Deep Learning for EEG Signals Analysis

Control of Autonomous Multi-Agent Systems
Gioia Mancini, Christian Brignone

***Abstract*—Deep Learning (DL) techniques are being more and more helpful in many applications, such as medical robotics, clinical decision support virtual reality-reality for rehabilitation and therapy and so on. Some of the most challenging and relevant approaches rely on the decoding of biomedical signals for brain disease diagnosis and Brain Computer Interface (BCI) applications. In this report we focused our attention on the most recent and relevant applications in the field of Deep Learning applied to EEG signals analysis. In particular, we presented two kinds of applications: epileptic seizure and Alzheimer's disease detection, describing in details, for each of them, two state-of-the-art examples. We deduced that the use of DL techniques for EEG data analysis is a growing field, where brilliant solutions may be limited only by the size of the available datasets.**

I. Introduction

During the last century, technological and medical innovations led to new important and exciting challenges in many fields of human knowledge. The growth and the appearance of technology-related more sophisticated and efficient solutions allowed the scientists to reach many fundamental milestones, guided by the aim of constantly crossing the limits of science and pushing them further and further away.

One of the most advanced techniques that have recently become widespread in many fields and applications is Artificial Intelligence (AI). A field in which the employment of AI is very promising is healthcare, where Deep Learning (DL) methods are being increasingly helpful in many applications, such as medical robotics, clinical decision support systems, virtual reality for rehabilitation and therapy, and so on. Some of the most challenging and relevant approaches rely on the decoding of biomedical signals for brain disease diagnosis and Brain Computer Interface (BCI) applications.

The Electroencephalogram (EEG) are multi-channel non-linear and non-stationary signals which are measure of the electrical activity of the brain. The recording is done through electrodes placed on the human scalp in a non-invasive fashion. The acquired EEG signals are characterized by belonging to different groups of frequency bands, *delta*, *theta*, *alpha*, *beta*, *gamma*. The EEG signals embed important features linked to specific brain states, which have to be extracted and analyzed to be meaningful and useful in practical applications. In doing so, one has to take into account that EEG signals comecomeh noise and *artifacts*, which have to be filtered out during a pre-processing stage, which also involves different procedures such as epoching and bad channels removal. After the pre-processing phase, a feature extraction procedure can be employed. It involves spectral or time-frequency estimation, discrete wavelet transform, bispectrum, continuous wavelet transform and many others.

The EEG analysis is carried out based on the task to be solved. Some of the most common applications are classification of brain states and patterns [1], [2], emotion detection [3]–[6], brain disease diagnoses such as Alzheimer's disease [7]–[14] and epileptic seizure prediction [15]–[21], rehabilitation after stroke and other related trauma by means of BCIs implementation and prosthesis control [22]–[27], robotics [28]–[30].

All these tasks have been tackled firstly with the use of classical Machine Learning (ML) methods, such as Support Vector Machines (SVM), K-Nearest Neighbours (KNN), K-means, Linear Discriminant Analysis (LDA) [31]. Recently, thanks to hardware improvements, neural networks began to be widely utilized with a large growth in particular for time series analysis. Multiple DL solutions for analyzing time series in healthcare field have been proposed, resulting in the development of Deep Neural Networks (DNNs), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs) and Convolutional Recurrent Neural Networks (CRNNs), which showed very promising and outstanding results in the above mentioned tasks.

In the following, some of the most recent, challenging and interesting applications which make use of EEG analysis through DL strategies are explored.

This report is organized as follows. In section II, a theoretical introduction of EEG signal processing is provided. In section III a summary which investigates the most common DL architectures in EEG-based applications is described. Section IV explores a series of meaningful applications which make use of EEG signals. In section V and VI EEG-based methods for epileptic seizure and Alzheimer's disease detection tasks are deeply described, respectively. Finally, section VII concerns the conclusions.

II. EEG signals

A. EEG

EEG is a typically non-invasive method introduced in the early 1920s [32] which is the most used technology employed to acquire the electrical activity of the brain due to its excellent temporal resolution, ease of use, safety and affordability [33]. Electrophysiological activity of the human brain concerns very complex non-linear and non-stationary signals, which can be represented with brain waves through EEG recorders. In order to record the EEG, electrodes are placed at specific points on the human scalp, by following precise international schemes, such as the $10-20$ [34] (Figure 1) and 10-10 systems.

Spontaneous EEG signals are characterized by different frequency bands: δ *delta*, which is less than 3.5 Hz, θ *theta*, between 4 and 7.5 Hz, α *alpha* from 8 to 13 Hz, β *beta*, between 14 and 30 Hz and γ *gamma*, above 30 Hz. Other rhythms observed in the same frequency range are the μ *mu*, κ *kappa* and τ *tau* rhythms, which have a relevant role in different context such as identifying motor activity from EEG data. EEG can also show *evoked* responses to various sensory stimuli, for example the *event related potentials* (ERP), that is the measure of the response generated by a specific sensory, cognitive or motor-related event. In table I the frequency bands and their meaning are showed.

B. Pre-processing and feature extraction

EEG signals contain valuable information about the brain state, which need to be extracted, processed and analyzed in order to provide appropriate diagnosis and solutions depending on the considered task. The raw EEG recording is a multidimensional time series which may contain *artifacts*, which are unwanted signals which consist of potential difference due to an extra-cerebral source. They can be either of physiological origin or not. For example blinking eyes, muscle contractions, cardiac activity, sweating are physiological artifacts, while technical ones can be power-line noise or experimental errors. Artifacts are represented by signals belonging to specific frequency ranges and an effective way to take care of them and remove them is band-pass filtering, which has to be done in the first step of the preprocessing procedure. Extracted features must reflect characteristics of the signal which are exploited to identify brain states for the considered task. So, after the filtering step, an important procedure for investigating stimulus/cognitive event/related potentials relies in the data epochs extraction and baseline values removal. Then, bad channels and bad epochs removal is applied, followed by the artifact removal procedure based on Independent Component Analysis (ICA) on EEG epochs [1], [35]. So, the right pre-processing methods to apply depends on the kind of artifacts one wants to remove and on the features one is interested on. For example, if one is interested in a eye-movement study it is not usefule to remove eye-related artifacts. Another example is an ERP task, which requires high temporal resolution, while for a motor imagery classification problem high spatial resolution is needed. Furthermore, choices for online and offline analysis may differ for computational resources problems, which must be taken into account for mobile Brain Computer Interface (BCI) applications, for example. The EEG feature extraction can be carried out through spectral estimation, which shows the change of signal power with respect to frequency, or time-frequency techniques with the use of Short-time Fourier transform (STFT), continuous wavelet transform (CWT), discrete wavelet transform (DWT), Bispectrum (BiS). STFT and CWT methods produce very similar scalograms, with the main difference that STFT uses a fixed window size, leading to images with uniform time and frequency resolutions. Hence, the use of STFT entails a trade-off between time and frequency resolution. Conversely, CWT method allow to use a variable scaled window size to create graphs with non-uniform time and frequency resolutions.

