DEVELOPING ARTIFICIAL INTELLIGENCE BASED ALGORITHMS FOR AUTOMATIC ANALYSIS OF BRAIN SIGNAL DATA FOR ADVANCED BCI SYSTEMS

A Dissertation Submitted by
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ABSTRACT

Motor disability is a limitation of a person's physical functioning, movement, ability or stamina to move and maintain balance. To eliminate this suffering from society, motor imagery (MI) based brain computer interface (BCI) performs a significant role. An MI-based BCI converts human intention into control signals to communicate with their external device through brain activity without direct physical movement. This brain activity can be recorded by electroencephalography (EEG). The EEG is a test that measures the electrical activity of the brain. EEG generates a vast amount of non-stationary, non-linear, and non-periodic signal data (called 'brain signal data'). Undesirable signals, called noise, commonly contaminate these signal data. Therefore, it is necessary to remove the noise in the raw EEG data to acquire helpful information that reflects brain activities and mental states to identify motor disabled people's intentions. The fast speed and accuracy of BCI systems for recognising MI activity or tasks based on EEG signals is another significant problem. Traditional techniques in BCI have some limitations. These include noise sensitivity, longer iteration, complex method, require enormous amounts of training data, time consuming, applicable only in small dataset which reduces the accuracy, efficiency and robustness of an anticipated method. Therefore, it is necessary to address these issues to develop optimised artificial intelligence (AI) based machine learning technique to identify human intentions of people with motor disabilities for an improved BCI system. Hence, this study aims to introduce AI-based algorithms for identifying human intentions of physical movements through EEG data in BCI's development and to compare them with existing traditional methods.

In this dissertation, we have developed three methods to fulfil our research objective by analysing two publicly available EEG-based BCI datasets:

1) a common spatial pattern (CSP) based Medium K-nearest neighbour machine learning approach

2) a hybrid method: CSP based optimised ensemble (OE)

3) Markov chain-based support vector method.

A short detail of the three developed approaches and their contributions are described.

Approach 1 (CSP-MKNN): To make a more robust approach with lower execution time, we utilized CSP algorithm for feature extraction technique and a MKNN for classification. For noise free data, we applied Butterworth filter ranges from 0.1 Hz to 4 Hz frequency and 5th-order derivations. Our advanced approach produced the highest score for all subjects more than 90% and achieved 3.4% to 14.52% advancements compared with the other existing approaches with the same dataset.

Approach 2 (CSP-OE): To improve the performance, we reformed the CSP- MKNN model by presenting a CSP- based OE algorithm. Our proposed system achieved 99.64% overall accuracy and 1.24% to 26.14% enhancement compared to the earlier machine learning algorithms.

Approach 3 (MC-SVM): We developed a Markov chain-based SVM algorithm to improve the classification of the MI tasks more directly and efficiently. Our proposed system produced the highest score for all individual subjects above 99%, compared with the existing prominent approaches.

The tentative results proved great achievement for detecting MI task. The algorithms can help clinical diagnosis and restoration of motor- impaired persons with external devices.

DECLARATION BY AUTHOR

I, Taslima Khanam, hereby declare that Master of Research thesis entitled *Developing Artificial Intelligence based algorithms for automatic analysis of brain signal data for advanced BCI systems* is no more than 50,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references and footnotes. The work presented in this dissertation is the work of my own except where otherwise acknowledged. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work.

I have conducted my research in alignment with the Australian Code for the Responsible Conduct of Research and Victoria University Higher Degree by Research Policy and Procedures.

[redacted] 17/1/2023

Signature Date

DEDICATION

TO

MY PARENTS

I dedicate this thesis to the living memory of my beloved parents. Thank you very much for your relentless love and compassion throughout your life to support me.

ACKNOWLEDGEMENTS

I would like to start this acknowledgment with my utmost gratitude and thanks to the Almighty God who bestowed fortune upon me to start and finish this challenging work. My Master of Research journey has reached its endpoint with the academic, and mental support of many. Further, without the financial support from the Victoria University, this thesis study would not have been completed.

I would like to acknowledge my late parents, Tafura Begum and Md. Abdul Wadud for their love, support and encouragement. They sowed the dream in me and from their example I have learned the value of hard work and perseverance, which enabled me to complete this research degree.

Most importantly, I want to thank my principal supervisor, Professor Hua Wang for his tremendous support and guidance. His profound support with moral encouragement always surprised me and helped me overcome any problem. I am also thankful and grateful to my associate supervisor, Dr Siuly Siuly, for her special contribution to higher research study journey, especially in developing my academic skills. She was devoted and caring mentors to enable me to gain success in the difficult pathway of achieving the milestones. I also want to express my deep gratitude to Dr. Enamul Kabir for his continuous support from the beginning of this journey.

Thanks also goes to my beautiful sons – Iftekhar Ahmad (Shian) and Ihtiram Ahmad (Shihab) – who have brought such joy to my life. You two have sacrificed more than anyone so that I may complete this journey.

Finally, thank you to my husband, Kabir Ahmad. You have been my source of inspiration through this critical journey. I am truly blessed to have been able to share my research thoughts and challenges and have insightful ‘pep talks’ with the same person that I am building a life and family with.

DETAILS OF INCLUDED PAPERS: THESIS WITH PUBLICATION

Chapter No.	Publication Title	Publication Status	Publication Details	Journal rank
Chapter 3	An optimized artificial intelligence based technique for identifying motor imagery from EEGs for advanced brain computer interface technology	Published	Khanam T, Siuly S, Wang H. An optimized artificial intelligence based technique for identifying motor imagery from EEGs for advanced brain computer interface technology. Neural Computing and Applications. 2022 Nov 24:1-2.	Q1
Chapter 4	Analysing Big Brain Signal Data for Advanced Brain Computer Interface System	Published	Khanam T, Siuly S, Wang H. Analysing Big Brain Signal Data for Advanced Brain Computer Interface System. In Australasian Database Conference 2022 (pp. 103-114). Springer, Cham.	Australasian
Chapter 5	A Markov chain-based feature extraction scheme for automatic analysis of brain signal data for advanced BCI system	Under review	Submitted in IEEE transactions on Cognitive and Developmental Systems	Q1

Declaration by: Taslima Khanam

Signature: [redacted] Date 17/11/2023

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CHAPTER 1

INTRODUCTION

1 Introduction

Motor disabilities are a common condition and disease symptom. Various conditions, such as strokes, brain injuries, and neuromuscular health disorders, cause the gradual deterioration of the use of motor functions and skills (Duncan et al., 2014). Motor skill impairment (MSI) or motor disability is a failure or impairment of a person's ability to perform a physical movement. Worldwide, approximately 15% of the population live with some form of disability; among them, 2–4% suffer significant complexities in motor functioning (Bickenbach, 2011). In Australia, among 18% of disabled people, 22% face motor disability (Health and Welfare, 2020). Generally, cognitive activities associated with motor performance stay intact in healthy people. These cognitive processes utilise brain areas that involve developing progressive muscle action to accomplish specific movements (Svoboda and Li, 2018). However, in the case of motor disability, a person with high motor impairment might go through a locked-in state, resulting in bodily movement hardship. This condition influences the quality of life of those experiencing neurological or neuromuscular syndromes. It prevents them from performing simple motor tasks, such as grasping or walking, resulting in motor paralysis (Penaloza and Nishio, 2018). In this connection, the Brain computer interface (BCI) can play an essential role in removing this pain from society.

A BCI technique is a mechanism that creates communication between human brain activity and the external environment (Buzsáki and Watson, 2022). It bypasses the typical communication networks, such as human nerve endings and muscles. It translates the user's purpose, such as moving into language and controls device inputs by analysing brain signals (Liu et al., 2022). Generally, BCI technologies aim to aid motor-disabled patients and enable entities to directly control mechanical components (such as arms or fingers), wheelchair navigation, visual simulation of games, smart home appliances, and medical assistive gadgets. In other words, we can say that the BCI system is a crossover technology, including a variety of fields such as neuroscience, psychology, signal detection, signal processing, and pattern recognition (Rodrigues et al., 2022).

In BCIs, the user generates various MI tasks or activities based on multiple brain configurations, for example, the imagination of a hand movement (Shen et al., 2022, Tibrewal et al., 2022). An MI-based BCI requires an interface with motor impaired patients or those in entirely locked-in-states to interact with the external environment by controlling robotic prostheses, wheelchairs, and other devices (Jeyakumar et al., 2022) (Fig. 1.1).

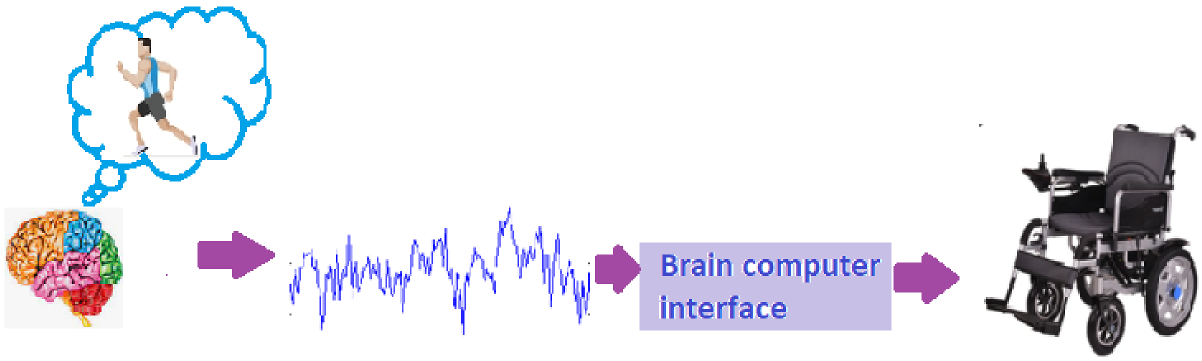

Fig. 1.1: MI-based BCI through EEG signal

Because of the development of MI-based BCI technology, it is feasible for neural signals to control the outside world directly (Shah et al., 2022). There are three required conditions for BCI to be understood. First there must be a signal that can consistently replicate the brain's thinking; second, the brain signal can be gathered instantly in real-time; and third, this neural signal has a clear-cut classification (Weller, 2022). Presently, the human neural signals that can be utilized for BCI are electromyography (EMG), electroencephalography (EEG) and functional magnetic resonance images (FMRI) (Berezutskaya et al., 2022). Therefore, in our study, we applied EEG based BCI systems with MI activities to identify the human intentions or communication intentions of motor disabled people.

An EEG is a medical test or approach which measures the electrical activity of the brain. An EEG records brain signals to identify abnormalities in brain waves (Supriya et al., 2020). Throughout the procedure, electrodes comprising of small metal discs with thin wires are attached to the top of the scalp of the subject (Tawhid et al., 2022b). The electrodes identify small electrical charges developed from brain cell activity (Tringides and Mooney, 2022). EEG signals are usually categorized as delta, theta, alpha, beta and gamma based on signal frequencies ranges from 0.1 Hz to more than 100 Hz (Islam and Kumar, 2022). The signals are nonstationary, nonlinear and noisy(Alvi et al., 2022b, Alvi et al., 2021, Supriya et al., 2018, Siuly et al., 2020b). Non-stationary means that the signal’s statistical characteristics change with time, and non-linear means the signal produced by the system does not follow superposition and scaling properties. EEG signals are often contaminated with noise which might lead to the loss of important information in the signal. These noises are generated from muscle movement, eye movement and blinking, power lines, and interference with other devices. Some noises are still undefined and overlap each other. Thus, it is necessary to remove these unwanted noisy signals in the raw EEG data to acquire important information about the brain activities of a subject. This unwanted data provides noise in the signal that declines an EEG-based MI task classification model's performance (Jin et al., 2019). In principle, EEG-based BCI systems usually contain functional links, for example, input, output, signal processing, and translation.

A BCI of an MI-based EEG dataset mainly comprises signal acquiring, pre-processing, feature extraction, classification, decision making, and feedback (Chugh and Aggarwal, 2022). The workflow of BCI is shown in Fig. 1.2.

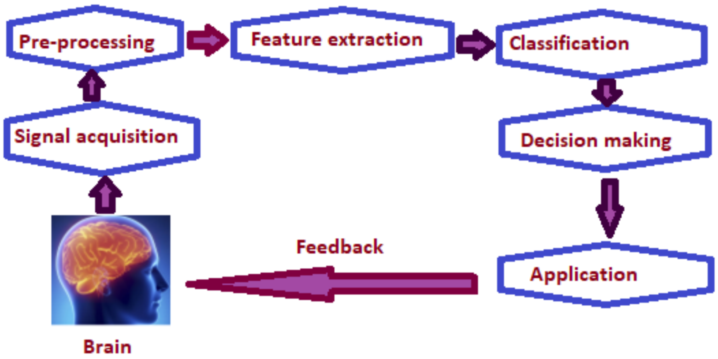

Fig. 1.2: Workflow of Brain Computer Interface technology

Feature extraction and classification are the essential phases of MI-based BCI signal processing. The most significant goal is to obtain a reliable and robust AI-based technique for an advanced BCI system to reintegrate the motor-impaired patient. Therefore, noise removal can be obtained by filtering the EEG data with filters such as a conventional filter, Butterworth filter, or a Hilbert transform filter. After the noise removal stage, the next step is feature extraction. In the feature extraction step, important features are collected from the filtered data—features consisting of specific characteristic properties of EEG signals that allow effective identification of anomalies of the signals. Some feature extractions were done manually in the past, which was costly and relied on specific and prior knowledge (Ming et al., 2022). In recent decades, data mining algorithms have been extensively adopted in BCI systems to learn various brain patterns for extracting features.

Several data mining methods for feature extraction on EEG signal data have been frequently used in BCI systems. These include frequency domain analysis, time-frequency domain analysis, and parametric and non-parametric methods. CSP is a conventional spatial analysis method, a more common method for space domain feature extraction in the field of MI-based EEG signals in recent years (Fang et al., 2022). This method is mainly applied to extract the different features by designing the spatial distribution of the EEG signal in multiple channels through the space domain filters. Another popular feature extraction method is the Markov chain (MC) algorithm. MC is a conditional probability distribution method and has a good effect on the state of the process. It is mainly used to extract important features by designing a simple transform rule which can easily produce a Markov chain for any particular time series and then utilises the processing technique of the Markov chain; features can be acquired as a substitute for the raw time series (Zang et al., 2018). The final stage is classification. To learn high-level features from EEG signals, different deep-learning methods have been progressively used for EEG signal classification (Siuly et al., 2016a, Tawhid et al., 2022c). There are different types of machine learning-based classifiers. Recently, applied machine learning classification methods use the support vector machine (SVM) (Aslan, 2022), K-nearest neighbour (KNN) (Dhiman, 2022), convolutional neural network (Huang et al., 2022), decision tree (Wang et al., 2022b) and linear discriminant analysis (LDA) (Mandal and Naskar, 2022). Other classifiers are the: genetic algorithm optimised back-propagation neural network (GA-BP) (Wang et al., 2022a), least squares support vector machine (LS-SVM) (Siuly et al., 2011), extreme learning machine (ELM) (Balmuri et al., 2022), and artificial neural network (ANN) (Uyanik et al., 2022).

The BCI aims to communicate the brain’s task into a command to control an external device to accomplish the communication task. It is a big challenge for BCI systems to identify human intention by applying suitable classification algorithms correctly and effectively. Generally, EEG produces enormous amounts of data, and visual assessment for differentiating EEGs is time-consuming, error-prone, expensive, and inadequate for reliable information. Thus, developing an automatic classification method for EEGs is essential to ensure an accurate evaluation and remedy for neurological disorders. We proposed three algorithms for identifying MI task-based EEG signals in BCI developments. The three proposed methods are CSP-based MKNN (CSP-MKNN), CSP-based optimised ensemble (CSP-OE) and MC-based

SVM methods (MC-SVM). These suggested methods can distinguish different categories of EEG signals and provide valuable information about brain states. Our proposed methods will be helpful for neurologists to identify brain diseases correctly and efficiently using the typical patterns of EEG signals. This study's outcomes will also help improve patients' quality of life with brain disorders.

1.1 Study motivation

Two reasons motivated me to develop an optimised AI-based machine learning technique to identify human intentions of motor-disabled people. The first is motor disability, which is dramatically increasing in Australia and around the world. Around AU$23.3 billion is spent on this sector every year, as reported by the Australian Government, which is an economic burden for Australia. To reduce this cost and improve motor-disabled people's treatment, communication, daily life, rehabilitation and quality of life, an optimised AI-based, accurate and improved data mining method needs to be developed.

The second reason is EEG data, which is large and quite challenging to handle. The high inconsistency of the EEG signals in the presence of eye or muscle movement, blinking, power lines, or interference with other devices influence the design of an accurate MI task identification approach.

In BCI systems, EEG signals efficiently help acute motor-disabled people to communicate with the outside world through brain waves. BCI technology determines a brain's activity connected with the user's intention and directly interprets the recorded brain activity into corresponding control signals. In recent decades, growing interest has been dedicated to classifying MI task challenges linked to BCI applications. MI tasks signify a practical mental approach to controlling BCI technology. A MI activity can be recognised as a mental rehearsal of motor action, such as movement of hands, feet, fingers, and the tongue, without any apparent motor activity (Collet et al., 2013, Guillot et al., 2012, Taube et al., 2014). Every MI activity is generally regarded as a class of data type. Thus, in this dissertation, we intend to develop improved methods to classify the brain activities in MI-based EEG signals for BCI applications.

1.2 Research problem of the study

It is a significant challenge for BCI technology to identify the human intention of the brain signals by utilising proper identification procedures appropriately and effectively. This thesis focuses primarily on two challenges:

Challenge 1: From the literature, it has been noted that most of the stated methods had a reduced success rate or poor performance in the case of MI task classification accuracy. This is the gap of the existing literature.

Challenge 2: The high computational cost or time, which affects improving classification accuracy. Computational cost is the execution time per time step during simulation. To estimate the time, it takes for any model to execute on real-time hardware, one needs to evaluate the simulation execution time budget for the real-time target machine. These two research challenges need to be solved. In this dissertation, to solve these research challenges, we aim to develop an automatic AI-based machine learning method to enhance the classification accuracy of motor-disabled people. Hence, our proposed research questions are:

- How can we develop an accurate and reliable novel AI-based machine learning method for identifying human intentions of motor-impaired patients?
- Why is the proposed method better than the existing methods?

To our knowledge, existing researchers did not achieve the highest subject-specific classification accuracy of more than 99% for BCI Competition III datasets IVa and IVb (https://www.bbci.de/competition/iii/desc_IVa.html and https://www.bbci.de/competition/iii/desc_IVb.html) with regard to the MI tasks signal classification. Conversely, in most cases, the reported techniques did not choose their parameters correctly, even though the parameters radically influenced the classification performance. In this dissertation, three proposed methods were applied for classifying MI task EEG signals in the BCI application to address these concerns.

1.3 Research Contributions

This dissertation concentrates on the subject-specific ability from different brain activities that can be classified to analyse MI tasks to balance efficiency, accuracy, and speed. The main objective of this study is to develop methods and techniques for identifying different EEG signals from different brain activities. In this dissertation, we have developed three methods for identifying binary classifications of MI tasks in BCI applications. To explore the performances of those techniques, we also evaluated our proposed methods and compared them with other recently established methods. This manuscript explains the work we have done to meet the two aims:

- Aim 1: To develop an accurate and reliable AI-based machine learning method for identifying human intentions of motor-impaired patients.
- Aim 2: At the conclusion, the proposed scheme will be evaluated through the performance measurements and compared with existing methods.

A brief discussion of the two aims is given below:

1: Develop an accurate and reliable AI-based machine learning method for identifying human intentions of motor-impaired patients.

To develop accurate and reliable AI-based machine learning methods for identifying the human intentions of motor-impaired patients, we developed three new approaches:

(1) common spatial pattern-based optimised ensemble (CSP-OE) machine learning method

(2) common spatial pattern-based medium K-nearest neighbour (CSP-MKNN) data mining method

(3) Markov chain-based support vector method (MC-SVM) machine learning method.

The proposed techniques were tested on two publicly available datasets, BCI Competition III, IVa and IVb. The performances of developed methods were evaluated through a k-fold cross-validation technique.

Method 1 (CSP-MKNN): To make a more robust method with less execution time, we developed a CSP-based MKNN method. In this algorithm, we applied the CSP technique for the feature extraction method and a MKNN classifier to classify the MI features. We also filtered the EEG signal data using a Butterworth filter with a frequency range from 0.1–4 Hz and 5th-order derivatives.

Method 2 (CSP-OE): To improve the performance, we modified the CSP-MKNN model's design by introducing a CSP-based optimised ensemble (OE) approach. The CSP method is used for discovering important features from EEG data, and finally, the extracted features are fed as an input to an optimised ensemble (OE) classifier. We used a Butterworth filter considering low frequency 0.1 Hz, high 4 Hz, and 5th-order derivatives to get noise-free EEG signal data.

Method 3 (MC-SVM): We developed a Markov chain-based support vector machine algorithm to improve the separability of the MI tasks classification more accurately and efficiently. This technique used the MC for feature extraction and support vector machine (SVM) classifier to classify MI task performance. We applied the Butterworth filter 0.1–4 Hz and 5th-order derivatives for noise-free data.

2. Proposed scheme will be evaluated through the performance measurements and compared with the existing methods.

Method 1 (CSP-MKNN): Our developed algorithm produced the highest accuracy score for all subjects above 90%, and the average score was above 95% where the CSP and MKNN were applied. It also achieved 3.4% to 14.52% improvements compared with the other ten existing methods with the same dataset.

Method 2 (CSP-OE): Our proposed method achieved 99.64% overall performance accuracy and 1.24% to 26.14% improvement compared to the eleven existing machine learning algorithms considering overall classification accuracy in identifying communicative intentions for BCI application.

Method 3 (MC-SVM): Our anticipated method produced the highest accuracy score in the case of all individual subjects above 99%, where the Markov chain and SVM were applied, compared with more than seven existing methods.

This dissertation aims to develop new algorithms to identify the EEG signals for different brain activities. We hope these algorithms will contribute to successful classification approaches, which can be applied for clinical purposes and brain studies.

1.4 Structure of the thesis

This dissertation comprises six chapters, and each chapter provides significant information on our research work. The rest of this thesis is designed as follows:

Chapter 2 provides an overview of the existing literature on MI-based EEG signals of BCI techniques and their background knowledge.

Chapter 3 presents our developed method based on a CSP-MKNN for classifying MI-based EEG signals.

Chapter 4 introduces our developed method based on a CSP-OE for classifying MI-based EEG signals.

Chapter 5 reports another developed method based on MC-SVM for classifying MI-based EEG signals.

Chapter 6 presents a summary and concluding remarks on the issues delivered by this research. This chapter also provides the limitations of our research.

CHAPTER 2

BACKGROUND KNOWLEDGE AND LITERATURE REVIEW

In order to have explicit knowledge of MI-based BCI through EEG signals, this chapter provides a brief discussion of MI-based BCI systems and EEG signals and their classification methods. In the end, existing literature and their applied various classification methods are reported.

2.1 Background knowledge of BCI, EEG, MI and its functional system

2.1.1 History of EEG and BCI

The first BCI development test was performed on monkeys in 1969 and 1970. In the year 1970, the University of California Los Angeles professor Jacques Vidal invented the term brain computer interface and confirmed that people could mentally guide a cursor through a simple virtual network. The history of BCI is entirely related to the invention of EEG. EEG was first recorded by German psychiatrist Hans Berger (21 May 1873 – 1 June 1941) (see Fig. 2.1). In the year 1924, Berger recorded the first human brain activity through brain signals, which led to the discovery of EEGs alpha and beta waves (İnce et al., 2021).

