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Robust analysis and spectral-based deep learning to detect driving fatigue from EEG signals

Antonio Quintero-Rincón
Department of electronics
Catholic University of Argentina (UCA)
Buenos Aires, Argentina
antonioquintero@uca.edu.ar

Lotfi Chaari
INPT-IRIT
University of Toulouse
Toulouse, France
lotfi.chaari@inp-toulouse.fr

Hadj Batatia
MACS School
Heriot-Watt University
Dubai, United Arab Emirates
h.batatia@hw.ac.uk

Abstract—Driver fatigue is a major cause of traffic accidents. Electroencephalogram (EEG) is considered one of the most reliable predictors of fatigue. This paper proposes a novel, simple and fast method for driver fatigue detection that can be implemented in real-time by using a single-channel on the scalp. The study has two objectives. The first consists of determining the single most relevant EEG channel to monitor fatigue. This is done using maximum covariance analysis. The second objective consists in developing a deep learning method to detect fatigue from this single channel. For this purpose, spectral features of the signal are first extracted. The sequence of features is used to train a Long Short Term Memory (LSTM), deep learning model, to detect fatigue states. Experiments with 12 EEG signals were conducted to discriminate the fatigue stage from the alert stage. Results showed that TP7 was the most significant channel, which is located in the left tempo-parietal region. A zone associated with spatial awareness, visual-spatial navigation, and the cautiousness faculty. In addition, despite the small dataset, the proposed method predicts fatigue with 75% accuracy and a 1.4-second delay. These promising results provide new insights into relevant data for monitoring driver fatigue.

Index Terms—Fatigue, EEG, Robust analysis, biLSTM.

I. INTRODUCTION

The EEG is a recording of the brain's electrical activity, detected by electrodes placed on the scalp. Variations in the brain waves traced by the EEG are correlated with neurological conditions, physiological states, and level of consciousness. Driver fatigue is a major cause of road accidents, related to 20% of the total cases [1]. They often result in more driver mortality and morbidity than other types of accidents because of the greater speed on impact [2]. To prevent this kind of accident from happening, real-time driver fatigue detection is of great importance. It would allow the development of effective devices capable of warning drivers showing signs of fatigue, especially when driving in monotonous conditions. According to Lal and Craig [3], EEG may be one of the most reliable predictors of driver fatigue. Numerous researchers have, hence, studied various fatigue detection methods based on EEG signals analysis [4]–[6]. In [3], EEG signals were analyzed in the brain rhythm. Their results reported that delta (δ) and theta (θ) magnitude increased by 22% and 26%, respectively, during the transition to the fatigue state and that alpha (α) and beta (β) activity increased only by 9% and 5%, respectively.

Based on these results, Lal and Craig [7] developed a reliable fatigue-detection algorithm that categorizes the mentioned frequency bands into four phases: alert, transition to fatigue, transitional-post-transitional, and post-transitional. Jap et al. [8] assessed these four states during monotonous driving. They showed an increase in the ratio of slow-wave to fast-wave EEG activities, with $(\theta + \alpha)/\beta$ showing a larger increase. Wei et al. [9] also transformed the collected EEG data into bands (θ , α , and β) and determined the optimal indicator of driver fatigue out of twelve types of energy parameters. Using Kernel Principal Component Analysis (KPCA), they selected FP1 and O1 electrodes as the significant electrodes. They evaluated their model and reported an accuracy of 92.3%. Simon et al. [10] studied the alpha spindles, which are short (0.5-2 s) bursts of high-frequency alpha activity [11]. They compared them to the band power measures as a fatigue indicator and found that alpha spindle parameters increase the sensitivity and specificity of fatigue detection. Entropy methods have been studied by many authors to detect driver fatigue using EEG signals. Hu [12] employed four types of entropy measures (spectral entropy, approximate entropy, sample entropy, and fuzzy entropy) to extract features from a single EEG channel and compared them using ten classifiers. The optimal performance was achieved with a random forest classifier when combining channel CP4 and fuzzy entropy, with an accuracy of 96.6%. Mu et al. [13] combined the above-mentioned four types of entropy measures to extract features from EEG signals (recorded in both alert and fatigue states). In terms of fatigue detection, results showed that combined entropy has superior performance compared to single entropy, with the average recognition accuracy being 98.75%. Electrodes performance was also assessed and results showed that T5, TP7, TP8, and FP1 performed better. Min et al. [14] proposed a multiple entropy fusion analysis to detect driver fatigue in an EEG-based system and achieved an accuracy of 98.3%, a sensitivity of 98.3%, and a specificity of 98.2%. The study of electrode performance concluded that the significant electrodes were T6, P3, TP7, O1, Oz, T4, T5, FCz, FC3, and CP3. There exists a wide range of methods to accurately detect driver states in EEG signals. Most of these methods are based on supervised machine learning techniques,

