CUKUROVA UNIVERSITY
INSTITUTE OF NATURAL AND APPLIED SCIENCES

PhD THESIS

Classification of EEG Signals in Individuals with Spinal Cord Injury

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Department of Electrical and Electronics Engineering

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CUKUROVA UNIVERSITY
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PhD THESIS APPROVAL

Classification of EEG Signals in Individuals with Spinal Cord Injury

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This Doctorate Thesis was evaluated by the following Jury Members on 28/02/2025 and was approved by unanimity of votes.

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ABSTRACT

An electroencephalogram (EEG) refers to the electrical activity of the brain, recorded through electrodes strategically placed on the scalp. EEG has diverse applications, including serving as a medium for establishing communication channels between individuals and their environment, aiding in understanding brain functions, and supporting both diagnostic and therapeutic interventions. Among the various EEG components, Movement-Related Cortical Potentials (MRCPs),neural signals associated with the planning and execution of voluntary movements play a pivotal role in advancing these applications.This research investigates the classification of EEG signals using two distinct feature extraction techniques: the Hadamard Basis Method and the Variance-Based MRCP Feature Extraction with Detrending (VB-MFED) approach.The Hadamard basis method utilizes orthogonal transformations to decompose EEG signals into unique basis functions, enabling the extraction of critical neural activity with enhanced precision. In contrast, VB-MFED represents a refined methodology specifically designed to improve the extraction of Movement-Related Cortical Potentials (MRCPs). It incorporates optimized preprocessing steps, such as adaptive filtering, baseline correction, and spatial filtering, to isolate and amplify neural signals relevant to movement-related tasks.This study focuses on classifying MRCPs associated with attempted movements, emphasizing distinct movement types such as hand opening, palmar grasp, lateral grasp, pronation, and supination in individuals with spinal cord injuries (SCI). Experimental results indicate that the VB-MFED approach achieves higher classification accuracy compared to traditional methods, highlighting its potential for real-time applications. The findings underscore the viability of utilizing MRCPs for advanced brain-computer interface (BCI) systems and lay the groundwork for innovative neurorehabilitation solutions tailored to individuals with motor impairments.

Keywords: Brain computer interface, Electroencephalography, Movement-related cortical potentials, Feature extraction

ÇUKUROVA ÜNİVERSİTESİ
FEN BİLİMLERİ ENSTİTÜSÜ

DOKTORA TEZİ

Omurilik Yaralanması Olan Bireylerde EEG Sinyallerinin Sınıflandırılması

Alhaji Osman BAH

Danışmanr: Doç.Dr. Ahmet AYDIN

Elektrik -Elektronik Mühendisliği

ÖZ

Elektroensefalogram (EEG), kafa derisine stratejik olarak yerleştirilen elektrotlar aracılığıyla kaydedilen beynin elektriksel aktivitesini ifade eder. EEG, bireyler ile çevreleri arasında bir iletişim kanalı kurma, beyin fonksiyonlarını anlama ve hem tanı hem de tedavi amaçlı müdahalelere destek olma gibi çeşitli uygulamalara sahiptir. EEG bileşenleri arasında, istemli hareketlerin planlanması ve gerçekleştirilmesiyle ilişkili nöral sinyaller olan Hareketle İlişkili Kortikal Potansiyeller (MRCP'ler), bu uygulamaların ilerlemesinde önemli bir rol oynamaktadır.Bu araştırma, EEG sinyallerinin sınıflandırılmasını, iki farklı özellik çıkarma tekniği olan Hadamard Temel Yöntemi ve Detrend Edilmiş Varyans Tabanlı MRCP Özellik Çıkarma (VB-MFED) yaklaşımı kullanarak incelemektedir.Hadamard Temel Yöntemi, EEG sinyallerini benzersiz temel fonksiyonlara ayrıştırmak için ortogonal dönüşümleri kullanarak kritik nöral aktivitelerin daha yüksek bir hassasiyetle çıkarılmasını sağlar. Buna karşılık, VB-MFED, Hareketle İlişkili Kortikal Potansiyellerin (MRCP'ler) çıkarılmasını geliştirmek için özel olarak tasarlanmış, optimize edilmiş bir yöntemdir. Uyarlamalı filtreleme, temel çizgi düzeltme ve uzamsal filtreleme gibi optimize edilmiş ön işleme adımları içererek, hareketle ilgili görevlerle ilişkili nöral sinyalleri izole eder ve güçlendirir.Bu çalışma, omurilik yaralanması (SCI) olan bireylerde el açma, palmar kavrama, lateral kavrama, pronasyon ve supinasyon gibi belirli hareket türlerine odaklanarak, denenen hareketlerle ilişkili MRCP'lerin sınıflandırılmasına odaklanmaktadır. Deneysel sonuçlar, VB-MFED yaklaşımının geleneksel yöntemlere kıyasla daha yüksek sınıflandırma doğruluğu sağladığını göstermekte, gerçek zamanlı uygulamalar için potansiyelini ortaya koymaktadır. Bulgular, MRCP'lerin gelişmiş beyin-bilgisayar arayüzü (BCI) sistemlerinde kullanımının uygulanabilirliğini vurgulamakta ve motor bozuklukları olan bireyler için yenilikçi nöroreabilitasyon çözümleri için temel oluşturmaktadır.