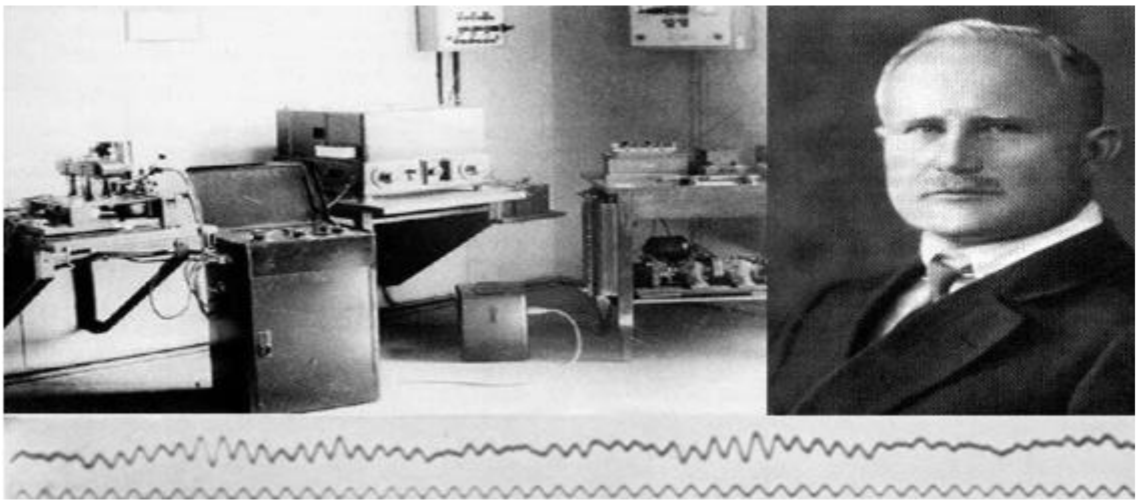

Fig. 2.1: Hans Berger's and the starting history of BCI (Troina, 2021)

Besides alpha and beta waves, there are three more rhythms or frequency bands of EEG signals, such as 0.5-4 Hz (delta, δ), 4-8 Hz (theta, θ), 8-13 Hz (alpha, α), 13-30 Hz (beta, β) and >30

Hz (gamma, γ) (Abhang et al., 2016). Fig. 2.2 demonstrates examples of these EEG rhythms. A brief discussion of these different rhythms of EEG signals is given below:

Delta wave lies between 0.5 to 4 Hz, and the shape is observed as the maximum amplitude and the slowest wave. It is mainly connected with deep sleep, severe brain syndrome, and in waking conditions.

Theta remains within the 4 and 8 Hz range with an amplitude typically larger than 20 µV. Theta starts from emotional stress, mainly frustration or dissatisfaction, unconscious material, creative inspiration, and deep meditation.

Alpha consists of a frequency range from 8 to 13 Hz, with 30-50 m µV amplitude, which occurs primarily in the posterior areas of the head (occipital lobe) when the subject has eyes closed or is in a relaxation state. It is generally correlated with intense mental activity, stress, and tension. Alpha activity recorded from sensorimotor regions is also called mu activity.

Beta is in the frequency range of 13 Hz-30 Hz. It is seen in a low amplitude and differing frequencies symmetrically on both sides in the frontal area. When the brain is awakened and actively involved in mental activities, it produces beta waves. Beta waves are attributes of an intensely involved mind. Beta is the brain wave generally connected with active things, active thoughts, and concentrating on the outside world or solving concrete difficulties.

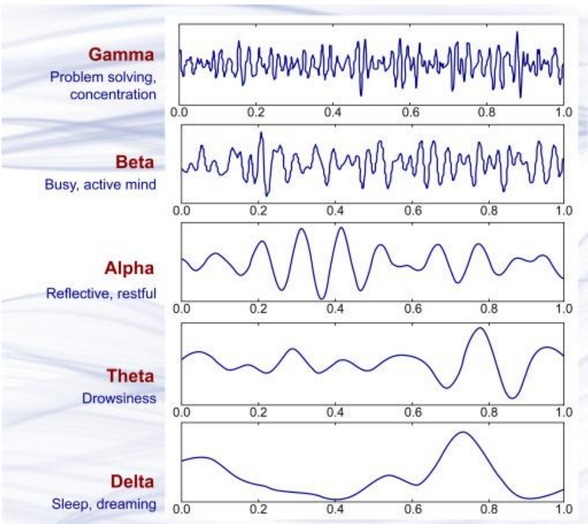

Fig. 2.2: Example of different types of normal EEG rhythms (Abhang et al., 2016)

Gamma waves have frequency ranges from 30 Hz and higher. This rhythm is sometimes characterized as having a maximal frequency across 80 Hz or 100 Hz. It is linked with different cognitive and motor functions.

To understand which brain part is reliable to produce these frequency band of EEGs, we first need to know the human brain structure and its functional activity.

2.1.2 The brain's structure and its role in developing EEG

The human brain consists of three parts: cerebrum, cerebellum and brainstem, shown in Fig. 2.3 (Spine, 2022).

Cerebrum: The first part is the most significant part of the brain and is known as the cerebrum. It is composed of the right and left hemispheres. It is generally connected with brain functions associated with interpreting touch, vision and hearing as well as speech, reasoning, emotions, learning and fine control of movement, thoughts, activities, emotions, and motor tasks.

Cerebellum: The second part is the cerebellum which is located under the cerebrum. The function of the cerebellum is to coordinate muscle movements and maintain posture and balance control.

Brainstem: Finally, the third part is the brainstem which acts as a relay center linking the cerebrum and cerebellum to the spinal cord. It operates many automatic functions, for example, breathing, heart rate, body temperature, wake and sleep cycles, digestion, sneezing, coughing, vomiting, and swallowing.

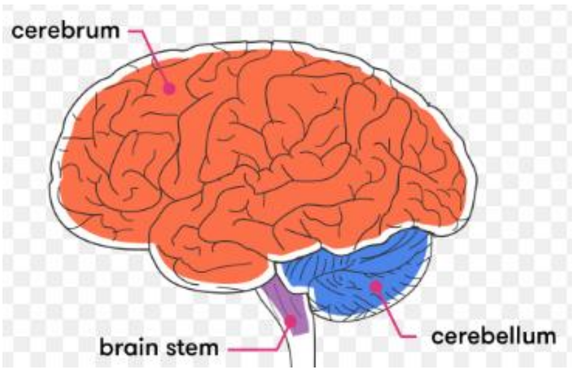

Fig. 2.3: three main parts of the brain: cerebrum, cerebellum and brainstem (Science, 2022).

There are 100 billion neurons in our brain, also known as nerve cells, and can send and receive signals or waves from the brain (Herculano-Houzel et al., 2007). This neurons vary in size, shape, and structure differing on their role and location. However, almost all neurons have three parts: a cell body, an axon, and dendrites shown in Fig. 2.4.

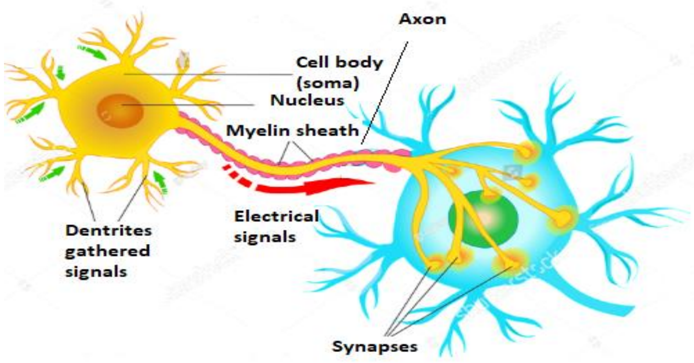

Fig. 2.4: A communication structure of a neuron (Healthline, 2022)

Cell body: also known as soma. It is the core section of the neuron. It contains genetic information, maintains the neuron's structure and delivers energy to drive activities.

Axon: is a tail-like long structure. Neurons typically have one central axon. Many axons are insulted with a fatty substance named myelin. Myelin assists axons in conducting an electrical signal.

Dendrites: It is fibrous roots that branch out from the cell body. It receives and process electrical signals from the axons of other areas.

The electrical activity of neurons is closely associated with action potentials (AP) and postsynaptic potentials (PSP). AP is the instant electrical flow from the soma and axon following a neuron's depolarization. The summed PSPs are longer in duration than APs and are accountable for most brain signals. On the contrary, PSP results from comparatively slower electricity after neurotransmitter release at the axon's terminal boutons. In the formation of brain signals, the main contributor is the pyramid cells of the synaptic potentials, where layers of cortical neurons play a primary source of the brain waves. These brain waves are recorded by EEG, which is a test that measures electrical activity in the brain using small metal discs (electrodes) attached to the scalp(Tawhid et al., 2021). Pyramidal cells are the major contributor to the synaptic potentials that contribute to recording brain signals through EEG, as shown in Fig. 2.5 (Tatum IV et al., 2008).

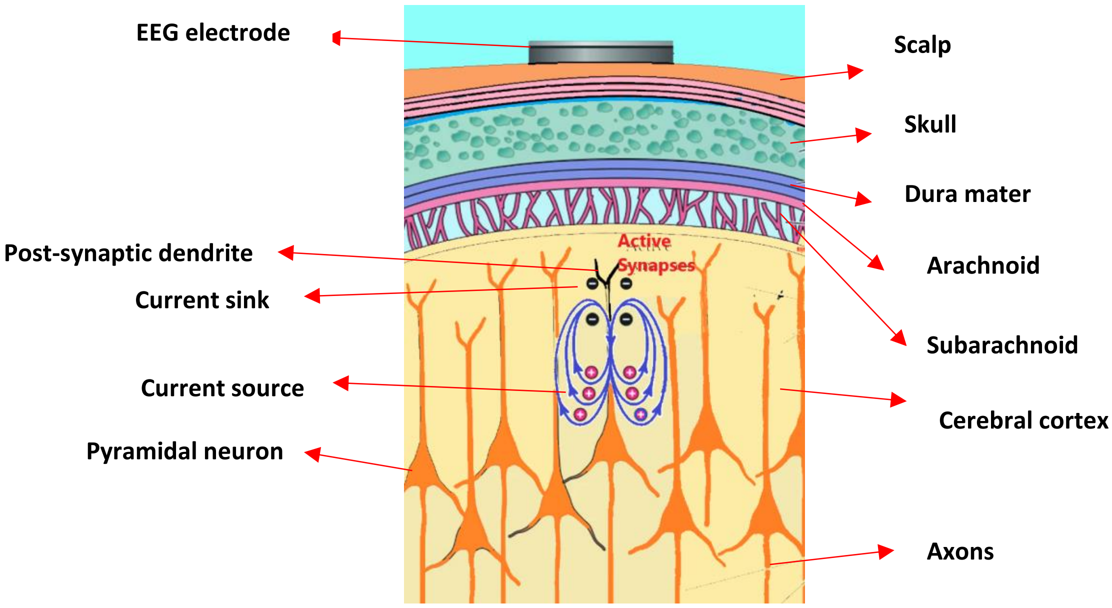

Fig. 2.5: The current flow that contributes to the surface EEG during a net excitatory input (Siuly, 2012)

In EEG recordings, the electrical activity of the cerebral cortex is recorded by wearing an EEG cap. This cap consists of several small discs termed electrodes. Electrodes are assigned to various positions on the electrode cap following the International 10-20 electrode placement system and connected with temporary glues shown in Fig. 2.6. Then, every electrode is attached to an amplifier (one amplifier per pair of electrodes) and an EEG recording device. Finally, the electrical signals from the brain are transformed into wavy lines on a computer screen to record the outcomes. Usually, one pair of electrodes represents a channel. Each channel generates a signal through an EEG recording (Homan et al., 1987).

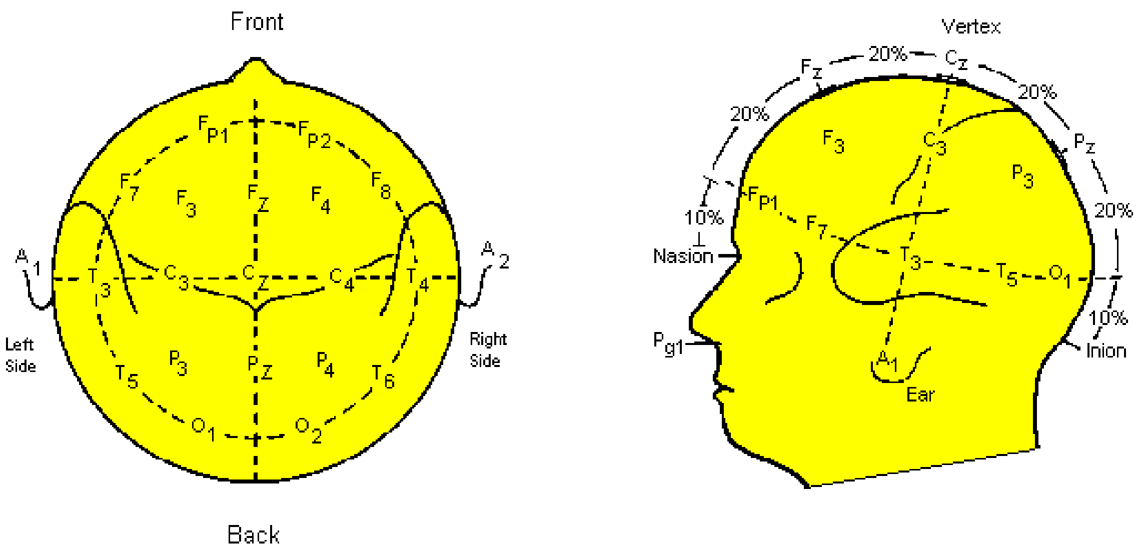

Fig. 2.6: The International 10-20 electrode placement system (Homan et al., 1987)

In BCI technology, this electrical activity of brain signals is recorded through EEGs and translated into a command to control an external device (Arshad et al., 2022, Khanam et al., 2022a). The recorded activity produced from electrical signals is called an artifact. The amplitude of artifacts is mainly relative to the amplitude size of the cortical signals of interest. Such artifacts always taint EEG data(Tawhid et al., 2022a). In EEG-based BCI, a person can communicate directly with others or control devices using brain activity without utilizing the normal channels of peripheral nerves and muscles. In other words, it is a direct communication route between the brain's electrical activity and an outside device, generally a computer or robotic limb. Moreover, this technique assesses the activity of the central nervous system (CNS). It translates it into artificial output that replaces, restores, supplements, or enhances natural CNS output and thereby differentiates the ongoing interactions between the CNS and its outward or inner environment by interpreting EEG signals (Wolpaw, 2013). There are two types of BCI. One is invasive and the other one is non-invasive. Invasive and non-invasive BCI technologies intend to extract and utilize brain signals. Both systems have pros and cons; invasive BCI is surgically and scientifically complicated, it can become unsteady over time but can be very worthwhile. At the same time, non-invasive BCI is reasonably safer and easy to apply but has limited capacity to replace or enhance lost bodily functions (Tangermann et al., 2008). In our thesis, we apply non-invasive MI-based BCI system with EEG signal data. In the next section we give a brief discussion about MI.

2.2 Motor imagery (MI)

MI is the performance of mental tasks without explicit movement or muscle or body stimulation. It is proven that MI performance execution leads to the same brain areas as actual movement (Papaxanthis et al., 2002).

Motor imagery classification is a vital issue in brain-computer interface (BCI) investigation that identifies a subject's intention to, for example, execute prosthesis control. It is the imagination of a task without truly performing the task. It also has a wide utilization to increase motor learning and develop neurological rehabilitation in patients after motor disabilities. On the other hand, the motor imagery (MI)-based brain-computer interface (BCI) is an intuitive interface that controls computer applications directly from brain activity. BCIs based on selective attention involving external stimuli required by a BCI system. The stimuli can be auditory or somatosensory. In this research, we work on the MI for the BCI systems. A brief discussion of the Functional model of the BCI system is given below.

2.3 Functional model of BCI system

Six steps in a BCI system work as a closed-up process: signal acquisition, signal pre-processing, feature extraction, classification, translating command, and device output (Siuly et al., 2016b), shown in Fig. 2.7.

1. **Signal acquisition**: In BCI technology, accurate brain activity measurement is critical for BCI communications. It is a process of modulating the electrical signals of human intentions that measure real-world physical conditions by using various types of electrodes and converting the resulting samples into digital numeric values that a computer can manipulate.

2. **Signal Pre-processing**: Generally, pre-processing converts raw data into a more suitable format for further analysis and is understandable for the user. In the case of EEG data, pre-processing generally indicates removing noise from the data to get nearer to the true neural signals. It simplifies subsequent processing operations by improving signal quality without losing information. (dos Santos et al., 2020).

3. **Feature extraction:** The brain signals utilized in BCIs are indicated by specific features. The selected features are anticipated to consist of the relevant information from the input data so that the desired activity can be accomplished by utilizing this reduced representation instead of the entire initial data. Feature extraction illustrates the signals by important information or values called "features" (dos Santos et al., 2020).

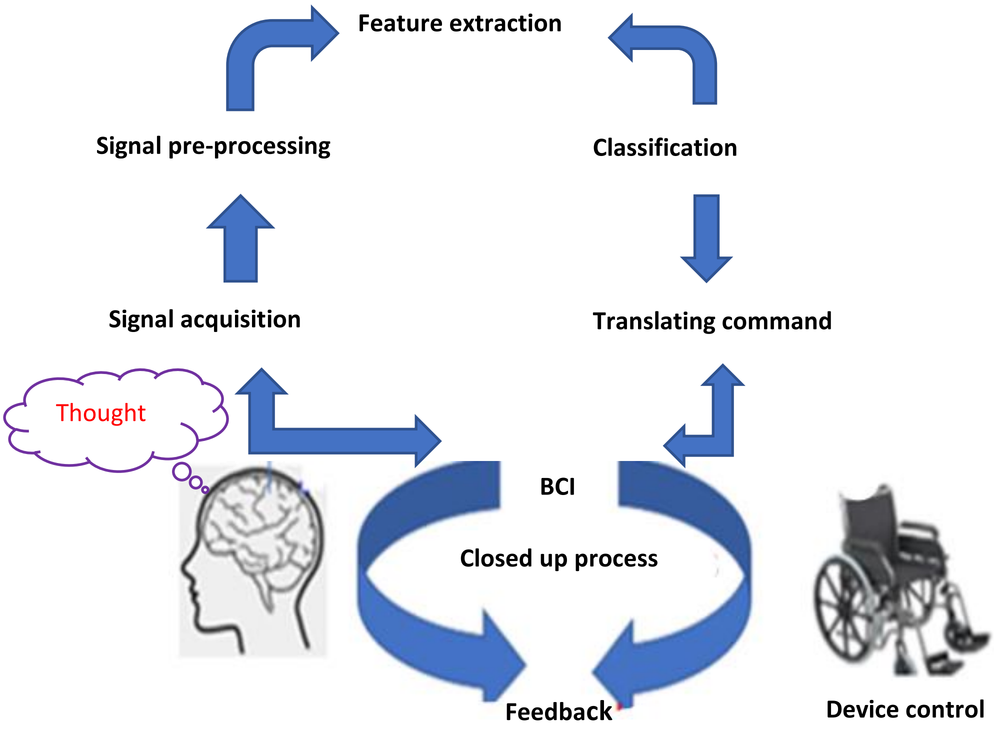

Fig. 2.7 Functional model of a BCI system

4. Classification: Classification of biomedical signals is vital in building Brain-Computer Interfaces (BCIs) to identify different mental activities. A higher resolution of signal classification is relative to the number of mental commands a single BCI system can handle. The classification step designates a class to a set of features extracted from the brain signals. This step can also be signified as "feature conversion." The classification aims to attribute class labels to the features extracted from specific problem-related observational data. A system that executes classification, mainly in a solid performance, is well-known as a classifier. It is mainly categorized into two types: supervised classification and unsupervised classification. In supervised classification, the observational data is linked with class labels. In unsupervised classification, the observational data are not labeled or designated to a recognized class (Jain et al., 2000).

The natural language processing task of classification depends on machine learning (ML) approaches. An AL based ML algorithm, applies accurate, probabilistic, and developed methods that enable computers to pick up from the past point of reference and distinguish hard-to-perceive patterns from huge, noisy, or compound datasets. ML algorithms create models from sample data, termed training data, to estimate or decisions without explicitly programmed to do so. A machine learning algorithm is a program that learns hidden patterns in data, predicts outcomes, and improves the performance of practices ML approaches are applied in many fields, for example, medicine, email filtering, speech recognition, agriculture, biomedical science and computer vision, where it is difficult or impossible to develop existing algorithms to perform the required activities. In machine learning, different algorithms can be used for different tasks. For example: Support vector machine (SVM), Linear discriminant analysis (LDA), K nearest neighbour (KNN), Naïve bayes (NB), optimized ensemble (OE), Decision tree (DT). Below is a short description of all the ML algorithms we applied in our thesis.

Support vector machine (SVM): SVM is a linear model for classification and regression problems. It can solve both linear and nonlinear problems and is suitable for many real-world problems. The basic idea of SVM is simple. Algorithms create lines or hyperplanes that divide data into classes (Sharma et al., 2022).

Linear discriminant analysis (LDA): Linear discriminant analysis is one of the most popular dimensionality reduction techniques used for supervised classification problems in machine learning. It is also considered a pre-processing step for differential modelling in ML and pattern classification applications. In a linear SVM, the data points are linearly divided into two classes (Echtioui et al., 2023).

K nearest neighbour (KNN): KNN is a supervised learning algorithm mainly used for classification problems, although K-Means (also known as K-means clustering) is an unsupervised learning algorithm. K in K-Means implies to the number of clusters, however K in KNN is the number of nearest neighbours (based on the chosen distance) (Echtioui et al., 2023). In medium k nearest neighbour (MKNN), the differences between classes are medium and 10 is set as the number of the neighbour, which is the parameter of the developed model (Khanam et al., 2023).

Naïve bayes (NB): The NB classifier is a ML algorithm applied for classification tasks. It is known as naive because it believes that each input variable is independent. This is a strong hypothesis and unrealistic in case of real data. However, this ML algorithms is very effective for a wide range of complicated challenges (Liu and Bao, 2023).

Optimized ensemble (OE): An ensemble model is a machine learning method that combines several different models in the prediction process. These models are known as base estimators.

Ensemble models offer a solution to overcome the technical difficulties of creating a single assessment tool (Khanam et al., 2022b).

Decision tree (DT): Decision trees are non-parametric supervised learning algorithms used for classification and regression tasks. It has a hierarchical tree structure consisting of a root node, branches, internal nodes and leaf nodes (Kaya and Saritas, 2023).

5. Translating commands: A command is associated with the mental state identification to control a given application, namely a computer or robot.

6. Feedback: in this last step, mental state identification feedback is provided to the user with the assistance of controlling his/her brain activities. The main objective is user performance improvement.

In brain computer communication, motor imagery (MI) plays a vital role. It recognizes the human intentions of brain activity which is generated by the user and can be translated by BCI.

In this dissertation, we are paying attention to classifying MI tasks based on EEG signals of BCI systems. The following section briefly discusses different use of BCI technology.

2.4 Usage of BCI technology

The primary purpose of BCI is to assist disabled patients in restoring their functional movement. It has a wide application across multiple and diverse fields and is not limited to the medical arena alone. For example, neurorobotics, medical, innovative environments (such as smart houses, transportation or workplaces), education and self-control, games and entertainment, neuromarketing and advertisement. It is a collaboration between a brain and a device that allows signals from the brain to some outward movement or task. It also enables a paralysed person to write a book or operate a wheelchair of the prosthetic limb over thought. Moreover, BCI helps in rehabilitation, control of prosthetics and neurofeedback.

Communication-based BCI technologies involve characteristic brain activity patterns that a subject can consciously produce and eventually accurately differentiate by a computer system. The performances of different mental activities (for example, the imagination of a hand movement) are produced by a person from various EEG responses and, therefore, can be interpreted into a control codebook for the user with the help of the BCI system. In this dissertation, we develop three techniques to recognize different mental activities (for example, MI tasks) to improve communication based BCI technologies.

In the past various types of MI-based EEG signal classification methods were developed to identify the human intention of motor disabled people. A brief discussion of these methods is given below:

2.5 Literature review of the methods used

Due to the fast-growing concern about MI-based BCIs, scholars have reported many methods for identifying human intentions of MI-based BCIs through EEG signals. In this chapter, we have provided a brief narrative of the most recently stated MI-based BCIs.

Suk and Lee in (Suk and Lee, 2012) developed a Bayesian spatial spectral filter optimization (BSSFO) based Bayesian algorithm for detecting feature extraction and classification in an MI-based BCI. In this method class, discriminatory frequency bands and the subsequent spatial filters are optimized by applying the probabilistic and information-theoretic algorithm. In this work, the spatiospectral filter optimization is developed to calculate an unknown posterior probability density function (pdf) that demonstrates the probability that a single-trial EEG of pre-set mental tasks can be categorized in a state. To assess the posterior pdf, they predicted a particle-based estimation method by developing a factored-sampling algorithm with a distribution method. The method achieved an average of 75.46% of classification accuracy. The drawback of their approach is that the classification performances are inadequate and not enough to contrast with the current techniques.