such as Support Vector Machine, k-Nearest Neighbor, and random forest, with a variety of feature vectors. A complete state-of-the-art about machine learning techniques for driving behavior analysis can be found in [15]. The Long Short-Term Memory network (LSTM) is a type of recurrent neural network (RNN) capable of learning long-term dependencies in time series through their memory gates [16]. The bidirectional variant of LSTM (biLSTM) is very efficient for processing data of fixed length [17]. Its two hidden layers, both connected to the input and output, allow information to flow in two directions through the layers. A number of researchers studied this technique for EEG signal processing [18]–[21]. Multivariate and univariate analysis are statistical methods used to analyze correlation in data. Among these, robust analysis techniques are those having properties such as resistance to outliers and applicability to non-normality. As an example, the classic mean and covariance methods are robust to non-normality, but not to outliers [22]. Robust analysis has been applied to EEG signal processing in a number of works [23]–[26]. In addition, EEG signals are reasonably assumed to have Gaussian distribution [27] allowing the application of optimal statistical methods [28]. In neuroscience, multivariate analysis of EEG signals is often employed to study simultaneously states and interactions of brain regions, while univariate methods concentrate on the characterization of single brain regions [29]. This study proposes a novel, simple, and fast method to detect driver fatigue in EEG signals using a single-channel on the scalp, with the ultimate aim of real-time implementation. The study composes of two stages. First, the most relevant EEG channel is selected using the maximum covariance robust analysis. Second, a biLSTM neural network is developed to differentiate fatigue and alert stages using spectral features extracted from the time-series data of the selected channel [16], [17]. Precisely, we transform the time-series data into a sequence of features fed to an LSTM network. In this work, we analyzed a fatigue dataset consisting of 32-channel EEG signals from 12 subjects provided by Jiangxi University of Technology [14]. When assessing the most relevant EEG region for detecting fatigue, we found the single channel (TP7), located at the left tempo-parietal region, the most significant, see Fig. 2. This brain region involves *spatial awareness and visual-spatial navigation* directly related to driving, therefore relevant to analyzing the effect of fatigue. Next, we developed a biLSTM neural network to detect fatigue alerts during long driving times. The techniques used in this study are all well-known. However, to the best of our knowledge, they have never been used in a structured method to study fatigue in EEG.

The remainder of this paper is organized as follows. Section II presents the proposed method in three stages: description of the data (Section II-A), selection the relevant channel (section II-A), spectral transformation of the data (Section II-B), and the predictive model (Section II-C). In Section III, we analyse and discuss the results. Finally, conclusions and perspectives

are in Section IV.

II. PROPOSED METHOD

A standard data science process, made of four stages, has been implemented for this study, as shown in Fig.1. First, a data search and acquisition were conducted. This was followed by dimension reduction and data transformation in stages two and three. More precisely, the second stage processed the data to extract the most relevant channel using a statistical method. Whereas, the third stage transformed the data from the temporal to the spectral domain by extracting two spectral features. Then, the third stage used the temporal sequence of spectral features to learn a predictive model for detecting fatigue. These stages are described in more detail in the next sections.

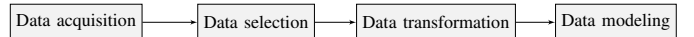


Fig. 1. Block-diagram illustrating the stages of the proposed method.

A. Data

A database with 12 unipolar fatigue EEG signals and 12 unipolar alert EEG signals was used from [14]. In this experiment, twelve university male students between the ages of 19 and 24 years were asked to drive a static car through a driving simulator in a software-controlled environment. For each subject, two EEG signals were recorded: one corresponding to alert driving and the other one corresponding to fatigue driving. The alert driving EEG signal was recorded after the subject had been driving for 15 minutes. The fatigue driving EEG signal was acquired once the subject showed signs of fatigue according to Lee’s subjective fatigue scale [30] and Borg’s CR-10 scale [31], after driving for 60-120 minutes. Both signals consist of a 32-channel EEG, of 5 minutes duration, digitized at $f_s = 1000$ Hz. See Fig 2.

