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3-Channel Motor Imagery Classification using Conventional Classifiers and Deep Learning Models

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Abstract: Brain-computer interfaces (BCIs) are one of the important applications based on motor imagery classification using EEG signals. BCIs are designed to help patients afflicted with motor disabilities. The purpose of this study is to assess how well various conventional machine learning and deep learning models work for motor imagery task classification from EEG data analyzed by three channels C3, C4, and Cz. A comprehensive methodology employed including preprocessing of raw EEG signals (Time, Frequency, Time-frequency domains) multi-feature extraction followed by classification based on conventional models (decision Tree, SVM, Random Forest) as well as deep learning methodologies like CNN, RNN, and TSFFnet-based architectures. The results indicate that random forest is consistently performed well across different domains. As it achieves high accuracy and the lowest mean absolute error among other conventional classification models. The accuracy of TSFFnet among deep learning models was 99.75%, precision is maximum seems like it has been configured to have a good recall with the values for recall being close to that, and mean absolute error is minimal at 0.0038. These results reveal that deep learning models especially the TSFFnet model outperform in the tasks of motor imagery classification.

Keywords: EEG signal Processing; Brain-computer interface (BCI); Neural Signal Analysis; Motor Imagery Decoding; Neuro Technology; Random Forest; Support Vector Machine (SVM); Machine Learning in EEG; Decision Tree; Time-Space-Frequency Fusion Network (TSFF-Net); Motor Imagery Classification; Convolutional Neural Networks (CNN).

1. Introduction

The study of brain function has made progress due to Electroencephalography (EEG) an invasive method to investigate the brain's electrical activities. By locating electrodes on the scalp EEG captures voltage fluctuations generated by currents [1]. Since its inception in the century, EEG has become a crucial tool for understanding how the brain's electrical behavior works providing valuable insights into cognitive and clinical phenomena.

The origins of EEG can be traced back to Hans Berger's groundbreaking work in 1924, which marked the recording of human brain waves. This discovery opened up avenues for studying brain activity [2]. Since then, it has been used in clinical and research contexts. The development of EEG technology including improvements in design, signal amplification, and data processing techniques has significantly enhanced the resolution and range of investigations based on EEG shown in Figure 1.

At the core of EEG is the recognition that neural activity is accompanied by signals. Berger’s initial observations laid the foundation for understanding that different brain states and activities correspond to patterns in EEG readings [2]. In this section, a chronological evaluation of the literature is presented to show how developments in technology have enabled the acquisition of EEG data that demonstrate the dynamic nature of brain activity and its importance in different contexts.

Research on the functions of the brain has advanced because of Electroencephalography (EEG) which is an invasive procedure to study the electrical signals of the brain. EEG records electrical activity by affixing electrodes on the scalp and getting currents' voltage positions. From the beginning of the century, this technique has been considered fundamental to investigate processes of cerebral electric activity being useful to give light to cognitive and clinic events.

The uses of EEG are exhaustive and complex. EEG is particularly significant for diagnosing several clinical conditions including epilepsy and sleep disorders because characteristic EEG patterns are considered diagnostic [3]. Besides, with the help of EEG, the processes that occur in the brain related to cognition, perceiving stimuli, or affective responses are truly time-sensitive and can be studied with high temporal resolution.

The incorporation of EEG into BCIs has enabled persons with motor-impaired disabilities to control external devices directly with the help of their neural signals which offers new paths of communication and control. Also, the ability of EEG to be used in neuropsychology has led to the assessment of neurological disorders such as autism and schizophrenia concerning the neural substrates [4].

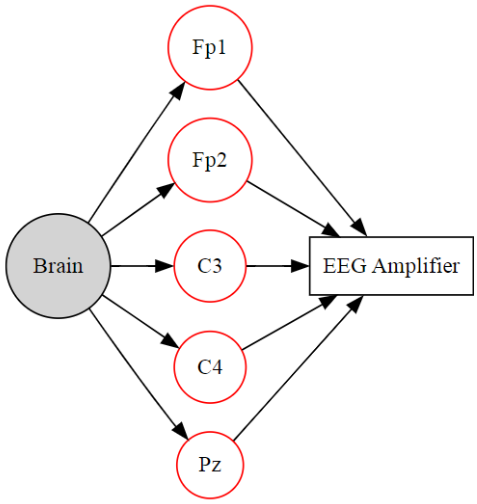

Figure 1. Brain to EEG Amplifier

The immense interdisciplinary cooperation has sustained the growth of EEG technology. An extended version of the EEG recording with a greater number of electrodes provides better spatial resolution for source localization [5]. Portable EEG systems have further expanded the possibilities of monitoring and may be used for cognitive screening and identification of mental disorders.

Current sophisticated signal processing methods such as machine learning paradigms are converting raw EEG data directly into intelligible information for classifying real-time cognitive states or even determining a person's mental health status [6]. Closed-loop systems signifying that EEG data initiates further adjustments, appear promising in the contexts of individualized medicine and treatment. Moreover, the combination of EEG with other imaging techniques like Functional Magnetic Resonance Imaging (fMRI) and Functional Near-Infrared Spectroscopy (fNIRS), functional and structural information correspond to the temporal and spatial domain [7].

Classification is the fundamental task in the field of machine learning where the objective is to predict the category or class based on the learned features from the labeled training dataset. This activity involves training a model to find patterns and relationships within the data. Afterward, this trained model is tested on unseen instances of the predefined classes [8]. Classification is widely used in various fields such as spam detection, image recognition and image fusion, and medical diagnosis. A specific and advanced application of classification is EEG motor imagery classification where the aim is to decode the brain signals through electroencephalography (EEG) to determine the motor imagery task imagined by an individual [9]. It has significant implications for developing brain-computer interface (BCI) and aiding individuals with motor disabilities. Based on the previous study, EEG signal classification is faced with several difficulties and limitations. More importantly, it is seen that the epilepsy type is variable across the patients and within the patients on different periods [10]. Thus, one needs an automated technique that should be capable of handling such shifts in the patient's characteristics. Also, signals related to EEG are more prone to noise interferences and artifacts which increases the challenge of classification. To tackle these challenges, machine learning and deep learning options have been adopted by the researchers. The last decade has demonstrated the application of deep learning approaches to the classification problems of EEG signals using conventional signal processing techniques [11].

Now deep learning is considered to be a revolutionary advancement in machine learning that has shown excellent results in speech and image recognition. EEG (electroencephalogram) signal classification has been a topic of significant interest in recent years. Many researchers have explored various techniques, including deep learning models to enhance the accuracy and performance of EEG signal classification. Deep learning in the recent past has revolutionized signal recognition with an emphasis on audio and visual signals [12]. It has also been applied in the classification of EEG signals and the performance has been marvelous. This method as used to enhance the recognition rate for the classification from EEG is known as Deep Learning. Compared to the previous models, these models are capable of learning and feature extraction from raw EEG signals on their own. This is especially helpful as it minimizes the application of post-processing methods like image processing tools to tackle raw EEG signals. Besides, the models of deep learning allow for encoding spatial aspects as well as temporal aspects of the data contained in the EEG signals that may be vague in other methods [13].

Motor imagery is one of those paradigms which are crucial for the development of BCI. It implies that a person imagines movement but does not perform it. The goal-directed motion information induces neural activity in the premotor cortex (PMC) and the Supplementary motor cortex (SMC) which in turn activates the sensorimotor cortex comprising the M1 region as well as the S1 region [14]. Motor imagery activities are aided by the event-related synchronization (ERS) and desynchronization (ERD) produced by these oscillations.

This study aims to observe motor imagery classification by testing both traditional classifiers with deep learning models and conducting a comparison of which classifier works best in the context of motor imagery classification from different conventional and deep learning models used to classify the motor imagery task with high accuracy with the lowest error rate.

