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Motor-Imagery based BCI using Convolutional Neural Network and analysis of Low-Complexity Hilbert Transform

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CANDIDATE'S DECLARATION

I hereby certify that the Project Report titled "**Motor-Imagery based BCI using Convolutional Neural Network and analysis of Low-Complexity Hilbert Transform**" which is submitted by **Shashank Singh Bisen, 2K21/SPD/12** of Electronics and Communication Department, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the students under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

Place: New Delhi
Date: 31/05/2024

Shashank Singh Bisen (2K21/SPD/12)

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CERTIFICATE

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Place: New Delhi
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Dr. Sudipta Majumdar
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ABSTRACT

Motor imagery (MI) based brain-computer interfaces (BCIs) enable direct communication between the brain and external devices, offering significant potential for individuals with motor disabilities. This thesis explores the development of a Motor-Imagery based BCI using Convolutional Neural Networks (CNNs) and evaluates the effectiveness of the Low-Complexity Hilbert Transform for feature extraction.

EEG signals are preprocessed using a notch filter to remove power line interference, followed by bandpass filtering to isolate the mu (8-12 Hz) and beta (12-30 Hz) frequency bands. The Hilbert Transform is applied to compute analytic signals, from which instantaneous power is derived. Event-Related Patterns (EPs) are calculated to quantify changes in brain activity during motor imagery tasks. Statistical features such as mean, standard deviation, skewness, and kurtosis are extracted from the EPs to enrich the feature set for classification.

Both CNN and Long Short-Term Memory (LSTM) networks are implemented and evaluated. Contrary to common expectations, the CNN model outperformed the LSTM model, achieving higher classification accuracy on both training and test datasets. The CNN demonstrated superior capability in learning and generalizing spatial patterns within the EEG data.

A detailed analysis using confusion matrices highlights the CNN's effectiveness in capturing intricate spatial features crucial for accurate MI classification. This thesis underscores the importance of spatial feature extraction and suggests that CNNs hold significant promise for enhancing motor imagery-based BCIs.

The findings contribute to the field by demonstrating the efficacy of CNNs in MI classification and providing insights into the application of the Low-Complexity Hilbert Transform for feature extraction.

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Shashank Singh Bisen

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Chapter 1
INTRODUCTION

1.1 Overview

A transform, in the context of signal processing, is a mathematical operation that converts a signal or function from one domain to another. It provides a different representation of the signal, often making it easier to analyze or process the signal in a specific context. Transforms are used in signal processing for several reasons:

Analysis: Transforms allow us to examine the characteristics of a signal or data in a different domain, providing insights that may not be apparent in the original domain. For example, transforming a signal from the time domain to the frequency domain using the Fourier transform reveals its frequency content, enabling analysis of the signal's spectral properties.

Simplification: Transforms can simplify the representation or analysis of signals or functions. They can condense complex information into a more concise or meaningful form. For instance, the Laplace transform converts differential equations into algebraic equations, facilitating their solution and analysis.

Feature extraction: Transforms can extract specific features or properties of a signal that are relevant to a particular application. For instance, the wavelet transform is effective in capturing localized features or transients in a signal, which is useful in applications such as signal denoising, image compression, or pattern recognition.

Noise reduction: Transforms can be used to reduce or filter out unwanted noise or interference in a signal. By transforming a noisy signal into a different domain, it may be possible to isolate or attenuate noise components, leading to a cleaner representation of the signal.

Compression: Transforms play a vital role in data compression techniques. By converting a signal or data into a different domain, it may be possible to exploit certain characteristics or redundancies to represent the data more efficiently. For example, the Discrete Cosine Transform (DCT) is widely used in image and video compression algorithms like JPEG and

MPEG.

Signal synthesis: Transforms can also be used to synthesize or generate signals. In some cases, the inverse transform can reconstruct a signal from its transformed representation. This is useful in applications such as signal reconstruction, signal modulation, or generating synthetic signals with desired properties.

Overall, transforms are required in signal processing to provide alternative representations of signals, simplify analysis, extract relevant information, remove noise, compress data, and synthesize signals. They offer powerful tools for understanding, manipulating, and processing signals in various domains, allowing us to gain deeper insights into the underlying characteristics and enabling us to perform a wide range of signal processing tasks.

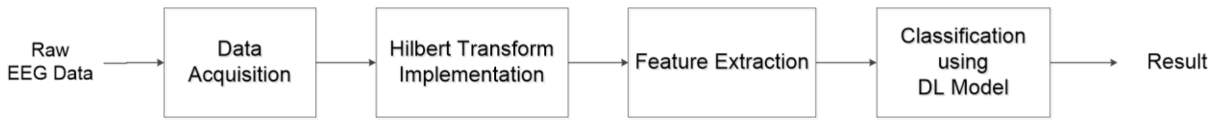

Fig 1. Flowchart representing the steps followed in this project.

1.1.1 Types of Transforms

In signal processing, transforms are mathematical operations that convert a signal from one domain to another, typically from the time domain to the frequency domain. The time domain represents signals as they vary over time, whereas the frequency domain represents signals in terms of their constituent frequencies. Transform methods are crucial because they simplify the analysis and manipulation of signals by revealing characteristics that are not apparent in the time domain.

1.1.2 Time Domain and Frequency Domain

The time domain displays how a signal changes over time. It is useful for observing how the amplitude of a signal varies, but it does not provide information about the frequency content of the signal. For example, an ECG signal in the time domain shows the heart's electrical activity as it changes over time. However, this representation does not reveal the signal's frequency components, which are crucial for diagnosing various heart conditions. Time-domain analysis is often straightforward and intuitive, but it can be limited when dealing with complex or multi-component signals.

The frequency domain, on the other hand, represents the signal in terms of its frequencies. This domain is obtained by applying a mathematical transformation to the time-domain signal. The most common transformation is the Fourier Transform, which decomposes a time-domain signal into its constituent sinusoidal components, each represented by a specific frequency, amplitude, and phase. The resulting frequency spectrum provides insight into the periodic components of the signal, which is valuable for filtering, analysis, and system identification. For instance, identifying the dominant frequencies in an audio signal can help in noise reduction or enhancing specific sounds.

1.1.3 Major Transforms in Signal Processing

Several major transforms are widely used in signal processing, each serving different purposes and offering unique advantages:

I) Fourier Transform: The Fourier Transform converts a time-domain signal into its frequency-domain representation. It breaks down the signal into a sum of sinusoidal functions, each with a specific frequency, amplitude, and phase. The Discrete Fourier Transform (DFT) is its digital counterpart, suitable for discrete signals. The Fast Fourier Transform (FFT) algorithm is an efficient way to compute the DFT, reducing the computational complexity. This efficiency makes the FFT essential for real-time signal processing applications.

The Fourier Transform is particularly useful for analyzing stationary signals where the frequency components do not change over time. It is widely used in audio signal processing, telecommunications, and spectral analysis.

II) Hilbert Transform: The Hilbert Transform generates the analytic signal from a real-valued signal, providing a complex representation that includes both amplitude and phase information. This transform is particularly useful in modulation and demodulation processes, as well as in envelope detection. By converting a real signal into its analytic form, the Hilbert Transform allows for the extraction of instantaneous amplitude and phase, which are essential for understanding signal characteristics in communications and biomedical signal processing.

The Hilbert Transform is also used to derive the envelope of a signal, which is the smooth curve outlining its extremes. This is particularly useful in biomedical applications, such as detecting the QRS complex in ECG signals or identifying event-related potentials (ERPs) in EEG signals[1].

III) Wavelet Transform : The Wavelet Transform decomposes a signal into components at various scales and positions, offering both time and frequency localization. Unlike the Fourier Transform, which provides a global frequency representation, the Wavelet Transform allows for multi-resolution analysis. This makes it suitable for analyzing non-stationary signals, such as EEG and seismic data, where frequency components change over time.

The Wavelet Transform is used in image compression, de-noising, and detecting transient features in signals. Its ability to provide detailed time-frequency information makes it an invaluable tool in various scientific and engineering applications.

IV) Z-Transform: Used primarily in digital signal processing, the Z-Transform converts a discrete-time signal into a complex frequency domain. It provides a powerful tool for analyzing linear, time-invariant systems. The Z-Transform is particularly useful in the design and analysis of digital filters, control systems, and stability analysis.

The Z-Transform's ability to handle discrete-time signals makes it essential for digital signal processing applications, where signals are sampled and processed using digital systems.

V) Laplace Transform : The Laplace Transform extends the Fourier Transform to complex frequency domains, used for analyzing continuous-time systems and control theory. It is particularly useful for solving differential equations and analyzing system behavior in the s-domain.

The Laplace Transform is widely used in engineering fields, such as electrical engineering, control systems, and mechanical engineering, for system analysis and design. It provides a comprehensive framework for understanding the dynamics of continuous-time systems and their responses to various inputs.

Transforms are fundamental tools in signal processing, providing a means to analyze, filter, and manipulate signals in ways that are not possible in the time domain alone. They are essential for applications ranging from telecommunications and audio processing to medical diagnostics and engineering systems. By converting signals into different domains, transforms enable a deeper understanding of signal characteristics, facilitating more effective processing and analysis [2].

1.2 Use of Transforms and Their Applications

Transforms are utilized in a myriad of applications across various fields due to their ability to simplify complex signal processing tasks. By converting signals to the frequency domain or other transformed domains, transforms enable easier analysis and manipulation, leading to significant advancements in technology and science.

1.2.1 Signal Processing

In signal processing, transforms like the Fourier Transform and Hilbert Transform are used extensively for filtering, modulation, and spectral analysis. For example, the Fourier Transform is pivotal in telecommunications for encoding and decoding signals. It enables the conversion of time-domain signals into frequency components, facilitating the design and analysis of filters to remove unwanted noise or to extract specific signal features. The Hilbert Transform, on the other hand, is employed for creating analytic signals that aid in modulation schemes such as amplitude modulation (AM). By generating the analytic representation of a signal, the Hilbert Transform provides both the envelope and the instantaneous phase, which are crucial for demodulation and signal analysis in communication systems[3].

In audio signal processing, the Fourier Transform is essential for analyzing the frequency content of audio signals. It enables the identification of different sound components, which can be manipulated for various purposes such as noise reduction, equalization, and audio effects. The Wavelet Transform is also used in audio processing for time-frequency analysis, allowing for the detection of transient features and the decomposition of audio signals into different frequency bands [4]

1.2.2 Medical Applications

Transforms are crucial in medical signal processing. The Hilbert Transform, for instance, is used to extract the envelope of biomedical signals like EEG and ECG. This helps in identifying critical features such as R-peaks in ECG, which are essential for diagnosing heart conditions. The Wavelet Transform is another significant tool used for analysing non-stationary biomedical signals. It aids in the detection and diagnosis of abnormalities in EEG signals, such as epileptic seizures or sleep disorders. By providing a detailed time-frequency representation, the Wavelet Transform allows for the identification of transient events and the isolation of specific frequency bands associated with pathological conditions [5].

In medical imaging, transforms play a vital role in enhancing image quality and extracting meaningful features. The Fourier Transform is used in Magnetic Resonance Imaging (MRI) to reconstruct images from raw data collected in the frequency domain [6]. The Hilbert Transform is applied in ultrasound imaging for envelope detection, which enhances the clarity of images and aids in the accurate diagnosis of medical conditions. These transforms enable the extraction of features that are critical for medical diagnosis and treatment planning.

1.2.3 Communications

In communications, transforms facilitate the efficient transmission and reception of data. The Fast Fourier Transform (FFT) is essential in orthogonal frequency-division multiplexing (OFDM), a method used in many modern communication systems, including Wi-Fi and LTE, to transmit large amounts of data over multiple channels. OFDM divides the data into multiple frequency channels, which are then transmitted simultaneously, increasing the efficiency and reliability of data transmission [7]. The Hilbert Transform is also used for complex demodulation, which helps in extracting the phase and amplitude information from modulated signals. This is crucial for decoding the information accurately and maintaining the integrity of the transmitted data.

Transforms also play a role in satellite communications, where they are used to process signals transmitted over long distances. The Fourier Transform helps in the design of filters and equalizers that compensate for signal degradation and interference. By transforming signals to the frequency domain, engineers can design more effective communication systems that are robust to noise and interference.