Anahtar Kelimeler:Beyin-bilgisayar arayüzü, Elektroensefalografi, Hareketle ilgili kortikal potansiyeller, Özellik çıkarma

GENİŞLETİLMİŞ ÖZET

Bu tez, EEG sinyali sınıflandırma alanındaki karmaşık ve gelişen alanı, iki farklı ve yenilikçi özellik çıkarım yöntemiyle incelemektedir: Hadamard tabanı ve detrendleme ve varyans tespiti, hareketle ilgili kortikal potansiyellerin (MRCP'ler) sınıflandırılması için. Çalışma, her bir yöntemin kendine özgü yaklaşımının EEG sinyallerinin doğru ve verimli bir şekilde kategorize edilmesine nasıl katkıda bulunabileceğini araştırmayı amaçlamaktadır; bu, beyin-bilgisayar arayüzü (BCI) sistemleri ve diğer nöroteknolojik uygulamaların geliştirilmesinde kritik bir faktördür.

Hadamard tabanı yöntemi, ortogonal dönüşümlerle ilgili matematiksel ilkelere dayanır. EEG sinyallerini bir dizi temel fonksiyona ayırarak, bu teknik sinyalin farklı yönlerini temsil eder. Verimliliği ve sadeliği ile tanınan Hadamard dönüşümü, EEG sinyallerini orijinal zaman alanından Hadamard alanına dönüştürmede önemli bir rol oynar. Bu dönüştürülmüş alanda, EEG verisi daha yapılandırılmış hale gelir ve belirli nörolojik aktiviteleri temsil eden anahtar özelliklerin tanımlanması ve izole edilmesi kolaylaşır. Bu özellikler, motor niyetler, bilişsel görevler veya diğer nörolojik süreçlerle ilişkili çeşitli beyin durumlarının ayrılmasında çok önemlidir. Bu yöntemin, bu özelliklerin netliğini ve ayrımını artırma yeteneği, EEG sinyali sınıflandırmasında güçlü ve güvenilir sonuçlar elde edilmesini sağlayarak, çeşitli uygulamalarda değerli bir araç olmasını sağlar.

Diğer taraftan, Detrendleme ve Varyans Tespiti (VB-MFED) yöntemi, özellikle MRCP'lerin tespiti ve analizine odaklanır. Bu yavaş kortikal potansiyeller, gönüllü hareketlerden önce ortaya çıkar ve beynin hazırlık faaliyetlerini yansıtır. MRCP'ler, BCI'ler, nörorehabilitasyon ve sinirbilim araştırmaları gibi alanlarda büyük öneme sahiptir, çünkü motor planlama faaliyetleri hakkında içgörüler sağlarlar. Bu tezde kullanılan optimize edilmiş ön işleme yöntemi, MRCP sinyallerini geliştirirken, gürültü ve diğer istenmeyen öğeleri etkili bir şekilde azaltmayı içerir. Adaptif filtreleme gibi teknikler, EEG sinyali özelliklerine dayalı olarak işleme parametrelerini dinamik olarak ayarlar, bu da sinyal-gürültü oranını iyileştirir. Temel düzeltme, sinyaldeki istenmeyen kaymaları veya sapmaları ortadan kaldırarak, çıkarılan özelliklerin altındaki sinirsel aktiviteyi doğru bir şekilde temsil etmesini sağlar. Uzamsal filtreleme, bir başka kritik bileşen olarak, belirli kortikal alanlardan gelen sinyalleri güçlendirirken, diğer bölgelerden gelenleri baskılar ve ilgili beyin bölgelerine odaklanmayı kolaylaştırır. Bu ön işleme tekniklerinin birleşimi, çıkarılan özelliklerin hem uygun hem de doğru olmasını sağlar, böylece MRCP'lerin sınıflandırma performansını iyileştirir.