Z hang et al. (Zhang et al., 2013) introduced an algorithm based on z-score linear discriminant analysis (Z-LDA), which proposes a different decision boundary definition scheme to carry out with the heteroscedastic class distributions. They employed a common spatial pattern (CSP) to calculate the spatial projection matrix, which endeavours the EEG signal from the previous sensor space to a surrogate sensor space in the feature extraction stage. In the end, they exploited the obtained features to the Z-LDA and then evaluated with LDA, support vector machine (SVM), nonparametric discriminant analysis (NDA) and heteroscedastic LDA (HLDA). The overall accuracy performance was 81.1% for their applied Z-LAD system, which is insufficient. Siuly and Li (Siuly and Li, 2012b) developed a system based on cross-correlation and least square support vector machine (LSSVM) to detect two-class MI signals. This research paper applied a cross-correlation algorithm for feature extraction and a least square support vector machine (LS-SVM) for classifying the extracted features. The effectiveness of the established classifier was investigated by restoring the LS-SVM classifier with a logistic regression (LR) classifier and a kernel logistic regression (KLR) classifier with the same extracted features. Experimental results revealed the merits of the LS-SVM classifier compared to the LR and KLR classifiers. Their technique attained an overall classification accuracy of 95.72%. This method may not be appropriate if the data is large in size as the cross-correlation method needs more time to operate.

Siuly et al. (Li and Wen, 2011) intended a clustering technique based on LS-SVM to categorize motor imagery EEG signals. They developed a clustering algorithm for feature extraction, and the LS-SVM employed the obtained features as the inputs for the differentiation of EEG signals. It used the 10-fold cross-validation algorithm for the performance evaluation. The mean accuracy was gained 88.32%. The drawback of that algorithm was that they did not select the parameters optimally over any method. They manually chose the parameters for the LS-SVM approach (Lu et al., 2010) by blending the principle of generating the covariance assessments and these parameters were not chosen optimally over the algorithm. They attained a mean accuracy rate of 74.2% for all subjects. It was asserted that the algorithm was mainly effective in small sample settings.

Williams et al. (Williams et al., 2018) utilize complex network procedures, i.e., mean clustering coefficient, to illustrate phase-locking at the level of EEG electrodes. These are employed as observables to a Markov chain (MC), which uses these observables to detect states and probabilities of transitions between states. Likewise, Ye et al. (Ye et al., 2022) apply an MVAR (multivariate auto-regressive) model to describe time postponed dependencies of MEG source-level action. The MVAR parameters are also applied as observables to an HMM (hidden Markov model). Yu et al. (Yu et al., 2021) deployed seven machine learning classifiers along with the Welch-PSD method and empirical wavelet transform (EWT) for modes selection. Each mode was decomposed into rapid amplitude and frequency components. The lack of this method was the selection of modes in EWT. Again, an algorithm was developed with multivariate EWT (MEWT) (Sadiq et al., 2019) to decompose MI-based EEG activity and then apply the correlation-based features extraction scheme. The drawback of this method was the complexity or requirement of multidomain features that hinder the practical application of advanced BCI systems.

In EEG signals, multiple studies have developed for the visual analysis of open-source graphical user interfaces (GUI), such as the studies of Dhiman et al. [23] and Wang et al. [25]. For this reason, several attempts have been made to solve the complex optimization problem by these stochastic algorithms, such as the algorithms of Padfield et al. (Padfield et al., 2021a), PSO Particle Swarm Optimization (PSO) (Wu et al., 2016), Ant Colony Optimization (Miao et al., 2020), Grey Wolf Optimization (Dhiman, 2022), Crow Search Algorithm (Qu and Fu, 2019), Common Spatial Pattern (CSP) (Gaur et al., 2021), Fisher score (Jin et al., 2021) and mutual information (Wang et al., 2019), Differential Evolution (Al-Qazzaz et al., 2021), and Butterfly Optimization Algorithm (Soto). The most usual drawback is the transformation of the data by the application of the natural logarithm function.

The MI-based EEG characterization based on generally adopted attribute acquisition systems are statistical (Yu et al., 2021), entropy (Sharma et al., 2014), geometrical (Akbari et al., 2021), matrix determinant (Sadiq et al., 2020), power spectral density (PSD) (Kim et al., 2018), autoregressive (AR) model (Yu et al., 2022), sparse representation (SR) based ones (MENG et al., 2022), continuous wavelet transform (CWT) (Lee and Choi, 2019), discrete wavelet transform (DWT) (Ak et al., 2022), Hilbert transform (HT) (Tosun and Çetin, 2022), and empirical mode decomposition (EMD) (Jaipriya and Sriharipriya, 2022); yet all existing strategies have some disadvantages. Among the variety of characteristic weaknesses these methods still have, the following are remarkable: mode mixing, closely spaced frequencies, end effects, noise sensitivity, involving longer iteration, complex method, requiring enormous amounts of training data, time consuming, applicable only in small dataset, mother wavelet selection, shift invariance, and wrong frequency order, etc. Therefore, an accurate and efficient automatic analysis of the classification algorithm requires to be developed to settle the difficulties faced in the investigation as mentioned above. Furthermore, because of a massive amount of EEG signal data, it is still inadequate to balance the effectiveness of the extracted features for recognizing motor disabled people's communication intention.

One of the most critical problems of BCI technology is the high speed and accuracy of classifying MI tasks based on EEG signals. Generally, in real-world applications, equally, the accuracy and processing speed precisely affect the execution of the BCI technology (Jia et al., 2019). Thus, it is essential to analyze the classification approaches from these two angles instantaneously. So, these issues must be addressed in analyzing classification procedures in machine learning techniques. This investigational disparity needs to be focused. To overcome this disparity, in this dissertation, we aim to develop an optimized artificial Intelligence based, three algorithms for identifying human intentions of physical movement through EEG data for advanced BCI system.

2.6 Link and implications

This chapter provides background knowledge of EEG signal and their classification, brain computer interface, and application. Initially, this chapter briefly discusses human brain function, the basic knowledge of EEG and the fundamentals of BCI systems. Furthermore, this chapter discusses EEG signal classification and provides some recently proven methodological frameworks applied in MI-based BCI. We can conclude from the literature review that there are some drawbacks related to the current methods. Hence, an automatic analysis robust classification method needs to be designed to resolve the weaknesses mentioned above for identifying human intentions of some neurodegenerative diseases. The next chapter presents an optimized artificial intelligence based technique based on a common special pattern feature extraction method and medium k nearest neighbour (CSP-MKNN) to identify MI tasks through EEG signals in BCI applications.

Chapter 3

This chapter is presented in the accepted format of the publication cited below.

Khanam, T., Siuly, S. & Wang, H. An optimized artificial intelligence based technique for identifying motor imagery from EEGs for advanced brain computer interface technology. *Neural Comput & Applic* **35**, 6623–6634 (2023).

https://doi.org/10.1007/s00521-022-08027-1

CHAPTER 3

AN OPTIMIZED ARTIFICIAL INTELLIGENCE BASED TECHNIQUE FOR IDENTIFYING MOTOR IMAGERY FROM EEGS FOR ADVANCED BRAIN COMPUTER INTERFACE TECHNOLOGY

The development of classification methods for the detection of motor imagery activities through EEG signals is vital in the field of biomedical research. The identification and estimation of brain signal can be distinguished through EEGs with the help of Classification algorithms. This chapter presents a classification technique based on common spatial pattern with medium k nearest neighbour (CSP-MKNN) to identify a binary class of the EEG signals. CSP is a feature extraction method that employs spatial filters to maximize the discriminability of two classes. In the CSP, the filtered data variance of one class is maximized, while the filtered data variance of the other class is minimized. This study aims to develop an optimized artificial Intelligence-based technique and to infer indications concerning the extracted feature by combining common spatial pattern with medium k nearest neighbour (CSP-MKNN).

The contents of this chapter have been published in the Neural computing and applications (Khanam et al.)

3.1 Introduction

Motor disability is increasing alarmingly. Currently, around 4% of the world's population is experiencing some form of motor disability (WHO, 2011). In Australia, 18% of people have disabilities among them 22% face motor disability (AIHW, 2020). Motor disability is a neurological problem that affects a person's ability to move and maintain balance and posture. Patients with high motor Impairment might go through a locked-in state, which results in difficulty in physical movement. The brain-computer interface (BCI) system plays a vital role in removing this pain from society. BCI translates human intention by brain activity into control signals to communicate with their external environment without direct physical movements (Sadiq et al., 2022b). It might also improve rehabilitation for people with strokes, head trauma, and other disorders (Shih et al., 2012, Wang and Zhang, 2016). It involves neuroscience, biomedical engineering, applied mathematics, computer science, psychology, and reintegration. In BCIs, the user produces different types of motor Imagery (MI) activities based on different brain configurations, for example, the imagination of a foot movement (Thomas et al., 2009, Siuly and Li, 2012b). A Motor Imagery based BCI provides an interface for patients with motor impairment or those in entirely locked-in-state for interact with the environment by controlling robotic prostheses, Wheelchairs, and other devices (Siuly et al., 2014, Chaudhary et al., 2020).

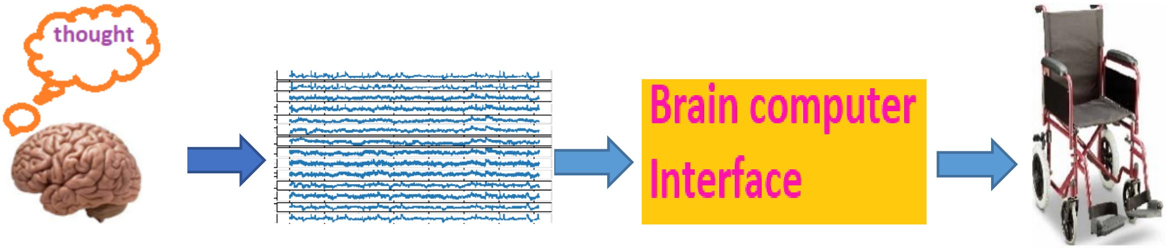

Fig 3.1: Motor imagery based BCI technique of EEG signal data

In BCI systems, Electroencephalogram (EEG) is a medical test used to measure the brain's electrical activity. For the measurement of EEG signal data, several electrodes are applied to our scalp by wearing a cap (Siuly and Li, 2012b, Siuly et al., 2016a, Sadiq et al., 2022a). It is non-invasive, transferrable, low price, with time consuming data and produces massive signal data [5]. In BCI techniques, the motor imagery tasks of changes in the amplitude of specific cortical rhythms, such as delta, theta, alpha, beta and gamma rhythms, have been considered important features (Pfurtscheller et al., 2006, Blankertz et al., 2007a, Ahn et al., 2013). The EEG signal data analytical methodology consists of three parts for example, noise removal from unexpected noisy data, feature extraction for important features and classifier for higher accuracy.

The overall objective of this chapter is to enhance the classification performance of the binary MI-based classification method. To fulfil our research objective, we are interested in applying the Common spatial pattern (CSP) data mining technique in this chapter. CSP is a feature extraction method that uses spatial filters to maximize the discriminability of two classes. We are motivated by this method because in CSP the filtered data variance of one class is maximised while the filtered data variance of the other class is minimised (Jin et al., 2020). Although extensive work exists, the combination of butter worth filter, CSP method and MKNN is a new combination method and resulted in an outstanding performance.

To investigate a sustainable classifier, this paper tested several machine learning classification methods such as linear discriminant analysis (LDA), Medium k nearest neighbour (MKNN), and Linear support vector method (LSVM) classifiers for the obtained feature set. These classifiers efficiently solve non-Gaussian, non-invasive and non-stationary EEG data and are also consistent in EEG-based BCI applications. However, three of the classifiers have strengths and weaknesses in terms of mathematical complication and their appropriateness in a specific application, which will be deliberated later. Here MKNN is one form of nearest-neighbour classifier that makes distinctions between classes with the number of neighbours set to 10. On the other hand, LSVM will disperse the dataset by linear classification.

3.1.1 Related work

Chaudhry et al (Chaudhary et al., 2021) developed a method using common spatial pattern (CSP) feature extraction method and Dynamic Weighted Majority (DWM) based classifier. Another author Miao et al developed a framework termed common time-frequency-spatial patterns (CTFSP) with Multiple support vector machine (SVM) classifiers. The disadvantage of this method is that several signal pre-processing and classification methods have been used in low-frequency movement related cortical potential (MRCP) detection including locality preserving projection (LPP) (Miao et al., 2021b).Tiwari and Chaturvedi, Cherloo et al. and Inbarani et al. achieved classification accuracy (CA) less than 90% by using different methods (Tiwari and Chaturvedi, 2021, Norizadeh Cherloo et al., 2021, Renuga Devi and Hannah Inbarani, 2021). In the research work, Djamal et al. showed that BCI systems using wavelet and recurrent neural networks (RNN) can drive external devices with an accuracy of 79.6% (Djamal and Putra, 2020). The drawback of this method is that it requires longer iterations. Rafi et al. 2020 developed a phase synchronization to complement the BCI system by analysing the phase stability between two input signals. Wang et al. 2017, also developed a feature extraction method for designated frequency domain CSP (FDCSP) (Wang et al., 2017). The limitation of this method is author conducted experiments without eliminating noise and artifacts by a band-pass filter. However, the noise and artifacts will damage essential components of input signals, so the classification accuracy will be severely affected. However, the above-mentioned methodological frameworks are not enough steady and sufficient to achieve a subject-specific classification accuracy above 90% for BCI signal output. Hence, automatic analysis of an accurate and efficient classification method needs to be designed to resolve the weaknesses faced in the above-mentioned research. Besides this, because of a large size of EEG signal data, it is still insufficient to balance the efficiency of the extracted features for identifying motor disable people’s intention.

Another major issue of BCI system is high speed and accuracy for identifying MI tasks based on EEG signals. Usually, in real world applications both the accuracy and processing speed directly influence the performance of the BCI system (Jia et al., 2019). So, it is necessary to simultaneously analyse the classification algorithms from these two angles. So, analysing classification algorithms considering these issues is necessary in machine learning techniques. This research gap needs to be addressed. To overcome this gap, this chapter aims to develop an optimised artificial Intelligence based technique for identifying human intentions of physical movement through EEG data for advanced BCI system.

The rest of this paper is organized as follows: Section 3.2 outlines the proposed method. It also describes the datasets and performance evaluation procedure. The experimental results with visual and tabular representation are depicted in Section 3.3. The comparison between the result outcomes of this chapter and other earlier existing studies are discussed in Section 3.4. Finally, Section 3.5 closes with concluding remarks and future benefits of the chapter results.

3.2 Materials and Methods

This section describes the experimental data that is used in this chapter and the proposed methodology design.

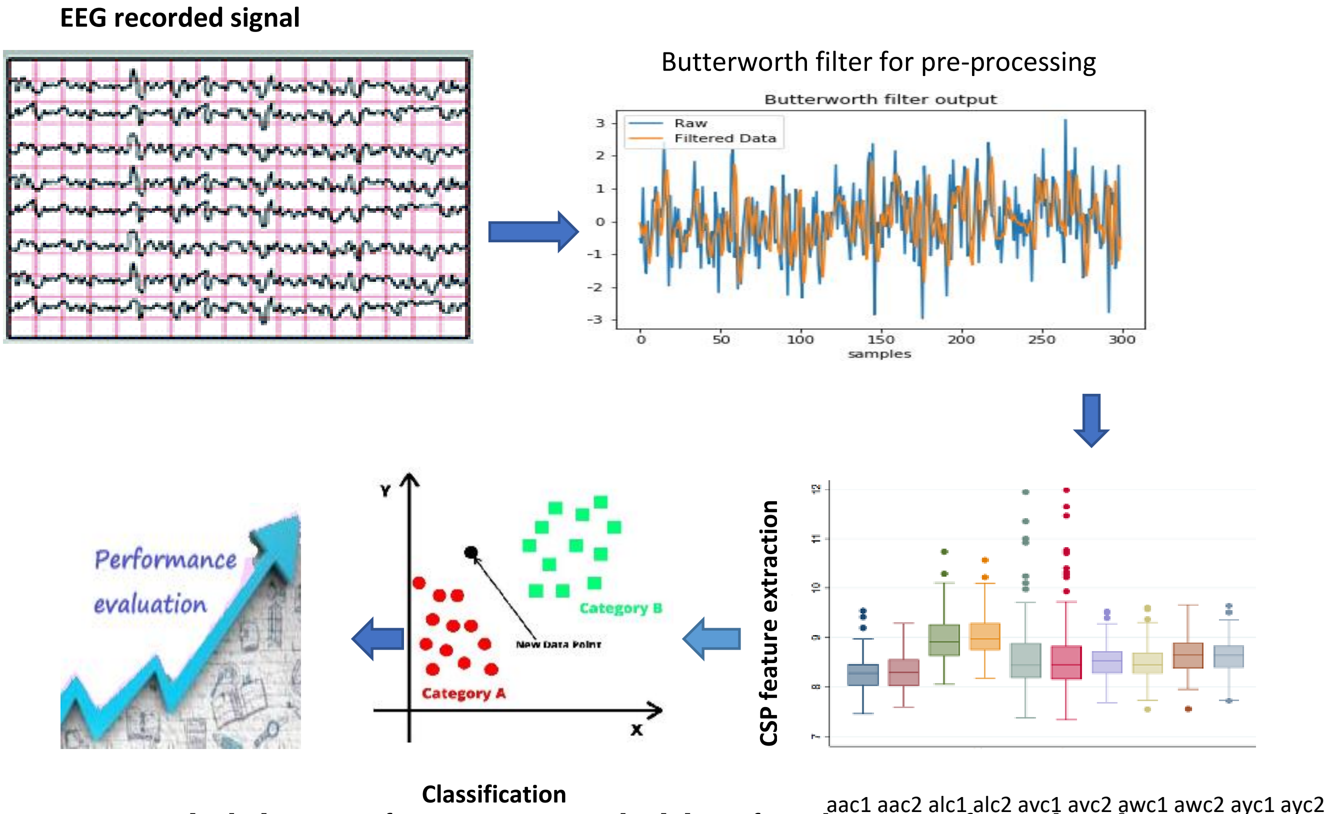

Fig 3.2: Block diagram of the proposed methodology for subject-specific MI-based EEG signal classification.

Fig 3.2 depicts this chapter's methodological framework for classifying BCI technique Neuro-prosthetic EEG data. The diagram shows the denoising of two classes MI-based EEG data (right hand and foot) - by using Butterworth filter to acquire maximum signal to noise ratio (SNR). Then important features were extracted by the CSP method. At the third step, three types of classifiers namely LDA, LSVM and MKNN machine learning algorithms were applied for the obtained feature set. At the end, the performance of the proposed methods was evaluated in terms of accuracy, sensitivity, and specificity.

3.2.1 Dataset

In this chapter, we applied a publicly available EEG database: dataset IVa from BCI Competition III (http://www.bbci.de/competition/iii/desc_IVa.html). The dataset comprises multichannel EEG documented from five healthy subjects settled in a relaxed chair with their arms on armrests. The dataset consists of 118 EEG signals which were then band-pass filtered from 0.05 to 200 Hz then sampled at a frequency of 1000 Hz and further down sampled to 100 Hz. An inter-trial interval of approximately 2s allowed contributors to take a short break. In total, 280 trials existed for each of the five subjects with 118 EEG channels recorded (Lotte and Guan, 2011). Table 3.1 shows the number of training trials and test trials for all five subjects, which has been provided by the data provider.

Table 3.1 Description of Dataset.

Dataset	BCI Competition III				
Channels	118				
Sampling rate	1000 Hz				
Subjects	aa	al	av	aw	ay
Training data	168	224	84	56	28
Test data	112	56	196	224	252

In our dataset IVa, EEG signals of 118 channels are treated as the independent variables or the features. Right hand=0 and right foot=1 are treated as response variable with the samples.

3.2.2 Signal pre-processing

The Butterworth filter was applied to remove maximum noises existing in EEG signals. The Butterworth filter is a signal processing filter designed in the passband to have a frequency response that is as flat as possible. As the Butterworth filter is maximally flat, this means that it is designed so that at zero frequency, the first 2n-1 derivatives for the power function concerning frequency are zero.

Butterworth filter can be defined with an amplitude response of

$$|H(\mathcal{JW})| = \frac{1}{\sqrt{1+\left(\frac{\omega}{\omega_c}\right)^{2n}}} \tag{3.1}$$

where, ω_c is the filter cut-off frequency and n is the filter order. At low frequencies, we can obtain a gain closer to one, and as the frequency increases, the gain decreases (AlHinai, 2020).

At first loaded the dataset into MATLAB R2021b and then used the Butterworth filter considering low frequency 0.1 Hz, high frequency 4 Hz and 5^{th} order derivatives which is the range of delta wave (0.1-4) Hz. Delta waves are oscillations that prevail in the 1- to 4-Hz range and are commonly described as slow wave activity in the EEG. It arises from the vicinity of a localized area of brain damage. Thus, we get the noise removed filtered data from the raw data (AlHinai, 2020, Hussain and Park, 2021).

3.2.3. Feature Extraction:

CSP is the most distinguished feature extraction method in MI-based BCI research which has been utilized in this chapter. The CSP method designs spatial filters so that the variances in the filtered data are optimum (in the least squares sense) for discriminating two mental states in EEG signals. The key reason for using this method in this chapter is because the CSP algorithm purposes to learn spatial filters which minimise the variance of a class whereas maximising the variance of another. This method is very useful for band-passing EEG signals with multiple channels (Blankertz et al., 2007b, Ramoser et al., 2000).

We used 2 pairs of filters to extract EEG based motor imagery features as a parameter. The number of features extracted will be twice the value of this parameter. The filters selected correspond to the lowest and highest eigenvalues (Ortner et al., 2015).
The sample covariance matrix of a trial is calculated as follows:

$$R = \frac{XX^T}{tr(XX^T)} \tag{3.2}$$

where T denotes the transpose of a matrix and tr(x) denotes the trace of a matrix. Then calculate the composite spatial covariance as follows:

$$\overline{R_H} + \overline{R_F} = U\Delta U^T \tag{3.3}$$

Where, $\overline{R_H}$ and $\overline{R_F}$ are the two covariance matrices of the sample data and calculated by averaging over all the trials of each group, U stands for the eigenvector's matrix and Δ is the eigenvalues' diagonal matrix, the full projection matrix is then formed as follow:

$$W = B^T \Delta^{\frac{1}{2}} U^T \tag{3.4}$$

Where B is the eigenvectors matrix for the whitened spatial covariance matrix. Only the first and last m eigenvectors corresponding to the first and last m eigenvalues sorted in descending order were employed

$$Z = W^T X \tag{3.5}$$

A 2m dimensional feature vector is then assembled from the variance of the rows of Z as follows:

$$f_q = log(\frac{var\ (z_q)}{\sum_{i=1}^{2m} var\ (z_i)}) \tag{3.6}$$

Where z_q denoted the q-th row vector of Z (wang et al 2017)

3.2.4 EEG signal classification

There cannot be any comprehensive best machine learning model because a group of hypotheses that works for one domain may not apply to another. As a result, an efficient machine learning algorithm classifier needs to be accomplished for a better result. This research applied multiple classifiers to identify the best classifier in binary class MI tasks. The mathematical formula and a short description of the three proposed classifiers are below.

Medium KNN can be used in both regression and classification predictive problems (Ortner et al., 2015, Nicolas-Alonso et al., 2015). MKNN classification is described as instance-based learning where the model is characterized by memorizing the training dataset. This algorithm is appropriate for classifying EEG data as it is a robust technique for a massive amount of noisy data. The sample data is classified by the majority vote of its neighbour's class. This classification method is the nearest neighbour classifier that makes fewer distinctions than a Fine KNN with the number of neighbours set to 10. So, in MKNN, distinctions between the classes are medium and the neighbour's number are set to 10, which is also a parameter of the proposed model.

In the MKNN algorithm, every training sample must be validated at the first step. The validity of each point is computed according to its neighbours. The formula which is proposed to compute the validity of every point in the train set is given below:

$$Validity(x) = \frac{1}{H}\sum_{i=1}^{H} S(lbl(x), lbl(N_i(x))) \tag{3.7}$$

Where H is the number of neighbours and lbl(x) is the true class label of sample x. $N_i(x)$ is the i^{th} nearest neighbour of the point x. S stands for the similarity between the point x and the i^{th} nearest neighbour defined below:

$$S(a,b) = \begin{cases} 1 & a = b \\ 0 & a \neq b \end{cases} \tag{3.8}$$

In the MKNN method, the parameter k=10. In this method, first the weight of each neighbour is computed using $\frac{1}{d_e + \propto}$ where d=10 and is calculated, where α=0.5. Here, d_e is the Euclidian distance. Then the raw weight is multiplied by the training sample considering Euclidian distance. In this method, the weight of each neighbour sample can be defined consequently:

$$W(i) = validity\ (i) \times \frac{1}{d_e + \propto} \tag{3.9}$$

Where W(i) and validity (i) is the weight and the validity of the i^{th} nearest sample in the train set, this method gives greater importance to the reference samples with greater validity and closeness to the test sample. So, the proposed MKNN algorithm is comparatively more robust than LDA and LSVM.

