Motor Imagery EEG Signal Classification Using Deep Learning Approach

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Annex A

THESIS ACCEPTANCE CERTIFICATE

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Dedicated to ***My Teachers****, whose tremendous continuous support led me to this accomplishment*

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Abstract

Motor Imagery electroencephalography (MI EEG) data are employed in brain computer interface (BCI) systems to identify the intention of participants. Several factors, such as poor signal to noise ratios and a scarcity of high-quality samples, complicate the classification of MI EEG signals. For BCI systems to operate well, it is necessary to analyse MI-EEG signals. Recent successful applications of deep learning methods have been observed in pattern recognition and other domains. Conversely, there have been few successful implementations of deep learning algorithms in BCI systems, particularly those based on machine intelligence. Brain-computer interfaces (BCI) can be crucial in facilitating communication with the external environment for those with movement impairments. Deep learning has achieved remarkable success across the many domains. Nevertheless, deep learning has achieved only limited progress in the analysis of Electroencephalogram (EEG) information. The present study suggests a novel approach to address the problem by integrating the Continuous Wavelet Transform (CWT) with deep learning-based transfer learning approach. Continuous Wavelet Transform (CWT) converts one-dimensional EEG signals into a two-dimensional representation of time, frequency, and amplitude images. This allows us to explore existing deep networks via transfer learning. The present work assesses the efficacy of the suggested methodology by utilising a publicly accessible dataset from the BCI competition VI-2b. Our study attained a promising validation accuracy of 81.72% by comparing the findings of the approach with previous efforts on the same dataset. A comparative analysis of the proposed algorithm with existing algorithms demonstrates its superior performance in classification tasks. The approach can enhance the classification accuracy of motor imagery (MI)-based brain-computer interfaces (BCIs) and BCI systems designed for individuals with impairment.

Keywords: Brain Computer Interface (BCI), Motor Imagery EEG signals (MI EEG), Time frequency images, CWT, VGG16

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Chapter 1

1 INTRODUCTION

1.1 BACKGROUND

A brain-computer interface, often known as a BCI, is a type of intercommunication system that allows for direct connection between the human brain and external technological entities, such as computers or other electronic equipment, without the need for any intermediaries to be involved. Through the use of brain-generated impulses, this method makes it possible for the user to directly manipulate the computer or smart device, hence eliminating the need for the user to rely on peripheral organs and muscles. In terms of theoretical applications, military applications, medical applications, and recreational applications, brain-computer interface (BCI) research is extremely relevant. The exploration of Brain-Computer Interfaces (BCI) holds a substantial amount of academic significance across a wide range of departments [1, 2]. When seen from a conceptual standpoint, it has the potential to offer an understanding of the functioning of the human mind that is unequaled. It is possible for it to improve the efficiency of soldiers when they are out in the field, which is a military use. When viewed from a medical point of view, it has the potential to be utilized in the treatment of particular conditions, such as paralysis, that were previously thought to be incurable. In the end, it makes it easier to build interesting recreational activities by providing users with the opportunity to explore virtual surroundings and interact with them in ways that are both unique and pioneering. Electroencephalography, sometimes known as EEG, is a signal that is frequently utilized in the process of developing Brain-Computer Interface (BCI) systems. There are numerous advantages associated with it, including its portability, non-invasiveness, and cost-effectiveness[3]. Concurrently, we face the challenge of dealing with the high-resolution spatial EEG signal suffering from inadequate robustness and a low proportion of signal to noise [4]. Furthermore, MI-EEG contains a irregular and inconsistent signal, so its statistics, including variance and mean, exhibit temporal variations [5]. Using a Brain-Computer Interface (BCI), an EEG signal is decoded and converted into practical messages[1]. A control system that is designed to drive a powered wheelchair for people who have lost their motor abilities is an example of a practical application of signal translation. A joystick control system that makes use of the subject's chin movement as a control mechanism is one solution that could be considered. On the other hand, however, this strategy is regarded as being difficult to implement and lacking in appeal[6]. The electroencephalogram (EEG) signal makes it possible for people with severe motor disabilities to use a device without using their hands by seeing the actions of their limbs. The combination of brain signal recording and decoding for the purpose of controlling an external device is what is known as a brain-computer interface (BCI) in the field of human-machine interaction (HMI) [7]. As a result of the incorporation of software technologies, the interaction between the human brain and the mechanical apparatus is made easier. Through the development of the BCI technology, one of the goals that is frequently sought is to make it possible for people who have physical limitations but are in good mental health to operate a computer on their own using only their brain impulses autonomously [8]. The development of neuro-prosthetics with the purpose of restoring movement, auditory function, and visual perception in those who have disabilities is the major objective under consideration. There is still room for improvement in terms of classification accuracy in order to achieve better system implementation, despite the fact that a number of studies on Brain-Computer Interfaces (BCI) have demonstrated its effective use in transmitting cerebral commands to control external devices such as computer cursors, prosthetic limbs, robotic arms, or wheelchairs.

Through the use of electroencephalography (EEG), it is possible to identify the electrical impulses that are generated by neurons in the human brain. In this procedure, the oscillatory activation map of the brain is collected from the scalp in a way that is not potentially invasive. The control command for the Brain-Computer Interface (BCI) can therefore be obtained by this method, which is completely suitable and reliable [7, 8]. Previous research has shown the use of EEG signals, namely motor imagery (MI) related to picturing finger or limb movement, for the purpose of controlling an artificial intelligence system [7]. A primary objective of these BCI investigations is to identify the EEG pattern generated by the MI-task. A great temporal resolution is exhibited by the non-stationary EEG signal [9]. The frequency spectrum of an EEG signal typically spans from 0.5 to 100 Hz and is further compartmented into several sub-frequency bands. Efficient detection of event-related synchronisation (ERS) is observed in the activity recorded from the sensorimotor cortex in the Mu (8-13 Hz) and Beta (13-30 Hz) frequency bands for MI-based BCI systems[10] and de-synchronization (ERD) pattern [11]. There is a characteristic of an EEG signal known as a mu band that occurs during motor events. This occurs when the rhythm patterns of the brain become less synchronized (desynchronized) during motor movements. The inverted electroencephalogram (EEG) patterns that are seen in the sensory-motor cortex during myocardial infarction (MI) are the source of the Mu rhythm. The echogenic resonant decay (ERD) characteristic of brain potentials, which displays a polarity inversion similar to that of the Greek letter Mu, is responsible for the production of these patterns. Beta band and mu rhythms have been shown to have a substantial association with event-related potential systems, according to a number of studies[12, 13]. It has also been brought to people's attention that frequency bands are subject-specific the majority of the time and can somewhat fluctuate from one subject to the next [14]. In the field of research that is based on Brain-Computer Interfaces (BCI), the extraction of information from recorded EEG signals in order to determine the specific activation pattern serves as an essential component. The precise transfer of the user's intention to the control device continues to be a significant challenge in the field of human-computer interaction (BCI), despite the fact that it was introduced many years ago. An efficient Brain-Computer Interface (BCI) system must have two key prerequisites: a comprehensive collection of EEG characteristics that are able to differentiate between brain activity caused by tasks, and a highly efficient machine learning framework for classifying the extracted features. Both of these requirements must be met for the system to be considered successful. As a result of the significance of both time and frequency information in EEG, a wavelet transform that is based on multiple resolutions is regarded as being more suitable for EEG analysis than techniques that are based on the Fourier domain [7]. Numerous studies have merged approaches for feature extraction based on wavelet transforms into applications for brain-computer interfaces[9, 11]. The usage of common spatial patterns (CSP) is yet another well-known technique for feature extraction that is utilised in MI applications[15, 16]. During common spatial pattern, also known as CSP, additive sub-windows of the signal are produced. These sub-windows display maximal difference invariance. The computational complexity is reduced as a result of these extracted features, which reflect the statistical qualities of the signal in the temporal domain. The determination of the activation pattern of BCI-based EEG is made easier with the use of classification algorithms to these statistical elements which are being considered. As a result, a number of different machine learning algorithms have been evaluated in order to determine which approach is the best effective for identifying tasks using machine intelligence. Conventional classification algorithms, such as artificial neural networks (ANN), have been observed to exhibit a significant improvement in the accuracy of categorization[17, 18], Bayesian classifier [19], K-nearest neighbor (KNN) [9], quadratic discriminant analysis (QDA) [9], linear discriminant analysis (LDA)[17] and support vector machine (SVM) [15, 17]. Conventional techniques like Artificial Neural Networks (ANN) can effectively train the network, but they are constrained by inherent limits, such as a finite number of hidden layers. These approaches were unable to fully leverage multi-dimensional information. Conventional approaches in Brain-Computer Interfaces (BCI) require spatial filtering to consider the position of electrodes and their spatial orientation. Convolutional Neural Networks[20] turn out to be a viable solution to the classification problems in practical applications as it uses two-dimensional images. Although the achieved results are already remarkable, there is still scope for enhancing accuracy, interpretability, and usability for real-time applications. The automatic identification of MI-based EEG necessitates a precise learning system. Deep learning using a convolutional neural network (CNN) is a recent advancement in the field of machine learning that has shown remarkable performance in the processing of EEG data[21, 22]. Recently, these learning algorithms had worked well in the detection of emotion[23].

1.2 PROBLEM STATEMENT

Within the framework of the Brain Computer Interface (BCI) system, the classification of EEG signals pertaining to motor imagery is an essential part of the process. An electroencephalogram, sometimes known as an EEG, is a dataset that is extremely nonlinear and hence presents substantial difficulties in terms of categorization. Brain-computer interface (BCI) systems make heavy use of motor imagery electroencephalogram (MI-EEG) signals from the left and right hands in order to determine whether or not a participant intends to manipulate external devices. The efficient classification of motor imagery, on the other hand, has considerable challenges due to a number of parameters, including low signal-to-noise ratios and a limited dataset. In order to successfully implement Brain-Computer Interface (BCI) systems, it is essential to identify the electroencephalogram (EEG) signals of both the left and right hands.In order to promote the formulation of methods that are more accurate and effective for classifying left and right hand two class motor imagery EEG data, the purpose of this work is to address the existing gaps in knowledge that have been identified. The domains of robotics, brain-computer interfaces, and rehabilitation are all potential areas of use for these systems.

1.3 RESEARCH QUESTION

"How does the performance of Continuous Wavelet Transform (CWT) combined with deep learning compare to other feature extraction and classification methods for two class motor imagery EEG signal classification?"

1.4 SIGNIFICANCE OF RESEARCH QUESTION

Those individuals who have major movement limitations and poor communication abilities would experience a significant improvement in their well-being if a reliable Brain-Computer Interface (BCI) technology were to be developed. Brain-computer interfaces, also known as BCIs, have the potential to offer people who have this disease a means of communication and control over their environment. As a result, these persons will be able to participate in more diverse activities that are part of their daily lives, which will ultimately improve their overall health and well-being. A technique known as brain-computer interface (BCI) has emerged as a viable solution for those who have movement impairments. This technology enables users to operate equipment by using brain impulses, which is a significant advancement. Through the development of a dependable Brain-

Computer Interface (BCI) system that enables more effective and pleasant communication with machines, it is possible to improve the quality of life and autonomy of these individuals at the same time. The methodology that has been provided shows promise in terms of helping the development of Brain-Computer Interfaces (BCIs) that are more sophisticated and accurate. This will allow people who have motor disabilities to use their brain signals for a wide variety of tasks.

