In Praise & Critique of EEG for BCI Applications

Theses of the Ph.D. Dissertation

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Abstract

Current EEG research has enriched our literature and societies with many prospects for fruitful applications. This sophisticated yet simple device allows monitoring of the human brain in various states for clinical applications and cognitive science studies. It can accurately identify the distinct sleep stages or the depth of anaesthesia and identifies seizures and other neurological disorders to diagnose neurodegenerative diseases and track their progression. Other methods reveal robust EEG correlations with cognitive processes associated with working memory, mental calculations, and selective attention. EEG is essential in measuring coma depth or determining cerebral death. It is also used in neurofeedback rehabilitation and psychopharmacology studies, perception, awareness, language production and comprehension, structure vs function in the brain, spatial navigation, alertness monitoring, depression, and mental state studies.

Since its first inception by Hans Berger almost a century ago, EEG has carried a massive burden in its core ideology, an irony to question telepathy, the dichotomy of whether it is actual or not, or to study higher brain abilities, mind genesis, cognition, and consciousness. Or as in the concept of (BCI), an acronym for Brain Computer Interface, that has fascinated researchers all around the world, to have the ability to read, interpret and control thoughts or control machines through thoughts instinctively and intuitively, restoring abilities, skills and control for people with disabilities who lost motor functions, providing alternative new means and tools for those with severe neuromuscular disorders, paraplegia, amyotrophic lateral sclerosis (ALS), locked-in syndrome (LIS), cerebral palsy, amputation, or trauma. More benefits would also be harnessed for non-medical applications in gaming, polygraphy, and personal identification.

BCI research is one of the most interdisciplinary and multidisciplinary subjects in contemporary neuroscience and engineering. It falls at the intersection of many fields as it combines mathematics, biology, physics, physiology and psychology, medicine, information technology, computer science, biomaterials, and the mainstream engineering disciplines of electrical, mechanical, and electronic engineering, in addition to biochemistry, signal processing, machine learning, statistics, control theory and more.

EEG is the most prominent candidate to realize BCI Sensorimotor Imagery (MI) Systems due to the non-invasive nature of data acquisition, low cost of fabrication, and a high degree of mobility and portability, which makes it the preferred module among researchers rather than the bulky and expensive functional Magnetic Resonance Imaging (fMRI) and Magnetoencephalography (MEG). Aiming to replace, restore, enhance, or improve the natural Central Nervous System (CNS) output to foster healthcare service and improve life quality. Different signal analysis methods, feature extraction, dimension reduction, and classification have been proposed. Our goal of having a plug-and-play system driven and enabled by oscillatory brain waves and rhythms is still in its early stages of research and exploration.

Aims and motive

This thesis aims to emphasize the role of EEG in clinical diagnosis, neurorehabilitation, cognitive sciences, psychopharmacology and sleep research, perception, awareness, attention and memory, language production, spatial navigation, alertness monitoring, and BCIs. EEG is typically used to diagnose or monitor conditions such as epilepsy, sleep disorders, and brain damage. The patterns and frequencies of the brain waves recorded by the EEG can provide insight into the functioning of the brain and its responses to various stimuli.

EEG-based BCI refers to a technology that interfaces with the human brain to translate electrical activity generated by neurons into commands that control a computer or a variety of other devices and assistive technologies, exoskeletons and robotic devices. The central goal of BCI research and development is for people severely disabled by neuromuscular disorders such as (ALS), stroke, spinal cord injury (SPI), cerebral palsy, multiple sclerosis, and muscular dystrophy. BCI systems would allow individuals with physical disabilities or locked-in syndrome to interact with the world using their brain activity, bypassing their physical limitations, and improving their quality of life, subsequently enabling them to live enjoyable and productive lives if provided with effective assistive technology.

Several challenges come with using and designing EEG-based BCI systems, including low signal-to-noise ratio (SNR), variability in brain signals, and the need for calibration and parameterization, in addition to the complexity of processing and interpreting neural signals. However, with improvements in signal processing and machine learning algorithms, EEG-based BCI systems are becoming more reliable and accurate. However, the rapid increase in BCI research has exposed an underappreciated problem: BCI Illiteracy. This problem remains unresolved across all major BCI approaches (P300, SSVEP, and ERD/ERS).

This work explores machine-learning methods for multi-class EEG Motor Imagery (MI) signal classification and comments on using EEG as a medium to construct BCIs and praises this selection, and addresses current challenges. Our results propose that Convolutional Neural Networks (CNNs) designs and Deep Learning (DL) algorithms are fit for implementing feature extraction and classification. Using fewer channels and feature vectors would also reduce the computational complexity and increase the classifier models' speed and accuracy.

The EEG

The EEG is a dynamic non-invasive, relatively inexpensive technique used to monitor the state of the brain. Despite the tremendous progress in structural and functional brain imaging over the last decades, scalp EEG has remained an indispensable diagnostic tool for studying physiologic and pathologic cerebral activity. An EEG is simply a record of the brain's electrical activities, recorded as a set of surface potentials by placing electrodes on the scalp [1] [8] [9].

Electrical recordings from the head's outer surface demonstrate continuous electrical activities within various underlying cortex regions. Both the intensities and patterns of these electrical activities are significantly determined by the overall levels of regional Inhibitory and excitatory postsynaptic oscillatory potentials, in other words, changes in the brain's electrical fields [7] [8] [9].

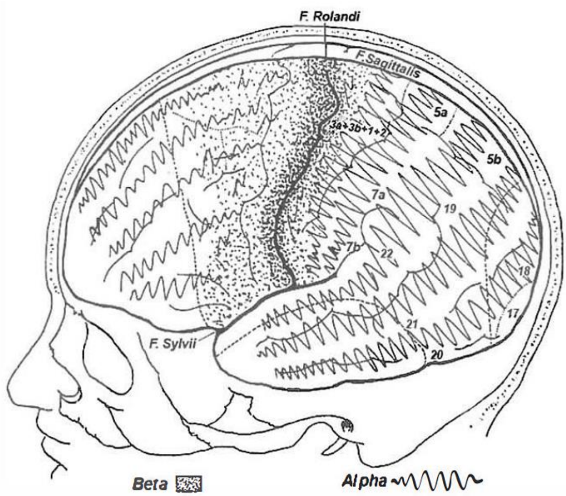

Figure 1: Cortical surface regions where alpha rhythms were recorded in a large population of epilepsy surgery patients arc indicated by wavy lines.