LSVM learning algorithm has been used widely for classifying electroencephalogram (EEG) signals for diagnosing neurological disorders (Rathipriya et al., 2013, Mondini et al., 2016). In LSVM, the parameter kernel='linear' is applied as like as SVC, but in terms of liblinear rather than libsvm. thus, in case of penalty choosing and loss functions, it has more flexibility, and efficient in larger numbers of sample. LDA assumes that the conditional probability density functions are normal distribution with mean and covariance parameters. The main goal of LDA technique is to reduce the dimensions by removing the redundant and dependent features by transforming the features from a higher dimensional space to a space with lower dimensions.

3.3 Results

In this chapter, we aim to acquire a robust model that can achieve high classification accuracy. To attain this aim, we intend an automatic technique CSP from EEG data in the entire time window within the frequency band (0.1-4 Hz) to acquire the sparse features from butter worth filtered EEG data. The ultimate decision output is determined by the elective result of three classifiers, and the default classifier parameters are considered.

To assess the consistency of the proposed method, this chapter applied a 10-fold cross-validation method [10 fold]. 10-fold cross-validation procedure estimates the models by distributing the original features into ten sub features, where only one is measured as the testing set and the rest of the nine are the training set used for the classifier. The technique is recurring ten times and are equally exclusive. This technique overcomes the challenges of underfitting and significantly decreases the variance of the data. Fig 3.3 displays the boxplots representing the distribution of feature values of each individual subject considering two classes. Fig 3.4 shows the line diagram of an exemplary pattern of CSP feature extraction of selected subjects av, aw and ay. Fig 3.5 shows the comparison of classification accuracy of the subjects by three different models LDA, LSVM and MKNN. From this figure, we may say that the testing

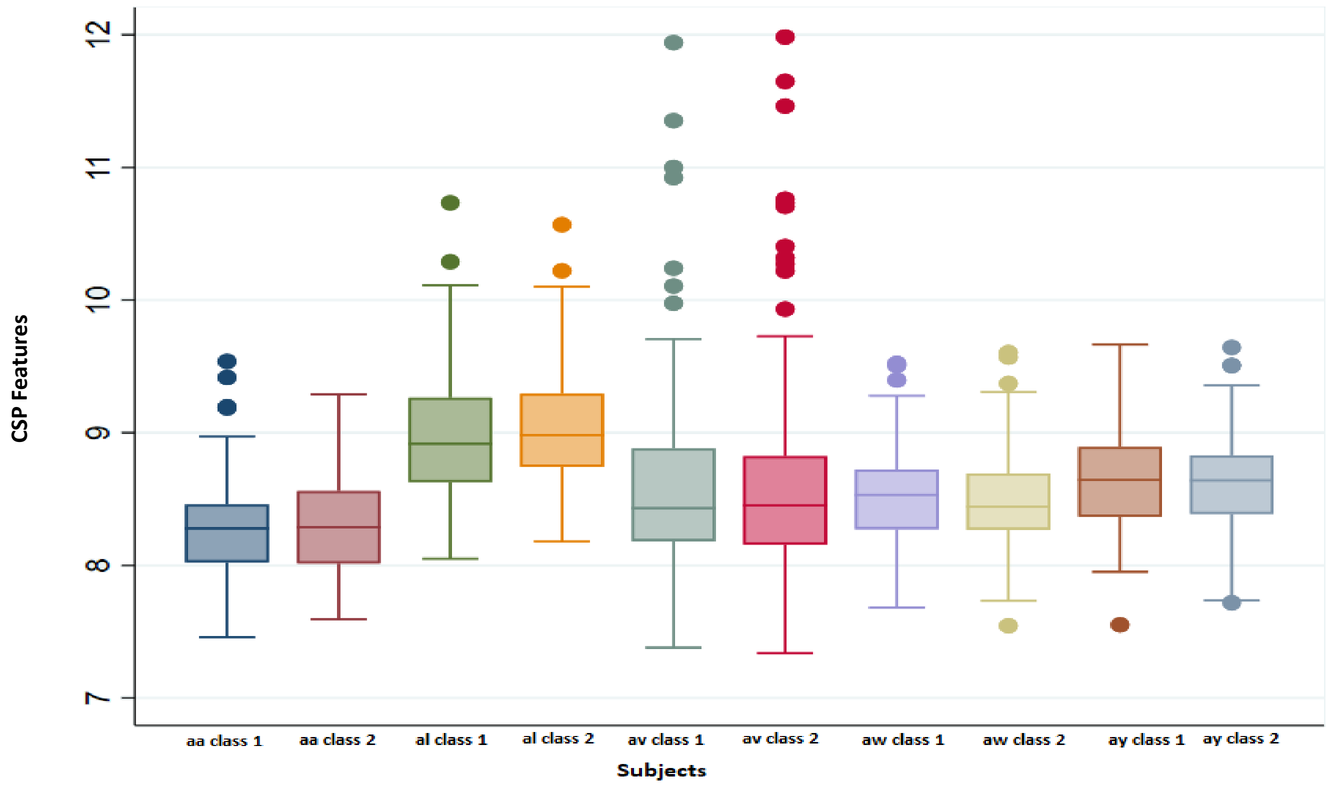

Fig 3.3. Boxplot of all subjects considering 2 classes

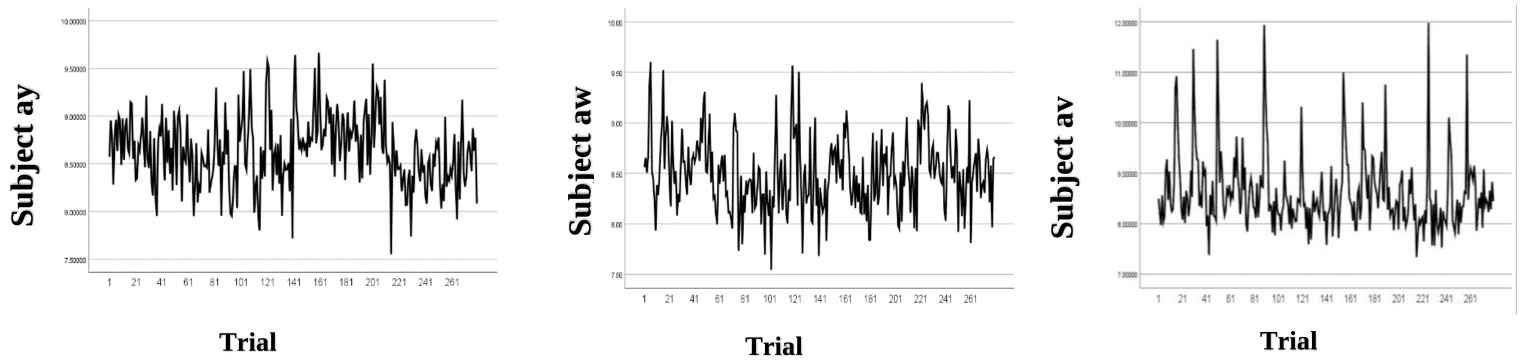

Fig 3.4. The line diagram of exemplary pattern of CSP feature extraction of selected subjects ay, aw and av.

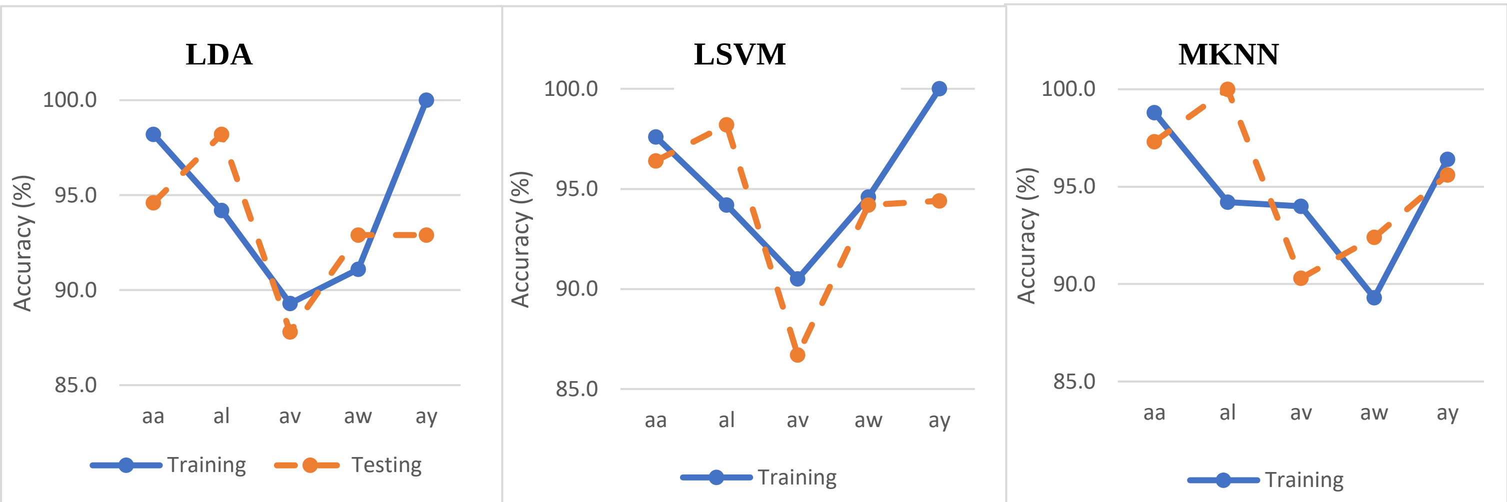

Fig 3.5. Comparison of training and testing classification accuracy of the subjects by three different models LDA, LSVM and MKNN

Table 3.2 provides a summary of results achieved utilizing our proposed classifiers. In this table, results for each subject are reported as mean ± standard deviation of accuracy 10-fold cross validation technique. It exhibits that MKNN arises as the best classifier surpassing others in classification accuracy except for the subject aw. It confirms that MKNN is a pledging and good choice for classifying EEG signals of MI tasks.

Table 3.2 accuracy using 10-fold cross validation technique for individual subject

Classifiers	10-fold cross-validation overall accuracy (%) (mean ±standard deviation)					
	aa	al	av	aw	ay	overall
LDA	94.6 ± 8.89	98.2±13.05	87.8±6.24	92.9±6.17	92.9±5.82	95.7±5.69
LSVM	96.4± 9.06	98.2± 13.02	86.7± 6.16	94.2±6.26	94.4± 5.91	96.4± 5.73
MKNN	97.3± 9.15	100± 13.29	90.3± 6.41	92.4±6.14	95.6±5.99	97.1±5.77

The calculation of classification accuracy applying multiple classifiers is done utilizing the 10-fold cross-validation technique. In table 3.2, the experimental results show that our chapter produces the highest accuracy score in all subjects above 90% and the average score is above 97% where the CSP and MKNN were applied.

Table 3.3 (a) Sensitivity, specificity using 10-fold cross validation for individual subjects.

Subject name		Mean ±standard deviation (%)				
		aa	al	av	aw	ay
Sensitivity	LDA	95±8.93	100±6.64	83.64±5.93	91.96±6.11	95.61±5.99
	LSVM	98.28±9.23	100±6.65	81.6±5.79	92.17±6.12	94.26±5.91
	MKNN	98.31±9.24	100±6.6	86.92±6.17	89.08±5.91	94.4±5.92
Specificity	LDA	94.23±8.85	96.55±6.41	93.02±6.61	93.75±6.23	90.58±5.67
	LSVM	94.44±8.87	96.55±6.42	93.9±6.67	96.33±6.40	94.62±5.93
	MKNN	96.2±9.04	100±6.65	94.38±6.7	96.19±6.39	96.85±6.06

Table 3.3(b) F1 score and Kappa statistic of individual subjects using 10 fold cross validation

Subjects		aa	al	av	aw	ay
F1 score	LDA	0.95	0.9818	0.8846	0.9279	0.937
	LSVM	0.9661	0.9818	0.8774	0.9422	0.9426
	MKNN	0.9748	1	0.9073	0.9258	0.9555
Kappa statistics	LDA	0.892	0.964	0.755	0.857	0.857
	LSVM	0.928	0.964	0.735	0.844	0.889
	MKNN	0.946	1	0.806	0.848	0.913

The classification efficiency of the endorsed method is evaluated in relation of accuracy (ACC), F1 score, kappa value, specificity (SPE) and sensitivity (SEN) parameters for the five subjects which are shown in Table 3.3(a) and 3.3(b). It is observed from all the tables (Table 3.2 , 3.3(a) & 3.3(b)) and figures of sensitivity, specificity, F1 score, and Kappa statistics is that the MKNN classifier with CSP based features delivered the best classification accuracy.

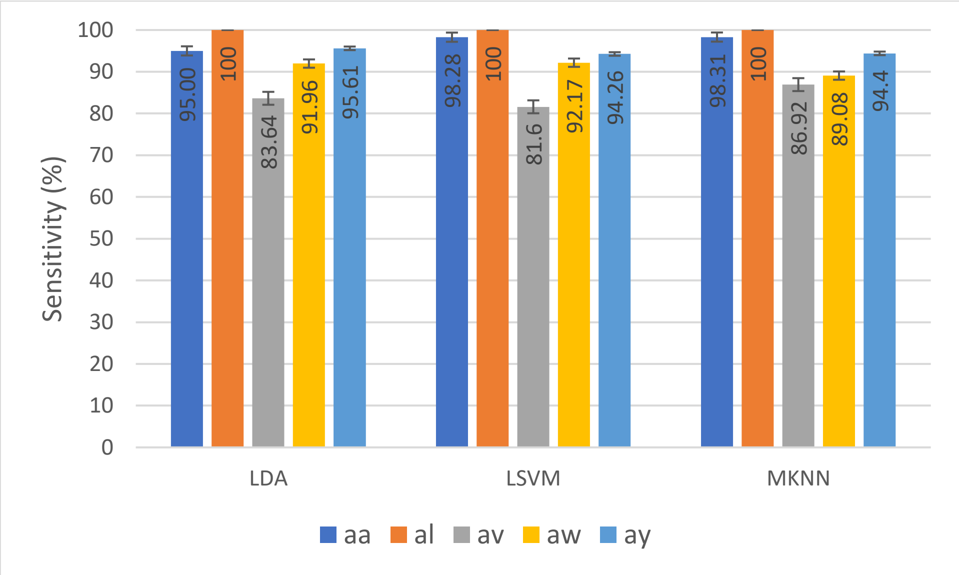

Fig 3.6. Sensitivity comparison for different classifiers by subjects. Error bars show the standard error.

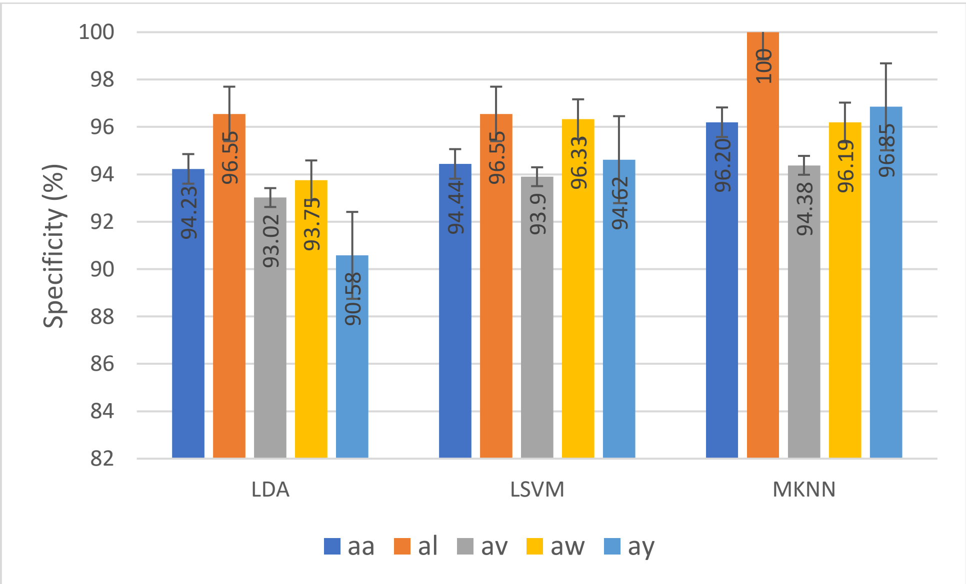

Fig 3.7. Specificity comparison for different classifiers by subjects. Error bars show the standard error.

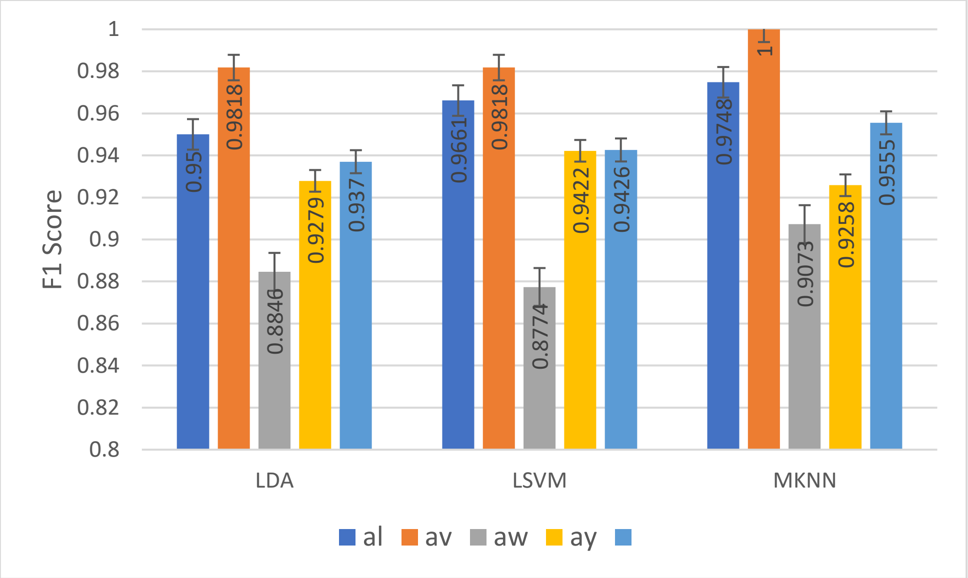

Fig 3.8. F1 score comparison for different classifiers by subjects. Error bars show the standard error.

Results of Sensitivity, specificity and F1 score compared with different classifiers by subjects are shown in Fig 3.6, 3.7 and 3.8 where error bars represent standard error. The best results of parameters are achieved for the subject al as ACC 100%, SEN 100%, SPE 1, F1 Score 1 and kappa value as 1. Other SBs have also specified significant results applying MKNN classifier. From Table 3.3, the sensitivity of 100% for subject Al reveals that all RH MI tasks are correctly classified as RH. Similarly, the specificity value of 100 designates the percentage of total RF MI tasks that are precisely predictable as RF tasks. The suggested method has also gained a high value of F1 Score as 1 which is the highest value for the subject al. This implies the precise performance of the proposed work. Also, a kappa value of 1 indicates the effectiveness of medium KNN classifier in identifying the two MI tasks. Thus, the classifier's performance is also appraised and in the assessment to other classifiers, it has been demonstrated to be the best for the cited purpose. Finally, the classification accuracy of 100% displays how successfully the available approach can distinguish the binary classes of MI tasks. Such high classification accuracy shows the consistency and robustness of the method concerning the identification of various MI tasks in a BCI system.

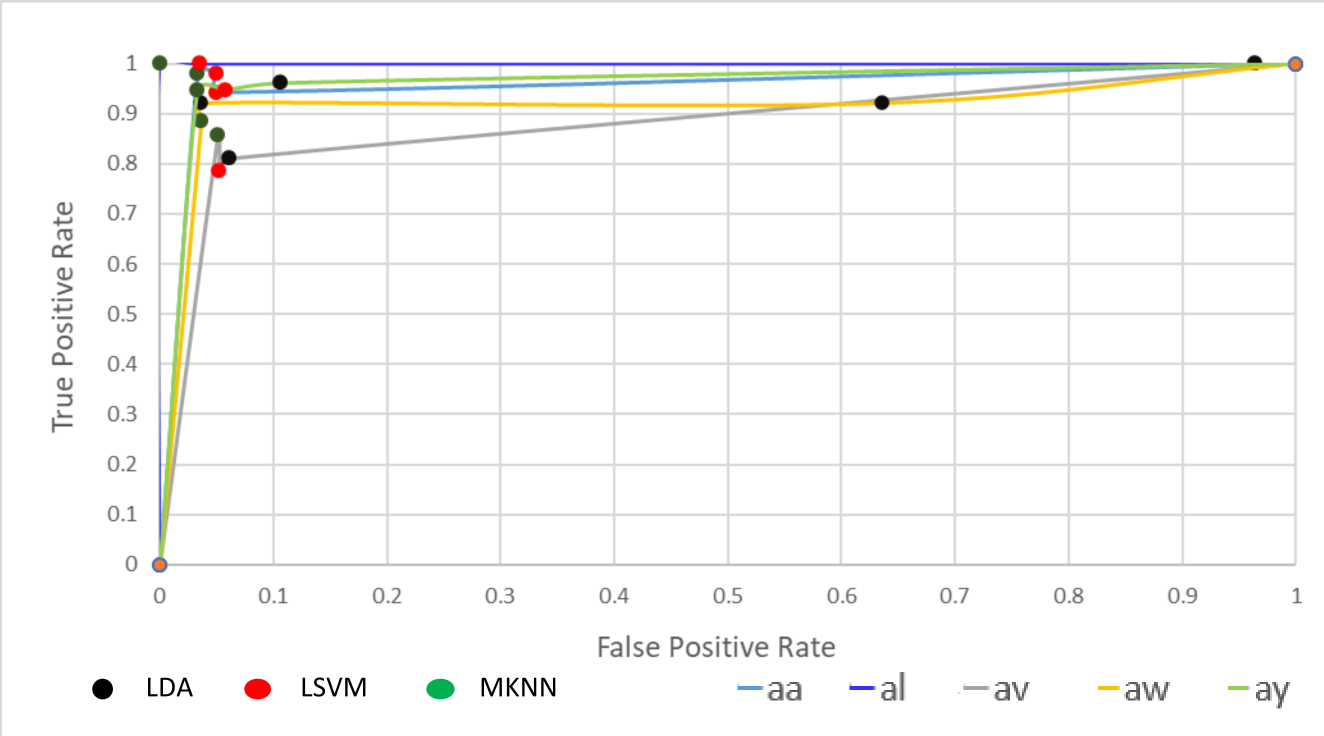

Fig 3.9. ROC graph comparison for different classifiers by subjects

In Fig 3.9, we have produced the ROC curves for the classifiers namely LDA, LSVM and MKNN by plotting sensitivity in y-axis and 1-specificity in x-axis. It is clear from the curve that the proposed CSP based MKNN model is on top as it has the highest sensitivity among all the classifiers and the CSP based LSVM has the lowest ROC curve as it has low sensitivity value.

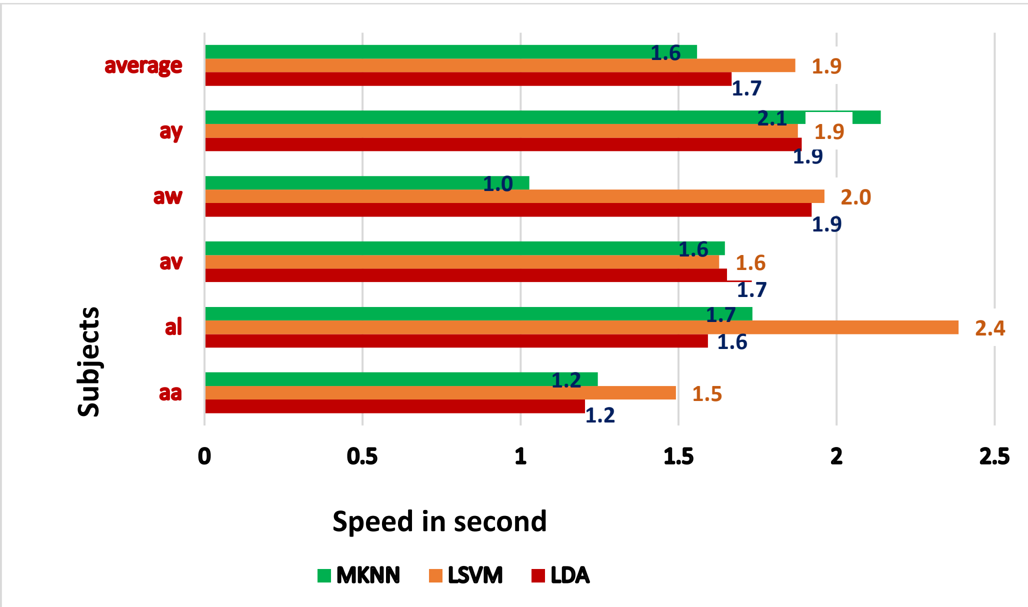

Fig 3.10. Speed (second) comparison for different classifiers by subjects

Finally, in Fig 3.10 the comparison of classification speed of three classifiers have been illustrated. For speed calculation the timer was set during the program of the training data. Ten times classifications of the three classifiers were counted to confirm accuracy. From the graph, we can say that the average of the five subjects for the 10 times cross validation of the MKNN classifier is only 1.6 seconds, whereas it is 1.9 s for LSVM and 1.7 s for LDA. Thus, the classification speed of MKNN is much higher than the rest of the classifiers.