Beyin-bilgisayar arayüzleri (BCI'ler), insan beynini dış cihazlarla iletişim kurabilen bir köprü olarak hizmet eden devrim niteliğinde bir teknolojidir. EEG aracılığıyla kaydedilen elektriksel beyin aktivitesini yorumlayarak, BCI'ler kullanıcıların cihazları kontrol etmelerini, iletişim kurmalarını veya fiziksel hareket olmadan çevreleriyle etkileşimde bulunmalarını sağlar. Bu yetenek, omurilik yaralanmaları veya nörodejeneratif hastalıklar gibi ağır motor bozukluğu olan bireyler için özellikle faydalıdır, çünkü bağımsızlıklarını yeniden kazanma yolunda bir fırsat sunar. Bu bağlamda, çalışma, omurilik yaralanması (SCI) olan bireylerde, farklı hareket kategorilerini sınıflandırmak için temel olarak kullanılan, denenen el hareketlerini içeren MRCP'lerin kullanılmasını araştırmaktadır. MRCP'leri tespit etme ve sınıflandırma yeteneği, BCI'lerin, kullanıcı niyetlerini yorumlayıp bunları yardımcı cihazlar için kontrol komutlarına dönüştürmesi için çok önemlidir.

Başlangıçta, Hadamard tabanı yöntemi önerilmiş ve EEG sinyallerinin sınıflandırılmasındaki etkinliği, dört sınıflandırıcı kullanılarak değerlendirilmiştir: Fisher'ın Lineer Ayrım Analizi (FLDA), çok sınıflı Destek Vektör Makineleri (SVM), K-En Yakın Komşu (KNN) ve Shrinkage Lineer Ayrımcı (sLDA). Bu sınıflandırıcılar, omurilik yaralanması (SCI) olan hastalardan elde edilen EEG sinyallerini sınıflandırmaya yönelik özel olarak geliştirilmiş Hadamard tabanlı özellik çıkarım tekniğinden türetilen aynı özellik vektörü seti üzerinde test edilmiştir. 4 kanal ve 61 kanal kurulumlarıyla, 0.5-1.5 saniye ve -2 ila 3 saniye gibi farklı ilgi pencerelerinde yapılan çeşitli yapılandırmalar üzerinde kapsamlı bir analiz yapılmıştır. Ancak, Hadamard tabanı ile elde edilen sonuçlar, 4 kanal için 0.5-1.5 saniye aralığında sırasıyla 23.58%, 24.42%, 28.79% ve 29.71%; 61 kanal için ise sırasıyla 20.42%, 23.96%, 28.46% ve 30.96% olarak SVM, KNN, FDA ve sLDA için alınmıştır. Ayrıca, -2 ila 3 saniye aralığında 4 kanal için sonuçlar sırasıyla 23.79%, 22. 71%, 29.38% ve 28.13%; 61 kanal için ise sırasıyla 21.54%, 23.33%, 28.83% ve 30.58% olarak SVM, KNN, FLDA ve sLDA için alınmıştır.

VB-MFED yöntemiyle ise, Hadamard tabanı yöntemindeki prosedür aynen uygulanmıştır. Elde edilen sonuçlar, 4 kanal için 0.5-1.5 saniye aralığında sırasıyla 83.18%, 68.12%, 78.59% ve 77.65%; 61 kanal için ise sırasıyla 66.23%, 47.65%, 52.12% ve 44.81% olarak SVM, KNN, FLDA ve sLDA için alınmıştır. -2 ila 3 saniye penceresi için, 4 ve 61 kanallar için sırasıyla SVM, KNN, FDA ve sLDA için elde edilen sonuçlar 76.03%, 83.28%, 29.48%, 26.99% ve 74.59%, 85.33%, 32.15%, 30.91% olarak sıralanmıştır.

Bu sonuçlar, önerilen yöntemin, özellikle doğru EEG sinyali sınıflandırmasına dayalı yardımcı teknolojilerden fayda sağlayabilecek omurilik yaralanması (SCI) olan bireyler için BCI sistemlerinde etkili bir araç olma potansiyelini vurgulamaktadır.

Sonuç olarak, bu tez, Hadamard tabanı ve VB-MFED işleme yöntemi gibi ileri düzey özellik çıkarım yöntemlerinin EEG sinyali sınıflandırmasını iyileştirmedeki potansiyelini vurgulamaktadır. Bu yöntemler, hassas sinirsel sinyalleri tespit etme ve yorumlama yeteneğini artırarak, daha sofistike ve güvenilir BCI sistemlerinin önünü açmaktadır. Bu çalışmanın bulguları, nöroteknoloji alanına katkıda bulunarak, yardımcı cihazlar, nörorehabilitasyon ve beyin fonksiyonları anlayışı alanlarında yeni ilerlemelere yol açabilecek içgörüler sunmaktadır.