{Selection of the relevant electrode Let $\mathbf{X} \in \mathbb{R}^{M \times N}$ denote the multivariate matrix gathering M EEG signals $\mathbf{x}_m \in \mathbb{R}^{1 \times N}$ measured simultaneously on different channels and at N time instants. Applying the MCD (Minimum covariance determinant) algorithm [32], we estimate the parameters $(\hat{\boldsymbol{\mu}}, \hat{\boldsymbol{\Sigma}})$ of the elliptically symmetric unimodal distribution of our multivariate data \mathbf{X} . These parameters are given by their expressions

$$\hat{\boldsymbol{\mu}} = \frac{\sum_{i=1} W(d_i^2) \mathbf{x}_i}{\sum_{i=1} W(d_i^2)} \quad (1)$$

$$\hat{\boldsymbol{\Sigma}} = c_0 \frac{1}{N} \sum_{i=1} W(d_i^2) (\mathbf{x}_i - \hat{\boldsymbol{\mu}})^* (\mathbf{x}_i - \hat{\boldsymbol{\mu}})^T \quad (2)$$

where $d_i = d(\mathbf{x}_i, \hat{\boldsymbol{\mu}}, \hat{\boldsymbol{\Sigma}})$ is the Mahalanobis distance, $W(\cdot) = I(\cdot \leq \sqrt{\chi_{M,0.975}^2})$ is a weight function with I as the indicator function, $*$ denotes the complex conjugate, $\mu_{\mathbf{X}}$ is the mean. The parameter c_0 called the consistency factor is given by $\alpha / F_{\chi_{M+2}^2}(q_\alpha)$, where q_α is the α -quantile of the χ_M^2 distribution, with $\alpha = \lim_{n \rightarrow \infty} h(n)/n$, and h taken such as $[(n+p+1)/2] \leq h \leq n$.

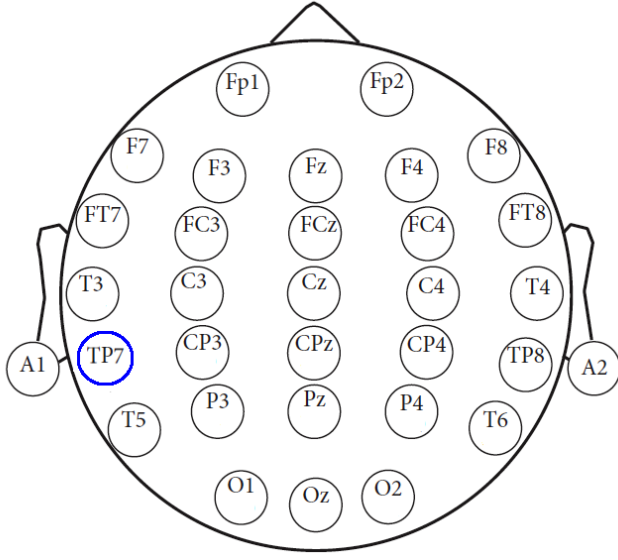


Fig. 2. Position and nomenclature of the electrodes showing underlying lobes, (T) temporal lobe, (P) parietal lobe, (O) occipital lobe and (F) frontal lobe

In order to estimate the most significant channel x_p , the maximum covariance was calculated into 2-second time segments using a rectangular sliding window with 0.5-second time overlap by solving

$$x_p = \max_{[X]^T} \hat{\Sigma}$$

See [28], [32], [33] for more details about the maximum covariance analysis method.

B. Spectral transformation

Our preliminary investigation showed that using data in the temporal domain does not allow characterizing fatigue. Therefore, we resorted to the spectral domain. For each state of alert and fatigue, the signal x_p has been divided into segments $x_p(t)$ with a rectangular sliding window without overlap. For each segment t , we estimated two spectral parameters, namely the instantaneous frequency $f(t)$ and the instantaneous spectral entropy $H(t)$, as follows.

