. As soon as the participants reached the simulated driving state, they were instructed to continue driving. During the EEG recording, a significant amount of EEG signals was recorded, indicating exhaustion. Various experimental participants experience exhaustion at varying times, resulting in this discrepancy. While conducting driver

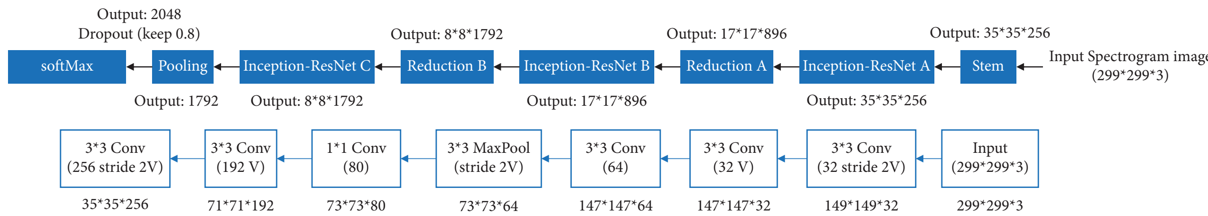


Figure 3: The overall architecture of Inception-ResNetV2 is illustrated. Details of parts A, B, and C are provided in Figure 4.

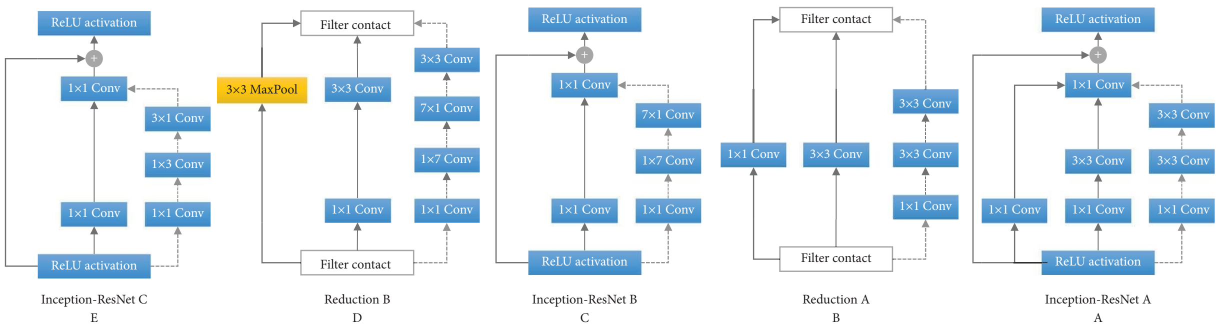


Figure 4: The Inception-reduction-network A, B, and C, as well as the reduction-network A and B, are characterized by the following structural outline.

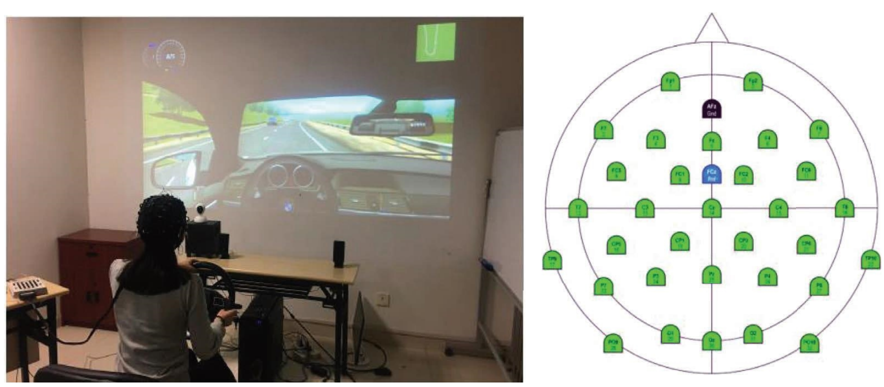


Figure 5: An illustration showing how video clips can also be used to record a signal sample. Moreover, the electrode location for a used cap can be seen in the figure to the right [43, 44].