1.5 RESEARCH OBJECTIVE

The primary objective of this thesis is to enhance the accuracy of classifying two-class MI EEG signals by utilising time-frequency pictures of MI EEG signals generated using CWT algorithm. Through a comparative analysis of the performance of our proposed approach with existing methods, we shall demonstrate its efficacy. Furthermore, this thesis will encompass a comprehensive examination of Motor Imagery EEG signal processing and analysis, CWT and spectral feature extraction approaches, as well as relevant research on Motor imagery EEG signal classification.

The particular goals are:

- To generate time-frequency pictures of Motor Imagery (MI) EEG signals using continuous wavelet transform (CWT)
- To categorise motor imagery EEG data to two classes using generated time-frequency pictures
- To assess the efficacy of the suggested approach in terms of classification accuracy by a comparative analysis with existing methodologies.

Although Brain-Computer Interfaces (BCIs) have the capacity to facilitate communication and equipment operation for individuals with motor impairments, the task of categorising motor imagery brainwaves (EEG) signals has shown to be a formidable one. A recent study has shown encouraging outcomes in collecting the frequency characteristics of EEG data and generating a robust set of features for classifying motor imagery EEG signals. The advancement of more accurate and reliable Brain-Computer Interface (BCI) technologies can greatly enhance the efficacy and comfort of communication and interaction for those with movement disabilities. The present thesis introduces a method for classifying two-class MI EEG data by using time-frequency pictures derived from Continuous Wavelet Transform (CWT). Commonly employed for the time-frequency analysis of non-stationary data such as EEG, Continuous Wavelet Transform (CWT) is a robust method.

Chapter 2

2 LITERATURE REVIEW

2.1 RELATED WORK

In order to enhance the dependability of the classification of electroencephalogram (EEG) data pertaining to motor imagery (MI), a substantial amount of research has been conducted. When it comes to the performance of these systems, the attributes that have been carefully chosen and the classification algorithm that is being used are the most essential elements that determine the performance. Convolutional neural networks have been utilized by a number of researchers in the field of academia over the course of the past few years in order to evaluate and extract information from electroencephalogram data. A significant reduction in the number of connections and features that are present in a deep network is achieved via the utilization of this strategy, which makes use of the relevant geographical or temporal interconnections between data points that are located in close proximity to one another. Taking this into consideration, it is possible to draw conclusions about relevant qualities for a particular machine learning application as a consequence of this. Refer to [24] additionally, it was proposed that convolutional neural networks (CNNs) make use of a method known as frequency complementary map selection (FCMS), which is founded on augmented convolutional support vectors (ACSP). In order to lessen the dependency on spatial mapping of features over a variety of frequency bands, this was carried out. The temporal information that is obtained by the EEG recording, on the other hand, is not utilized to the extent that it could be by means of this instrument. Refer to [16] For the purpose of converting EEG impulses into image signals, a technique known as short-time Fourier transformation (STFT) was utilised. Next, convolutional neural networks (CNN) and automated stacking encoding (SAE) were employed in order to extract features and categorise them. In [25], A Convolutional Neural Network (CNN) is utilized in order to collect the temporal information that is contained inside an electroencephalogram (EEG). The utilization of envelope representations, which are supplemented by Hilbert transform calculations, is what allows this to be performed. It is feasible to downsample the envelope signal because of its low frequency, which will result in a reduction in the number of dimensions that are accurately represented by the data. This will be the case since the envelope signal is low in frequency. A substantial quantity of data is required for the use of computational neural networks (CNNs) and other deep learning approaches in order to get a reasonable presentation on the task at hand. There is a possibility that a shortage of data for training deep learning models could lead to the overfitting of particular characteristics to a particular training set. This would then result in the model's generalizability being restricted. Because the model has only been trained on a specific dataset, its capacity to accurately predict or comprehend new data is already restricted. This is because the model has only been trained on a single dataset. An inherent limitation of the paradigm is that this is the case. The acquisition of additional data and the verification that it is representative of the hypothetical data that we anticipate coming across in the future are both essential procedures that need to be completed in order to increase the accuracy of the model. Both of these steps are necessary in order to achieve the desired result. Following the implementation of this method, the model's ability to generalise will be enhanced, and the outcomes will be more accurate in terms of forecasting. As a result of the extensive procedures and tight guidelines that were utilized in the research for the acquisition of MI-EEG signals, it is difficult to acquire sufficient training data in order to classify MI-EEG signals[26]. Both irregular and body unsteady have the potential to produce sudden spikes in the electroencephalogram (EEG) data. These spikes are known as eye movement artefacts and muscle measure artefacts, correspondingly [27]. A variety of preparatory procedures need to be carried out in order to obtain a sample that can be depended upon. In addition, this is necessary in order to obtain a sample. When performing these actions, it is necessary to mentally visualize the motion and to follow the pointing arrows displayed on the computer. The next step is a brief period of rest that comes after them. In light of this, it is imperative that the subject keep their focus during the whole of this time period; yet, as the duration of the experiment continues to increase, it becomes increasingly difficult to retain attention in a consistent manner. As a result, it is highly challenging to perform the task of collecting a substantial quantity of high-quality MI-EEG signals for the training assignment. The problem of general overfitting is usually addressed by academics through the utilization of data augmentation (DA) technology, which is widely employed by these individuals. The application of data augmentation techniques, which include data processing and overtaking, can result in an increase in the size of the data sets that are already available [28]. Numerous fields, including target recognition and image analysis, have been shown to benefit from the application of DA, as proved by experimental evidence [29]. In general, the usage of two different approaches results in the generation of improved data. The first strategy makes use of geometric alterations, whereas the second method involves the incorporation of noise into the training data that was previously accessible. Refer to [30] proposed a convolutional neural network (CNN) with many inputs for the purpose of identifying multi-channel MI-EEG signals to be received. Transforming the MI-EEG image by rotating and flipping it was done in order to increase the amount of data that was collected. Refer to [26] This article presents a Data Augmentation (DA) that incorporates rotating images with incremental noise. The electroencephalogram (EEG) is a collection of dynamic, highly significant (both temporally and spatially), non-stationary time series that are collected from several electrodes. This is in contrast to visuals, which are static. In order to avoid the possibility of time-domain properties being distorted, it is not possible to directly apply geometric transforms to EEG data[31]. Refer to [32] The empirical mode decomposition (EMD) technique was utilized by us in order to produce novel synthetic EEG frames. After that, we utilized complex Morlet wavelets as inputs for the neural network, which allowed us to transform all of the EEG data into tensors. By employing the EMD method, the electroencephalogram (EEG) signal is segmented into its intrinsic mode functions (IMFs), which are typically narrowband in configuration. It is conceivable to do research on each of these IMFs apart from one another in order to acquire information concerning particular frequency bands that are believed to be connected with various cognitive functions. Methods of DA [28, 33, 34] At the present moment, it is of the utmost importance to carry out research on methods that are appropriate for monitoring EEG signals. In general, the process of developing a CNN that is adequate for feature extraction and classification over a segment of exceedingly complicated and unstable EEG signals is a considerable challenge. This is because the procedure involves a lot of moving parts. On the other hand, the utilisation of CNNs for the purpose of signal classification can call for the utilisation of a significant amount of data as well as the robustness of the system. Throughout the course of this investigation, we approached these problems from two distinct points of view, both of which were founded on the characteristics of EEG signals. An initial proposal was made for a data set that integrated the time domain with the frequency domain. Higher-order statistics of Power Spectral Density (PSD) at different orders led to the generation of characteristics such as logarithmic amplitudes and spectral moments for both the first and second orders. These characteristics were produced for both orders. By utilizing Support Vector Machines (SVM) and Linear Discriminant Analysis (LDA), it was discovered that a misclassification rate of ten percent was the lowest attainable rate. Wavelet transform is one of the technologies that has garnered a lot of trust due to its capacity to analyze EEG signals. As a consequence of this, researchers have utilized it for the purpose of feature extraction [35, 36]. Significant features are contained within the brain's spatial patterns, and the properties of common spatial patterns (CSP) have been utilised extensively for EEG signal processing, primarily for the purposes of brain-computer interfaces (BCI). CSP is utilised in conjunction with SVM in [15], This results in an accuracy of classification of 82.6% for the third data set of the BCI competition II. Various classification algorithms, such as KNN classification, [9] This results in a classification accuracy of 84.29 percent for two-class motor imaging, with the average band power of the Alpha (Mu) frequency band and the Beta band. Using the support vector machine (SVM) classifier, a recent study found that Shannon entropy as a feature yielded an accuracy of classification of 86.4% [12].

In recent times, deep learning has emerged as a significant platform that has captured the attention of researchers. Deep learning is mostly available in the field of image and video classification. It is relatively new to the field of biological signals, and in recent years, numerous public assessments have been conducted [37], The application of deep learning to the field of biomedicine has been addressed. Deep learning has been applied to the classification challenge for MI data by utilising CNN and stacked autoencoders (SAE) in conjunction with Short Time Fourier Transform (STFT). The results that have been achieved are a 9 percent improvement over the system that was qualified for the EEG dataset [16]. Despite the fact that STFT is a competing tool for time-frequency analysis, there is still room for development in terms of the time-frequency tradeoff. According to our methodology, CNN acquires knowledge of the activation patterns by analysing the input data of MI signals. The application of convolution operations is only performed on the time axis; it does not take into account the location or frequency of the observation. Therefore, the convolutional layer is responsible for learning both the shape of the activation patterns (i.e., the power values at different frequencies) and the occurrence of these patterns (i.e., the position of the EEG channel). The categorisation is then improved by a vibrational autoencoder (VAE) that has five hidden layers. This is accomplished by a deep neural network. Transfer Learning is making it possible to implement tasks for the purpose of training and testing models for research that span multiple topics [38].

Researchers from the field participated in BCI and examined several implementation options for transfer learning [39]. Implementation of transfer learning across subjects through the use of CNN systems [40] exhibited, as well as an analysis of the kernel approach for determining the parameter relationship of the classifier which was demonstrated [41] has been scrutinised in previous research. The suggested framework, which is built on CapsNet, is able to classify the motor imagery into two distinct classes, right-hand motions and left-hand movements. Through the application of the short-time Fourier transform (STFT) technique, the motor imagery EEG signals are initially converted into two-dimensional images. These images are then utilised for the purpose of training and testing the capsule network. The proposed framework was tested based on its performance on the BCI competition IV 2b dataset, and the model achieved an average accuracy of 78.44% across all subjects under consideration.Refer to [42] The classification of motor imagery EEG signals was proposed using a Convolutional Neural Network (CNN) that was built on AlexNet in two dimensions. CNNs have the potential to be used for feature extraction and classification in motor imaging tasks, as demonstrated by their technique, which was used to the BCI Competition IV Dataset 2a and achieved a classification accuracy of 81.09%.

In a similar vein, [43] A CNN was applied to Dataset 2b, which was a part of the same competition. The accuracy of their model was demonstrated to be 80.30 percent, which provides additional evidence that CNNs are useful in the classification of motor images. According to the findings of both research, CNNs, particularly those that have representations of EEG signals in two dimensions, operate effectively for this task. Refer to[44]also employed a CNN model but applied it to both the Graz BCI-IV Dataset 2a and Dataset 2b. Their results, however, showed a slightly lower accuracy of 73.86%. This performance gap may be attributed to differences in model architecture or preprocessing techniques, suggesting that CNN-based models may be sensitive to these factors.