Dotted region near the central motor strip indicates beta activity. From Nunez adapted from Jasper and Penfield (1949) [8].

Neuroscientists have always longed for a method with a sufficient spatial and temporal resolution to monitor the ever-changing patterns of brain activity. The definition of "sufficient" in this context is a complex issue, and to acquire precisely a brain activity without seriously interfering with it while compromising between spatial and temporal resolution, is indeed a dilemma [15]. The desired temporal resolution is the concordance of the wave with the speed of neurons, that is, on the millisecond scale. The desired spatial resolution, which means better localization of the source of any specific signal, depends on the goal of the investigation and expands from the global scale of the brain down to the spines of individual neurons. No current method can continuously zoom from the decimeter to the micrometer scale, which is why several approaches are being used, often in combination [15].

EEG activity is a non-stationary, non-linear, non-deterministic, non-Gaussian, stochastic, and chaotic process. EEG signals have a high temporal resolution, poor spatial resolution, and discriminative spectral features. Data acquisition is affected by the skin-electrode interface, electrode material, configuration, and reference, in addition to motion artifacts like EMG, EOG, ECG, swallowing, breathing, power line interference, cross talk, volume conduction, posture, mental state and mood of the subject and else more of intrinsic and extrinsic sources of artifacts [10] [15].

These characteristics of scalp EEG depend not only on the nature and location of the current sources but also on the electrical and geometrical properties of the brain, skull, and scalp. The connection between surface and depth events is thus intimately dependent on the physics of electric field behaviour in biological tissue. Physical principles directly apply to neural tissue; we only need to interpret variables and consider tissue properties to provide a good picture of head volume conduction and how it relates to broader issues concerning EEG, brain dynamics, cell assemblies, cognition, motor and behaviour [10] [15]

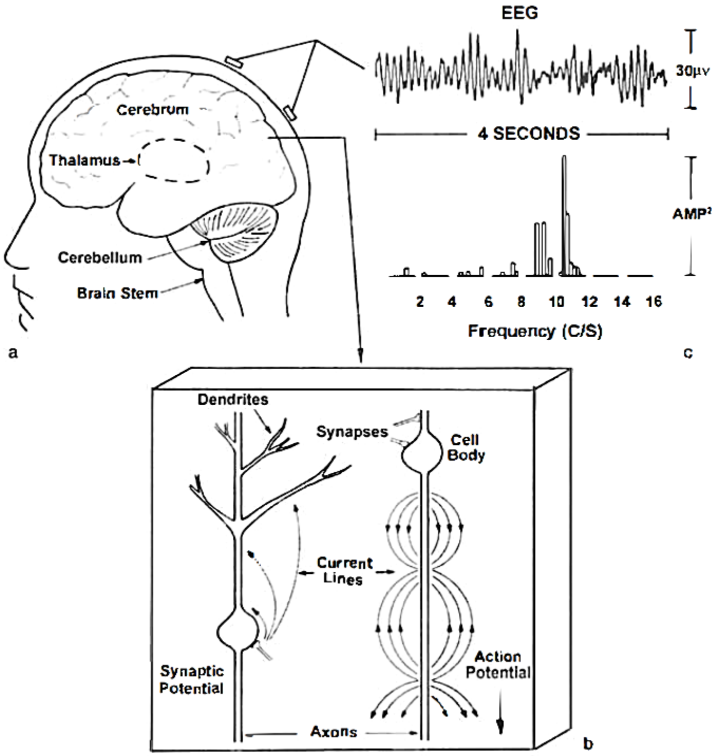

Figure 2: The human brain. (b) Section of cerebral cortex showing microcurrent sources due to synaptic and action potentials. (c) Each scalp EEG electrode records space averages over many square centimeters of cortical sources. A four-second epoch of alpha rhythm and its corresponding power amplitude

As mentioned, an EEG can be recorded as a set of surface potentials by placing electrodes on the scalp. In a recording application, the electrode couples galvanically to capture the local field potential. The dimensions, geometry, and composition are paramount to design requirements. Signal degradation due to inferior electrode design or placement is unlikely to be ameliorated by design improvements in blocks further down the signal chain, thus avoiding garbage-in garbage-out (GIGO) scenarios that give inaccurate data or unreliable results. Both conductive-gel and sponge-saline electrode systems (wet electrodes) are used. The sponge-saline electrodes are easier to apply but have limited recording time (about an hour) because impedances rise as the sponges dry. Dry electrodes technology is also now available. The electrodes themselves are usually metallic and made from tin (Sn), silver/silver chloride (Ag/AgCl), gold (Au), or platinum (Pt) [9] [10] [11].

Any voltage measurement requires both a recording electrode and a reference electrode. EEG practitioners have long been perplexed about finding a proper reference electrode for EEG recordings. Reference recordings involve choosing some fixed location, typically an ear, mastoid, or neck site, and recording all potentials with respect to this static site. The number of electrodes applied varies between 8 to 256. Increasing the number of recording sites is valid only up to a limit because scalp electrodes placed too close together will sense the same electrical fields without further enhancing spatial resolution.

The monitored signals range between 0 and 300 μV, and their frequencies range from 0.5 to approximately 50 Hz. The characteristics of the recorded waves, and the EEG patterns, are (after subtraction of artifacts) highly dependent on the degree of activities within the cerebral cortex. The features of these waves change markedly between states of wakefulness, sleep, and coma [9]. Even in a healthy individual, EEG patterns are often irregular, but distinct patterns do appear under certain conditions [9] [10] [11].