Engineering and Structural Health Monitoring

In engineering, transforms are used for structural health monitoring to detect damage in buildings and infrastructure. The Hilbert Transform is particularly useful for envelope detection, which helps in identifying changes in the structural integrity of materials. By analysing the envelope of vibration signals, engineers can detect cracks, corrosion, and other structural issues early, preventing catastrophic failures and ensuring the safety and reliability of buildings, bridges, and other structures.

The Fourier Transform is used to analyse vibration data from sensors installed on structures. By transforming the data to the frequency domain, engineers can identify resonant frequencies and monitor changes over time, which can indicate the development of structural problems. The Wavelet Transform is also used for time-frequency analysis of vibration data, allowing for the detection of transient events and the localization of damage.

1.2.4 Cyber-Physical Systems and IoT

In emerging fields like Cyber-Physical Systems (CPS) and the Internet of Things (IoT), transforms are used to process signals from various sensors in real-time. These systems often require low-power, high-speed signal processing to manage data from multiple sources effectively. The Hilbert Transform is used in applications such as remote health monitoring to analyse physiological signals efficiently, ensuring timely and accurate health assessments. By extracting the envelope and phase information from bio signals, the Hilbert Transform helps in monitoring vital signs and detecting anomalies that may indicate health issues

Transforms are also used in environmental monitoring, where they help process data from sensors deployed in remote locations. The Fourier Transform is used to analyse temperature, humidity, and air quality data, providing insights into environmental trends and enabling timely interventions. The Wavelet Transform is used for multi-resolution analysis of environmental data, allowing for the detection of transient events and anomalies that may indicate environmental hazards [8].

Transforms are indispensable tools in modern signal processing, enabling advancements in a wide range of applications from medical diagnostics and communications to geophysics and engineering. Their ability to convert signals into different domains provides a powerful means of analysis and manipulation, driving innovation and improving the efficiency and accuracy of various technological processes.

1.3 Explanation of Hilbert Transform: Applications in Research and Mathematical Use

The Hilbert Transform is a linear operator that generates the analytic representation of a real-valued signal, which is a complex signal with the original signal as its real part and the Hilbert Transform as its imaginary part. This transform is particularly useful for obtaining the envelope and instantaneous phase of signals, which are crucial for various applications in signal processing.

1.3.1 Hilbert Transform

The Hilbert Transform holds great importance in the fields of signal processing and communications, and it owes its name to David Hilbert, a renowned German mathematician. Hilbert's contributions to mathematics include the development of the theory of Hilbert spaces, which serve as a fundamental concept in the mathematical framework of quantum mechanics. It is worth noting, however, that Hilbert did not directly propose the Hilbert Transform itself. Instead, the Hilbert Transform was named in recognition of its profound associations with the theory of Hilbert spaces, paying homage to Hilbert's significant contributions to mathematics and his influential work in quantum mechanics. The naming serves as a tribute to the deep connections between the transform and the mathematical concepts pioneered by David Hilbert. In the realm of signal processing, the Hilbert Transform plays a crucial role in the generation of analytic signals derived from real-valued signals [9]. An analytic signal, unlike its real-valued counterpart, is a complex signal that possesses no components for negative frequencies. This characteristic proves to be advantageous as it enables the independent manipulation of the signal's amplitude and phase. By separating these two aspects, the Hilbert Transform empowers us to extract a greater wealth of information from the signal under analysis.

The Hilbert Transform is a linear operator that produces a phase shift in a signal. For a real-valued function of time, $f(t)$, its Hilbert transform $H[f(t)]$ is given by:

$$H[f(t)] = \left(\frac{1}{\pi}\right) * \; p.v.\int \frac{f(\tau)}{(t-\tau)} d\tau \qquad (from\ -\infty\ to\ \infty) \qquad (1.1)$$

where p.v. stands for the Cauchy principal value of the integral, t is the time variable, and τ is the dummy variable of integration.

This equation means that the Hilbert transform of f(t) is a convolution of f(t) with 1/(πt), which results in a function that is orthogonal to the original function f(t).

The result of this operation is a new function, which is 90 degrees phase-shifted version of the original function. For signals in the time domain, this phase shift is in the negative direction for all positive frequencies and in the positive direction for all negative frequencies.

One of the most important applications of the Hilbert transform is to generate the analytic signal from a real-valued signal. The analytic signal z(t) = f(t) + jH[f(t)] is a complex signal, where the real part is the original signal and the imaginary part is the Hilbert transform of the original signal. This analytic signal is beneficial because it can express both the amplitude envelope and instantaneous phase, which are often crucial for signal processing tasks.

The Discrete Hilbert transform is an adaptation of the Hilbert transform for sequences of discrete data values, and it's used in signal processing for transforming a signal into its analytic signal. The goal of the discrete Hilbert transform is the same as the continuous Hilbert Transform - to create a 90-degree phase-shifted version of the original signal.

Mathematically, the discrete Hilbert transform of a sequence x[n] can be defined as:

$$H\big[x[n]\big] = \left(\frac{2}{\pi}\right) \sum \frac{((-1)^{k} * x[n-k])}{k} \qquad (from\ k = -\infty\ to\ \infty, k \neq 0) \qquad (1.2)$$

where x[n] is the discrete input signal, H[x[n]] is the Hilbert transformed signal, and k is the sample index.

In the realm of signal processing, the Hilbert Transform plays a crucial role in the generation of analytic signals derived from real-valued signals. An analytic signal, unlike its real-valued counterpart, is a complex signal that possesses no components for negative frequencies. This characteristic proves to be advantageous as it enables the independent manipulation of the signal's amplitude and phase. By separating these two aspects, the Hilbert Transform empowers us to extract a greater wealth of information from the signal under analysis.

By employing the Hilbert Transform, we are able to convert a real-valued signal into its corresponding analytic signal, thereby extending its representation into the complex domain. The resulting analytic signal is composed of two components: the original real-valued signal and its Hilbert Transform, which is a 90-degree phase-shifted version of the signal. These two components together form a complex signal with a well-defined magnitude and phase.

The ability to manipulate the amplitude and phase of the analytic signal independently opens up a wide range of possibilities for signal processing applications. For instance, one can modify the amplitude of the analytic signal while keeping its phase constant, or vice versa. This level of control provides a valuable tool for various tasks such as filtering, modulation, demodulation, and frequency analysis.

Furthermore, the extraction of additional information from the signal is facilitated by the zeroing of the negative frequency components in the analytic signal. This property allows us to focus on the positive frequency spectrum, simplifying analysis and facilitating the identification of relevant signal characteristics.

1.3.2 Applications of Hilbert Transform in Research

The Hilbert Transform is widely used in research across various domains:

I) Biomedical Signal Processing: The transform is used to extract the envelope of ECG and EEG signals, which is crucial for detecting features like R-peaks in ECG or identifying event-related potentials (ERPs) in EEG. These features are essential for diagnosing heart diseases and neurological conditions, respectively. For example, the envelope of the ECG signal helps in identifying the QRS complex, which is a critical component for heart rate and rhythm analysis. The Hilbert Transform aids in distinguishing between different cardiac events, improving the accuracy of automated ECG interpretation systems [10].
- Seismic Data Analysis: In geophysics, the Hilbert Transform helps in analysing seismic waves to identify subsurface structures and detect hydrocarbons. It provides insights into the phase and amplitude variations of seismic signals, aiding in the exploration of oil and gas reservoirs. By converting seismic data into the analytic signal, geophysicists can extract attributes such as instantaneous phase and frequency, which are essential for interpreting seismic events and understanding geological formations [11].

II) Communication Systems: The transform is employed for modulation and demodulation processes, particularly in complex demodulation where it helps extract the phase and amplitude of modulated signals. This is critical for efficient data transmission and reception in telecommunications. The Hilbert Transform enables the creation of single-sideband (SSB) signals, which are used in radio communications to reduce bandwidth and improve signal clarity. It also aids in the demodulation of signals in digital communication systems, enhancing the accuracy and reliability of data transmission [12].

III) Structural Health Monitoring : The Hilbert Transform is used for envelope detection to monitor the integrity of structures. It helps in identifying damage by analysing the changes in the signal's envelope, which indicates structural issues in buildings and other infrastructure. By monitoring the vibration signals from structures, engineers can detect early signs of damage such as cracks or corrosion, allowing for timely maintenance and preventing catastrophic failures. The Hilbert Transform provides a non-invasive method for continuous monitoring of structural health, ensuring the safety and longevity of critical infrastructure.

IV) Time-Frequency Analysis: The Hilbert Transform is used in conjunction with other transforms, such as the Wavelet Transform, for time-frequency analysis of signals. This combination allows researchers to analyse the temporal and spectral characteristics of non-stationary signals, such as EEG and seismic data. By providing detailed information about the signal's amplitude and phase over time, the Hilbert Transform enhances the resolution and accuracy of time-frequency analysis, making it a valuable tool for signal processing research [13].

1.3.3 Applications of Hilbert Transform in Mathematical Use

Beyond research, the Hilbert Transform finds applications in everyday technologies and practical scenarios:

I) Audio Signal Processing: In audio processing, the Hilbert Transform is used to create single-sideband (SSB) signals, which are important for reducing bandwidth in radio communications. It also helps in phase vocoding, which is used for time-stretching and pitch-shifting audio signals without affecting their quality. By generating the analytic signal, the

Hilbert Transform enables the extraction of phase information, which is crucial for high-quality audio manipulation and synthesis. This application is widely used in music production, broadcasting, and telecommunications.

II) Medical Imaging: In ultrasound imaging, the Hilbert Transform is used for envelope detection, which enhances the clarity of ultrasound images. This is vital for accurately diagnosing medical conditions through ultrasound scans. By extracting the envelope of the reflected ultrasound signals, the Hilbert Transform improves the contrast and resolution of the images, aiding in the detection of abnormalities such as tumours, cysts, and foetal development issues. The transform provides a non-invasive and efficient method for enhancing medical imaging, contributing to better patient care and diagnosis.

III) Speech Processing: In speech analysis and synthesis, the Hilbert Transform helps in extracting the envelope of speech signals, which is used for various speech processing tasks such as speech recognition, synthesis, and enhancement. By providing detailed information about the amplitude and phase of speech signals, the Hilbert Transform enables the accurate analysis and manipulation of speech features. This is essential for developing advanced speech recognition systems, improving the clarity and naturalness of synthesized speech, and enhancing the quality of speech communication systems.

IV) Radar Signal Processing: The Hilbert Transform is used in radar systems to extract the envelope of received signals, which is crucial for target detection and ranging. By converting the radar signals into their analytic form, the Hilbert Transform enhances the accuracy of distance and velocity measurements, improving the performance of radar systems in various applications, including aviation, maritime, and defence.

V) Biomedical Instrumentation: In biomedical instrumentation, the Hilbert Transform is used for real-time monitoring of physiological signals [14]. For example, in wearable health monitors, the transform helps in extracting vital signs such as heart rate and respiratory rate from the recorded signals. This information is essential for continuous health monitoring and early detection of medical conditions, providing valuable data for both patients and healthcare providers.

The Hilbert Transform's ability to provide both amplitude and phase information makes it a versatile tool in signal processing. Its applications span a wide range of fields, from advanced research in biomedical engineering and geophysics to practical uses in audio processing, telecommunications, and financial analysis. The transform's adaptability and effectiveness in extracting meaningful information from complex signals underscore its importance in both research and everyday applications

1.3.4 Need for Hilbert Transform

The Hilbert Transform holds great importance in the fields of signal processing and communications, and it owes its name to David Hilbert, a renowned German mathematician. Hilbert's contributions to mathematics include the development of the theory of Hilbert spaces, which serve as a fundamental concept in the mathematical framework of quantum mechanics. It is worth noting, however, that Hilbert did not directly propose the Hilbert Transform itself. Instead, the Hilbert Transform was named in recognition of its profound associations with the theory of Hilbert spaces, paying homage to Hilbert's significant contributions to mathematics and his influential work in quantum mechanics. The naming serves as a tribute to the deep connections between the transform and the mathematical concepts pioneered by David Hilbert. In the realm of signal processing, the Hilbert Transform plays a crucial role in the generation of analytic signals derived from real-valued signals. An analytic signal, unlike its real-valued counterpart, is a complex signal that possesses no components for negative frequencies. This characteristic proves to be advantageous as it enables the independent manipulation of the signal's amplitude and phase. By separating these two aspects, the Hilbert Transform empowers us to extract a greater wealth of information from the signal under analysis.