Gelecekteki araştırmaların, daha büyük veri kümeleri ve gelişmiş derin öğrenme teknikleriyle desteklenerek EEG sınıflandırma performansını daha da artırması beklenmektedir. Özellikle derin öğrenme tabanlı yaklaşımlar, EEG sinyallerindeki karmaşık örüntüleri daha iyi öğrenme ve genelleme kapasitesine sahip olduğundan, bu alandaki ilerlemeleri hızlandırabilir. Bunun yanı sıra, EEG verilerinin daha geniş ve çeşitli veri setleriyle eğitilmesi, modelin farklı bireylerde ve koşullarda daha tutarlı sonuçlar üretmesine olanak tanıyacaktır. Veri çeşitliliği artırıldıkça, sınıflandırma sistemlerinin adaptif kapasitesi gelişecek ve farklı bireylerin beyin aktivitesini daha doğru bir şekilde yorumlama yeteneği elde edilecektir.

Ayrıca, farklı hasta grupları üzerinde yapılan çalışmaların genişletilmesi, bireysel farklılıkların sınıflandırma performansına etkisinin araştırılması ve gerçek zamanlı uygulamaların geliştirilmesi, bu alandaki ilerlemeleri daha da hızlandıracaktır. Bireyler arasında anatomik ve nörofizyolojik farklılıklar göz önüne alındığında, bu çeşitliliğin EEG sinyal işleme ve sınıflandırma süreçlerine olan etkisi detaylı bir şekilde incelenmelidir. Özellikle yaş, cinsiyet, bilişsel durum ve nörolojik bozukluklar gibi faktörlerin EEG sınıflandırmasına olan etkisinin anlaşılması, daha kişiselleştirilmiş BCI sistemlerinin geliştirilmesine katkı sağlayabilir. Bu bağlamda, bireysel farklılıklara duyarlı, adaptif ve özelleştirilmiş EEG sınıflandırma modellerinin oluşturulması, BCI sistemlerinin kullanım alanlarını genişletebilir.

Gerçek zamanlı EEG sinyal işleme algoritmalarının geliştirilmesi de büyük önem taşımaktadır. Günümüzde birçok EEG tabanlı sistem çevrimdışı analizlere dayanırken, gerçek zamanlı işlemeye olan talep giderek artmaktadır. Özellikle BCI sistemlerinde kullanıcı geri bildiriminin hızla işlenmesi, sistemin yanıt süresini iyileştirerek kullanım deneyimini daha akıcı ve etkili hale getirebilir. Bu doğrultuda, düşük gecikmeli veri işleme tekniklerinin ve optimize edilmiş hesaplama yaklaşımlarının geliştirilmesi, EEG tabanlı sistemlerin pratik uygulanabilirliğini artıracaktır. Gerçek zamanlı EEG analizi, özellikle hareket bozukluğu olan bireyler için geliştirilen yardımcı cihazlar ve nörorehabilitasyon uygulamalarında büyük bir devrim yaratabilir.

Son olarak, EEG sinyali sınıflandırma tekniklerinin klinik ortamlarda kullanımına yönelik testlerin artırılması, BCI sistemlerinin günlük yaşama entegrasyonunu sağlayarak bu teknolojilerin pratik faydasını artıracaktır. Klinik ortamda doğrulanan EEG sınıflandırma teknikleri, sadece laboratuvar koşullarında değil, gerçek dünya senaryolarında da uygulanabilir hale gelecektir. Bu kapsamda, hasta başı EEG sistemlerinin geliştirilmesi, kullanıcı dostu arayüzlerin tasarlanması ve taşınabilir EEG cihazlarının yaygınlaştırılması, teknolojinin daha geniş bir kesime ulaşmasını sağlayacaktır.

Beyin sinyallerine dayalı kontrol sistemleri, yalnızca tıbbi uygulamalarla sınırlı kalmayıp, geniş bir kullanıcı kitlesine hitap eden yenilikçi etkileşim araçları olarak da kullanılabilir hale gelecektir. Bu sistemlerin sanal ve artırılmış gerçeklik uygulamalarıyla bütünleştirilmesi, engelli bireylerin günlük yaşamda daha bağımsız hareket edebilmesine olanak tanıyabilir. Ayrıca, oyun ve eğlence endüstrisinde BCI tabanlı sistemlerin kullanımı, insanların beyin dalgaları aracılığıyla doğrudan etkileşim kurmalarını sağlayarak yeni deneyimler sunabilir. Gelecekte EEG tabanlı sistemlerin eğitim, zihinsel sağlık izleme ve stres yönetimi gibi alanlarda da kullanımı yaygınlaşarak, bireylerin bilişsel süreçlerini anlamalarına ve optimize etmelerine yardımcı olabilir.