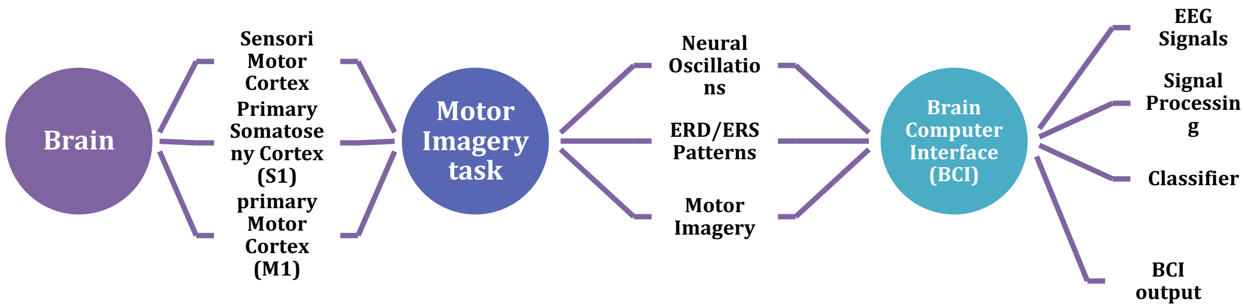

Figure 2. Human Brain to BCI Evaluation Using Deep Learning Models

2. Literature Review

The classification methods for Motor imagery EEG play a critical role in several fields, comprising of brain-computer interfaces, clinical rehabilitation as well and cognitive neuroscience. These methods include signal decoding linked with motor imagery tasks that are performed by the subject by imagining specific movements without performing the movements [15]. This enables the information to be transferred to other appliances directly from the brain without passing through other conventional channels of the human body. Recording and processing of MI EEG signals are known to be very important in creating good ML classification models. The conventional approaches of classification in motor imagery EEG include machine learning techniques like support vector machines and decision trees etc. The aim is to identify and classify the supposed movements based on the spatial characteristics of the EEG. Nevertheless, the performance of the above traditional methods is generally poor in terms of multi-class motor imagery movement and has restricted application in exercise and rehabilitation fields. In the relatively recent past, a few works have suggested methods based on deep learning to classify motor imagery EEG data [16].

An issue that can be attributed to EEG is in the analysis and processing of the data obtained [17]. This is because the EEG signals are somewhat more complicated and of multivariate nature where the severe and straightforward signal processing fails. In particular, the deep learning techniques seemed to overcome these limitations based on the experimental results. The deep learning models also have the suitability of automatically extracting the features from the raw EEG signals without a lot of pre-processing [18]. In addition, the results of the present study also reveal that deep neural networks surpass human-engineered features possibly due to the consideration of more complex patterns and relations in the EEG features not easily discerned by humankind. In general, the classification of EEG signals has a few challenges that have been countered using different types of deep learning in the field. Convolutional neural networks (CNNs) are among the best deep learning models used for classifying EEG signals [19].

Convolutional neural networks perform better in image classification problems as compared to traditional classifiers because they can identify attributes inherent in the data fed to the model. The specific implementation of convolutional neural network (CNN) is as follows:

$$z^l = f^l W^l * a^{l-1} + b^l \quad (1)$$

Where z^l is the output of l^{th} layer, f^l is the activation function, W^l is the weight matrix, a^{l-1} is the input from the previous layer and b^l is the bias.

Another extensively used deep learning model, which has been employed for classification of the EEG signals is the Convolutional Neural Network. CNNs have a special predisposition for image-related tasks and have been successfully used in the classification of EEG data [20]. Moreover, Recursive Neural Networks and Long Short-Term memory-based models have also been used mainly in the classification of EEG signals. [21]. The Recursive Neural network (RNN) is implemented as follows:

$$h_t = \sigma(W_{hx X_t} + W_{hh} h_{(t-1)} + b_h) \quad (2)$$

Where h_t is the hidden state at time t, X_t is the input at time t, W_(hx)and W_hh are weight matrices, b_h is the bias and σ is the activation function.

These networks have been fine-tuned for the classification of EEG signals and performance tests carried out to indicate the ability of the networks to detect epileptic and non-epileptic signals. Another study used epileptic seizure identification where a two-dimensional supervised deep convolutional Autoencoders was employed [22]. The deep convolutional Autoencoders was chosen to learn directly from raw EEG data so that the features necessary for classification could be learned by the model.

In the classification of the EEG signal process, recursive neural networks and long short-term memory networks have been utilized with several scholars performing research on the efficacy of deep learning in these kinds of signal classification [23]. Consequently, traditional methods of signal processing in the classification of EEG signals have drawbacks, namely the intricate and multivariate nature of signals, as well as the inability to detect detailed regularities within them. Some deep learning studies such as Convolutional Neural Networks have been used to classify EEG signals due to their capability of learning and extracting features from raw EEG data. These approaches are expected to get over the imperativeness of traditional methods and enhance the accuracy and efficiency of EEG signal classification [24].

Some of the recent ones are lightweight neural network architectures that are specifically developed for extracting motor imagery feature sets. However, there are some limitations which reveal that there is a dearth in the low-channel EEG decoding area. As mentioned above, it is hardly possible to add more electrodes due to some constraints, and thus, new approaches to enhance the classification rate are to be explored [25]. To fill this gap, this study combines time-series and frequency-based neural networks to enhance the accuracy of motor imagery classification with low-channel EEG. ML-based EEG classification methods identified are deep stacked Autoencoders, deep residual convolutional networks, and multimodal deep learning frameworks [25]. The deep residual convolutional network (DRes-CNN) used deep learning and CNN in its model, and it could classify EEG signals with much higher accuracy [16]. The deep residual convolutional network (DRes-CNN) is implemented as:

$$Z^l = f^l\left(W^l * a^{(l-1)} + b^{(l-1)} + a^{(l-1)}\right) \quad (3)$$

Where z^l represents the output of l^{th} layer, W^l denotes the weight of the matrix of the l^{th} layer, $*$ denotes the convolution operation, f^l is the Rectified Linear Unit activation function and the term $a^{(l-1)}$ denotes the input feature maps from the previous layer and $b^{(l)}$ represents the bias term specific to l^{th} layer.

The combination of a residual neural network and a recurrent neural network can achieve a recognition accuracy of 90% [26]. Through rigorous optimization, this typical model can serve as a bridge framework for more powerful subject-independent BCI. Another research direction is to divide the EEG signal into sub-signals by a certain window size and then extract features from the original signal or sub-signals as the input of the model for EEG classification [26]. Deep learning algorithms can extract complex characteristics from raw signals and create a hierarchical representation, unlike conventional techniques that have restricted feature extraction capabilities. Features that are difficult to be expressed using a fixed formula can be more accurately distinguished. Thus, it has been shown that the deep learning model outperforms conventional machine learning models [27].

For extracting frequency-dependent information from the frequency components of the raw signal, the widely used short-time Fourier transform (STFT) is used for multi-scale analysis of the raw signal. The BCI community has proposed many methods for EEG feature extraction, such as wavelet transform and symbolic dynamics. Some research studies have used signal-processing algorithms to extract characteristic information [28].

A kernel function is used to extract these characteristics and build a classification model. However, due to the complexity of the EEG signal and the arbitrary selection of the parameters, the feature extraction results may be biased. This problem is solved by using deep neural network models for feature extraction and classification [29]. As shown in Figure 3, two FC layers and a final SoftMax layer are added to classify the output of the LSTM, and then the 64-dimensional characteristics of the LSTM layer are reduced to the same number of dimensions as the length of the time domain signal (in this case, the same as the 64-dimensional input dimension of the time domain signal) to facilitate the matching of the convolutional layer [30].