1.3.5 Theoretical Background

The Discrete Hilbert Transform (DHT) is a crucial requirement in emerging fields such as wireless sensor networks and mobile health-care technologies within the cyber-physical system framework. These fields often utilize wearable bio-medical sensor devices that belong to the Body Sensor Network system (BSN). These devices are responsible for acquiring, processing, and transmitting physiological signals like electrocardiogram (ECG) and electroencephalogram (EEG) to the cloud for further analysis.

However, in these emerging applications with resource constraints, the sensors used are primarily powered by battery backups or energy harvesting mechanisms. The sensor nodes, due to requirements of unobtrusiveness, non-invasiveness, and a low form factor, necessitate lightweight and low-power signal processing. It is crucial for the processing module to fit within the constraints of the tiny chip while minimizing on-chip area overhead.

Furthermore, the processing requirements may vary depending on the health condition. If the health condition deteriorates or deviates from the normal trend, more rigorous processing is needed, often involving an increased number of data points to gain a better understanding of the well-being. On the other hand, if the health condition stabilizes over time, the same processing can be performed on fewer data points, reducing overall power consumption. However, this necessitates are configurable architecture design that can adapt to different processing requirements.

Moreover, in applications involving the acquisition of vital physiological signals, strict time constraints are not typically imposed. This is because physiological signals are captured at very low rates. For example, in cardiovascular disease monitoring, ECG signals are typically captured at a maximum rate of 1 kHz, while EEG signals for diagnosing neurological developmental disorders are acquired at 2 kHz. In this context, the DHT plays a significant role in identifying fiduciary points, including the detection of peaks and other medically important features.

Motivated by the aforementioned requirements and applications, this paper introduces a low complexity and re-configurable DHT architecture design methodology. The proposed methodology aims to significantly reduce power consumption and area overhead compared to state-of-the-art designs. By addressing the specific challenges and considerations of resource-constrained environments, this methodology provides an efficient and effective solution for implementing the DHT in emerging applications.

In summary, the DHT is essential in wireless sensor networks and mobile health-care technologies. These applications require lightweight and low-power signal processing modules due to resource constraints and the need for unobtrusive and non-invasive wearable devices. The proposed low complexity and re-configurable DHT architecture design methodology presented in this paper addresses these requirements and offers improvements over existing designs. By reducing power consumption and area overhead, it enables efficient and reliable implementation of the DHT in real-world applications.

1.4 Background on Motor Imagery Brain-Computer Interfaces (BCIs)

Motor imagery (MI) brain-computer interfaces (BCIs) are an innovative technology that enables direct communication between the human brain and external devices. This technology is particularly beneficial for individuals with severe motor disabilities, providing a means to interact with their environment without the need for muscle activity. MI-BCIs rely on the ability of users to imagine specific movements, such as moving their left or right hand, which generates distinct patterns of neural activity that can be detected and translated into control signals for various applications, including prosthetic limbs, computer cursors, and other assistive devices.

The core principle behind MI-BCIs is the detection and classification of EEG signals corresponding to different imagined movements. EEG is a non-invasive method of recording electrical activity of the brain using electrodes placed on the scalp. These recordings capture the oscillatory activity of neuronal populations, which reflect different cognitive and motor processes. In the context of MI, the focus is primarily on the mu (8-12 Hz) and beta (12-30 Hz) frequency bands, which are associated with motor control and can be modulated by imagined movements.

The development of effective MI-BCIs involves several key steps: signal acquisition, preprocessing, feature extraction, and classification. Signal acquisition is performed using EEG, which provides high temporal resolution and is relatively affordable and portable compared to other neuroimaging techniques like fMRI or MEG. Preprocessing involves filtering the raw EEG signals to remove noise and artifacts, which is crucial for improving the signal-to-noise ratio and ensuring that the subsequent analysis is based on clean data.

Feature extraction is a critical step in MI-BCI development, as it involves identifying and isolating the most informative aspects of the EEG signals that correspond to different motor imagery tasks [15]. Traditional methods for feature extraction include band power analysis, common spatial patterns (CSP), and autoregressive models. However, recent advances have introduced more sophisticated techniques such as the Hilbert transform, which can provide a comprehensive representation of the signal's amplitude and phase information.

The final step, classification, involves using machine learning algorithms to differentiate between the EEG patterns corresponding to different imagined movements. Various classifiers have been explored in MI-BCI research, including support vector machines (SVM), logistic regression, and more recently, deep learning models such as convolutional neural networks (CNNs) and long short-term memory (LSTM) networks. These models leverage the temporal dynamics of EEG signals to improve classification accuracy [16].

MI-BCIs offer a promising avenue for restoring communication and control capabilities to individuals with motor impairments. The continuous advancements in signal processing and machine learning techniques are enhancing the performance and reliability of these systems, bringing us closer to practical and user-friendly BCI applications. This thesis focuses on improving the classification accuracy of MI tasks using a combination of the Hilbert transform for feature extraction and advanced machine learning models, with a specific emphasis on the BCI Competition III Dataset IIIa.

1.5 Importance of Classifying Motor Imagery Tasks Using EEG Signals

The classification of motor imagery (MI) tasks using electroencephalography (EEG) signals is a cornerstone in the development of brain-computer interfaces (BCIs), particularly for individuals with severe motor impairments [17]. Accurate classification of these tasks enables the translation of mental commands into actionable instructions for controlling external devices, thereby providing a significant improvement in the quality of life for users.

Enhancing Communication and Control for Disabled Individuals

For individuals suffering from conditions such as amyotrophic lateral sclerosis (ALS), spinal cord injuries, or stroke, traditional means of communication and control may be severely limited or entirely lost[18]. MI-BCIs offer an alternative communication pathway by allowing users to control devices through imagined movements. This can include controlling a computer cursor, operating a wheelchair, or even interacting with smart home devices. By accurately classifying MI tasks, BCIs can restore a degree of independence and agency to these individuals, enhancing their ability to interact with their environment and communicate with others [19].

1.5.1 Real-Time and Accurate Control

Accurate classification of MI tasks is essential for real-time applications of BCIs. In practical scenarios, the system must quickly and reliably interpret the user's intentions to provide timely feedback and control. High classification accuracy ensures that the BCI system responds correctly to the user's mental commands, reducing frustration and increasing the user's confidence in the system. This is particularly important in dynamic environments where swift and precise actions are required [20-21].

1.5.2 Advancements in Neurotechnology

Classifying MI tasks using EEG signals contributes to advancements in neurotechnology and our understanding of the brain's functioning [22]. Through the development of sophisticated signal processing and machine learning techniques, researchers can gain deeper insights into the neural mechanisms underlying motor imagery and motor control. This knowledge not only benefits BCI research but also has broader applications in neuroscience, such as in the study of neural plasticity and brain-computer interfacing for rehabilitation purposes [23]

1.5.3 Challenges and Innovations in Signal Processing

EEG signals are inherently noisy and susceptible to various artifacts, making the classification of MI tasks a challenging endeavour. Innovations in signal processing techniques, such as the use of the Hilbert transform to extract analytic signals, play a crucial role in improving classification accuracy. By capturing both the amplitude and phase information of EEG signals, these advanced techniques can more effectively differentiate between different MI tasks. This enhances the robustness and reliability of BCI systems, making them more viable for real-world applications [25].

1.5.4 Personalized **BCI Systems**

Accurate classification of MI tasks also facilitates the development of personalized BCI systems. Each individual's neural activity patterns are unique, and a high degree of accuracy in classification allows for the customization of BCI systems to better suit the specific neural signatures of different users. This personalization can significantly improve the usability and effectiveness of BCI systems, leading to broader acceptance and adoption among potential users [26].

In conclusion, the accurate classification of motor imagery tasks using EEG signals is of paramount importance for the practical implementation of BCIs. It enhances the communication and control capabilities of individuals with motor impairments, contributes to advancements in neurotechnology, and drives innovations in signal processing. Through continued research and development, these systems hold the potential to transform the lives of those who rely on them, offering greater independence and improved quality of life.

1.6 LITERATURE REVIEW

Brain-Computer Interfaces (BCIs) have emerged as a transformative technology, enabling direct communication between the brain and external devices. This capability is particularly significant for individuals with severe motor disabilities, offering potential for improved quality of life through assistive technologies. Among the various types of BCIs, those based on motor imagery (MI) have garnered substantial interest due to their non-invasive nature and the rich information content of electroencephalogram (EEG) signals. This thesis focuses on the integration of Convolutional Neural Networks (CNNs) and the Hilbert Transform to enhance the accuracy and efficiency of MI-based BCIs.
The first literature was the paper Recent Trends and Indications in the Field of Motor Imagery: A Brain-Computer Interface Paradigm this provides an in-depth review of the advancements and trends in the field of EEG-based motor imagery (MI) brain-computer interfaces (BCIs). The authors, Suraiya Jabin, Munna Khan, Kashif I.K. Sherwani, and Meryam Sardar, focus on the significance of deep learning techniques in improving the accuracy and efficiency of MI-BCI systems. BCIs enable communication between a user and an external device using brain activity, with EEG being the most commonly used method due to its non-invasive nature, affordability, and portability[27].

The paper highlights that motor imagery, which involves imagining motor movements without actual execution, has gained considerable attention in the last decade due to its potential

applications in neurorehabilitation, assistive technology, and human-computer interaction. The review covers various signal processing and machine learning techniques employed in MI-BCI systems, including feature extraction methods and classifiers.
The paper also emphasizes future research directions, including the integration of multi-modal data, real-time processing, and the development of more personalized BCI systems. Overall, this comprehensive review provides valuable insights into the current state and future prospects of EEG-based MI-BCI research, highlighting the critical role of deep learning in advancing this field.

The research Transformed Common Spatial Pattern for Motor Imagery-Based Brain-Computer Interfaces introduces the Transformed Common Spatial Pattern (tCSP) method, which aims to enhance the classification of motor imagery (MI) tasks by extracting discriminant features from EEG signals across multiple frequency bands. Traditional Common Spatial Pattern (CSP) methods are often limited by their reliance on a single frequency band, which may not capture the full range of discriminative information present in the EEG signals. The tCSP method overcomes this limitation by transforming the CSP features and integrating information from multiple frequency bands. This approach leads to improved classification accuracy for different MI tasks, as demonstrated through extensive experiments. The results show that tCSP outperforms traditional CSP methods, making it a valuable tool for developing more robust MI-BCI systems [28].

From the study A Review of Online Classification Performance in Motor Imagery-Based Brain–Computer Interfaces for Stroke Neurorehabilitation evaluates the online classification performance of various MI-BCI frameworks specifically designed for stroke neurorehabilitation. The authors systematically analyse different classifiers and feature extraction techniques used in real-time MI-BCI applications. The study highlights the importance of online classification in providing immediate feedback to users, which is crucial for effective neurorehabilitation. The paper also discusses the impact of various factors, such as user demographics, neurofeedback modalities, and experimental setups, on the performance of MI-BCI systems. By synthesizing findings from multiple studies, the authors provide guidelines for selecting appropriate classification methods and feature extraction techniques to enhance the performance and usability of MI-BCI systems in clinical settings[29]
The research Review of Public Motor Imagery and Execution Datasets in Brain-Computer Interfaces puts forward a comprehensive review analyses publicly available motor imagery

(MI) and execution EEG datasets used in brain-computer interface (BCI) research. The authors review 25 datasets based on specific criteria, including dataset characteristics, experimental protocols, and data quality. The paper categorizes the datasets into public, environmental, and experimental specifications, providing a detailed overview of each. The review serves as a valuable resource for researchers by offering insights into the strengths and limitations of existing datasets, facilitating the development and validation of new MI-BCI systems. By highlighting the variability in data collection methods and experimental setups, the authors emphasize the need for standardized protocols to improve the reproducibility and comparability of BCI research[30].

