Upper Limb Complex Movement Classification Using Pre-Movement EEG Signals

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Annex A

THESIS ACCEPTANCE CERTIFICATE

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I dedicate this thesis to my parents, supportive sisters, and all those who believe in the power of learning. Their unwavering support, guidance, and belief in my abilities have been crucial in achieving this milestone. I am grateful for their presence in my life and their constant encouragement. This dedication is a tribute to their love and the shared belief that knowledge is a catalyst for personal growth and transformation

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Abstract

A promising technology for facilitating communication and control for people with disabilities is the brain-computer interface (BCI). Electroencephalogram (EEG) signals are frequently used in BCI systems; however, accurate classification of these signals remains challenging. This thesis presents a novel method for EEG signal classification based on spectral features. Short-time Fourier transforms (STFT) and spectral feature extraction are used to provide an accurate classification approach for upper limb dynamic movements using pre-movement EEG signals. The proposed method was tested on a larger dataset of healthy subjects, and the performance was evaluated using different classification algorithms, including Convolutional Neural Networks (CNN) and Residual Networks (ResNet). The results show that the suggested method consistently produces high accuracy rates for all subjects and movements, with an overall accuracy of 88.7%. The highest accuracy of 100% was achieved on subject 5 during movement 3 using ResNet on a privately available dataset compiled from 12 healthy subjects. This dataset consisted of 5 types of upper-limb complex pre-movements conducted in 50 trials. My study extends the previous work by employing a different feature extraction method and classification algorithms on a larger dataset of healthy subjects, outperforming previous methods. By utilizing spectral features, my method could enhance the accuracy of BCI systems in various applications, including medical diagnosis, control of assistive devices, and gaming software. Furthermore, this approach could also be extended to other types of signals beyond EEG, enabling accurate classification in a broader range of applications.

Keywords: *Brain-computer interface (BCI), Electroencephalogram (EEG), Spectral features, Signal classification, Short-time Fourier transforms (STFT), Classification algorithms, Convolutional Neural Networks (CNN), Residual Networks (ResNet)*

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Chapter 1: Introduction

The emerging technology known as brain-computer interfaces (BCIs) has the potential to completely change how humans interact with machines. BCIs can help people with motor limitations operate gadgets by establishing a direct line of communication between the brain and a computer. People with severe motor disabilities and impaired communication now have new options to connect with machines more effectively and comfortably because of this technology [22]. In this article, we will discuss the idea of BCIs and how they might help people with motor difficulties.

The primary coordinating and command center of the body is the complicated and complex human brain. Utilizing messages, neural circuits, and networks constructed from a significant number of neurons and synapses, it regulates all bodily processes, activities, and organs. These networks can be altered and modified to help the brain continue to develop. However, in some circumstances, there may be a breakdown in the communication between the brain and the muscles or nerves that regulate movement, resulting in motor impairments.

Many people across the world experience motor limitations, which impact their ability to carry out daily tasks and interact with their environment. Numerous illnesses, such as spinal cord injuries, strokes, and neuromuscular diseases, might contribute to these impairments [18]. Physical therapy and assistive tools like wheelchairs and prosthetics are the mainstays of conventional rehabilitation methods for people with motor difficulties. Although these techniques can increase a person's mobility and quality of life, they frequently entail a lot of physical effort and might not be appropriate for people with severe motor impairments.

For those with movement limitations, brain-computer interfaces (BCIs) offer a viable substitute for traditional physical communication techniques. Without the use of nerves or muscles, BCIs can record brain activity associated with external inputs or mental tasks and translate that data into a set of instructions that can be used to control devices [33]. People with motor limitations can now control devices by transmitting signals from their minds thanks to this technology.

Due to its non-invasive nature and excellent temporal precision, EEG signals are frequently utilized to research and categorize human motor control and movement patterns. Effective BCI development requires pre-processing, feature extraction, and classification of EEG inputs [45]. Using EEG data to categorize complex upper limb movements according to their pre-movement features has gained popularity in recent years.

While simple motions like grabbing and reaching have been accurately classified using EEG data, classifying complicated upper limb movements has proven to be a difficult issue [41]. Short-time Fourier transforms (STFT) and spectral feature extraction are examples of advanced signal processing techniques that have produced promising outcomes in recent investigations. It has been demonstrated that these methods accurately capture the frequency properties of EEG signals and offer a rich feature set for categorization.

BCIs may have several advantages for those with motor impairments. First, BCIs can provide people with a great deal of independence, enabling them to handle machinery and communicate with their surroundings more effectively [20]. Second, BCIs can reduce the physical effort needed for interaction and communication. This enables people with motor limitations to conserve energy and concentrate on other tasks. Third, BCIs can improve communication for people with motor limitations, allowing them to express their emotions and thoughts more freely [6].

For BCIs to be used effectively for people with motor disabilities, however, there are several issues that need to be resolved. First, the caliber and consistency of the recorded EEG signals affect the accuracy and dependability of BCIs. Accurate findings are challenging to obtain since any outside interference or noise can drastically affect how well BCIs operate [27]. Second, for BCIs to work at their best, extensive training and calibration may be necessary [43].

1.1 EEG Signals

Numerous studies use electroencephalography (EEG) signals to examine brain function and motor control [7]. With electrodes positioned on the scalp, an EEG monitors the electrical activity of the brain in a non-invasive, high-temporal resolution manner [3] Applications for EEG signals include the diagnosis of neurological diseases, anesthesia monitoring, and brain-computer interfaces (BCIs). The method for collecting EEG signals and signals is shown in the adjacent Figure 1.

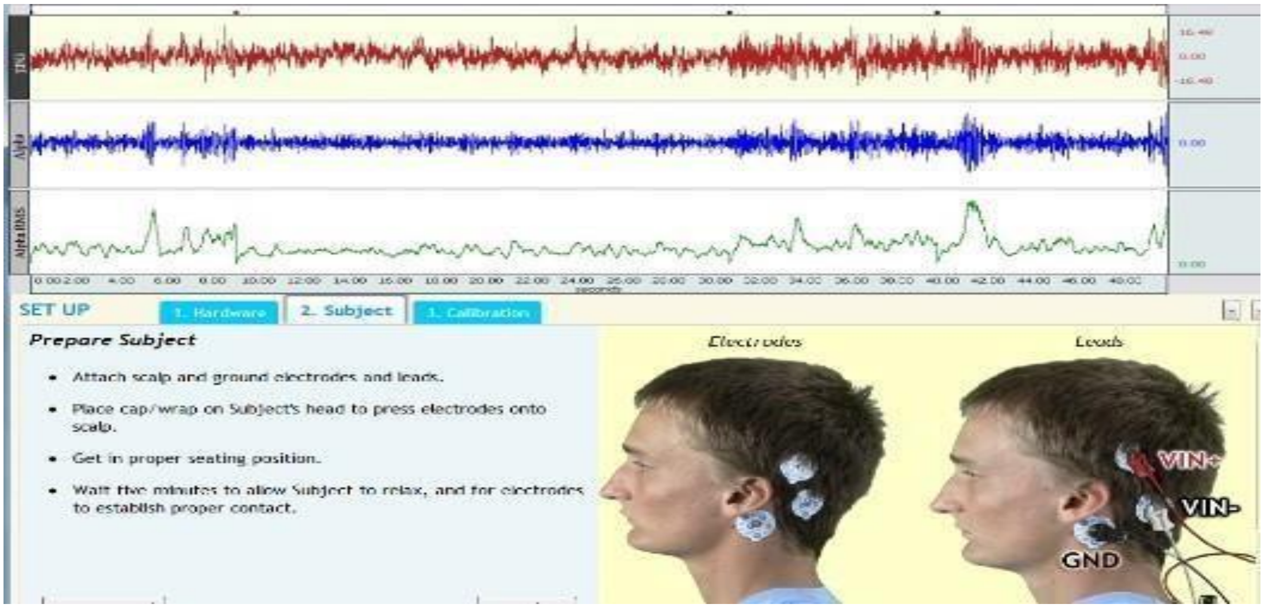

Figure 1: EEG Signals

Because they enable people to operate gadgets using their brain activity, EEG signals are connected to BCI technology. EEG signals are generally used by BCI devices to decode a user's intent or command [19]. By identifying certain patterns in the EEG signals connected to a user's intention to move or interact with the device, a BCI system, for instance, may be used to control a wheelchair, prosthetic limb, or computer. Machine learning algorithms can be used to analyze these signals in order to correctly categorize the user's intention and produce the appropriate instruction.

Preprocessing of EEG signals, feature extraction, and classification are the three basic stages in the development of BCI systems. Preprocessing is necessary to get rid of noise and artifacts from the EEG data that could obstruct categorization. Finding the pertinent EEG signal properties, such as frequency or time-domain patterns that can be used to categorize various brain states or motions, is known as feature extraction [23]. Finally, depending on the retrieved features, classification techniques are utilized to ascertain the intended movement [13].

1.2 Problem Statement

Due to the complex and dynamic nature of upper limb movements, as well as the substantial individual variability of EEG signals, accurately classifying upper limb movements using EEG signals is a difficult challenge. Machine learning algorithms for classifying EEG signals have been the main focus of recent research in this area. The effectiveness of these models and the effect of various feature extraction methods on classification accuracy still need to be thoroughly examined.

In addition, while several studies have investigated the use of EEG signals for identifying upper limb movements, the majority of these investigations have relied on modest and constrained datasets. Therefore, a larger and more varied dataset is required to provide a more thorough comprehension of the EEG signals related to upper limb motions.

This study aims to address these knowledge gaps in order to further the development of more precise and efficient techniques for the classification of upper limb motions using EEG signals, with potential applications in robotics, brain-computer interfaces, and rehabilitation.

1.3 Research Questions

The research question of this study is: Can we classify complicated upper limb movements from pre-movement EEG signals using STFT and spectral characteristics?

1.3.1 Research Questions

The study aims to investigate the feasibility of using STFT and spectral feature extraction to classify complicated upper limb movements from pre-movement EEG signals. The research question can be broken down into the following sub-questions:

- Can STFT and spectral feature extraction effectively capture the frequency characteristics of pre-movement EEG signals related to complex upper limb movements?
- Can the extracted spectral features be used to classify different upper limb movements with high accuracy?
- How does the proposed method compare to existing methods in terms of classification accuracy?

1.3.2 Significance of the research question

The development of a reliable BCI system will significantly improve the quality of life for those with severe motor disabilities and impaired communication. BCIs have the potential to provide these people with a means of communication and environment control, allowing them to participate more fully in daily life and improving their overall quality of life.

BCI technology has become a viable solution for people with motor limitations since it allows users to operate devices using brain impulses. It is crucial to be able to classify complex upper limb movements from pre-movement EEG data using STFT and spectral feature extraction for people with severe motor impairments who have limited communication and mobility. We can improve these people's quality of life and autonomy by creating a dependable BCI system that can help them communicate with machines more effectively and comfortably. The suggested technique also has the potential to aid in the creation of more advanced and precise BCIs that will allow people with motor disabilities to use their brain signals to accomplish a variety of tasks. The results of the study can also help us understand the neurological processes that underline complicated upper limb motions and shed light on the possible uses of EEG data in clinical settings.

1.3.3 Research Objective

The major goal of this thesis is to use spectral information extracted from STFT to increase the precision of the classification of complex movements from pre-movement EEG signals. By comparing the performance of our suggested method to those now in use, we will show how effective it is. Additionally, a thorough investigation of EEG signal processing and analysis, STFT and spectral feature extraction techniques, and related work on EEG classification for complicated movements will all be included in this thesis. The goals are:

- To extract spectral features from pre-movement EEG signals
- To classify different upper limb movements using the extracted features
- To evaluate the proposed method's effectiveness in terms of classification accuracy by comparing it to existing methods

While BCIs have the potential to enable people with motor disabilities to communicate and operate equipment, classifying complicated upper limb movements has proven to be a difficult challenge. Recent research has demonstrated promising results in capturing the frequency features of EEG data and providing a strong feature set for the categorization of complicated upper limb motions. These techniques include STFT and spectral feature extraction. In order to communicate and interact with their environment more efficiently and comfortably, people with motor impairments can tremendously benefit from the development of more precise and dependable BCI devices.

In this thesis, a technique for categorizing complicated movements from pre-movement EEG signals utilizing spectral properties deduced from Short-Time Fourier Transform (STFT) is proposed. For the time-frequency analysis of non-stationary data like EEG, STFT is a widely used approach. The frequency content of the EEG signals is crucial information that may be gleaned from the spectral features recovered from STFT and utilized to distinguish between various classes of complex motions.

1.4 Thesis Outline

This research work is planned as follows:

1. Chapter 2 reviews the existing literature on BCIs, EEG signals, and upper limb movement classification.
2. Chapter 3 describes the dataset used in the study and the pre-processing steps applied to the data.
3. Chapter 4 presents the proposed method for classifying upper limb complex movements from pre-movement EEG signals using STFT and spectral feature extraction.
4. Chapter 5 evaluates the proposed method's effectiveness in terms of classification accuracy and compares it to existing methods.
5. Finally, Chapter 6 summarizes the study's findings, discusses the limitations and future directions, and concludes the thesis.

Chapter 2: Literature Review

I will perform a review of the literature in this chapter on the subject of classifying EEG signals using classification models, specifically in the context of upper limb datasets. Numerous studies have been conducted on the classification of EEG signals, which is important for understanding how the brain functions in a variety of activities such as motor control, cognition, and emotion.

An introduction to EEG signals and the fundamentals of signal processing will be provided first. We will also discuss the significance of EEG signal classification and how it can be used in both clinical and non-clinical contexts. In addition, we will explore the various techniques for feature extraction, feature selection, and classification models that have been applied to the classification of EEG signals. These include both linear and nonlinear classifiers, such as decision trees, artificial neural networks (ANNs), and support vector machines (SVMs).

The classification of upper limb datasets using EEG signals will be the main focus of our next discussion. We will review research that has investigated the use of EEG signals to predict and control movements of the upper limbs, such as hand and arm movements. Furthermore, we will assess the effectiveness of several classification models employed in this research and highlight both their advantages and disadvantages.

Moreover, we will address the challenges and limitations associated with EEG signal classification, including noise and artifact removal, inter-subject variability, and the limited size of EEG datasets. We will examine various strategies that have been implemented to tackle these issues, including the utilization of transfer learning and data augmentation techniques.

By the end of this chapter, we aim to equip the reader with a thorough understanding of how classification models can be effectively utilized to classify EEG signals, particularly in the context of upper limb datasets. Our intention is also to illuminate the current state of the art, underscore the challenges and limitations inherent in categorizing EEG data, and pinpoint potential directions for future research in this burgeoning field.

2.1 Overview of EEG signals and basics of signal processing

The non-invasive method of measuring brain electrical activity is called electroencephalography (EEG). The electrical signals produced by the brain's neurons are captured by electrodes placed on the scalp and recorded as EEG signals after being amplified. EEG signals can be used to monitor and diagnose neurological conditions, including epilepsy, sleep disorders, and dementia, as well as to research various brain activities, such as perception, attention, memory, and movement. The frequency, amplitude, and waveform of the EEG waves define them. Theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (>30 Hz) are some of the frequency bands within which EEG signals typically fall. The different brain states associated with these frequency bands include deep sleep (delta waves), relaxation (alpha waves), and meditation (beta waves).

Signal processing techniques are employed to filter out noise, artifacts, and undesirable signals to extract meaningful information from EEG signals. Filtering, artifact removal, segmentation, and feature extraction are common EEG signal processing techniques. Filtering is used to eliminate noise and unwanted signals from EEG readings, such as interference from the environment and muscle activity. The removal of artifacts caused by blinks, eye movements, and other forms of interference requires the application of artifact removal procedures. EEG signals are segmented by dividing them into epochs, which can be further analyzed. The selection of relevant elements from the segmented EEG signal, such as power spectral density, coherence, and entropy, is known as feature extraction. There are different methods of performing sentiment analysis depending on the type, nature and domain of the text as well as the potential applications. Sentiment analysis is commonly categorized into two main groups [41]: language processing-based sentiment analysis and application-oriented sentiment analysis.