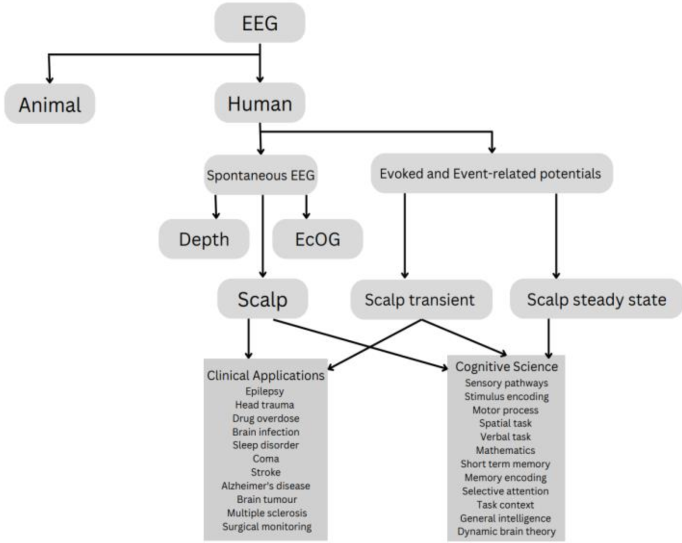

Figure 3: Survey of EEG applications. adapted from Nunez [8].

Brain Computer Interfaces (BCIs)

A BCI system measures CNS activity and converts it into artificial output that replaces, restores, enhances, supplements, or improves natural CNS output [10]. BCIs have emerged as a novel technology that connects and bridges the brain with external devices. They have been developed to decode human intention, leading to direct brain control of a computer or device without going through the natural neuromuscular pathway [21]. The central goal of BCI research and development is for people severely disabled by neuromuscular disorders such as ALS, stroke, SCI, cerebral palsy, multiple sclerosis, and muscular dystrophies to live enjoyable and productive lives provided with effective assistive technology [9] [10].

In the 1970s, Jacques Vidal developed a system that used the scalp-recorded visual evoked potential (VEP) to determine the eye gaze direction (i.e., the visual fixation point) in humans and thus to determine the direction in which a person wanted to move a computer cursor. At that time, Vidal coined the term brain-computer interface. The pace and breadth of BCI research began to increase rapidly in the mid-1990s, and this growth has continued almost exponentially into the present. In BCIs that measure EEG Sensorimotor Rhythms (SMR), the user typically employs mental imagery to modulate SMR to produce the BCI output [12] [13] [14]

In 1988, Farwell and Donchin proposed the successful BCI paradigm known as the "P300 speller", based on event-related potentials (ERP) in response to a specific event or stimulus. Wolpaw and his colleagues developed a BCI for 1D cursor control based on operant conditioning in 1991 [10] [13]. Gert Pfurtscheller and his team were developing another BCI-based SMR, in which users had to explicitly imagine left or right-hand movements that were translated into a command for the computer by using machine learning; this defined the motor imagery (MI)–based BCIs. Niels Birbaumer and his colleagues worked on a third type of BCI paradigm based on slow cortical potential (SCP). Yet, Brendan Allison and others have lately rejected this type owing to generally inferior performances [17] [19] [20] [22].

In general, BCI systems can be categorized as either [(invasive vs non-invasive) (endogenous vs exogenous) (or synchronous vs asynchronous) (active, reactive, or passive) (evoked vs spontaneous) and hybrid] depending on the recording method, brain signal pattern, stimulus modality, mode and strategy of operation. Considering the user's attention, efforts, cognitive/mental state, and engagement [10] [13] [21].

However, the translation of intent into action depends on the expression of the intention in the form of measurable signals. Each signal acquisition method is associated with an inherent spatial and temporal resolution. EEG is the most prevalent, popular and promising signal acquisition method for BCIs; even though it has a low spatial resolution, it has excellent temporal resolution and zero clinical risk, increased mobility and portability, and is low-cost and feasible to manufacture.

P300-based BCIs are the only BCIs in daily use by severely disabled people in their homes. The P300 speller uses EEG to detect and analyze the P300 wave, a signal in the brain associated with cognitive processing, selective attention, and decision-making in the brain, particularly the recognition of essential stimuli, such as a target among distractors. When using the P300 speller, the user is presented with a matrix of letters or symbols on a computer screen and instructed to focus on the desired letter or symbol as it flashes in a random sequence. As the brain responds to the target stimulus, the P300 wave is detected by the EEG and translated into a selection on the computer screen [10] [16].

The P300 speller has effectively enabled communication and improved the quality of life for individuals with severe motor impairments. However, it requires significant concentration and training to use effectively and may only be suitable for some as it may accompany Uncomfortable fatigue and workload. Advances in BCI technology continue to improve the accuracy and ease of use of the P300 speller and other BCIs, offering hope for improved communication options for individuals with disabilities. The P300 speller technology has demonstrated high accuracy rates, with users able to type at speeds of up to 10 characters per minute. It has been mainly used for communication but has potential in virtual gaming and neuro-rehabilitation applications. The P300 speller was first developed in the 1980s and has undergone significant refinement and optimization, resulting in various system versions. The technology is being continuously developed and improved, with ongoing research focused on enhancing its usability, reliability, and accessibility for individuals with diverse needs and abilities [13] [21].

ERD/ERS is a time-locked ERP associated with sensory stimulation or mental imagery tasks. Task-related modulation in SMR usually manifests as an amplitude decrease in the low-frequency components (alpha/beta band), also known as event-related desynchronization (ERD), a reduction of oscillatory activity. In contrast, an amplitude increase in mu and gamma frequency bands is known as event-related synchronization (ERS) that occurs before movement onset. Such characteristic changes in EEG rhythms can be used to classify brain states relating to the planning/imagining of different types of limb movement. This is the basis of neural control in BCIs [22].

An increased widespread ERD could result from the involvement of a more extensive neural network in information processing. Due, for example, to increased task complexity or the need for more effort and attention. Moreover, with training, people can learn to increase and decrease SMR amplitude. However, a substantial training period is typically required for users to develop the skill to maintain and manipulate various mental states to enable control. This can be pretty demanding for users, especially disabled users [9] [10].

Datasets

Three different data sets were used in our method's evaluation process, the Physionet EEG Motor Movement/ MI Dataset, which the developers of the BCI2000 system recorded. It has a 64-electrode EEG setup, sampled at 160 Hz. The data contains recordings of motor execution, as well as MI tasks. There are recordings from 109 different subjects performing two different MI tasks (left/right fist or both fists/feet) in two-minute runs of each MI of the two tasks. One trial consists of 2 s rest, 4 s of cued MI, and again 2 s of rest before the next trial starts.