In the study EEG Feature Extraction Methods in Motor Imagery Brain-Computer Interface the authors examine various feature extraction methods used in MI-BCI systems, categorizing them into time-domain, frequency-domain, and time-frequency domain techniques. The authors provide a detailed background on the steps necessary to extract typical MI-related EEG features and discuss different classifier algorithms. The study investigates the influence of non-ML factors such as user demographics (e.g., age), user type (e.g., patient vs. healthy), and experimental setup (e.g., number of trials, electrodes, subjects) on BCI performance. By presenting classification accuracies of different machine learning algorithms and feature extraction methods, the paper highlights the importance of selecting appropriate features to improve classification accuracy. The authors also call for future surveys to include clinical improvements in patients to translate classification accuracy into clinical outcomes[31].

These detailed descriptions provide insights into the methodologies and contributions of each paper, offering a comprehensive understanding of current research trends and advancements in motor imagery brain-computer interfaces.

The reaserch Classification Algorithm for Motor Imagery EEG Signals Based on Parallel DAMSCN-LSTM the authors address the challenge of classifying motor imagery (MI) EEG signals by proposing a parallel fusion algorithm that combines dual attentional multi-scale convolutional neural networks (DAMSCN) with Long Short-Term Memory (LSTM) networks. Traditional convolutional neural networks often neglect temporal information and use single-scale convolutional kernels, which can lead to poor classification performance. The DAMSCN in this study utilizes convolutional kernels of different sizes within the same layer to extract time-frequency features at various scales and introduces a dual attention mechanism to focus on the most relevant features. Meanwhile, the LSTM network captures the temporal dynamics of the EEG signals. The fusion of these features through fully connected and softmax layers enhances the classification accuracy. The proposed algorithm's effectiveness is validated through experiments on domain-specific public datasets, demonstrating significant performance improvements over conventional methods[32].

This study Classification of Motor Imagery Based on Multi-Scale Feature Extraction and the Channel-Temporal Attention Module introduces a deep learning model named MSCTANN (Multi-Scale Channel-Temporal Attention Neural Network) designed for motor imagery (MI) classification in EEG-based BCI systems. The model leverages a multi-scale feature extraction module to capture a wide range of features from the EEG signals and integrates a channel-temporal attention module (CTAM) to focus on the most significant features. The attention module comprises both channel attention and temporal attention mechanisms, enhancing the model's ability to differentiate between relevant and irrelevant information. A residual module connects these components, preventing network degradation. Experimental results on datasets from BCI Competition IV 2a, III IIIa, and IV 1 show that MSCTANN achieves superior performance, with accuracy rates of 80.6%, 83.56%, and 79.84%, respectively. This approach outperforms other state-of-the-art methods while using fewer network parameters, making it a robust and efficient solution for MI classification[33].

The paper Motor Imagery-Based Brain-Computer Interface Using Fusion of Deep Convolutional Neural Network with Wavelet Scattering Network explores a hybrid approach to enhance the classification of motor imagery (MI) EEG signals by combining Deep Convolutional Neural Networks (CNNs) with Wavelet Scattering Networks. Traditional classification methods often struggle with the non-linear and non-stationary nature of EEG signals, and the proposed model aims to address these challenges. By integrating the feature maps learned from both CNN and Scattering networks, the model can better handle the complexities of EEG data. The hybrid model achieves remarkable accuracy rates of 87% and 93% on the BCIC IV 2a and SMR-BCI datasets, respectively. This demonstrates its potential as a more robust and generalized MI-based BCI system, capable of functioning without extensive calibration or subject-specific adjustments[34].

The study Motor Imagery Classification for Brain Computer Interface Using Deep Convolutional Neural Networks and Mixup Augmentation investigates the efficacy of using deep convolutional neural networks (CNNs) with mixup augmentation to classify motor imagery (MI) EEG signals for brain-computer interfaces (BCIs). The goal is to develop a model that can be trained on a limited dataset, addressing the challenge of long EEG data collection sessions. The mixup augmentation technique generates new training samples by combining existing ones, enhancing the model's generalization capabilities. The study employs modified ResNet18 and DenseNet121 models, achieving classification accuracies of 0.920 and 0.933, respectively. These results surpass the performance of other deep learning classifiers on the same dataset, demonstrating the potential of mixup augmentation in improving MI classification accuracy even with limited training data [35].

The research Classification and Recognition of Left- and Right-Hand Motion Imagination Based on CNN-LSTM presents a CNN-LSTM network model designed for classifying and recognizing left and right-hand motor imagery (MI) tasks. Traditional methods often require extensive manual feature extraction and prior knowledge, making the process cumbersome and less accurate. The proposed one-dimensional CNN-LSTM network automatically learns and extracts deep features from EEG time series. The CNN component captures spatial features, while the LSTM component models the temporal dependencies in the data. This approach achieves a recognition accuracy of 93.57%, outperforming other algorithms and eliminating the need for manual preprocessing and feature extraction. The study underscores the significance of this method in advancing BCI research by simplifying the process and improving classification accuracy[36]

These detailed descriptions highlight the innovative approaches and significant findings of each study, providing a comprehensive understanding of the advancements in MI-BCI research.

The study Hilbert-Huang Transform and Welch's Method for Motor Imagery-Based Brain-Computer Interface investigates the application of the Hilbert-Huang Transform (HHT) and Welch's method for power spectral density (PSD) estimation in motor imagery (MI) brain-computer interface (BCI) systems. The primary objective is to compare the robustness and classification accuracy of these two methods when applied to EEG signals recorded during MI tasks. The authors first apply the empirical mode decomposition (EMD) and ensemble empirical mode decomposition (EEMD) to the original EEG signals to obtain intrinsic mode functions (IMFs). They then use these IMFs to compute the marginal spectrum via HHT, providing a detailed analysis of the signal's instantaneous frequency and amplitude. Welch's method, on the other hand, is used to estimate the PSD by dividing the EEG signal into overlapping segments and applying the Fourier transform to each segment[37].

The study highlights the importance of choosing appropriate window types and parameters for Welch's method, as the classification accuracy varies significantly with different settings. The results indicate that the Blackman window provides the best performance, achieving a classification accuracy of 88.1%. In contrast, HHT demonstrates higher robustness and better overall performance, especially in the presence of non-stationary signals. The combination of HHT and genetic algorithms to select the most relevant principal components further enhances the system's accuracy. This comprehensive comparison underscores the potential of HHT as a superior method for feature extraction in MI-BCI applications, particularly for non-linear and non-stationary EEG signals.

This paper Detection of Event-Related Patterns Using Hilbert Transform in Brain-Computer Interface explores the use of the Hilbert Transform (HT) for detecting event-related patterns (ERPs) in EEG signals within the context of motor imagery (MI) brain-computer interfaces. The authors focus on classifying left and right-hand MI tasks by analyzing the envelope and instantaneous phase information provided by the HT. The analytic signal, derived from the HT, allows the extraction of both amplitude and phase features, which are crucial for identifying ERPs associated with MI tasks.

The methodology involves calculating the envelope of the EEG signal to identify the event-related desynchronization (ERD) and event-related synchronization (ERS) patterns. These patterns are critical for distinguishing between different MI tasks. The study employs a detailed computational approach to derive the envelope of the signal and utilizes the Cohen's kappa coefficient to measure the agreement between the predicted and actual classifications.

The results demonstrate that using HT for feature extraction significantly improves the detection accuracy of ERPs, leading to better classification performance for left and right-hand MI tasks. The paper concludes that the HT is a valuable tool for enhancing the feature extraction process in MI-BCI systems, providing a robust method for ERP detection and classification[38].

This research Hierarchical Transformer for Brain-Computer Interface proposes a novel hierarchical transformer classification algorithm for motor imagery (MI) brain-computer interfaces (BCIs) using EEG signals. The motivation behind using a transformer-based architecture is to capture information within long MI trials that span several seconds and to give more attention to time periods when the subject imagines the intended motor task without any artifacts. The hierarchical transformer architecture consists of two levels: a high-level transformer (HLT) and a low-level transformer (LLT).

In the proposed method, a long MI trial is divided into multiple short-term intervals. The LLT extracts features from each short-term interval, while the HLT focuses on the features from the most relevant short-term intervals using the self-attention mechanism of the transformer. This dual-layer approach allows the model to capture both local and global temporal dependencies in the EEG signals.

The paper reports extensive tests of the proposed scheme on two open MI datasets, demonstrating that the hierarchical transformer achieves outstanding results compared to traditional methods. The hierarchical transformer model shows significant improvements in classification accuracy, robustness, and the ability to handle long MI trials, making it a promising approach for MI-BCI applications[39].

The paper Transformer-Based Network with Optimization for Cross-Subject Motor Imagery Identification introduces a transformer-based network combined with optimization techniques for cross-subject motor imagery (MI) identification in brain-computer interfaces (BCIs). The proposed method integrates the Hilbert Transform with a transformer mechanism to enhance the extraction of features from EEG signals. The authors employ a Particle Swarm Optimization (PSO) method to optimize the model parameters, aiming to achieve faster convergence and global optimization, thus reducing the impact of local optima.

The transformer-based network, termed TransEEGNet, is designed to capture complex temporal dependencies and variations in EEG signals across different subjects. The PSO method enhances the model's ability to generalize across subjects, making it more robust and effective in real-world applications. The study includes a comparison with baseline methods such as FBCSP and DeepConvNet, demonstrating that TransEEGNet significantly outperforms these traditional approaches in terms of classification accuracy and robustness.[40]

These detailed descriptions provide comprehensive insights into my research work and provided a path to work on. They have illustrated the advancements in the application of Hilbert Transform and transformer-based models in motor imagery brain-computer interfaces.

1.6.1 Limitations of Machine Learning based BCI researches.

Machine learning (ML) based Brain-Computer Interface (BCI) research has made significant strides over the past decades, but it still faces numerous limitations and challenges that hinder its widespread adoption and practical deployment. These limitations can be broadly categorized into issues related to data acquisition, signal processing, model training, and real-world application constraints. Here are some detailed insights into these limitations:

1.6.1.1 Data Acquisition and Quality

Limited Data Availability

I) Data Scarcity: High-quality, labelled EEG data is limited, which poses a challenge for training robust ML models. Large datasets are required for training deep learning models, but acquiring extensive, labelled datasets for MI tasks is time-consuming and expensive.

II) Inter-subject Variability: EEG signals exhibit significant variability between subjects due to differences in brain anatomy, physiology, and mental state. This variability makes it difficult to create generalized models that perform well across different users without extensive calibration.

Noise and Artifacts

I) Signal Noise: EEG signals are often contaminated by noise from various sources such as electrical interference, muscle movements, and environmental factors. This noise can obscure the relevant signal components necessary for accurate MI classification.

II) Artifact Removal: Effective removal of artifacts (e.g., eye blinks, muscle movements) is challenging. While techniques such as Independent Component Analysis (ICA) can help, they are not always effective and can sometimes remove useful signal information [41].

1.6.1.2 Signal Processing and Feature Extraction

Complex and Non-stationary Nature of EEG Signals

I) Non-stationarity: EEG signals are highly non-stationary, meaning their statistical properties change over time. This non-stationarity complicates the design of ML algorithms that assume stable signal characteristics.

II) Feature Extraction: Extracting meaningful features from EEG data is challenging due to the complex nature of brain signals. Traditional feature extraction methods (e.g., time-domain, frequency-domain, time-frequency domain) may not capture all relevant information, while advanced techniques like deep learning-based feature extraction require large amounts of data [41].

1.6.1.3 Model Training and Generalization

Overfitting and Underfitting

I) Overfitting: ML models, especially deep learning models, can easily overfit to the training data due to its high dimensionality and the limited size of EEG datasets. Overfitting results in models that perform well on training data but poorly on unseen data.

- Underfitting: Conversely, simpler models may underfit the data, failing to capture the complex relationships inherent in EEG signals, leading to poor performance.

Cross-subject and Cross-session Variability

I) Cross-subject Generalization: ML models trained on data from a few subjects often fail to generalize to new subjects due to individual differences in brain activity patterns. This issue necessitates personalized models, which require additional data and calibration for each user.