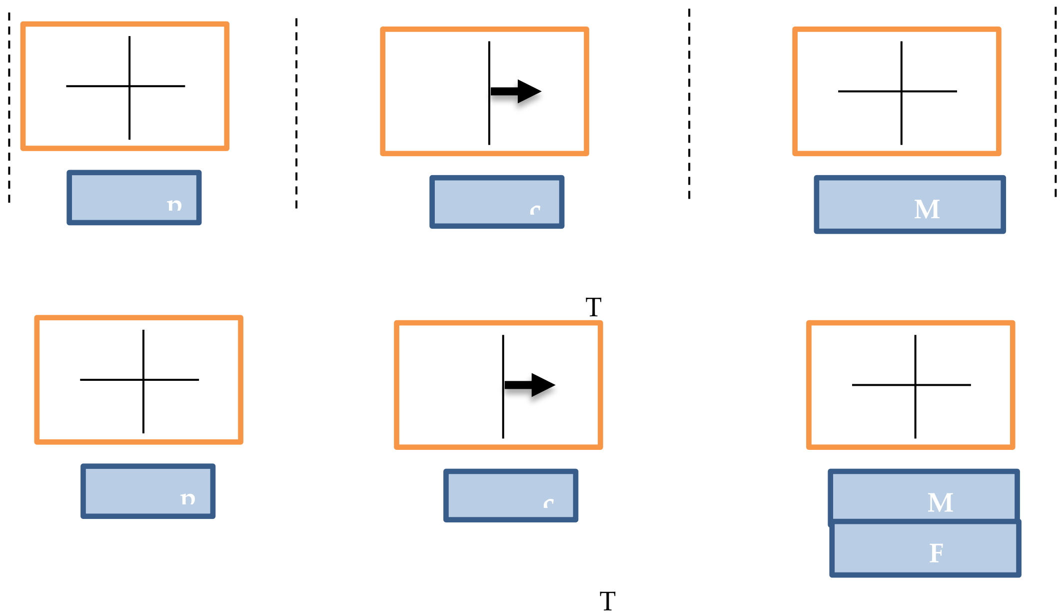

Figure 3. Deep Neural Network Evaluation

These methods seek to include comparatively efficacious and tractable models including the recurrent neural networks as well as the convolutional neural networks with the view of improving the chances of classification. For instance, using deep learning-based classification methods has been proven to be more accurate and more reliable as compared to traditional machine learning-based methods. The structure of the deep learning model, such as Convolutional neural Network(CNN) and recurrent Neural Network(RNN), and how it is used in the classification of Motor Imagery Electroencephalogram (MI-EEG) the impact of deep learning for MI-EEG classification, and its future developments [31]. According to the obtained study results, the proposed method of EEG classification using CNN and Wavelet packet Decomposition (WPD) is more accurate in classification [32]. The classification of EEG for motor imagery is a usual technique in the noninvasive detection of the human brain which serves as the connection between the human brain and outer devices. That is why it plays a significant role in the BCIs. BCIs are employed to enable those within the disabled category to perform certain tasks that are very hard or even impossible to do because of their physical or mental state [33]. A BCI system mainly includes recording the brain signal analyzing and classifying the recorded signal and using the recorded signals to control external devices or applications through a computer [33]. Contrary to that, in the case of motor imagery EEG signals, real-time and accurate classification is of primary importance for the BCI system's performance. Among them, the classification of the electroencephalogram (EEG) signal is one of the most crucial processes in the construction of the BCI system. Previous work has typically used basic classification techniques of the machine learning domain like support vector machines, and random forests, for motor imagery EEG classification [34]. Deep learning, BCI applications, support vector machine, electroencephalogram signals, motor imagery tasks, traditional machine learning methods brain-computer interfaces neural network hand-crafted feature detection.

Deep learning-based models for EEG classification include deep stacked Autoencoders, deep residual convolutional networks, and multimodal deep learning frameworks [35]. The combination of a residual neural network and a recurrent neural network can achieve a recognition accuracy of 90% [26]. This common MLP can act as a transitional framework for more intricate subject-independent BCI that has advanced optimization. Another research direction is to divide the EEG signal into sub-signals by a certain window size and then extract features from the original signal or sub-signals as the input of the model for EEG classification [36]. In contrast to the limited feature extraction ability of traditional algorithms, deep learning algorithms can automatically learn a hierarchical representation of complex features from raw signals. Features that are difficult to express using a fixed formula can be more accurately distinguished. Thus, the deep learning model has been proven to be better in performance than traditional machine learning models [37].

For extracting frequency-dependent information from the frequency components of the raw signal, the widely used short-time Fourier transform (STFT) is used for multi-scale analysis of the raw signal [38]. The BCI community has proposed many methods for EEG feature extraction, such as wavelet transform and symbolic dynamics. Some research studies have used signal-processing algorithms to extract characteristic information [39]. A kernel function is used to extract these characteristics and build a classification model. However, due to the complexity of the EEG signal and the arbitrary selection of the parameters, the feature extraction results may be biased [40]. This problem is solved by using deep neural network models for feature extraction and classification [41]. The two FC layers and a final softmax layer are added to classify the output of the LSTM, and then the 64-dimensional characteristics of the LSTM layer are reduced to the same number of dimensions as the length of the time domain signal to facilitate the matching of the convolutional layer.

It has been reported that the frequency domain can provide many features that are important for identifying different EEG signals [41]. These features have the potential to play an important role in identifying different brain signals. Therefore, we added two convolutional layers, pooling layers, and FC layers to the CNN model to extract spatial features and time domain and frequency domain features [41].In a previous study, a local and public motor imagery (MI) data set with two classes and two electroencephalogram (EEG) channels was used to extract spectral images with 2-60 Hz frequency range of EEG data, and a convolutional neural network (CNN) and a hybrid CNN/ recurrent neural network

(RNN) were used to classify MI signals [41]. The characteristics of the time-frequency plane are used as an input feature for the CNN model, which can effectively extract the emotional features of the EEG signal. Another study used a smoothed pseudo-Wigner-Ville distribution to transform the two-channel (mu and beta) band-pass filter (BPF) -filtered MI data into a 3D pseudo-image, and then extracted the character vector in the FC layer of the deep network to achieve a better effect in the detection of different classes of motor imagination signals. The research literature has shown that the end-to-end deep neural network can extract valuable information from the raw EEG time series for a more accurate diagnosis of the emotional state [42].

Another novel approach used to classify the EEG signal that targets the multi-dimensional features of EEG signals is the Time-space-frequency fusion network (TSFFnet) [43]. The TSFF-Net is introduced as a solution. Comprising distinct components, including time-frequency representation, spectral-based and time-series-based feature extraction layers, and feature fusion, TSFF-Net is evaluated on two public motor imagery datasets [43]. The outcomes showcase its superiority over existing methods and traditional 22-channel approaches, even when utilizing just three EEG channels. TSFF-Net holds promise for advancing low-channel EEG decoding, resonating within the evolving landscape of EEG applications.

TSFFnet is a novel deep learning network model that combines CNN and long short-term memory (LSTM) to classify brain signal activity [43]. The multidimensional characteristics of the convolutional layer can obtain the location invariance of the feature matrix of the input image, and the time and frequency dimension features can be extracted, while the one-dimensional or two-dimensional characteristics of the LSTM layer can be matched with the convolutional layer. In addition, some studies have shown that integrating end-to-end learning into a classifier or building an end-to-end deep neural network can improve the performance of the method [44]. At the same time, in terms of feature extraction, some researchers have also tried to use an automatic feature extraction method using deep learning algorithms [44]. This feature extraction method can save time and avoid error accumulation caused by the complicated processing steps of traditional feature extraction [45]. Time-frequency representation, scalogram, and recurrent representation were also used to improve the performance of the deep neural network. TSFFnet introduced an end-to-end deep learning framework with multisource data and different neural network structures for disease recognition, and the results showed that the CNN-LSTM model can better extract the feature information of the signal [46]. The TSFFnet could be implemented as:

$$\text{TSFF-Net} = \text{CNN}_{\text{spatial}}(x) \oplus \text{LSTM}_{\text{temporal}}(\text{CNN}_{\text{spatial}}(x)) \quad (4)$$

The TSFF-Net incorporates several key components to effectively process EEG data. Initially, the input data, denoted as x, represents the raw EEG signals or features extracted from these signals. The spatial convolutional layers CNNspecial play a vital role in extracting spatial features from the input EEG data through a series of convolutional operations followed by non-linear activation functions, typically ReLU. These layers analyze spatial patterns present in the EEG signals. Subsequently, the temporal LSTM layers (LSTMtemporal) operate on the spatial features extracted by the CNN. These LSTM layers are specifically for temporal characteristics of the feature maps present in the spatial domain so that the model can understand the temporal aspect of the EEG data. Last but not least, the fusion operation (⊕) combines the features from the spatial domain of CNN and respectively from the temporal domain of LSTM. This fusion process produces a holistic map that includes both the spatial and temporal domain of the EEG signals, hence the easy classification of the EEG data into various classes [47-50].