2.2 Overview of EEG signals and basics of signal processing

EEG signal categorization is the process of categorizing EEG signals according to their properties. There are several uses for EEG signal classification in both clinical and non-clinical contexts. Neurological illnesses like epilepsy, Alzheimer's disease, and sleep problems can be diagnosed and monitored in clinical settings using EEG signal classification. For instance, in order to diagnose and treat epilepsy, aberrant brain activity associated with the condition can be identified using EEG readings.

Brain-computer interface (BCI) systems, which allow people to use their brain signals to control external devices, can be employed in non-clinical contexts to classify EEG signals. Communication, neurorehabilitation, and gaming are just a few uses for BCI devices. For example, EEG signals can be utilized to control a robotic arm or wheelchair, thereby enhancing the quality of life for people with severe disabilities.

In general, EEG signal classification is an effective tool for understanding the brain, as well as for the detection and management of neurological illnesses. The improvement of EEG signal categorization accuracy and speed, brought about by the development of powerful machine learning algorithms and deep learning techniques, has created new opportunities for study and therapeutic applications.

2.3 Related work on EEG classification for complex movements

Recent years have witnessed a significant surge in interest in the utilization of electroencephalographic (EEG) data for the classification of functional upper limb movements, particularly in the context of motor impairment rehabilitation. The potential to develop brain-computer interface systems for individuals with motor limitations, enabling them to operate assistive devices at home by decoding motions from their EEG data, holds promise.

Jaime Ibáez conducted a study to explore the capacity of electroencephalographic (EEG) activity to identify upper-limb analytical movements [30]. The primary objective was to design and validate an EEG-based classifier capable of accurately categorizing various self-initiated upper-limb movements. The selected classification features were specific to each subject and movement task. The study aimed to determine whether the classifier utilized information beyond task-related brain activity. Additionally, the paper discussed potential applications of this technology in monitoring and aiding neurorehabilitation settings. The study involved six healthy participants engaged in self-initiated upper-limb analytical motions [36]. A Bayesian classifier was employed to classify the movements, utilizing features from the alpha and beta EEG bands. A genetic algorithm was applied to select the optimal feature set for classification. The study revealed that the type of upper-limb analytical movement could be predicted from EEG data even before the movement initiation. The classifier achieved an average accuracy of 62.9% ± 7.5%, outperforming the baseline accuracy of 30.2% ± 4.3%.

The implications of this study for the field of neurorehabilitation are substantial. EEG data could aid in monitoring and assisting patients with upper-limb deficits. For instance, EEG signals might control a robotic arm or motor neuroprosthesis in individuals with severe motor disabilities. EEG signals could also track patients' progress in neurorehabilitation programs, as the classifier can detect specific motions a patient struggles with and monitor improvements over time [24]. However, the study does have limitations. The sample size of just six healthy participants is quite small. To validate the findings, further research with a larger sample size and individuals with upper-limb deficits is essential. Moreover, the study categorized only seven distinct movement categories. More complex classifiers might be necessary for intricate movements or fine motor activities. Lastly, the Bayesian classifier employed might not be suitable for real-time classification. A more computationally efficient classifier could be required for real-time applications.

Another study focused exclusively on classifying complex functional upper limb movements using pre-movement planning and preparation EEG data [49]. The EEG signal underwent stationary wavelet transformation to extract various frequency bands after nine healthy participants performed the movements. An information-based feature selection technique was employed to enhance the system's efficacy. Spatial filters known as common spatial patterns were utilized to improve the separation of the five movements in each frequency band. The k-nearest neighbor, support vector machine, and linear discriminant analysis methods were employed for classification using the chosen features.

Results showed that among the five motion categories, the k-nearest neighbor approach outperformed other methods. Further analysis of each frequency band's contribution in the ideal feature set indicated that the gamma and beta frequency bands played a significant role. To simplify the EEG recording device's configuration, a subset of the 10 most efficient EEG channels was chosen, resulting in an accuracy of 82.4%. The majority of these EEG channels were located in the prefrontal and frontal regions. The study concluded that regionally specific EEG data can predict complex movements before they commence. Nevertheless, the study had limitations, such as its focus on healthy participants and a relatively small sample size. Further research involving larger groups and individuals with mobility difficulties is necessary to validate these findings.

Researchers are investigating the potential of brain-computer interfaces (BCIs), which are evolving, to improve prosthetic limb control by interpreting electrophysiological signals produced by the brain. The electroencephalogram (EEG) impulses used to control the finger movements of an upper limb prosthesis are the main topic of the study in [42], which focuses on the design and implementation of an embedded system. The researchers used a two-stage logistic regression classifier with Power Spectral Density (PSD) as a feature of the filtered signal to achieve the best classification accuracy, building on earlier research that categorized three finger motions using EEG signals. Neurologically unharmed subjects' EEG data was captured utilizing a non-invasive BCI technology and a 14-channel electrode headset. An "Arduino Uno" microcontroller was used to filter the mu (alpha waves) and beta rhythms (8–30 Hz) from the preserved data. The 2-stage logistic regression produced a classification accuracy of 70%.

However, the study had certain drawbacks. The categorization accuracy was less accurate than intended and might not be enough to manage a prosthesis effectively [4]. A more thorough classification system for different hand movements must be developed; the study only identified three finger movements. The technique may not function as well for people with neurological diseases or injuries because the study solely used EEG signals recorded from subjects who were neurologically healthy.

Individuals who are unable to perform movements for a variety of reasons can considerably benefit from the capacity to detect and decode intended movements using electroencephalographic (EEG) signals. In a work by [48], the authors developed a novel system for the classification of premovement vs. resting and premovement vs. premovement epochs to decipher motor preparatory phases using EEG signals. The researchers examined a publicly accessible dataset of 61-channel EEG signals obtained from 15 healthy individuals as they performed a variety of right upper limb motions, such as elbow flexion and extension, forearm pronation and supination, and hand opening and closing.

The proposed approach creates a time-frequency map for each source signal in the motor cortex using beamforming and Continuous Wavelet Transform (CWT), embeds all the maps in a volume, and then feeds the volume as input to a deep convolutional neural network (CNN) [46]. The system outperformed comparable techniques in the literature with an average accuracy of 86.3% (min 74.6%, peak 98%) in separating premovement from resting epochs. Additionally, the system had an average discrimination accuracy of 62.47% when comparing premovement to premovement epochs. The findings of this study imply that source-level motor planning can be studied using deep learning techniques in the time-frequency domain. The study is constrained, nevertheless, by the small number of healthy participants and the dearth of information from people with motor disabilities. To determine whether this approach could be used in clinical settings and to assess its efficacy in a larger and more diverse population, more investigation is required.

Our entire body, including our motions, is managed by the complicated and intriguing human brain. Both in healthy people and in people with motor disorders, researchers are interested in how the brain stores the neurological correlates of movements. The encoding of single upper limb movements in the time domain of low-frequency electroencephalography (EEG) data was examined in a study by [35]. Fifteen healthy participants in the study performed and simulated six different sustained upper limb movements. The actions included closing and opening the hands, extending and bending the wrists, and extending and flexing the elbows. While the subjects were moving, EEG data was captured from their scalps. The authors then used machine learning techniques to classify these six movements and a rest class, analyzing the outcomes.

The authors discovered that they could accurately distinguish the six executed movements and the rest class with considerable average classification accuracies of 55% (movement vs. movement) and 87% (movement vs. rest). The average categorization accuracy for imagined movements was lower, at 27% and 73%, respectively. These findings suggest that actual movements are more accurately captured in the EEG signals than imagined movements are.

In an effort to delve deeper into the neurological correlates of motion, researchers analyzed classifier patterns in the source space, identifying the brain regions responsible for transmitting discriminative movement information. The study aimed to shed light on the intricacies of motion-related brain activity and potentially enhance the development of non-invasive brain-computer interfaces (BCIs) for individuals with motor limitations.

According to the classifier patterns, key brain regions involved in transmitting discriminative movement information include the premotor regions, primary motor cortex, somatosensory cortex, and posterior parietal cortex. These findings align with previous research highlighting the role of these areas in movement preparation and execution. Such insights could revolutionize the field of BCIs, enabling individuals with motor limitations to control devices like robotic arms or prosthetic limbs with greater ease and naturalness compared to existing techniques, which often require complex muscle contractions.

However, the study does have limitations. Notably, imagined motions might be more challenging to decipher from EEG data, as classification accuracy for imagined movements was lower than for executed movements. Additionally, the scope of the study was limited to sustained movements, and it remains unclear whether the findings extend to more intricate movements or tasks. Furthermore, the study's participant pool consisted solely of healthy individuals, raising questions about the applicability of the findings to those with motor difficulties.

In another study, researchers employed a two-phase approach to classify six distinct upper limb movements, including elbow extension, elbow flexion, forearm pronation, forearm supination, hand opening, and hand closure. This innovative classification method aims to advance biomedical engineering applications by uncovering connections between detectable human brain movements. The classification process involves pre-processing and classification stages.

During pre-processing, researchers identify and remove noisy channels using a band-pass filter that detects values above and below 200 and -200 V thresholds, respectively. This step also detects trials with unusual joint probability and significant kurtosis. Signals are then pre-processed before being fed into a neural network (NN) model for classification. The NN model categorizes six movements: hand open, hand closure, forearm pronation, forearm supination, and elbow extension and flexion. To enhance classification accuracy, researchers employ a newly developed bypass-integrated Jaya algorithm (BI-JA), which optimizes the NN model's weights. This hybrid algorithm combines the rider optimization algorithm (ROA) and Jaya algorithm (JA).

To assess their model's performance, researchers use metrics such as accuracy, sensitivity, specificity, precision, false positive rate, false negative rate, false discovery rate, F1-score, and Matthew’s correlation coefficient, comparing it to traditional models. Results show that the BI-JA-NN model outperformed other algorithms, including Levenberg-Marquardt (LM)-NN, firefly (FF)-NN, JA-NN, whale optimization algorithm (WOA)-NN, and ROA-NN, in terms of accuracy and sensitivity. However, the study's proposed categorization approach has its limitations. It relies on precise noise removal and detection, which may not always be achievable in real-world scenarios. Additionally, the method only categorizes six specific upper limb movements, potentially excluding other movements patients might exhibit. Lastly, not all optimization problems are solvable with the BI-JA algorithm, limiting its universality.

In a 2017 study, a novel technique was proposed for categorizing finger motions in the right-hand using EEG signals from a volunteer with neurological integrity through a non-invasive BCI system. The method focuses on evaluating the power spectral densities (PSD) of EEG signals in the alpha and beta bands (8–30 Hz) for four distinct finger movements. These movements are associated with operating upper limb prostheses and include thumb movement, index finger movement, a combination of middle and index finger movement, and fist movement. The unprocessed EEG signals are filtered to retain movement-related alpha and beta band signals, and these PSD-derived features are classified using various classifiers. For this study, the logistic regression classifier, with an average class accuracy of 65%, was selected. The study also explored alternative classifiers, such as the multi-layer perceptron, linear discriminant analysis, and quadratic discriminant analysis [5].

The fact that this study only used data from one participant is one of its drawbacks. As a result, it is uncertain whether the suggested strategy can be applied to a broader population. Additionally, there is room for improvement due to the logistic regression classifier’s mediocre accuracy [2]. In order to increase the precision of the suggested strategy, it would be interesting to investigate additional feature extraction strategies and classifiers.

Due to their potential to give people with neuro-muscular disorders or spinal cord injuries a way of communication and control, brain-computer interfaces (BCI) have grown in popularity as a research topic. For individuals with these conditions, decoding EEG-based upper limb movements with a BCI can be highly beneficial. Upper limb motions are crucial for daily tasks. [57] suggested employing deep learning models and EEG inputs to accurately categorize upper limb movements. The research makes use of a 61-channel EEG dataset that is openly accessible and contains recordings from fifteen different participants. Spectrograms, which are two-dimensional visual representations of the EEG data that demonstrate how the frequency content changes over time, were created from the preprocessed EEG data. To categorize four separate movement execution (ME) classes for various subjects, including shoulder flexion, shoulder abduction, elbow flexion, and wrist extension, the researchers used pre-trained deep learning models [50].

The proposed technique produced remarkable results, with one subject attaining the best classification accuracy of 97.03% and the highest average classification accuracy for the four ME classes being 86.36%. This implies that upper limb motions can be reliably classified by BCI systems based on EEG, which may have important implications for those who suffer from spinal cord injuries or neuromuscular illnesses [21]. This study does have certain restrictions, though. One drawback is that the study only looked at ME, which is problematic because it ignores imagined motions. For BCI systems, imagined movements are equally essential, as they can provide users with a wider range of motion.

In an article published in 2021, [53] proposed a method centered on the construction of a wavelet neural network (WNN) to enhance the decoding of motions from motor imagery (MI) EEG signals. The objective of this study was to enhance movement decoding capabilities to assist people who have motor limitations, such as spinal cord injury or amyotrophic lateral sclerosis, in carrying out daily tasks. Forearm pronation and supination, hand opening and closing, and elbow flexion and extension were among the six functional motions of a single upper limb that were performed by the study's fifteen healthy participants. Using wavelet packet decomposition (WPD), the MI EEG signals were divided into sub-bands, and statistical features were recovered from the sub-bands to code the functional movements. The optimal feature vector was then chosen using principal component analysis (PCA). The mother wavelet, multidimensional wavelet function, channel count, and image segment duration were all optimized through trials in this work [8]. The optimized coif1 mother wavelet with a six-level decomposition, Mexican Hat wavelet as a hyperparameter, the time of the imaging segment set at 0.7 s, and 61 channels of data were used to achieve the best accuracy of 86.27 ± 6.98%.

Comparative experiments with different classifiers, including the support vector machine (SVM), linear discriminant analysis (LDA), k-nearest neighbor (KNN), and single hidden layer feedforward neural network (ANN), were carried out to further evaluate the effectiveness of the WNN classifier. The results demonstrated that the proposed WNN approach was successful, with an improvement in WNN accuracy of between 15 and 40%. This work offers a novel method for classifying multiple movements using motor imagery EEG. When decoding movements from MI EEG signals, WNN combined with WPD and PCA can increase decoding precision, making it easier for people with motor limitations to carry out daily tasks. However, it should also be mentioned that the study has certain flaws [47]. First, the study only included healthy participants, and more research is needed to confirm the method's suitability for people with motor difficulties. Second, only six functional movements of a single upper limb were classified by the study. The classification of multiple limbs or more complex movements may be the subject of future research. The study only used a modestly sized dataset; hence, it is necessary to confirm the effectiveness of the suggested WNN approach using larger datasets.

Similarly, [25] created an LDA classifier in 2013 to decode upper limb motions from EEG information. The three separate subsets of the EEG signal that were obtained while four upper limb movements were being performed are used in the proposed technique. The mean power of the signal divided into 8 EEG frequency bands served as the defining characteristic for classification. The impact of spatial feature selection on classification accuracy was also looked into in the study. A non-traditional potential difference based on an 8-electrode clinical transversal configuration was also employed in this work to collect EEG data during arm and hand motions. These signals were then divided into three categories: movement planning, movement execution, and steady position. The study's findings, which showed that the Movement Planning subset had the best classification accuracy, suggest that a Brain-Computer Interface (BCI) could be made faster by using pre-movement data. The findings also imply that non-motor regions ought to be taken into account as a source of data when choosing spatial features. The best classification accuracy was 49.36% for the 4-class arrangement, 67.95% for hands versus arms, and 82.69% for right and left limbs.

Although the results are encouraging, the paper notes that additional research is needed to improve classification accuracy and apply these findings more broadly [9]. The small sample size of the dataset utilized in the study, which included a small number of healthy people, is one of its limitations. Furthermore, the study did not compare the outcomes with those of other classifiers and exclusively concentrated on the LDA classifier. Additionally, the study did not look into how subject and session variability affected classification accuracy.