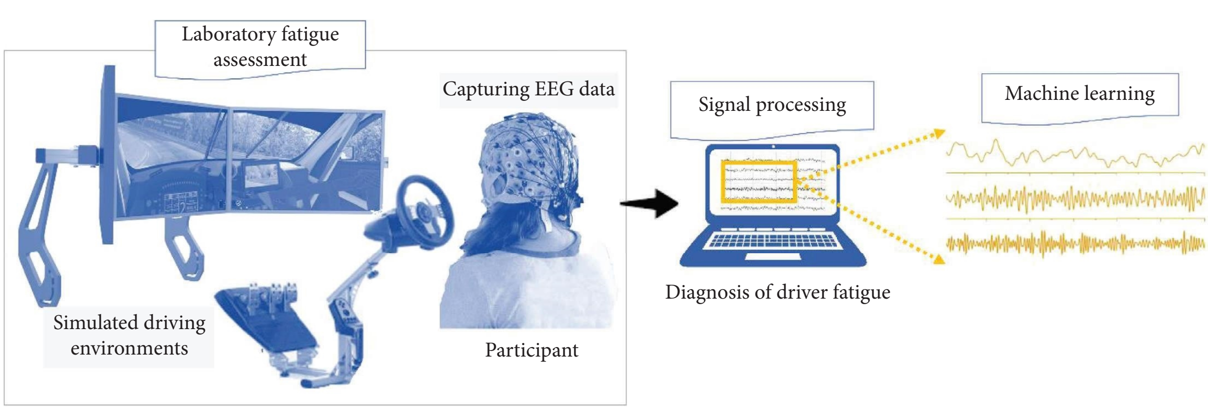


Figure 6: In this illustration, the driving system and environment are shown.

Table 1: Based on the Figshare dataset, we measured the lowest, maximum, and average output values to determine the reliability of fatigue identification.

Cross validation	Number of windows	Accuracy of model		
		Best value	Average value	Lowest value
10-fold (a)	1 to 10	0.981 ± (0.002)	0.976 ± (0.016)	0.967 ± (0.025)
	10 to 20	0.992 ± (0.002)	0.985 ± (0.012)	0.973 ± (0.020)
	20 to 30	0.991 ± (0.003)	0.985 ± (0.015)	0.974 ± (0.021)
10-fold (b)	1 to 10	0.983 ± (0.002)	0.988 ± (0.017)	0.973 ± (0.028)
	10 to 20	0.996 ± (0.002)	0.992 ± (0.014)	0.985 ± (0.022)
	20 to 30	0.994 ± (0.002)	0.985 ± (0.014)	0.976 ± (0.021)
10-fold (c)	1 to 10	0.982 ± (0.001)	0.974 ± (0.019)	0.970 ± (0.021)
	10 to 20	0.997 ± (0.003)	0.974 ± (0.013)	0.971 ± (0.028)
	20 to 30	0.988 ± (0.003)	0.981 ± (0.016)	0.971 ± (0.025)
10-fold (d)	1 to 10	0.996 ± (0.001)	0.983 ± (0.019)	0.978 ± (0.023)
	10 to 20	0.996 ± (0.001)	0.984 ± (0.013)	0.983 ± (0.014)
	20 to 30	0.984 ± (0.003)	0.989 ± (0.018)	0.975 ± (0.023)
10-fold (e)	1 to 10	0.983 ± (0.002)	0.971 ± (0.017)	0.966 ± (0.025)
	10 to 20	0.990 ± (0.002)	0.986 ± (0.015)	0.986 ± (0.016)
	20 to 30	0.991 ± (0.001)	0.986 ± (0.018)	0.973 ± (0.020)

tests, Li's subjective fatigue scale and Borg's CR-10 scale were used to measure fatigue.

The signal of the sample was determined in the laboratory by neurologists, so the signals are classified into two categories. Participants with consciousness are grouped first, while participants with fatigue are grouped second. It is possible, however, that fatigue in the EEG signal does not exist completely in the received signals. Because a brain signal is nonstationary and highly complex, it represents fatigue in a greater number of samples than a stationary signal, so fatigue appears in the whole signal. Moreover, this protocol takes into account consciousness signals as well. In both datasets, the signals were intersected by experts and the parts that may contain fatigue or alertness were carefully examined. In our study, each window label is treated as a signal fragment in the alertness or fatigue vector.

The Inception-ResNetV2 model consists of several layers, including batch normalization, scaling, addition, rectified linear units (ReLUs), two-dimensional global average pooling, and depth concatenation. The Inception-ResNetV2 model was initialized with an initial learning rate of 0.001. The model's learning efficiency had a considerable improvement during training that spanned from 100 to 1000 epochs. The Inception-ResNetV2 architecture was refined using Stochastic Gradient Descent (SGD) and Root Mean Square Propagation (RMSprop) optimization methods. The Inception-ResNetV2 model required a 10–16 hours processing time on a single CPU prior to its use in commercial applications.