Tüm bu gelişmeler ışığında, EEG sınıflandırma teknikleri yalnızca akademik ve klinik araştırmalarla sınırlı kalmayıp, günlük hayatta da yaygın olarak kullanılan teknolojiler haline gelebilir. Bu alandaki ilerlemeler, beyin ve makine arasındaki etkileşimi daha doğal ve akıcı hale getirerek, insan-makine arayüzlerinde yeni bir çağın kapılarını aralayacaktır.

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This work is dedicated to the memory of Prof. Dr Arica and is also a reflection of the ongoing support and mentorship from Assoc. Prof. Aydın. It is with immense gratitude that I acknowledge the contributions of those who have been instrumental in bringing this work to completion.

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ABBREVIATIONS

ADHD	: Attention-Deficit/Hyperactivity Disorder
AM	: Attempted Movement
ARMA	: AutoRegressive Moving Average
BCI	: Brain-Computer Interface
BNCI	: Brain Nueral Computer Interface
BPF	: Band Pass Filter
BP	: Break Point
CAR	: Common Average Reference
CSP	: Common Spatial Pattern
DVD	: Detrending and variance detection
EEG	: Electroencephalography
ECoG	: Electrocorticography
EOG	: Electrooculography
ERD	: Event-Related Desynchronization
ERS	: Event-Related Synchronization
ERPs	: Event-Related Potentials
EPSPs	: Excitatory Postsynaptic Potentials
FLDA	: Fisher Linear Discriminant Analysis
FN	: False Negatives
FP	: False Positives
fMRI	: Functional Magnetic Resonance Imaging
GB	: Gigabyte
GA	: Genetic Algorithms
GHz	: Gigahertz
HPF	: High Pass Filter
HT	: Hadamard Transform
HM	: Hadamard Matrices
Hz	: Hertz
IPSPs	: Inhibitory Postsynaptic Potentials
KNN	: K-Nearest Neighbors
LDA	: Linear Discriminant Analysis
LPF	: Low Pass Filter
MEG	: Magnetoencephalography
MI	: Motor Imagery
MRI	: Magnetic Resonance Imaging

MRCP : Movement Related Cortical Potential

MRP : Movement Related Potential

NN : Neural Network

OvA : One-vs-All

PET : Positron Emission Tomography

P01 : Participant number one

RAM : Random Access Memory

S-to N : Signal to Noise

SCP : Slow Cortical Potentials

SCI : Spinal Cord Injury

SD : Standard Deviation

SLDA : Shrinkage Linear Discriminant Analysis

SPECT : Single Photon Emission Computed Tomography

SL : Surface Laplacian

S1 : Subject number one

SSVEP : Steady-State Visual Evoked Potential

SVM : Support Vector Machine

T & F : Time & Frequency

TN : True Negatives

TP : True Positives

VB-MFED: Variance-Based MRCP Feature Extraction with Detrending

WPD : Wavelet Packet Decomposition

1. INTRODUCTION

1.1. Electroencephalogram (EEG)

The electroencephalogram (EEG) is a cornerstone of modern neuroscience, offering a noninvasive method to monitor and record electrical activity generated by the brain (Schomer and Silva, 2011). By placing electrodes on the scalp, EEG enables researchers and clinicians to capture brainwave patterns, reflecting the underlying neural processes responsible for various cognitive and motor functions. This technique provides a window into the dynamic workings of the brain, offering valuable insights into how different regions interact and respond to stimuli, which has proven essential in advancing both basic research and applied fields.

One of the most significant advantages of EEG is its ability to record brain activity in real time, offering unparalleled temporal resolution (Michel and Brunet, 2019). This real-time monitoring is crucial for studying cognitive functions, such as attention, memory, and sensory processing, as well as identifying abnormalities that could indicate the presence of neurological disorders. Conditions like epilepsy, sleep disorders, and traumatic brain injuries often manifest distinct electrical patterns, making EEG an indispensable tool for early diagnosis and ongoing management.