Let $S(t, f) = |X_p(t, f)|^2$ be the spectrogram of the signal segment, $x_p(t)$ with $X_p(t, f)$ being the discrete Fourier transform of $x_p(t)$. The probability distribution of the spectrogram at instant t is given by

$$P(t, m) = \frac{S(t, m)}{\sum_f S(t, f)}$$

We can hence compute the instantaneous frequency of the signal using the short term Fourier transform [34], [35]

$$f(t) = \frac{\sum_m mP(t, m)}{\sum_m P(t, m)}$$

Moreover, we calculate the instantaneous spectral entropy following [36]

$$H(t) = - \sum_m P(t, m) \log_2 P(t, m)$$

The result is a transformation of the signal in the relevant channel to a sequence of pairs of spectral parameters $\{(f(t), H(t))\}, 1 \leq t \leq T$. This sequence is considered to learn a predictive model to classify EEG segments into alert or fatigue states.

C. Predictive model

In order to differentiate alert and fatigue states, we designed a bidirectional recurrent network classifier with long-short term memory (biLSTM). The input to this network is the sequence of spectral parameters $\Theta_t = (f(t), H(t))$ obtained from the previous transformation stage. The parameters were all normalized according to the z-score approach, by subtracting the mean and dividing by the standard deviation over all segments. Following the standard approach, the architecture of the network consists of three gates: input, output, and forget [37]. The forget gate is a sigmoid function

$$F_t = \sigma(W_F \Theta_t + U_F h_{t-1} + b_F)$$

where the hyperparameters W_F and U_F are matrices, and b_F is a bias vector. σ is the sigmoid activation function. As such, $F_t \in (0, 1)$ represents the fraction of the past state to be forgotten, depending on the previous state h_{t-1} and the input Θ_t at iteration t . Similarly, the input gate is defined by

$$I_t = \sigma(W_I \Theta_t + U_I h_{t-1} + b_I)$$

with the hyperparameters W_I , U_I and b_I . And the output gate

$$O_t = \sigma(W_O \Theta_t + U_O h_{t-1} + b_O)$$

with the hyperparameters W_O , U_O and b_O . The update function updates selectively the internal memory of the network with

$$c_t = F_t \otimes c_{t-1} + I_t \otimes \tanh(W_c \Theta_t + U_c h_{t-1} + b_c)$$

with the hyperparameters W_c , U_c and b_c , with $h_t = O_t \otimes \tanh(c_t)$. The network sequences of 10520 pairs of parameters. It composes of 100 cells. A bidirectional layer has been added to take into consideration dependence with future sequences. A fully connected layer is responsible for reducing the scale from 100 to two dimensions. The actual classification of a segment into alert or fatigue states is finally obtained by the normalised exponential function layer.

III. RESULTS AND DISCUSSION

In this Section, we report the results of our method applied to the TP7 channel from the dataset described in section II-A. The proposed methodology uses one channel from each EEG signal from the database introduced in Section II-A. Fig. 3 shows time-domain plot examples of alert and fatigue signals from the electrode TP7. In general, due to the high dynamics of the EEG signals, it is difficult to discriminate between fatigue and alert by visual inspection.

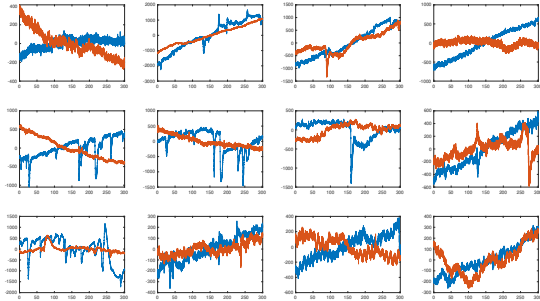


Fig. 3. Plots of alert (blue) and fatigue (orange) EEG signals correspond to electrode TP7. We can observe the high dynamic variability in the time domain of the signals.