In summary, the literature review engages the challenges that are associated with EEG signal classification, especially concerning epilepsy detection. It highlights the unsuitability of traditional classification techniques due to patient characteristics' fluctuation and signal noise. To solve these challenges, what is commonly referred to as the shift in paradigm towards deep learning techniques has happened. The study also revealed that deep learning especially Convolutional Neural Networks (CNNs) works way better than other classical and deep learning approaches but the Time-Space-Frequency fusion network (TSFFnet) has presented an even more encouraging approach to automatically extract relevant features from raw EEG data and thereby improving classification's accuracy and encountered low signal noise.

Classical EEG classification problems have been solved using various deep learning architectures such as CNNs and the combined CNN-RNN models and outperformed the former approach commonly used. In addition, the areas of future development are based on the motor imagery EEG classification, for example, the applications of BCI and clinical rehabilitation. The efficiency of using CNNs and the use of a hybrid framework have gained acceptance while decoding of motor imagery EEG signals is particularly prominent for reduced numbers of EEG channels.

3. Methodology

The current study is to perform classification of the motor imagery tasks based on the EEG signal that is acquired from 13 different patients, and specific channels C3, C4, and Cz are selected from their event-driven dataset which includes the important role in motor functionality. The raw EEG data, recorded from event-driven files, is preprocessed to extract meaningful features in three distinct domains: The time domain, the frequency domain, and the time-frequency domain. Some of the examples of features that are related to the time domain are the mean value, the variance value, the measure of skewness, and the measure of kurtosis. This gives the frequency domain characteristics through tools such as the Fast Fourier Transform (FFT) in the analysis of the EEG signals. Also, the time-frequency features are obtained through methods such as STFT and Wavelet Transform thus giving a broad description of the temporal and frequency change of the signal. These features are then used in the training of diverse conventional classifiers like the decision tree, support vector machines, and random forests. In addition to C-VAD, CNNR, CNN-GTR, CNN-PL, and DSS-FC-LSTM, other deep learning models including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs) and TSFFnet (Time space feature fusion network) are used taking advantage of the network capacity for recognizing high density and temporal correlations in the data. The efficacy of these models in EEC motor imagery classification is, thus, quantitatively assessed by correlation coefficient, mean absolute error, accuracy, F1 score, precision, and recall and confusion matrix, kappa statistics, ROC-AUC.

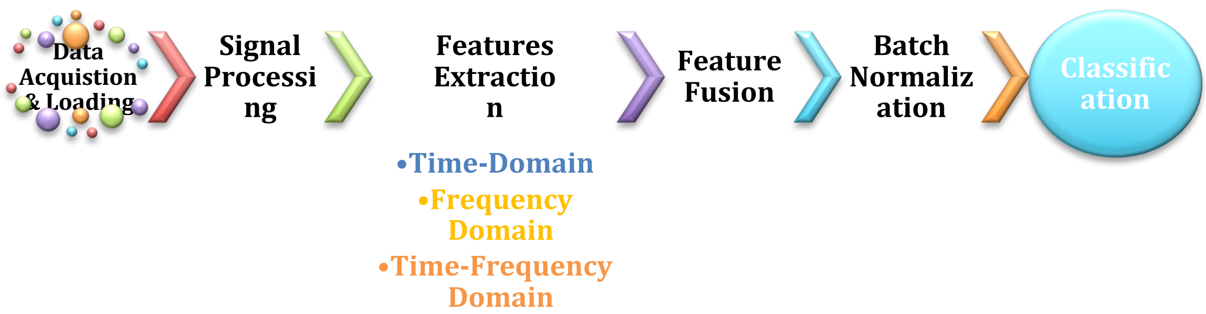

Figure 4. Data Preparation

Data Preparation and Features Extraction: EEG signals were obtained from event-related data files in the European data format (EDF) of a few sample patients. These files include multiple channel EEG signals with the event markers pointing to the start of various kinds of motor imagery tasks. The data were loaded using the MNE library as this is specialized in the handling of electrophysiological data. Afterward, the data files from the analysis were preloaded for further processing in the subsequent stages. The preprocessing stage was aimed at the choice of a certain channel of the EEG signal, which was used for the classification of the motor imagery. This selection can be changed according to particular needs, for example, in our case we have included EEG channels C3, C4, and Cz to record the time-domain, frequency-domain, and time-frequency domain features along with the event labels. Feature extraction was performed in three domains: time, frequency, and time-frequency, to capture a comprehensive set of characteristics from the EEG signals.

Time Domain Features: Time-domain analysis involves evaluating signals concerning time using various statistical functions. This approach represents signals as real numbers and captures their attributes over different time intervals. It allows us to determine the magnitude of a signal at various points, such as its mean value. Commonly used statistical functions to extract time-domain features include mean energy, maximum and minimum values, zero-crossing values, Wigner Ville coefficients, variance, Renyi entropy, arithmetic mean, spectral entropy, Petrosian fractal dimension, median, standard deviation, skewness, kurtosis, mean curve length, approximate entropy, permutation entropy. Hjorth parameters, Hurst exponent, and wavelet transform are shown in Figure 5 below [38].

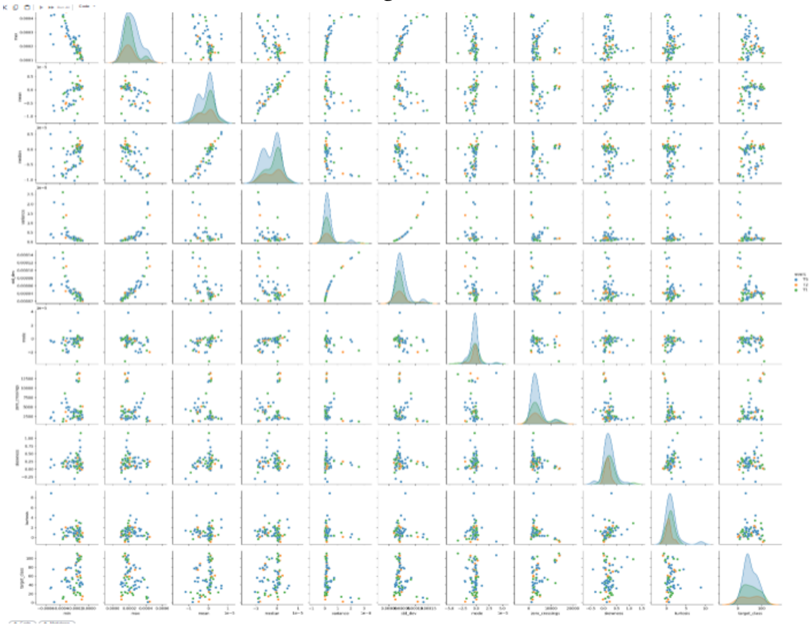

Figure 5. Captured Time Domain Features

Frequency Domain features: Analyzing signals in the frequency domain involves employing mathematical operations and functions related to frequency rather than time. The frequency-domain analysis offers information on phase shifts essential to reconstruct the original time signal from its frequency components and shows signal fluctuations throughout frequency bands, In contrast to time-domain analysis, which only displays signal differences across time. In this study, we used mathematical techniques in the frequency domain to compute various features. For instance, the median frequency was derived from the frequency table. Our study also utilized parametric modeling for frequency domain features, which is particularly effective for short signal lengths. These parametric ones construct a higher resolution by attempting to model the data as a linear system with white noise and then estimating the parameter of this system shown in Figure 5 below [38].

Time-Frequency Domain: Indeed, the time-frequency domain is a very efficient representation of real-world signals since it possesses properties both from the time and the frequency domain. TFR analysis referred to as Time-Frequency Representation helps maintain the facet features of sound such as amplitude and energy density. In the present study, the method utilized to process the EEG signals included the STFT method and the classification of the data with the help of several conventional and DL algorithms. Power spectral density is used in the process of obtaining time-frequency characteristics of the EEG signal, and the latter includes the frequency domain too. This technique involves a process of breaking the signal into individual overlapping segments and obtaining the PSD for each to allow investigation of the signal's frequency content at a given instance. Thus, the time-frequency characteristics of the signal are obtained through the averaging of the power of the signal in each of the segments for all the frequency bins. The given approach finally offered a selected time-frequency analysis, which described certain characteristics of the signal for subsequent processing [38]. The features extracted are shown in Figure 6 and described in Table 1 below.