A different approach was introduced by[45], who utilized a Capsule Network (CapsNet) for motor imagery classification on Dataset 2b. Their model achieved a classification accuracy of 78.44%. CapsNets, which are designed to capture spatial hierarchies in data more effectively than traditional CNNs, offer a compelling alternative to CNN-based methods, though the performance was slightly lower compared to CNN models.

Lastly, a ref.[46], In addition, the method that was provided in the research paper titled Distribution-Based Learning Network for Motor Imagery Electroencephalogram Classification was utilised on Dataset 2b, and it was successful in obtaining an accuracy of 79.69%. The potential of distribution-based approaches in EEG classification is brought to light by this method, which provides a fresh viewpoint in comparison to the CNNs and CapsNets that are more widely utilized. As long as there are human subjects involved, it is always desirable for the BCI application to have reliable classification accuracy. There is a promise of more dependable outcomes and improved response if the precision of the system is improved using new algorithms and methodologies. For the purpose of improving the classification accuracy utilising our method, we plan to employ transfer learning on top of deep neural networks that are already in existence in the present research. Some noteable work is done in past on bci competition iv dataset 2b and 2a is listed in table 1.

Reference Article	**Methodology**	**Dataset**	**Model Performance**
(Anwar and Eldeib 2020)**[42]**	2D AlexNet Convolutional Neural Network (CNN)	The proposed approach was analyzed and evaluated using dataset 2a from BCI Competition IV	81.09%
(Roy, McCreadie et al. 2019)**[43]**	Convolutional Neural Network (CNN)	To conduct this study, dataset 2b from BCI competition IV used	80.30%
(Arı and Taçgın 2023)**[44]**	CNN	Graz BCI-IV-2A and BCI-IV-2B datasets	73.86%
(Ha and Jeong 2019)**[45]**	Capsule Network(CapsNet)	BCI Competition IV Dataset 2b	78.44%
(Wang, Annan 2021)**[46]**	Distribution Based Learning (DBL) framework based on deep learning	BCI Competition IV Dataset 2b	79.69

Table 2-1: Summary of literature review

The approach that we have developed operates in both the time domain and the frequency domain in order to modify the data. This is in contrast to the methods that are currently being employed, which operate specifically in the frequency domain. This operation ensures that the models will be successful in their intended purpose. The second stage was to generate inputs for a deep learning model that had been pretrained and was dubbed VGG16. This was then followed by the addition of raw images and continuous wavelet transform (CWT) transformations of EEG images as inputs. Finally, in order to test the effectiveness of the system, classification experiments were carried out using a data set that was already available to the public. This model not only highlights the most significant features of the original data, but it also maintains other important aspects of the original data. It is vital to notice that this model does not simply highlight its most important aspects. In order to extract elements from the various frequency spectrums and features from the EEG data, the Fourier transform has been utilized. This has been done in order to accomplish the aforementioned aim.

2.2 SUMMARY OF THE CHAPTER

From literature review it concluded that CNN-based approaches have consistently demonstrated strong performance in motor imagery EEG classification, with accuracy rates typically ranging between 73% and 81.09%. Methods like Capsule Networks and DBL frameworks also offer competitive alternatives, suggesting that deep learning models, particularly those focusing on time-frequency transformations of EEG signals, are highly effective for motor imagery classification tasks.

Chapter 3

3 DATASET

The purpose of this chapter is to provide a complete review of the dataset that served as the basis for our research on the categorization of EEG signals by making use of a bci competition iv dataset. The participants participated in motor imagery activities as part of an experimental paradigm, and the electroencephalogram (EEG) signals were acquired utilizing EEG technologies of a high grade. In the course of our research, we made use of the BCI competition IV 2b dataset in order to divide the EEG data that was associated with motor imagery into two distinct groups [47]. Using the experimental methods, the dataset was collected from nine individuals who were involved in a motor imaging task. These participants were divided into two groups: those who were left-handed and those who made use of their right hand. In this particular investigation, the collection of electrical EEG data was carried out with a sampling frequency of 250 Hz using three bipolar electrodes (C3, Cz, and C4). The electroencephalogram (EEG) data were subjected to band-pass filtering with a notch filter at a frequency of 50 Hz throughout the entire frequency range stretching from 0.5 Hz to 100 Hz.Because there were a total of five participation sessions, the dataset contains information about each and every individual participant. Instructional sessions are incorporated into the initial three segments, whilst the evaluation segment is specifically dedicated for the last two segments.

3.1 EXPERIMENTAL PARADIGM

Empirical framework This dataset comprises EEG data obtained from 9 participants listed in a study published in reference [47]. Participants included those who were right-handed and had normal or corrected-to-normal vision. They were compensated for their participation in the trials and got pay for their participation. Every single participant was seated in an armchair, and they were all looking at a flat screen monitor that was approximately one meter away and at eye level. Each participant is allotted a total of five sessions, with the first two sessions consisting of training material that does not include any feedback (screening), and the next three sessions being recorded with feedback. Figure 1 illustrates that each session is comprised of numerous runs simultaneously. At the beginning of each session, an initial recording that lasted around five minutes was carried out in order to evaluate the effects of electroencephalography (EOG). The recording was broken up into three parts: (1) a two-minute period during which the eyes were open (which was pointed towards a fixation cross on the screen), (2) a one-minute period during which the eyes were closed, and (3) a one-minute period during which eye movements were observed. The artefact block was divided into four sections, each of which had artefacts that lasted for fifteen seconds and included a five-second break in between each segment. The participants were instructed to perform either eye blinking, rolling, up-down, or left-right motions by means of text that was displayed on the monitor displaying the instructions. Each assignment was accompanied by a low warning tone at the beginning of the assignment and a high warning tone at the end of the assignment, respectively[48]. (Refer to figure 3.1 for a comprehensive list of all participants)

ID	Training	Evaluation
1	B0101T, B0102T, B0103T	B0104E, B0105E
2	B0201T, B0202T, B0203T	~~B0204E~~, ~~B0205E~~
3	B0301T, B0302T, B0303T	~~B0304E~~, ~~B0305E~~
4	B0401T, B0402T, B0403T	~~B0404E~~, ~~B0405E~~
5	B0501T, B0502T, B0503T	~~B0504E~~, ~~B0505E~~
6	B0601T, B0602T, B0603T	~~B0604E~~, ~~B0605E~~
7	B0701T, B0702T, B0703T	~~B0704E~~, ~~B0705E~~
8	B0801T, B0802T, B0803T	~~B0804E~~, ~~B0805E~~
9	B0901T, B0902T, B0903T	~~B0904E~~, ~~B0905E~~

Figure 3-1 Dataset description

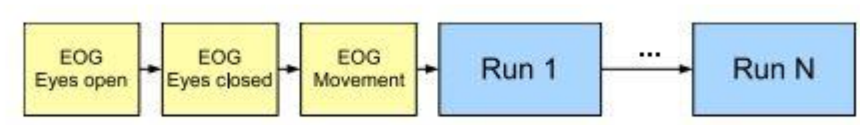

Figure 3-2: Description Scheduling of a single session (including screening and feedback).

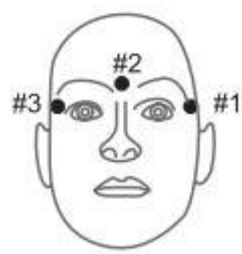

Figure 3-3: Three monopolar EOG channels' electrode montage [48]

3.2 DATA RECORDING

It was determined that a sampling frequency of 250 Hz was appropriate for the acquisition of triple bipolar recordings (C3, Cz, and C4). During the screening procedures, the recordings exhibited a dynamic range of around 100 µV, while during the feedback sessions, the range was approximately 50 µV. Bandpass filtering was applied to the signals over the frequency spectrum, which ranged from 0.5 Hz to 100 Hz. Additionally, a notch filter was applied at a frequency of 50 Hz. When it came to the positioning of the three bipolar recordings for each individual, there was a slight variance in the placement of the recordings depending on whether they were conducted at long or short distances and whether they were more anterior or posterior(for additional details, see [47]). When the EEG ground was placed, it was at the location of electrode Fz. In addition, the electrooculogram (EOG) was recorded by employing three monopolar electrodes (as shown in Figure 3.3, with the left mastoid serving as a reference). The amplifier settings were same, but the dynamic range was raised to ±1 mV. This was done on top of the electroencephalogram (EEG) channels. One of the key goals of the EOG channels is to simplify and improve the efficiency with which artefact processing activities are carried out [49] and should not be utilised for categorisation purposes. The motor imagery (MI) of the left hand (class 1) and the right hand (class 2) were composed of the two classes that were included in the screening paradigm that was dependent on cues. Over the course of two weeks, each participant was subjected to two screening sessions that were videotaped on separate days. These sessions were conducted without any comments being made. A total of six distinct runs were included in each session, with each run consisting of ten trials and two categories of imagery. Consequently, there were twenty trials carried out during each run, and a total of one hundred and twenty trials were included in each session. A total of 120 repetitions of each MI class were included in the sample for each distinct individual. The participant performed and envisioned a variety of movements for each body part prior to embarking on the initial motor imagery training. They then selected the movement that they were able to visualize with the greatest degree of clarity, such as the compression of a ball or the application of a brake. Every trial started with a fixation cross, which was then followed by a brief auditory warning tone that lasted for seventy milliseconds and had a frequency of one kilohertz. A visual indication in the shape of an arrow that indicated either the left or right direction, depending on the class that was defined, was displayed for a duration of 1.25 seconds after a few seconds had passed. Following that, it was necessary for the participants to mentally picture the corresponding manual motion for a period of four seconds. After every single test, there was a small pause that lasted for at least one and a half seconds on average. An additional randomised duration of up to one second was incorporated into the break in order to combat the phenomenon of adaptation. Every one of the three online feedback sessions consisted of four runs, each of which offered feedback with a smile. Every single run consisted of twenty trials for every single form of motor imagery. The feedback, which was depicted as a grey smiley and was precisely positioned in the middle of the screen, was displayed at the beginning of each trial, which was the second zero. At the second and a half mark, a brief alert beep was emitted, which had a frequency of 1 kHz and lasted for 70 milliseconds. When the score was between three and seven and a half, the cue was presented. It was informed to the participants that they should mentally visualize motions of their left or right hand in order to maneuver the smiley towards either the left or right side, according on the cue that was given to them. In the course of the feedback period, the smiley altered its color to green when it was positioned appropriately, but it changed to red in all other circumstances. A determination was made regarding the distance between the smiley and the origin by utilizing the integrated classification output that was accomplished during the course of the preceding two seconds (for additional information, please refer to). Furthermore, the output of the classifier was found to be connected with the curvature of the mouth, which led to the smiley face being interpreted as either a sign of happiness (with the corners of the mouth facing upwards) or a sign of sadness (with the corners of the mouth facing downwards). At the 7.5th second, the screen went completely black, and a random interval that lasted anywhere from one to two seconds was incorporated into the experiment. It was stated to the participant that they should keep the happy face on the correct side for as long as it was possible to do so, which would result in the longest possible duration of the movement inhibition(MI)[48].