The BCI Competition IV-2a dataset is also publicly available. It contains recordings from nine subjects who performed four motor imagery tasks (Left Hand, Right Hand, Both Feet and Tongue). The data collection is divided into short runs, each containing 48 trials of each motor imagery activity. The data was collected in two sessions in two days, comprising six runs per session with a short break between them. So, the data contains 288 trials of each motor imagery activity. The EEG data were recorded with 22 Ag/AgCl electrodes arranged in a standard 10-20 system, sampled at 250 Hz and band pass-filtered between 0.5 And 100 Hz. The amplifier sensitivity was set to 100 microvolts. An additional 50 Hz notch filter was enabled to suppress line noise. In addition, three mono-polar Electrooculography (EOG) channels were recorded and sampled at 250 Hz.

The third dataset used in this research is the MTA-TTK dataset from the Hungarian Academy of Sciences, which belongs to Peter Pazmany Catholic University. It contains 25 recording subjects, 63 EEG sensor channels, and a 500 Hz sampling frequency. Five classes were considered: rest, imagined movements of the left hand, right hand, left leg, and right leg. No filtering was applied to the original raw signals; however, a 0.5-Hz low-pass filter removes the DC component from the signal and enhances its accuracy.

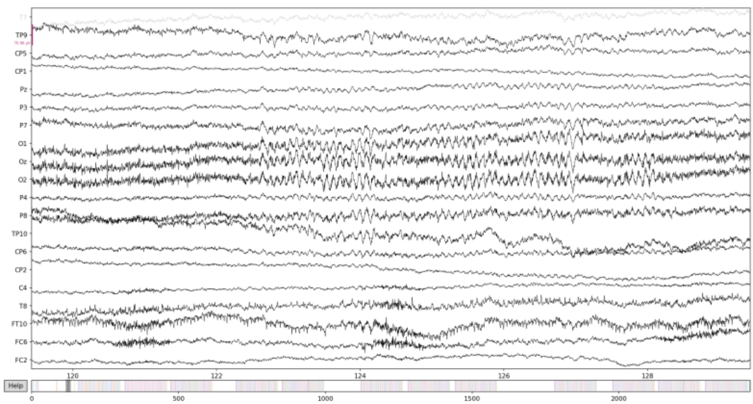

Figure 4: TTK dataset - raw data

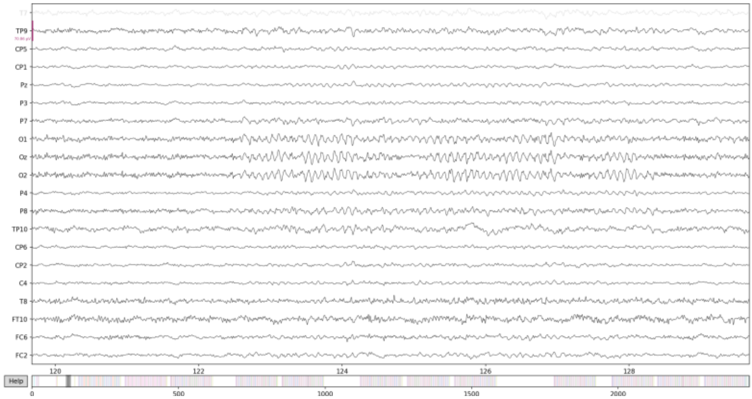

Figure 5: TTK dataset - Filtered data

Methods

A BCI translation algorithm uses features extracted from brain signals to produce device commands that convey the user's intent. The core component of an effective translation algorithm is an appropriate model. A model is a mathematical abstraction of the relationship between independent variables (i.e., brain signal features) and dependent variables (i.e., the user's intent as expressed by the BCI outputs). The two other components of a translation algorithm are the method for selecting the features used by the model and determining the model's parameters and weights. The primary goal in developing a translation algorithm is to maximize its ability to generalize to new data since BCIs must operate online in real time [10].

Classification algorithms depend on the label output type, whether learning is supervised or unsupervised, and whether the algorithm is statistical or non-statistical. Statistical algorithms can be further categorized as generative or discriminative. The algorithms in supervised classification procedures predicting categorical labels are Linear discriminant analysis (LDA), Support vector machine (SVM), Decision trees, Naive Bayes classifier, Logistic regression, K-nearest-neighbor (kNN) algorithms, Kernel estimation, Neural networks (NN), Linear regression, Gaussian process regression, Kalman filters and more [11].

Unsupervised classification attempts to find inherent patterns for unlabeled data that can then be used to determine the correct output value for new data instances. Some standard algorithms of unsupervised machine learning classification are K-means clustering, Hierarchical clustering, Principal Component Analysis (PCA), Kernel Principal Component Analysis (Kernel PCA), Hidden Markov Models, Independent Component Analysis (ICA), Categorical mixture model, etc. Semi-supervised learning combines the two classification procedures [12] [16].

PCA is a well-established method for feature extraction and dimensionality reduction in which the dimensional data is represented in a lower-dimensional space. Such a representation would reduce the degrees of freedom and the space and time complexities. *ICA* helps segregate the brain and non-brain components from the acquired EEG. It converts random signals with multiple variables into one, which measures the frequency strength at a time. They properly visualize the EEG waves to get the frequency wave bands.

Common Spatial Pattern (CSP) is a signal processing technique used in neuroscience and machine learning to enhance EEG, MEG, fMRI and ECoG data information. CSP is a supervised machine learning method that exploits the information about differences in brain signals between cognitive tasks/states or motor commands. It involves finding the spatial filters that maximize the contrast of variance in brain signals between two classes of conditions [16].

CSP has been shown to improve the classification accuracy and speed of BCI systems, which can be applied to assistive technology for people with motor disabilities or to enhance the performance of healthy individuals in tasks requiring neurofeedback training. CSP has been successfully applied in various BCI applications, including motor imagery, speech recognition, and emotion recognition. It has also been used in clinical applications, such as detecting seizures in epilepsy patients and diagnosing Alzheimer's disease. One of the advantages of CSP is that it is a data-driven method, meaning that it can be applied to any EEG data without requiring prior knowledge of the underlying neural mechanisms or signal characteristics. However, it does require a sufficient amount of training data to learn the optimal spatial filters. Overall, CSP is a powerful technique for feature extraction in EEG-based BCIs. Its effectiveness in enhancing the SNR and increasing classification accuracy has been demonstrated in various neuroscience and machine learning applications.