Moreover, the utility of EEG extends beyond diagnostic applications. In therapeutic settings, EEG plays a vital role in neurofeedback and brain-computer interface (BCI) systems, enabling individuals to modulate their brain activity intentionally. These applications open new avenues for treating conditions such as anxiety, ADHD, and even motor disabilities(Sitaram et al., 2017). For instance, in rehabilitation, EEG-based BCIs can assist patients with motor impairments, such as those recovering from stroke or spinal cord injuries, by translating their brain signals into commands that control external devices like prosthetic limbs or computer cursors.

EEG's ability to capture the intricate complexities of brain function also underpins its role in research focused on understanding higher cognitive functions, such as decision-making, language processing, and emotional regulation. By analyzing the frequency, amplitude, and synchronization of brainwaves, researchers can gain deeper insights into how the brain organizes and processes information, paving the way for innovations in fields such as artificial intelligence, machine learning, and neuroprosthetics(Wu et al., 2023).

Overall, EEG's capacity to reveal the rich and complex nature of brain activity underscores its fundamental importance in both advancing scientific knowledge of the human mind and improving clinical practices aimed at promoting neurological health and well-being. From diagnosing brain disorders to enhancing therapeutic approaches, EEG continues to shape the future of neuroscience and medicine.

1.2. Origin of EEG

The history of EEG traces back to the pioneering work of Richard Caton, a British scientist. In 1875, Caton made a groundbreaking discovery by successfully detecting the electrical activity of the brain in living mammals. He achieved this by putting two metal electrodes on the scalp of the animal and measuring the brain's electrical signals with a sensitive galvanometer. This early work laid the foundation for the field of EEG, demonstrating for the first time that brain activity could be monitored externally.

The advancement of EEG technology continued with Hans Berger, a German psychiatrist and neurologist, who is credited with being the first to record human brain waves. Berger's interest in brain activity was deeply personal, driven by a desire to find scientific explanations for his own extraordinary experiences. In 1924, he made a significant leap forward by recording the electrical activity in the brain using a Siemens double-coil galvanometer, a more advanced and sensitive device than Caton's original apparatus. Berger's meticulous work involved placing electrodes on the human scalp to capture the brain's electrical impulses. His recordings were the first to demonstrate the existence of different brain wave patterns, which he meticulously documented and analyzed.

Hans Berger's contributions were pivotal, as he provided clear evidence of the brain's rhythmic electrical activity, which he termed the "electroencephalogram" or EEG. His work laid the groundwork for modern neuroscience, offering a new window into understanding brain function and its various states of activity. Figure 1.1, illustrates one of Berger's original EEG recording attempts, highlighting the historical significance of his work (Arjoonsingh et al., 2024)

Through the efforts of Caton and Berger, the field of EEG was born, evolving from rudimentary experiments with animal brains to sophisticated recordings of human brain activity. Their pioneering research opened new possibilities for diagnosing and studying neurological conditions, significantly influencing the development of neurophysiology and related discipline.