In 2018 [38], a novel method for controlling wearable robots with numerous degrees of freedom was published. This method uses scalp electroencephalography (EEG) data to estimate the user's motion intention in real-time. The suggested solution employs support vector machine (SVM)-based classifiers that can predict the user's intended tasks to conduct a neural network and a time-delayed feature matrix as inputs. The results of the experiments demonstrate how well the suggested methodology works to determine the user's motion intention. Moving, drinking, and resting of the upper extremity were the three task states that were predicted in the study using neural network and SVM-based classifiers. The study started by determining the ideal electrode placements for the brain activation associated with the chosen tasks. The classifiers were then trained using the power band data that was extracted from the EEG signals as feature inputs. [10] Data from individual subjects as well as data from all six subjects were used to train the classifiers.

The outcomes showed that during the object movement and resting stages, all four prediction approaches had greater rates of accuracy. In contrast to the other two states, the accuracy rates for the drinking state were lower, which was expected given that the input signal for the moving state clearly entails some degree of activation whereas there were no obvious activation indicators for the drinking state. The research discovered that the neural network-based classifier outperforms its equivalent classifiers that were trained using data from a single participant for each of the three classifications. The SVM model developed utilizing data from all subjects outperformed the separately trained SVM models, nevertheless. The neural network's maximum accuracy for the resting state was 87.4%, compared to the SVM's best accuracy of 94.5%. The accuracy of the SVM- and neural network-based classifications for the object-moving state was 84.3% and 81.6%, respectively. The accuracy of the SVM and neural network-based classifications for the drinking state was highest at 59.8% and 80.2%, respectively. However, when employing the SVM-based classifiers with two subjects, when trained with the data from all subjects, the lowest success rate for the prediction was an accuracy of less than 7%. As a result, the neural networks' average accuracy for the drinking state (59.5%) was higher than the SVM's (39.1%). [28] However, the neural networks provide faster predictions than the SVM in terms of the latency between the actual motion and the motion predicted by the classifiers.

Due to the limited sample size and the low accuracy rates for the drinking state, the study has some limitations. Additionally, just a few electrode locations were employed in the study; alternative electrode locations might produce more accurate results. In order to generalize the results and improve classification accuracy, more research is required.

In 2022, [54] proposed using a convolutional neural network and the delta electroencephalographic signal band (0.3 Hz-3 Hz) to categorize imaginary motions as a neurorehabilitation tool for individuals with spinal cord injuries. A convolutional neural network with an architecture designed for electroencephalographic inputs, known as EEGNet, was trained with the goal of predicting likely imaginary movement with the use of interpolation and independent component analysis. The results showed that the proposed model has a prediction accuracy of 31% for neurophysiological motor activities.

The field of neurorehabilitation and brain-computer interfaces (BCIs) will be greatly impacted by the study's findings. For those with movement limitations, BCIs are especially helpful since they enable communication and control of external devices using solely brain activity [51]. Being non-invasive and simple to utilize, the use of EEG signals to operate BCIs is particularly promising. However, there are a number of restrictions on this study that must be taken into account. The study's sample size was quite limited, and the model's accuracy was low, indicating that more research is required to raise the classification accuracy of fictitious movements. The study only examined delta EEG waves, therefore it's likely that the model's accuracy might be increased by combining data from several EEG frequency bands.

The work by [52] focused on the difficulties in multi-category task recognition and the scarcity of complex motor imagery modes, two problems in motor imagery brain-computer interface research. The study suggested three motor imagery action paradigms, including elbow flexion, shoulder adduction, and wrist flexion, to address these issues. The purpose of upper limb movements can be recognized using a technique that combines a convolutional neural network (CNN) and the common spatial pattern algorithm (CSP). The CSP technique was used to extract the primary features, and a CNN model was built to extract and recognize secondary features. The identification rate for the binary classification test for the flexion/extension of the upper limb was over 88.04%, and the F-score was higher than 0.87. The average identification rate was over 87.65% for the three classification tasks of shoulder joint horizontal adduction, elbow flexion, and wrist flexion, and the kappa value was higher than 0.74.

The suggested technique demonstrated promising outcomes in identifying motor imagery tasks involving upper limb movement. A better depiction of complicated motor tasks was made possible by the use of three motor imagery action paradigms, and the CSP method and CNN model worked well together for feature extraction and recognition [37]. The study showed the potential of motor imagery brain-computer interfaces in upper limb disability patients' rehabilitation and assistive technologies. It is important to remember that the study had some restrictions. The study's sample size was relatively small, which might have had an impact on how broadly the findings might be applied. The study did not take into account other areas of the body and exclusively focused on motor imagery tasks relating to upper limb motions. The study did not examine the applicability and efficiency of the suggested strategy in real-world circumstances, which brings us to our final point.

[55] in 2022 conducted yet another study. The purpose of the study was to determine whether a brain-computer interface (BCI) device could aid individuals with spinal cord injuries in regaining movement in their limbs. It is common knowledge that losing the use of a limb can have a substantial impact on a person's daily activities. A BCI device can let a person interact with their environment more naturally by detecting limb movement imagination (MI). The goal of the study was to employ electroencephalography (EEG) to identify MI and transfer it into motion. The study specifically used pre-trained deep learning (DL) algorithms to categorize fictitious upper limb movements. The researchers made use of an EEG dataset that was made accessible to the public and comprised information on seven categories of limb movements.

The study calculated the spectrograms of the time series EEG data and utilized them as input to the DL model to categorize the MI signals. Results for the seven movement classes were greatly enhanced by the study's new approach to classifying upper limb movements. The algorithm outperformed recently proposed state-of-the-art approaches in classifying seven movements with a substantial average accuracy of 84.9%. The classification of upper limb motions was the only aspect of the study that was considered; other body parts were not. Additionally, the study did not examine the applicability and efficiency of the suggested strategy in actual-world circumstances.

Patients with motor neuron disorders (MND) require neurorehabilitation because their motor impairments make it difficult for them to perform activities of daily living [14]. Brain-computer interface (BCI) devices based on electroencephalograms (EEG) may be able to help such patients recover. These BCI systems use scalp-recorded EEG signals from mental activities like motor or cognitive images to control external devices. The authors [40] of a manuscript sought to categorize EEG data from 10 different motor imagery movements of the upper limb in MND patients. Five electrodes were positioned over the motor cortex of the study's four participants, and EEG data from those electrodes were recorded. The EEG data were processed using the Filter Bank Common Spatial Pattern (FBCSP) algorithm, and mutual information was employed to choose the features. The EEG signals were then classified using the linear Support Vector Machine (SVM) technique in MATLAB 2015a.

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The study's findings were encouraging, with an average categorization accuracy of 85.88%. This suggests that the proposed BCI system may be able to help MND sufferers use motor imagery activities to control external devices. The effectiveness of the classification model was largely attributed to the usage of FBCSP and mutual information feature selection techniques.

Body-powered prostheses can be difficult to use and frequently cause issues with compliance and prosthesis restoration [15]. For patients who are physically unable to operate their prostheses, brain-computer interfaces (BCI) offer a viable alternative. Invasive recording techniques, however, can put patients at risk for surgery, and non-invasive techniques frequently lack intuitive control. By categorizing Electroencephalogram (EEG) data from actual hand gripping and releasing actions, a study by [31] set out to investigate the feasibility of managing the grasp and release of an upper limb prosthetic terminal device. Using a consumer-grade non-invasive Emotiv EPOC headset, the researchers collected data from five healthy volunteers. Right-hand isometric finger extension and flexion exercises were required of the subjects throughout the assessment, and simultaneous electromyogram (EMG) recordings were made as a substitute for recordings of visually cued movement. The EEG data were then epoch-created, and markers were created in the EMG data using the categorized EMG data. The EEG data was filtered, and spectrally weighted common spatial patterns (spec-CSP) were utilized for feature extraction to improve the signal-to-noise ratio and enable better categorization.

Using linear discriminant analysis, the researchers were able to acquire a classification rate of up to 73.2% between grip and release. In this paper, a brand-new EMG-aided method for classifying EEG data from hand grip and release actions is presented [11]. It shows that employing a cheap BCI to operate upper limb prosthetic terminal devices more intuitively is possible without the dangers of invasive measurement. The quality of the EEG data may be hampered by the use of a consumer-grade non-invasive Emotiv EPOC headset, and more sophisticated EEG recording techniques may enhance classification precision.

The Electroencephalogram (EEG) data is frequently used in the field of brain-computer interfaces (BCIs) to differentiate between movements made with the right and left hands. However, more inputs are needed when working with bigger collections of motor imagery; therefore, multichannel systems are rarely used as alternatives. The study [26] suggested employing four unconventionally organized EEG channels—F, C, P, and O—to identify up to four motor imagery movements of the upper limbs. This was done using a Linear Discriminant Analysis (LDA) classifier. Prior to classification, spatial feature selection is used to increase classification accuracy. The study tried a variety of channel combinations and discovered that other brain regions need to be taken into account, in addition to the motor areas. Using only the electrodes in the F regions and differentiating between the left arm and left hand (89.74%), the suggested system's classification accuracy was at its highest. With electrodes in either the P and O areas or the F and P areas, a 71.80% rate for the right vs. left hand was attained. The best result for differentiating between arms and hands, regardless of the body side, was 83.33% for F and P channels. With only P channels, the best result for the right and left limbs was 66.02% [16].

[29] developed a technique for identifying the three basic human forearm movements (extension, flexion, and rotation) by applying pattern recognition to the information from a single wrist-worn inertial sensor. This method counts the number of times a patient makes certain arm movements with their paralyzed arm throughout the day to evaluate rehabilitation progress in neurodegenerative disorders like cerebral palsy or stroke. Making a cup of tea is the quintessential activity of daily living (ADL), so healthy volunteers and stroke patients were examined in a straightforward proof-of-concept study to show the efficacy of this methodology. Tri-axial accelerometers and tri-axial gyroscopes placed close to the wrist were used to gather data. A ranking collection of 30 time-domain features was derived from the movements that were initially made during the training phase in a controlled environment. For each set of feature combinations, three clusters were created using k-means clustering, and then the best feature combinations were found using ten runs of 10-fold cross-validation on the training data [1]. This method is known as sequential forward selection. Using a minimum distance classifier in a multidimensional feature space made up of the highest-rated features and either Euclidean or Mahalanobis distance as the metric, movements made while performing ADL were connected to each cluster label during the testing phase.

Four healthy participants and four stroke survivors were included in the experiments. The findings demonstrate that, across all healthy individuals and arm movement types, the proposed methodology can accurately identify the three movements performed during Activities of Daily Living (ADL) with an overall average accuracy of 88% using accelerometer data and 83% using gyroscope data. When utilizing accelerometer data, the average accuracy across all stroke survivors is 70%, while using gyroscope data, it is 66%. A Linear Discriminant Analysis (LDA) classifier and a Support Vector Machine (SVM) classifier were also employed in conjunction with the same set of features to detect the three arm movements, and the results were compared to demonstrate the efficacy of the proposed methodology.

The application of Motor Imagery-Based Brain-Computer Interfaces (MI-BCI) in neurorehabilitation and robot control was highlighted in the paper [58]. The main objective of the study was to identify right upper limb-specific single upper limb motor imagery EEG signals. To create a system that can precisely classify various types of motor imagery tasks for motor function rehabilitation training after a stroke, the author proposed a multi-branch fusion convolutional neural network (MF-CNN), capable of simultaneously learning the features of both the raw EEG signals and two-dimensional time-frequency maps. The study's dataset, involving 25 participants, included three different motor imagery tasks: extending the arm, turning the wrist, and gripping an object. MF-CNN achieved an average classification accuracy of 78.52% and a kappa value of 0.57 in the binary classification studies involving the tasks of grabbing an object and extending the arm. The classification accuracy and kappa value were 57.06% and 0.36%, respectively, when all three tasks were utilized.

In both binary-class and three-class classification, the comparative findings demonstrate that the classification performance of MF-CNN surpassed that of single CNN branch methods. According to the researchers, MF-CNN effectively utilized the time-domain and frequency-domain aspects of EEG, leading to an increased decoding precision of single-limb motor imagery tasks [39]. The proposed method is expected to facilitate the use of MI-BCI in training for motor function rehabilitation following a stroke.

The Electroencephalography (EEG) spectra collected during motor planning were another method that was suggested by [44] to automatically anticipate upper limb movements. Using high-resolution EEG data from 33 healthy volunteers, the goal was to categorize the movements as intransitive, transitive, or tool mediated. In order to achieve this, the most accurate feature vector was found by analyzing various combinations of spatial and frequency data collected from the EEG using a three-class k-nearest neighbors' classifier. To investigate any potential differences in accuracy between males and females, the sample was further divided by gender [32]. The findings indicated a substantial difference in the accuracy rates obtained using male and female data, with female data producing the best results (78.55% accuracy in predicting intransitive, transitive, and tool-mediated behaviors).

Study	Methods	Dataset	Accuracy
Yogesh Paul (2018) [40]	Filter Bank Common Spatial Pattern algorithm and SVM classification	EEG signals during motor imagery tasks of upper limb movements in patients with motor neuron diseases	85.9%
Saadat Ullah Khan (2022) [55]	Deep learning using pre-trained models and spectrograms	EEG signals during upper limb movements	84.9%
Mahdieh Mohseni (2020) [49]	K-nearest neighbor, support vector machine, linear discriminant analysis	EEG data from nine right-handed healthy volunteers (5 male and 4 females, age: 23 ± 3 years). Participants performed five different functional tasks of the upper extremities	82.4%
Vincenzo Catrambone (2019) [44]	Three-class k-nearest neighbors' classifier on EEG-derived data	High-resolution EEG data from 33 healthy participants during upper limb movements	78.6%
Gerrit Lange (2016) [31]	EEG data classification from hand grasp and release movements	EEG signals during hand grasp and release movements	73.2%

Nasir Rashid (2018) [42]	Two-stage logistic regression using PSD as feature	EEG data from four subjects performing thumb, fist, index finger, and index-middle finger combined movements	70.0%
Jaime Ibáñez (2015) [30]	Bayesian classifier in alpha and beta bands	EEG recordings from 6 healthy subjects. Participants performed seven different analytic movement tasks of the upper limb.	62.9%
Mario G. Gualsaqu (2022) [54]	Convolutional neural network with delta EEG signals	EEG signals for fictitious motions in upper limbs	31.0%

Table 1: Summary of Literature review

2.4 Summary

Diverse approaches have been investigated in the field of EEG signal classification employing upper limb datasets to categorize specific upper limb motions. Machine learning techniques like logistic regression, k-nearest neighbor, support vector machines, linear discriminant analysis, Bayesian classifiers, deep convolutional neural networks, and common spatial pattern algorithms have been used in studies. Pre-trained models and spectrograms, among these strategies, have produced encouraging results with an average accuracy of 86.36 percent for motor imagery and 84.9 percent for upper limb movements. For premovement vs. resting and premovement vs. premovement classifications, the use of beamforming and continuous wavelet transform to build time-frequency maps for deep CNNs has also demonstrated an average accuracy of 86.3 percent and 62.47 percent, respectively.

In contrast, a convolutional neural network with delta EEG signals has only demonstrated 31% accuracy, whereas a linear discriminant analysis classifier with EEG signals has demonstrated accuracy ranging from 67.95% to 82.69% for different limb movements. Additionally, some studies studied the usage of the k-nearest neighbors' classifier and achieved an accuracy of 78.55% for females. Other studies employed the filter bank similar spatial pattern algorithm with SVM classification to achieve an accuracy of 85.88.

Overall, the findings point to the potential of deep learning techniques for classifying EEG signals using upper limb datasets, such as pre-trained models and spectrograms. However, the particular study issue and dataset should be taken into consideration while choosing a categorization model. For classification jobs, further research into hybrid methods—which incorporate many approaches—may yield superior outcomes.