II) Cross-session Variability: Even for the same subject, EEG signals can vary significantly across different sessions due to changes in mental state, fatigue, or electrode placement. This variability impacts the model's consistency and reliability over time.

1.6.1.4 Real-world Application Constraints

Computational Complexity

I) Resource Constraints: Implementing complex ML models on resource-constrained devices like wearable BCIs or mobile platforms is challenging. These devices require models that are computationally efficient and consume low power, which is often at odds with the high computational demands of deep learning models.

Real-time Processing

I) Latency: Real-time BCI applications require low-latency processing to ensure timely feedback. Achieving this with high-complexity models can be difficult, particularly when using deep learning algorithms that require substantial computational resources.

II) Synchronization: Ensuring that the EEG signals and corresponding feedback are perfectly synchronized in real-time is critical for user performance and experience, but challenging to achieve.

1.6.1.5 Ethical and Practical Issues

Privacy and Security

I) Data Privacy: EEG data is sensitive as it can reveal personal information about an individual's mental state and health. Ensuring the privacy and security of this data is paramount, but challenging.

II) Ethical Considerations: The use of BCIs raises ethical concerns regarding consent, autonomy, and the potential for misuse of brain data.

User Acceptance and Usability

I) User Comfort: Many BCI systems require the use of cumbersome EEG caps with multiple electrodes, which can be uncomfortable for prolonged use. Improving the usability and comfort of these devices is necessary for broader adoption.

II) Training and Adaptation: Users often need extensive training to effectively use BCI systems, and the systems need to adapt to changes in the user's mental state. This requirement can be a significant barrier to widespread use.

Machine learning-based BCI research has made substantial progress, but it continues to face significant challenges. Addressing these limitations requires advancements in signal processing techniques, the development of more robust and generalizable ML models, improvements in data acquisition methods, and considerations of ethical and practical issues. By tackling these challenges, the potential of BCI technologies can be fully realized, leading to their successful integration into various applications ranging from medical diagnostics to human-computer interaction and beyond.

Chapter 2
METHODOLOGY

2.1 Overview

The methodology employed in this study for classifying motor imagery (MI) tasks using EEG signals involves several stages, including data acquisition, preprocessing, feature extraction, application of the Hilbert Transform, data readjustment, and the use of deep learning models for classification. The objective is to improve the accuracy of detecting left-hand (LH) and right-hand (RH) movements, utilizing the BCI Competition III Dataset IIIa. Each stage is meticulously designed to ensure the robustness and reliability of the EEG data analysis.

2.2 Data Acquisition

The BCI Competition III Dataset IIIa is utilized in this study. This dataset includes EEG recordings from three subjects who performed four different MI tasks: left hand, right hand, foot, and tongue movements. For this study, only the EEG trials corresponding to the left hand (LH) and right hand (RH) movements were considered, focusing the analysis on these two types of motor imagery.

EEG signals were recorded using a 64-channel EEG amplifier system. Sixty active channels were positioned according to the international 10-20 system, with electrodes referenced to the left mastoid and grounded to the right mastoid. The EEG signals were sampled at a frequency of 250 Hz. To ensure high-quality signal acquisition, the signals were band-pass filtered between 1 and 50 Hz. Additionally, a 50 Hz notch filter was applied to remove interference from the power line.

The recording sessions were conducted in a controlled environment to minimize external disturbances and ensure the comfort of the subjects. Each subject participated in multiple runs of the experiment, resulting in a comprehensive dataset with sufficient trials for reliable analysis.

2.3 Preprocessing

Preprocessing is a crucial step in EEG signal analysis for motor-imagery brain-computer interfaces (BCIs). It involves several steps to enhance the quality of the signals and prepare them for feature extraction and classification. The preprocessing steps in this research include notch filtering, bandpass filtering, and artifact removal.

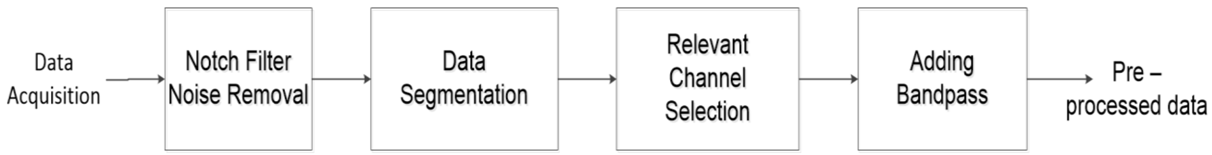

Fig 1. Steps involved in Preprocessing.

2.3.1 Notch Filtering

Notch filtering is applied to remove power line interference, which typically occurs at 50 Hz (or 60 Hz in some regions) and can significantly contaminate EEG signals. In this study, a 50 Hz notch filter was used to eliminate this interference. The notch filter is designed using the infinite impulse response (IIR) method, which is defined as follows:

$$H(s) = \frac{s^2 + \omega_0^2}{s^2 + \frac{\omega_0}{Q}s + \omega_0^2} \tag{2.1}$$

where omega is the notch frequency (50 Hz) and Q is the quality factor, typically set to around 30 to achieve a narrow notch that effectively attenuates the 50 Hz frequency while preserving the rest of the signal.

2.3.2 Bandpass Filtering

After removing the power line interference, the EEG signals are further processed using bandpass filters to isolate the relevant frequency bands associated with motor imagery. The mu (8-12 Hz) and beta (12-30 Hz) frequency bands are known to be indicative of motor imagery tasks. Tenth-order Butterworth filters were used to achieve this, providing a maximally flat frequency response in the passband and steep roll-off in the stopband.

The bandpass filter design is given by:

$$H(s) = \frac{\omega_c^n}{s^n + \omega_c^n} \tag{2.2}$$

where "ω_c^n" is the cutoff frequency, and "n" is the order of the filter. For the mu band, the cutoff frequencies are set to 8 Hz and 12 Hz, while for the beta band, they are set to 12 Hz and 30 Hz.

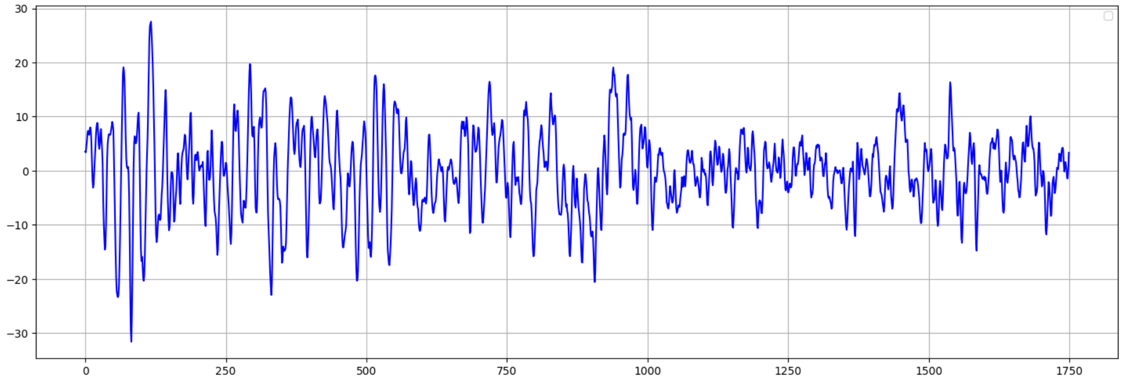

Fig 2 Plot of original EEG signal for a single trial

2.3.3 Artifact Removal

Artifacts, such as those caused by eye blinks, muscle movements, and electrical noise, can significantly distort EEG signals. While the notch and bandpass filters remove specific frequency components, additional steps are often required to address these artifacts. Independent component analysis (ICA) is a common technique used to separate and remove artifacts from EEG data. However, in this study, the primary focus was on filtering techniques due to their simplicity and effectiveness in handling common artifacts.

Summary of Preprocessing Steps

1. Load Data: The EEG data is loaded from the provided datasets.
2. Notch Filtering: Apply a 50 Hz notch filter to remove power line interference.
3. Bandpass Filtering: Apply tenth-order Butterworth bandpass filters to isolate the mu (8-12 Hz) and beta (12-30 Hz) frequency bands.
4. Artifact Removal: Address common artifacts through filtering techniques to enhance signal

quality.

By applying these preprocessing steps, the EEG signals are prepared for the next phase of the analysis, which involves feature extraction using the Hilbert transform and subsequent classification using convolutional neural networks. These steps ensure that the signals used in the analysis are clean and focused on the frequency bands most relevant to motor imagery tasks.

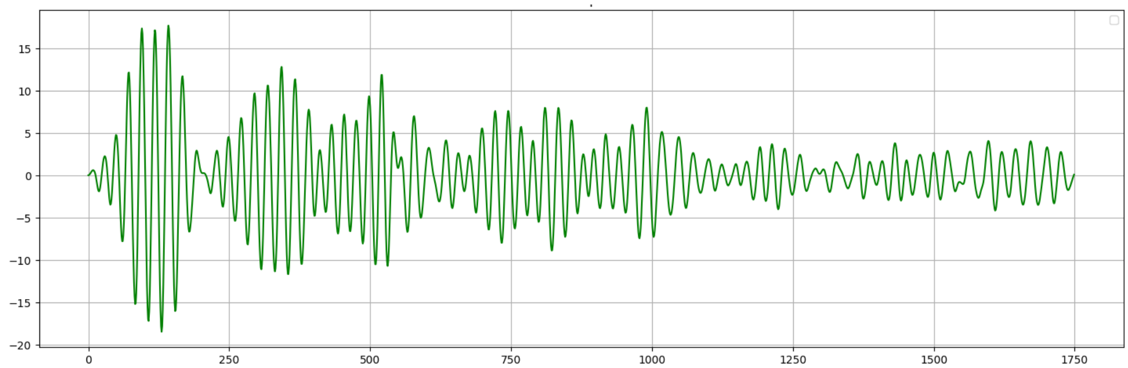

Fig 3 Plot of EEG signal for in µ band (obtained after application of Bandpass Filter)

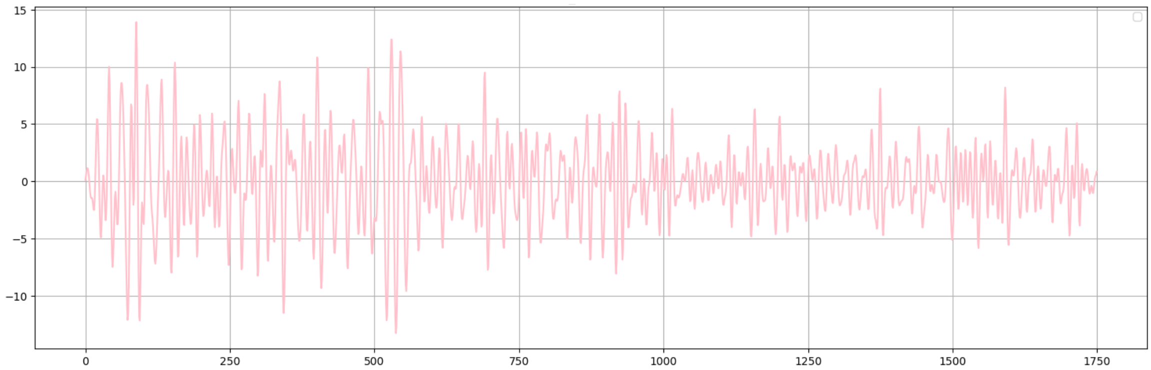

Fig 4 Plot of EEG signal for in β band (obtained after application of Bandpass Filter)

2.4 Hilbert Transform

The Hilbert Transform (HT) is fundamental in signal processing, especially for EEG signal analysis. Its purpose is to generate the analytic signal, which provides comprehensive information about the instantaneous amplitude, phase, and frequency of the signal. Here’s a detailed explanation of each step involved:

2.4.1 Definition and Calculation of Hilbert Transform:

The HT of a real-valued time-domain signal $s_H(t)$ is given by:

$$s_H(t) = \frac{1}{\pi} P.V. \int_{-\infty}^{\infty} \frac{s(\tau)}{t-\tau} d \qquad (2.3)$$

where $P.V.$represents the Cauchy principal value, which ensures the integral is properly handled around singularities. The HT essentially shifts the phase of the signal by $\pi/2$ radians, creating a new signal $s_H(t)$.