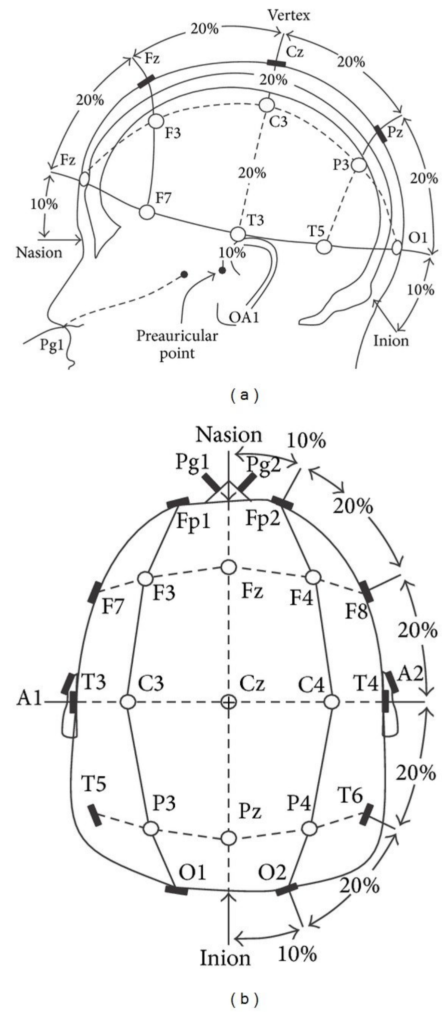


Fig. 1. The 10-20 EEG electrodes placement. (a) Side view. (b) Top view. [36]

III. Deep learning solutions for EEG analysis

A. Multilayer Perceptron

Multilayer Perceptron (MLP) is the most common feedforward neural network, in which the information flows unidirectionally from the input layer to the output layer, passing through one or more hidden layers. Each connection between neurons has its own weight. The MLPs with an arbitrary number of hidden units have been shown to be universal approximators for continuous maps to implement any function.

B. Convolutional Neural Networks

Convolutional Neural Networks is a feed forward neural network able to extract features from data through convolution structures. They provide a scalable approach to image classification and object recognition tasks, leveraging principles from linear algebra, specifically matrix multiplication, to identify patterns within an image. The main advantages of CNNs are: local connections (each neuron is connected to a small number

TABLE I
EEG FREQUENCY BANDS DESCRIPTION WITH PROPERTIES.

Band	Frequency (Hz)	Amplitude (μV)	Location	Activity
Delta	<3.5	100-200	Frontal	Deep sleep
Theta	4-7.5	5-10	Various	Drowsiness, light sleep
Alpha	8-13	20-80	Posterior region of head	Relaxed
Beta	14-30	1-5	Left and right side, symmetrical distribution, most evident frontally	Active thinking, alert
Gamma	>30	0.5-2	Somatosensory cortex	Hyperactivity

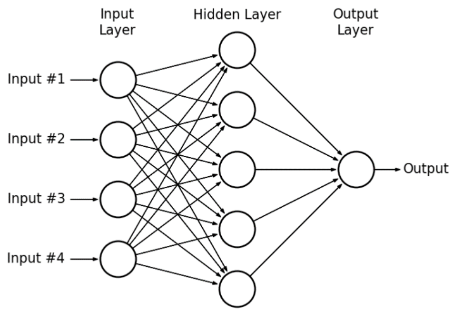
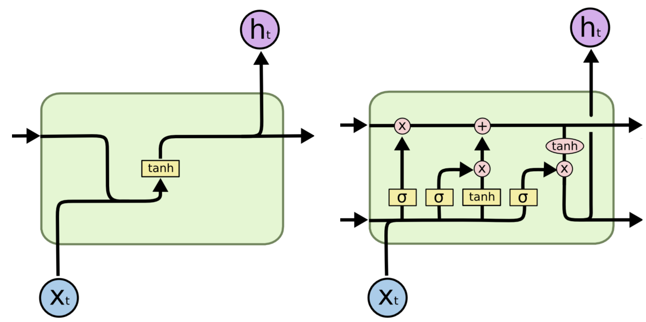


Fig. 2. A simple example of a Multilayer Perceptron.



(a) *RNN Unit* (b) *LSTM Unit*

Fig. 3. RNN (a) and LSTM (b) units.

of neurons, allowing to reduce the number of parameters and speed up convergence), weight sharing, down-sampling dimensionality reduction. In the context of EEG signals, CNNs are widely used in varuois applications [8], [11], [16], [18], [20], [21], [24], [37], [38].

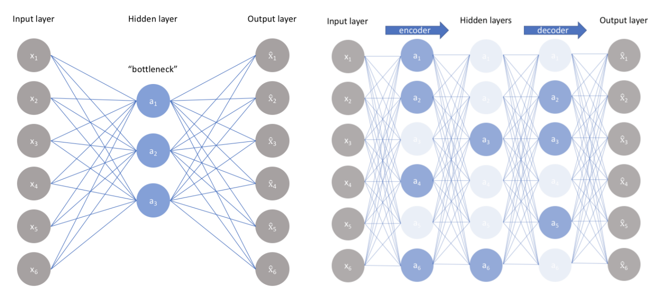
C. Recurrent Neural Networks and Long Short-Term Memory

A recurrent neural network (RRN) is a special kind of ANN adapted to analyze time series data. Differently from feed forward neural networks, which are designed for data points which are mutually independent, in the processing of time series a data point depends on the previous ones. In order to incorporate the dependencies between these data points, the RRN layer allows the model to store memory, and thanks to this, is capable to link the output to the input, so to have a feedback connection. Even if RNNs can ideally keep track of arbitrary long-term dependencies in the input sequences, in practice, when using back-propagation, the vanishing or exploding gradient problem can be encountered. To avoid this problem, Long Short-Term Memory (LSTM) networks has been proposed [39]. A common LSTM unit is composed of a cell, an input gate, an output gate and a forget gate. The cell remembers values over arbitrary time intervals and the three gates regulate the flow of information into and out of the cell. The RNN and LSTM units are illustrated in figure 3.