3.4 Discussion

As stated earlier, the objective of this chapter is to gain better classification accuracy for the difference of RH and RF MI activities using EEG signals. This chapter proposes CSP feature extraction of various MI activities of EEG signals because of the non-stationary nature of EEG signals. Ultimately, the classification performance of extracted CSP based features is assessed applying multiple classifiers in order to gain the best classification accuracy. Three multiple classification models are applied for the anticipated CSP-based features where outstanding results are obtained using the subspace MKNN classifier. Thus, the multi-classifier method discovers the efficacy and robustness of the collaborative technique based on KNN. We applied a 10-fold cross validation method to gain consistent and reliable performance and avoid model over-fitting.

In this chapter, Table 3.3 indicates our method's accuracy in engaging multiple classifiers. In BCI system MI-based activities of classification considering CSP as a feature extraction has been applied many times in the literature. In our multiple classifier investigation, we utilized classic classifiers and their variants. Variants of KNN namely medium has outperformed attaining the maximum accuracy of 100% for subject av. Likewise, Linear variants of SVM and LDA classifier have been utilized. The results found applying these classifiers are highly satisfactory. Thus, we can conclude that the medium k nearest neighbour (MKNN) has achieved the highest classifier accuracy compared with the other classifier. Multiple classifier methods utilizing different base classifier and their modifications facilitated to discover the robustness and effectiveness of the ensemble learning classifier and finally, MKNN is proven as the best classifier for our purpose.

Table 3.4: Comparison between the results of our proposed methods with some reported research outcome.

Author and year	Methods + classifier	Accuracy					
		aa	al	av	aw	ay	Average
This study	CSP based LDA	94.6	98.2	87.8	92.9	92.9	95.7
This study	CSP based LSVM	96.4	98.2	86.7	94.2	94.4	96.4
This study	**CSP based MKNN**	**97.3**	**100**	**90.3**	**92.4**	**95.6**	**97.1**
Miao et al., 2021	CTFSPLIBSVM	86.05	98.57	52.14	96.07	92.14	85
Hermosilla et al, 2021	ERD/ERS-SCNN	94.33	97.24	79.90	93.54	87.58	90.52
Padfield et al, 2021	CSP+SVM-RBF+MSMV	79.64	94.64	75	78.57	94.64	84.51
Cherloo et al, 2021	RCSSP+DT	82.14	96.42	68.87	98.21	88.88	86.91
Tiwari and chaturvedi, 2021	MEMD+SVM	93.6	79.2	94.6	85.54	84.94	87.57
Jin et al., 2020	BCS-CSP	82.1	95.0	72.1	90.7	91.8	86.34
Singh et al, 2019	(R-MDRM)	81.25	100	76.53	87.05	91.26	87.21
Abougharbia et al, 2019	Hybrid features +LSVM	89.6	99.3	77.9	97.5	94.3	91.72
Y Miao et al, 2019	R-AdaBoost	79.6	93.9	53.2	87.9	88.2	80.6
Park and Chung, 2019	FBCSP-LSSVM	92.85	89.28	71.43	83.04	94.05	86.73
Dai et al, 2018	TKCSP-LKSVM	68.10	93.88	68.47	90.58	84.65	81.14
Selim et al, 2018	CSP\AM-BA-SVM	86.61	100	66.84	90.63	80.95	85.01

3.5 Performance Comparison

We compared alongside various existing methods applying the same dataset to further investigate our proposed system's efficiency. Table 3.4 illustrates a comparison of performance analysis among the present method with the earlier numerous prominent methods which have previously been testified for the same dataset, BCI competition III dataset IVa. Miao et al extracted features using CTFSP algorithm. LIBSVM is the classifier of that method, and their average accuracy was 85%, while two subjects' accuracies were less than 90% (Miao et al., 2021b). Another author Hermosilla et al. applied ERD/ERS-SCNN as a machine learning algorithm and achieved 90.52% average accuracy. In this article subject av and ay have 79.90% and 87.58% CA, respectively which is lower than our proposed method (Hermosilla et al., 2021). On the other hand, Tiwari and Chaturvedi used MEMD-SVM algorithm, subjects al, aw and ay accuracies were less than 90% and the average score were 87.57% (Tiwari and Chaturvedi, 2021).

Jin et al. applied BCS- CSP method and their average accuracy was 86.34%. Singh et al. achieved 87.21% average accuracy and 3 subjects accuracy were less than 90% by applying R-MDRM feature extraction and classifier (Jin et al., 2020). Abougharbia et al., applied hybrid features as a feature extraction method and LSVM as a classifier. In this article, the average CA score was 91.72%, and not all subjects scored more than 90% (Abougharbia et al., 2019). In case of, Y Miao et al., Park and Chung, Dai et al. and Selim et al. they applied R-AdaBoost, FBCSP-LSSVM, TKCSP-LKSVM and CSP\AM-BA-SVM machine learning algorithm (Miao et al., 2019, Park and Chung, 2019, Dai et al., 2018, Selim et al., 2018). No one achieved average CA score above 97% and subject specific CA more than 90% So, from Table 3.4, it is evident that majority of the compared methods accomplished average accuracy scores below 90% and not all the individual subjects' accuracy more than 90%. Thus, from the above discussion we can firmly say that our chapter produces the highest accuracy score in case of all subjects above 90% and the average score is above 97% where the CSP and MKNN were applied.

Finally, we developed an improved method not a new method which is more accurate, efficient, and speedy compared with the traditional methods. It achieved 5.32% to 16.5% accuracy improvements compared with the other existing methods. When the accuracy is higher, right hand and right foot movement identification would be more accurate. This research assists the experts to process and analyse EEG signals for BCI applications and can apply it for the rehabilitation of motor disabled patients.

3.6 Conclusion

In conclusion, we may say that our developed method seems to be onward in the task of distinguishing MI tasks-based non-stationary EEG signals in evaluating with such eminent methods. It has outstripped all other approaches by attaining the highest classification accuracy of major subjects and an average accuracy above 97%. It also improved 5.32% to 16.5% accuracy compared with the other existing methods. This indicates that our proposed method exceeds other noteworthy feature extractors and classifier combinations. Thus, from Table 3.4 it confirms that our developed framework is more accurate, efficient, and speedy compared to earlier existing methods. Hence, applying CSP for restoring EEG signals into images united with deep learning model authorizes as a robust method. It is highly dynamic, and this proposed technique will rapidly identify the intentions of motor disabled people that will assist patients' treatment, communication, daily life, and rehabilitation. Thus, this framework will help technologists to create knowledge on how software or Apps can be developed for the betterment of motor disabled people.

Furthermore, this developed software can be engaged in different utilizations such as wheelchair controlling for motor disabled, robotic arm, computer mouse controlling, etc. It can be applied to create a massive inspiration in the lives of its beneficiaries. Hence, this developed method will support the creation of frontier medical science technology and significantly improve current EEG based BCI technologies in Australia and worldwide.

3.7 Link and Implications

Finally, our developed method seems to be forward in differentiating MI tasks-based nonstationary EEG signals in assessing with such eminent methods. It has surpassed all other techniques by attaining the highest classification accuracy of major subjects and an average accuracy above 97%. It outshines previously established different noteworthy combinations of feature extractors and classifiers. Table 3.4 confirms that our introduced algorithm is accurate and reliable compared to earlier existing methods and establishes the robustness and effectiveness of the anticipated technique. Thus, applying CSP for restoring EEG signals in combination with the deep learning model is authorized as a robust method. It is exceptionally dynamic and can undoubtedly be engaged for the betterment of motor disabled people and can be involved in diverse applications such as wheelchair controlling for motor disabled, robotic arm, computer mouse controlling, etc. It can generate massive inspiration in the lives of its beneficiaries. Even though, our developed CSP-MKNN algorithm achieved higher accuracy for detecting MI task performance, there exist a limitation in MKNN classifier which is difficult to pick the correct value of K, involves high memory, and is sensitive to irrelevant features. To overcome this limitation, we develop another improved approach based on CSP-OE.

In the next chapter, we will introduce another improved algorithm considering CSP-based OE method for identifying the communication intention of motor disabled people.

Chapter 4

This chapter is presented in the accepted format of the publication cited below.

Khanam, T., Siuly, S., Wang, H. (2022). Analysing Big Brain Signal Data for Advanced Brain Computer Interface System. In: Hua, W., Wang, H., Li, L. (eds) Databases Theory and Applications. ADC 2022. Lecture Notes in Computer Science, vol 13459. Springer, Cham.

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CHAPTER 4

ANALYSING BIG BRAIN SIGNAL DATA FOR ADVANCED BCI SYSTEM

The main intention of BCI research is to generate a new communication pathway enabling direct transmission of communications from the brain by estimating the brain's mental tasks for those suffering from acute neuromuscular disabilities [2]. The main challenge of BCI systems is to recognize motor imagery (MI) task based big brain signal data in the biomedical engineering research area. Although BCI technologies have progressed rapidly in recent years, many unsolved challenges, for example, the advancement of MI signal classification, still exist. Hence, automatic analysis of robust classification techniques needs to be designed to resolve the limitations faced in the existing investigation. Our proposed framework is based on common spatial pattern (CSP) data method and optimized ensemble (OE) machine learning technique for the application of BCI technologies. The CSP method is applied to learn essential features from EEG data, and then the extracted features are fed as input to the optimized ensemble (OE) classifier. The developed method was tested on BCI Competition III dataset IVa, which comprises motor imagery-based EEG signal data. The experimental outcomes show that our developed technique can handle brain signal big data for detecting communicative intentions for an improved BCI system. We evaluated our intended algorithm's performance with several other existing methods. In contrast with other established techniques, our algorithm achieves higher classification accuracy. This research will help the experts to process and analyse EEG signals for BCI applications.

The contents of this chapter have been published in the Australian database conference (ADC 2022) (Khanam et al.)

4.1 Introduction

Electroencephalography (EEG) signal data called brain signals data plays an essential role in biomedical science and brain computer interface systems (BCI).(Alvi et al., 2022a) (Abhang et al., 2016, Alvi et al., 2022b). This EEG records are used to monitoring and recording electrical activity in the brain using electrodes placed on the scalp(Siuly et al., 2020a). EEG signal data is a very large amount of data. Traditional scanning and analysis of EEGs is time-consuming since these records may last hours or days. Therefore, high performing automated analysis of EEGs can lower time to diagnosis and develop real-time applications by identifying communicative intentions for brain computer interface application (BCI) (Golmohammadi et al., 2019).

A BCI, sometimes called a brain–machine interface (BMI), is a direct communication pathway between the brain's electrical activity and an external device, most commonly a computer or robotic limb (Chaudhary et al., 2020). A BCI is a computer-based system that receives brain signals, analyses them, and converts them into commands that are conveyed to an output device to carry out the desired action (see Fig.1) (Chaudhary et al., 2020). The primary purpose of BCI research is to generate a new communication pathway permitting direct transmission of communications from the brain by evaluating the brain's mental imagery task for those who are suffering from severe neuromuscular disabilities (Sadiq et al., 2022b).

The big challenge of BCI systems is the identification of motor imagery (MI) task-based EEG for discovering the communicative intentions of motor disabled people (Siuly et al., 2011, Alvi et al., 2022b). So, our research problem is how to develop more accurate and robust methodological framework to identify communicative intentions from motor imagery BCI brain signal data. Hence, we are interested in developing a method which would be capable of executing a computationally complex machine learning algorithm on big data platforms with high speed and accuracy.

The transition of brain activities into EEG signals in BCI systems involves a robust and accurate classification to create a communication system for motor immobilized people (Alvi et al., 2022b). Although BCI techniques have been improving quickly in recent years, there exists a number of unsolved challenges related to MI signal classification, which is still unable to achieve 100% accuracy(Graham et al., 2019). Now we are presenting some recent studies which have been worked on mental state identification for BCI application. Chaudhry et al. (Chaudhary et al., 2021) deployed a machine learning method using the common spatial pattern (CSP) and dynamic weighted majority (DWM) based classifier. The author’s employed procedure reached 85.6% accuracy, which is not satisfactory. Another author Miao et al. (Miao et al., 2021b) established a framework termed common time-frequency-spatial patterns (CTFSP) with multiple support vector machine (SVM) machine learning algorithm. The accuracy was achieved 85% in this study. The drawback of this procedure is various signal processing and classification techniques have been used in low-frequency movement-related cortical potential (MRCP) detection involving locality preserving projection (LPP). Tiwari and Chaturvedi, Cherloo et al. and Inbarani et al. (Tiwari and Chaturvedi, 2021, Renuga Devi and

Hannah Inbarani, 2021, Cherloo et al., 2021) gained less than 90% accuracy by using several machine learning methods. Rashid et al. (Rashid et al., 2021) accomplished 89.64% and 88.56% accuracy by using CSP-SVM, CSP-KNN machine learning methods, respectively. Siuly et al. (Siuly and Li, 2012a) established a novel cross-correlation based machine learning technique with a least square support vector machine (LS-SVM) for two-class MI signals recognition. The LS-SVM classifier produced average accuracy performance of 88.32%. The drawback of that method was that they did not select the parameters optimally through any method. They manually selected the parameters for the LS-SVM method.

The above-mentioned existing literatures show that most of the methods are very complex for practical application and also their performance is not satisfactory for identifying communicative intentions in BCI signal output. Hence, an automatic analysis robust classification method needs to be designed to resolve the weaknesses faced in this research. In line with the literature gap we proposed an algorithm of CSP for feature extraction and OE for classification of the obtained features for getting closer to 100% accuracy for identifying communicative intentions in the development of BCI systems.

4.2 Proposed Framework

This research represents a scheme based on data mining and machine learning methods for analysis of big EEG signal data (Sarki et al., 2022a, Yin et al., 2022). Fig. 4.1 show a diagram of the proposed plan that can be used for handling big amount of brain signal data (for example, EEG data). This figure is an example of how EEG signal data are processed for analysis in the proposed plan for each subject. The proposed methodology is divided into several parts such as signal pre-processing, feature extraction and classification. The detail of each part is provided in the following sections.

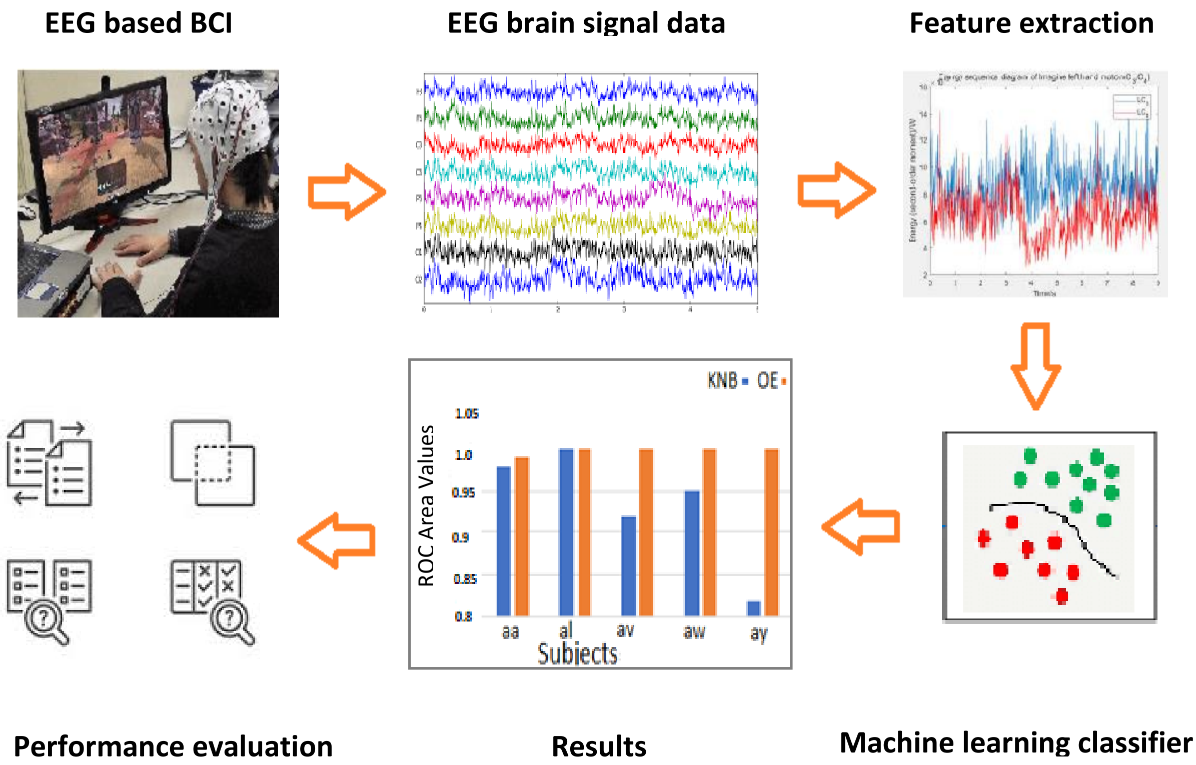

Fig. 4.1. Proposed methodological diagram for the analysis of big brain signal data

Signal pre-processing: EEG signal is more often contaminated with noises or unwanted signal. The most common noises in EEG signals are the eye movement or blinking, power line or interference with other device and muscle. These noises are overlapping each other (Milne, 2011). To overcome these noises from the brain signal EEG data, we applied Butterworth filter. Butterworth filter is a type of electronic filter, which was first designed by British engineer Stephen Butterworth (1930). There are two advantages of Butterworth filter: one is the frequency response curve in the pass band is flat to the maximum extent and the other one is selecting a higher order filter will then have a steeper attenuation slope near the cut-off frequency each time the order of the filter is increased. Hence, we used Butterworth filter considering low frequency 0.1 Hz, high frequency 4 Hz and 5th order derivatives in order to getting a noise free EEG signal data. Thus from the raw data we get the noise removed filtered data (AlHinai, 2020).

Butterworth filter can be defined with the first 2n-1 derivatives response of

$$|H(\mathcal{JW})| = \frac{1}{\sqrt{1 + \left(\frac{\omega}{\omega_c}\right)^{2n}}}$$

Where, ω_c is the filter cut-off frequency and n is the filter order. At low frequencies, we can obtain a gain closer to one, and as the frequency increases, the gain decreases (AlHinai, 2020). **Feature extraction:** After getting noise free data, the next step is to discover representative information from EEG data that acts as features. Signals undertaking the feature extraction process will be differentiated by using different types of data mining methods. Our proposed feature extraction method is common spatial pattern (CSP) method. This is an efficient spatial filtering algorithm and has been proven to be an effective algorithm for the binary motor imagery tasks classification. This method examines spatial patterns of imagined hand and foot movements (Wang et al., 2006). CSP method depends on the concurrent diagonalization of the covariance matrices of two classes. The standardized spatial covariance of the EEG can be represented as follow

$$R_1 = (X_1 X_1^T)/(t_1(X_1 X_1^T))$$
$$R_2 = (X_2 X_2^T)/(t_2(X_2 X_2^T))$$

X_1 of size (n, t_1) and X_2 of size (n, t_2) are two windows of multivariate signal, where n is the number of signal and t_1 and $t_2$are the respective number of samples.

Classification

After getting important features from the feature extraction method, our next step is to conduct classification of the features data(Li et al., 2022, Pandey et al., 2022). In this study, we used two classification methods. One is naive bayes classifier and the other one is ensemble classifier. Naïve bayes is one of the simple and most effective classification algorithms which helps in building the fast machine learning models that can make quick predictions. It is a probabilistic classifier, which means it predicts based on the probability of an object. It is highly scalable with the number of predictors and data points. It is fast and can be used to make real-time predictions. Since a naive bayes text classifier is based on the Bayes's theorem, which helps us compute the conditional probabilities of occurrence of two classes (right hand and right foot) based on the probabilities of occurrence of each individual event, encoding those probabilities is extremely useful.

$$P(A/B) = \frac{P(B/A)P(A)}{P(B)}$$

Where,

P(A): The probability of hypothesis H being true. This is known as the prior probability, P(B): The probability of the evidence.

P(A|B): The probability of the evidence given that hypothesis is true, P(B|A): The probability of the hypothesis given that the evidence is true.

The reason of choosing naïve bayes classifier because it is easy and fast to predict the class of the test data set. It also performs well in binary-class prediction. When assumption of independence holds, a naive bayes classifier performs better compared to other models like logistic regression and we need less training data (Wang and Zhang, 2016). In order to evaluate the performance of the obtained features, we use another machine learning model called ensemble learning**.** Ensemble learning is a general meta-approach to machine learning that seeks better predictive performance by combining the predictions from multiple models. Each classifier in the ensemble is a decision tree classifier and is generated using a random selection of attributes at each node to determine the split. During classification, each tree votes and the most popular class is returned. The reason of choosing this classifier is it's better performance and robustness. An ensemble can make better predictions and achieve better performance than any single contributing model and ensemble reduces the spread or dispersion of the predictions and model performance (Chatterjee et al., 2019).

4.3 Experimental data

Our proposed method will be tested on publicly available EEG databases from BCI Competition III dataset IVa (https://drive.google.com/u/0/open-BCI-data-file). This dataset was recorded from five healthy subjects (labelled aa, al, av, aw, ay) who performed right hand (class 1) and right foot (class 2) MI tasks. Subjects sat in a comfortable chair with arms resting on armrests. This data set contains MI EEG data from the four initial sessions without feedback. EEG signals were recorded from 118 electrodes according to the international 10/20 system. There were 280 trials for each subject, namely 140 trials for each task per subject. During each trial, the subject was required to perform either of the two (right hand and right foot) MI tasks for 3.5s. Among 280 trials, 168, 224, 84, 56 and 28 trials composed the training set for subject aa, al, av, aw and ay respectively and the remaining trials composed the test set.

4.4 Results and discussions

In this section, we provide the experimental results of our proposed method for BCI Competition III, IVa dataset. For removing unexpected signal, we used Butterworth filter and then we applied CSP method for feature extraction. In this dataset, there are five healthy subjects each subject accomplished two tasks. Task one is imagination of right-hand movement and task two is imagination of right-foot movement. Each task or effort is counted as a class of EEG data. Figure 4.2 shows the box plots of the data after feature extraction of all subjects considering two classes: right hand and right foot. To assess the consistency of the proposed method, this study applied a 10-fold cross-validation method. 10-fold cross-validation process estimates the models by distributing the original features into ten sub features, where only one is computed as the testing set and the rest of the nine are the training set applying for the classifier. Figure 4.3 represents the comparison of training and testing classification accuracy of the individual subject by kernel naïve bayes and optimized ensemble machine learning model.

Table 4.1 shows the classification outcomes of the classifier kernel naïve bayes and optimized ensemble of each subject which is reported as mean ± standard deviation of accuracy, sensitivity and specificity using 10-fold cross validation. It gives information about accuracy, sensitivity, and specificity for each subject. From Table 4.1, it is very clear that optimizable Ensemble machine learning algorithm achieves higher classification results comparing to the Kernel naïve bayes machine learning algorithm for each of the subject. From this observation, we may conclude that optimizable Ensemble classifier is more accurate to classify EEG based motor imagery tasks.