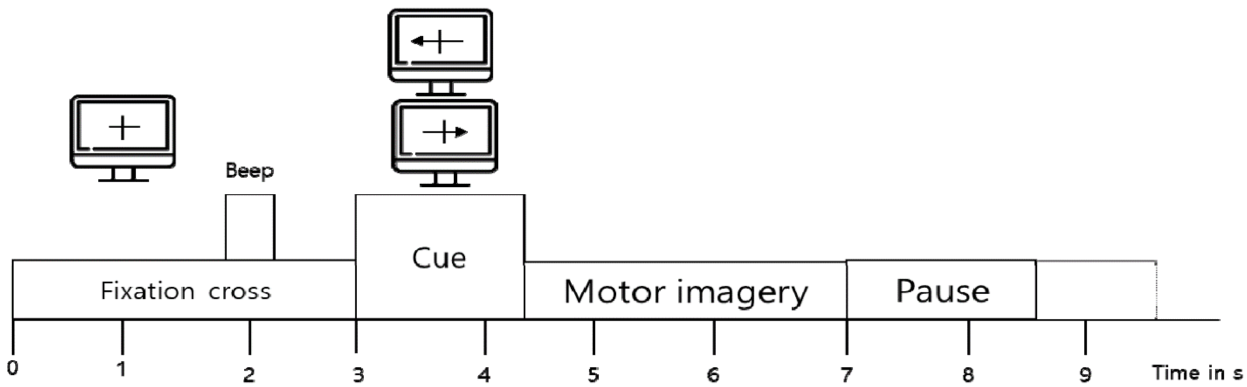

Figure 3-4 Screening [48]

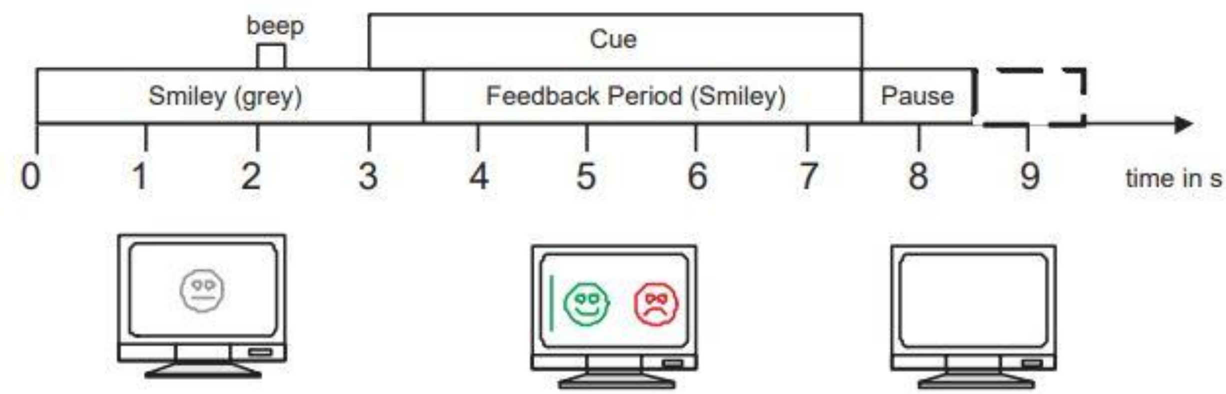

Figure 3-5 Smiley Feedback [48]

3.3 SUMMARY OF CHAPTER

The dataset chapter provides a comprehensive description of the techniques and procedures employed to gather, analyse, and define the BCI MI EEG dataset utilised in this work. The introduction lines establish the context for the study's results by presenting important participant characteristics and ethical considerations. Comprehensive details on the EEG acquisition procedure, experimental paradigm, marker positioning, and data organisation are provided to guarantee the data is of superior quality and suitable for further analysis. The methods employed to prepare the raw EEG data for analysis will be elaborated upon in the subsequent methodology chapter. Artefact elimination, filtering, epoch determination, and feature extraction techniques such as time-domain and frequency-domain analysis will be addressed. Furthermore, the chapter also addresses techniques for categorising EEG data into different types of motor imagery. In this thesis, a detailed overview of the EEG data collecting, processing, and analysis procedure is presented, including a summary of the dataset chapter and a preview of the methodology chapter.

Chapter 4

4 METHODOLOGY

4.1 CHAPTER INTRODUCTION

This chapter includes a description of the approach that may be used to process and analyze the motor imagery bci dataset. The goal of this chapter is to facilitate the development of EEG-based motor imagery classification algorithms. Pre-processing, feature extraction, and classification are the focal points of this chapter, which is divided into three distinct sections. This section will cover the procedures that were used during the pre-processing step in order to filter and remove artefacts from the raw EEG data. These procedures were used in order to ensure that the data was accurate. The significance of these parameters in the classification of motor imagery tasks will be discussed in the following section. In addition, the spectral features that were recovered using the Continuous wavelet transform (CWT) will also be discussed. We shall discuss the classification algorithms that were utilized for the pretrained deep learning model vgg16 in the third section of this article. Through the application of these algorithms, the motor imaging tasks were classified according to the features that were retrieved. The methods that were carried out in order to get the raw EEG data ready for statistical analysis are described in detail in the preprocessing part of the methodology chapter. In order to achieve this goal, wasted data segments that contain an excessive amount of noise or artefacts are eliminated. Additionally, band-pass and notch filters are applied in order to reduce the amount of noise and artefacts that are present in the data. In addition, we will proceed to explore the utilization of Independent Component Analysis (ICA) in order to breakdown electroencephalogram (EEG) signals into their component elements and eliminate artefacts. Utilising the CWT allows for the determination of the spectrum features of the EEG signals, which is the objective of the use. In addition to this, there will be a focus on the importance of these characteristics in relation to the categorization of motor imagery tasks. At the end of this paper, a full discussion of the classification algorithms that were used to classify the motor imagery tasks based on the retrieved characteristics will be offered. These methods were used to classify the tasks. A deep learning vgg16 was used to perform the prettraining for these algorithms. This part will provide an overview of the architecture of each network, as well as the training and testing techniques that were utilized in order to optimize the settings of the network. In addition, we will discuss the procedures that were used to test and train the network. We will also talk about the metrics that were used in order to evaluate the degree to which each algorithm contributed to the classification process. This will be done in addition to the previous point. A thorough description of the methodologies and procedures that were used to manage and analyze the EEG data in order to construct EEG-based motor imagery categorization algorithms is provided in the methodology chapter. This chapter is referred to as the "methodology" chapter. The approach that was utilized in the most significant aspects of this investigation is illustrated in Figure 5.1, which can be found on the page concerned. Furthermore, a functioning block diagram of the proposed methodology is presented in figure 5.2 to illustrate its components.