D. Autoencoder

Autoencoders (AEs) are a class of feed forward neural networks used to learn efficient coding of data (figure 4 a). In particular it uses a set of generative weights to convert the code vector into an approximate reconstruction of the input vector, in this way, the AE learn a representation (encoding) for a set of data, typically for dimensionality reduction, by training the network to ignore negligible data. The encoding is validated and refined by attempting to regenerate the input from the encoding [40].

Sparse Autoencoders (SAEs) [41], differently from the standard AE, may include more (rather than fewer) hidden units than inputs (figure 4 b), but only a small number of the hidden units are allowed to be active at the same time (thus, sparse). In this way, the network can sensitize individual hidden layer nodes toward specific attributes of the input data.



(a) *Autoencoder* (b) *Sparse Autoencoder*

Fig. 4. Autoencoder (a) and Sparse Autoencoder (b) architectures.

IV. APPLICATIONS

A. Motor Imagery

Motor imagery (MI) is the process of converting a participant's motor intentions into control signals employing motor imagery conditions [42]. This task is often tackled through the use of Brain Computer Interfaces (BCIs) which are systems that, by measuring and converting the central nervous system (CNS) activity, produce an artificial output. This output translates in the replacement, restoring or improvement of a natural CNS output, so a BCI creates a real-time interaction between the user and the environment [43] (figure 5). The

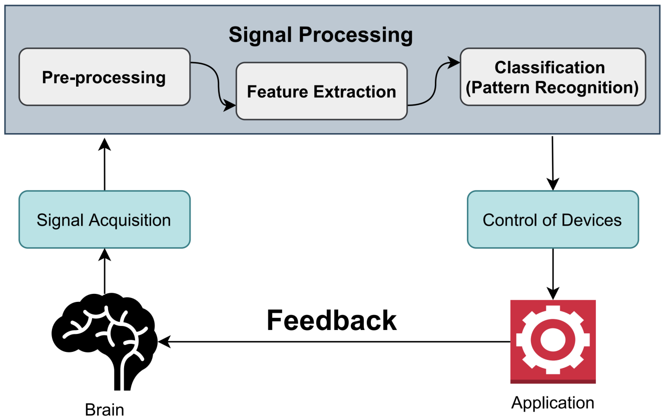


Fig. 5. Basic architecture of a BCI system. [33]

BCI operation depends on the interaction of two adaptive controllers, the user and the BCI itself. Indeed, the user express an intent as a brain signal, for example the will to move an hand. Then, the BCI must analyze the brain signals and translate them into commands which allow the user to achieve the goal. The user receives as feedback the BCI's output and its next intention may be consequentially influenced by such output. The EEG-based MI experiments on human subjects are complex processes. In fact, the available datasets are often very small and the EEG-based MI classifiers are subject-dependent due to variations of neuronal feedbacks among different subjects. It is evident that the BCI development is a very challenging task, which is at the center of many ongoing researches. In [22], a non-invasive MI-based BCI is presented. The goal consists in achieving linear control of an upper-limb neuroprosthesis. A comparison between some of the latest deep learning architectures for MI classification is presented in [44] and in [45] is proposed an end-to-end CNN-based MI classification which, through the use of data augmentation, have high potential for a subject-independent EEG-based MI classification.

B. Epileptic seizure detection and classification

One of the most common neurological diseases is epilepsy. Epilepsy is a neurological disorder identified by the frequent and unexpected occurrence of symptoms called epileptic seizure, due to abnormal brain activities. Seizure's characteristics include loss of awareness or consciousness and disturbances of movement, so its prediction would be useful for improving the quality of life of epileptic patients [15]. In literature, there are many approaches for seizure detection, classification and prediction based on Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). In some cases a feature extraction phase is performed on EEG signals, for example using Short-Time Fourier Transforms (STFT) based on Synchrosqueezing Transform (SST) [17] or, as in the case of [18], employing Power Spectrum density energy diagrams (PSDED), which are used as input for different DCNNs based on transfer learning to classify different epileptic states. In [21] they propose a lightweight DCNN method with an initial decomposition of input signals by a DWT algorithm. In [20] Qin et al. designed a feature fusion CNN model based on dilated convolution kernel to classify different brain states and, once the features are extracted by the CNN, they use a PSD method to study them. Instead, a different approach consists of feeding directly the neural network with the raw EEG signals [19], as described in depth in section V together with the first CNN-approach to solve EEG-based classification task for epilepsy states, by Acharya et al. [16].

C. Alzheimer's disease detection

Alzheimer's diseases (AD) is the most common form of dementia. It is a form of neural degenerative disorder, which slowly and silently occours in elderly. Patients diagnosed with AD show a progressive and irreparable decline of their cognitive functions. The disease often starts with Mild Cognitive Impairment (MCI) and progressively gets worse. If AD is diagnosed as early as possible, symptoms can be delayed through medication. Hence, AD detection is fundamental and it is carried out through many different systems such as EEG analysis. An effective method to analyze EEG is the functional connectivity measure, which allows to represent correlations between signals from different brain areas. They have been widely used as AD indicators and they represent low-order functional connectivity (LOFC), together with high order functional connectivity (HOFC) measurement methods in four frequency bands, which help to analyze more complex inter-regional interactions or similarities between all pairs of LOFC profiles. [9]. Other features that can be easily used as input for training deep learning methods are for example average Time-Frequency Maps (aTFMs) [12], Relative Power (RP) [10], CWT and BiS [13], [46], which are widely described in section VI.

D. Emotion detection

One of the most engaging applications of EEG signals is emotion recognition. When categorizing human emotions, two conventional rules are adopted: the discrete basic emotion description and the dimension approaches [6]. According to the first one, emotions can be classified into six basic emotions: joy, surprise, sadness, anger, fear and disgust, while the second states that emotions can be classified into two (valence and arousal) or three dimensions (valence, arousal and dominance) [5]. Valence is associated to the level of positivity or negativity of a person, arousal characterize the level of excitement or apathy while the dominance ranges from submissive (without control) to dominance (empowered). The frontal and parietal lobes are the most informative about the emotional states, while the alpha, gamma and beta waves appear to be the most discriminative [47]. Emotions can be very useful in the field of Human-Computer Interaction (HCI). For this purpose, Affective Computing (AC) aspires to narrow this gap by developing computational systems that recognize and respond to human emotions, often by making use of pattern recognition and machine learning techniques. EEG-based emotion recognition can be employed in different areas such as entertainment, e-learning, virtual reality, e-healthcare applications [5]. In literature, it is possible to find many relevant examples of EEG-based DL systems for emotion detection. In [4] the authors presented a neural network model which involves a combination of CNN, Sparse Autoencoder (SAE) and DNN, able to convert the EEG time series into 2D images for the emotion classification task.