A total of 16 volunteers in good health ranging in age from 17 to 25 gave their EEGs for analysis. We collected normal mode signals and fatigue test signals from 16 participants, including eight men and eight women. According to a 10-fold cross validation, Table 1 shows the results of tests that recognize fatigue. Furthermore, Table 2 shows the results of classification similar to Table 1 for SEED-VIG dataset. The dispersion between the answers in both tables is insignificant. For both datasets, there are 10 folds per repetition. After the finishing touches have been applied, participants return to normal.

A few minutes later, the recording of normal EEG data began, and it would run for five minutes. Participants were instructed to continue driving after entering the virtual environment. A total of 480 EEG signals were obtained following the canoeing activity. There were 480 signals indicating weariness and 480 signals indicating rest [43, 44]. In this division, we were able to reach a computation accuracy of 99.1% and 82.9% for Figshare and SEED-VIG datasets, respectively, by dividing the data into 30 segments with a 40% overlap (the 30% overlap in the settings section is an example of a different degree of overlap). In comparison with other similar methods, we tested the method several times. Based on a set of all models with the best performance, the proposed method performed well compared to other methods. Additionally, both Inception-v4 and Inception-ResNetV2 had near identical performance on the ImageNet validation dataset and outperformed advanced single-frame performance. These structures combined resulted in better responses to identifying fatigue in drivers through EEG signals.

In similar studies, accuracy improved by about 2 to 3.5 percent, and computational complexity was moderate. The method was compared to other similar structures in order to make an accurate comparison. A similar windowed dataset was also given to it, and the result is shown in Table 3. Considering this fact that the best accuracy is seen in a large number of windows, the appropriate overlap is higher than 30% between two consecutive windows, therefore, in Table 3 we show the results for both datasets. We compared the accuracy and computational complexity of overlapping types between consecutive windows for several capable architecture examples. The Inception-ResNetV2 structure achieves the best accuracy if maximum overlap is obtained with windows. However, to avoid high computational complexity, the average number of windows and the overlap between 30 and 40% have been considered. On the other

Table 2: Based on the SEED-VIG dataset, we measured the lowest, maximum, and average output values to determine the reliability of fatigue classification.

Cross validation	Number of windows	Accuracy of model		
		Best value	Average value	Lowest value
10-fold (a)	1 to 10	0.828 ± (0.002)	0.826 ± (0.002)	0.817 ± (0.006)
	10 to 20	0.831 ± (0.001)	0.828 ± (0.002)	0.813 ± (0.005)
	20 to 30	0.829 ± (0.001)	0.826 ± (0.003)	0.814 ± (0.006)
10-fold (b)	1 to 10	0.829 ± (0.001)	0.826 ± (0.002)	0.813 ± (0.005)
	10 to 20	0.832 ± (0.001)	0.830 ± (0.001)	0.825 ± (0.003)
	20 to 30	0.831 ± (0.001)	0.829 ± (0.001)	0.826 ± (0.003)
10-fold (c)	1 to 10	0.829 ± (0.001)	0.827 ± (0.002)	0.820 ± (0.005)
	10 to 20	0.831 ± (0.001)	0.829 ± (0.001)	0.821 ± (0.004)
	20 to 30	0.831 ± (0.001)	0.829 ± (0.001)	0.811 ± (0.006)
10-fold (d)	1 to 10	0.828 ± (0.001)	0.826 ± (0.002)	0.818 ± (0.005)
	10 to 20	0.831 ± (0.001)	0.829 ± (0.001)	0.823 ± (0.003)
	20 to 30	0.828 ± (0.002)	0.825 ± (0.002)	0.815 ± (0.005)
10-fold (e)	1 to 10	0.829 ± (0.001)	0.827 ± (0.002)	0.816 ± (0.004)
	10 to 20	0.830 ± (0.001)	0.828 ± (0.001)	0.826 ± (0.003)
	20 to 30	0.831 ± (0.001)	0.829 ± (0.001)	0.823 ± (0.003)

Table 3: Comparison between similar structures and the structure used in this study.