Support vector machine (SVM) is a supervised machine learning algorithm that can be used for classification, regression or outlier detection purposes. The algorithm was developed by Vladimir Vapnik and his team in the 1990s. The basic idea behind SVM is to find the optimal hyperplane that separates the different classes by maximizing the margin between them. The margin is the distance between the hyperplane and the closest data points from each class, and SVM finds the hyperplane that maximizes this distance.

SVM works by transforming the input data into a higher-dimensional space using a kernel function, which allows it to identify complex nonlinear relationships between the features. The most commonly used kernels are linear, polynomial and radial basis functions (RBF) or sigmoid functions. SVMs can be used for both linear and nonlinear classification. It effectively handles noise and outliers in data and can be used for binary and multi-class classification problems. Additionally, SVM has a regularization parameter that can be used to control overfitting and improve generalization performance [10] [11] [15].

Nevertheless, SVM can be sensitive to kernel function and hyperparameters, which require careful tuning. Moreover, the training time of SVM can be slow in high-dimensional datasets, which can be computationally expensive, especially for large datasets. However, various optimization techniques, such as stochastic gradient descent, have been developed to overcome this issue. In summary, SVM is a robust and widely used algorithm in machine learning, and it has been shown to perform well in various applications.

While conventional methods like LDA, AR, KNN, and CSP along variants of different filter banks and augmentation strategies, SVMs, Riemannian, Laplacian and Bayesian methods, have made significant progress in terms of classification accuracy, deep transfer learning-based systems have shown the potential to outperform them. Deep learning (DL) techniques, especially convolutional neural networks (CNNs), have been extensively used in the field of BCI motor imagery (MI) signal analysis for their high classification accuracy and simple construction procedure. Many trials were conducted using a combination of a long short-term memory (LSTM) network and a spatial CNN, or a multiscale fusion CNN based on an attention mechanism, separable convolution, depth-wise convolution, or temporal convolution network (TCN). Compared to CNNs, RNNs were originally used to model data that involve sequential characteristics such as time series, language modelling, and speech synthesis, to name a few. Because of their ability to model sequential dependencies, RNNs are a natural choice for EEG-based BCI, where brain signals are treated as time series. Trade-offs must be invected in selecting from these general family models. Complex models fit existing data better than simple models, but they may not generalize as well to new data. Limiting the model to only the most relevant signal features often improves its generalization ability.

CNN is a deep neural network that is renowned for image processing applications. The convolution operation takes place by applying multiple filters to the data to extract features generating feature maps from the data set. Following up is typically a pooling operation in which the dimensionality of feature maps is reduced. Therefore, CNN proved very useful in classifying MI signals since the raw EEG signal can be used directly as an input without needing a preprocessing stage, like a WT. A CNN model can be integrated within a BCI-based system for real-time applications.

Nevertheless, it depends on the software development kit available to perform predictions and commands. Tuning DNNs can help improve a DL model's classification accuracy or generalization capabilities. Batch normalization is typically applied to normalize intermediate representations between layers, improving generalization and accuracy, especially for CNNs. Dropout layers combat overfitting by randomly disabling a certain percentage of neurons in a layer; this ensures that a network learns generalized features rather than relying on individual neural connections. Dropout is only used during the training phase and turned off for validation and testing. Regularization to reduce overfitting by penalizing weights. Data augmentation aims to produce more training data from available data artificially. In the case of image data, it is possible to rotate, scale or flip the images without changing the meaning. By feeding augmented data to the network, the network learns some degree of invariance to this type of image transformation [25] [26] [29].

Thesis 1

"In this research, I co-created a software code utilizing Python named *Coleeg,* an open-source initiative for facilitating the evaluation of EEG signal classification using neural networks. It is a platform to compare the performance of different CNN architectures [31]."

First, we systematically studied the following models:

- [Basic] represents the simplest neural network model with only one layer and no convolution. This model is not suggested for real-life applications but rather for performance comparison.

- [CNN1D], which performs convolution along the time axis only.

- [CNN2D], where time and sensor channels are considered for two-dimensional convolution.

- [CNN3D and TimeDist] are video classification models that convert the sensor channels into a 2D image that changes with time. 3D convolution and time-distributed 2D convolution are used in CNN3D and TimeDist models, respectively. A simplified diagram for the proposed models is shown below.

- We also added the models [EEGNet], [ShallowConvNet], and [DeepConvNet] proposed in the literature.

Three arrays are produced from reading each dataset:

- ***data_x***, which contains time samples obtained from the dataset with the following dimensions: time-epochs x time-samples x sensors x frequency-bands.

- ***data_y*** contains the class label corresponding to each time epoch.

- ***data_index*** has two columns; the first is the index of the first epoch for each subject, and the second is the subject number

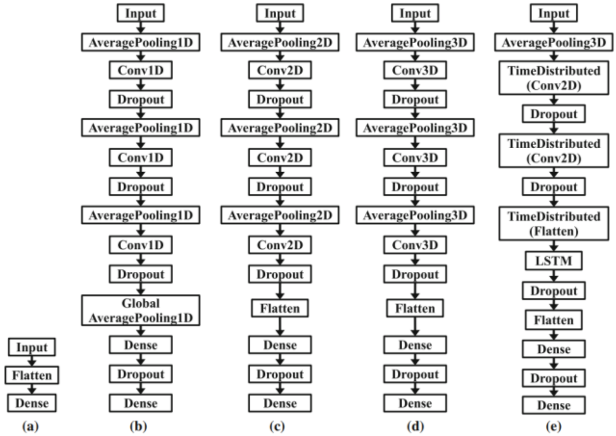

Figure 6: A simplified diagram for the models: a Basic. b CNN1D. c CNN2D. d CNN3D. e TimeDist

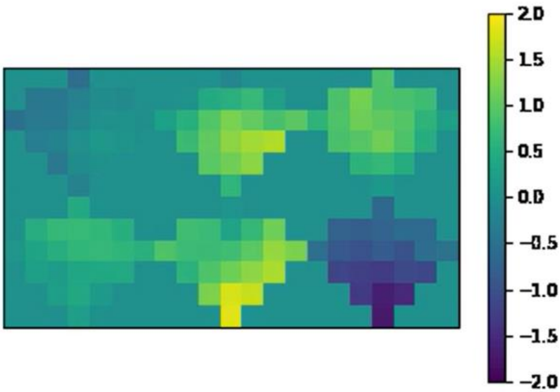

Figure 7: 2D Mapping visualization of Physionet dataset sensors

Results

The models CNN2D, CNN3D, and TimeDist show low accuracy while having high training times, and this might be because of the increased complexity of the models, which makes them tend to have an over-fitting problem and require more training time. The ShallowConvNet architecture was designed specifically to extract log band power features; in situations where the dominant feature is signal amplitude, as in ERP BCIs, ShallowConvNet performance tended to suffer. The opposite situation occurred with DeepConvNet; its architecture was designed to be a general-purpose architecture not restricted to specific feature types, such as extracting frequency features, so its performance was lower when frequency power was the dominant feature.