V. Epileptic seizure detection and classification

A. Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals

Acharya et al. [16] were the first to build a DCNN system for the automated detection and diagnosis of epileptic seizures using EEG signals. They used EEG segments collected at Bonn University, Germany [48], selected from continuous multichannel EEG recordings. Such recordings were cleaned from artifacts via visual examination. The dataset is obtained from five subjects and three out five sets of data are considered, corresponding to the normal, preictal and seizure classes. Each dataset contains 100 EEG signals, each of which is a single-channel EEG signal with a duration of 23.6 s. In a pre-processing stage, the EEG signals were normalized through Z-score normalization, zero mean and standard deviation of 1, with sampling rate set to 173.61 Hz. The proposed model is a DCNN composed of 13 layers which receives a 4097 long input sample. The architecture is composed of five convolutional layers, each followed by a max-pooling stage. Then, there are three FC layers, with the last one having the role of predicting which class the input EEG signal belongs to, by using the softmax activation function. All paramters are carefully fine-tuned in order to obtain a model with optimal convergence rate. For testing and evaluating the model, a 10-fold cross-validation approach was employed. The results were evaluated through the following metrics:

$$\begin{aligned}
&\text{Sensitivity} = \frac{TP}{TP+FN}\\
&\text{Specificity} = \frac{TN}{TN+FP}\\
&\text{Precision} = \frac{TP}{TP+FP}\\
&\text{F1-score} = 2\,\frac{\text{sensitivity}\cdot\text{precision}}{\text{sensitivity}+\text{precision}}\\
&\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN}
\end{aligned} \tag{1}$$

The presented work's main novelty relies on the implementation of a DCNN model for the automated classification of EEG signals into normal, preictal and seizure classes. Even though such model does not outperform the state-of-the-art results, it is able to achieve very good performances. In fact, 88.67% is easily obtained, with 95% sensitivity and 90% specificity. This application had a huge impact in the literature, leading the way to many other researchers in developing similar approaches with more powerful architectures, possibly to be tested on larger datasets to improve performances.

B. Deep C-LSTM Neural Network for epileptic seizure and tumor detection using high-dimension EEG signals

Many DL contributions proved to be very effective in classifying seizures from EEG signals, but they are limited in the context of multiple-class classification with automatic feature extraction. Moreover, in most cases the identifiable EEG segment is too long to be used in real time epileptic seizure detection. In [19] a novel deep Convolutional LSTM (C-LSTM) model is proposed. The main contribution concerns the ability of the neural network to classify five brain states and the possibility to detect a seizure with a short EEG signal segment of only one-second. The EEG signals for epileptic seizures and tumors are adopted from the same dataset employed in [16], so it consists of 128-channel raw EEG signals organized into five sets, where A and B represent the awake state of eyes open and closed respectively, set C and D are the selected EEG signals from the hippocampal and epileptogenic zone during seizure-free intervals, while set E is the seizure activity. In this paper, differently from [16] where they perform a three-class classification task, the objective consists in a five-class classification task using high dimensions EEG signals for accuracy enhancement and noise robustness. First of all, raw signals need to be reconstructed for feeding the neural network. Hence, the inputs are a sequence of matrices of dimension $100 \times L_d$ changing over time, where L_d is a fixed detection length used for sliding window strategy. The reason behind the choice of building a deep C-LSTM architecture is due to two main facts. First, DCNN and LSTM models alone are proven to be powerful to handle time sequence and noise robustness, but without mantaining a high and stable classification accuracy. Second, LSTM model results to be time-consuming for containing too much redundancy. While, a C-LSTM method, which consists of a DCNN module and a LSTM one, aims to extract the features, reduce the dimension of raw EEG signals and enhance recognition accuracy. The architecture is depicted in figure 6.

In the DCNN module, there are two 2D convolutional blocks followed by a batch normalization (BN) and a Rectified Linear Unit (ReLU) activation function. Then, a dropout layer is added before the fully connected (FC) and softmax layer. Adam optimizer for adaptive estimates of low-order moments is used. The output of the DCNN block is passed to the LSTM network. It consists of 30 nodes to learn the information from the time sequence. In fact, since the EEG signals are time-based, each sample has a strong relationship with the previous ones. Similarly to the previous module, the LSTM block adopts the Adam optimizer as well. Subsequently, another dropout layer are used before the last FC layer. In fact, dropout can mitigate the overfitting problem and aims to imporve the generalization error along with the increasing layers of the neural networks. It also contributes to reduce the training time. After the FC layer, the softmax activation function is employed. In the experimental phase, they have chosen

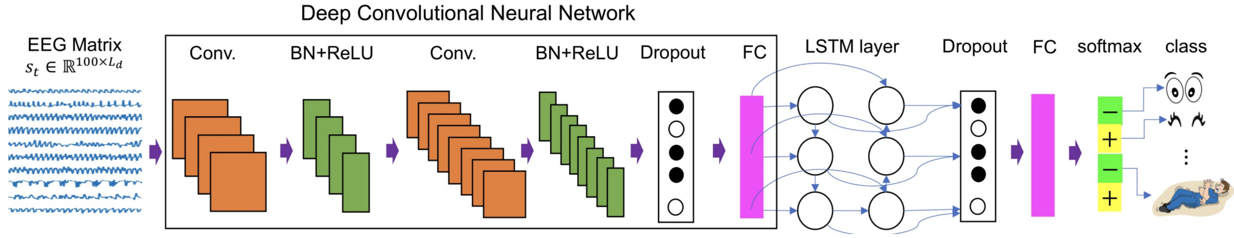


Fig. 6. C-LSTM architecture proposed in [19] for epileptic seizure detection task.

three types of detection length to evaluate the classification accuracy, namely 1s, 1.5s and 2s. For evaluation purposes, overall accuracy, sensitivity and F1-score are used, which are expressed as in equation 1.

The results confirm that the C-LSTM model obtains the highest accuracy compared to the DCNN and LSTM models. It also achieves an accuracy higher than 98% for shorter detection periods. Another comparison is done between the networks by employing F1-score metric. Even in this case, C-LSTM outperforms the other ones, resulting in the highest F1-score, proving that it is the best method for accuracy enhancement and robustness. Moreover, the average sensitivity is also computed. Although the C-LSTM method achieves the best sensitivity score, the DCNN model seems better in recognizing seizure activity, as opposed to the LSTM network, which gets a higher recognition rate for identifying eyes open or closed instead. The noise robustness tests, which are conducted by adding different white noises to the raw EEG signals, are done in order to prove the effectiveness of the method in practical operation. The results show that C-LSTM model obtained the best accuracy (99.38%) for noise robustness and also the lowest standard deviation.