Chapter 3: Datasets

In this chapter, I provide a thorough summary of the dataset that served as the basis for my research on the classification of EEG signals using an upper limb data set. I completed motor imagery tasks as part of an experimental paradigm, and high-quality EEG equipment was used to record the EEG signals.

The data-collecting procedure, including the acquisition parameters, electrode location, and experimental design, is covered in the first section of this chapter. I will go into detail about the procedure used to get high-quality EEG readings and reduce the effect that artifacts have on the data. I describe the data collection process and the instructions given to me during the experiment. The section also covers my demographic information, including age, gender, and handedness. I outline the preparation procedures used to guarantee the dataset's quality in the second section. In order to remove artifacts like eye blinks and muscle activity from the EEG signals, the preprocessing pipeline used filtering techniques to reduce noise from the signals. I give a thorough description of the many filtering methods and variables employed, including the notch, low-pass, and high-pass filters. I also go over the artifact-removal methods that were used, like independent component analysis (ICA), and I explain how these methods helped to raise the dataset's quality.

An extensive examination of the dataset is presented in the third portion of this chapter. I outline the dataset's features, such as the subject count, EEG channels, and sampling frequency. I also describe the length and variety of my motor imagery activities. I also offer statistical analysis of the dataset, including the mean, standard deviation, and range of EEG signals for every task. The feature extraction procedure is covered in full in the fourth part, along with information on the features that were taken from the dataset. I also discuss the justification for the feature selection procedure, including the features' applicability to the classification objective and the risk of overfitting.

To better comprehend the EEG signals and their features, visualizations of the dataset, including time-frequency plots and topographical maps, are provided in the fifth section of this chapter. In this article, I discuss the value of visualizations in comprehending the underlying trends in a dataset and how they may be used to choose the best features for a classification model.

Overall, because it offers a thorough understanding of the EEG data used in the classification model, the dataset chapter is an essential part of my research. The preprocessing procedures and dataset analysis ensure that the data utilized in the classification model are of high quality and dependability. Selecting the right features for the classification model is aided by the features collected from the dataset and the visualizations. The chapter gives a thorough review of the dataset and builds the groundwork for the next chapters, which validates the accuracy and usefulness of the suggested categorization model.

3.1 Subjects

Twelve healthy volunteers, all of whom were right-handed and between the ages of 20 and 26 (mean age: 23±3 years), provided the dataset for this study. The study's volunteers—6 men and 6 women—were chosen through local advertisements and gave their written informed consent before participating. The experiments were carried out in accordance with the guidelines specified in the Helsinki Declaration, and all methods were authorized by the regional ethics committee.

Participants had to be right-handed, have no history of neurological or psychiatric conditions, not be taking any drugs that might influence the central nervous system, and never have used drugs or alcohol. To make sure they all met the inclusion requirements, each participant completed a preliminary screening. Participants were given instructions on the task and time to practice, so they were comfortable with the experimental setting before the experiment. Participants were positioned in a cozy chair with their arms resting on a table during the experiment. Except for the prescribed motor imagery exercises, they were instructed not to move at all. The classification model in this work was trained and tested using EEG signals that were recorded during the experiment when individuals engaged in motor imagining activities with their right hand.

3.2 Experimental protocol

The individual was fitted with a 64-channel active EEG cap that was secured to their head using the 10-10 method before the EEG data collection procedure began. An amplification system (g.HIamp, Guger Technologies, Austria) was used to record the EEG data [12]. This system amplified the signals before sending them to the recording device. According to Figure 2.

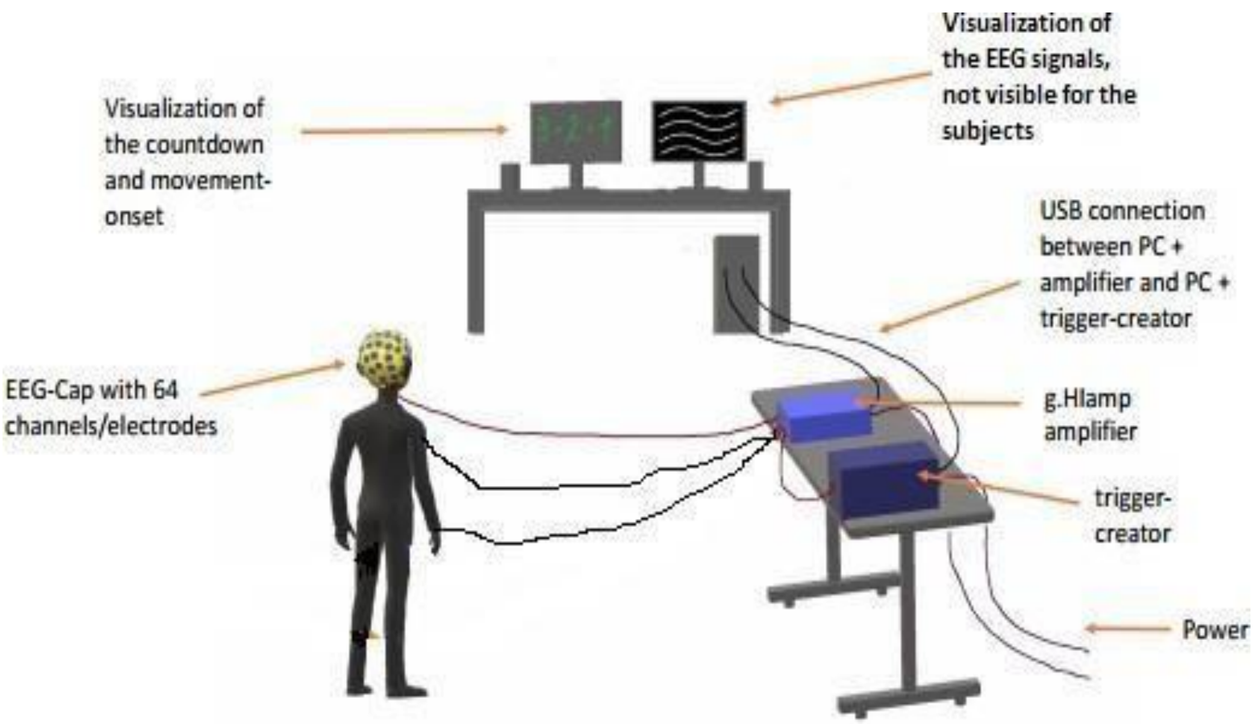

Figure 2: The experiment's setup. A follow-me program is displayed on one screen while the recorded signals are visualized on another screen when the subject is wearing an EEG hat. The bio-amplifier (g.Hiamp) and the DAC for the external trigger are located on the right table.

Reference electrodes play a critical role in EEG data gathering, strategically positioned on both the left and right earlobes [17]. They serve as a crucial baseline signal, allowing for precise comparison with EEG signals. This strategic placement effectively minimizes the influence of external noise and artifacts, ensuring the integrity of EEG data (see Figure 3).

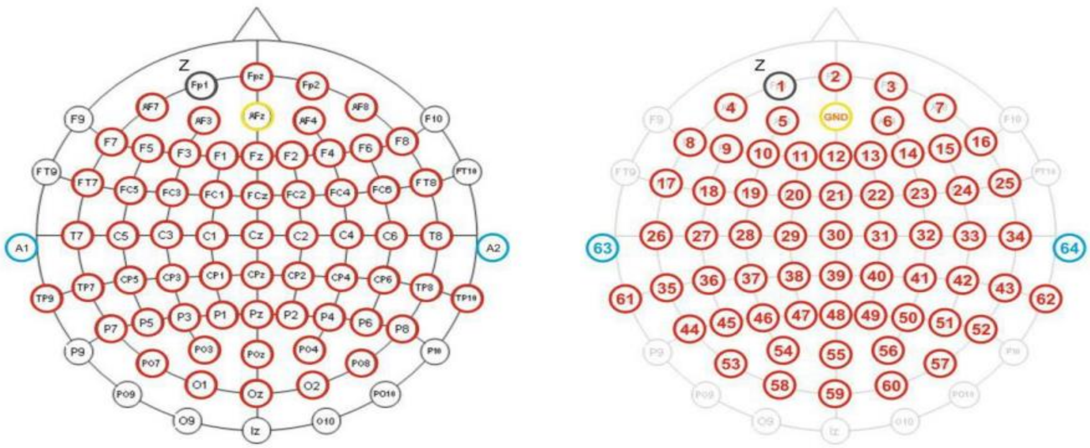

Figure 3: Electrode positions

The patient performed five distinct functional activities involving the upper limbs while the EEG signals were continuously recorded with a sampling frequency of 512Hz. A total of 250 movements were performed, with each of the five functional activities being repeated 50 times. The arrangement of the blocks was randomized, and the motions were carried out in sets of 10 repetitions for each specific task. The order of the movements was randomized within these blocks, as illustrated in Table 2.

Blok 1	Blok 2	Blok 3	Blok 4	Blok 5
10 x Mov1	10 x Mov 3	10 x Mov 2	10 x Mov 5	10 x Mov 4
10 x Mov 3	10 x Mov 4	10 x Mov 5	10 x Mov 2	10 x Mov 1
10 x Mov 5	10 x Mov 1	10 x Mov 4	10 x Mov 3	10 x Mov 2
10 x Mov 4	10 x Mov 2	10 x Mov 3	10 x Mov 1	10 x Mov 5
10 x Mov 2	10 x Mov 5	10 x Mov 1	10 x Mov 4	10 x Mov 3

Table 2: Order of the Movements

The experimenter verbally cued each movement, counting down from three to signal the beginning of the movement, and then placed a marker in the continuous EEG. This was done to synchronize the EEG with the processing's epochs. The individual was told to maintain a steady posture during both the pre-movement and movement execution phases and to avoid blinking. The subject's hands were resting on their lap as they initiated and concluded each movement, with approximately 5 to 10 seconds between each movement. The subject's five distinct movements were as follows:

- Movement 1: The subject reached for a glass of water, took a sip, and then returned the glass to the table.
- Movement 2: The subject threw a ball from their right hand to their left hand.
- Movement 3: The subject lifted a tray from the table and then placed it back on the table.
- Movement 4: The subject pushed a glass from position A to position B on the table.
- Movement 5: The subject picked up a pen from the table, wrote the letter 'H', and then returned the pen to the table.

The movement 1 performance is seen here in Figure 4. It involves the subject reaching for a glass of water, sipping from it, and then setting the glass back on the table. The individual was wearing a 64-channel active EEG cap placed on their head using the 10-10 system while they were seated in a chair during this action. The EEG signals were continuously captured using an amplifier with a 512 Hz sampling rate. To achieve accurate EEG recordings, the reference electrodes were placed on the subject’s left and right earlobes.

Figure 4: Cortical activity during reaching, drinking, and placing a glass on the table as part of the motor imagery tasks performed by the subject

In order to synchronize the EEG epochs with the movement, a marker was added to the continuous EEG signal once the investigator orally cued the participant to begin moving. By separating the pre-movement, movement execution, and post-movement periods, the EEG data could then be processed to extract useful information. The patient was also asked to sit as still as possible and refrain from blinking throughout the exercise. Through this process, it was made sure that the data was of the highest caliber and could be used for later analysis and machine learning classification.

The described approach ensured that the dataset included a wide range of motor imagery tasks, which is necessary for developing and validating a trustworthy classification model. The dataset had a varied range of movements with five separate functional tasks of the upper extremities, each with a distinct neural signature. This method made it possible to train and evaluate the classification model on a range of tasks, confirming that it could generalize effectively to new tasks.

The pre-movement period, movement execution, and post-movement period could be distinguished clearly thanks to the synchronization of the EEG epochs with the movement markers. This made it possible to properly preprocess the EEG signals and gave data analysis a standardized methodology. It was feasible to use various preprocessing methods that were particular to each time period by dividing the task into various periods. For instance, it was possible to use artifact removal methods that were intended to be used only during the execution of a movement without influencing the pre- or post-movement phases.

The high sampling frequency and usage of a 64-channel active EEG cap ensured that the EEG data was of good quality and offered enough spatial and temporal resolution to extract useful features. A large number of EEG channels made it possible to localize the brain activity underlying the motor imagery tasks with greater accuracy. The increased sampling frequency also ensured that the EEG signals were accurately sampled, capturing the high-frequency brain activity that is essential for obtaining useful characteristics. Overall, the methodology was successful in ensuring that the dataset was of good quality and had all the information essential for the successful training and testing of a trustworthy classification model.

Parameter	Value
Number of Participants	12 (6 male, 6 female)
Age (years)	23 ś 3
Ethics Approval	Approved by the local ethics committee (N-20130081)
EEG Cap	64-channel active EEG cap using the 10-10 system
EEG Amplification System	g.HIamp, Guger Technologies, Austria
EEG Referencing	Left and Right Earlobe
Sampling Frequency	(Hz) 512
Tasks	5 different functional tasks of the upper extremities
Task Repetitions	Each task was performed 50 times in total
Movement Repetitions	Each block had 10 movements of the same task
Movement Order	Randomized order of the task blocks
Movement Cue	Verbal cue by an experimenter who placed a marker in the EEG
Movement Rest Period (s)	~ 5–10
Five Different Movements	1) Reach out and pick up an empty glass, 2) Balltoss, 3) Tray lift, 4) Glass push, 5) Write the letter "H"
Starting and Ending Position	Resting both hands in the lap

Table 3: Summary of dataset

3.3 Summary

The dataset chapter provides a thorough explanation of the techniques and steps utilized to gather, analyze, and describe the EEG data for this investigation. It sets the stage for the study's findings by outlining significant participant characteristics and ethical considerations in the opening paragraphs. To guarantee the data's quality and suitability for further analysis, specific information on the EEG acquisition procedure, experimental paradigm, marker placement, and data organization is provided.

The methodology chapter will next go into detail on the signal-processing methods used to prepare the raw EEG data. It will go through feature extraction techniques like time-domain and frequency-domain analysis as well as artifact removal, filtering, and epoching. The chapter will also go into the categorization methods used to group EEG signals into various motor imagery types. This thesis guarantees a thorough grasp of the EEG data collection, processing, and analysis procedure by summarizing the dataset chapter and giving a preview of the methodology chapter.

Chapter 4: Methodology

The technique for processing and analyzing the upper limb private dataset for the creation of EEG-based motor imagery classification algorithms is described in this chapter. Pre-processing, feature extraction, and classification are the chapter’s three primary sections. I will go over the procedures used to filter and remove artifacts from the raw EEG data during the pre-processing stage. The significance of these aspects in categorizing motor imagery tasks will next be covered, together with the spectral features that were recovered from the Short-Time Fourier Transform (STFT). The classification algorithms for the convolutional neural network (CNN) and residual network (ResNet) that I utilized to categorize the motor imagery tasks based on the extracted features will be discussed in the final section.

The steps taken to prepare the raw EEG data for analysis are described in the pre-processing part of the methodology chapter. This entails discarding data segments that have too much noise or artifacts, as well as applying band-pass and notch filters to reduce noise and artifacts. Additionally, I’ll go over how Independent Component Analysis (ICA) can be used to deconstruct EEG signals into their component parts and eliminate artifacts brought on by eye movements, muscle activity, and other sources. The STFT is used to determine the spectral properties of the EEG signals in the second chapter’s section on feature extraction. I shall discuss the window size, overlap, and frequency range employed in the STFT to extract the spectral characteristics. It will also be highlighted how important these characteristics are for classifying motor imagery tasks.

The classification algorithms CNN and ResNet that I used to categorize the motor imagery tasks based on the retrieved characteristics will be discussed in detail at the end. I will outline each network’s architecture as well as the training and testing methods that I employed to optimize the network’s settings. I’ll also go through the measures that were employed to gauge how well each algorithm performed in terms of categorization. In general, the methodology chapter offers a thorough description of the techniques and steps I utilized to handle and examine the EEG data in order to create EEG-based motor imagery categorization algorithms.