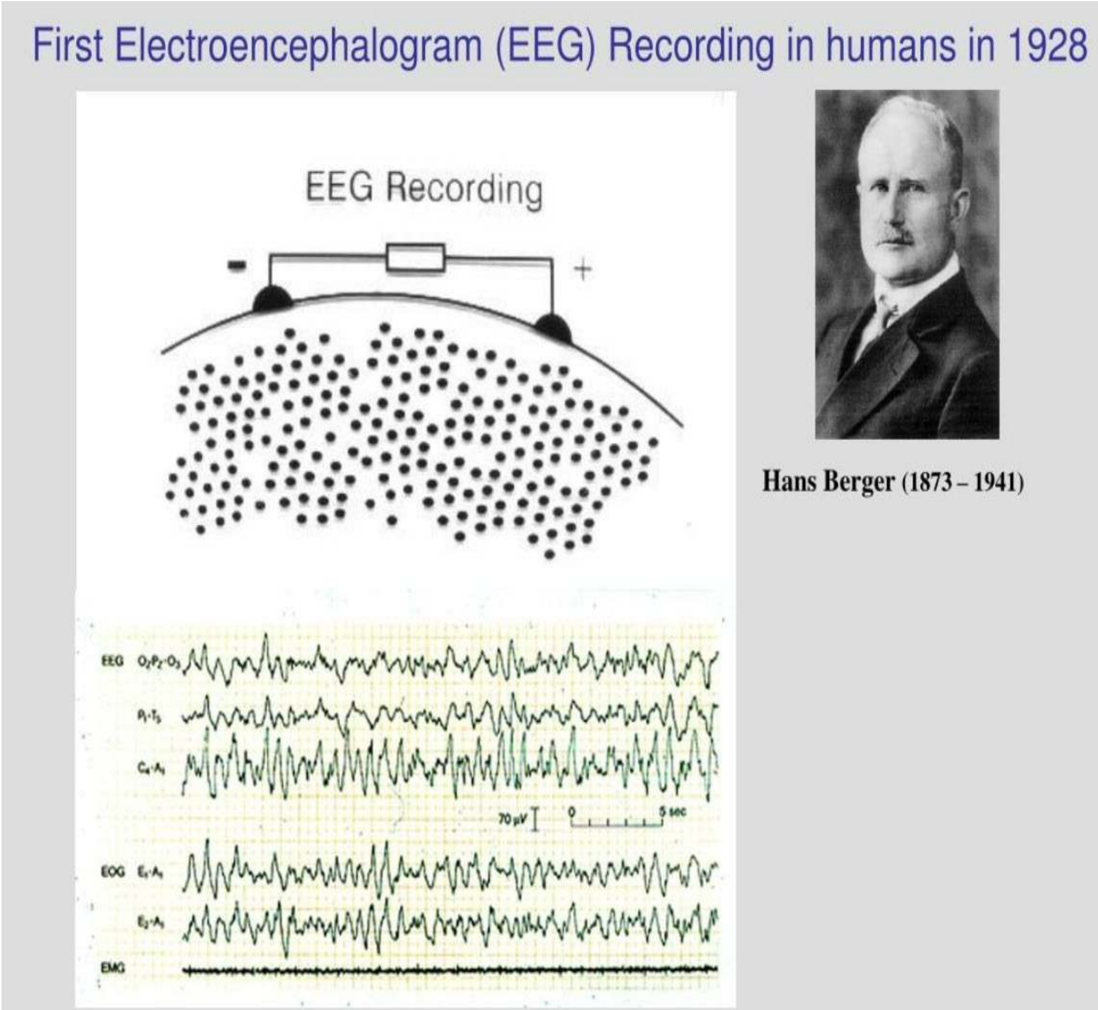

Figure 1.1 In 1920s EEG monitoring by Hans Berger (Sanei, 2013)

1.3.The Electro-encephalography (EEG) Monitoring

Figure 1.2 illustrates how an EEG extracts signals from the brain. Neuronal activity within the brain generates electrical signals at synapses due to ion movement, creating positive and negative charges. These electrical signals propagate through the brain tissue and pass through the protective meninges layers (pia mater, subarachnoid space, arachnoid, and dura mater) before traveling through the skull and scalp. EEG electrodes placed on the scalp detect these weak electrical signals, which are then sent to an amplifier to boost their strength. The amplified signals are recorded and displayed as waveforms, representing the brain's electrical activity over time, allowing for analysis and interpretation of brain function and diagnosis of neurological conditions (Salahuddin and Gao, 2021).