Architecture	Figshare			SEED-VIG		
	Overlap (%)	Accuracy (%)	Computational complexity	Overlap (%)	Accuracy (%)	Computational complexity
VGG16	30	96.47	Low	30	80.52	Low
	40	96.95	Low	40	81.75	Low
	50	97.22	Moderate	50	81.03	Moderate
VGG19	30	97.01	Low	30	80.90	Low
	40	97.32	Moderate	40	81.12	Moderate
	50	97.57	High	50	81.35	High
DenseNet-201	30	98.09	Moderate	30	81.30	Moderate
	40	98.53	Moderate	40	81.89	Moderate
	50	98.84	High	50	82.12	High
ResNet-34	30	97.20	Low	30	81.03	Low
	40	97.41	Moderate	40	81.26	Moderate
	50	97.81	Moderate	50	81.50	Moderate
ResNet-101	30	98.17	Low	30	81.69	Low
	40	98.35	High	40	81.81	High
	50	98.92	High	50	82.28	High
InceptionV2	30	95.88	Low	30	80.58	Low
	40	96.12	Low	40	80.92	Low
	50	96.45	Moderate	50	81.13	Moderate
InceptionV4	30	96.02	Low	30	80.89	Low
	40	96.55	Low	40	81.06	Low
	50	96.73	Moderate	50	81.44	Moderate
Inception-ResNetV2	30	98.87	Low	30	82.38	Low
	40	99.02	Moderate	40	82.59	Moderate
	50	99.11	High	50	82.73	High

For both datasets, we present the results including accuracy and computational complexity of the types of overlap between consecutive windows.

hand, the stability of accuracy with these settings shows the strength of the method in overcoming the problem of nonstationarity of the sample signal. An estimated forty percent overlap was estimated in the section devoted to the findings.

Low overlap is defined as less than 20%, and high overlap is defined as more than 30%, as shown in Figures 7 and 8. In Figure 7, the overlap between two consecutive frames is quite low, while in Figure 8, it is very high. Three tests resulted in two test sets that were accurate to a satisfactory level, as shown in Figure 9. Therefore, only channels with the highest percentage of reliable signal classification are selected.

In Figure 9, the plus sign indicates the most accurate classification, the broadest box indicates the highest accuracy, and the narrowest box indicates the least accurate classification. A comparison is made between all of these

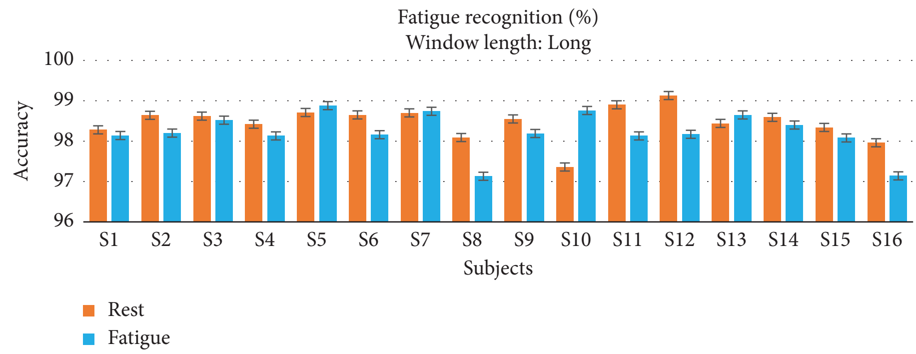


FIGURE 7: Quantitative sampling accuracy (8 men and 8 women). Furthermore, there is minimal confluence between successive signals.

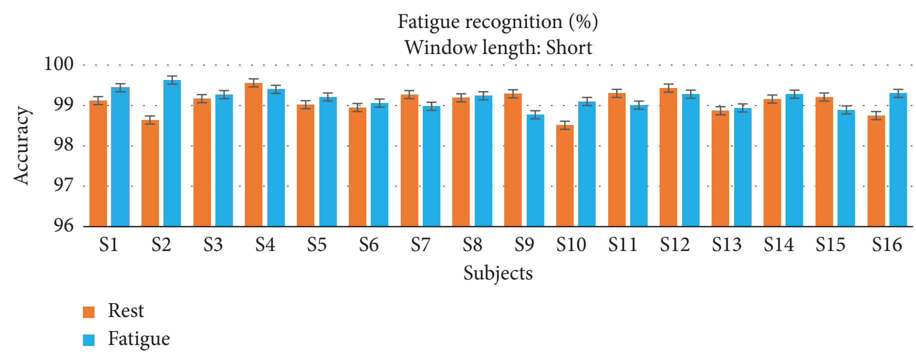


FIGURE 8: Quantitative sampling accuracy (8 men and 8 women). Furthermore, there is also a lot of overlap between successive signals.