The first stage of our study found that TP7 contains the most relevant information on driving fatigue. This left tempo-parietal region channel is related to the lobe where spatial awareness and visual-spatial navigation are shared, see Fig. 2. Besides, the physical structure of the brain reflects its mental organization. In general, higher mental processes occur in the upper regions, while the brain's lower regions take care of basic support [38]. Therefore, this finding is credible since it is related to the cautiousness and affective faculty [39]. We hypothesize that melatonin is responsible for the high variability of the temporal waveform of the signal, see Fig. 3. It is a hormone produced by the pineal gland that helps regulate the sleep-wake cycle. According to [38], the suprachiasmatic nucleus (SCN) located in the hypothalamus plays a key role in sleep-wake cycles. Light levels are sensed by the retina, and this information is relayed to the SCN, which then sends a signal to the pineal gland. This triggers the release of melatonin, the hormone that tells the body when to sleep. At this point, the brain becomes less alert and fatigue starts to take over. When melatonin levels fall in response to increased light, the waking part of the cycle begins. Based on this result, data from the TP7 channel was used for the automatic detection of fatigue. Data from all subjects were processed according to our spectral feature extraction (Section II-B). The resulting feature-sequences were organized into 80% for training our biLSTM network and 20% for testing. It is important to clarify that our data is balanced, the two classes have identical weights. Therefore, the classifier does not have minority classes to be overlooked [40].

Various metrics are commonly used to evaluate the performance of classifiers. Recently, El Assad et al. [15] analyzed the performance metrics used in different studies and found that accuracy, recall, and specificity were the most popular ones. According to this study, the *accuracy* was adopted in 65.85% of the 82 primary studies published in the decade between 2009 and 2019, while recall and specificity were used in 35.36% and 32.92% of them, respectively. In order to make our results comparable to existing methods, we report our results in terms of accuracy, sensitivity, and specificity. The testing phase of our biLSTM classifier yielded 75% accuracy, 67.7% sensitivity, and 86% specificity. The ANOVA test gave a p -value < 0.01 . And the prediction time-delay was 1.4 seconds. These results were compared with some classical machine learning (ML) techniques, such as Decision Trees, Naive Bayes, Support Vector Machines (SVM), 10-Nearest-Neighbor, and Ensemble Boosted Trees. Note that, the k parameter from k -NN technique was set based on \sqrt{N} , where N is the number of samples in the training dataset, in our case $N = 10$, $k \approx 3$ [41]. These techniques showed better accuracy, sensitivity (TPR), and specificity (TNR), but with a prediction time-delay significantly larger than the biLSTM network, see Table I. This makes the proposed method better suited for real-time implementation.

TABLE I
COMPARISON BETWEEN biLSTM NETWORK AND SOME ML TECHNIQUES.
ACCURACY (ACC.), TPR, AND TNR IN %, AND PREDICTION TIME-DELAY
IN SEC.

Techniques	Acc.	TPR	TNR	Delay
biLSTM	75.0	67.7	86.0	1.40
Decision tree	84.8	83.0	86.0	6.60
Naive Bayes	85.1	84.0	86.0	19.80
SVM	84.2	80.0	89.0	16.40
10-NN	85.3	85.0	86.0	5.82
Boosted ensemble tree	85.4	84.0	87.0	6.26

Table II reports some examples of channels used in different works. For example, in [9] the Grey relational analysis (GRA) and the Kernel Principal Component Analysis (KPCA) were used in order to extract the most relevant channels (FP1, O1) and data classified using a linear regression equation (LRE); only the accuracy has been reported. Hu [12] compared the effectiveness of four different features combined with ten different classifiers to detect driver fatigue and concluded that optimal performance was achieved using fuzzy entropy (FE) features and a Random Forest (RF) classifier, with an accuracy of 96.6%. In [13], a combined entropy-based method with the support vector machine (SVM) classifier gave 98.75% accuracy, 97.50 % specificity, and 96% sensitivity. Min et al. [14] proposed a multiple entropy fusion (EF) with a back-propagation neural network classifier (BPNN) and reported an accuracy of 98.3%. Yeo et al. [42] used power spectrum features from 19 channels with an SVM to distinguish between alert and fatigue EEG signals. The model achieved an accuracy

of 99.3%. In [43], Chen et al. used two features: one from the functional brain network (FBN), and the second from power spectrum density. They used an extreme learning machine (ELM) classifier to detect fatigue and reported an accuracy of 95%, a sensitivity of 95.71%, and a specificity of 94.29%. Note that, although these methods have good accuracy, they have relatively high computational complexity, especially at the feature extraction stages. Whereas our proposed method achieves good results with a single channel and with low complexity, allowing low-cost real-time implementation, which is the ultimate objective of this application.