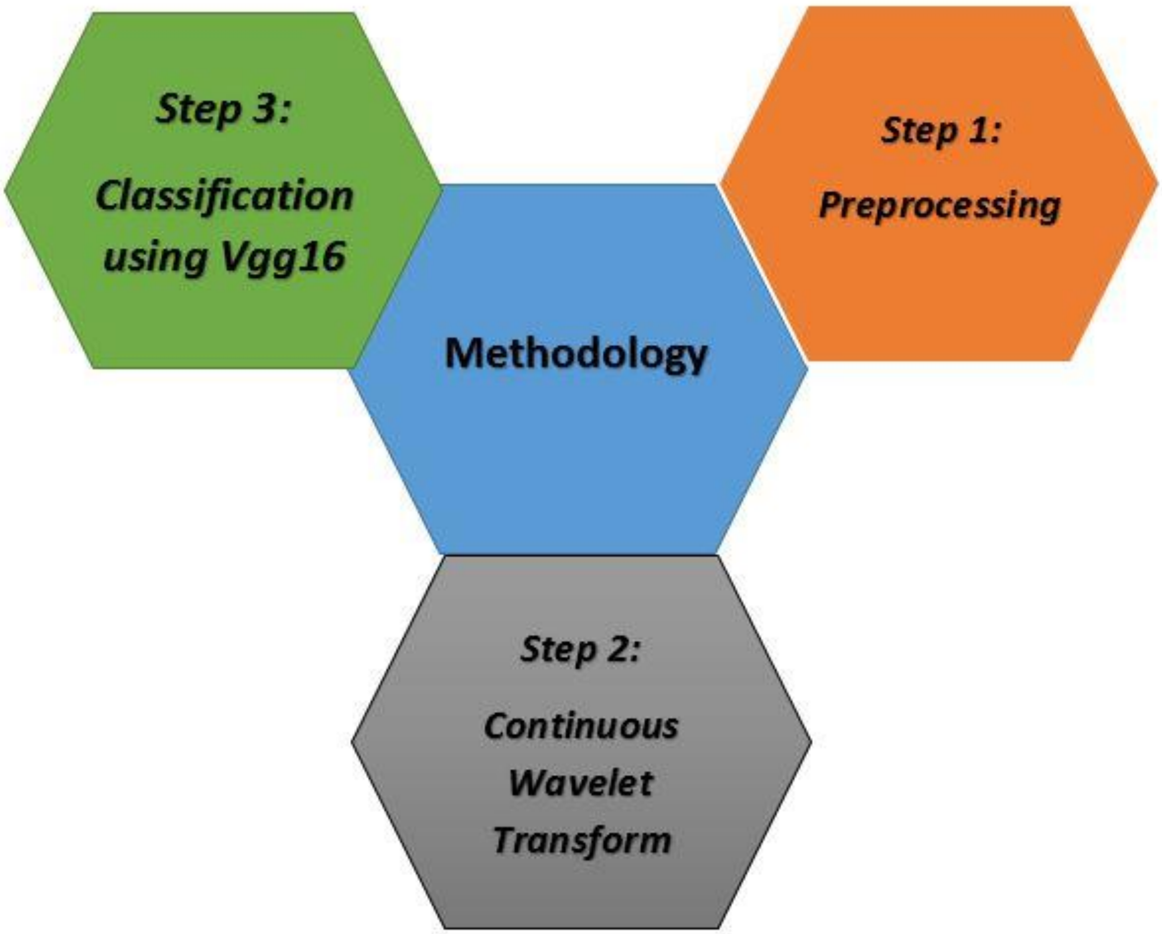

Figure 4-1 Key portions of methodology chapter

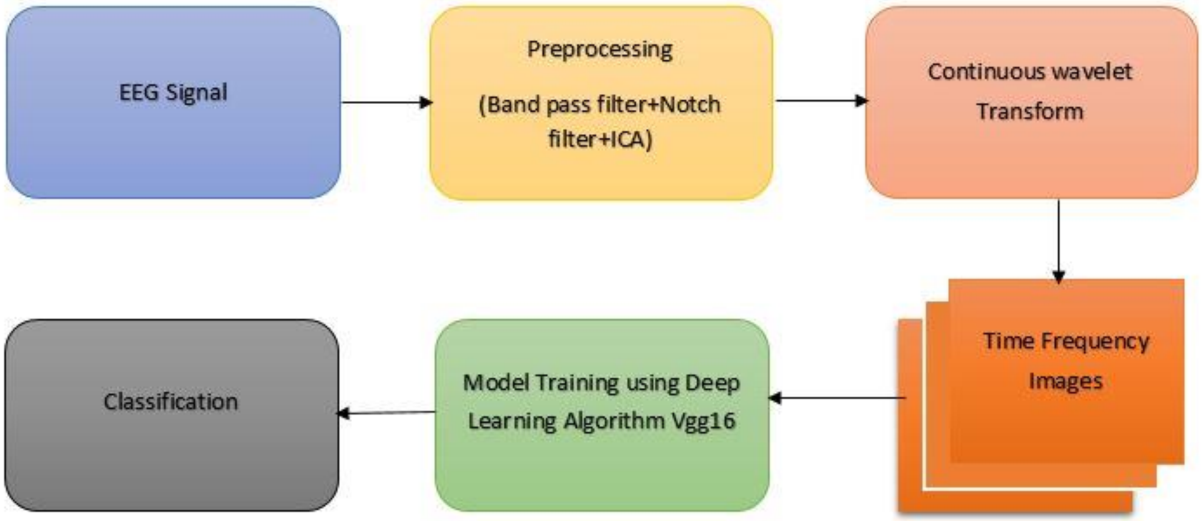

Figure 4-2: Block diagram of proposed methodology

4.2 PREPROCESSING

Both non-physiological artifacts and physiological artifacts are able to be distinguished from one another when it comes to recorded electroencephalogram (EEG) signals. Interference brought on by a power frequency of fifty hertz is the principal cause of anomalies that are not related to the body's physiological processes. A total of nine individuals were included in the Motor Imagery EEG dataset that was analyzed for this investigation. Each topic is broken up into five separate sessions. Within the scope of this study, the initial three sessions were utilized for each participant. There are six channels that are made up of EEG and EOG signals that make up the motor imagery EEG signal collection. Three channels, cz, c3, and c4, have been kept, but the EOG channels have been removed from the lineup. A total of 769 events for class 1 left and 770 events for class 2 right are the primary events that are the focus of the dataset that is now being discussed. Those occurrences that are still occurring are ignored. In each session, there are a different amount of challenges and activities to complete. In the initial step of the process, the raw motor imagery eeg signals are subjected to a band pass filter with a frequency range of 5Hz to 30Hz. Following the implementation of the band pass filter, a notch filter operating at 50Hz was utilized in order to reduce the likelihood of signal degradation brought on by interference from power lines. After the filtering operation was completed, additional preprocessing processes were put into place in order to reduce the impact of noise and artifacts that were present in the EEG data. Due to the fact that they obscure the underlying brain activity that is of interest, these artifacts have the potential to either distort or inhibit the appropriate analysis of EEG data. Additionally, in order to guarantee that the EEG signal is clear and trustworthy for subsequent analysis, it is typical to make use of a number of different techniques in order to remove these distortions from the data. Independent Component Analysis, sometimes known as ICA, is a method of signal processing that divides a high-dimensional signal into discrete components that are not Gaussian. Using ICA to analyze EEG data enables the identification and removal of signal components that are associated with artifacts, such as eye blinks or muscle movements. This is made possible by the application of image correlation analysis (ICA). By separating and removing these components, the ICA technique ensures that the residual EEG signal will be clear and reliable for subsequent analysis. This is accomplished by the elimination of these components. The techniques known as ICA are well acknowledged for their effectiveness in removing artifacts from the processing of EEG raw data. Important patterns of brain activity that may have been concealed by artifact interference can be uncovered with the assistance of this approach, which guarantees the purity and reliability of the EEG signal for subsequent investigation. Additionally, it is vital to keep in mind that both ICA and AAR have limits, and that they should be utilized in conjunction with other approaches in order to ensure that the analysis of EEG data is reliable. Because of its ease of calculation and its capacity to offer a basic method for minimizing the influence of intrinsic noise across a variety of channels, this method is frequently utilized in the processing of electroencephalogram (EEG) data. The filtering, blind source separation, and re-referencing approaches improved the quality of the electroencephalogram (EEG) data by removing undesirable artifacts and noise. This made it possible to analyze the EEG characteristics that are linked with tasks that involve motor imagining. Following that, event markers are utilized in order to extract and epoch the data in a manner that is distinct from one another, dividing it into intervals of two seconds that correspond to motor imagery tasks that involve movements of either the left or right hand, and additionally performing baseline correction. In the end, the epochs are converted into NumPy arrays, and labels are generated for the purpose of classification jobs. The left hand is assigned a value of 1, while the right hand is assigned a value of 0. The result is EEG data that has been preprocessed and is ready to be used for the training of machine learning or deep learning models during the training phase. An illustration of the EEG data after it has been preprocessed can be found in Figure 4.5. The segmented data were subjected to preprocessing procedures in accordance with the technique that was proposed in order to make subsequent analysis more readily available. Using a deep learning model that had been pretrained, the suggested method intended to identify EEG signals that were associated with motor imagery. Additionally, the preprocessed EEG data was intended to be transformed into time frequency images by means of continuous wavelet transform (CWT). In order to generate time frequency images, the technique involved the utilization of segmented EEG data as input. Every single image was utilized to represent a single occurrence, which was subsequently incorporated into the classification models as a feature. In the following sections, you will find some additional information that is more detailed regarding the algorithm that was suggested and the process of extracting spectral features.

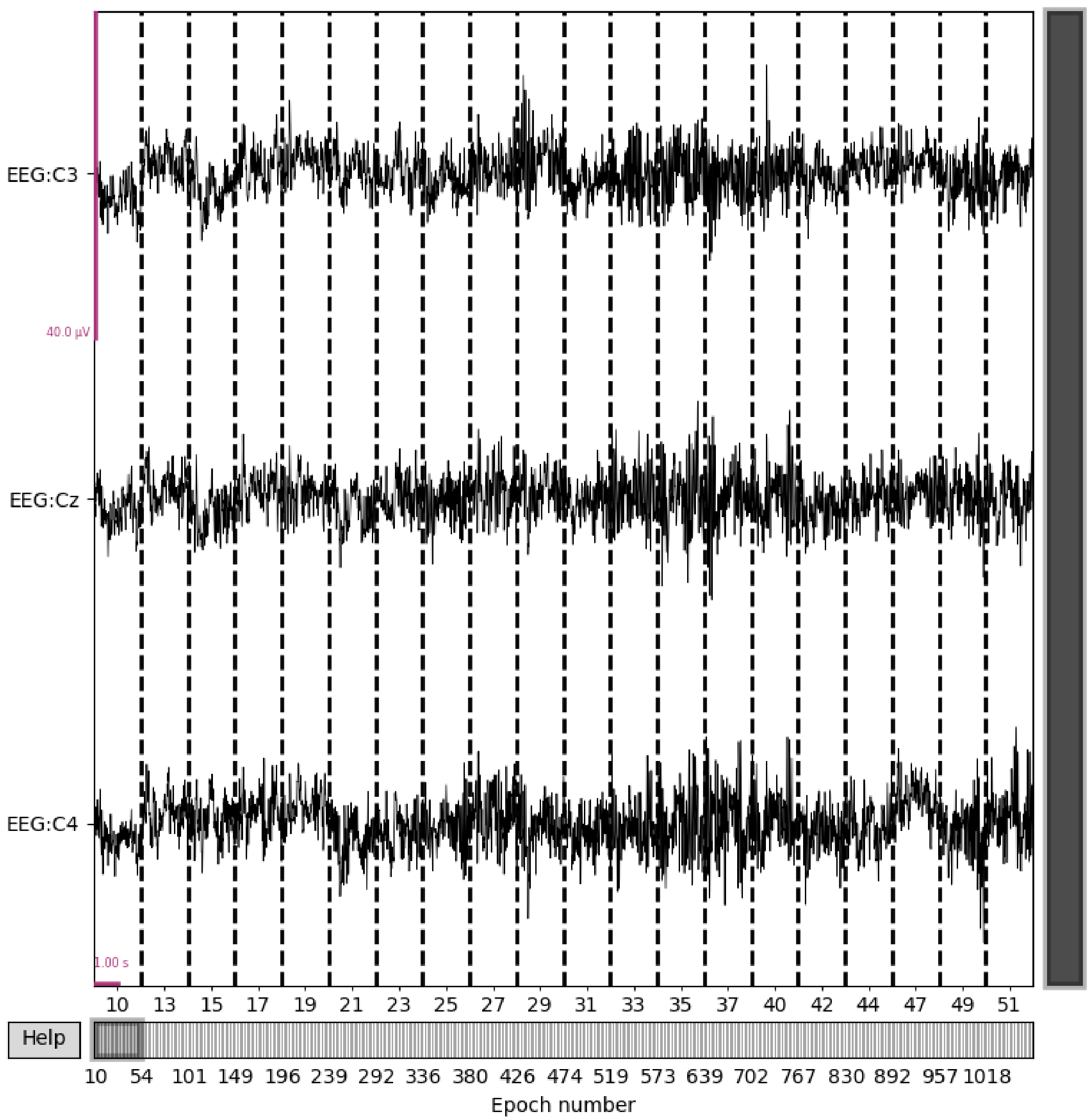

Figure 4-3: After the initial preprocessing of raw EEG signals

4.3 CONTINUOUS WAVELET TRANSFORM

The Continuous Wavelet Transform (CWT) is a method that is often used for the purpose of evaluating the time-frequency of signals. This approach is known as a technique. Morlet and Grossman were the ones who initially put up the concept in the year 1987. A time-frequency representation of signals can be generated using the Continuous Wavelet Transform (CWT) method. This method works by dividing a signal into wavelets of varying sizes from the beginning. Specifically, this is performed through the utilization of signal processing. It is important to note that the wavelets in question are functions that are employed for the purpose of conducting an analysis of the various frequency components of the signal. This makes it possible to conduct a more comprehensive investigation of signals, in contrast to the conventional methods of frequency analysis, which only offer a single frequency representation of the signal at a certain instant in time. As a result of this, it is able to conduct a more in-depth investigation of signals. In terms of the frequency and temporal characteristics of the EEG data, it has been demonstrated that the Continuous Wavelet Transform (CWT) is an excellent method for decoding the data. For the purpose of gaining a knowledge of brain activity and diagnosing a wide range of neurological conditions, this is a vital component[50, 51]. Within the realm of wavelet analysis, there are five basis functions that are utilized rather frequently. The Morlet wavelet, the Mexican Hat wavelet, the Haar wavelet, the Daubechies wavelet, and the SymN wavelet clusters are some examples of these wavelets. To serve as the foundational function for the wavelet representation, the Morlet wavelet has been selected from among the various possibilities that are accessible. In order to perform preprocessing on the fundamental signal, the Continuous Wavelet Transform, which is more commonly referred to as CWT, is utilized. After that, the mapped time-frequency domain image that was produced is used as one of the inputs for the VGG16 deep learning model that was advised. This is performed after the previous step has been completed. In this particular inquiry, a scalogram was utilized, and the values of the scalogram were specifically determined by the absolute values of the Continuous Wavelet Transform (CWT) of the signal. A graphical representation of the scalogram that is a function of both time and frequency is something that can be done. Reference, [18] Motor Imagery (MI) signals are composed of progressively changing events that are occasionally disrupted by abrupt shifts, which exhibit unique properties at different scales. The utilization of scalograms enables enhanced temporal localization of high frequency, short-duration events and superior frequency localization of longer-duration, low-frequency events. Using Continuous Wavelet Transform (CWT) within a filter-bank [52], The data from the one-dimensional electroencephalogram (EEG) is converted into a single image that contains both time-frequency and amplitude information. The filter-bank is made up of the parameters that have been developed expressly for the purpose of applying the circular wavelet transform (CWT) on the signal that has been provided. Throughout the entirety of the experiment, each and every filterbank parameter for the Compressed Wavelet Transform (CWT) was maintained at a constant value. The Continuous Wavelet Transform (CWT) makes use of the analytic Morse wavelet because of the greater time-frequency localization that it provides. There was no change made to either the gamma symmetry parameter or the temporal bandwidth product for the complex more (cmor) wavelet. Both parameters were kept at their original values of 1. In each octave, there were ten different voices that were used. In order to offer a cohesive portrayal of a single event (either Left or Right) hand imagery, the data that was collected from electrodes C3 and C4 are organized in a stacked fashion, with C4 succeeding C3. After the data has been analyzed, it is further utilized in the training of the model by employing the VGG16 pretrained deep learning neural network. A deep learning model that has been pretrained and created specifically for the purpose of feature recognition is known as the VGG16 model. As a result of the fact that the pre-trained CNN architectures that were utilized in this work require two-dimensional image data as input, these networks are unable to accommodate one-dimensional EEG signals. It is possible to employ Continuous Wavelet Transform (CWT) for training deep neural networks because of its capability to translate electroencephalogram (EEG) signals into appropriate visuals. This is one of the most significant advantages of CWT. Data pertaining to amplitude, scale, and temporal information are included in the post-cyclic wavelet transform (CWT) image. For the purpose of motor imagery classification, the study makes use of time-amplitude values at a variety of scales as the primary criteria. The final stage of preprocessing entails rescaling the two-dimensional image that was produced so that it conforms to the input conditions of the particular deep neural network. To get started, you will need to create an image for a single channel. There is a total of three channels available. Afterwards, you will need to concatenate these photographs in order to produce a single image for a single event. The visuals for each of these three events are denoted by the letters cz, c3, and c4. After that, the photos that were concatenated are saved in the directory as images of the.png file type, and the process is repeated for each and every event. A total of 400 photographs are produced in the case that a single subject is photographed for a total of 400 times over the course of three sessions. Without exception, each and every person is required to go through the same process. Following the generation of photographs, the labels are further saved in a.csv file for each and every image. Because of this, it is essential for each and every subject to have scalogram photos and labels stored in a.csv file. Constructing the scalogram time frequency pictures that are displayed in Figure 4.4 for the left hand and Figure 4.5 for the right hand was accomplished through the utilization of the continuous wavelet transform. In the subsequent step, these photographs are incorporated into the VGG16 model as input in order to train the model.