VI. Alzheimer's disease detection

A. A novel multi-modal machine learning based approach for automatic classification of EEG recordings in dementia

Ieracitano et al. [13] presented a multi-modal ML based approach aimed to integrate engineered features for classification of brain states. They proposed a similar work in [12] where a feature extraction phase with the use of CWT was adopted. Here we will describe an improved and more interesting version which was proposed in 2020. EEG signals were acquired from 189 subjects diagnosed with AD, MCI and HC. The dataset is balanced and consists of 19-channels recordings acquired according to the $10-20$ system at 1024 Hz and notch-filtered at 50 Hz. A pre-processing stage was performed in order to clean the signals from artifacts and noise. In particular, a band-pass filter between 0.5 Hz and 32 Hz was applied and the signals were down-sampled to 256 Hz. An epoching was performed ending with M non-overlapping epochs of 5 s. Each epoch is composed of $N = 1280$ samples so, for each considered subject, M epochs of size $n \times N$ were stored to be processed. After the pre-processing, a time-frequency analysis was performed to extract the features from the EEG segmented signals. Using spectral representations leads to many computational advantages in neural networks learning, but the spectral content of the signals is often insufficient. The EEG dynamics should be also considered, in fact some relevant information can be captured through a time-frequency (TF) approach. The problem is that Fourier analysis does not capture nonlinear high order interaction among EEG signal components. Bispectral analysis is an alternative methodology able to detect the nonlinear changes in cortical generating processes which induce alterations in the signals collected at the scalp. It has been observed that nonlinear interactions that generate multivariate time series can be estimated by higher-order phase coupling. So, the main contribution by the authors is a feature extraction method, called *multi-modal*, which involves the CWT with *Mexican hat* mother wavelet and the Bispectrum (BiS) methods. First, for each epoch and for each channel the time-frequency representation (TFR) is estimated. So 19 TFR are estimated and averaged, resulting in a single average TFR (ATFR). The BiS analysis is performed to analyze the higher-order statistics (HOS). For each channel, a bispectrum representation (BiSR) is computed and then averaged, giving a single average BiSR (ABiSR). For each epoch two sets of features are extracted, namely one from the ATFR map and the other from the ABiSR. In the CWT features extraction, each ATFR is partitioned into five time-frequency sub-maps corresponding to the five EEG rhythms (*delta*, *theta*, $alpha_1$, $alpha_2$, *beta*) and five CWT features are extracted: mean, standard deviation, skewness, kurtosis and entropy. Similarly, for the BiS features extraction, each epoch is divided into five bispectrum maps corresponding to the EEG rhythms and finally the following BiS features are extracted from the sub-bands: normalized bispectral entropy, normalized bispectral squared entropy, sum of logarithmic amplitudes of diagonal elements of the bispectrum, first-order spectral moment of the amplitudes of diagonal elements of the bispectrum and second-order spectral moment of the amplitudes of diagonal elemets of the bispectrum. Then, three features vectors are generated and used as input to the multi-modal ML classifiers. In particular, a vector made by CWT features only (25), a second vector with BiS features only (30) and a third vector composed of the concatenation of the two sets of features (55). The classification task was performed as three single binary classification tasks (AD vs HC, AD vs MCI, MCI vs HC) and a three-class classification task as well (AD vs MCI vs HC). Four standard ML techniques were considered, specifically the Autoencoder (AE), Multilayer Perceptron (MLP), Logistic Regression (LR) and Support vector Machine (SVM). The reason for this choice rely on the more suitable use of these methods for practical applications and clinical acceptance. Moreover, DL models are powerful but they require larger datasets to learn good representations. The schematic representation of the proposed architecture can be appreciated in figure 7.

The AE consists of an encoder and a decoder module. The input vector is mapped into the compressed representation in the encoding stage, then the encoded representation is mapped back to the input through the decoding stage. The role of the AE is to minimize the error between the original input data and its reconstructed version. This is done by minimizing a loss function, that is the mean square error (MSE). The authors built four different AE architectures, which differ for the number of hidden layers and units. AE_1 and AE_2 were employed with the *only-CWT* and *only-BiS* inputs, while AE_3 and AE_4 were used when the multi-modal feature vector was considered as input. The features extracted from the AE passes through a FC layer with softmax activation function to perform the classification task. Similarly, four MLP classifiers were built which differ in number of hidden layers and units. All the MLP have at the end a softmax activation function, each hidden layer has a saturating ReLU activation function and they employ cross-entropy loss function. The LR classifier in this case provides the probability of a given input to belong to one of the classes. For the SVM classifier, a linear kernel has been used to perform the classification task. For evalutation purposes, the metrics in 1 were used. The experiments have shown that in the case of *only-CWT* features based classification, for each of the binary classification tasks, although the AE classifiers reported good performances, MLP classifiers achieved the highest accuracy and F-score. In particular, in the three-class classification task, MLPs outperformed all other architectures, obtaining acceptable accuracy values. Classification based on *only-BiS* showed slightly lower values for the considered metrics for each classifier. The best performances were obtained by MLP classifiers also in this case. Finally, the multi-modal *CWT+BiS* based classification led to the most valid results. In fact, all the classifiers achieved high results, even though MLP ones demonstrated to be the best choice also in this case.

The main contribution by the authors was the description of the potential of both CWT and BiS features extracted from time-frequency and bispectrum representations. They proved the ability of different ML models to better discriminate among AD, MCI and HC EEG epochs thanks to the multi-modal approach. This proved the hypothesis that high-order features extracted from the bispectrum and TF maps enhance the classification. They suppose that the improved classification performance depends on the ability of the bispectrum to capture nonlinear couplings between channels in the frequency domain, while CWT helps to observe how the frequency content changes over time. A comparison of all the methods employed for this task showed that MLP_3 classifier achieved the highest accuracy of 96.95% in AD vs HC, 90.24% in AD vs MCI, $96,24\%$ in MCI vs HC and 89.22% in AD vs MCI vs HC classification. This was a very simple architecture (1 hidden layer with 30 neurons) which requires a minimal number of parameters and short training time. The MLP models outperformed the AE ones, this is due probably to the fact that AEs are useful to extract features from high-dimensional representations, but since the input size was very small, the compression ability of these networks was not exploited in this case, leading to misclassification of the EEG epoch in some cases.