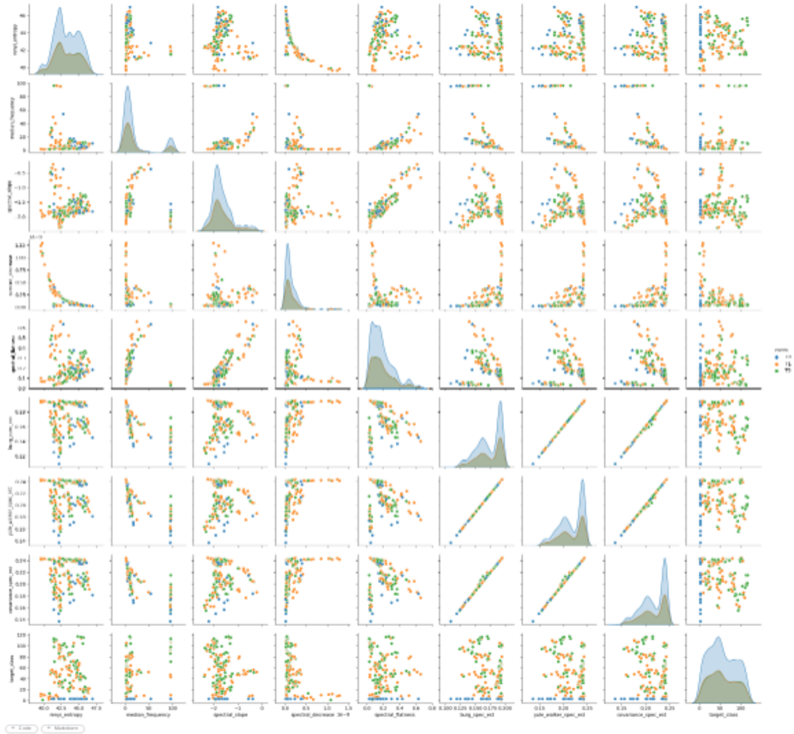

Figure 6. Captured Frequency Domain Features

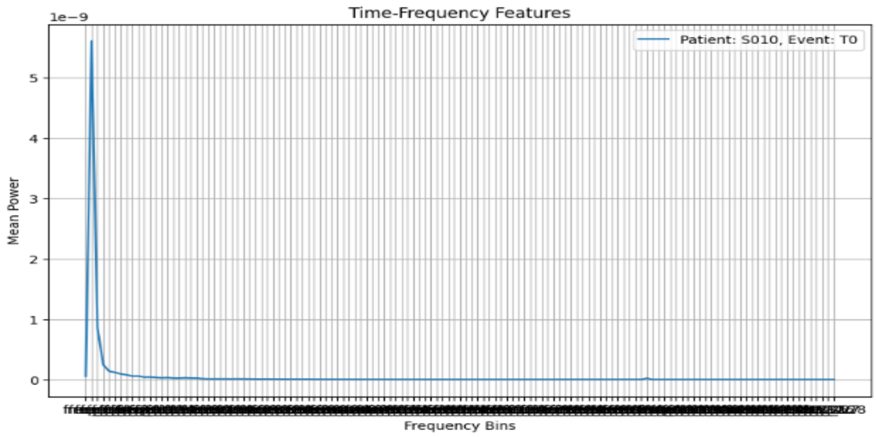

Figure 7. Captured Time-Frequency Features

Table 1. Time, Frequency, Time-Frequency Domain Features

Domain	Features
Time Domain	Mean
	Min
	Max
	Median
	Mode
	Variance
	Standard deviation
	Zero crossing
Frequency Domain	
	Renyi Entropy
	Median frequency
	Burge spectral estimation

	Yule-walker spectral estimation Covariance Spectral Estimation Spectral Slope Spectral Decrease Spectral flatness
Time-Frequency Domain	STFT based features

Feature Fusion: Thus, the features of time, frequency, and time-frequency were combined into one dataset. Such integration will make it possible to have an enhanced representation of the EEG signals in that several attributes regarding the signal acquires a unified profile.

Batch Normalization: Normalization of targets was done on the fused features to make them have a zero mean and unit variance. This process entailed normalization of the features such that they would be in the range of zero mean and unit variance. Batch normalization enhances the efficiency and stability of the regular classifiers, in addition to neural network classifiers, since features that are fed to the classifiers should be standardized to minimize internal covariate shifts while at the same time accelerating the training process.

Classification: Therefore, in this study, the main goal and scope was to maximize the classification of motor imagery tasks with the help of various machine learning approaches. To utilize temporal and spectral characteristics of the acquired EEG signal, the classical methods of classification as Decision Trees, SVM, and Random Forests were used. The selection of these algorithms was since they are more suitable for use in structural data fields, and the fact that they will capture the interactions between the corresponding feature spaces. Moreover, the study also incorporated innovative deep learning approaches such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN) as well as enhanced Time-Space Feature Fusion Net (TSFFnet) to analyze the applicability of learning the hierarchical and temporal features from EEG data. Concretely, this research proposed applying both sorts of techniques in motor imagery classification and then comparing their performances systematically. Besides, this research also helps to develop the method of neuro-informatics and improve the applications of brain-computer interfaces based on elaborate machine learning techniques.

3.1. Contributions

This study makes several key contributions to motor imagery MI-EEG classification. First it employs a comprehensive feature extraction approach across the time, frequency, and time-frequency domains, incorporating a variety of statistical measures, spectral analysis tools, and time-frequency representations such as STFT-based features. This broad analysis offers a more holistic perspective on MI-EEG signals as compared to traditional approaches that focus on a single domain. Additionally the study systematically compares the performance of classical machine learning models like decision trees, support vector machines (SVM), and Random forests with advanced deep learning models such as Convolutional Neural Networks(CNN), Recurrent Neural Networks(RNN), and Time-Space-Feature Fusion Networks(TSFFnet). This dual-method approach provides valuable insights into the strengths and weaknesses of each classification technique when applied to motor imagery tasks.

Another key contribution of the research is introducing advanced deep learning architectures including CNN-GTR, CNN-PL, CNNR, DSS-FC-LSTM, and TSFFnet which are specifically designed to capture both high-density spatial and temporal correlations within EEG signals. The novel TSFFnet in particular enhances the classification process by fusing spatial and temporal features into a unified framework, allowing for more accurate and efficient motor imagery analysis. The study incorporates batch normalization in the preprocessing stage which improves the performance and stability of both classical and deep learning models by standardizing the input features. Thus accelerating the training process and minimizing covariate shifts.

Moreover, the research evaluates model performance using a compressive set of metrics including correlation coefficient, Mean Absolute error, F1 score, precision, recall, kappa statistics, and ROC-AUC which offers a robust and multi-dimensional understanding of each classifier's effectiveness. This thorough evaluation provides a more detailed view of model performance as compared to studies that rely solely on accuracy metrics. Furthermore, the advancements demonstrated in this study have practical implications for Brain-Computer Interface (BCI) systems. The improved classification techniques for MI-EEG data can enhance the accuracy and reliability of BCIs used in neuro-rehabilitation and assistive technologies. At last, using open open-access EEG dataset the research promotes reproducibility and transparency, encouraging future studies to build on these findings in the BCI field.

4. Results and Discussion

Traditional Classifiers: In evaluating the performance of classifiers for motor imagery classification using time-domain features, Decision Tree, Support Vector Machine (SVM), and Random Forest models were assessed across three key metrics: thus, the effective measure of accuracy that is MAE as well as the correlation measure of the results. All classifiers achieved high accuracy, with Decision Tree and Random Forest both attaining 99.58%, marginally surpassing the SVM, which achieved 99.47% shown in Table 2 below. Thus, as far as the mean absolute error is concerned, the lowest error was characteristic of SVM – 0. 1603, meaning it was the closest to the actual values, followed by the Decision Tree with an MAE of 0.1985 It was found that for the given problem, models performing at par include 1985 and Random Forest with an MAE of 0.3185. In addition, SVM achieved the highest value of correlation coefficient equal to 0 of the relationship between the actual and predicted values of protein Secondary Structure. Instead, 9966 demonstrated the strongest linear correlation between the predicted and actual values as compared to Decision Tree with a score of 0.9953 and Random Forest's 0. 9875. From these outcomes, it can be stated that all models show high efficiency, but SVM gives maximal accuracy and stability making it the most appropriate for the classification of motor imagery.