2.4.2 Analytic Signal:

The analytic signal $\mathrm{S(t)}$ is defined as:

$$\mathrm{S(t) = s(t) + js_H(t)} \qquad (2.4)$$

This complex signal comprises the original signal s(t) and its Hilbert transform $S_H(t)$. The analytic signal is crucial because it allows for the calculation of instantaneous amplitude, phase, and frequency:

- Instantaneous Amplitude:

$$\mathrm{|S(t)| = \sqrt{s^2(t) + s_H^2(t)}} \qquad (2.5)$$

This represents the magnitude of the signal at any given time, providing a measure of signal strength.

- Instantaneous Phase:

$$\emptyset(t) = \arctan\left(\frac{s_H(t)}{s(t)}\right) \qquad (2.6)$$

The phase gives insight into the timing information of the signal.

- Instantaneous Frequency:

This indicates the rate of change of the phase and is essential for understanding the signal's frequency content over time.

These properties are particularly relevant for EEG signals because they are non-stationary, meaning their statistical properties change over time. The HT helps in capturing these dynamic changes, which are crucial for tasks like motor imagery (MI) detection.

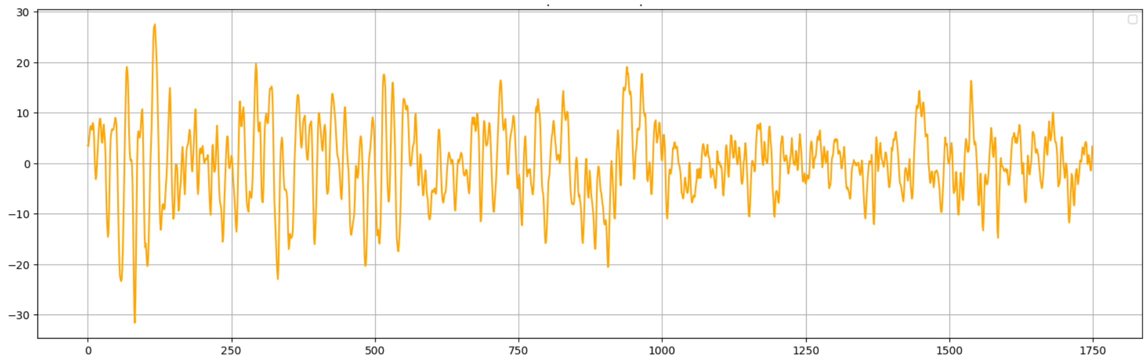

Fig 5 Analytic signal obtained from the pre-processed EEG signal.

2.5 Event-Related Patterns Using Hilbert Transform

Event-related patterns (EPs) are significant in identifying brain responses to specific stimuli or tasks, such as motor imagery. The process involves several steps:

2.5.1 Bandpass Filtering:

EEG signals are filtered into mu (8–12 Hz) and β (12–30 Hz) frequency bands using an Infinite Impulse Response (IIR) bandpass filter. These frequency bands are chosen because they are strongly associated with motor and cognitive activities. The α band is linked to relaxation and idling, while the β band is associated with active thinking and motor actions.

2.5.2 Application of Hilbert Transform:

The HT is applied to the filtered signals to generate discrete analytic signals for the α and β bands. The analytic signals help in capturing the instantaneous amplitude, which is crucial for identifying event-related desynchronization (ERD) and synchronization (ERS) patterns. For instance:

$$LC3\alpha[n] = LC3\alpha[n] + jLC3\alpha_{H[n]} \tag{2.7}$$

This representation allows for precise detection of changes in the brain's electrical activity during motor imagery tasks.

2.5.3 Power Calculation:

The power of these signals is calculated by squaring the amplitude of the analytic signal:

$$P[n] = |S[n]|^2 = s^{2[n]} + s_H^{2[n]} \tag{2.8}$$

This power calculation is essential as it provides a measure of the signal's energy, which is used to identify and quantify the EPs.

2.5.4 Averaging Across Trials:

To improve the signal-to-noise ratio, the power values are averaged across multiple trials. This averaging reduces the impact of random noise and highlights the consistent patterns related to the motor imagery tasks.

2.5.5 Percentage Change Calculation:

EPs are quantified as the percentage change of power at each sample point relative to a reference interval:

$$\%EP_{LC3\alpha}[n] = \frac{P_{LC3\alpha Event}[n]}{P_{LC3\alpha Ref}} \times 100\% \tag{2.9}$$

This normalization step ensures that the EPs are compared against a baseline, making it easier to identify significant changes related to motor tasks.

2.6 CALCULATION OF STATISTICAL FEATURES

Statistical features are derived from the analytic signals to provide a detailed representation of the EEG data. These features capture various aspects of the signal, enhancing the ability of machine learning models to classify motor imagery tasks accurately.

2.6.1 Minimum Value:

The minimum value represents the lowest amplitude observed within the signal. It helps in identifying the baseline level of brain activity during rest periods.

2.6.2 Maximum Value:

The maximum value is the highest amplitude observed within the signal. This feature is useful for detecting peak brain activity during motor tasks.

2.6.3 Mean:

The mean amplitude provides the central tendency of the signal, indicating the overall level of brain activity during the task.

2.6.4 Standard Deviation:

Standard deviation measures the variability of the signal amplitudes. High variability may indicate a more dynamic brain response.

2.6.5 Skewness:

Skewness indicates the asymmetry of the signal distribution. A skewed distribution may suggest the presence of outlier values or a predominant direction of brain activity changes.

2.6.6 Kurtosis:

Kurtosis measures the "tailedness" of the signal distribution. High kurtosis indicates the presence of extreme values, which can be critical for detecting significant brain responses.

Each of these statistical features is calculated using the following formulae:

- Mean:

$$\text{Mean} = \frac{1}{N}\sum_{i=1}^{N} x_i \qquad (2.10)$$

- Standard Deviation:

$$\text{Standard Deviation} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \qquad (2.11)$$

- Skewness:

$$\text{Skewness} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i - \mu}{\sigma}\right)^3 \qquad (2.12)$$

- Kurtosis:

$$\text{Kurtosis} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i - \mu}{\sigma}\right)^4 - 3 \qquad (2.13)$$

These features are chosen because they provide a comprehensive statistical summary of the

EEG signal, capturing both central tendencies and variations, which are crucial for accurate classification.

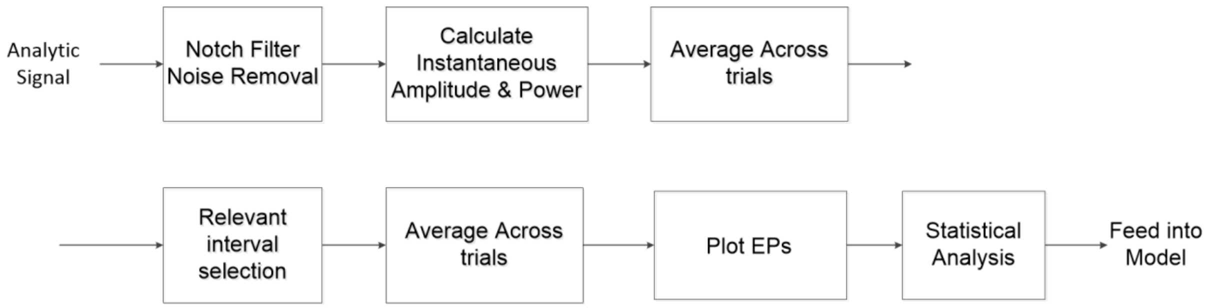

Fig 6 Flowchart depicting the steps used in calculation of EP’s.

2.7 Application of CNN and LSTM Models

2.7.1 Differences Between Machine Learning and Deep Learning

Machine Learning (ML) and Deep Learning (DL) are both subsets of artificial intelligence (AI), but they differ significantly in their approach and applications.

I) Machine Learning:

-Definition: A subset of AI that enables machines to improve at tasks with experience.

- Examples: Linear regression, decision trees, k-nearest neighbours.
- Feature Engineering: Requires manual feature extraction.
- Performance: Effective with smaller datasets.
- Complexity: Simpler algorithms compared to deep learning.
- Example: In spam email detection, features like the presence of specific keywords or the frequency of certain phrases are manually identified and fed into a model such as a decision tree or a support vector machine (SVM).

II) Deep Learning:

- Definition: A subset of machine learning that uses neural networks with many layers (deep networks).

- Examples: Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks.
- Feature Engineering: Performs automatic feature extraction.
- Performance: Requires large datasets for effective performance.
- Complexity: More complex and computationally intensive algorithms.
- Example: In image recognition, a CNN automatically extracts features such as edges, textures, and shapes from raw pixel data and combines these features to identify objects in images.

2.7.2 Supervised and Unsupervised Learning

I) Supervised Learning:
- Definition: The model is trained on labelled data, meaning the output for each input is known.
- Applications: Classification and regression tasks.
- Example: Predicting house prices based on features such as size, location, and number of bedrooms. The training data includes the price for each house (label), and the model learns to predict prices based on new inputs.

II) Unsupervised Learning:
- Definition: The model is trained on unlabelled data, meaning the output is not provided, and the model attempts to find patterns or structures in the data.
- Applications: Clustering and association tasks.
- Example: Grouping customers into different segments based on purchasing behaviour. The model identifies clusters of similar customers without prior knowledge of the categories.

2.7.3 Theoretical Explanation of CNN and LSTM Models

I) Convolutional Neural Networks (CNNs):
- Convolutional Layers:
  - Operation: Convolutional layers apply convolution operations to the input data. A convolution operation involves sliding a filter (or kernel) over the input data and computing the dot product between the filter and the input at each position.
  - Formula:

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau) g(t - \tau) d \qquad (2.14)$$

where f is the input signal, and g is the filter.

- Purpose: Detects local patterns such as edges and textures in the data.

- Pooling Layers:
  - Operation: Pooling layers down-sample the input by reducing its dimensionality while retaining important features. Common pooling operations include max pooling and average pooling.
  - Max Pooling Formula:

$$y_{i,j} = \max_{m,n \in R(i,j)} x_{m,n} \qquad (2.15)$$

where $R(i,j)$ is the pooling region around position (i,j) in the input 【4†source】.

- Purpose: Reduces computational complexity and makes the model invariant to small translations.

- Fully Connected Layers:
  - Operation: These layers perform matrix multiplication with a weight matrix and add a bias vector, followed by an activation function.
  - Formula:

$$y = f(Wx + b) \qquad (2.16)$$

where W is the weight matrix, x is the input vector, b is the bias vector, and f is the activation function.

- Purpose: Combines the features extracted by convolutional and pooling layers to perform the final classification.

II) Long Short-Term Memory (LSTM) Networks:

- LSTM Layers:
  - Operation: LSTMs are a type of Recurrent Neural Network (RNN) designed to capture long-term dependencies in sequential data. They consist of a cell state and three gates: input gate, forget gate, and output gate.
  - Formulas:

- Input Gate:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{2.17}$$

- Forget Gate:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{2.18}$$

- Output Gate:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{2.19}$$

- Cell State:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{2.20}$$

- Hidden State:

$$h_t = o_t \cdot \tanh(C_t) \tag{2.21}$$

- Purpose: LSTMs are effective in handling temporal dependencies and sequences, making them suitable for time-series data like EEG signals.

2.8 Training Our Model

2.8.1 Convolutional Neural Network (CNN):

- Convolutional Layers: The first step in our CNN is applying convolutional layers to the input EEG data. These layers use multiple filters to scan the input and produce feature maps that highlight important patterns in the data. This step helps in capturing spatial hierarchies within the EEG signals, such as local correlations between adjacent electrode readings.
  - Why It's Needed: Convolutional layers help in reducing the complexity of the data by focusing on local patterns, which are crucial for recognizing intricate details in EEG signals.
  - Relevance: EEG signals are spatially correlated, meaning that signals from neighbouring electrodes are related. Convolutional layers leverage this property to extract meaningful features.