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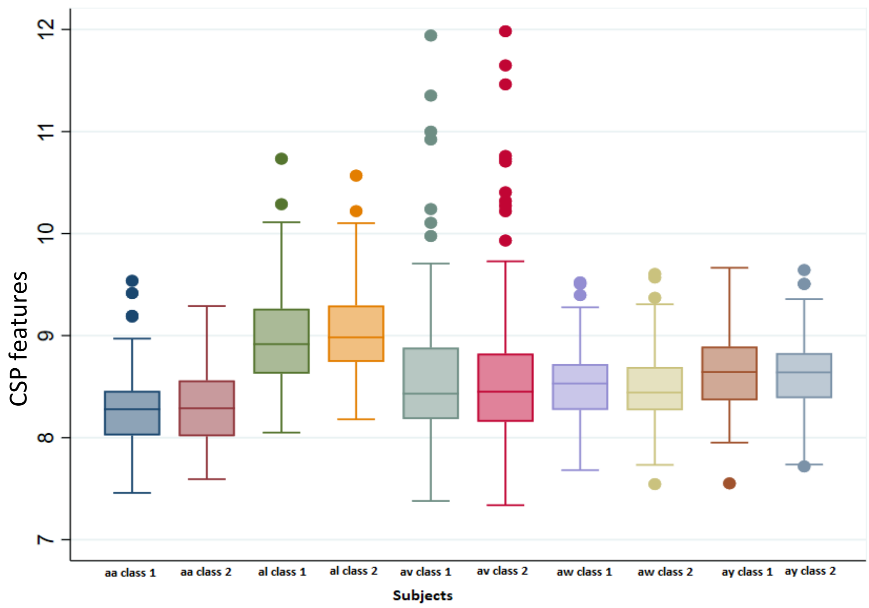

Fig 4.2: Boxplot shows the feature extraction of all subjects considering two classes

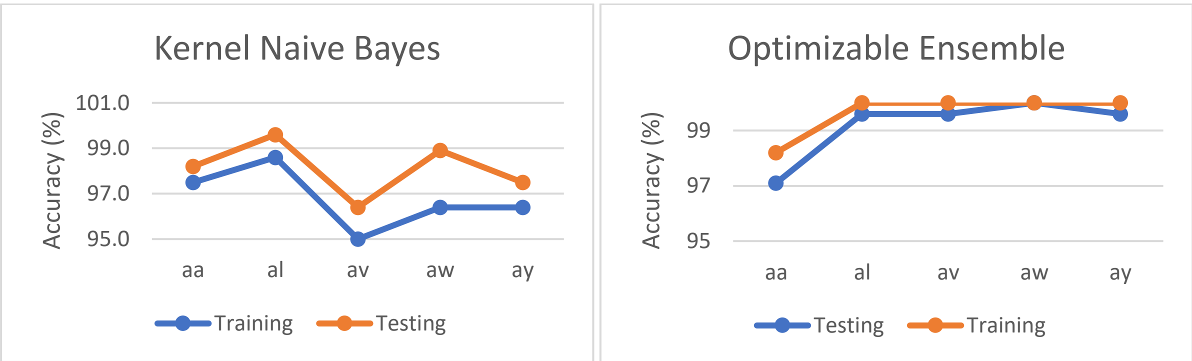

Fig 4.3. Comparison of training and testing classification accuracy of the individual subject among Kernel naïve bayes and optimizable ensemble

Fig 4.4 shows the F1 score comparison for KNB and OE classifiers by subjects. Here error bars show the standard error. From the figure it is clear that in case of OE classifier, F-1 score is closer to 1 for all the subjects. So, OE is a better model than KNB. Kappa Statistic is used to measure the level of agreement between two raters or judges who each classify items into mutually exclusive categories. We know that kappa of >0.81 represents excellent agreement. From Fig 4.5, we found that both the classifier's score is good.

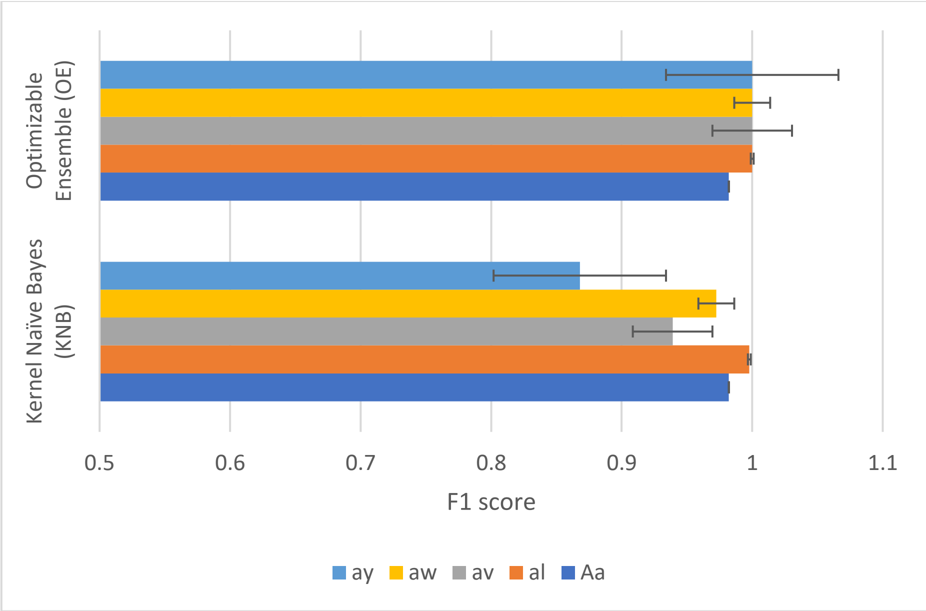

Fig 4.4. F1 score comparison for KNB and OE classifiers by subjects. Error bars show the standard error.

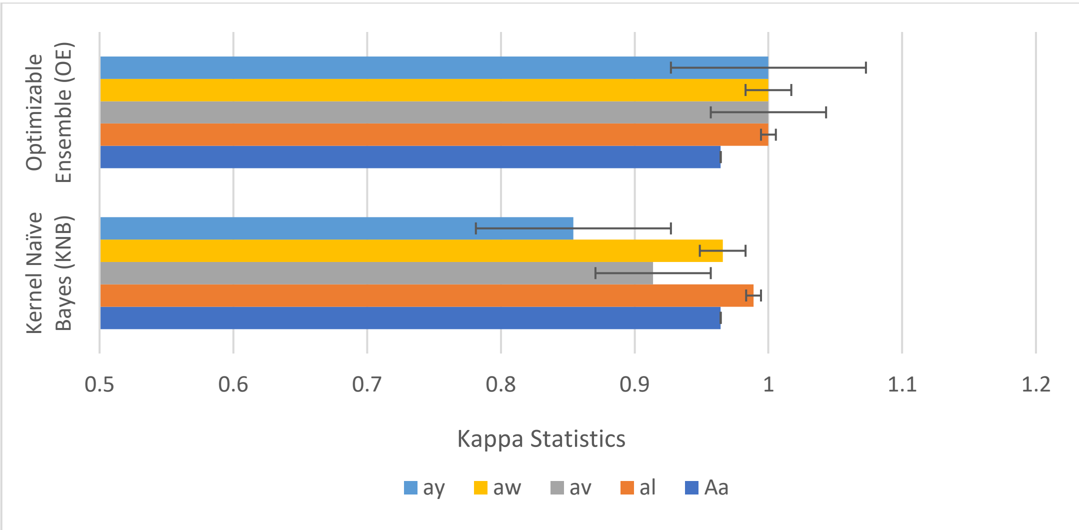

Fig 4.5. Kappa comparison for KNB and OE classifiers by subjects. Error bars show the standard error.

Table 4.1. Overall accuracy, Sensitivity and specificity using 10-fold cross validation for individual subject

Subjects	Kernel naïve bayes machine learning algorithm (mean ± standard deviation)			Optimizable ensemble machine learning algorithm (mean ± standard deviation)		
	Accuracy (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)
aa	98.20 ± 9.23	97.86 ±9.20	98.57 ±9.27	98.20 ±9.23	97.86 ±9.19	98.57 ±9.2
al	99.60 ±5.92	100.00 ±5.94	98.25 ±5.84	100.00 ±6.64	100.00 ±5.95	100.00 ±6.64
av	96.40 ±5.73	91.67 ±6.51	98.47 ±5.85	100.00 ±5.95	100.00 ±	100.00 ±5.95
aw	98.90 ±5.83	94.64 ±5.62	100.00 ±5.94	100.00 ±6.64	94.92 ±5.64	100.00 ±5.94
ay	97.50 ±5.8	82.14 ±4.87	99.21 ±5.89	100.00 ±6.21	100.00 ±5.9	100.00 ±5.94
average	98.12 ±5.83	93.26 ±5.54	98.90 ±5.88	99.64 ±5.92	98.55 ±5.85	99.71 ±5.93

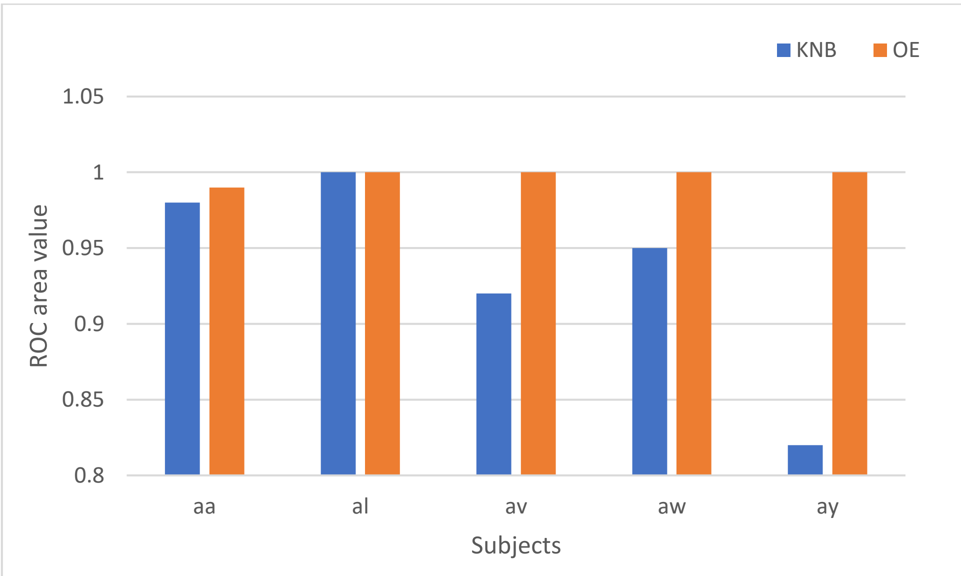

Fig 4.6. ROC area for KNB and OE classifiers by subjects

Fig 4.6 depicts the ROC areas for the KNB and OE classifiers for each of the individual subject. An ROC curve (receiver operating characteristic curve) is a graph shows the performance of a classification model at all classification thresholds. We know, ROC area 0.8 to 0.9 is considered excellent, and more than 0.9 is considered outstanding. So, from this experimental result it is clear that OE classifier is better than KNB.

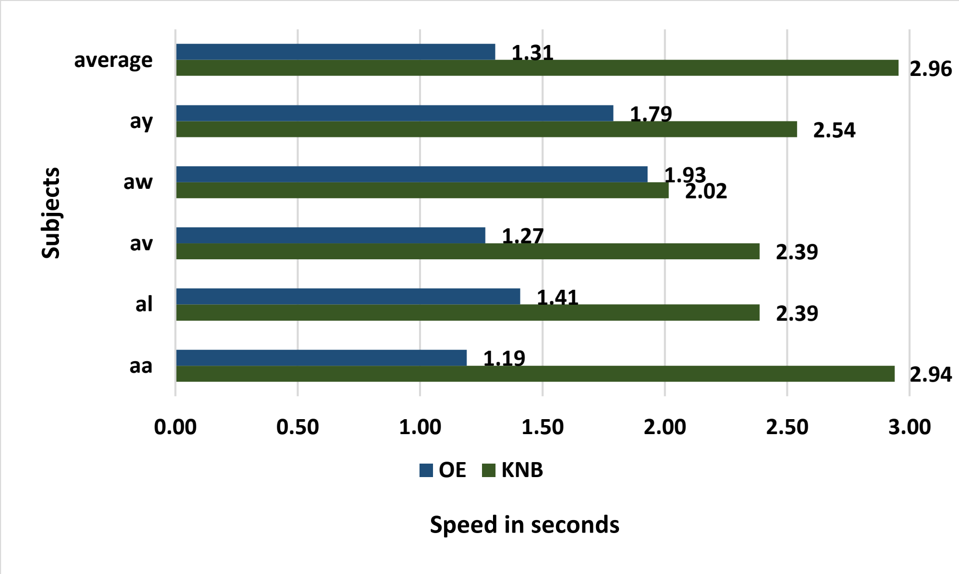

Fig 4.7. Comparison of both the classifiers KNB and OE by subjects based on speed (second)

At the end, we compare the classifiers based on speed which has been illustrated in Fig 4.7. A timer was set for speed calculation during the training data program. Accuracy was checked by counting 10-fold classifications of both the classifiers. From the graph, we can say that the 10-fold cross-validation of OE classifier took only 1.31 seconds on average for 5 subjects, whereas it took 2.96 seconds for KNB. Therefore, the classification speed of OE is much faster than other classifiers.

Table 4.2 shows the performance comparison between our proposed method based on OE classifier and eleven existing machine learning algorithms considering individual subject's classification accuracy and overall classification accuracy for EEG dataset. Our proposed method achieved 99.64% overall performance. This is the highest performance achievement among the other existing methods. In this study, for subject aa, CA rate is 98.2%, all other subject's (al, av, aw and ay) CA rate is 100%. The overall classification accuracy of MSPCA based LR (Sadiq et al., 2022b), OA+NB (Siuly and Li, 2015), CS+SVM (Ince et al., 2009), CC+LS-SVM (Siuly and Li, 2012a), ISSPL (Wu et al., 2008) and Clustering with LS-SVM (Li and Wen, 2011) are 97.7%, 96.36%, 96%, 95.72%, 94.21% and 88.32% respectively. Some other studies average classification accuracy Z-LDA (Zhang et al., 2013), SSFO(Yong et al., 2008), R-AdaBoost(Miao et al., 2019), FBCSP-LSSVM (Park and Chung, 2019) and CSP\AM-BA-SVM (Selim et al., 2018) are 81.1%, 73.50%, 80.6%, 86.73% and 85.01% respectively. So, the overall results show that our proposed method succeeds by 1.24% to 26.14% improvements comparing with the eleven existing machine learning algorithm considering overall classification accuracy in the identification of communicative intentions for BCI application.

Table 4.2. Comparison between the results of our proposed methods with some reported research outcome.

Author	Method	Classification accuracy (%)					
		aa	al	av	aw	ay	average
Proposed method	Common spatial pattern based optimized ensemble	98.20	100.00	100.00	100.00	100.00	99.64
Sadiq et al. (Sadiq et al., 2022b)	Multiscale principal component analysis based Linear regression	97.80	98.80	98.90	100.00	93.20	97.70
Siuly et al. (Siuly and Li, 2015)	Optimal allocation based Naïve Bayes algorithm	97.92	97.88	98.26	94.47	93.26	96.36
Ince et al. (Ince et al., 2009)	Class separability based Support Vector method	95.06	99.70	90.50	98.40	95.70	96.00
Siuly et al. (Siuly and Li, 2012a)	Cross correlation based Least square Support Vector machine	97.88	99.17	98.75	93.43	89.36	95.72
Wu et al. (Wu et al., 2008)	Iterative Spatio-Spectral Patterns Learning algorithm	93.57	100.00	79.29	99.64	98.57	94.21
Siuly et al. (Li and Wen, 2011)	Clustering with Least square Support Vector machine	92.63	84.99	90.77	86.50	86.73	88.32
Zhang et al. (Zhang et al., 2013)	Z score Linear Discriminant Analysis	77.70	100.00	68.40	99.60	59.90	81.10
Yong et al. (Yong et al., 2008)	Sparse Spatial Filter Optimization based Linear Discriminant Analysis	57.50	86.90	54.40	84.40	84.30	73.50
Y Miao et al. (Miao et al., 2019)	Regularized Common Spatial pattern based on AdaBoost algorithm	79.60	93.90	53.20	87.90	88.20	80.60

Author	Method	Classification accuracy (%)					
		aa	al	av	aw	ay	average
Park and Chung (Park and Chung, 2019)	Filter Bank Common Spatial Pattern based on Least Square Support Vector Machine	92.85	89.28	71.43	83.04	94.05	86.73
Selim et al. (Selim et al., 2018)	Common Spatial Pattern with Bat Optimization algorithm based on Support Vector Machine	86.61	100.00	66.84	90.63	80.95	85.01

4.5 Conclusion

In this study, we propose a CSP method based OE method for exploring big EEG signal data for the application of BCI systems. For analytical purposes we used some important statistical characteristics to establish design of the distribution. We applied CSP method for feature extraction and OE as a machine learning model, which was tested on EEG brain signal data BCI Competition III dataset IVa. Our experimental results show that our proposed method is capable of handling big brain signal data for identifying communicative intentions for advance BCI system. We compared the performance of classification accuracy of our proposed method with several other existing methods. In comparison with other established method our method achieves higher performance of classification accuracy. This research assists the experts to process and analyse EEG signals for BCI applications. It also supports technologist to create a new EEG data analyser for BCI systems.

4.6 Link and Implication

In this study, we develop a machine learning technique for investigating big brain signal data. Our proposed method can handle brain signal big data for advanced BCI systems. For investigative purposes, we employed the CSP data mining method for feature extraction and the classifier OE as a machine learning model, tested on BCI Competition III dataset IVa. Our experimental results show that our proposed method achieved 99.64% overall performance considering five subjects. Our developed algorithm succeeds by 1.24% to 26.14%

improvements compared with the eleven current machine learning algorithms considering overall classification accuracy in recognizing mental states for BCI application.

Our developed CSP-OE data mining method has some limitations. The CSP feature extraction method is noise sensitive and susceptible to overfitting, which significantly influence the experimental outcomes. The OE classifier is less interpretable, hard to predict, and any incorrect assortment can lead to lower predictive accuracy than an individual model. To overcome these limitations, we develop another improved artificial Intelligence based technique considering the Markov chain as a feature extraction method and the support vector method as a machine learning classifier. In the next chapter, we will discuss this improved technique which is more accurate and efficient for detecting motor imagery tasks.

CHAPTER 5

A MARKOV CHAIN-BASED FEATURE EXTRACTION SCHEME FOR AUTOMATIC ANALYSIS OF BRAIN SIGNAL DATA FOR ADVANCED BCI SYSTEM

This chapter will introduce an improved method for differentiating MI tasks through EEG signal data. In order to develop a more efficient and accurate optimized artificial Intelligence based technique for identifying human intentions of physical movement through EEG data for an advanced BCI system, we proposed a Markov chain-based feature extraction method along with three classifiers support vector method (SVM), decision tree (DT), and k nearest neighbour (KNN) classifier. The proposed method was tested on BCI Competition III dataset IVa and IVb, which contains motor imagery-based EEG signal data. Firstly, the time series was converted into forms of a Markov chain. Then, the transfer probability matrix of the Markov chain was estimated, and we refer to it as Markov feature. Therefore, Markov features were collected with the key parameters (L=length, δ =boundary value of the sample, and N =number of states). These features were extracted using two statistical features (mean and variance). Among the classifiers, SVM achieved more than a 99% classification accuracy score in each subject, which is an excellent result. Our improved method will assist to rehabilitate motor-disabled people by developing advanced BCI technology.

5.1 Introduction

Brain computer interface technology allows a human brain and an external device to talk to one another—to exchange signals. It gives humans the ability to directly control machines without the physical constraints of the body. It helps motor disabled patients to regain the activities they lost due to a stroke, a brain injury, or even severe accidents(Sadiq et al., 2022b). A BCI can be designed with the most convenient basis of motor imagery (MI) signals. Thus, MI is a cognitive process in which a subject imagines that he/she performs a movement without actually performing the movement and without even tensing the muscles. It is a dynamic state during which the representation of a specific motor action is internally activated without any motor output. As MI-based BCI provides high degree of freedom, it helps motor disabled people to communicate with the device by performing the sequence of MI tasks for example, hand movement, foot movement etc. and can be recorded via electroencephalography (EEG). Fig. 5.1 illustrates the workflow of MI-based BCI technique of EEG signal data. As can be seen in Fig.5.1, first a brain injury patient's brain signals are measured by wearing an electrode cap. In an electrode cap, the electrodes are connected with wires to an instrument that amplifies the brain waves and records them on computer equipment for measuring the EEG signals. After measuring the EEG signals, BCI decodes them and translates them into commands to an output device such as a wheelchair, robotic arm etc., that accomplishes the motor disabled people's intention.

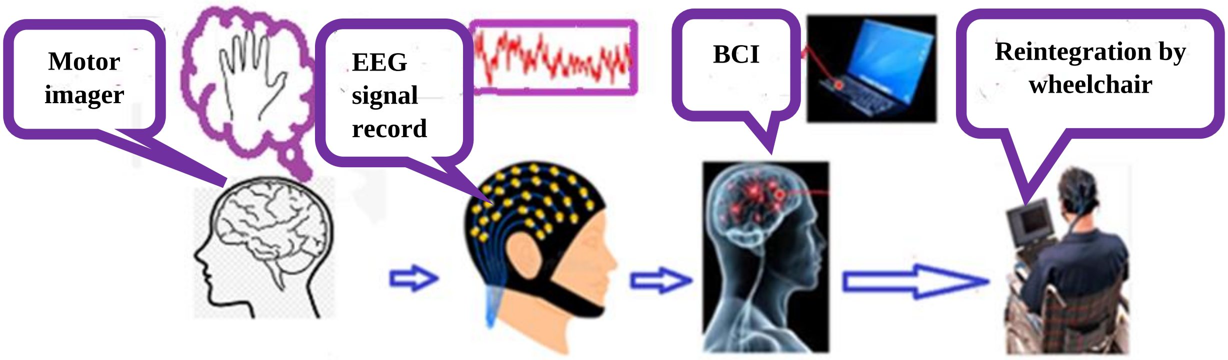

Fig. 5.1: Work flow of MI-based BCI technique of EEG signal data

EEG is a medical test which identifies anomaly of brain signals and records electrical brain activity. It is used to collect brain signals from the scalp of the human brain. It is non-invasive, complex, cost-effective, transferrable, and produces vast brain signal data. It also has a higher signal-to-noise ratio and excellent temporal resolution properties(Siuly and Li, 2012b, Siuly et al., 2016a). These properties make it useful in medical and non-medical applications. There are five kinds of brain signals which are: beta, alpha, theta, and delta bands and gamma waves(Blankertz et al., 2007a). In this chapter, we applied delta wave, which ranges from (0.1-4) Hz and is defined as slow-down wave activity in the EEG. It arises from the neighbourhood of a localized area of brain damage(Ahn et al., 2013). Analysis of MI-based EEG signals over the cortical area is essential for making the BCI system more robust and accurate.

There are three parts to analysing the MI-based EEG signals: noise removal for getting noise-free data, feature extraction for achieving essential features, and classification for identifying MI task performance. However, because of the nonlinear, non-gaussian, nonstationary characteristic and a large amount of data, EEG signals are still difficult to classify. Moreover, Traditional methods also have some drawbacks in detecting subject-specific MI task classification accuracy more accurately and efficiently, which needs improvement. A brief literary gap in the most recent BCI research is discussed in this part. Various machine learning classifier methods have been explored in the literature for MI-based EEG classification.

Functional signals acquired through EEG are also investigated for classifying different mental tasks, such as MI (Tiwari and Chaturvedi, 2021). The structure of these EEG representations has various changes to account for the spatial distribution of the electrodes used for the raw EEG recording. For example, ref. (Moumgiakmas and Papakostas, 2022, Sarki et al., 2022b) introduces a methodology that combines the spectrograms for a CNN model for a classification activity. Another method for MI-based EEG signal classification is described in (Taheri et al., 2020), an ensemble SVM-based voting system is proposed. In each line of this system, the EEG signal is transformed into different representations based on discrete cosine transform, Fourier transform, common spatial pattern, and empirical mode decomposition, and then these representations are combined in a triple-frame matrix. These frames are fed into a pre-trained deep convolutional neural network as a feature extractor. For each line, an SVM is employed to classify the extracted features. Finally, a decision is made based on voting between these SVMs. Another example is the combination of the fast Fourier transforms (FFT) feature extraction method with the classifiers linear discriminant analysis (LDA) and Naive Bayes for classification. The drawback of this method is without large training data it does not performance well.(Machado and Balbinot, 2014).

In this paper (Miao et al., 2021a), the author developed a methodological term, common time-frequency-spatial patterns (CTFSP), with Multiple support vector machine (SVM) classifiers. The classification accuracy of a subject's lowest one is 52.14%. Tiwari and Chaturvedi (Tiwari and Chaturvedi, 2021)applied a Multi-objective X-shaped Binary Butterfly Optimization Algorithm (MX-BBOA) with a support vector machine, and the classification accuracy of any subject lowest is 79.2%, and Khanam et al (Khanam et al., 2022c) achieved CA of lowest subjects accuracy is 90.30% by using a common spatial pattern with medium k-nearest neighbor methods. Cherloo et al. (Cherloo et al., 2021) achieved the lowest accuracy of a subject specific, 68.87%, by applying regularized common spatio spectral pattern with a decision tree. Correlation-based channel selection algorithm was utilized to identify the accuracy of a proposed dataset with 118 channels by Jin et al (Jin et al., 2019). The lowest accuracy of any subject is 70.4%, which needs improvement. Binias et al (Binias et al., 2016)applied the Box-Cox method and got the 70.24% lowest accuracy for any tested subject.