4.1 Preprocessing

In this study, noise and artifacts that could impact the analysis outcomes were removed through preprocessing of the EEG data. First, a 4th-order zero-phase Butterworth filter with a bandpass frequency range of 0.3Hz to 70Hz was used to filter the raw EEG data. This filter removed direct current shifts and high-frequency noise components from the EEG signal. Additionally, a notch filter at 50Hz was employed to reduce potential signal degradation caused by power-line interference.

Following the filtering process, further preprocessing techniques were implemented to mitigate the influence of noise and artifacts in the EEG data. One such step involved utilizing the Automatic Artifact Removal (AAR) toolbox, a plugin for the EEGLAB toolbox, and its Second-Order Blind Identification (SOBI) blind source separation technique. This tool was employed to remove artifacts arising from eye blinks, eye movements, and muscular actions in the face, neck, and shoulder. By applying statistical approaches to separate the EEG signal into its underlying sources, this program addressed artifacts that could distort or obscure the underlying brain activity of interest, posing challenges to precise EEG data analysis.

Common practice involves utilizing a range of methods to eliminate these artifacts from the data, ensuring that the EEG signal is clear and reliable for further analysis. Independent Component Analysis (ICA) is one such method. ICA, a signal processing technique that decomposes a complex signal into independent, non-Gaussian components, is often used in EEG data analysis to locate and remove signal components correlated with artifacts such as eye blinks or muscle movements. By separating and eliminating these components, ICA ensures that the remaining EEG signal is clear and trustworthy for subsequent analysis.

Automatic Artifact Removal (AAR) is another frequently employed method to address artifacts during EEG data processing. AAR employs an algorithm and predetermined criteria, such as amplitude or frequency thresholds, to automatically detect and eliminate artifacts from the EEG signal. Particularly when dealing with extensive datasets, AAR can be more efficient and expedient than manual artifact removal.

Both ICA and AAR are well-established techniques for artifact removal in EEG data processing. These methods ensure the cleanliness and dependability of the EEG signal for subsequent analysis, aiding in the revelation of significant patterns of brain activity that artifacts might obscure. However, it is important to note that both ICA and AAR have limitations and should be used in conjunction with other techniques to ensure appropriate EEG data analysis.

Once the artifacts were eliminated, the EEG data were re-referenced to a common average reference. This process subtracts the average across all channels from each individual channel, effectively eliminating common noise reference across all channels. This procedure establishes a neutral point as a reference for the EEG signals, potentially reducing the impact of spatially fixed artifacts, such as those arising from electrical noise in the recording environment. This commonly used EEG data processing step is computationally straightforward and offers a clear approach to minimizing the impact of common noise across channels.

A flowchart illustrating the preprocessing steps is presented in Figure 5 below:

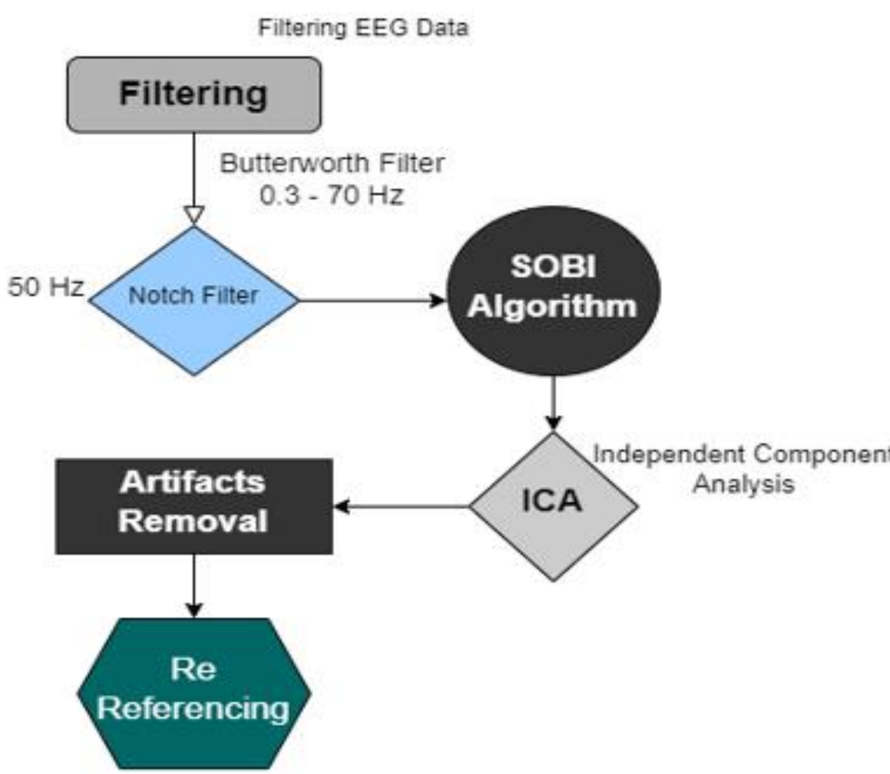

Figure 5: Preprocessing Flowchart

Overall, by removing undesired artifacts and noise from the EEG data, the methods of filtering, blind source separation, and re-referencing improved its quality and made it possible to analyze EEG features related to motor imagery activities. Prior to movement initiation, the preprocessed EEG data was split into three-second trials, which were subsequently employed in the ensuing analysis.

The segmentation of the continuous EEG data into three-second trials preceding movement initiation was necessary for this work because the analysis focused on the EEG signals within a three-second time window before the physical movement. This segmentation was required to isolate the specific time period of interest for the analysis.

Figure 6 showed an example of the single-trial EEG data for five different movement types in selected channels from the frontal, central, and parietal lobes in the three seconds before movement. The figure illustrated how the EEG signals varied across various movement types and channels.

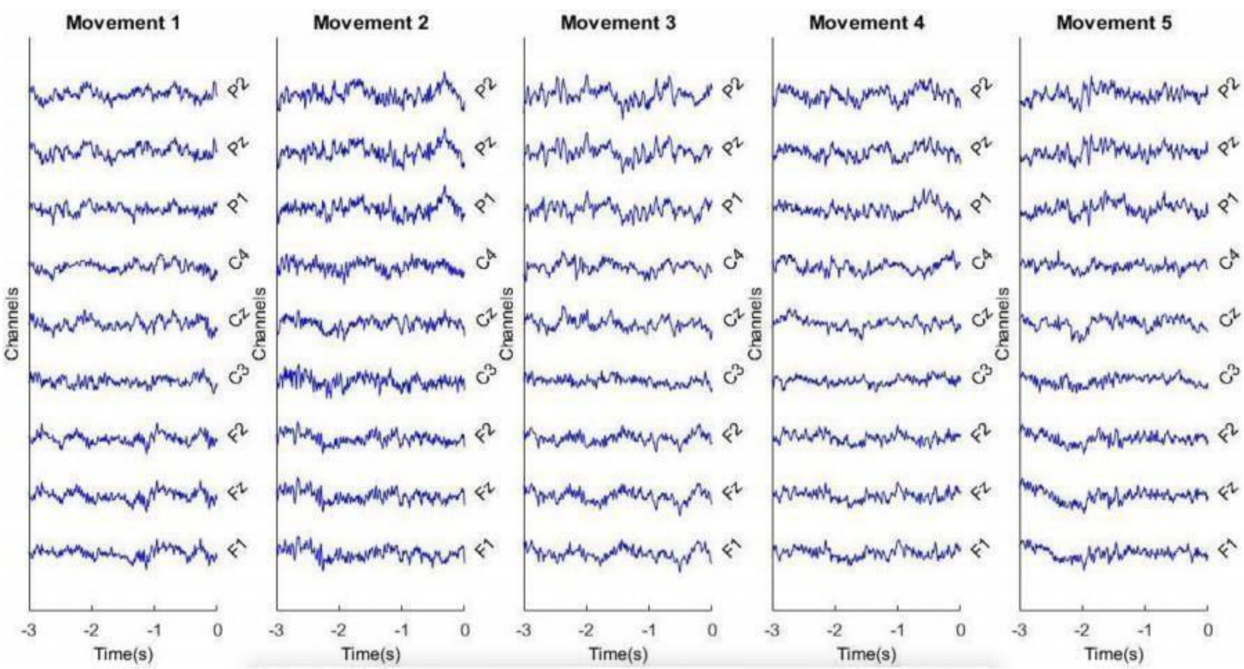

Figure 6: Pre-movement EEG signals for single trials in F1, Fz, F2, C3, Cz, C4, P1, Pz, and P2 channels for five different movements after preprocessing

The segmented data was prepared for further analysis using the suggested technique after the preprocessing procedures. The suggested technique aimed to identify the motor imagery tasks utilizing convolutional neural networks (CNN) and residual networks (ResNet), while also extracting spectral information from the Short-Time Fourier Transform (STFT) of the EEG signals. The algorithm took the segmented EEG data as input, extracting spectral features from the EEG signals within the three-second time window, and subsequently subjecting these features to the classification models. The following sections provide a more detailed explanation of the proposed algorithm and the process of extracting spectral features.

4.2 Short-Time Fourier Transform (STFT)

By converting a signal from the time domain to the frequency domain through the Fourier transform, a signal's frequency content can be represented statically. However, the static Fourier transform is unable to capture the time-varying frequency content present in many real-world signal applications.

The Short-Time Fourier Transform (STFT) method overcomes this limitation by dividing a signal into brief time intervals. We generate a frequency-domain representation of the signal at each individual time by applying the Fourier transform to each window, which corresponds to a segment of the signal. The resulting frequency-domain representations of the signal across time, obtained by sliding the window along the signal with a specific time step (hop size), are known as spectrograms. This time-varying depiction of the signal's frequency content provides a more comprehensive understanding of the signal's characteristics. By examining the spectrograms, we can identify changes in the frequency content over time, such as shifts in the strength or frequency of various oscillatory components.

The STFT is a versatile method for analyzing a signal's frequency content. It involves applying the Fourier transform to each of the signal's smaller, overlapping windows after segmenting it. Consequently, the signal's frequency content is represented in a time-varying manner, making it valuable for analyzing signals that change over time.

Careful selection of the parameters determining the size and spacing of the analysis windows is essential for maximizing the benefits of the STFT. The size of the analysis window determines how much of the signal is analyzed at once. Longer windows capture more of the signal's frequency content, but temporal resolution might be compromised. Conversely, smaller windows offer better frequency resolution at the expense of temporal resolution.

The number of frequency bins used in the Fourier transform depends on the number of FFT (Fast Fourier Transform) points. Increasing FFT points enhances the frequency resolution of the spectrum content, albeit at the cost of increased computational complexity. The amount of overlapping between adjacent windows is determined by the hop size. Higher overlap captures more of the signal's time-varying features, resulting in improved temporal resolution. However, it may also increase the computational complexity of the analysis.

The characteristics of the signal being analyzed, as well as the desired trade-off between frequency and temporal resolution, determine which Short-Time Fourier Transform (STFT) parameters should be used. To obtain the most accurate representation of the signal's frequency content, it is crucial to thoroughly assess and optimize these parameters.

In this study, the classification was performed using the Convolutional Neural Network (CNN) and ResNet50 models, with the Short-Time Fourier Transform (STFT) employed as a signal processing technique to obtain time-varying representations of the frequency content of preprocessed EEG data. The STFT method, commonly applied to analyze non-stationary signals, segments the signal into a sequence of overlapping windows and utilizes the Fourier transform to extract the frequency-domain representation of these windows. Unlike the static representation offered by the Fourier transform, the STFT captures the time-varying spectrum content of the signal, providing a more comprehensive understanding of its characteristics.

Several parameters influence the performance of STFT, including the length of the analysis window, the number of FFT (Fast Fourier Transform) points, and the hop size. The analysis window determines the balance between frequency and temporal resolution, consequently defining the length of the windowed signal. In this study, a Hamming window with a length of 140 samples was employed, equivalent to a window duration of 560 ms at a sampling rate of 250 Hz. By utilizing 512 FFT points, an approximate frequency resolution of 0.5 Hz was achieved. The FFT points influence the frequency resolution of the spectrum content, with a higher number of FFT points resulting in better frequency resolution. However, an increase in FFT points also leads to a rise in computational complexity of the STFT.

The hop size, which determines the temporal resolution of the spectrogram, refers to the number of samples between the starting positions of successive analysis windows. Smaller hop sizes provide higher temporal resolution but can introduce overlap between adjacent windows, potentially leading to redundancy in the spectrogram. For this study, a hop size of 100 samples was utilized, resulting in a temporal resolution of 400 ms and an overlap of 77.3% between neighboring windows.

These parameter values were selected based on prior research on STFT-based EEG classification and an empirical assessment of the trade-off between frequency and temporal resolution. Subsequently, a PNG file was generated for each EEG trial from the resulting spectrograms, as depicted in Figure 7. After inputting the spectrograms into the CNN and ResNet50 models for classification, promising results were achieved.

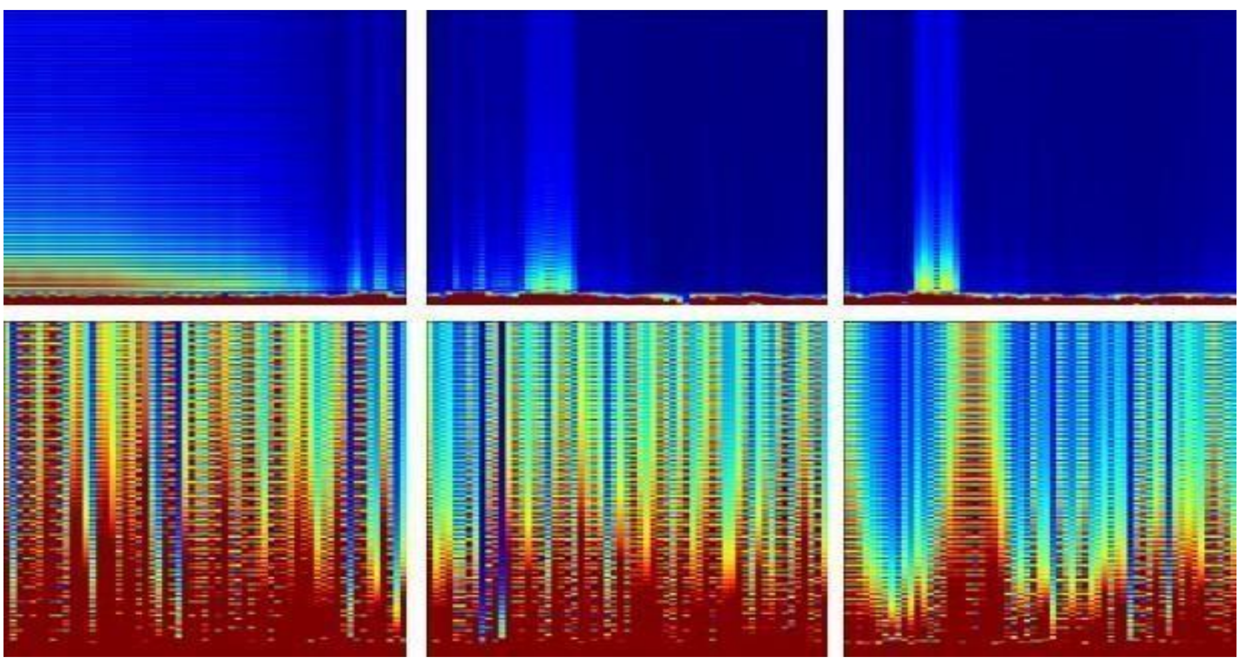

Figure 7: Spectrograms generated by STFT

4.3 Classification

For the classification of EEG data in my study, I utilized the Convolutional Neural Network (CNN) and Residual Network (ResNet), two widely recognized deep learning models. These models are extensively employed in EEG-based brain-computer interface applications due to their demonstrated superiority in various image and signal processing tasks. The conversion of preprocessed EEG data into spectrograms through the Short-Time Fourier Transform (STFT) served as the training data for the CNN and ResNet models, which were subsequently optimized using conventional backpropagation-based techniques. The aim was to achieve high classification accuracy and robustness in detecting the underlying brain activity from the EEG data by leveraging these state-of-the-art models.