B. Deep learning of resting-state EEG signals for three-class classification of Alzheimer's disease, mild cognitive impairment and healthy ageing

In 2021 Huggins et al. [46] proposed a CNN model for three-class classification of AD vs MCI vs HA. The dataset used in this task consisted in resting-state EEG samples acquired at 200 Hz with 21 electrodes using $10-20$ system, from age-matched groups of 52 AD subjects, 37 MCI subjects and 52 HA ones, for a total of 141 subjects. The raw data were pre-processed to remove artifacts and noise, using a band-pass filter, a FIR filter, ICA and notch filters and they were split into epochs of 5 s. Each sample was subsequently processed with the CWT using the *Morse* mother wavelet, which was chosen because directly applicable to the complex and non-stationary nature of EEG signals. This results in time-frequency graphs with a wavelet coefficient scale range of 0-600, characterized by a plot of frequency against time, with the energy of the CWT coefficients indicated by the colour of the plot. These scalograms were combined into tiled topographical maps governed by the $10-20$ system for electrodes placement, ending with 16197 topographical images (6020 AD, 4289 MCI and 5888 Ha). The obtained set of images obtained was used to train an AlexNet DL model, composed of five hidden convolutional layers (figure 8), which was optimized for many hyperparameters. The model was validated through *k*-fold cross-validation with *k*=10 and the results were analyzed through the overall accuracy metric. Their model achieved an overall accuracy of 98.9%, which outperforms all other solutions considered, even the one from [13]. They also made a comparison of their AlexNet model between ResNet-18 and GoogLeNet. This test showed that even though ResNet-18 and GoogLeNet was more complex than the proposed ones, they suffered from different drawbacks such as long training time and worse accuracy results, proving that AlexNet solution was the best for this task. Moreover, the use of CWT made possible to have graphs with non-uniform resolutions, which allow lower frequencies in the data to be seen at longer time intervals and higher frequency trends to be seen at shorter time intervals. They claim to have appropriately chosen CWT signal processing method because of the non-stationary nature and varied frequency range of EEG signals.

VII. Conclusions

In the last decades, Artificial intelligence techniques, in particular the deep learning ones, have been widely used in

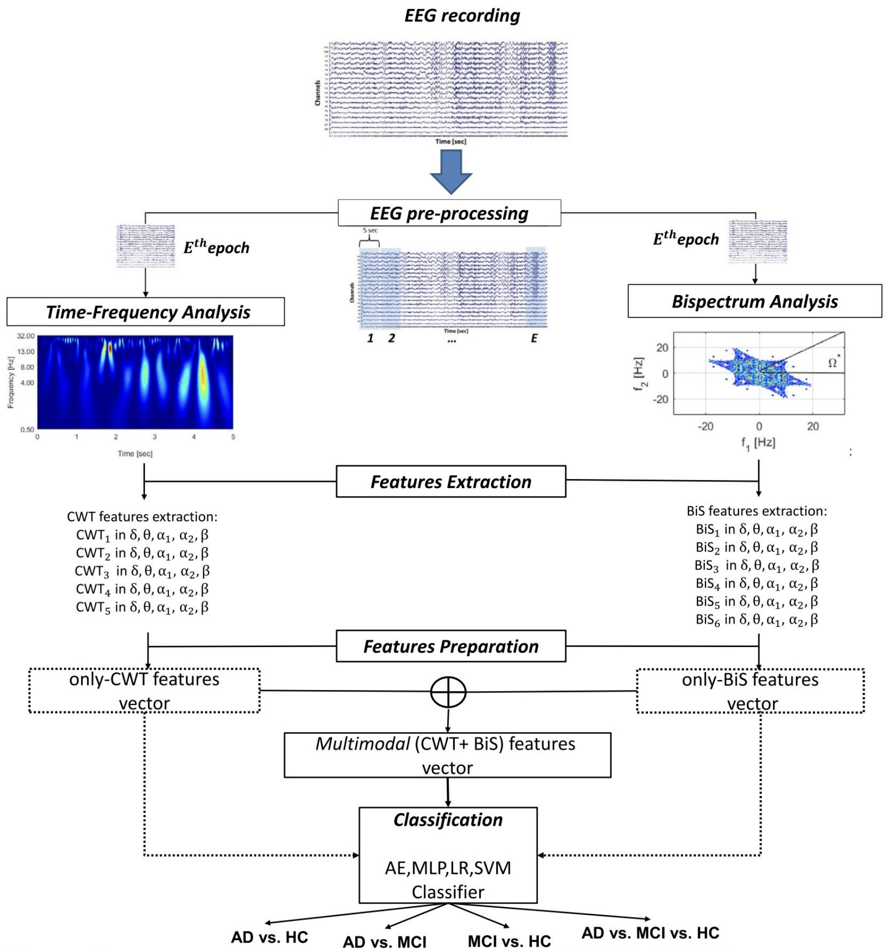


Fig. 7. The multi-modal approach proposed in [13] for Alzheimer's disease classification.

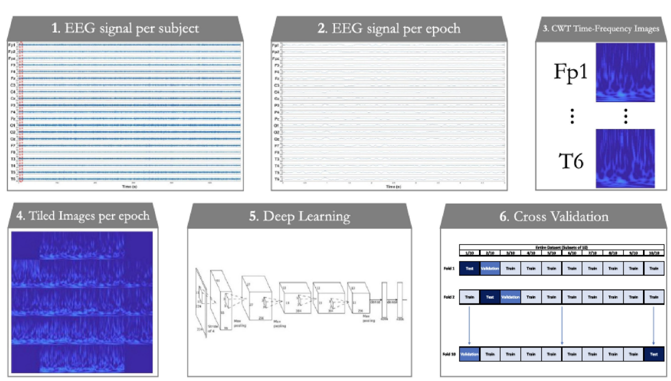


Fig. 8. The model architecture proposed by Huggins et al. [46] for Alzheimer's disease classification.

various contexts and successfully employed for time series data, such as EEG signals. EEG analysis applications are several, ranging from diseases detection to motor imagery, each one having peculiarities which characterize both the problem and its solution. In literature various approaches achieved significant results in dealing with these problems, bringing out that the pre-processing and feature extraction of the signals are often crucial and application-dependent, even if some of the newest works exploit effectively an end-to-end approach, leaving the feature extraction task entirely to the Neural Network. In this report we focused our attention on the most recent and relevant applications in the field of Deep Learning applied to EEG signals analysis. In particular, we presented two kind of applications: epileptic seizure and Alzheimer's disease detection, describing in details, for each of them, two state-of-the-art examples. The seizure detection task aims to improve the quality of life and treatment of the patients by predicting the seizure event. In literature this task has been widely tackled, but we choose two recent contributions. Acharya et al. [16] were the first to build a DCNN system for the detection and diagnosis of epileptic seizures using EEG signals as raw inputs to the neural network, achieving very good accuracy metrics. Liu et al. [19] proposed a novel C-LSTM model for five-class classification, achieving outstanding results in accuracy metrics. For the Alzheimer's disease detection and classification task, Huggins et al. [46] proved the ability of a deep CNN to achieve the highest accuracy score for a three-class classification task of AD vs MCI vs HA, which had a solid impact in literature. In the case of Ieracitano et al. [13], a three-class classification task is proposed with a novel multi-modal feature extraction phase, which substantially improved the performances for each of the proposed classification tasks. We deduced that the use of DL techniques for EEG data analysis is a growing field, where brilliant solutions may be limited only by the size of the available datasets. In fact, more efficient and high-performance solutions may be obtained if there were larger and better organized datasets.