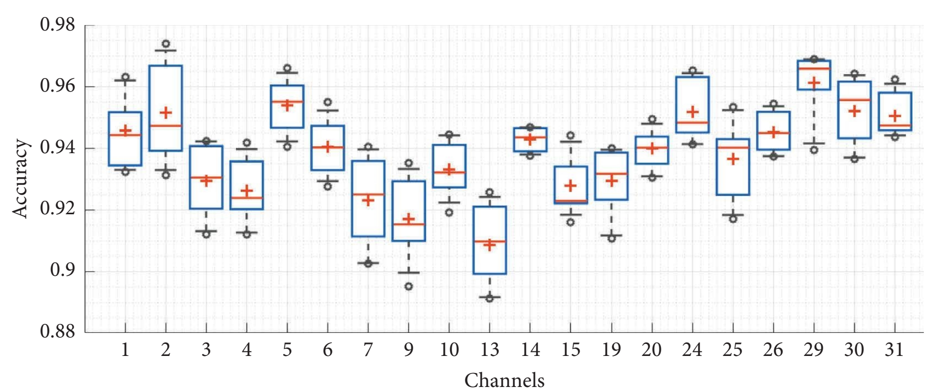


FIGURE 9: There are additional data related to weariness on the frontal and occipital electrodes.

boxes. Channels 5, 14, 25, 29, 30, and 31, as well as FP1 and FP2, all show stronger growth than the others. A channel's efficiency increases when its box size, median, upper and lower quartiles (width at the top and bottom), and width at the quartiles are closer to 100.

A supervised model may use characteristics from an unsupervised deep model that has been trained in advance to predict an individual's level of fatigue. A logistic regression model would be a good example of this type of model. Deep features produced by DBN have been used by SVM and Bagging classifiers [45, 46]. Table 4 compares our proposed architecture with some current methods for assessing whether or not a driver is highly weary based on physiological indicators.

Table 4: Analyses of the responsiveness of the suggested approach in comparison with that of other methods for determining whether or not EEG data are indicative of fatigue.

Reference-year	Dataset	Learning model	Classifier	Metric (%)
Wen and Zhang [47]-2018	Figshare	Autoencoder	AdaBoost	ACC = 95
Wu et al. [48]-2019	Figshare	Autoencoder	Softmax	ACC = 91.67
Rundo et al. [49]-2019	Figshare	Stacked autoencoder	Softmax	ACC = 100
Ma et al. [50]-2019	Figshare	Modified-PCANet	SVM	ACC = 95.14
Panwar et al. [51]-2019	Figshare	GAN	Softmax	AUC = 66.49
Paulo et al. [32]-2021	SEED-VIG	ST encoding CNN	Softmax	ACC = 69.98
Xu et al. [33]-2021	SEED-VIG	CNN-attention	Softmax	ACC = 78.64
Wu et al. [52]-2021	SEED-VIG	CNN + LSTM	Softmax	ACC = 75.67
Zhang et al. [53]-2021	SEED-VIG	BiLSTM	Softmax	ACC = 69.55
Cui et al. [54]-2022	SEED-VIG	Interpretable CNN	Softmax	ACC = 79.62
Gao et al. [39]-2023	SEED-VIG	CSF-GTNet	Softmax	ACC = 81.48
Proposed structure	Figshare SEED-VIG	ResNet-InceptionV2	Softmax	ACC = 98.87 ACC = 82.73

5. Conclusion

The aim of this work was to develop a technique that could detect exhaustion using a single EEG channel and a hybrid CNN. By using the Inception architecture, we can discover which characteristics of a signal are essential for classification. A number of additional people evaluated the model's accuracy using the same publicly available dataset. The suggested algorithm outperforms both the standard and deep learning baseline models when it comes to extracting physiologically interpretable architectures from EEG data and applying them to the problem of distinguishing between EEG signals collected during wakefulness and sleep. As a result, the proposed model can more effectively apply these architectures. This model uses a hybrid method to extract aberrant neurophysiological events from EEG data. In addition to producing detailed ablation reports, AutoAblation provides insights into how different components affect model performance. A visual representation of feature importance and ablation curves is also included in the reports. In reports, for example, features can be highlighted and suggestions can be made regarding how the model can be improved by removing certain components. The authors' work, however, will be taken into consideration for future study. Nevertheless, the absence of supplementary experiments, such as model ablation and feature visualization, attributed to hardware limitations, warrants careful consideration. Despite this limitation, the outlined strategy to address this aspect in future work is indicative of the dedication to advancing the research. This forward-looking perspective underscores a commitment to continual improvement and the exploration of more nuanced aspects of the proposed methodology.

Data Availability

A complete set of implemented codes is available from either the first, the third, or the corresponding authors (mghanem@zu.edu.jo; kh.rezaee@meybod.ac.ir; m.khosravi@wfust.edu.cn) that can be provided upon reasonable request. The used dataset has been addressed in the text.

Disclosure

Part of the idea has been inspired from a past research of the co-authors, solely presented in a conference [55].

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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