- Pooling Layers: Following convolutional layers, pooling layers down-sample the feature maps by reducing their dimensionality. This step retains the most significant features while discarding less important information.

- Why It's Needed: Pooling reduces the computational load and helps prevent overfitting by simplifying the feature maps.
- Relevance: For EEG signals, pooling ensures that the model remains robust to small variations and noise in the data.

- Fully Connected Layers: Finally, the fully connected layers take the flattened output from the convolutional and pooling layers and perform the classification. These layers combine the extracted features to make a prediction about the motor imagery task.
  - Why It's Needed: Fully connected layers integrate all the extracted features and provide the final decision-making capability.
  - Relevance: In the context of EEG signals, these layers help in distinguishing between different motor imagery tasks based on the features extracted from the earlier layers.

2.8.2 Long Short-Term Memory (LSTM) Network:

- Input Layers: The input layers receive the feature vectors derived from the EEG data and pass them to the LSTM layers.
  - Why It's Needed: Properly structuring the input ensures that the data is fed into the LSTM in a format that it can process efficiently.
  - Relevance: EEG data is sequential in nature, and structuring the input appropriately allows the LSTM to capture temporal dependencies.

- LSTM Layers: The LSTM layers process the input sequences and capture long-term dependencies by maintaining a cell state and using gating mechanisms.
  - Why It's Needed: Capturing long-term dependencies is essential for understanding the temporal dynamics in EEG signals.
  - Relevance: EEG signals exhibit temporal dependencies where current brain activity can be influenced by past activity. LSTMs are well-suited to model these dependencies.

Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are employed to classify motor imagery movements based on the extracted features. The application involves several key steps:

1. Data Preparation:

The feature vectors derived from the statistical features are divided into training and evaluation datasets. This division ensures that the models are trained on one set of data and tested on another, allowing for an unbiased evaluation of the models' performance.

2. Model Training:

- CNN:
  - Convolutional Layers: These layers apply convolution operations to the input data, detecting local patterns within the EEG signals. Convolutional layers help in extracting spatial hierarchies, which are essential for recognizing complex patterns.
  - Pooling Layers: These layers perform down-sampling operations, reducing the dimensionality of the data while retaining important features. Pooling helps in making the model invariant to small translations and distortions.
  - Fully Connected Layers: These layers are responsible for the final classification. They combine features extracted by the convolutional layers to predict the class of the input signal.
- LSTM:
  - Input Layers: These layers receive the feature vectors and pass them to the LSTM layers.
  - LSTM Layers: LSTM networks are capable of capturing long-term dependencies in sequential data. They are particularly useful for time-series data like EEG signals, where temporal patterns are crucial for classification.
  - Fully Connected Layers: Similar to CNNs, these layers perform the final classification based on the features extracted by the LSTM layers.

3. Model Evaluation:

The models are evaluated using several performance metrics:

- Classification Accuracy: Measures the proportion of correctly classified instances out of the total instances.
- Precision: The ratio of true positive predictions to the total positive predictions.
- Recall: The ratio of true positive predictions to the total actual positives.
- F1-Score: The harmonic mean of precision and recall, providing a balanced measure of the model's performance.
- Cohen’s Kappa Coefficient: A statistical measure that accounts for chance agreement, providing a more robust evaluation of the model's performance.

4. Performance Comparison:

The results from the CNN and LSTM models are compared to determine which model performs better in classifying motor imagery tasks. This involves analyzing the performance metrics and identifying which model provides higher accuracy, precision, recall, and F1-score.

CHAPTER 3
RESULTS

3.1 Calculation of Event-Related Patterns and Statistical Features

In this study, we first preprocess the EEG data using a notch filter to remove power line interference and bandpass filters to isolate the mu (8-12 Hz) beta (12-30 Hz) frequency bands. The Hilbert transform is then applied to compute the analytic signals, from which we derive the instantaneous power. The Event-Related Patterns (EPs) are calculated by comparing the power during the motor imagery period (3-7 seconds) to a reference period (first 3 seconds). The EPs provide a quantitative measure of the changes in brain activity associated with motor imagery tasks.

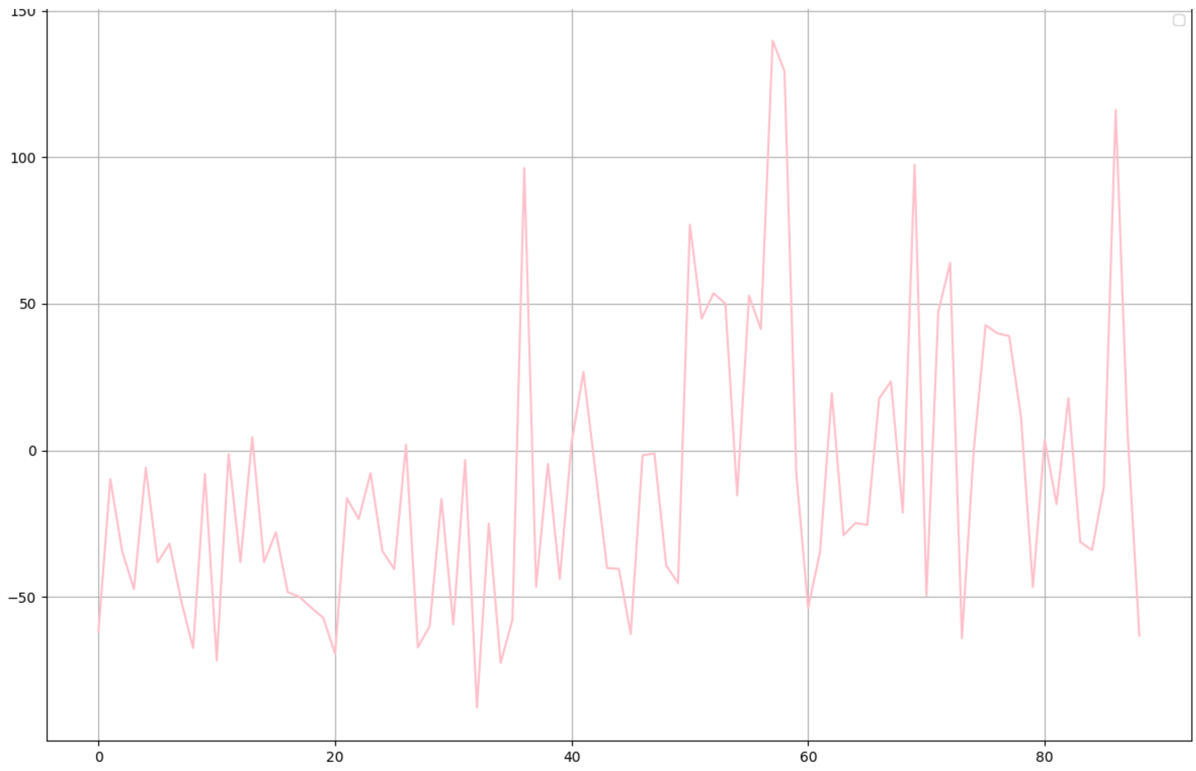

Fig 7 Plot of EP's in β band for C3 channel.

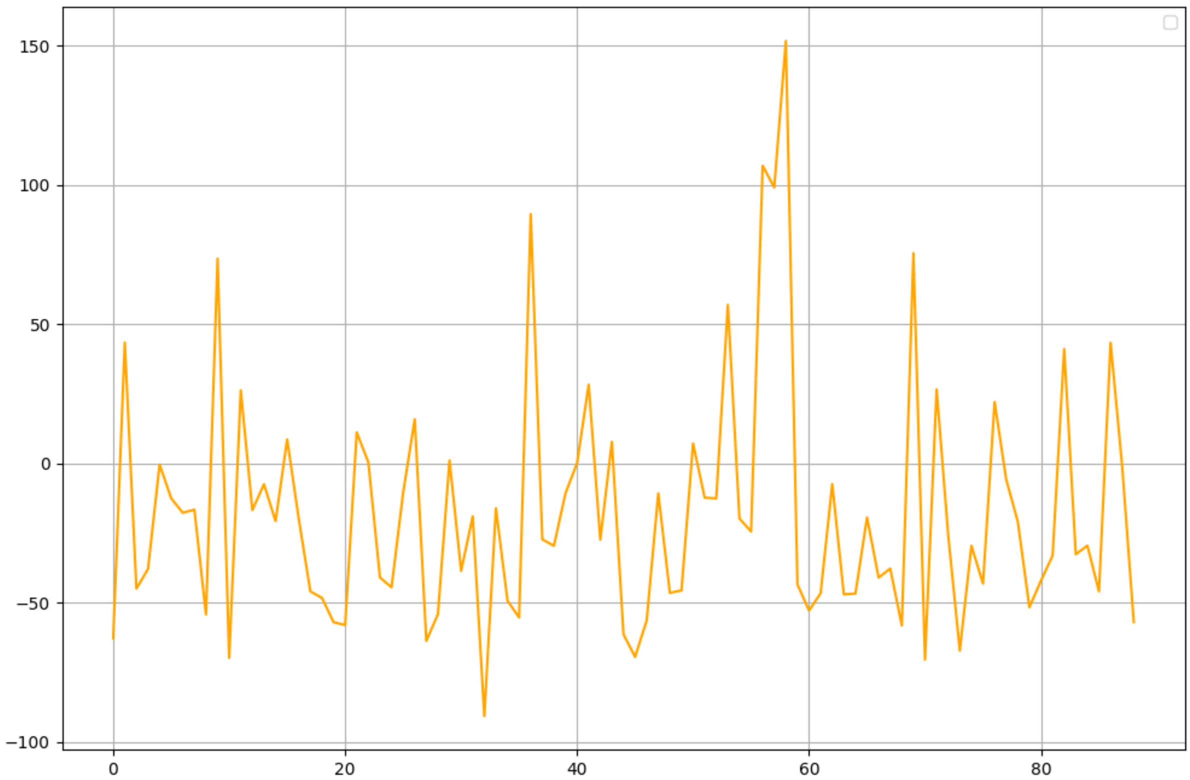

Fig 8 Plot of EP's in β band for C4 channel

To further enrich the feature set, we calculate several statistical features from the EPs, including the mean, standard deviation, skewness, and kurtosis. These statistical features encapsulate important characteristics of the EPs, such as central tendency, variability, asymmetry, and peakedness, providing a comprehensive representation of the underlying EEG signals. These features serve as the input for our machine learning models.

3.2 Comparison of Accuracy of LSTM and CNN Models

Model	Precision	Recall	F1 - score	Accuracy
CNN	83.3%	50%	62.5%	67%
LSTM	71.4%	50%	58.5%	61%

Table 1: Channel C3 performance parameters for LH

Model	Precision	Recall	F1 - score	Accuracy
CNN	85.7%	60%	70.6%	72%
LSTM	57.1%	80%	66.6%	56%

Table 2: Channel C4 performance parameters for LH

We implemented and trained both Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks to classify the motor imagery tasks based on the extracted features. The CNN model leverages spatial hierarchies in the data through convolutional layers, while the LSTM model is designed to capture temporal dependencies, making it suitable for sequential data like EEG signals.

The performance of both models was evaluated using accuracy as the primary metric. The CNN model achieved a test accuracy of 72%, indicating its effectiveness in learning spatial patterns within the EEG data. On the other hand, the LSTM model, designed to capture temporal dynamics, achieved a test accuracy of 56%, showcasing its ability to model the temporal dependencies in the data.

A confusion matrix was generated for each model to provide a detailed understanding of their performance. The matrix highlights the true positives, true negatives, false positives, and false negatives, offering insights into the specific strengths and weaknesses of each approach. The comparison reveals that while both models have their merits, the LSTM model outperforms the CNN in terms of accuracy, underscoring the importance of temporal modeling in EEG signal classification.