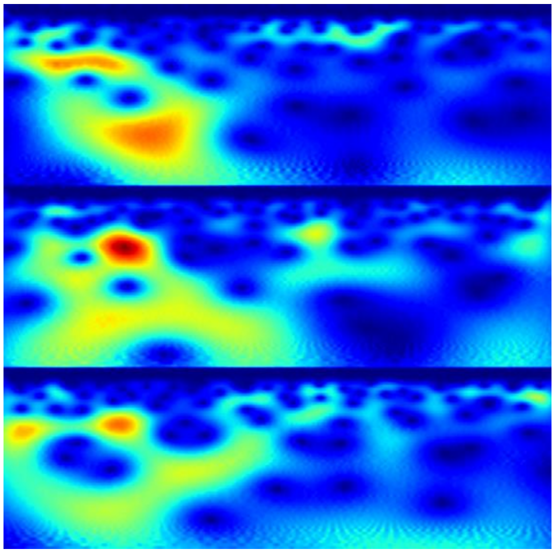

Figure 4-4: Time frequency image for Left

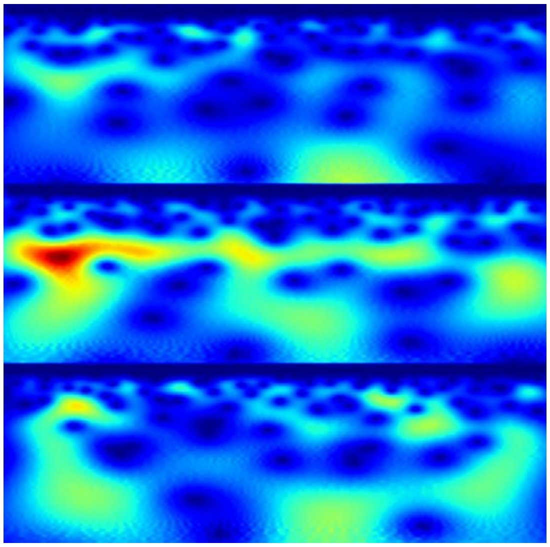

Figure 4-5: Time frequency image for Right

4.4 CLASSIFICATION

In this particular investigation, the classification of EEG data was carried out by means of a pretrained deep learning model, which is a well-known and widely recognized deep learning model. These models are frequently used in EEG-based brain-computer interface applications because, in comparison to other models, they have demonstrated superior performance in a variety of picture and signal processing tasks. The Continuous Wavelet Transform (CWT) was utilized in order to generate scalogram images from the EEG data that had been preprocessed. These photos were used as the training data for the VGG16 model, and after that, the model was enhanced by tweaking the hyperparameters. The purpose of our research was to make use of sophisticated techniques in order to achieve a high level of classification accuracy and robustness in the process of determining the fundamental brain activity based on the EEG data.

4.4.1 Transfer Learning

Transfer learning is an approach that is used in the disciplines of machine learning and deep learning. This strategy involves using a model that has already been trained as a starting point for a new task that is linked to, or related to, the model that was previously taught. Through the process of transfer learning, we are able to make use of the information that has already been obtained by a pre-trained model. This is in contrast to the conventional way of constructing a model from the ground up and training it on a large dataset. Pre-trained models are frequently trained on big datasets like ImageNet in order to solve a wide range of computer vision problems. This is done for the aim of resolving the problem. It is feasible to reuse the feature representations that have been learned by making use of this model that has already been through the training process. It is possible to use these representations for a new job that is connected to it, such as recognizing Rock-Paper-Scissors motions, because they are sufficiently broad. During the process of transfer learning, the model that has been pre-trained is often utilized, and the last layer is substituted with a new layer that is specifically designed to address the new task. After this, the new layer is trained on the smaller dataset that is specific to the new task, while the rest of the pre-trained model is frozen and its weights are fixed. This is done while the new layer is doing its training. By doing so, we are able to fine-tune the pre-trained model on the new assignment while simultaneously avoiding overfitting and reducing the amount of time spent on training. This allows us to achieve both success and efficiency. As a result of the deployment of transfer learning, which has become an important technique in deep learning, there has been a large gain in both the accuracy and speed of a wide variety of computer vision tasks. This has led to a significant increase in the overall performance of these tasks[53].

4.4.2 VGG16

This inquiry makes use of a bespoke VGG-16 model that has been pre-trained in order to do the analysis. In 2014, the VGG16 model became triumphant in the ImageNet competition, establishing itself as one of the image classification models that experiences the greatest amount of usage. There are sixteen layers that make up this structure, thirteen of which are convolutional layers, and three of which are fully connected. Because it was trained on a large number of images, the VGG16 model that has been pretrained is able to recognize a wide variety of features. This is because it was trained on that collection. The output layer of the model, on the other hand, is a feature that is exclusive to the dataset that it was previously trained on. In the event that this is the case, you will be required to replace the output layer with a new layer that is specific to the dataset that is being considered [53]. Figure 4-6 illustrates the fundamental constructs that make up the vgg16 model.

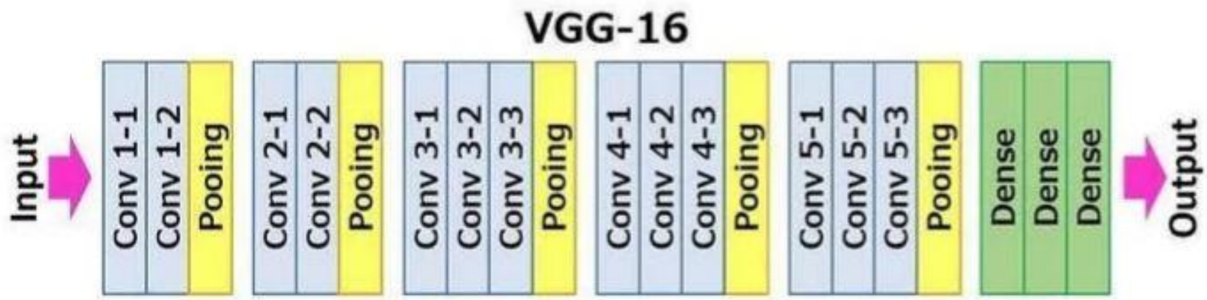

Figure 4-6: Fundamental structure of the VGG16 model

In order to achieve the objective of separating the EEG signals that are linked with motor imagery into two different groups, the VGG16 model is utilized. There are currently nine individuals that participated in the research project, and scalogram time frequency images have already been made for each of them. Additionally, a label that is prepared for the subjects using the.csv file format is also prepared that is included in the preparation. Given the limited quantity of data available, the time frequency images ought to be separated into training and validation sections. This is because there is only a little amount of data. Twenty percent of the images are used for the purpose of validating and testing the trained model, while ninety percent of the photographs are divided up as part of the training procedure. The training technique is comprised of ninety percent of the photographs. During the training phase, the Adam optimiser is utilized, and the training procedure is carried out over a period of fifty epochs. This is done in order to train the original model. The loss of validation, on the other hand, has a tendency to increase rather than decrease when the precision of the validation is increased. This is the source of model overfitting. This is due to the fact that the validation is evolving to become more precise. Due to the fact that this has occurred, this model has been enhanced, and adjustments have been made to the hyperparameters, with the goal of achieving the desired outcomes and achieving improved performance. Following the completion of the hyperparameter tuning, the epoch size is set to thirty, and the Adam optimizer is utilized with a learning rate of 0.0001; this is done in order to achieve optimal results. The training process begins once the model has achieved the highest possible level of performance that is reasonable. This takes place following the step that came before it. In total, there are nine distinct individuals, and the same procedure is carried out for each and every one of them. The VGG16 model that was used for pretrained training is depicted in a summary diagram that may be seen in Figure 4.7.

Layer (type)	Output Shape	Param #
input_layer_21 (InputLayer)	(None, 224, 224, 3)	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1,792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36,928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73,856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147,584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295,168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590,080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590,080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1,180,160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2,359,808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2,359,808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2,359,808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2,359,808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2,359,808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
flatten_10 (Flatten)	(None, 25088)	0
dense_10 (Dense)	(None, 2)	50,178

Figure 4-7: summary of vgg16 proposed model for Motor Imagery EEG signal classification

4.5 SUMMARY OF CHAPTER

The primary objectives of the research were, as outlined in the chapter on methodology, the classification of EEG data through the utilisation of a variety of preprocessing techniques, the generation of time frequency images through the Continuous wavelet transform (CWT), and the utilisation of a pretrained deep learning VGG16 model for classification. The Independent Component Analysis (ICA) technique was utilised during the data preparation step in order to eliminate artefacts and enhance the overall quality of the electroencephalogram (EEG) data. After completing the preprocessing stage, the CWT method was utilised to convert the preprocessed EEG data into spectrograms, which exhibited the data in the form of images during the subsequent stage. After then, these time frequency photos were used as input for the VGG16 models. The VGG16 model, which consists of sixteen layers, made it possible to train longer and more complex networks. In the course of the classification phase, the pre-trained VGG16 model was utilised in order to extract features from the EEG data. The models were educated by the application of techniques such as transfer learning. During the training process, the models were trained using the Adam optimiser, a binary cross-entropy loss function, and a training dataset that contained ninety percent of the data. Using a different test dataset, the performance of the models was evaluated, and it was determined whether or not the class labels that were projected were accurate. The technique chapter provides a comprehensive framework for preprocessing, producing time frequency imags, and classifying EEG signals. Throughout general, this framework is described throughout the chapter.