TABLE II

EXAMPLES OF CHANNELS USED IN DIFFERENT WORKS. MOST METHODS HAVE HIGH ACCURACY (ACC.) VARIOUS TECHNIQUES ARE USED TO SELECT THE CHANNELS: ROBUST ANALYSIS (RUA), GREY RELATIONAL ANALYSIS (GRA), KERNEL PRINCIPAL COMPONENT ANALYSIS (KPCA). VARIOUS FEATURES: SAMPLE ENTROPY (SA), SPECTRAL ENTROPY (SE), APPROXIMATE ENTROPY (AE), FUZZY ENTROPY (FE), ENTROPY FUSION (EF), POWER SPECTRAL DENSITY (PSD), FUNCTIONAL BRAIN NETWORK (FBN). AND DIFFERENT CLASSIFIERS: LONG SHORT TERM MEMORY (LSTM), RANDOM FOREST (RF), SUPPORT VECTOR MACHINE (SVM), BACK PROPAGATION NEURAL NETWORK (BPNN), EXTREME LEARNING MACHINE (ELM).

Channels	Method	Classifier	Accuracy	Ref.
TP7	RA	biLSTM	75.0%	our
FP1, O1	GRA+KPCA	LRE	92.3%	[9]
CP4	SE+FE+AE+PE	RF	96.6%	[12]
T5, TP7, TP8, FP1	SE+AE+SE+FE	SVM	98.7%	[13]
T6, P3, TP7, O1, Oz, T4, T5, FCz, FC3, CP3	EF	BP	98.3%	[14]
all 22	PSD	SVM	99.3%	[42]
all 22	FBN-PSD	ELM	95.0%	[43]

IV. CONCLUSIONS

This work presented a new method to detect driver fatigue events in EEG signals using one single-channel. The method consists of analyzing data from all channels using the maximum covariance robust statistical technique. The analysis led to the identification of the channel TP7 located at the tempo-parietal region as being the most relevant to monitor driving fatigue. This region is associated with spatial awareness and visual-spatial makes out finding credible. The second contribution of the paper consists in transforming the time-domain signal into a sequence of spectral features, which reveals the characteristics of alert and fatigue states when driving. A bidirectional recurrent network with short long-term memory has been trained with these spectral sequences. Experimentation was conducted with a peer-reviewed dataset of 24 real EEG signals from Jiangxi University of Technology [14]. Results showed an accuracy of 75% with a prediction time delay of 1.4 sec. The main advantage of the proposed method is related to its very good prediction of delay-time which makes it an

affordable solution for real-time implementation. And it is easy to deploy as it uses a single channel.

The main limitation of this method is the small size of the dataset. One perspective consists in augmenting the volume of data by conducting a larger pilot study and using a generative adversarial network (GAN) to simulate realistic EEG data [44]. Another perspective consists in integrating the spectral transformation within the neural network using convolutional LSTM [45].