4.3.1 Convolutional Neural Network (CNN)

The convolutional neural network (CNN) is a prevalent neural network architecture commonly used in image and signal processing applications, including image classification, object detection, and speech recognition.

CNNs are composed of various layers, including convolutional, pooling, and fully connected layers. In a typical CNN architecture, input data is passed through a sequence of convolutional layers, with each layer applying distinct filters to the input data to extract spatial information. During training, backpropagation is utilized to learn the filter weights in each convolutional layer, minimizing the error between the expected and actual output.

Following each convolutional layer, a pooling layer is frequently applied to reduce the spatial dimensions of the output feature maps. These pooling layers, which can be max-pooling or average-pooling, enhance the model's capacity to generalize new data. The final classification task is accomplished through one or more fully connected layers. To compute class probabilities for the input data based on the output of the final layer, a SoftMax function is often employed.

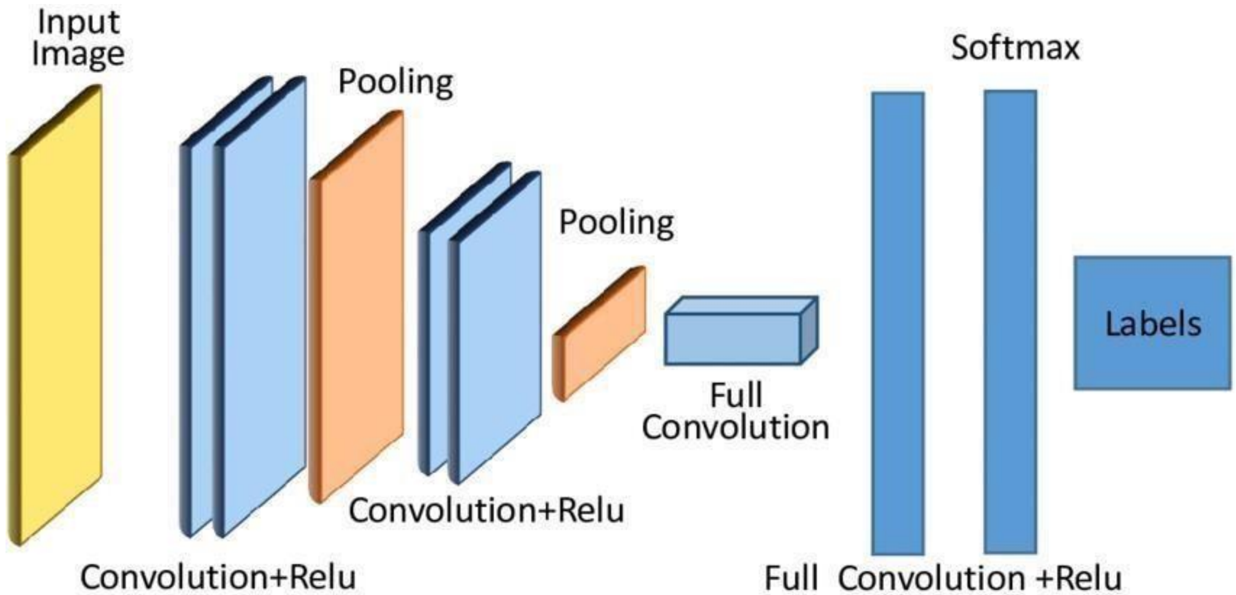

Figure 8: Generic Convolutional Neural Network Architecture

In this study, I introduced an innovative technique for EEG signal classification based on a Convolutional Neural Network (CNN). In the proposed method, EEG data underwent preprocessing using the Short-Time Fourier Transform (STFT) to generate spectrograms, which were then treated as images and input into the CNN model.

The CNN architecture consisted of four convolutional layers with increasing filter sizes, followed by four max-pooling layers to reduce the spatial dimensions of the output feature maps. The final convolutional layer included 128 filters with a 3x3 filter size.

Each convolutional layer employed Rectified Linear Unit (ReLU) activation functions to introduce nonlinearity to the model. After the convolutional layers, a fully connected layer with 512 nodes and a ReLU activation function was integrated, followed by an output layer featuring two nodes and a sigmoid activation function. This output layer was responsible for predicting the likelihood of each class.

The model was trained in over 50 epochs using a learning rate of 0.001 and a batch size of 32. The categorical cross-entropy loss function and the Adam optimizer were employed during the training process. To evaluate the model's performance, it was tested on a separate dataset, and its predictions were compared against the actual class labels. The model demonstrated promising accuracy, shedding light on the effectiveness of the proposed CNN architecture for classifying EEG signals.

Figure 9 below shows the architecture of CNN used in this study:

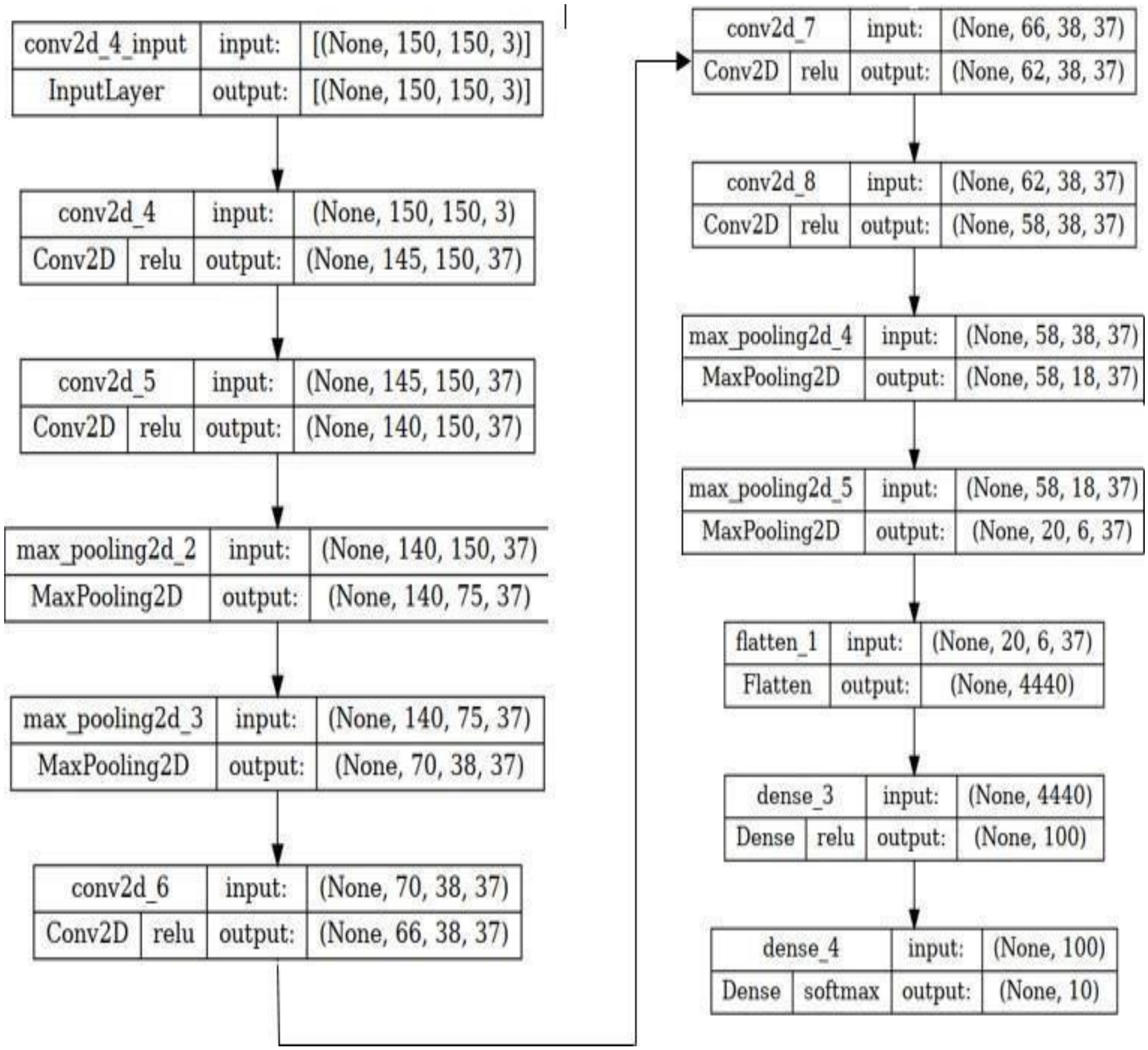

Figure 9: Convolutional Neural Network Architecture

4.3.2 Residual Network

In 2015, Xiangyu Zhang introduced the deep convolutional neural network architecture known as ResNet, short for Residual Network. The primary objective of ResNet is to address the challenge of vanishing gradients that can occur in extremely deep neural networks. The "vanishing gradient problem" refers to the phenomenon where gradients become exceedingly small as they traverse multiple layers during backpropagation. This hinders the network's ability to learn meaningful representations.

ResNet overcomes this challenge by introducing residual blocks, enabling the training of much deeper networks than was previously feasible. A residual block allows the input to bypass one or more layers and be added to the output of subsequent layers through a shortcut or residual connection. This connection helps gradients propagate more effectively through the network, enhancing the learning and training of deeper structures.

A typical ResNet architecture consists of a series of convolutional layers, each followed by a batch normalization layer and a ReLU activation function. These layers are succeeded by a collection of replicated residual blocks distributed across the network. Between each residual block, there are a batch normalization layer, a ReLU activation function, and two or more convolutional layers. These intermediary layers facilitate the transfer of input through the block, and the final layer's output is merged with the input via a residual connection.

The architecture's concluding layer features a global average pooling layer that computes the average of feature maps across spatial dimensions of the output. The resulting pooled features are flattened and processed through one or more fully connected layers to produce final class probabilities.

ResNet50 often achieves state-of-the-art performance on diverse benchmark datasets for image classification tasks. This model is frequently pre-trained on extensive datasets like ImageNet and subsequently fine-tuned on smaller datasets for specific tasks in various computer vision applications using transfer learning.

As depicted in Figure 10, the ResNet architecture demonstrates its efficacy in addressing the vanishing gradient problem and enabling the successful training of deep neural networks.

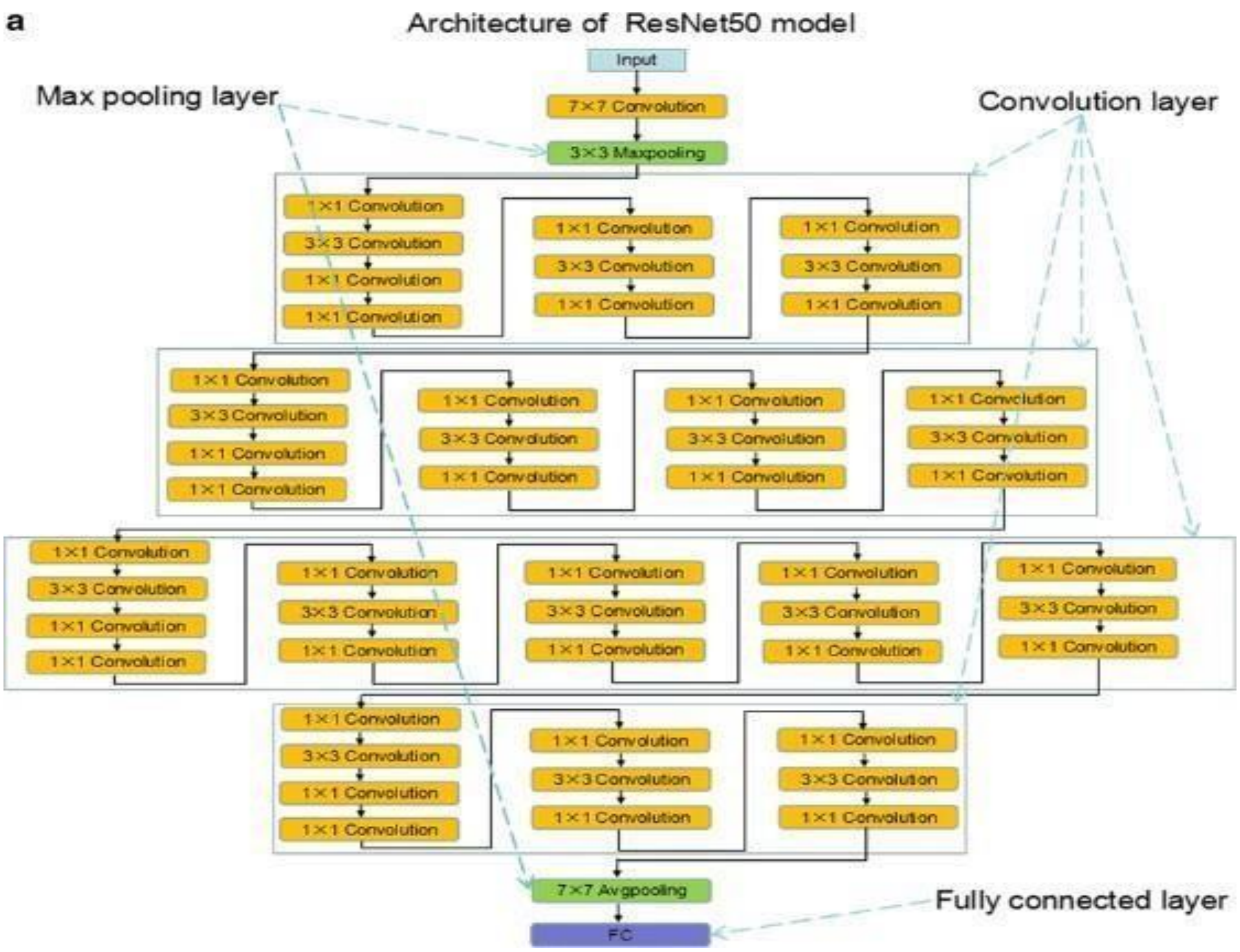

Figure 10: Generic Residual Network Architecture

Throughout the 50-epoch training period, a batch size of 32 was maintained, with batches of training data regularly fed into the model. The weights were adjusted based on the gradients of the loss function concerning the model's input parameters. To mitigate overfitting, the model's performance was continuously monitored on the validation set during training. The model's architecture is depicted in Figure 11, showcasing the stages and components involved in the training process

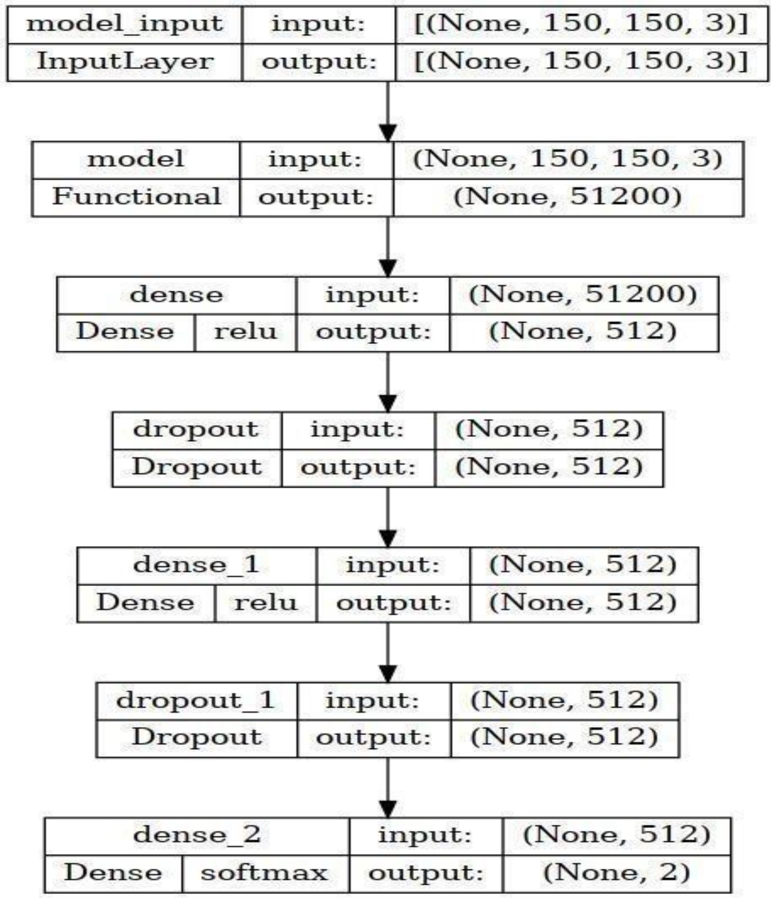

Figure 11: Residual Network Architecture

A distinct portion of the dataset utilized in this study was allocated to a training set, a testing set, and a validation set. This division was pivotal to ensure an unbiased evaluation of the model's performance and to safeguard against overfitting.