Chapter 5

5 RESULTS

5.1 TOOLS TO BE USED

- Google Colab for the Implementation of Research Systems
- We used the Pro edition of Google Colab to speed up the training and convergence process. This version provides access to 15 to 40 GB of GPU Memory, 12.7 to 83.5 GB of RAM, and a storage size of 78.2 GB. Python version 3 is currently supported by Google Colab, and Google Compute Engine is used at the backend (T4 and A100 GPUs).
- For the purpose of dataset preprocessing and model training and classification, the Python programming language was utilised, along with the Numpy, mne, keras, tensorflow, and matplotlib Python libraries.
- When it comes to handling references, Endnote is utilised, whereas Microsoft Word is utilised for documentation.

5.2 PREPROCESSING RESULTS

The electroencephalogram (EEG) data were subjected to a comprehensive analysis during the preprocessing stage of the inquiry. The purpose of this analysis was to identify any noise or artefacts that would have possibly impacted the accuracy of the findings. The purpose was to eliminate any signals that were not desired and to make certain that the EEG data was adequately prepared for further examination. The significance of this step cannot be overstated because of the possibility that artefacts and noise will cause the conclusions to be skewed and the data to be distorted. For the purpose of removing the artefacts and noise, a variety of techniques were utilized. These techniques included bandpass filtering, notch filtering, and artefact rejection through the utilization of independent component analysis (ICA). The final stage consisted of applying ICA to identify and eliminate any remaining sources of noise or artefacts. This was done after the initial two approaches had been completed. Immediately after the preprocessing phase, an evaluation of the quality of the EEG data was carried out in order to determine whether or not the noise and artefacts had been successfully eliminated. The purpose of this step was to guarantee that the data had been sanitized in the appropriate manner. In general, the findings of the preprocessing stage suggest that the electroencephalogram (EEG) signals were successfully cleaned up and are now adequately prepared for the upcoming analysis methods. Establishing the foundation for appropriate categorization of motor imagery EEG data is accomplished by the application of CWT time frequency image generation as the analytical method.

5.3 CLASSIFICATION PERFORMANCE

In order to determine how well the algorithm performed in terms of classification by making use of the method that was suggested, it is necessary to conduct an evaluation of the algorithm. The evaluation of the algorithm is one way to accomplish this. The analysis that was carried out to evaluate the effectiveness of the categorization strategy revealed that it consistently produced good accuracy rates. This was discovered during the course of the investigation. The conclusions of this evaluation are broken down into their component elements in the paragraphs that are to follow. topic 4, which was the topic with the highest possible score, was chosen as the subject with the highest possible score. Subject 4 gained the best possible score. When all nine subjects were taken into consideration together, it was found that an overall average accuracy of 81.72 was reached at the individual level. An indication of the best level of accuracy that the VGG16 model has yet achieved may be found in Table 5.1, which can be found further down on this page. The table contains this information, which may be obtained there. It is clear from the data presented in the table that the proposed model VGG16 achieves a higher level of performance for subject 4, despite the fact that it achieves a lower level of performance for subject 3, yet the total average score is 81.72. Figure 5.1 is a bar graph that provides a visual representation of the performance of the suggested model for each of the subjects.

Subject	Model Performance %
Subject 1	95.00
Subject 2	83.68
Subject 3	65.00
Subject 4	95.78
Subject 5	83.00
Subject 6	80.00
Subject 7	73.00
Subject 8	80.00
Subject 9	80.00

Table 5-1 : Performance results of the model for all subjects

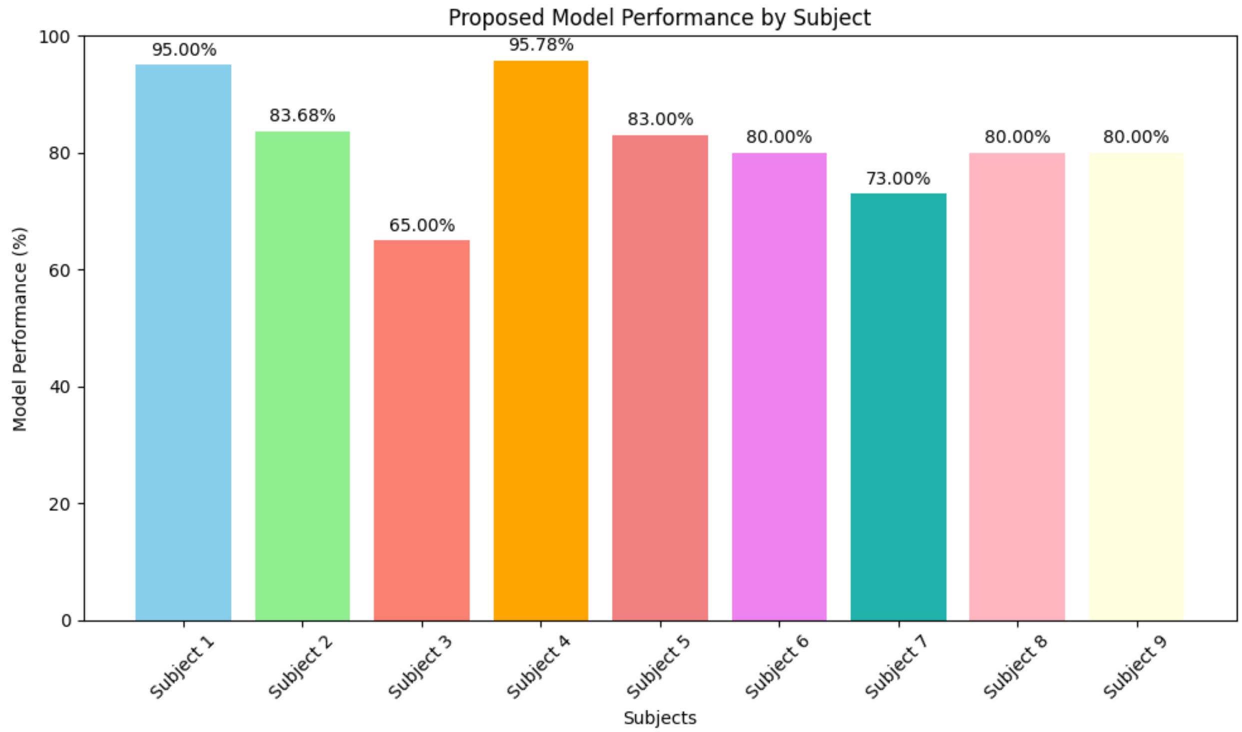

Figure 5-1 Proposed Model Performance Graph for each subject

5.4 EVALUATION METRICS

The term "evaluation metrics" refers to the instruments that are utilised in the process of measure the effectiveness of classification models. Within the scope of this investigation, the metrics that were utilised included the F1 score in addition to accuracy, sensitivity, specificity, and precision. Accuracy can be defined as the proportion of samples that were correctly classified in comparison to the total number of samples under consideration. An individual is able to ascertain the sensitivity of a test by dividing the total number of positive results by the quantity of "true positives," which are positives that have been appropriately recognised. The specificity of a negative is determined by dividing the total number of real negatives, which are negatives that have been properly identified, by the total number of actual negatives. As a measure of accuracy, the "precision" ratio is defined as the proportion of actual positive results to the total number of expected positive results. It is the F1 score that is a statistic that takes into consideration both sensitivity and precision. Following the findings of the investigation, it was determined that the technique that was suggested was successful in reaching high accuracy rates. The fact that a large portion of the samples were placed in the appropriate categories is demonstrated by this. Considering that the values for sensitivity, specificity, accuracy, and F1-score were satisfactory, it would appear that the method that was provided is capable of accurately classifying the two class motor imagery eeg signals.

5.5 COMPARISON WITH PAST STUDIES

Multiple studies have been conducted on the classification of Motor Imagery EEG signals, and each of these investigations has made use of the same dataset. In the accompanying table 5.2, a comparison is made between the results that were obtained from the CapsNet model with STFT spectrogram pictures and the results that were obtained from the suggested model when it was applied to the same dataset. The findings of the analysis of the table suggest that the results for subjects 1, 2, and 3 have shown an improvement, whilst the results for the remaining subjects indicate that there is only a tiny difference between them. The model that was being used before has a lower average accuracy for all nine subjects when compared to the model that was being used for the same dataset. The model that was being used before has a higher average accuracy. Comparative graphs for each of the nine individuals are displayed in Figure 5.2. These graphs were created using the indicated approach using capsNet. The proposed model CWT with vgg16 model performance is represented by the brown bars, while the CapsNet model performance results are represented by the blue color bars.

Subject	CapsNet[45]	Proposed Model(CWT+VGG16)
S1	78.75	**95.00**
S2	55.71	**83.68**
S3	55	**65.00**
S4	95.93	**95.78**
S5	83.12	**83.00**
S6	83.43	**80.00**
S7	75.62	**73.00**
S8	91.25	**80.00**
S9	87.18	**80.00**
Average	78.44	**81.72**

Table 5-2: Comparative analysis of outcomes using STFT+CapsNet and the proposed approach CWT+VGG16