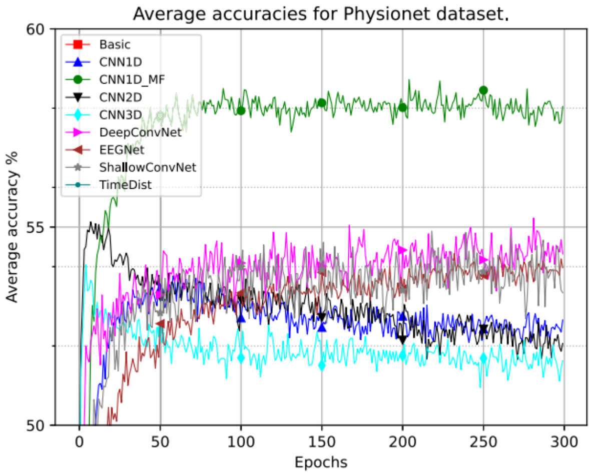

Figure 8: Average Accuracies for Physionet dataset

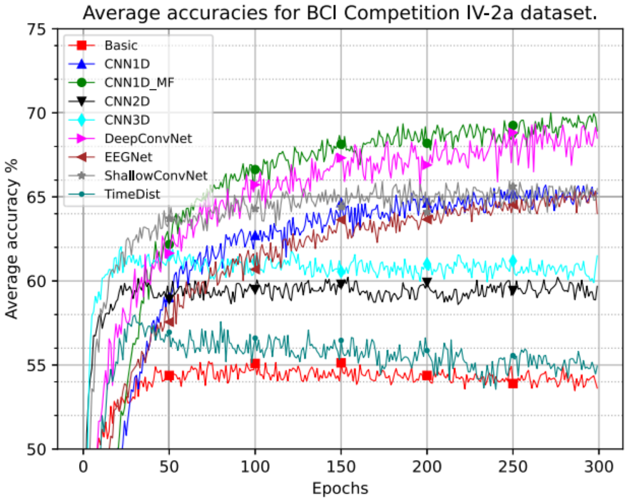

Figure 9: Average accuracies for BCI Competition IV-2a dataset

Then we modified the CNN1D model to have a multiband frequency input CNN1D_MF; doing so has improved the accuracy significantly. Any other model can accept multiple frequency band inputs. However, only the CNN1D model has been considered because it performs best among other proposed models. The subbands are 0.5–8.0 Hz, coinciding with the combined delta (δ) and theta (θ) waves. The band 8.0–13.0 Hz contains the alpha (α) rhythm, while the band 13.0–40.0 Hz coincides with the beta (β) wave and some of the lower parts of the gamma (γ) wave. A finite impulse response (FIR) filter with a linear phase and Hamming window define the bands. Results are presented in Tables 1 and 2 for the Physionet and BCI competition IV-2a datasets, respectively.

Thesis 2

"I present a novel "Multifrequency Band Fusion Method (MFBF)" for EEG MI decoding. Its mechanism divides the signal spectrum into multiple frequency bands and feeds each band into duplicates of the selected CNN model. All the model duplicates are then concatenated to give the required classification."

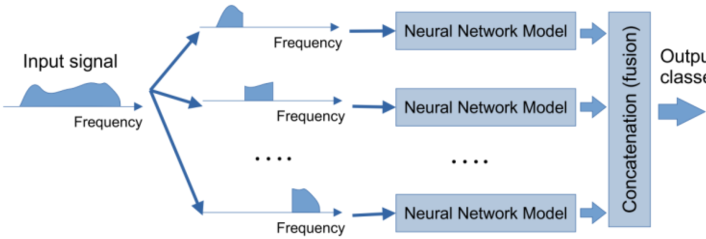

Figure 10: MFBF method illustration

The CNN1D model and the frequency bands mentioned above were used in the experimental evaluation to form the CNN1D-MFBF model. Considering two scenarios, it was evaluated against the EEGNet-fusion model on the three datasets. The first one is where no multiband filtering is used, and it was applied to the CNN1D and the EEGNet-fusion models. The second scenario is applied to the CNN1D and CNN1D-MFBF models. The preprocessing applied to the EEG signals was resampling all datasets to 100 Hz. The data were also normalized to have zero mean and a standard deviation of 1. The results are shown in Figures below.