Table 2. Time Domain features Classification results

Performance Measures	Decision Tree	Support Vector Machine	Random Forest
Accuracy (%)	99.58	99.47	99.58
Mean Absolute Error	0.1985	0.1603	0.3185
Correlation Coefficient	0.9953	0.9966	0.9875

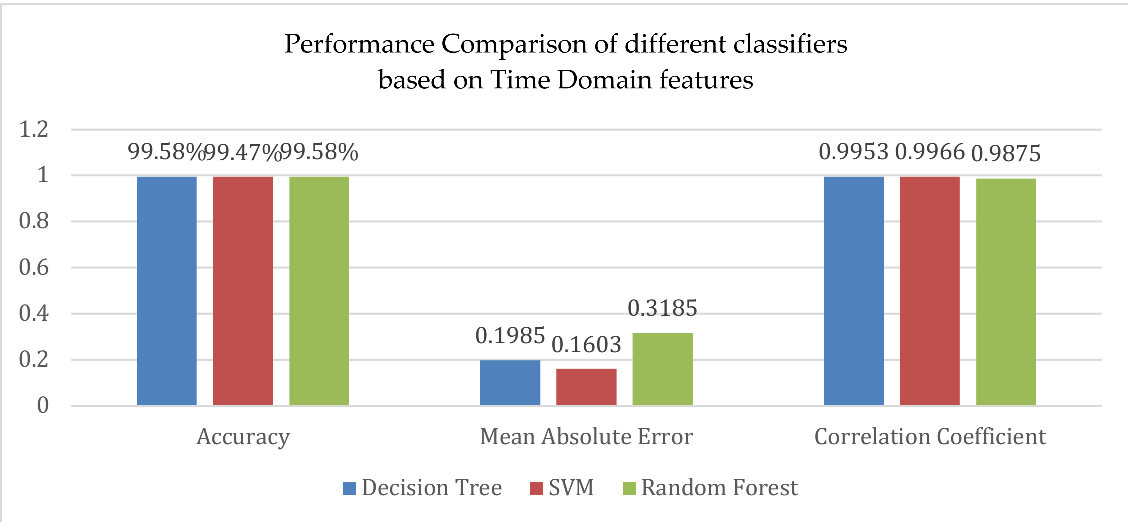

Figure 8. Performance Comparison of different Deep Learning Models

In the assessment of classifiers for motor imagery classification using frequency-domain features, Decision Tree, Support Vector Machine (SVM), and Random Forest models were evaluated on accuracy, mean absolute error (MAE), and correlation coefficient. Both Decision Tree and Random Forest achieved an accuracy of 99.47%, outperforming SVM, which attained an accuracy of 97.24% shown in Table 3. In the aspect of MAE, Random Forest outperformed the other algorithms with a result of 0. MAE was calculated for each model for its ability to predict the test data with low average prediction error; Random Forest recorded the lowest MAE of 0. 2091 followed by Decision Tree at 0. 3036 and Support Vector Machine with an MAE of 0. 3747. For the correlation coefficient, SVM and Random Forest both reached 0.9948 and 0.9949 where random forest reflected the strongest linear relationship between predicted and actual values whereas Decision Tree had a slightly lower coefficient of 0.991. These results suggest that Decision Tree and Random Forest deliver the highest accuracy with Random Forest showing the best performance in terms of mean absolute error while SVM and Random Forest achieve superior correlation coefficients. Overall, Random Forest stands out as the best-rounded model in the aspect of learning frequency domain features and classifying the motor imagery task. As it demonstrates high accuracy, minimal prediction error, and a strong correlation with frequency-domain features.

Table 3. Frequency Domain Features Classification Results

Performance Measures	Decision Tree	Support Vector Machine	Random Forest
Accuracy (%)	99.47	97.24	99.47
Mean Absolute Error	0.3036	0.3747	0.2091
Correlation Coefficient	0.9906	0.9948	0.9949

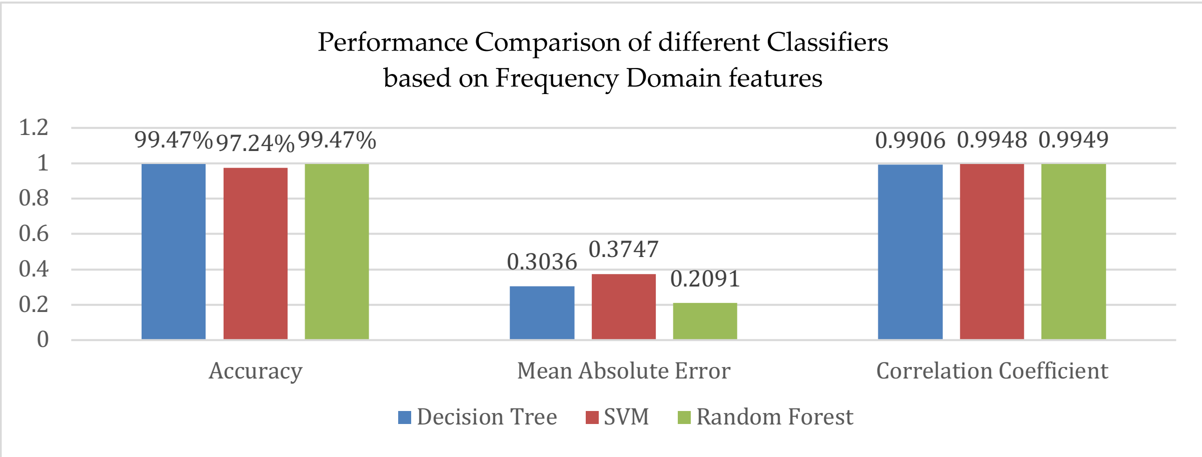

Figure 9. Performance of Different Classifiers using Frequency Domain Features

In the assessment of classifiers for motor imagery classification using time-frequency domain features, Decision Tree, Support Vector Machine (SVM), and Random Forest models were evaluated on accuracy, mean absolute error (MAE), and correlation coefficient. Random Forest demonstrated the highest accuracy at 99.58%, outperforming Decision Tree, which achieved an accuracy of 99.47%, and SVM, which recorded an accuracy of 95.12% shown in Table 4 below. In terms of MAE, Random Forest again excelled with a value of 0.1274, indicating the lowest average prediction error, compared to Decision Tree with an MAE of 0.2367 and SVM with an MAE of 0.5626. For the correlation coefficient, Random Forest achieved the highest value of 0.9979, reflecting the strongest linear relationship between predicted and actual values. In contrast, Decision Tree and SVM had coefficients of 0.9928 and 0.9919, respectively. These results highlight that Random Forest not only provides superior accuracy but also exhibits the lowest prediction error and the highest correlation, making it the most effective classification model based on time-frequency domain features.

Table 4. Time-Frequency Domain Features Evaluation Results

Performance Measures	Decision Tree	SVM	Random Forest
Accuracy (%)	99.47	95.12	99.58
Mean absolute error	0.2367	0.5626	0.1274
Correlation Coefficient	0.9928	0.9919	0.9979

4.1. Deep Learning Classifiers:

Convolutional neural network evaluation (CNN): The Convolutional Neural Network (CNN) model demonstrated outstanding performance in motor imagery classification. A larger number of Nano devices means that their fabrication costs are higher, but simultaneously they guarantee much higher accuracy, at least 99%. 34%, it also achieved a high precision of 99. 97% and recalls 99. 98% overall, resulting in an F1 score of 99. 98%. The last result of the Mean absolute error was relatively small and equal to 0. 0082 suggesting that the forecasts are accurate with close estimates to the precise values.

At the same time, the Kappa statistic was equal to 0. 991231 also presents high accordance with the predicted and actual classification and the ROC-AUC score of 1. Indeed, as seen it has a superior discriminative ability.