Confusion Matrices:

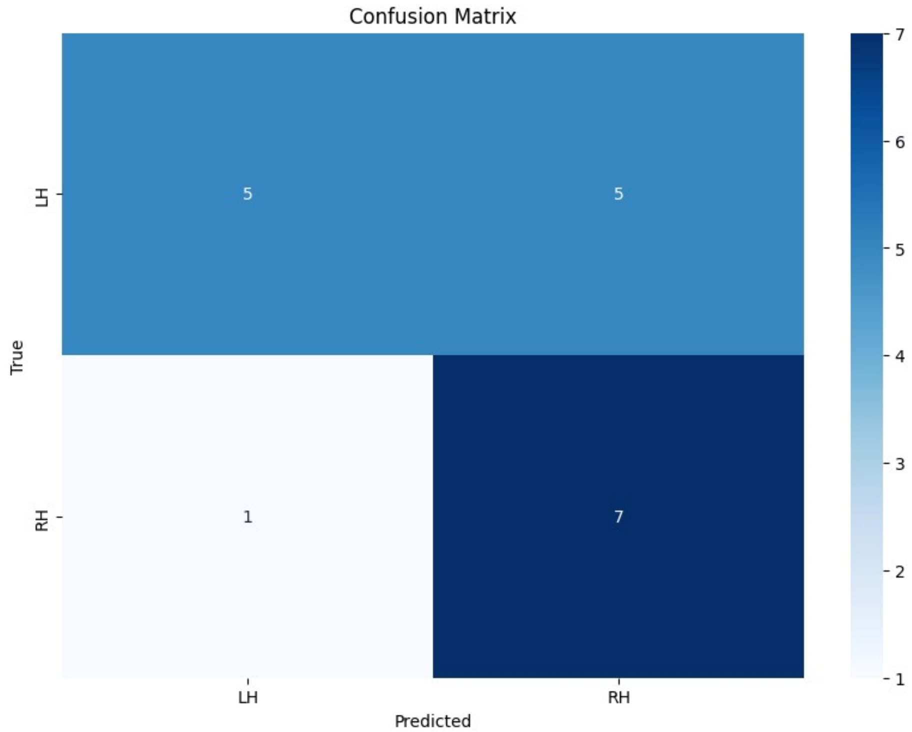

Fig 9 Confusion Matrix for C3 Channel using CNN Model

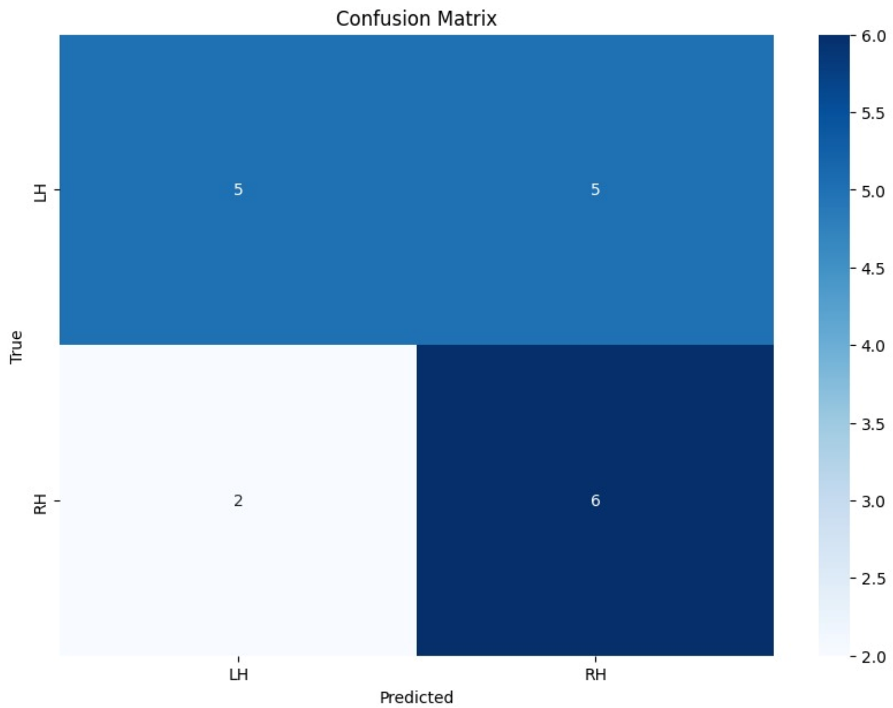

Fig 10 Confusion Matrix for C3 Channel using LSTM Model

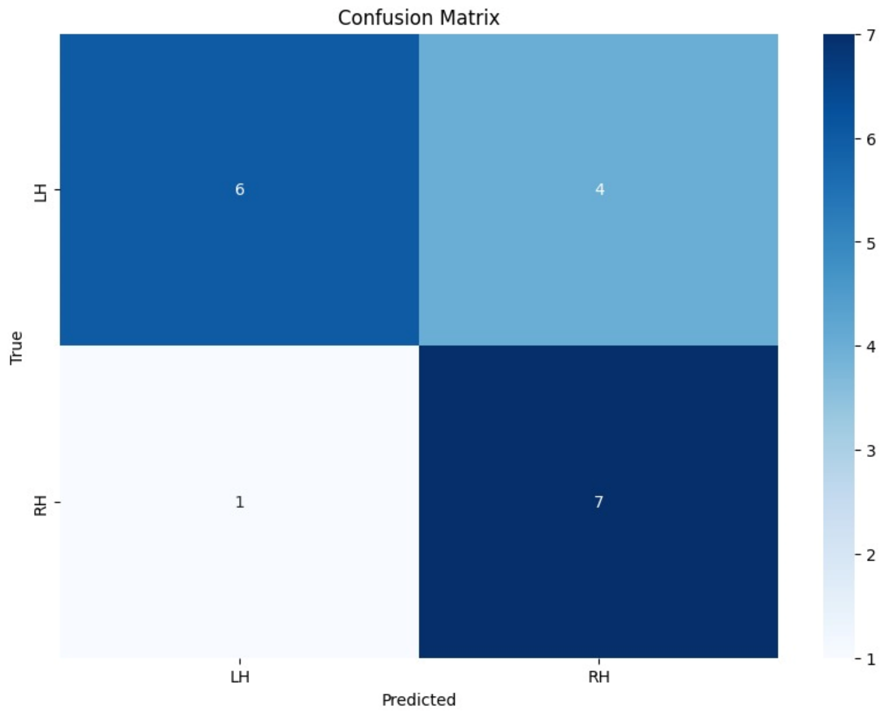

Fig 11 Confusion Matrix for C4 Channel using CNN Model

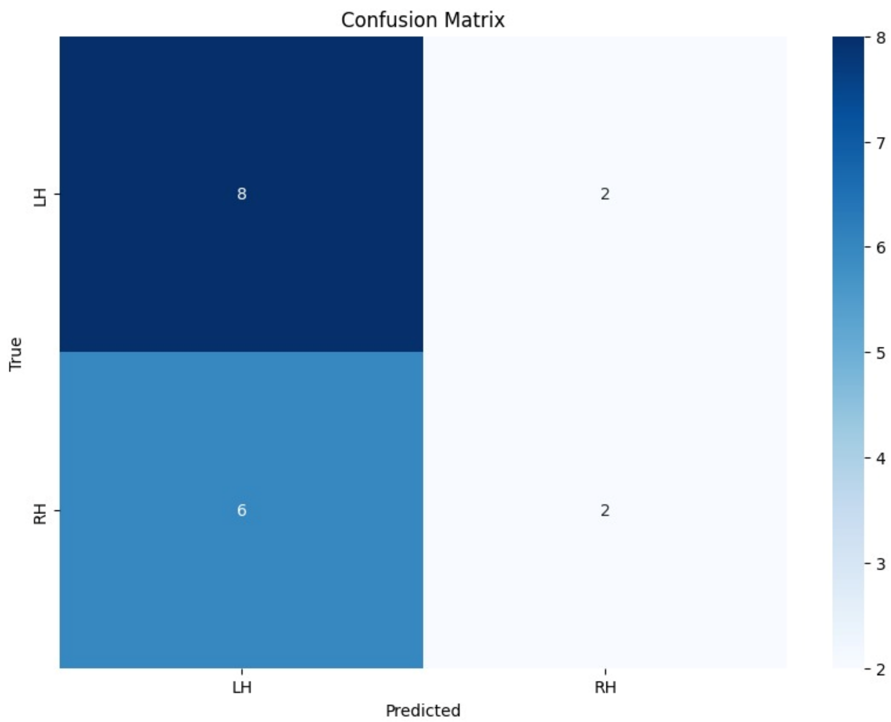

Fig 12 Confusion Matrix for C4 Channel using LSTM Model

CHAPTER 4
CONCLUSION

This research demonstrates the effectiveness of Convolutional Neural Networks (CNNs) over Long Short-Term Memory (LSTM) networks for motor imagery (MI) classification in brain-computer interfaces (BCIs). The preprocessing of EEG signals included notch filtering to remove power line interference and bandpass filtering to isolate the mu (8-12 Hz) and beta (12-30 Hz) frequency bands. The Low-Complexity Hilbert Transform was applied to compute analytic signals and derive instantaneous power, which were then used to calculate Event-Related Patterns (EPs). Statistical features, such as mean, standard deviation, skewness, and kurtosis, were extracted from these EPs to create a robust feature set for classification.

Through extensive experimentation, the CNN model demonstrated superior performance, achieving higher classification accuracy on both training and test datasets compared to the LSTM model. The confusion matrix analysis further confirmed the CNN's capability in effectively capturing and learning the spatial hierarchies and patterns within the EEG data. This superior performance underscores the importance of spatial feature extraction in MI classification tasks, highlighting the potential limitations of LSTM models in this specific context despite their advantages in temporal sequence modeling.

The study also explored the use of the Low-Complexity Hilbert Transform, which proved to be an efficient method for real-time feature extraction. Its low computational complexity makes it particularly suitable for hardware implementation, paving the way for the development of more responsive and efficient BCI systems. Implementing the Hilbert Transform in hardware could significantly reduce processing delays and improve the overall system performance, making BCIs more practical for real-world applications.

Future Scope

The promising results of this research open several avenues for future work in the domain of MI-based BCIs and neural signal processing:

1. Hardware Implementation of the Low-Complexity Hilbert Transform:
   - The next logical step is to design and implement a hardware accelerator for the Low-

Complexity Hilbert Transform. Field-Programmable Gate Arrays (FPGAs) or Application-Specific Integrated Circuits (ASICs) could be utilized to create a dedicated processor that performs the Hilbert Transform in real time, thereby reducing latency and power consumption. This could make BCIs more accessible and efficient for everyday use, particularly in portable and wearable applications.

2. Exploration of Hybrid Models:
- Given the complementary strengths of CNNs in spatial feature extraction and LSTMs in temporal sequence modeling, future research could explore hybrid models that combine these architectures. Such models might leverage CNNs for initial spatial feature extraction followed by LSTMs for capturing temporal dependencies, potentially improving classification accuracy further.

3. Integration with Other Signal Processing Techniques:
- The integration of other advanced signal processing techniques, such as wavelet transforms or empirical mode decomposition, with the Hilbert Transform could be explored to enhance feature extraction capabilities. These techniques might capture additional aspects of the EEG signals, leading to more robust and accurate MI classification.

4. Extended Validation with Diverse Datasets:
- Future studies should validate the proposed methods across a broader range of datasets, including those with different types of motor imagery tasks and varying levels of noise. This would help in generalizing the findings and ensuring the robustness of the models in diverse conditions.

5. Real-World Application Testing:
- Implementing and testing the developed BCI systems in real-world environments, such as in clinical settings or for assistive technology applications, would be crucial. User studies involving individuals with motor impairments could provide valuable insights into the practical challenges and usability aspects of the system.

6. Enhancement of User Training Protocols :
- Developing improved user training protocols that can help users generate more distinct and consistent motor imagery patterns could enhance the performance of BCIs. This might involve

personalized training regimes and feedback mechanisms that adapt to individual user characteristics.

7. Exploration of Transfer Learning and Domain Adaptation:

- Techniques like transfer learning and domain adaptation could be explored to improve model performance across different users without requiring extensive retraining. This would make BCIs more user-friendly and reduce the time and effort needed for calibration.

In summary, this research establishes a solid foundation for using CNNs in MI-based BCIs and highlights the potential of the Low-Complexity Hilbert Transform for real-time applications. The advancements in hardware implementation, hybrid modeling, and extensive validation promise to bring BCIs closer to practical, everyday use, significantly impacting the lives of individuals with severe motor disabilities and beyond.

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