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REFERENCES

- [1] V. BalasuBramanian and R. Bhardwaj, "Can cECG be an unobtrusive surrogate to determine cognitive state of driver?" *Transportation Part F*, vol. 58, pp. 797–806, 2018.
- [2] J. Horne and L. Reyner, "Sleep related vehicle accidents," *BMJ Clinical Research*, vol. 310, no. 6979, pp. 565–567, 1995.
- [3] S. Lal and A. Craig, "Driver fatigue: Electroencephalography and psychological assessment," *Psychophysiology*, vol. 39, no. 3, pp. 313–321, 2002.
- [4] A. Boudaya, B. Bouaziz, S. Chaabene, L. Chaari, A. Ammar, and A. Hökelmann, "Eeg-based hypo-vigilance detection using convolutional neural network," in *International Conference on Smart Homes and Health Telematics*. Springer, 2020, pp. 69–78.
- [5] Y. Abichou, S. Chaabene, and L. Chaari, "A sleep monitoring method with eeg signals," in *Digital Health in Focus of Predictive, Preventive and Personalised Medicine*. Springer, 2020, pp. 25–32.
- [6] S. Chaabene, B. Bouaziz, A. Boudaya, A. Hökelmann, A. Ammar, and L. Chaari, "Convolutional neural network for drowsiness detection using eeg signals," *Sensors*, vol. 21, no. 5, p. 1734, 2021.
- [7] S. K. Lal, A. Craig, P. Boord, L. Kirkup, and H. Nguyen, "Development of an algorithm for an EEG-based driver fatigue countermeasure," *Journal of Safety Research*, vol. 34, no. 3, pp. 321–328, 2003.
- [8] B. T. Jap, S. Lal, P. Fischer, and E. Bekiaris, "Using EEG spectral components to assess algorithms for detecting fatigue," *Expert Systems with Applications*, vol. 36, no. 2, pp. 2352–2359, 2009.
- [9] L. Wei, H. Qi-chang, F. Xiu-min, and F. Zhi-min, "Evaluation of driver fatigue on two channels of EEG data," *Neuroscience Letters*, vol. 506, no. 2, pp. 235–239, 2012.
- [10] M. Simon, E. A. Schmidt, W. E. Kincses, M. Fritzsche, A. Bruns, C. Aufmuth, M. Bogdan, W. Rosenstiel, and M. Schrauf, "EEG alpha spindle measures as indicators of driver fatigue under real traffic conditions," *Clinical Neurophysiology*, vol. 122, no. 6, pp. 1168–1178, 2011.
- [11] V. Lawhern, S. Kerick, and K. Robbins, "Detecting alpha spindle events in EEG time series using adaptive autoregressive models," *BMC Neuroscience*, vol. 14, no. 101, pp. 1–9, 2013.
- [12] J. Hu, "Comparison of different features and classifiers for driver fatigue detection based on a single EEG channel," *Computational and Mathematical Methods in Medicine*, vol. 2017, no. 51095, p. 30, 2017.
- [13] Z. Mu, J. Hu, and J. Min, "Driver fatigue detection system using electroencephalography signals based on combined entropy features," *Applied Sciences*, vol. 7, no. 2, pp. 150–167, 2017.
- [14] J. Min, P. Wang, and J. Hu, "Driver fatigue detection through multiple entropy fusion analysis in an EEG-based system," *Plos One*, vol. 12, no. 12, p. e0188756, 2017.
- [15] Z. E. A. El Assad, H. Mousannif, H. A. Moatassime, and A. Karkouch, "The application of machine learning techniques for driving behavior analysis: A conceptual framework and a systematic literature review," *Engineering Applications of Artificial Intelligence*, vol. 87, no. 10331, p. 2, 2020.
- [16] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural computation*, vol. 9, no. 8, pp. 1735–1780, 1997.