References

[1] M. S. Murtazina and T. V. Avdeenko, "Classification of brain activity patterns using machine learning based on eeg data," in *2020 1st International Conference Problems of Informatics, Electronics, and Radio Engineering (PIERE)*, 2020, pp. 219–224.

[2] Y. Ming, D. Wu, Y.-K. Wang, Y. Shi, and C.-T. Lin, "Eeg-based drowsiness estimation for driving safety using deep q-learning," *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 5, no. 4, pp. 583–594, 2021.

[3] Q. Zhang, X. Chen, Q. Zhan, T. Yang, and S. Xia, "Respiration-based emotion recognition with deep learning," *Computers in Industry*, vol. 92-93, pp. 84–90, 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0166361516303104

[4] J. Liu, G. Wu, Y. Luo, S. Qiu, S. Yang, W. Li, and Y. Bi, "Eeg-based emotion classification using a deep neural network and sparse autoencoder," *Frontiers in Systems Neuroscience*, vol. 14, p. 43, 2020. [Online]. Available: https://www.frontiersin.org/article/10.3389/fnsys.2020.00043

[5] W.-L. Zheng and B.-L. Lu, "Investigating critical frequency bands and channels for eeg-based emotion recognition with deep neural networks," *IEEE Transactions on Autonomous Mental Development*, vol. 7, pp. 1–1, 09 2015.

[6] van den Broek, "E.l. ubiquitous emotion-aware computing." *Pers Ubiquit Comput*, vol. 17, p. 53–67, 2013.

[7] M. Ismail, K. Hofmann, and M. A. A. El Ghany, "Early diagnoses of alzheimer using eeg data and deep neural networks classification," in *2019 IEEE Global Conference on Internet of Things (GCIoT)*, 2019, pp. 1–5.

[8] C. Ieracitano, N. Mammone, A. Hussain, and F. C. Morabito, "A convolutional neural network based self-learning approach for classifying neurodegenerative states from eeg signals in dementia," in *2020 International Joint Conference on Neural Networks (IJCNN)*, 2020, pp. 1–8.

[9] F. Duan, Z. Huang, Z. Sun, Y. Zhang, Q. Zhao, A. Cichocki, Z. Yang, and J. Solé-Casals, "Topological network analysis of early alzheimer's disease based on resting-state eeg," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 10, pp. 2164–2172, 2020.

[10] D. Kim and K. Kim, "Detection of early stage alzheimer's disease using eeg relative power with deep neural network," in *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2018, pp. 352–355.

[11] F. C. Morabito, M. Campolo, C. Ieracitano, J. M. Ebadi, L. Bonanno, A. Bramanti, S. Desalvo, N. Mammone, and P. Bramanti, "Deep convolutional neural networks for classification of mild cognitive impaired and alzheimer's disease patients from scalp eeg recordings," in *2016 IEEE 2nd International Forum on Research and Technologies for Society and Industry Leveraging a better tomorrow (RTSI)*, 2016, pp. 1–6.

[12] C. Ieracitano, N. Mammone, A. Bramanti, S. Marino, A. Hussain, and F. C. Morabito, "A time-frequency based machine learning system for brain states classification via eeg signal processing," in *2019 International Joint Conference on Neural Networks (IJCNN)*, 2019, pp. 1–8.

[13] C. Ieracitano, N. Mammone, A. Hussain, and F. C. Morabito, "A novel multi-modal machine learning based approach for automatic classification of eeg recordings in dementia," *Neural Networks*, vol. 123, pp. 176–190, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0893608019303983

[14] X. Shi, T. Wang, L. Wang, H. Liu, and N. Yan, "Hybrid convolutional recurrent neural networks outperform cnn and rnn in task-state eeg detection for parkinson's disease," in *2019 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC)*, 2019, pp. 939–944.

[15] H. Daoud and M. A. Bayoumi, "Efficient epileptic seizure prediction based on deep learning," *IEEE Transactions on Biomedical Circuits and Systems*, vol. 13, no. 5, pp. 804–813, 2019.

[16] U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, and H. Adeli, "Deep convolutional neural network for the automated detection and diagnosis of seizure using eeg signals." *Computers in Biology and Medicine*, 2017.

[17] O. K. Cura, M. A. Ozdemir, and A. Akan, "Epileptic eeg classification using synchrosqueezing transform with machine and deep learning techniques," in *2020 28th European Signal Processing Conference (EUSIPCO)*, 2021, pp. 1210–1214.

[18] Y. Gao, B. Gao, Q. Chen, J. Liu, J. Liu, and Y. Zhang, "Deep convolutional neural network-based epileptic electroencephalogram (eeg) signal classification." *Frontiers in Neurology*, 2020.

[19] Y. Liu, Y. Liu, Y. Liu, Y.-X. Huang, X. Zhang, W. Qi, J. Guo, Y. Hu, L. Zhang, and H. Su, "Deep c-lstm neural network for epileptic seizure and tumor detection using high-dimension eeg signals," *IEEE Access*, 2020.

[20] H. Qin, B. Deng, B. Deng, J. Wang, G. Yi, R. Wang, R. Wang, and Z. Zhang, "Deep multi-scale feature fusion convolutional neural network for automatic epilepsy detection using eeg signals," *2020 39th Chinese Control Conference (CCC)*, 2020.

[21] N. Nemati, S. Meshgini, and A. Farzamnia, "A robust framework epileptic seizures classification based on lightweight structure deep convolutional neural network and wavelet decomposition," *2020 28th Iranian Conference on Electrical Engineering (ICEE)*, 2020.