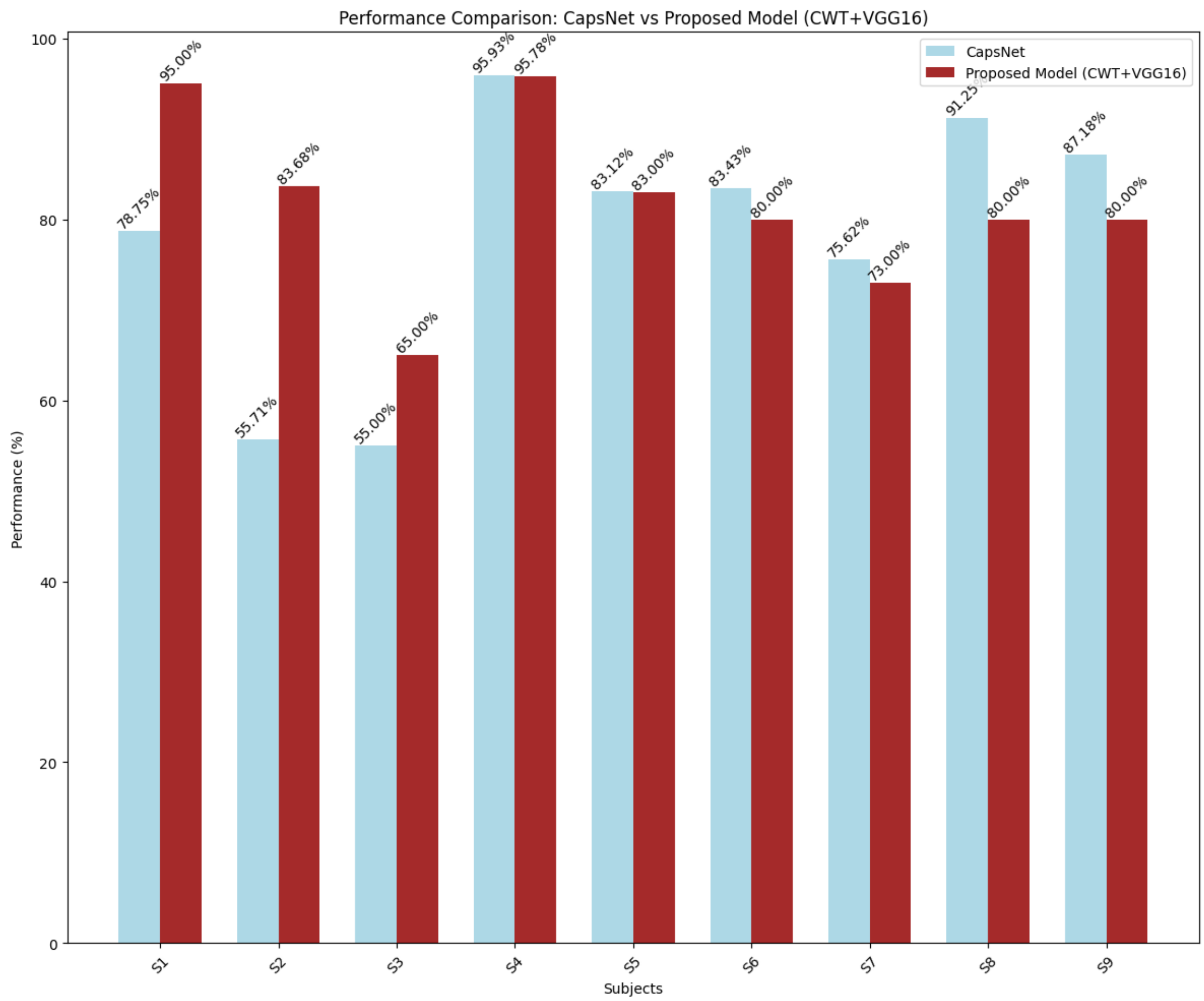

Figure 5-2 Comparison Of Proposed Model with CapsNet Across Each Subjects

A comparison is conducted between the findings of the suggested approach and the findings of previous research on motor imagery EEG signals BCI competition datasets, which are included in the table that is shown below. This comparison is shown in Table 5.3. The average degree of accuracy that is maintained by the approaches is brought to the forefront via the utilization of this comparative emphasizing. The information that is shown in the table makes it abundantly evident that the approach that has been proposed delivers superior performance in comparison to the original study in terms of the average accuracy. This is made clear by the fact that the table contains the information. In addition, the comparison graph between the recommended model and past methodologies is displayed in Figure 5.3.

Reference Article	Methodology	Dataset	Model Performance
(Anwar and Eldeib 2020)**[42]**	2D AlexNet Convolutional Neural Network (CNN)	The proposed approach was analyzed and evaluated using dataset 2a from BCI Competition IV	81.09%
(Roy, McCreadie et al. 2019)**[43]**	Convolutional Neural Network (CNN)	To conduct this study, dataset 2b from BCI competition IV used	80.30%
(Arı and Taçgın 2023)**[44]**	CNN	Graz BCI-IV-2A and BCI-IV-2B datasets	73.86%
(Ha and Jeong 2019)**[45]**	Capsule Network(CapsNet)	BCI Competition IV Dataset 2b	78.44%
(Wang, Annan 2021)**[46]**	Distribution Based Learning (DBL) framework based on deep learning	BCI Competition IV Dataset 2b	79.69
Proposed Methodology	**CWT+VGG16**	**BCI Competition IV Dataset 2b**	**81.72**

Table 5-3: Assessment of Accuracy in Relation to Other Cutting-Edge Models

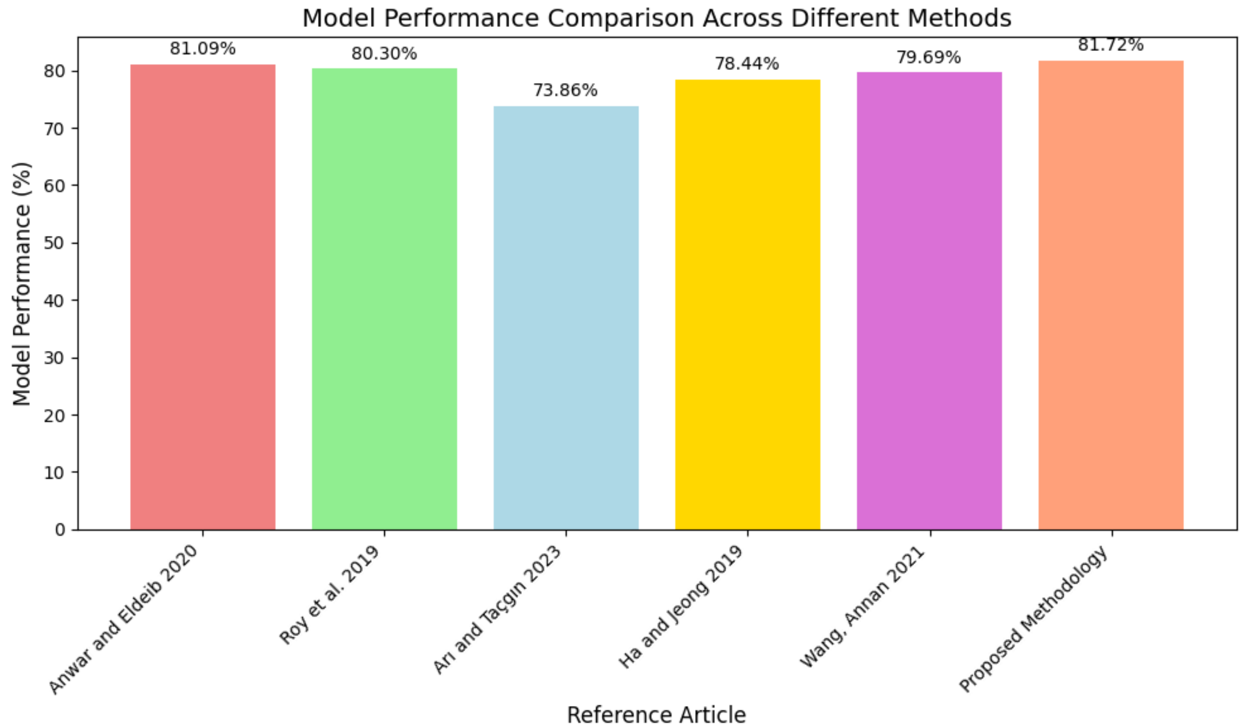

Figure 5-3 Proposed Model Performance Comparison across Different Methods

5.6 SUMMARY OF CHAPTER

The findings of this research indicate that the strategy that was developed for detecting motor imagery EEG signals by utilising continuous wavelet transform (CWT) with temporal frequency images is a technique that is capable of being implemented. Considering the significant differences in the temporal frequency patterns of motor imagery EEG signals that were observed across all of the subjects, the findings of the experiment indicate that these characteristics have the potential to be utilised for classification purposes in an efficient manner. By utilising the method that was provided, it was possible to successfully obtain high accuracy rates while also preserving appropriate levels of sensitivity, specificity, precision, and F1-score indices. Even when noise is present, the proposed method is able to efficiently classify two distinct categories of motor imagery

EEG data. This is demonstrated by the robustness study, which reveals that the proposed method is resistant to noise. Furthermore, this method is able to accomplish this goal even in situations when the quantity of the dataset is rather restricted. The findings of the analysis confirm beyond a reasonable doubt that this is the situation that was seen. Based on the results of the real-time performance investigation, it has been demonstrated that the technique that has been proposed is effective in correctly classifying two different types of motor imagery, more specifically EEG signals. When compared to CapsNet and other methods, the suggested method produced significantly higher overall accuracy in classification than the other approaches.

Chapter 6

6 DISCUSSION AND CONCLUSION

6.1 DISCUSSION

To begin, we conducted a series of exhaustive quantitative tests to demonstrate that the VGG16-based technique is feasible in the EEG domain. This was the first thing that we accomplished. Following that, we made certain that the recommended method was not only effective but also successful by contrasting it with other options that served as a baseline. The outcomes of the experiments make it abundantly clear that VGG16 is capable of successfully learning important properties from MI-EEG data, which ultimately leads to an improvement in the system's overall performance. This is the case because the trials were conducted. In spite of the fact that all of this is taken into account, there are still a great lot of difficult problems that need to be solved. Through the utilization of hyper-parameter tuning, which enabled us to collect this knowledge, we were able to determine the configuration that was most suitable for the network. However, there is a constraint in that we only evaluated the optimization of network parameters, rather than the architecture of VGG16. This meant that we did not take into account. Consider this a drawback. This is a limitation that needs to be taken into consideration. Although it generally surpasses other baseline techniques in terms of average classification accuracy, we are of the opinion that the current form of the proposed VGG16-based approach has limited capability to detect discriminative patterns or features from EEG signals. This is despite the fact that it achieves a higher level of accuracy than other baseline techniques. Specifically, this is because the VGG16 algorithm forms the basis for the VGG16-based technique, which is the reason why this is the case. According to what was mentioned in this section, there are a number of distinct aspects of the use of VGG16 in the EEG domain that have the potential to be enhanced. There are a variety of approaches that could be taken to accomplish these enhancements. As a means of increasing the performance of motor imagery EEG classification tasks, we are going to work on overcoming the concerns that were brought up in the part that came before this one.

6.2 CONCLUSION

Within the confines of this investigation, we developed a novel approach to the classification of two-class motor imagery EEG signals data by making use of VGG16 on our end. The method that was proposed made use of a series of CWT time frequency images that were extracted from raw EEG data. These images were used as the input for the strategy. The entire network was trained to do a classification task while the VGG16 operation was being carried out. This training took place simultaneously. An study and optimisation of the configuration of the VGG16 architecture that was proposed was carried out. This analysis and optimisation took into consideration a range of factors, including the number of channels and the number of routing iterations. We were able to perform the objective of analysing the effectiveness of the method that was provided by making use of the dataset that was made available to us by the BCI competition IV 2b. Within the context of the experiment, we first assessed whether or not the proposed method was viable, and then we evaluated it in relation to other ways that are deemed to be state-of-the-art in terms of classification accuracy and efficiency. The results of the trials demonstrated that the proposed approach has a greater classification accuracy than both the conventional methods and the alternative CNN-based, CapsNet method. This was demonstrated and demonstrated by the findings of the studies. By employing visualisation, it is predicted that a deeper knowledge of the relationships that exist between the aforementioned components will result in the acquisition of more significant insights. This is because visualisation allows for the visualisation of information. In conclusion, in order to develop more practical applications of BCI, it is required to take into consideration a lot of distinct components simultaneously within the same context. Aspects such as accuracy, efficiency, and usefulness are included in this category.

6.3 FUTURE WORK

In spite of the fact that the method that was suggested was successful in delivering the outcomes that were sought, there are still issues that have not been resolved and will need to be addressed in the future. To begin, as was indicated in the section under "Discussion," our method can be improved by incorporating a broad variety of creative optimisation algorithms for hyper-parameter tunnig and network topologies. This is something that can be done. Within the scope of this investigation, we will investigate the ways in which the performance of BCI applications could be enhanced by utilising new and sophisticated methods for deep learning. In addition, it is of utmost significance to study whether or not the technique that is based on VGG16 can be employed for more sophisticated tasks, such as those that involve a bigger number of individuals, electrodes, and class labels.

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