- [17] M. Schuster and K. Paliwal, "Bidirectional recurrent neural networks," *IEEE Transactions on Signal Processing*, vol. 45, no. 11, pp. 2673–2681, 1997.
- [18] G. Li and J. Jung, "Maximum marginal approach on EEG signal preprocessing for emotion detection," *Applied Sciences*, vol. 10, no. 7677, pp. 1–11, 2020.
- [19] Y. Hou, S. Jia, S. Zhang, X. Lun, Y. Shi, Y. Li, H. Yang, R. Zeng, and J. Lv, "Deep feature mining via attention-based bilstm-gcn for human motor imagery recognition," *ArXiv*, pp. 1–8, 2020, arXiv:2005.00777.
- [20] J. Yang, X. Huang, H. Wu, and X. Yang, "EEG-based emotion classification based on bidirectional long short-term memory network," *Procedia Computer Science*, vol. 174, pp. 491–504, 2020.
- [21] A. Fares, S.-h. Zhong, and J. Jiang, "EEG-based image classification via a region-level stacked bi-directional deep learning framework," *BMC medical informatics and decision making*, vol. 19, no. 6, pp. 1–11, Dec 2019.
- [22] D. J. Olive, D. J. Olive, and Chernyk, *Robust Multivariate Analysis*. Springer, 2017.
- [23] L. Molinari and G. Dumermuth, "Robust multivariate spectral analysis of the EEG," *Neuropsychobiology*, vol. 15, no. 3-4, pp. 208–218, 1986.
- [24] X. Yong, R. K. Ward, and G. E. Birch, "Robust common spatial patterns for EEG signal preprocessing," in 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE, 2008, pp. 2087–2090.
- [25] R. Sameni and E. Seraj, "A robust statistical framework for instantaneous electroencephalogram phase and frequency estimation and analysis," *Physiological Measurement*, vol. 38, no. 12, pp. 2141–2163, 2017.
- [26] T. Uehara, M. Sartori, T. Tanaka, and S. Fiori, "Robust averaging of covariances for EEG recordings classification in motor imagery brain-computer interfaces," *Neural Computation*, vol. 29, no. 6, pp. 1631–1666, 2017.
- [27] A. Quintero-Rincón, M. Pereyra, C. D’Giano, M. Risk, and H. Batatia, "Fast statistical model-based classification of epileptic EEG signals," *Biocybernetics and Biomedical Engineering*, vol. 38, no. 4, pp. 877–889, 2018.
- [28] R. A. Maronna, R. D. Martin, V. J. Yohai, and M. Salibián-Barrera, *Robust statistics Theory and methods with R*. Wiley, 2019.
- [29] A. Quintero-Rincón, J. Prendes, M. Pereyra, H. Batatia, and M. Risk, "Multivariate bayesian classification of epilepsy EEG signals," in 2016 *IEEE 12th Image, Video, and Multidimensional Signal Processing Workshop (IVMSP)*. IEEE, 2016, pp. 1–5.
- [30] K. A. Lee, G. Hicks, and G. Nino-Murcia, "Validity and reliability of a scale to assess fatigue," *Psychiatry Research*, vol. 36, no. 3, pp. 291–298, 1991.
- [31] G. Borg, "Psychophysical scaling with applications in physical work and the perception of exertion," *Scandinavian Journal of Work*, vol. 16, no. 1, pp. 55–58, 1990.
- [32] P. J. Rousseeuw and K. V. Driessen, "A fast algorithm for the minimum covariance determinant estimator," *Technometrics*, vol. 41, no. 3, pp. 212–223, 1999.
- [33] M. Hubert and M. Debruyne, "Minimum covariance determinant," *Wiley Interdisciplinary Reviews: Computational statistics*, vol. 2, no. 1, pp. 36–43, 2010.
- [34] B. Boashash, "Estimating and interpreting the instantaneous frequency of a signal-part 1: Fundamentals," *Proceedings of the IEEE*, vol. 80, pp. 520–538, 1992.
- [35] —, "Estimating and interpreting the instantaneous frequency of a signal-part 2: algorithms and applications," *Proceedings of the IEEE*, vol. 80, no. 4, pp. 540–568, 1992.
- [36] Y. Pan, J. Chen, and X. Li, "Spectral entropy: a complementary index for rolling element bearing performance degradation assessment," *Proceedings of the Institution of Mechanical Engineering Science, Part C: Journal of Mechanical Engineering Science*, vol. 223, no. 5, pp. 1223–1231, 2009.
- [37] O. Calin, *Deep learning architectures. A mathematical approach*. Springer, 2020.
- [38] R. Carter, *The Human Brain Book: An illustrated guide to its structure, function, and disorders*. Penguin, 2019.
- [39] B. R. Postle, *Essentials of Cognitive Neuroscience*. John Wiley & Sons, 2020.
- [40] A. Fernández, S. García, M. Galar, R. C. Prati, B. Krawczyk, and F. Herrera, *Learning from Imbalanced Data Sets*. Springer, 2018, vol. 11.
- [41] A. Quintero-Rincón, C. D’Giano, and H. Batatia, "Statistical model-based classification to detect patient-specific spike-and-wave in EEG signals," *Computers*, vol. 9, no. 4, pp. 1–14, 2020.
- [42] M. V. M. Yeo, X. Li, K. Shen, and E. P. V. Wilder-Smith, "Can svm be used for automatic EEG detection of drowsiness during car driving?" *Safety Science*, vol. 47, no. 1, pp. 715–728, 2018.
- [43] J. Chen, H. Wang, C. Hua, and E. P. V. Wilder-Smith, "Electroencephalography based fatigue detection using a novel feature fusion and extreme learning machine," *Cognitive Systems Research*, vol. 52, pp. 115–124, 2009.
- [44] A. Radford, L. Metz, and S. Chintala, "Unsupervised representation learning with deep convolutional generative adversarial networks," in 4th *International Conference on Learning Representations*, Y. Bengio and Y. LeCun, Eds., May 2016.
- [45] A. M. Abdelhameed, H. G. Daoud, and M. Bayoumi, "Deep convolutional bidirectional lstm recurrent neural network for epileptic seizure detection," in 2018 *16th IEEE International New Circuits and Systems Conference (NEWCAS)*. IEEE, 2018, pp. 139–143.