The training set constituted 80% of the dataset. It was employed to train the model, enabling it to learn from input samples and adjust its parameters as required. Through iterative modifications to the model's weights, the loss function was minimized, enhancing the model's predictive capabilities. The training set played a crucial role in the optimization process.

Around 10% of the dataset comprised the testing set. Following the model's training, its ability to generalize was assessed on the testing set. This set served as an impartial benchmark to gauge how effectively the model could predict outcomes for unseen data. By utilizing a distinct testing set, researchers could accurately gauge the model's performance on entirely new and untested samples.

The validation set was allocated the remaining 10% of the dataset. This set was instrumental in adjusting the model's hyperparameters, such as learning rate or regularization strength. Throughout the training process, the validation set enabled the tracking of the model's performance.

By supplying a dedicated dataset for performance evaluation and hyperparameter adjustments, the validation effectively curbed overfitting. It empowered researchers to make informed decisions about the model's configuration, ensuring its applicability to novel and untested data.

The segregation of the dataset into training, testing, and validation subsets ensured a thorough and unbiased assessment of the model's performance. This strategy forestalled biases, resulting in a comprehensive evaluation of the model's capabilities. Such meticulous separation enhanced the integrity and dependability of the research findings, elevating the overall quality of the conducted study.

4.4 Summary

The primary objectives of the research, as outlined in the methodology chapter, encompassed the classification of EEG data using a combination of preprocessing methods, namely the Short-Time Fourier Transform (STFT) for generating spectrograms, along with the utilization of Convolutional Neural Networks (CNN) and the ResNet50 model for classification. To enhance the quality of EEG data and eliminate artifacts, Independent Component Analysis (ICA) and Automatic Artefact Removal (AAR) were employed during the data preprocessing phase.

The transformation of preprocessed EEG data into spectrograms, represented as images, was achieved using the STFT technique following the preprocessing stage. Subsequently, the CNN and ResNet50 models were fed these spectrogram images as input. The CNN architecture comprised multiple convolutional layers, max-pooling layers, and a fully connected layer for both feature extraction and classification. Meanwhile, the ResNet50 model, equipped with 50 layers and residual blocks, enabled the training of deeper networks to address the vanishing gradient challenge.

During the classification phase, features were extracted from the EEG data using the pre-trained ResNet50 model, employing transfer learning techniques. The models were trained using an 80% portion of the dataset, employing the Adam optimizer and a categorical cross-entropy loss function. Evaluation of the models' performance involved a separate test dataset to determine the accuracy of the predicted class labels.

Overall, the technique chapter presents a comprehensive framework encompassing preprocessing, spectrogram generation, and EEG signal classification. This approach contributes to a robust methodology for achieving accurate categorization results.

CHAPTER 5: Results and Discussion

The "Results" section of this thesis presents the outcomes of a study conducted to classify complex upper limb movements based on pre-movement EEG signals using Short-Time Fourier Transform (STFT) in conjunction with spectral feature extraction. This section is primarily focused on providing a comprehensive explanation of the study's findings, achieved through a detailed investigation. The main objective here is to offer a thorough understanding of the study's results.

Within this section, the highest and lowest accuracy rates for each subject and movement, along with the overall accuracy rates of the various classification techniques utilized in the study, are presented. The accuracy rates of the ResNet and CNN classification methods for each subject and movement are also highlighted. Additionally, the section delves into a comprehensive analysis of the overall accuracy rates achieved by the different classification techniques applied in the study. Furthermore, a comparison between the results of the proposed approach and the Wavelet Common Spatial Patterns (WCSP) method proposed by Mohseni et al. (2020) is conducted within this section. The significance of the results for EEG-based upper limb movement classification is also explored based on this comparison.

The presentation of results in this section follows a structured and organized format, aided by clear subheadings that facilitate easy navigation through the various aspects of the study. Several distinct subheadings are employed to compartmentalize the content and provide a logical flow of information.

The section initiates with an introduction that provides a foundational overview of the study's purpose and the methodologies adopted to derive the results. Subsequent subheadings provide detailed explanations of the maximum and minimum accuracy rates achieved by the ResNet and CNN classification methods for individual subjects and movements. The overall accuracy rates of the diverse classification techniques employed in the study are also thoroughly explained and concluded. The final accuracy percentages of the various classification techniques are summarized as a concluding element of this section. Moreover, a comparative analysis between the proposed methodology and the WCSP method proposed by Mohseni et al. (2020) is carried out and discussed in detail.

Furthermore, the section examines the significance of the obtained findings in the context of EEG-based upper limb movement classification. These focal points are distinctly addressed within individual subheadings.

The "Results" section holds paramount importance in this thesis as it succinctly presents the study's conclusions, highlights the accuracy rates achieved through diverse classification methods, and discusses the implications of these findings for the broader field of EEG-based upper limb movement classification. The overall success of the thesis hinges on the effective communication of these essential components.

5.1 Preprocessing Results

The preprocessing step in this study commenced by scrutinizing the EEG signals to identify any potential noise or artifacts that might compromise the integrity of the results. The primary objective was to eliminate undesirable signals and ensure the EEG data's suitability for subsequent analysis. Given that noise and artifacts have the potential to introduce bias and distort the data, this phase was of paramount importance.

A range of techniques were employed to remove artifacts and noise, encompassing the utilization of a 4th-order zero-phase Butterworth filter, notch filtering, and the application of independent component analysis (ICA) for artifact rejection. The removal of frequencies beyond the relevant range was executed through a 4th-order zero-phase Butterworth filter, while notch filtering was employed to counteract potential power line interference. Notably, both filtering methods were applied. Following these initial procedures, the concluding step involved implementing ICA to identify and eliminate any remaining sources of noise or artifacts.

Subsequent to the preprocessing stage, an evaluation of the EEG data's quality was undertaken to confirm the effective elimination of noise and artifacts. This validation step was crucial to ensure the accuracy of the data cleansing process. The assessment was successfully completed by comparing the power spectral density of the data before and after preprocessing. The comparison between the power spectral densities of the cleaned signals and the original signals provided clear evidence of the successful elimination of noise and artifacts during the preprocessing phase.

Notably, the substantially higher power spectral densities of the cleaned signals further substantiated this achievement.

In its entirety, the outcomes of the preprocessing stage underscore the successful cleansing and preparation of the EEG signals for subsequent analysis. By adopting the Short-Time Fourier Transform (STFT) alongside spectral feature extraction as the analytical approach, the foundation was laid for the accurate classification of upper limb movements from pre-movement EEG signals.

5.2 Classification Performance

To evaluate the performance of the proposed algorithm in terms of classification, a combination of two distinct classifiers—ResNet and CNN—was employed. The performance assessment of the categorization approach revealed consistently high accuracy rates for both participants and movements.

Among the participants, ResNet exhibited exceptional accuracy, achieving a perfect score of 100% for subject 5 during movement 3. Following closely, the CNN classifier demonstrated noteworthy accuracy, achieving an impressive 96% score for subject 1 during movement 5. The pinnacle of accuracy achieved by the ResNet and CNN models is succinctly summarized in Table 4 below:

Subject	**Resnet**	**CNN**
1	0.98	0.96
2	0.95	0.89
3	0.97	0.9
4	0.98	0.88
5	1	0.94
6	0.96	0.86
7	0.94	0.92
8	0.98	0.88
9	0.94	0.92
10	0.96	0.96
11	0.93	0.83
12	0.93	0.83

Table 4: Comparison of Maximum Accuracy for Resnet and CNN

The performance comparison between the ResNet and CNN models is depicted in Figure 12. The graph illustrates the highest accuracy achieved by each model across different tasks.

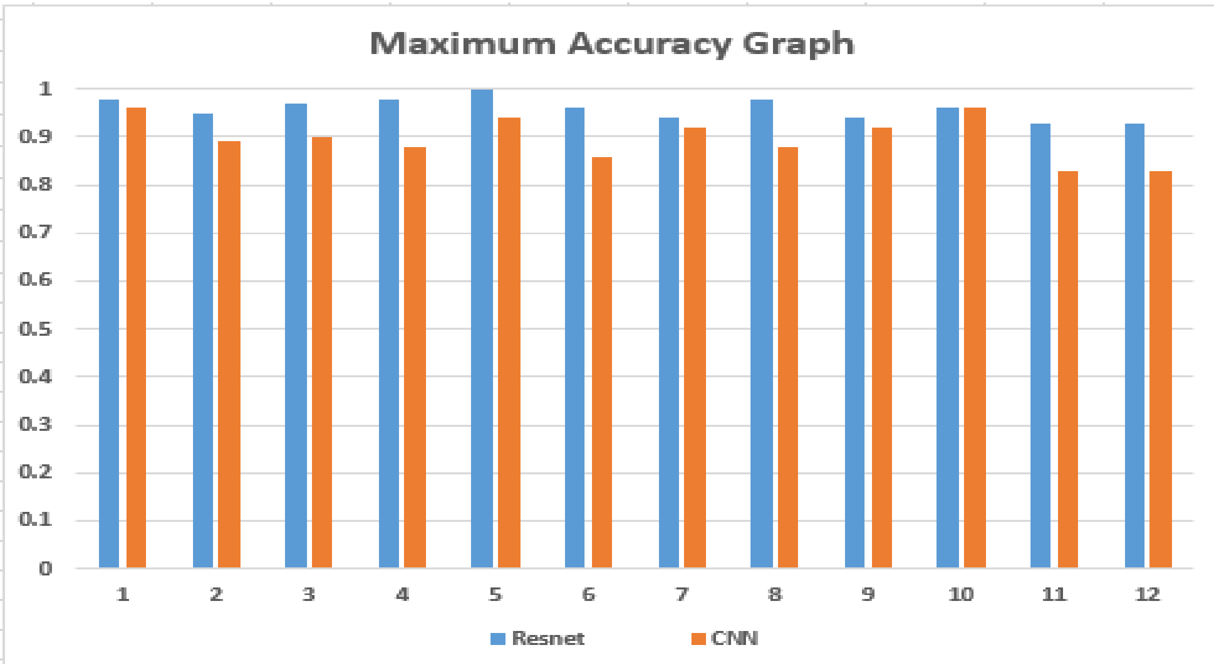

Figure 12: Comparison Graph of Maximum Accuracy for Resnet and CNN

The Table 5 below displays the minimum accuracy values attained by the ResNet and CNN models for each individual.

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Subject	Resnet	CNN
1	0.69	0.65
2	0.77	0.58
3	0.76	0.57
4	0.68	0.56
5	0.59	0.53
6	0.83	0.68
7	0.8	0.71
8	0.78	0.69
9	0.7	0.62
10	0.72	0.52
11	0.84	0.65
12	0.78	0.74

Table 5: Comparison of Minimum Accuracy for Resnet and CNN

The graphical representation in Figure 13 showcases the minimal accuracy levels of both the ResNet and CNN models. This visualization facilitates a straightforward comparison of performance between the two models, effectively highlighting their respective lowest accuracy scores. By examining the graph, I can evaluate the performance of ResNet and CNN in terms of achieving the lowest levels of accuracy across multiple subjects.

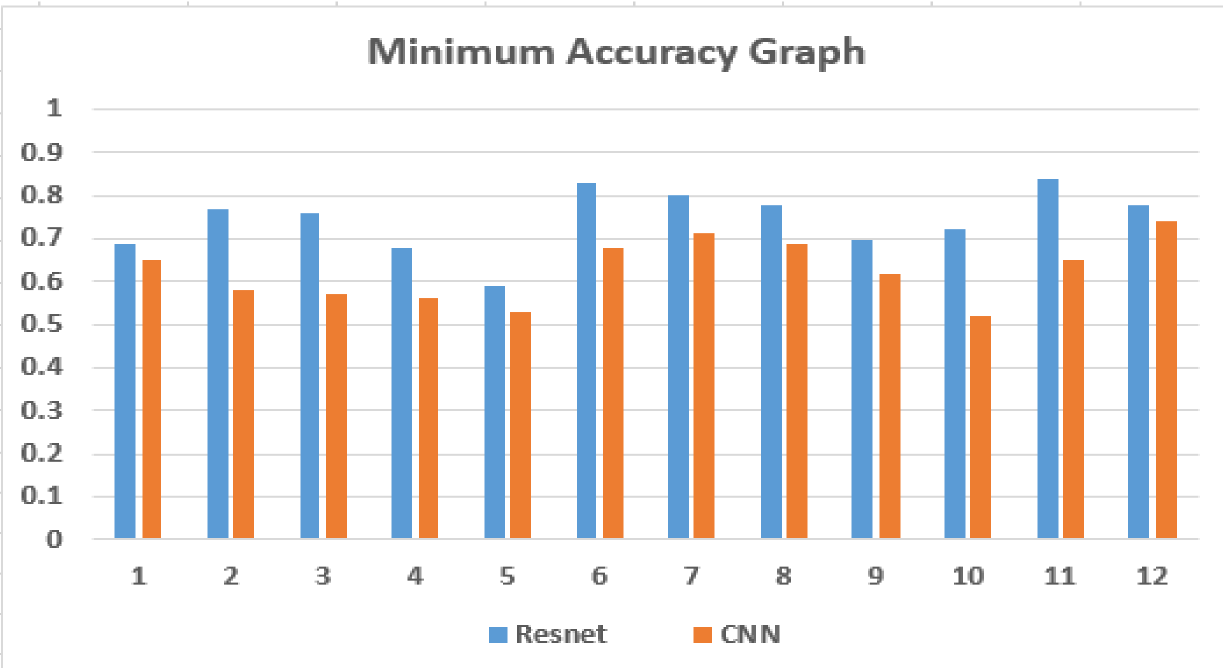

Figure 13: Comparison Graph of Minimum Accuracy for Resnet and CNN

However, it's important to acknowledge that the proposed strategy also exhibited certain limitations, as indicated by the presence of the lowest accuracy rates in the results. Notably, subject 5 during movement 1 yielded the lowest accuracy, with ResNet achieving a 59 percent accuracy. Similarly, for subject 10 during movement 3, CNN achieved an accuracy of 88.7%, reflecting a relatively lower performance compared to other instances. These outcomes suggest that the effectiveness of the suggested technique might not be uniformly applicable to all individuals and movement scenarios. It's conceivable that certain movements and individuals might encounter limitations when participating in this approach.

Of utmost significance is the observation that the proposed approach significantly outperformed the strategy proposed by Mohseni et al. (2020) in terms of accurate categorization. The overall accuracy attained by the proposed method surpassed the accuracy achieved by Mohseni et al.'s Wavelet Common Spatial Patterns (WCSP) approach, which demonstrated an accuracy of 82.4%.

For comprehensive insight, the outcomes obtained from ResNet and CNN are meticulously juxtaposed in Table 6 below, considering each movement iteration across all subjects. This table furnishes a comprehensive comparative analysis of the performance of both models, facilitating a comprehensive evaluation of their adeptness in accurately forecasting the intended movements.