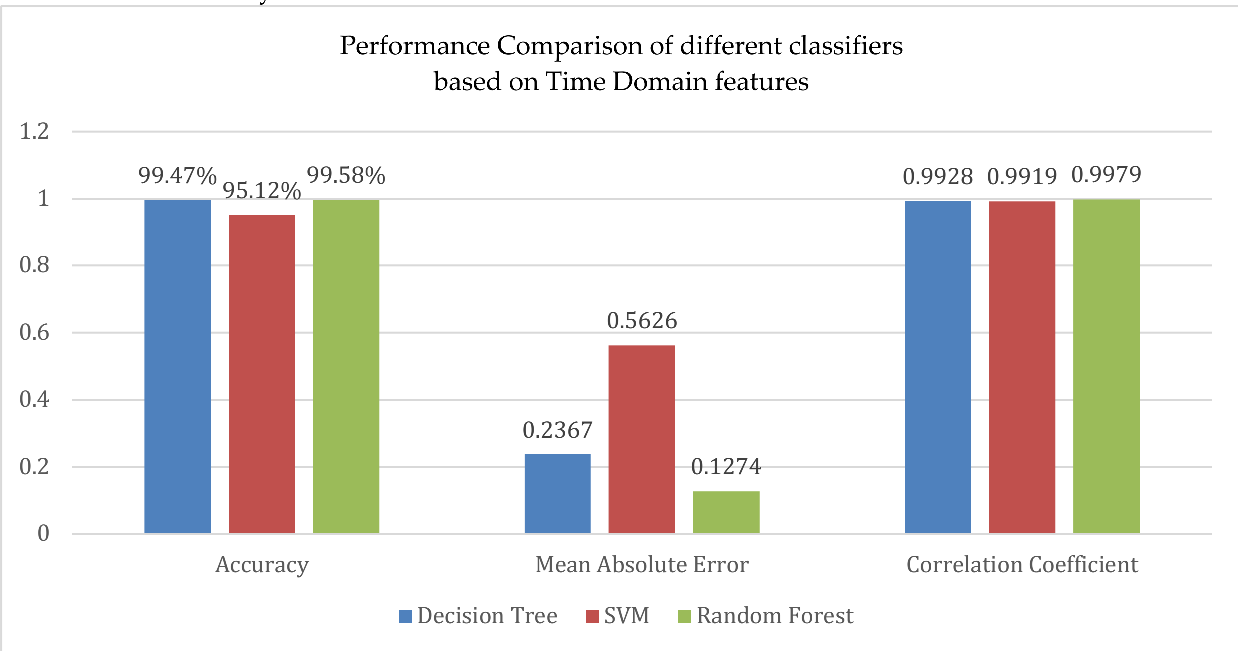

Figure 10. Performance Comparison of Traditional Classifiers using Time-Domain Features

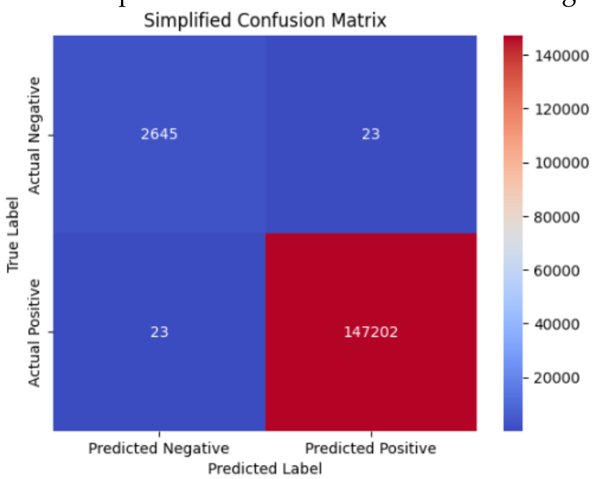

Figure 11. Convolutional Neural Network Confusion Matrix

This is also supported by the confusion matrix which has correct negative instances as 2645, incorrect positive instances as 23, incorrect negatives as 23, and correct positive instances as 147202 thereby establishing that the model is accurate in its classification of both the classes with minimal mistakes.

Table 5. Convolutional neural network evaluation results (CNN)

Performance Measures	CNN(Convolutional Neural network)
Accuracy	0.9934
Precision	0.9997
Recall	0.9998
F1-Score	0.9998

Mean Absolute Error	0.0082
Kappa Statistic	0.991231
ROC-AUC	1.0

Recurrent Neural Network Evaluation (RNN): The applied Recurrent Neural Network (RNN) model for the motor imagery classification proves to have significantly better performance than CNN The accuracy of the model is 99. 35%, to which the model proves to be highly reliable. Its precision as well as the recall rate are almost perfect and are at 99%. 99% and therefore F1-measure reaches 99%. 98%. The mean absolute error is also relatively low at 0. This is very accurate denoted by the number; 0077 expressing perfect forecasts away from the mark. The level of concordance defined by the Kappa statistic was 0.991237. The percentage reveals a high degree of congruity between predicted and actual classification, along with an ROC-AUC score of 1, which is the optimal result. Based on the above ROC curve analysis in Fig 2, the AUC of 0 highlights the model's great discriminative capacity in differentiating between classes.

When comparing the RNN performance to the CNN model, the two models brushed themselves up in all the descriptors. The primitives compared with the RNN attain a little higher accuracy at 99. of the participants reported 35% and better precision was reported as 99 The means of this study show better precision at 99 but only 35% of the participants scored in this region; The means of this study show that 35% of the participants scored 35% and better, although the better precision was 99. 99% where both F1-scores are equal to 99. 98%. The mean absolute error is slightly lower here in the RNN 0. 0077 Kappa statistics of both models are the same and ROC-AUC values are 1.

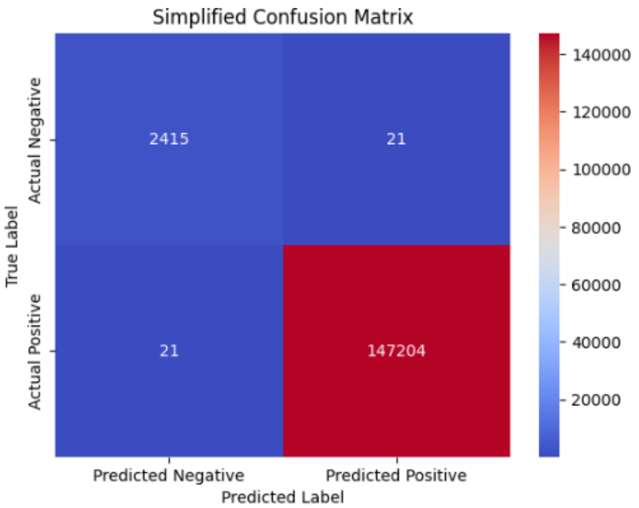

Figure 12. Recurrent neural network confusion matrix

The confusion matrix for the RNN shows 2415 TN, 21 FP, 21 FN, and 147204 TP which is like the CNN's performance matrix. Based on the results obtained in both models, the approach shows low misclassification rates, which indicates the models' stability and the ability to correctly classify motor imagery. Altogether, the results of both models are rather outstanding, yet the score of RNN is just a tad higher with regards to the measures of precision and mean absolute error.

Table 6. Recurrent Neural Network Evaluation Results (RNN)

Performance Measures	RNN(Recurrent Neural Networks)
Accuracy	0.9935
Precision	0.9999
Recall	0.9999
F1-Score	0.9998
Mean Absolute Error	0.0077
Kappa Statistic	0.991237
ROC-AUC	1.0

Time space frequency fusion network (TSFFnet): The Time Space Frequency Fusion Network (TSFFnet) model demonstrates superior performance in motor imagery classification. With an accuracy of 99.75%, it surpasses both the CNN (99.34%) and RNN (99.35%) models. TSFFnet also excels in precision and recall, both at 99.99%, resulting in an outstanding F1-score of 99.99%. The mean absolute error is remarkably low at 0.0038, significantly lower than both the CNN (0.0082) and RNN (0.0077), indicating highly accurate predictions with minimal deviation.