Djamal et al.(Djamal and Putra, 2020) showed that BCI systems using wavelet and RNN could drive external devices with an accuracy of 79.6%. The difficulty of this method is that it demands extended iterations. Even in the 500th epoch, the accuracy is still rising. Siuly et al. (Siuly et al., 2014). developed a cross-correlation-based feature extractor with the least square support vector machine (LS-SVM) to recognize two-class MI signals. The LS-SVM classifier produced any subjects' accuracy, not above 80%. The detriment of that method was that they did not choose the parameters optimally through any technique. They manually chose the parameters for the LS-SVM approach.

However, all of the above-mentioned methodological frameworks have some limitations for example, needs longer iteration, does not work well with large data set, noise sensitivity, methodical complexity and not specified parameter. Moreover, all of the method did not achieve more than 99% of the subject-specific accuracies for BCI signal output. This implies that existing literature still have some limitations for identifying MI-based EEG activities. To overcome these existing gaps, we were motivated to develop an automatic analysis of a robust classification method to eliminate the limitations faced in the above-mentioned research. So inspiring by this, we developed our research questions: how to develop an accurate and reliable AI-based machine learning method for identifying human intentions of motor-impaired patients, and why the proposed method would be better than the existing methods? In reply to the research questions, our key research objective is to develop an automatic AI-based technique for automatically identifying MI task through EEG data for advanced BCI systems to optimize efficiency and accuracy. To fulfil our chapter objective, we are interested in deploying a Markov chain (MC) based feature extraction method. We were motivated by this algorithm because the Markov chain is exceptionally useful in the case of discrete time series, and the reliability parameters for the system is calculated in effect by a formula that contributes to achieving higher accuracy.

To investigate performance of the obtained features, we also applied three classifiers which are k-nearest neighbour (KNN), decision tree (DT), and support vector method (SVM), along with MC for recognizing MI-based EEG task performance. These classifiers efficiently solve non-Gaussian, non-invasive, and nonstationary EEG data and are also consistent in EEG-based BCI applications. However, three of the classifiers have strengths and weaknesses in terms of mathematical complication and their appropriateness in a specific application, which deliberated on later. Here SVM works relatively well when there is a clear margin of separation between classes. It is also more effective in high dimensional spaces and is relatively memory efficient. The most significant advantage of decision trees is that they make it very easy to interpret and visualize nonlinear data patterns. They also work very fast, especially for exploratory data analysis. In the case of the small dataset, decision trees deliver a high accuracy score. On the other hand, KNN has advantages in nonparametric architecture, is simple and powerful, and requires no training time.

The remainder of this paper is organized as follows: Section 5.2 describes some of the basic concepts and practical tools and algorithms used in the chapter. In section 5.3, the obtained results are analysed and presented in addition to the described approach, including discussion, and section 4 is the conclusion.

5.2 Materials and methods

This section illustrates the experimental data that are applied in this research and the planned methodological framework.

Figure 5.2 shows the methodological framework of our chapter for classifying MI-based EEG data for the BCI technique. The diagram demonstrates that the unexpected noises were removed the denoising of by applying the Butterworth filter to obtain the maximum signal to noise ratio (SNR) for the binary classes of MI-based EEG data (hand and foot). The key features were isolated by the MC method. In the third step, three types of classifiers were employed for the acquired feature set, specifically KNN, DT and SVM machine learning algorithms. Finally, the performance of the planned methods was estimated in terms of accuracy, sensitivity, and specificity.

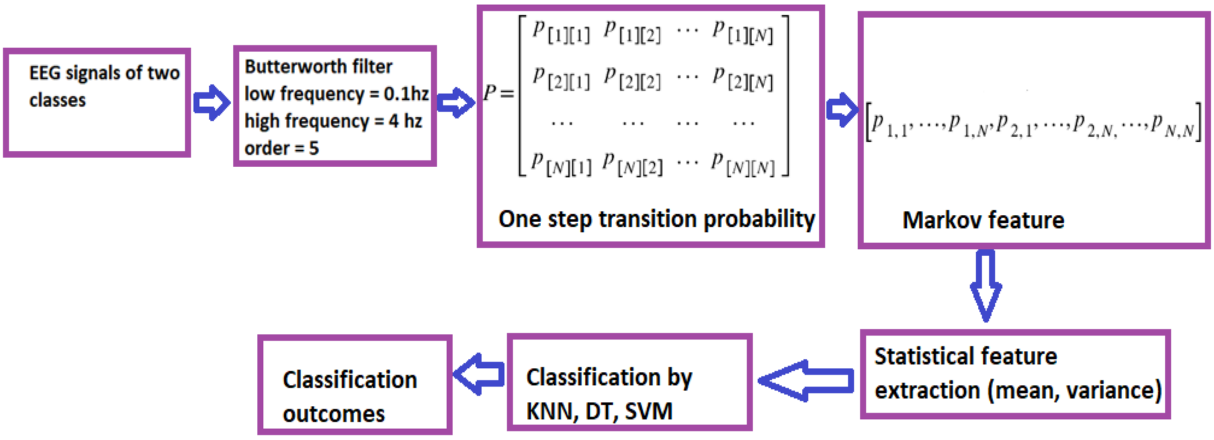

Fig. 5.2 Block diagram of the proposed technique for identifying MI task through EEG signal classification in BCI development

5.2.1 Data acquisition

The proposed method was tested on publicly available EEG databases from BCI Competition III datasets IVa and IVb (https://drive.google.com/u/0/open-BCI-data-file). The data set was provided by Fraunhofer FIRST, Intelligent Data Analysis Group (Klaus-Robert Müller, Benjamin Blankertz), and Campus Benjamin Franklin of the Charité - University Medicine Berlin, Department of Neurology, Neuro-physics Group (Gabriel Curio).

Technically, each data set consists of single trials of spontaneous brain activity, one part labelled (training data), another part unlabelled (test data), and a performance measure.
Dataset 1: Dataset IVa (BCI competition III 2005; Blankertz et al. 2006) was recorded from five healthy subjects (labeled aa, al, av, aw, ay) who performed right hand (class 1) and right foot (class 2) MI tasks. Technically, each data set consists of single trials of spontaneous brain activity, one part labelled (training data) and another part unlabelled (test data), and a performance measure. Subjects sat in a comfortable chair with arms resting on armrests.
EEG signals were recorded from 118 electrodes according to the international 10/20 system. There were 280 trials for each subject, namely 140 trials for each task per subject. During each trial, the subject was required to perform either of the two (right hand and right foot) MI tasks for 3.5 s. Among 280 trials, 168, 224, 84, 56, and 28 trials comprised the training set for subject aa, al, av, aw, and ay, respectively, and the remaining trials comprised the test set.
Dataset 2: "Dataset IVb" ((BCI competition III 2005; Blankertz et al. 2006) was recorded from one healthy subject. This EEG data consisted of two classes: left hand and right foot MI. He sat in a comfortable chair with arms resting on armrests. 118 EEG channels were measured at the positions of the extended international 10/20 system. Signals were recorded from 118 channels in 210 trials.

5.2.2 Signal pre-processing

Pre-processing is a series of signal-processing steps implemented on data prior to analysis (statistical analysis) and interpretation. Virtually all forms of neuroimaging data, including EEG, consists of noises; as a result of that, signal pre-processing is necessary for obtaining noise free clean signal data. The Butterworth filter was applied on the entire EEG dataset to eliminate the maximum noises in EEG signals. The applied filter linked with the output signal to the input signal, which is shown in the following equations.

$$y(n) = \sum_{i=0}^{N} (a_i x(n-i)) + \sum_{j=1}^{N} (b_i y(n-j)) \tag{5.1}$$

The z transfer function of the used filter us as follows:

$$H(z) = \frac{\sum_{i=0}^{N} a_i z^{-i}}{1+\sum_{j=1}^{N} b_j z^{-i}} \tag{5.2}$$

where x(n) is the input signal, y(n) is the output signal, N is the filter's order and a_i and b_j are the filter's coefficients.

Butterworth filter considering (0.1-4) Hz and fifth order derivatives, which is the delta wave (0.1-4) Hz range, was utilized in this chapter. Thus, we get the noise-removed filtered data from the raw data (AlHinai, 2020, Hussain and Park, 2021).

5.2.3 Feature extraction

Feature extraction is the next step of the noise removal stage. Discovering an efficient feature extraction method is valuable and essential. We applied the Markov chain-based feature extraction method to extract meaningful features from the EEG signal data. By constructing a Markov chain one can obtain a sample of the desired distribution by recording states from the chain. The more steps that are included, the more closely the distribution of the sample matches the actual desired distribution. Considering the general attributes of discrete time series, we planned a simple transform rule which can instantly produce a Markov chain for any given time series. Then, applying the Markov chain processing method, we get features from the noise free filtered raw data. To reduce the dimensions of the Markov chain sequences, this chapter considers two simple but effective statistical features, mean, and variance, as the representatives ideally include all valuable information of the raw signal data. These features were computed from Markov chain sequence or Markov features to create feature sets. These extracted features are then entered into the classifiers for gaining classification accuracy. The feature extraction procedure of the Markov chain is given in detail below:

Firstly, we choose the size of the sample. Assuming a given time series $X_t\colon (x_1, x_2, \cdots x_L)$, it contains L sample points. Then we transferred it into a Markov chain by locating an appropriate boundary to extract its transfer probability.

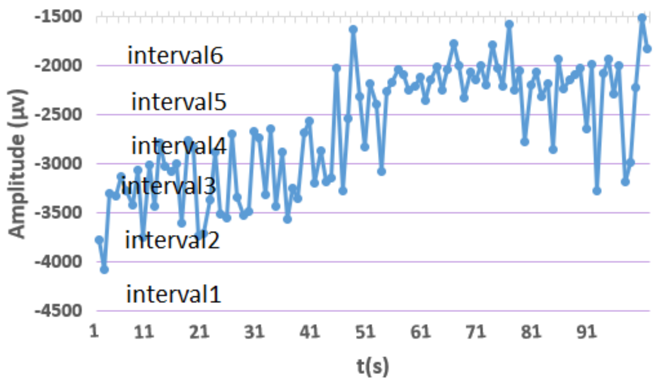

Fig 5.3: Process of generating Markov chain of subject aa

Fig. 5.3. represents an exemplary pattern of 6 state Markov chain of selected subject aa, where a 100-length time series is converted into a 6-states Markov chain by the above transform rule.

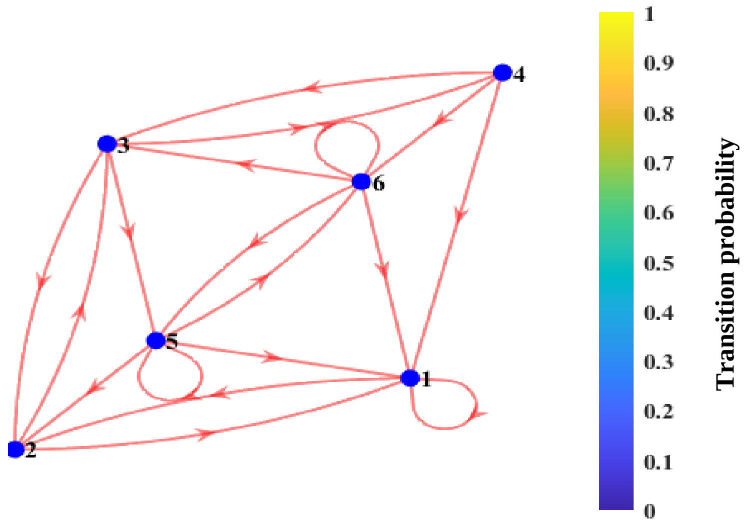

Fig. 5.4 State transition diagram

Fig. 5.4 Illustrates the possible transfer among every state, which can be estimated by statistical analysis of the Markov chain and by this way, the change of the time series can be distinguish accurately.

For Markov chain S_i gained from step 1, express its one-step transfer frequency information of Markov chain. Assuming that when the value of S_t is k at time t, if the value of S_{t+1} is k, then statement $F_{kk} = F_{kk} + 1$, represents state k, stays unaffected at t + 1 moment. If the value of S_{t+1} is j, for the moment, j is not equal to k, then we observe $F_{kj} = F_{kj} + 1$, represents t+ 1 moments that have transferred from state k to state j. By this rule, we can find the Markov chain transfer frequency data, which can be expressed as follows:

$$F_{re} = \begin{bmatrix} F_{[1][1]} & F_{[1][2]} & \cdots & F_{[1][N]} \\ F_{[2][1]} & F_{[2][2]} & \cdots & F_{[2][N]} \\ \cdots & \cdots & \cdots & \cdots \\ F_{[N][1]} & F_{[N][2]} & \cdots & F_{[N][N]} \end{bmatrix} \quad (5.3)$$

And its one-step transition probability P can be calculated:

$$P = \begin{bmatrix} p_{[1][1]} & p_{[1][2]} & \cdots & p_{[1][N]} \\ p_{[2][1]} & p_{[2][2]} & \cdots & p_{[2][N]} \\ \cdots & \cdots & \cdots & \cdots \\ p_{[N][1]} & p_{[N][2]} & \cdots & p_{[N][N]} \end{bmatrix} \quad (5.4)$$

Reform one-step transition probability P of the Markov chain to a row vector, and name it as Markov feature, as is shown in Equation (5.3):

$$F_1 = P_{N\times N} \rightarrow P_{1\times[N\times N]} = [P_{1.1}, \ \cdots, P_{1.N}{'}p_{2.1}{'} \cdots, P_{2.N.} \ \cdots {'}P_{N.N}] \quad (5.5)$$

The state transition probability matrix of a Markov chain provides the probabilities of transitioning from one state to another in a single time unit, and the null vector of this matrix, normalized, So the sum of its elements to 1, is the vector of probabilities of states.

After getting the Markov features, we performed feature extraction by applying some statistical analysis like average and standard deviation from the obtained Markov features.

5.2.4 Classification

In this paper, three machine learning methods named support vector machine (SVM), k nearest neighbour (k-NN) and decision tree (DT) are used to test the effectiveness of the proposed method.

Support vector machine

Support vector machine (SVM) has been used usually for the classification of electroencephalogram (EEG) signals for the identification of neurological disorders such as epilepsy and sleep disorders [29, 30]. SVM shows good overview performance for high dimensional data owing to convex optimization. Incorporating prior knowledge about the data makes it a better optimized classifier and relatively memory efficient [31]. Our proposed chapter focused on two class feature classification, and the sample set is

$$y_i[(w.x_i) + b] - 1 \geq 0, \ \ i = 1,2, \dots, l. \quad (5.6)$$

where $(x_i, y_i), i = 1,2, \dots, n$ are the data points of a normal vector dataset, in which y_i take the value of either 1 or -1 (MILANÉS et al., 2021).

K nearest neighbour

K Nearest Neighbour is a simple algorithm that stores all the available cases and classifies the new data or case based on a similarity measure. It is mostly used to classify a data point based on how its neighbours are classified. 'k' in KNN is a parameter that refers to the number of nearest neighbours to include in the majority of the voting process. 'k' in KNN algorithm is based on feature similarity choosing the right value of K is a process called parameter tuning and is important for better accuracy. The advantage of this classifier is, it is simple, flexible to feature, naturally handles multi class cases and need large set of data. There are some disadvantages of KNN classifier which are, should have a meaning distance among the neighbours and computation cost is quite high.

Decision tree

A decision tree is a non-parametric supervised learning algorithm, which is utilized for both classification and regression tasks. It has a hierarchical, tree structure, which consists of a root node, branches, internal nodes, and leaf nodes. A decision tree starts with a root node, which does not have any incoming branches. The outgoing branches from the root node then feed into the internal nodes, also known as decision nodes. Based on the available features, both node types conduct evaluations to form homogenous subsets, which are denoted by leaf nodes, or terminal nodes. The leaf nodes represent all the possible outcomes within the dataset. The merits of Decision tree classifier are simple to understand and interpret, requires little data preparation, able to handle both numerical and categorical data. However, the disadvantages are prone of overfitting, feature reduction and data resampling.

5.3 Results and discussions

This section provides the experimental results of our proposed method Markov chain-based feature extraction method different classifiers for BCI Competition III, datasets IVa and IVb. In both datasets, the experiments of our proposed methods are accomplished on each subject distinctly because of the highly subject oriented dependency of MI-based EEG signals on physical activities. The experimental works of our research are performed in MATLAB R2021b. We filter the brain signal data with the help of the Butterworth filter at the signal pre-processing stage. For the feature extraction method, considering the general attributes of discrete time series, we plan a simple transform rule which can instantly produce a Markov chain for any given time series. And then, applying the Markov chain processing method, we get features from the noise free filtered raw data. We deployed mean and variance for getting significant features from Markov features. In the end, extracted features were given to the classifier.

One of the propositions of the Markov chain is a steady-state vector. Some outstanding results were obtained by determining the steady state of the Markov chain.

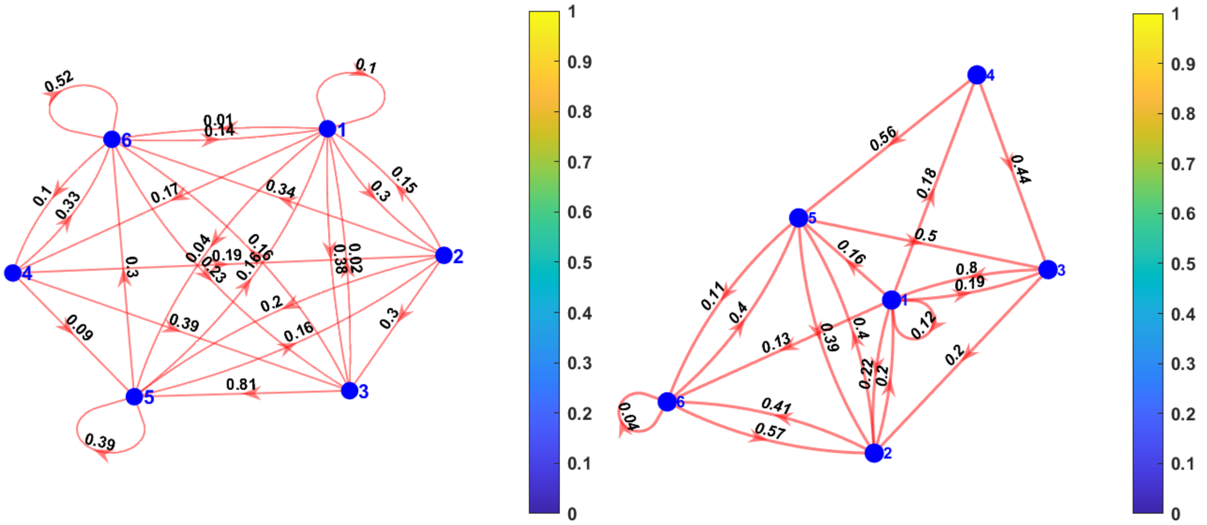

Fig. 5.5 Functional systems for each state and estimated transition probabilities between states for individual subject aa of dataset IVa and al of dataset IVb, respectively.

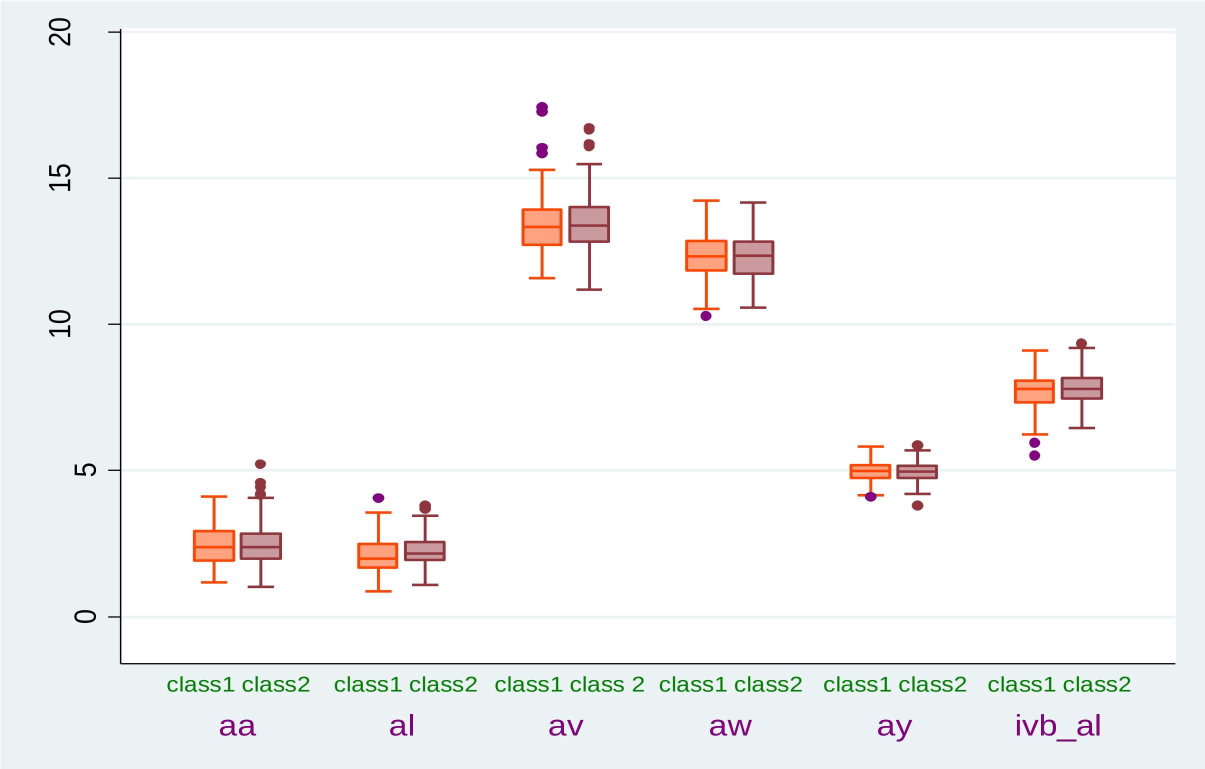

Fig 5.6 Boxplot of all subjects considering 2 classes by applying MC feature extraction method

5.3.1 The choice of parameters

Table 5.1 Selecting the best value of L, setting δ = 0.001, N = 6,5

subject		KNN	SVM	DT
aa	500	64.9	99.4	97.6
	300	62.5	89.9	87.5
	200	63.1	75.6	87.5
al	500	62.9	99.1	87.1
	300	73.8	76.8	88.7
	200	70.2	74.4	71.4
av	500	58.1	100	90.5
	300	57.1	95.2	83.3
	200	59.5	70.2	71.4
aw	500	58.9	99.3	89.3
	300	67.9	85.7	85.7
	200	57.1	96.4	82.1
ay	500	64.3	100	92.9
	300	64.3	92.9	92.9
	200	60.7	89.3	89.3
IVb	500	68.1	99.5	88.6
	300	64.8	85.7	89.0

Table 5.2 Selecting the best value of N, setting L = 500, δ = 0.001

subject		KNN	SVM	DT
aa	5	64.9	99.4	97.6
	4	67.3	76.8	87.5
	6	64.9	83.3	88.1
al	6	62.9	99.1	87.1
	4	67.9	76.2	85.1
	5	66.1	82.7	81.5
av	6	58.1	100	90.5
	4	63.1	86.9	84.5
	5	66.7	98.8	82.1
aw	6	55.4	96.4	87.3
	5	58.9	99.3	89.3
	4	57.1	96.4	71.4
ay	6	64.3	100	92.9
	5	85.7	53.6	89.3
	4	64.3	89.3	92.9
IVb	6	68.1	99.5	88.6

Table 5.3 Selecting the best value of δ, setting L = 500 and N=5,6

Subject		KNN	SVM	DT
aa	.001	64.9	99.5	97.6
	.005	66.7	86.7	90.5
	.0001	69.6	90.5	88.7
al	.001	62.9	99.1	87.10
	0.005	67.3	75	88.7
	.0001	70.2	73.1	86.3
av	.001	58.1	100	90.5
	.005	66.7	(94)	85.7
	.0001	63.1	73.8	71.4
aw	.001	58.9	99.3	89.3
	.005	58.9	89.3	91.1
	.0001	57.1	96.4	82.1
ay	.001	64.3	100	92.9
	.005	64.3	82.1	89.3
	.0001	67.9	78.6	78.6
IVb	.001	68.1	99.5	88.6
	.005	61.9	87.6	90
	.0001	66.2	85.7	87.6

We can see from the above analysis that when L = 500, δ = 0.001, N = 6, the classification model of all the subjects has the best performance except the subject aa and aw achieved the highest accuracy when N=5.