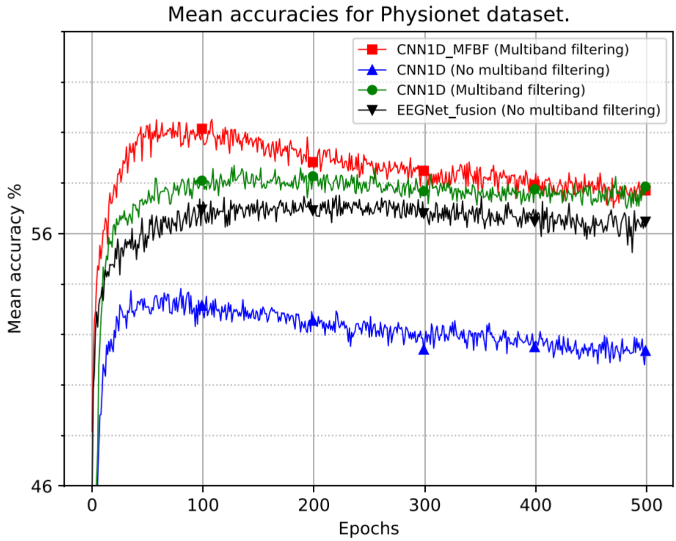

Figure 11: mean Accuracies for Physionet dataset

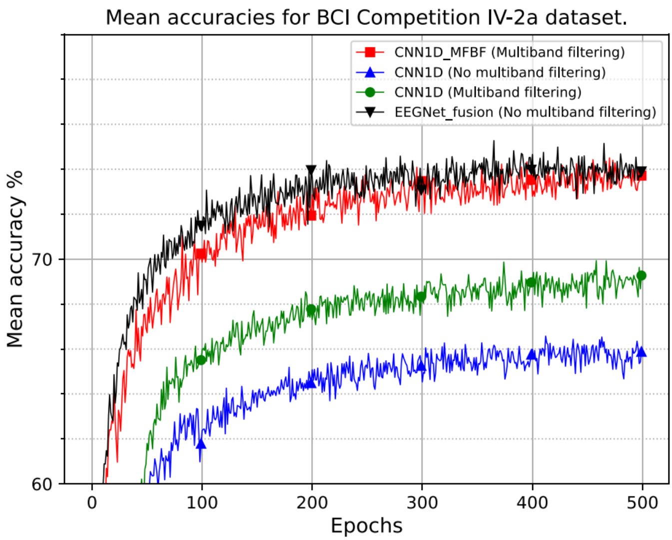

Figure 12: Mean accuracies for BCI Competition IV-2a dataset

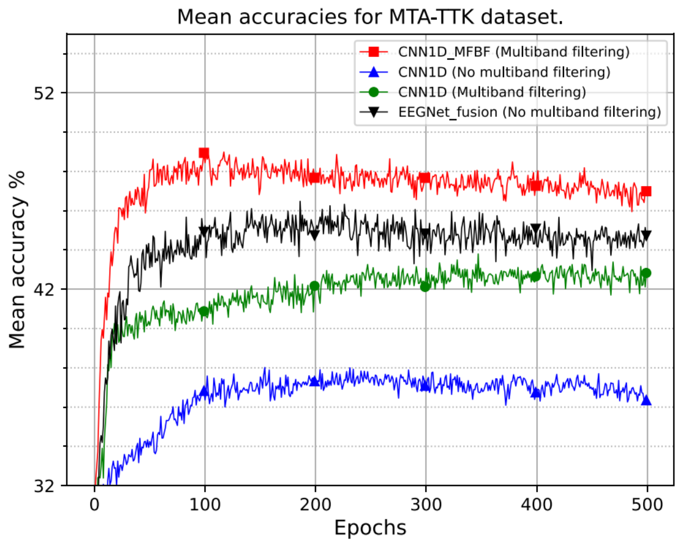

Figure 13: Mean accuracies for MTA-TTK dataset

Our experimental result shows that CNN1D_MFBF has the best accuracy and training time performance, as it takes advantage of the convolution process while keeping the model as simple as possible. They also show that applying multiple filter bands on the input data increases the accuracy results significantly, mainly due to data augmentation. Additional minimal improvement in accuracy using 4 s of the trial time instead of 2 s and performing cross-validation for every subject at the expense of increased computational time and cost.

Coleeg has matured to provide many utility functions that facilitate dealing with different datasets and models, such as applying various filter bands, applying notch filters, resampling data, specifying included and excluded subjects, classes and shuffling, data visualization and augmentation features were also added along the choice, to use local runtime, which allows researchers to utilize the power of local hardware and overcome the limitations imposed by

Colab-hosted runtime, in addition to evaluation metrics, like Cohen Kappa, specificity and sensitivity and plotting the results and saving the plots as pdf files [31].

Discussion

Most EEG-based BCIs use the P300 evoked potential, sensorimotor rhythms (SMRs), or steady-state visual evoked potential (SSVEP). All three BCI types can help to restore essential communication and control to people with severe neuromuscular disabilities. At present, their capabilities are limited. Improved EEG recording methods are needed to provide stable, high-quality signals in all environments, be comfortable, and be easy to use. New dry-electrode systems have considerable promise. Improved signal analysis algorithms that can consistently maintain accurate performance are also required. While much algorithmic development has relied on offline analyses of archival data, online testing of new algorithms is essential because it considers the ongoing adaptive interactions between the user and the BCI. BCIs, particularly SMR-based BCIs, also show promise as new methods for enhancing functional recovery for people with strokes or other chronic disorders. Several strategies for using BCIs to induce beneficial plasticity are under study. Evidence that these methods can enhance recovery beyond what can be achieved by conventional methods alone is just beginning to emerge [11].

Recent advances in digital recording and signal processing, together with the leaps in computational power, are expected to spawn a revolution in the processing of measurements of brain activities, primarily EEGs and ERPs. This will enable the implementation of more complicated denoising techniques of ERP than ensemble averaging and more complicated EEG quantification analysis methods than the amplitude and frequencies, including nonlinear dynamics and higher-order statistics. Furthermore, this will help implement various techniques describing the interactions between different regions of the brain, which offer more insights into the functional neural networks in the brain [8] [15]

Current DL-based EEG classification studies aim to improve classification accuracies, proposing a new way to interpret the features and enhancing real-time feasibility. The ability of DL models to properly clean the artifacts and learn from neurological signals still needs to be improved and needs further research. It is crucial in EEG to understand what was learned in the model because the end goal of EEG-based studies is to understand the brain and utilize the signals extracted from the brain. Many studies still need to open-source the data and code, which would be vital in increasing replicability. Open sourcing the data could also help the community train the DL model and transfer the knowledge to a target domain where such a large dataset is unavailable [11] [17].

End-to-end DL classification in EEG data processing and modelling pipeline has the potential to remove the necessity of preprocessing that tends to rely on either specific domain knowledge or visual interpretation by experts. Also, it allows us to focus on one optimization model from the beginning to the end. However, at the current stage, end-to-end is still difficult without a thorough analysis of how and what the DL is learning and relying on to make decisions and proper interpretation and decoding [24].

DL for EEG neural classification is still in the emerging stage. There is growing interest in increasing the reliability and usability of such models with the intent of using them for real-time implementation. However, **no real-time implementations currently employ these deep learning models for EEG decoding tasks**. Several attempts to analyze EEG signals using CNN models were postulated. Many showed promising accuracy results concerning motor imagery and laterality of motion. None proved superior or reliable, but experiments are ongoing, searching for better, well-formed software to extract more information from EEG signals [36] [40].