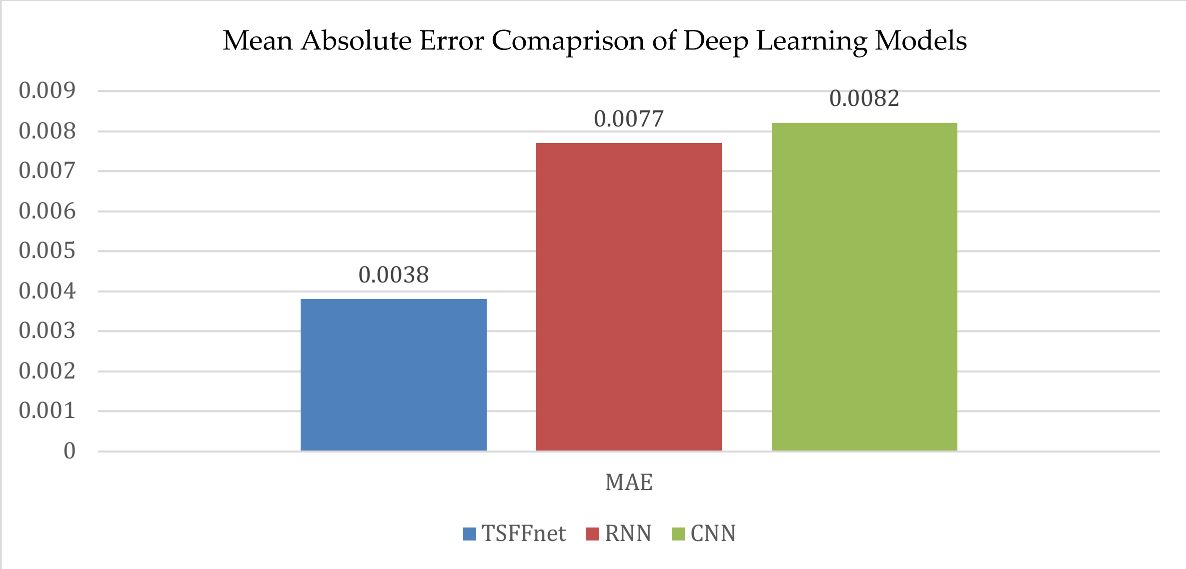

Figure 13. MAE Comparison of Deep Learning Models

The Kappa statistic for TSFFnet is 0.9913, slightly higher than the CNN (0.991231) and RNN (0.991237), reflecting excellent agreement between predicted and actual classifications. The perfect ROC-AUC score of 1.0 underscores the model's exceptional discriminative ability.

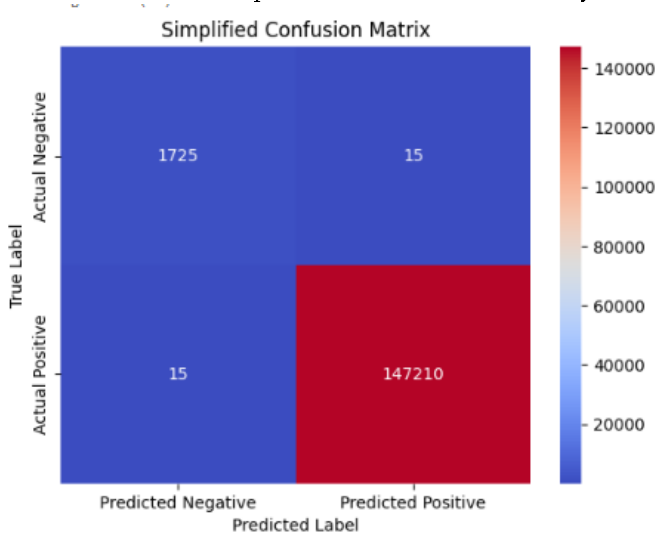

Figure 14. Time-space frequency fusion (TSFFnet) confusion matrix

The confusion matrix for TSFFnet shows 1725 true negatives, 15 false positives, 15 false negatives, and 147210 true positives. This indicates fewer misclassifications compared to the confusion matrices of CNN and RNN, emphasizing TSFFnet's robustness.

Table 7. Time Space Frequency Fusion Network (TSFFnet)

Performance Measures	**TSFFnet (Time Space Frequency Fusion Network)**
Accuracy	0.9975
Precision	0.9999
Recall	0.9999
F1-Score	0.9999
Mean Absolute Error	0.0038

Kappa Statistic	0.9913
ROC-AUC	1.0

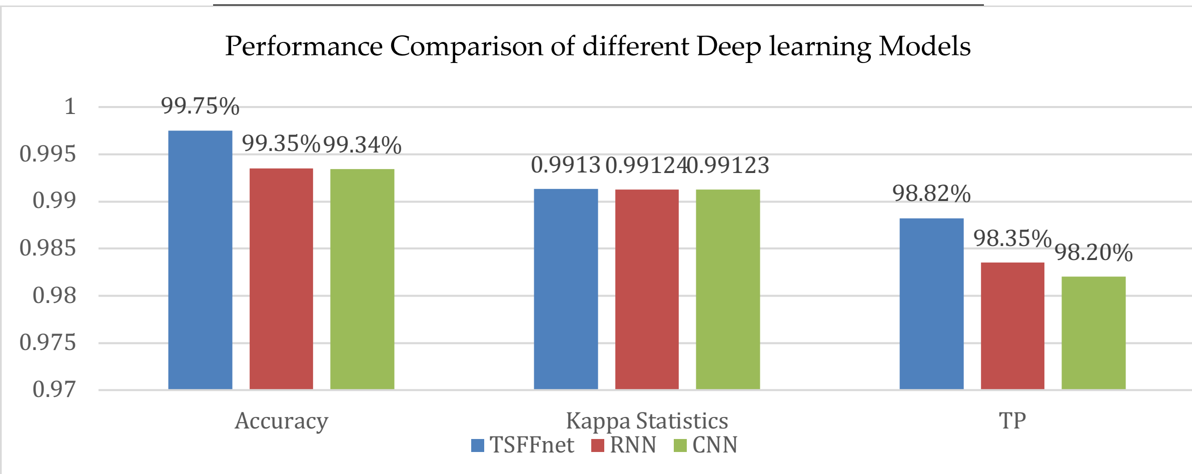

Figure 15. Other Performance Comparisons of Deep Learning Models

TSFFnet outperforms the other models in almost all performance measures, achieving the highest accuracy at 99.75%, the highest kappa value at 0.9913, and the best True positive (TP) rate at 98.82%. RNN and CNN have very similar performance with RNN slightly edging out CNN in both accuracy and kappa statistics while CNN lags just behind in all matrics. Overall, TSFFnet is the most effective model, although the differences between RNN and CNN are minimal.

5. Conclusion

Motor imagery classification using EEG signals is an essential area of research and promotes enhanced communication and control systems for people suffering from motor impairments. This study aimed to analyze EEG data across channels C3, C4, and Cz for the classification of different imagery tasks using several machine learning and deep learning techniques. In this study, we discussed the significance of multi-domain features like Time-domain, Frequency Domain, and Time-Frequency domain extraction to encompass prominent signal characteristics. This work included preprocessing EEG signals, feature extraction using statistical (a combination of spectral and time-frequency methods) utilizing traditional classifiers i.e decision tree, SVM, random forests as well advanced deep learning models like CNN, RNN, and Time-space-frequency fusion model (TSFFnet).

One of the major results was that the tree-based model random forest was highly competitive in most feature domains both in accuracy and mean absolute error as Random forest managed to have high accuracy for time, frequency, and time-frequency domain features in contrast to decision tree and support vector machine (SVM). On the other hand, having an accuracy of 99.75%, a precision of 99.99%, and a recall value along with a minimum of MAE 0.0038. The performance of the deep learning model TSFFnet has shown better results than those methods independently from the best representation technique (signal to frequency mapping) as compared to CNN, RNN, and other traditional classification models. An ROC-AUC score is 1.0 for all models shows that the discrimination achieved was very high. These results demonstrate the robustness of deep learning methods specifically TSFFnet for motor imagery classification.

Our future work will consider adding more EEG channels and testing on different datasets to make the model as generalizable as possible. Another area that could provide a huge leap towards efficient interventions of BCIs in real-world applications is the development of real-time implementations and adaptive algorithms. Furthermore, a hybrid model involving the strengths of different classifiers could be developed to achieve better performance for complex motor imagery tasks.

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