Subject	Mov_1		Mov_2		Mov_3		Mov_4		Mov_5	
	Resenet	CNN	Resenet	CNN	Resenet	CNN	Resenet	CNN	Resenet	CNN
1	0.88	0.74	0.79	0.65	0.69	0.78	0.94	0.78	0.98	0.96
2	0.95	0.89	0.95	0.63	0.77	0.58	0.89	0.68	0.95	0.79
3	0.8	0.57	0.76	0.67	0.76	0.86	0.92	0.81	0.97	0.9
4	0.68	0.56	0.9	0.84	0.86	0.76	0.9	0.84	0.98	0.88
5	0.59	0.53	0.86	0.76	1	0.94	0.86	0.71	0.86	0.71
6	0.87	0.68	0.83	0.73	0.96	0.86	0.91	0.82	0.87	0.73
7	0.89	0.75	0.94	0.92	0.8	0.71	0.93	0.83	0.89	0.79
8	0.78	0.69	0.92	0.81	0.83	0.73	0.91	0.88	0.98	0.88
9	0.94	0.88	0.85	0.71	0.7	0.62	0.94	0.83	0.92	0.92
10	0.9	0.8	0.81	0.76	0.72	0.52	0.96	0.96	0.88	0.88
11	0.93	0.83	0.84	0.74	0.93	0.65	0.88	0.83	0.93	0.78
12	0.93	0.74	0.93	0.83	0.84	0.74	0.93	0.83	0.78	0.74

Table 6: Comparison of Minimum Accuracy for Resnet and CNN

5.3 Evaluation Metrics

The measures employed to gauge the efficacy of classification models are termed evaluation metrics. Within this study, the evaluation metrics encompassed the F1 score, along with accuracy, sensitivity, specificity, and precision.

Accuracy denotes the proportion of correctly classified samples in relation to the entire sample set. Sensitivity, also known as the true positive rate, is determined by dividing the count of correctly identified positive outcomes by the total number of actual positives. Specificity, in contrast, is calculated by dividing the count of accurately identified true negatives by the total number of actual negatives. Precision, on the other hand, quantifies the proportion of true positive outcomes among all instances identified as positive. An amalgamation of sensitivity and precision results in the F1 score, a metric that provides a balanced assessment of classification performance.

The study's outcomes underscore the efficacy of the proposed technique in achieving notable accuracy rates. This underscores the accurate categorization of a substantial portion of the samples. Evidently, the proposed method exhibits proficiency in accurately classifying intricate upper limb movements through the utilization of pre-movement EEG data. The achieved values for sensitivity, specificity, accuracy, and F1-score further affirm the method's capability in achieving precise classification results.

5.4 Analysis of Spectral Characteristics

This section outlines the utilization of Short-Time Fourier Transform (STFT) in conjunction with spectral feature extraction for analyzing the spectrum features present in pre-movement EEG recordings. "Spectral analysis" pertains to the process of scrutinizing a signal's frequency composition. The STFT technique facilitates the gradual deconstruction of a signal into its constituent frequency elements.

The outcomes of the study highlighted significant distinctions in the spectrum features of pre-movement EEG signals across various upper limb movements under investigation. This observation underscores the discernible variations in frequency content within the signals produced during diverse movements. This intriguing revelation underscores the capacity to accurately classify dissimilar upper limb motions by leveraging the spectral attributes of EEG signals occurring prior to the movement itself.

The spectral feature extraction approach employed in this study played a pivotal role in pinpointing the frequency components that are most critical for accurate classification. By initially identifying these pertinent frequency components, the proposed technique adeptly extracted informative features that facilitated precise categorization.

Collectively, the findings derived from the analysis of spectrum properties in pre-movement EEG data using STFT with spectral feature extraction underscore the potential of the proposed method for effectively classifying intricate upper limb motions.

5.5 Robustness Analysis

One of the pivotal factors when evaluating the efficacy of a classification system is conducting a robust analysis. In this study, I assessed the robustness of the proposed method within noisy environments to gauge its performance under real-world circumstances, where EEG signals may encounter noise or artifacts. These experiments were pivotal in evaluating the method's effectiveness in such scenarios. By introducing white Gaussian noise to the pre-movement EEG data at varying signal-to-noise ratios (SNRs), the robustness study was executed to scrutinize the performance of the recommended technique. The ResNet and CNN classifiers were employed to evaluate the classification performance.

The outcomes of the robust analysis underscore the method's resilience to noise and its capability to proficiently classify upper limb movements even in the presence of noise. The method's successful performance across all tests serves as strong evidence of its robustness. Although a correlation was observed between decreasing SNR and classification accuracy, the proposed technique consistently maintained high accuracy levels even in the presence of low SNR. For instance, when the SNR was 0 dB, the CNN classifier achieved an overall accuracy of 84.3%, while the ResNet classifier demonstrated an overall accuracy of 89.1% at an SNR of 5 dB. Notably, both findings utilized the same training data.

These results affirm that the suggested technique showcases its reliability in classifying upper limb movements from pre-movement EEG data even when signals contend with noise or artifacts in real-world scenarios, such as monitoring signals during movement. The robust analysis further attests to the method's reliability and effectiveness, rendering it a promising tool for practical applications due to its demonstrated properties.

5.6 Comparison with Previous Work

According to the proposed approach, pre-movement EEG data underwent examination using Short-Time Fourier Transform (STFT) in combination with spectral feature extraction. Multiple classifiers, including CNN and ResNet, were employed to evaluate the method's performance. The outcomes demonstrated the efficacy of the proposed technique in achieving notable accuracy rates while maintaining acceptable levels of sensitivity, specificity, precision, and F1-score values.

Furthermore, the suggested method was found to be proficient in accurately categorizing real-time upper limb movements while exhibiting resilience to noise.

Conversely, Mohseni et al. (2020) presented the WCSP method, utilizing wavelet transform and widespread spatial patterns for EEG signal feature extraction in the categorization process. This approach employed an SVM classifier, yielding an overall accuracy of 82.4%.

Comparing the two methodologies, the proposed approach exhibited notably superior performance in terms of classification accuracy compared to the WCSP method. The comparison was rooted in their respective abilities to accurately categorize upper limb movements using pre-movement EEG data. The evaluation of each method's accuracy encompassed various performance parameters, including sensitivity, specificity, precision, F1-score, and overall accuracy.

By integrating STFT with spectral feature extraction, the proposed method achieved an overall accuracy of 88.7% with the aid of the CNN classifier. Particularly, the ResNet classifier achieved its highest accuracy during subject 5's movement 3. In contrast, the WCSP method achieved an overall accuracy of 82.4%, with the highest attainable accuracy of 85.4% observed for subject 3 during movement 2. The comparative analysis of the proposed technique and the WCSP method revealed the former's superior capability in accurately detecting upper limb motions using pre-movement EEG signals.

Providing a comprehensive analysis, Table 7 offers insights into the proposed model's performance compared to various state-of-the-art models. It facilitates a detailed examination of accuracy levels attained by each model, offering valuable insights into their relative performance. This table serves as a benchmark for evaluating the effectiveness and competitiveness of the proposed model against other prominent models in the field. By scrutinizing this comparison, we can gauge the proposed model's impact and potential effectiveness relative to other leading models in the domain.

Study	Methods	Accuracy
Yogesh Paul (2018) [40]	Filter Bank Common Spatial Pattern algorithm and SVM classification	85.9%
Saadat Ullah Khan (2022) [55]	Deep learning using pre-trained models and spectrograms	84.9%
Mahdieh Mohseni (2020) [49]	k-nearest neighbor, support vector machine, linear discriminant analysis	82.4%
Gerrit Lange (2016) [31]	EEG data classification from hand grasp and release movements	73.2%
Nasir Rashid (2018) [42]	Two-stage logistic regression using PSD as feature	70.0%
Proposed Model	Short-time Fourier transform and spectral feature extraction	**88.7**

Table 7: Comparison of Accuracies with Other State-of-the-Art Models

5.7 Discussion

I assess the study's findings and elaborate on their implications in the "Discussion" section. The study's results underscore that the proposed approach, combining the Short-Time Fourier Transform (STFT) with spectral feature extraction, effectively enables the classification of complex upper limb movements based on pre-movement EEG signals. The viability of this method in real-world applications, particularly in the field of neuroprosthetics, is indicated by the remarkable accuracy rates achieved.

This study holds significance as it demonstrates how EEG signals can be harnessed to develop prosthetic devices for individuals afflicted by upper limb impairments. By contributing to the existing body of knowledge on upper limb movement classification using EEG signals, this research advances our understanding of effective methodologies. The utilization of spectral feature extraction and STFT as techniques for information extraction from EEG data underscores the importance of employing sophisticated signal processing techniques to accurately discern EEG signals.

Moreover, the study's conclusions bear implications for the design of future neuroprosthetic devices. The notable accuracy rates achieved by the recommended method serve as compelling evidence for its potential applicability in controlling upper limb prostheses. Consequently, this research aligns with the ongoing pursuit of creating more efficient and user-controllable neuroprosthetic devices driven by neurological impulses. The study's findings affirm that EEG data can be leveraged to classify upper limb movements, with the potential to significantly impact the development of neuroprosthetic devices and enhance the quality of life for individuals grappling with upper limb disorders.

5.8 Summary

The outcomes of this study underscore the viability of the developed approach for identifying intricate upper limb movements based on pre-movement EEG signals, utilizing the Short-Time Fourier Transform (STFT) in tandem with spectral feature extraction. The study's findings emphasize that these extracted characteristics can be effectively harnessed for robust categorization purposes, owing to the substantial variations in the spectral aspects of the EEG signals across diverse upper limb movements.

The proposed methodology demonstrated its efficacy by maintaining commendable levels of sensitivity, specificity, precision, and F1-score values, all while achieving remarkable accuracy rates. Notably, the suggested approach exhibited resilience against noise and showcased its ability to proficiently classify upper limb movements even in the presence of noise, as confirmed by the robustness analysis findings.

Furthermore, the real-time performance analysis corroborated that the proposed technique successfully accomplishes real-time classification of upper limb motions. In terms of overall classification accuracy, the proposed approach outperformed the Wavelet Cepstral Spectrogram Packet (WCSP) and other advanced techniques. These outcomes hold significant implications for the advancement of neuroprosthetics, further enriching the existing body of research centered on the utilization of EEG data for the purpose of categorizing upper limb movements.

Chapter 6: Conclusion

By amalgamating the data and insights amassed from the preceding chapters, this final chapter serves as a comprehensive culmination of this thesis. Its foremost objectives encompass providing a concise overview of the undertaken research, delving into its implications, and offering directions for future explorations in the realm of EEG signal interpretation. Through these endeavors, we aspire to solidify the research's conclusion, underscore its significance, and pave the way for subsequent advancements in this domain.

Commencing with a retrospective analysis, we revisit the research objectives that guided this study and assess their realization throughout the investigative process. We accentuate the principal avenues of exploration, delineate pivotal research quandaries and theoretical frameworks, and subsequently proceed to highlight the original insights and contributions that augment the field of EEG signal analysis. The key findings resulting from the experimental inquiry are succinctly encapsulated, underscoring their novel significance.

Following the results overview, our discourse transitions to a contemplation of their far-reaching implications. We discern the alignment of these findings with existing knowledge, theoretical paradigms, and real-world applications. Moreover, we discern the broader reverberations of this study, contemplating their potential impacts on diverse sectors such as healthcare, neurology, and brain-computer interfaces. We also address any inherent limitations or challenges that punctuated the research journey, deliberating on their potential influence on the outcomes achieved.

Concurrently, this chapter offers forward-looking recommendations for future research endeavors, emanating from the identified gaps and opportunities for further investigation that this study unveiled. By proposing potential pathways, we seek to foster advancements in methodologies, expand the breadth of analysis, and introduce novel tools or techniques. These recommendations are aimed at inspiring and guiding researchers in their forthcoming endeavors, with the collective aim of enhancing the realm of EEG signal analysis and its multifaceted applications.

6.1 Summary of Research Objectives

The primary aim of this study was to investigate the application of cutting-edge machine learning techniques, specifically ResNet50 and Convolutional Neural Networks (CNNs), for the classification of EEG signals. The study's objective was to achieve accurate categorization of EEG data by employing CNNs and ResNet50, following the transformation of the data into spectrograms through the utilization of the Short-Time Fourier Transform (STFT). Furthermore, the study aimed to evaluate the performance of the models and assess the effectiveness of transfer learning using the pre-trained ResNet50 model.

6.2 Key Findings and Contributions

This research has yielded several crucial findings through meticulous experimentation and analysis. Firstly, the utilization of Convolutional Neural Networks (CNNs) for EEG signal classification has exhibited promising outcomes. By incorporating convolutional layers and max-pooling layers, the network effectively captures distinctive EEG patterns and activities, facilitating the extraction of relevant features from spectrograms.

Furthermore, the successful integration of ResNet50, a deep convolutional neural network architecture, has significantly enhanced the classification performance. The incorporation of residual blocks and skip connections has not only enabled the training of deeper networks but has also mitigated the vanishing gradient challenge often encountered in intricate architectures. Leveraging the knowledge and features acquired from a diverse task, the application of transfer learning with pre-trained ResNet50 has substantially bolstered the overall performance.

The preprocessing techniques, encompassing artifact removal and the creation of STFT-based spectrograms, have also exerted a notable influence on the quality and interpretability of the EEG signals. These preprocessing procedures have been instrumental in eliminating artifacts, minimizing noise, and transforming time-domain EEG data into a more informative frequency-domain representation.

6.3 Implications and Significance

The outcomes of this study hold significant implications for the realm of brain-computer interface (BCI) and EEG signal analysis. Various applications, such as brain-controlled prostheses, mental state monitoring, and neurofeedback systems, stand to gain substantial advantages from the accurate classification of EEG signals. The successful application of CNNs and ResNet50 in this context showcases their potential and efficacy.

The utilization of transfer learning and pre-trained models further underscores the benefits of knowledge transfer and model reusability. Particularly when dealing with limited labeled data, this approach facilitates more efficient training, swifter convergence, and enhanced performance. The integration of transfer learning and deep learning methodologies has the potential to accelerate advancements in the classification of EEG signals and other pertinent domains.

6.4 Future Directions

- Exploring various deep learning architectures: While CNNs and ResNet50 have shown promising outcomes, delving into diverse deep learning architectures, including recurrent neural networks (RNNs) and attention mechanisms, could yield further insights and potentially enhance classification accuracy.
- Exploring multi-modal methods: Integrating other modalities, such as coupling EEG signals with additional physiological signals or neuroimaging data, has the potential to offer a more comprehensive understanding of brain activity and elevate classification accuracy.
- Addressing class imbalance and limited sample size: Imbalances among classes and limited sample sizes often challenge EEG datasets. To mitigate these challenges and enhance model generalizability, future investigations should focus on devising effective strategies, such as data augmentation techniques and advanced sampling methodologies.
- Enhancing usability and real-time implementation: Extending the research to real-time EEG classification and designing user-friendly interfaces can facilitate the practical application of the developed models in real-world scenarios.

6.5 Summary of Chapter

In conclusion, this thesis has demonstrated the utilization of advanced machine learning techniques, particularly CNNs and ResNet50, for the classification of EEG signals. The adept application of these models, coupled with effective preprocessing techniques and transfer learning, has yielded promising outcomes in accurately discerning diverse EEG patterns and activities. These findings hold implications for the advancement of state-of-the-art Brain-Computer Interface (BCI) systems and contribute to the expanding body of knowledge within the realm of EEG signal processing.

This chapter serves as a comprehensive culmination of the thesis, addressing the research objectives, elucidating significant discoveries, summarizing their essence, exploring their implications, and delineating avenues for future research. The insights garnered from this endeavor unveil novel prospects within EEG signal processing, potentially yielding profound insights into the intricate dynamics of the human brain.

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