[22] J. Pascual, F. Velasco-Élvarez, K.-R. Müller, and C. Vidaurre, "First study towards linear control of an upper-limb neuroprosthesis with an eeg-based brain-computer interface," in *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2012, pp. 3269–3273.

[23] T.-j. Luo, Y.-c. Fan, J.-t. Lv, and C.-l. Zhou, "Deep reinforcement learning from error-related potentials via an eeg-based brain-computer interface," in *2018 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, 2018, pp. 697–701.

[24] E. Santamaría-Vázquez, V. Martínez-Cagigal, F. Vaquerizo-Villar, and R. Hornero, "Eeg-inception: A novel deep convolutional neural network for assistive erp-based brain-computer interfaces," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 12, pp. 2773–2782, 2020.

[25] A. Partovi, F. Goodarzy, E. S. Nurse, P. Karoly, D. Freeston, M. Cook, A. N. Burkitt, and D. Grayden, "A convolutional neural network model for decoding eeg signals in a hand-squeeze task¡sup¿1¡/sup¿," in *2020 8th International Winter Conference on Brain-Computer Interface (BCI)*, 2020, pp. 1–6.

[26] R. Alazrai, M. Abuhijleh, H. Alwanni, and M. I. Daoud, "A deep learning framework for decoding motor imagery tasks of the same hand using eeg signals," *IEEE Access*, vol. 7, pp. 109 612–109 627, 2019.

[27] D. Achanccaray and M. Hayashibe, "Decoding hand motor imagery tasks within the same limb from eeg signals using deep learning," *IEEE Transactions on Medical Robotics and Bionics*, vol. 2, no. 4, pp. 692–699, 2020.

[28] R. Kar, L. Ghosh, A. Konar, A. Chakraborty, and A. K. Nagar, "Eeg-induced autonomous game-teaching to a robot arm by human trainers using reinforcement learning," *IEEE Transactions on Games*, pp. 1–1, 2021.

[29] O. P. Idowu, P. Fang, X. Li, Z. Xia, J. Xiong, and G. Li, "Towards control of eeg-based robotic arm using deep learning via stacked sparse autoencoder," in *2018 IEEE International Conference on Robotics and Biomimetics (ROBIO)*, 2018, pp. 1053–1057.

[30] I. Akinola, Z. Wang, J. Shi, X. He, P. Lapborisuth, J. Xu, D. Watkins-Valls, P. Sajda, and P. Allen, "Accelerated robot learning via human brain signals," in *2020 IEEE International Conference on Robotics and Automation (ICRA)*, 2020, pp. 3799–3805.

[31] M.-P. Hosseini, A. Hosseini, and K. Ahi, "A review on machine learning for eeg signal processing in bioengineering," *IEEE Reviews in Biomedical Engineering*, vol. 14, pp. 204–218, 2021.

[32] E. D. Adrian and B. H. C. Matthews, "The Berger Rhythm: Potential Changes From The Occipital Lobes In Man," *Brain*, vol. 57, no. 4, pp. 355–385, 12 1934. [Online]. Available: https://doi.org/10.1093/brain/57.4.355

[33] M. F. Mridha, M. F. Mridha, S. C. Das, M. M. Kabir, M. M. Kabir, A. A. Lima, M. R. Islam, M. R. Islam, Y. Watanobe, and Y. Watanobe, "Brain-computer interface: Advancement and challenges." *Sensors*, 2021.

[34] H. H. Jasper, H. H. Jasper, and H. H. Jasper, "The ten-twenty electrode system of the international federation," *Electroencephalography and Clinical Neurophysiology*, 1958.

[35] L. Hu and Z. Zhang, *EEG Signal Processing and Feature Extraction*, 01 2019.

[36] C. J. A. Sanei S., *EEG Signal Processing*, 2007.

[37] V. J. Lawhern, A. J. Solon, N. R. Waytowich, S. M. Gordon, C. P. Hung, and B. J. Lance, "Eegnet: A compact convolutional network for eeg-based brain-computer interfaces," *Journal of Neural Engineering*, 2018.

[38] R. T. Schirrmeister, J. T. Springenberg, L. D. J. Fiederer, M. Glasstetter, K. Eggensperger, M. Tangermann, F. Hutter, W. Burgard, and T. Ball, "Deep learning with convolutional neural networks for eeg decoding and visualization," *Human Brain Mapping*, vol. 38, no. 11, pp. 5391–5420, 2017. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/hbm.23730

[39] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Computation*, 1997.

[40] G. E. Hinton and R. Zemel, "Autoencoders, minimum description length and helmholtz free energy," in *Advances in Neural Information Processing Systems*, J. Cowan, G. Tesauro, and J. Alspector, Eds., vol. 6. Morgan-Kaufmann, 1994. [Online]. Available: https://proceedings.neurips.cc/paper/1993/file/9e3cfc48eccf81a0d57663e129aef3cb-Paper.pdf

[41] A. Makhzani and B. J. Frey, "K-sparse autoencoders," *ICLR*, 2013.

[42] M. D. Golub, S. M. Chase, A. P. Batista, and B. M. Yu, "Brain–computer interfaces for dissecting cognitive processes underlying sensorimotor control," *Current Opinion in Neurobiology*, vol. 37, pp. 53–58, 2016, neurobiology of cognitive behavior. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S095943881500183X

[43] J. Wolpaw and E. Wolpaw, *Brain-Computer Interfaces: Principles and Practice*, 01 2012.

[44] N. Lu, T. Yin, and X. Jing, "Deep learning solutions for motor imagery classification: A comparison study," *2020 8th International Winter Conference on Brain-Computer Interface (BCI)*, 2020.

[45] C. Zhang, Y.-K. Kim, and A. Eskandarian, "Eeg-inception: An accurate and robust end-to-end neural network for eeg-based motor imagery classification," *Journal of Neural Engineering*, vol. 18, 03 2021.

[46] C. J. Huggins, J. Escudero, M. A. Parra, B. Scally, R. Anghinah, A. V. L. de Araújo, L. F. H. Basile, and D. Abásolo, "Deep learning of resting-state electroencephalogram signals for 3-class classification of alzheimer's disease, mild cognitive impairment and healthy ageing." *Journal of Neural Engineering*, 2021.

[47] S. M. Alarcão and M. J. Fonseca, "Emotions recognition using eeg signals: A survey," *IEEE Transactions on Affective Computing*, 2019.

[48] R. G. Andrzejak, K. Lehnertz, F. Mormann, C. Rieke, P. David, and C. E. Elger, "Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state," *Phys. Rev. E*, vol. 64, p. 061907, Nov 2001. [Online]. Available: https://link.aps.org/doi/10.1103/PhysRevE.64.061907