EEG has several benefits compared to other imaging techniques. The most prominent benefit of EEG is its excellent time resolution; that is, it can take hundreds to thousands of snapshots of electrical activity across multiple sensors within a single second. EEG is an ideal technology for studying the precise time course of cognitive and emotional dynamics, most occurring within tens of milliseconds. The second reason that EEG is an advantageous technique for studying neurocognitive processes is that it allows the direct measure of neural activity. EEG signals directly reflect biophysical phenomena occurring in neuron populations. This is a clear advantage over other methods, such as fMRI, that do not directly measure neural activity but introduce an extra relationship between what is measured (changes in blood flow in the case of fMRI) and the actual neural activity. Finally, EEG is non-invasive, and the required equipment is relatively cheap, portable and relatively easy to operate [15] [21].

On the other hand, the main disadvantage of EEG is its poor spatial resolution. Neural activity is conducted through the brain volume to the scalp and electrodes by volume conduction. The concept of volume conduction carries important implications for surface EEG measurements as currents are not restricted to the immediate neighborhood of the source, and the electrical activity measured between electrodes has more to do with their orientation to the actual generator than with the proximity of the electrodes to the generator. Because the skull is a poor conductor, current tends to "splash off of it", and each electrode receives signals from millions of neurons, reducing potential spatial localization. This is exacerbated by the fact that the head tissues' conductivities vary across individuals and within the same individual due to variations in age, disease state, and environmental factors. The inference of the location of the current sources from electrode voltage measurements on the scalp is known as the EEG inverse problem. It is comparable to reconstructing an object from its shadow; only generic features are uniquely determined [8] [9] [15].

EEG is also very sensitive to subject movement and external noise. Electrodes used in EEG recording do not discriminate the electrical signals they receive. Intrinsic and extrinsic Artifacts contaminate the recordings in both temporal and spectral domains within a wide frequency band. The internal source of artifacts may be due to the subject's physiological activities (e.g., eye movement, electrocardiographic activity, sweat or muscle artifacts) or their movement. External sources of artifacts are environmental interferences such as power line interference, improper contacts between electrodes and skin, or interferences from recording equipment and cable movement [15] [21].

Four criteria are a must for a system to function as a BCI system:

- The system must rely on activity recorded directly from the brain.
- Intentional control: At least one recordable brain signal, which can be intentionally modulated, must provide input to the BCI (electrical potentials, magnetic fields or hemodynamic changes).
- Real-time processing: Signal processing must occur online and yield a communication or control signal.
- Feedback: The user must obtain feedback about the success or failure of his/her efforts to communicate or control.

The primary goal has been to introduce and articulate a framework capable of synthesizing some results and theories in motor control, imagery, perception, and perhaps even cognition and language rather than providing compelling data for its adoption. These considerations are not theoretically insignificant but are also quite far from conclusive. BCI development relies heavily on offline analyses of data gathered during BCI operations or various open-loop psychophysiological studies. These analyses can be instrumental and imperative in comparing different models, feature selection, and parameterization methods and testing alternative algorithms.

Conclusion

The path of the signal:

"Brain – scalp-electrode interface – electrodes (composition material, specifications and configuration) – Amplification and Filtering (Analog circuitry) – ADC – Signal processing (Artifact removing – Feature extraction, dimension reduction, feature selection and classification) – then to application circuit (Digital/analogue commands) leading to intention decoding & neuro-control".

BCI is an emerging field where EEG techniques are used as a direct nonmuscular communication channel between the brain and the external world. BCI research and development is a highly complex, interdisciplinary, and demanding endeavour that depends on carefully evaluating and comparing many different brain signals, signal processing methods, and output devices. Most current BCI systems' inflexibility, unreliability and limited capabilities significantly pose a considerable challenge for designers and users alike. A few people with severe disabilities already use a BCI for essential communication and control in their daily lives. With better signal-acquisition hardware, clear clinical validation, viable dissemination models, and increased reliability, BCIs may become an essential new communication and control technology for people with disabilities and possibly the general population [11] [21] [22].

The present report sheds light on the difficulties encountered in BCI technology. Problems in the field today are accuracy, reliability, and number of commands, Bandwidth as the Information Transfer rate (ITR) (i.e., speed of the system) and new applications and paradigms, and lack of shared codes. Users' comfort needs to be addressed as cognitive workload and mental fatigue may appear as side effects of using the system. Calibration is also challenging in BCI because the SNR is unfavorable, and the subject-to-subject variability is immense.

Visual ERP-based BCIs often have the advantage that the stimulus presentation mode leads to a unique structure of the collected brain signal data, which supervised and unsupervised learning methods may exploit. Without significant improvements, the real-life usefulness of BCIs will, at best, remain limited to only the most basic communication functions for those with the most severe disabilities. In current BCIs, the BCI, rather than the user, typically determines when output is produced. Ideally, BCIs should be self-paced so that the BCI is always available, and the user's brain signals alone control when the BCI output is produced.

EEG phenomena's complexity requires computer simulations to understand the underlying generation processes. New tools for studying nonlinear dynamic systems have been introduced in this domain of theoretical neurophysiology. Furthermore, the availability of powerful computer tools opens new possibilities for modelling complex membrane phenomena and network properties. Academic studies are justified if combined with experimental investigations (hence, offline and online examinations, invasive and noninvasive techniques). In this way, one may obtain new insights about the generation of EEG patterns and formulate hypotheses to be tested under experimental conditions. In the last decades, a shift of attention from models describing the behaviour of neuronal networks in the temporal domain toward models considering complex networks' spatial and spectral properties has occurred. The person interested in interpreting the EEG must draw conclusions based on the brainwaves' frequency, amplitude, morphology, and spatial distribution. However, the diversity of EEG patterns cannot be wholly explained by any single mathematical or biological model available today. Therefore, EEG interpretation remains a phenomenological medical discipline with undoubted prospects in the BCI domain.

‘It remains sadly true that most of our present understanding of mind would remain as valid and useful if, for all we knew, the cranium were stuffed with cotton wadding’ [41] [42]. [Ralph Gerard (1949), Robert Maxwell Young (1970), Christopher Lawrence (2021)]

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