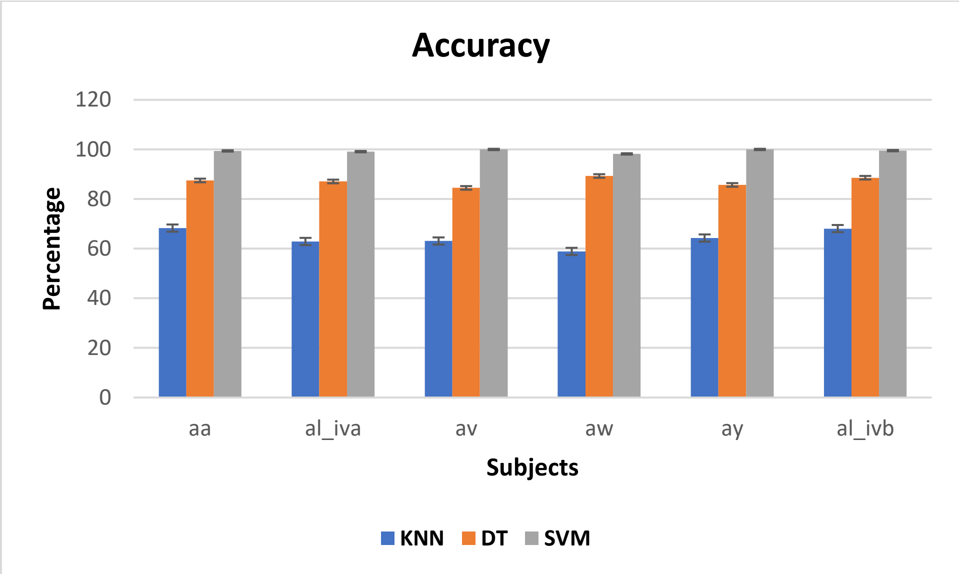

Figure 5.7 Classification accuracy of the individual subject among KNN, DT, and SVM classifiers. Error bars show the standard error.

Classification accuracy is a metric that summarizes the performance of a classification model and is the fraction of predictions that our model got right. We can see from the above results that accuracy detection is high enough for these three machine learning methods, especially when using the SVM method as the classifier. All the accuracy were achieved for each of the subjects close to 100. The classification accuracy of MCSVM (Markov chain based support vector method) for subject aa, al_iva, av, aw, ay and al_ivb are 99.5%, 99.1%, 100%, 99.3%, 100%, and 99.5% respectively. This implies that the proposed feature extraction method effectively identifies the human intention of physical movement through EEG data for advanced BCI systems. Finally, our chapter produced the highest accuracy score in the case of every subject above 99%, where the Markov chain and SVM were applied.

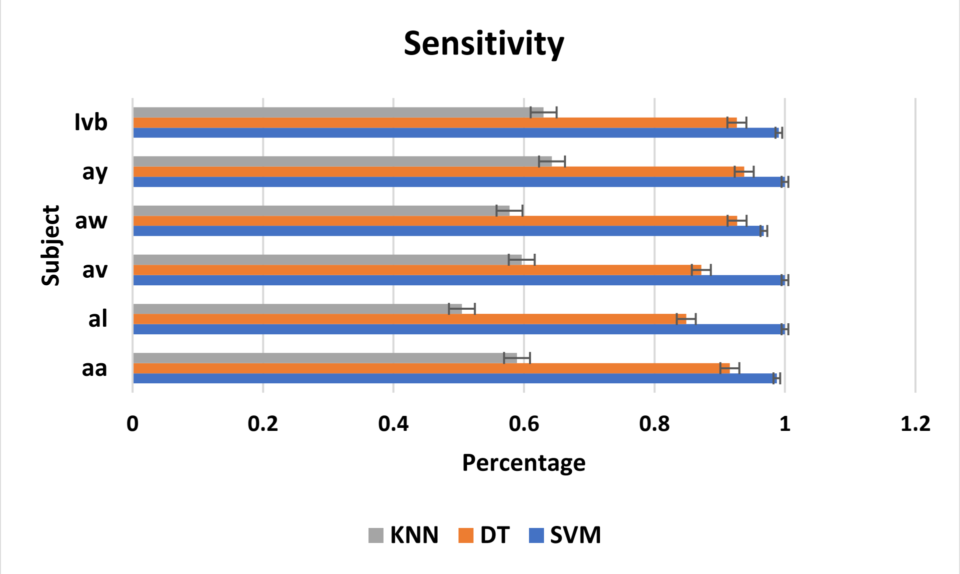

Fig. 5.8 Sensitivity comparison for different classifiers by subjects. Error bars show the standard error.

Fig. 5.8 represents the sensitivity for each subject of datasets IVa and IVb. This figure shows the individual sensitivity for the five subjects, aa, al, av, aw, ay, and ivb. As shown in Fig. 5.8, most of the MCSVM approach's sensitivity values are close to 100 for each subject, showing that the proposed approach is relatively stable.

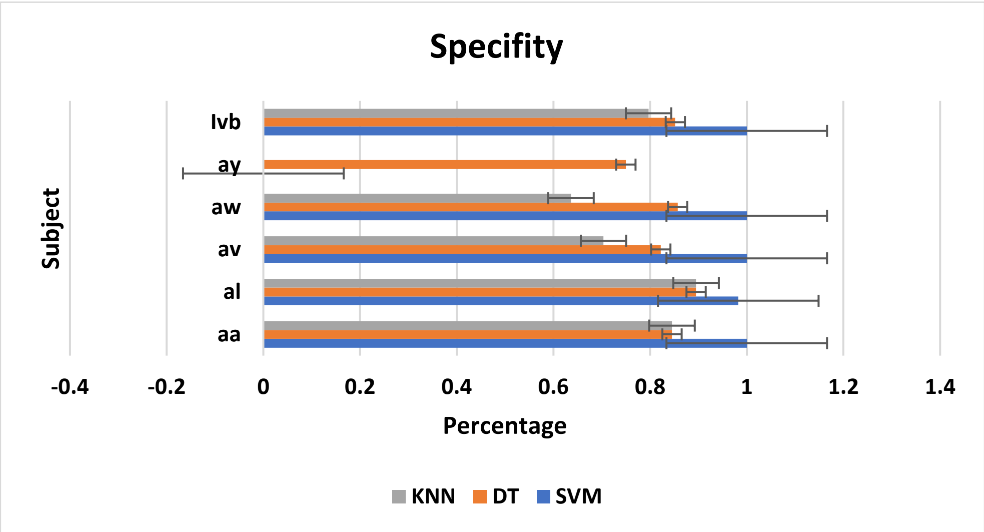

Fig. 5.9. Specificity comparison for different classifiers by subjects. Error bars show the standard error.

The outline of the specificity for each of the six subjects is shown in Fig. 5.9. For datasets IVa and IVb, the TNR indicates to the accurate recognition rate for the RF class of all subjects. From Fig. 5.9, it is detected that SVM classification of TNR for each subject is approximately

100% and there is no significant variation of the TNR among DT and KNN classification methods of each subject. This implies that our developed method is reliable and robust. Along with Table 5.3, Figs. 5.2 and 5.3, it can be concluded that, although there is a bit of variability in performance among the subjects, generally, the proposed approach provides higher performance for all subjects and is consistent and stable.

Table 5.4 Precision, recall, F1 score and false alarm rate using for individual subjects.

Subject	classifier	precision	recall	F1 score	false alarm rate
aa	SVM	1	0.99	0.99	0
	DT	0.8125	0.92	0.8609	0.1875
	KNN	0.74	0.59	0.65	0.5875
al	SVM	0.98	1	0.99	0
	DT	0.9	0.85	0.87	0.0982
	KNN	0.81	0.7	0.69	0.1875
av	SVM	1	1	1	0
	DT	0.88	0.87	0.85	0.1904
	KNN	0.81	0.7	0.69	0.1904
aw	SVM	1	0.97	0.98	0
	DT	0.87	0.93	0.9	0.1333
	KNN	0.87	0.64	0.69	0.1333
ay	SVM	1	1	1	0
	DT	0.9	0.94	0.88	0.1666
	KNN	1	0.64	0.78	0
Ivb	SVM	1	0.99	1	0
	DT	0.93	0.93	0.89	0.1619
	KNN	0.88	0.8	0.73	0.1238

Table 5.4 represents the Precision, recall, F1 score, and false alarm rate using 10-fold cross-validation for individual subjects of datasets IVa and IVb. As shown in Table 5.4, the individual performance of each subject aa, al, av, aw, ay and IVb with classifier SVM mainly had 1 in the case of Precision, recall, F1 score. The false-alarm rate is the proportion of incorrect *yes* responses in a task. It is 0 for each subject along with the SVM classifier, which indicates that the identification of each motor imagery task of all the subjects was perfect.

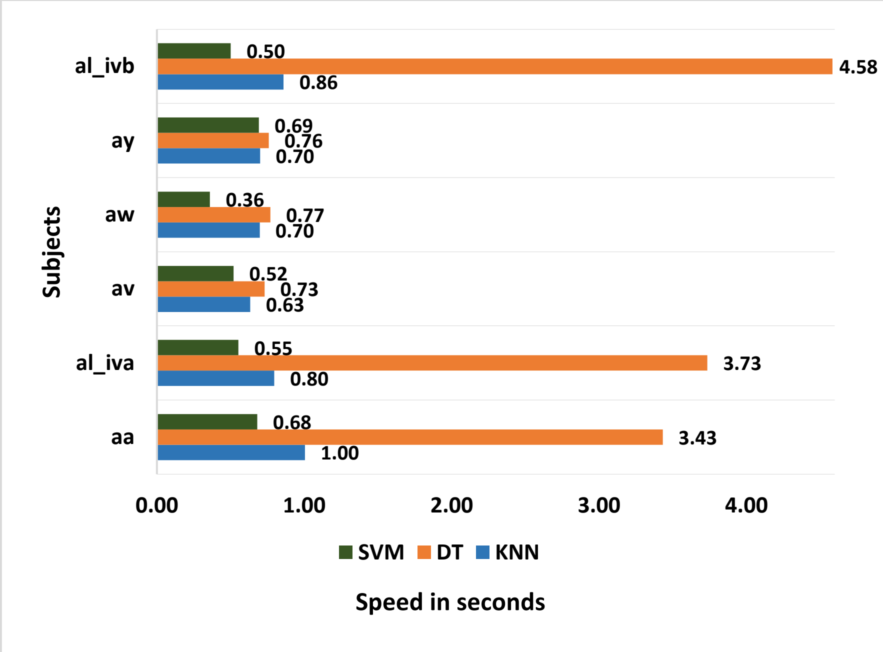

Fig. 5.10. Comparison of speed (second) based on the proposed classifiers by subjects

In Fig. 5.10 classifiers' classification speeds were compared and illustrated. The timer was set during the program of the training data in order to calculate speed. We can infer from the graph that the SVM classifier's average across the six subjects for the 10 times cross validation is lower than that of the DT and KNN classifiers. So, compared to the other classifiers, SVM has a much faster classification speed.

The classification efficiency of the proposed method was evaluated with accuracy (ACC) (Figure 5.6), specificity (Figure 5.7), sensitivity (Figure 5.8), Precision, recall, F1 score, and false alarm rate for the six subjects. It can be concluded from the tables (Tables 5.1, 5.2,5.3 &5.4) and figures (Figures 5.6,5.7 & 5.8) that the SVM classifier with Markov chain-based features delivered the best classification accuracy compared with the rest of the classifiers DT and KNN.

Table 5.5: A comparative chapter for our proposed method with some existing methods for same data sets.

Authors	Methods + classifier	Accuracy					
		aa	al	av	aw	ay	IVb
This Study	**MC-SVM**	**99.5**	**99.1**	**100**	**99.21**	**100**	**99.52**
Sadiq et al.	MSPCA	95.22	98.63	92.91	72	100	99.52
Yu et al	IEFD+WELCHPSD	99.52	99.35	98.89	99.52	100	93.19
Siuly et al	OA &NB based approach	100	100	90.91	90.91	95.45	86.36
Khanam et al	CSP-MKNN	97.3	100	90.3	92.4	95.6	
Miao et al.	CTFSPLIBSVM	86.05	98.57	52.14	96.07	92.14	-
Padfield et al	CSP+SVM-RBF+MSMV	79.64	94.64	75	78.57	94.64	-
Cherloo et al	RCSSP+DT	82.14	96.42	68.87	98.21	88.88	-

In this section, we compared our developed method with various existing methods applying the same dataset to further investigate our proposed system's efficiency. Table 5.5 illustrates a comparison of performance analysis among the proposed method with the earlier prominent methods that have previously been testified for the same dataset, BCI competition III dataset IVa and IVb, This Table illustrates the classification performance for each of the six subjects. Miao et al. extracted features using the CTFSP algorithm. LIBSVM is the classifier of that method, where none of the subject's accuracy was more than 99% (Miao et al., 2021a). Another author, Sadiq et al., applied MSPCA as a machine learning algorithm, and two subjects' accuracies were more than 99%, whereas, in our proposed method, all subjects' accuracies were above 99% (Sadiq et al., 2020). On the other hand, Siuly et al. applied the Clustering OA &NB based approach method, and two of the subjects achieved more than 99% CA(Wang and Zhang, 2016).

Yu et al. applied the IEFD+WELCHPSD method, and among the testified six subjects, four achieved to gain above 99% accuracy (Jin et al., 2020). In Padfield et al., the subject's accuracy was less than 99% by applying CSP+SVM-RBF+MSMV feature extraction and classifier(Padfield et al., 2021b). Cherloo et al. applied RCSSP as a feature extraction method and DT as a classifier. In this article, none of the scores of the subject was more than 99% (Cherloo et al., 2021). So, from Table 5.5, it is apparent that the majority of the compared methods accomplished individual subjects' accuracy of less than 99%. Thus, it can be specified that usually, the proposed approach significantly outperforms the seven existing methods. When the accuracy is higher, the identification of right hand and right foot movement would be more accurate in dataset IVa and left hand and foot movement for dataset IVb. Thus, from the above discussion, we can firmly say that our chapter produced the highest accuracy score in the case of all subjects above 99%, where the Markov chain and SVM were applied.

5.4 Conclusion

Motor disability is a fatal disease demanding a more thorough investigation and can be explored by EEG brain signal data. EEG brain signals consist of a massive volume of data. Because of their large volume of information, specific data mining techniques and computational statistic approaches are required to analyse MI-based BCI systems. In this paper, we developed a MC based SVM method explored by computational and statistical methods for automatically identifying human intention through EEG data for advanced BCI systems that optimize efficiency and accuracy. Our proposed method produced the highest accuracy score for every subject above 99% by applying the Markov chain and SVM (MCSVM) tested on the bci competition III dataset IVa and dataset IVb. We compared our proposed method with several other existing methods. The comparison shows that our developed method on two publicly available datasets, IVa and IVb of BCI Competition III, outperforms the state-of-the-art approaches in MI task identification. The performance also appears that MI-based EEG signals with binary classes can be consistently identified by applying the developed approach, making EEG-based BCI systems more robust and efficient. Our advanced method will help to rehabilitate motor-disabled people by developing advanced BCI technology. This advanced method is expected to support a new arena for future research. The proposed automatic analysis will be implemented all around the world.

5.5 Link and Implication

In this study, we established a unique feature extraction algorithm based on the transfer probability of the Markov chain for having important information from the raw time series EEG data. At first, the time series was translated into the forms of a Markov chain. Then, the transfer probability matrix of the Markov chain was computed, and we identified it as a Markov feature. Hence, Markov features were accumulated by choosing the key parameters, and these features were extracted by employing two statistical features (mean and variance). At the end of the performance evaluation, we used three machine learning algorithms (i.e., k-NN, DT, and SVM). The proposed Markov chain based model developed the best performance with the parameter values of L(length) = 500, δ (boundary value of the sample) = 0.001, N (number of states) = 6. The extracted features with the SVM achieved the best performance in contrast with the other classifiers, reaching more than 99% accuracy in each subject. Experimental outcomes illustrate that the proposed MI task recognition method is more accurate and effective. Our advanced method will help rehabilitate motor-disabled people by developing advanced BCI technology.

In the next chapter, we will discuss the conclusion and limitations of our research work.

CHAPTER 6

CONCLUSION AND LIMITATIONS

6.1 Summary and conclusions of the thesis

Motor imagination is a mental task in which the subject imagines that they are performing an action. Motor imagery classification tasks are vital for some motor-disabled patients. This activity can be accomplished by utilising EEG signals. The MI-based BCI is an intuitive interface requiring control over computer applications directly from brain activity through brain signals without any explicit movement or peripheral (muscle) activation. Electroencephalogram (EEG) is an example of these brain signals, which is an important measurement of brain movement and has an excellent possibility to identify and manage mental and brain neuro-degenerative disorders and anomalies. Identification of various types of motor imagery tasks of MI-based EEG signals is a difficult challenge because of the involvement of the analysis of vast sets of EEG data. Representative features from an extensive dataset play a vital role in identifying the human intention of physical activity through EEG data for advanced MI-based BCI systems in biomedical signal handling. In this thesis, we studied and developed optimised AI-based techniques for identifying the human intention of physical movement through EEG data for advanced BCI systems with two main goals:

(1) Develop accurate and reliable AI-based machine learning methods for identifying human intentions of motor-impaired patients.

(2) The proposed scheme will be evaluated through the performance measurements and compared with the existing methods.

Concerning MI task classification and to reach these objectives, we first developed three methods—common spatial pattern-based medium K-nearest neighbour (CSP-MKNN), common spatial pattern-based optimised ensemble (CSP-OE) and Markov chain-based support vector method (MC-SVM)—to contribute to the identification of human intentions of motor-impaired patients. If the MI activities are consistently recognised through identifying typical patterns in EEG data, motor-impaired people could connect with a device by composing a chronological sequence of these mental states. These three methods were examined on two benchmark datasets—IVa and IVb of BCI Competition III (BCI Competition III 2005). In both datasets, each subject was studied separately for experiments as the MI task EEG signals are inherently highly subject specific, depending on physical and mental activities.

In the CSP-MKNN, the Butterworth filter was applied to remove maximum noise in EEG signals considering 0.1–4 Hz and 5th-order derivatives. After getting noise-free data, the next step is feature extraction, and a CSP based feature extraction method was introduced. We applied two pairs of filters to extract EEG-based features in the filtered data. The number of features extracted will be twice the value of this parameter. The filters selected correspond to the lowest and highest eigenvalues. The CSP algorithm proposes to learn spatial filters which minimise the variance of a class whereas maximising the variance of another. This method is very effective for band-passing EEG signals with multiple channels. After getting the important features from the feature extraction method, we applied the MKNN classifier for classifying MI tasks to reduce experimental time and achieve higher classification accuracy. We used the 10-fold cross-validation method for the evaluation of classification performance. The experimental results showed that the proposed CSP-MKNN classifier achieved better performance than the linear variants support vector method (LVSVM) and LDA classifiers for the same features in the BCI Competition III, dataset IVa. It has outstripped all other approaches by attaining the highest classification accuracy of major subjects and an average accuracy above 97% with high speed. It also improved 5.32% to 16.5% accuracy compared with the other existing methods and took much less time to run the program. This indicates that our proposed method exceeds other noteworthy feature extractors and classifier combinations. Thus, it confirms that our developed framework is more accurate, efficient, and speedy than existing methods. To further verify the effectiveness of the CSP-MKNN algorithm, we also compared it with the eight most recently reported methods in the literature. The experimental results also indicated that this proposed approach improved by at least 16.5% over the other twelve recently reported methods in BCI Competition III, dataset IVa. It demonstrated that our method performed the best for the MI signal classification in BCI applications. This study concluded that the CSP-based MKNN algorithm is a promising technique for MI signal recognition. It offers excellent potential for developing MI-based BCI analyses, which assist clinical diagnoses and rehabilitation tasks.

To improve the classification performance, we developed another methodological framework CSP-OE. In the CSP-OE method, we first filtered the data by applying the Butterworth filter considering low frequency 0.1 Hz, high 4 Hz and 5th-order derivatives to get noise-free EEG signal data. After getting noise-free data, the next step was to perform the feature extraction, and a CSP based feature extraction method was introduced. We selected the feature samples by employing the concurrent diagonalisation of the covariance matrices of two classes. We used OE for classification, where those extracted features were employed as inputs. We gained an average classification accuracy of 99.64% from the experimental evaluation for MI task EEG data. Our experimental results show that our proposed method can handle big brain signal data for identifying communicative intentions for an advanced BCI system. This procedure can assist in delivering clinical information about patients with a neurological disorder and mental or physiological difficulties.

To increase the MI task recognition accuracy, we proposed another more accurate and effective method, MC-SVM. Initially, the time series was converted into forms of a Markov chain. Then, the transition probability matrix of the Markov chain was computed as a Markov feature. Therefore, Markov features were accumulated considering the three parameters: L=length, δ =boundary value of the sample and N=number of states. These features were extracted by operating two statistical features (mean and variance). Finally, we applied three machine learning algorithms (i.e., k-NN, DT, and SVM) to assess the performance. The developed approach was analysed on two BCI Competition III datasets, IVa and IVb, which comprise MI-based EEG signal data. The outcome of the result shows that for the majority of the subjects, the anticipated Markov chain-based model generated the best performance with the parameter values of L(length) = 500, δ (boundary value of the sample) = 0.001, N (number of states) = 6. Among the three classifiers, SVM performed best, achieving more than 99% accuracy in each subject. Experimental results show that the proposed MI task identification method is more accurate and effective.

Finally, it can be concluded that the research stated in this dissertation has discovered accurate and effective methods for the consistent classification of EEG signals for advanced BCI applications. The outcomes will assist brain disorder patients in enhancing their quality of life.

6.2 Limitations

Our three developed algorithms presented in this dissertation have proven to be a successful method for identifying MI tasks through EEG signals for the advanced BCI technology. Though we have achieved the highest accuracy for the task’s detection of MI-based EEG, our research work has some limitations. The major limitation of our study is that we could not collect primary data because of our short study tenure. Besides this, there exists some other limitations of our study and developed methodologies, which are addressed below.

We have tested our developed algorithms in BCI Competition III datasets IVa and IVb, which is also a limitation of our research. This dataset has a small amount of training data, which was a big challenge for us. Another limitation is that only two tasks or activities of each subject are available in our tested dataset.

Our developed algorithms have some drawbacks. The drawbacks of CSP-MKNN developed methods are that both the CSP feature extraction and MKNN classifier have some weaknesses. One disadvantage of traditional CSP is that the anticipated CSP method differs in the hypothesis that data in each class follow the Gaussian distribution. However, this hypothesis is not always true for EEG data in practice, particularly in the research of vigilance recognition-based EEG (for example, during sleep). Further, the demerits of the MKNN classifier are that it is difficult to pick the correct value of K, requires high memory, and is sensitive to irrelevant features.

In the CSP-OE approach, the CSP data mining method's demerits are noise sensitivity and susceptibility to overfitting, which significantly influence the experimental outcomes. Even though the CSP feature extraction method has some disadvantages, it projects the multi-channel EEG data onto a low-dimensional spatial subspace with a projection matrix capable of maximising the variance ratio of the two class signal matrices. The disadvantages of an optimised ensemble classifier are that it needs to be more interpretable, the output of the ensembled model is hard to predict, and any wrong selection can lead to lower predictive accuracy than an individual model. In contrast, it has some advantages. Ensemble methods increase performance and reduce the risk of overfitting.

The Markov chain is good with time series data so that it can be utilised with many computer science and AI methods concerned with interactions between human intentions and brain-computer language problem solutions. In the MC-SVM proposed approach, the disadvantages of the Markov chain are generally inappropriate over sufficiently short time intervals and stationery or limiting probability distribution. The disadvantage of the SVM algorithm is that it is not suitable for large datasets with more noise, but it works relatively well when there is a clear separation between classes. Even though the MC-SVM algorithm has some drawbacks, the advantages outweigh the disadvantages. We produced the highest classification accuracy score for every subject above 99% for MI-based EEG task classification.

Although all of our developed methods have limitations, we tried to minimise these drawbacks by approximately selecting the parameters. Finally, we believe that the research work presented in our thesis can correctly identify the distinction between MI tasks, proving the method's superiority in classification performance evaluation over the existing methods. Our developed algorithms have found improved and productive methods for detecting MI-based EEG signals in neuroscience, brain disorders and biomedical science.

6.3 Future work

The techniques in this dissertation would deliver promising outcomes in the MI task identification from EEG signals for the advanced BCI techniques. A broad range of future work will explore the possibility of utilising the methods in applying BCI technology. To accelerate the advanced improvement of those proposed methods, we have emphasised a few key issues, which are given below.

Concerning the CSP-MKNN, CSP-OE and MC-SVM algorithms, these three techniques could be extended for multiclass MI-based EEG signal identification considering a large training dataset.

This study only studied offline classification algorithms, but real-life practical application is desirable, for example, controlling a robotic arm or wheelchair. This real-life practical application needs more involvement, for example, to train participants or subjects, and build a closed loop and real-time processing scheme. Thus, all our developed algorithms would be applied to online classification.

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