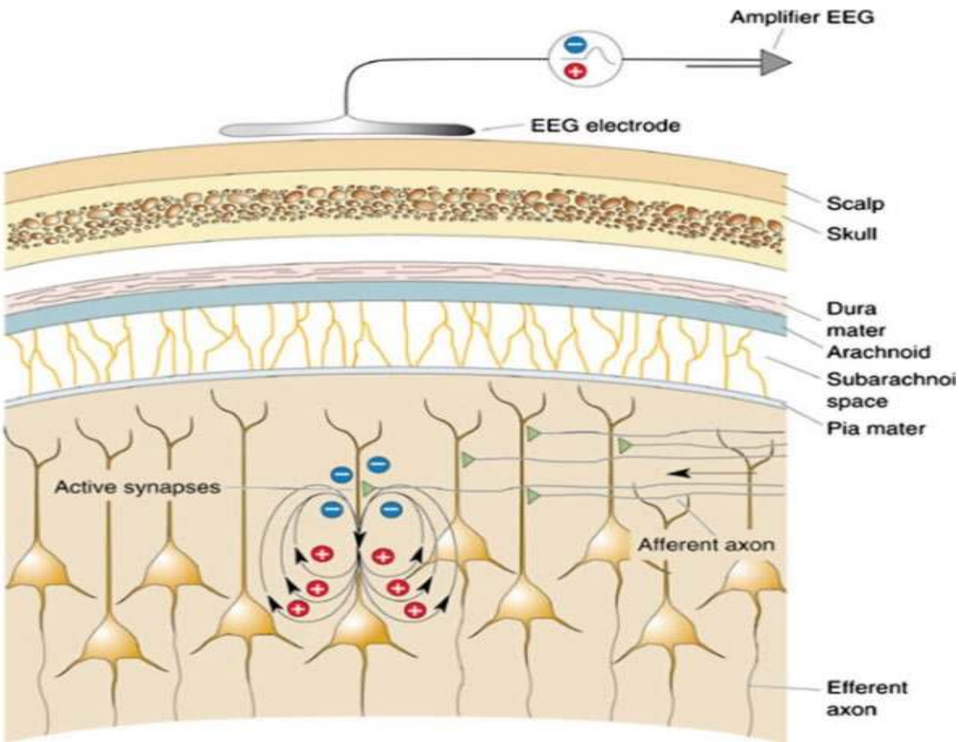

Figure 1.2 Pathway of Neural Activity to Surface EEG Detection (Siuly et al., 2016)

The EEG monitoring system comprises several essential components necessary for capturing brain activity.

a. **Metal Electrodes**: These metals are discs like and are positioned at specific position on the human scalp to record brain waves.

b. **Amplifiers:** The amplitude range of signals measured on the scalp with metal electrodes is 10 to 100 µV, and amplifiers are needed to increase the signal levels.

c. **Filters:** EEG signals require filters to reduce noise effects. Such as, HPF, LPF, and notch filters are primarily applied

d. **Recording Unit**: EEG signals are preserved through permanent recordings. Initially, EEG recordings were done on paper, but now digital EEG is favored as it alleviates paper storage issues.

1.4. EEG Brain Waves

The classification of EEG waves into specific frequency bands—alpha, beta, theta, delta, and gamma—is essential for understanding brain activity and its correlation with various cognitive and physiological states. These frequency bands help define different aspects of mental processes such as relaxation, attention, memory, and sleep, providing valuable insight into brain function. Each of these bands represents a distinct range of brain wave frequencies and is associated with specific cognitive states and brain regions (Abhang et al., 2016).

- Alpha Band (8-13 Hz)

  The alpha band, covering frequencies between 8 and 13 Hz, is most commonly associated with relaxed and alert mental states. Alpha waves are typically observed when a person is calm and awake but not actively engaging in tasks requiring high concentration. These waves are predominantly seen in the occipital and parietal lobes, often emerging when the eyes are closed, which is why they are linked to restful and introspective mental activities. Alpha activity has been associated with optimal cognitive performance during relaxation, and altered alpha rhythms are often noted in anxiety and depression disorders (Nayak and Anilkumar, 2024).

- Beta Band (13-30 Hz)

  Beta waves, ranging from 13 to 30 Hz, are linked to active cognitive processes such as problem-solving, focused attention, and decision-making. These waves typically become more prominent when a person is engaged in tasks that require alertness and intellectual effort, such as solving a complex problem or engaging in a conversation. Beta waves exhibit a broad distribution across various regions of the brain depending on the cognitive demands. While moderate beta activity is indicative of a healthy, focused brain, excessive beta waves can be observed in individuals suffering from anxiety, stress, or conditions like insomnia, where the brain remains overly active(Nayak and Anilkumar, 2024).

- Theta Band (4-8 Hz)

  Theta waves, ranging from 4 to 8 Hz, are closely tied to memory consolidation, emotional processing, and meditative or drowsy states. They are most often seen in the frontal midline areas and can increase during deep reflection or light sleep. Theta activity is crucial in facilitating creativity, memory recall, and relaxation. For individuals engaged in meditative practices, theta waves often reflect a deep, relaxed mental state, while in neurofeedback training, enhanced theta wave activity can help individuals achieve greater emotional balance and cognitive flexibility (Nayak and Anilkumar, 2024).

- Delta Band (0.5-4 Hz)

  Delta waves, the slowest EEG waves, occur within the frequency range of 0.5 to 4 Hz and are characteristic of deep sleep. These waves are associated with non-REM sleep, during which the brain and body undergo essential restorative processes. Delta activity is generally not present in wakeful states, although its presence in awake individuals can indicate neurological impairment, such as brain injuries or dementia. In healthy individuals, delta waves support the body's restorative functions, enhancing immune function, growth, and healing(Nayak and Anilkumar, 2024).

- Gamma Band (30-40 Hz)

  Gamma waves, ranging from 30 to 40 Hz, are the fastest brain waves and are associated with higher-level cognitive functions such as perception, problem-solving, and the integration of sensory information. These waves are critical for coherent and synchronized brain function, allowing different brain regions to communicate and work together efficiently. Gamma waves are often linked to moments of heightened awareness, learning, and complex cognitive tasks that require integrating sensory and mental processes (Nayak and Anilkumar, 2024)

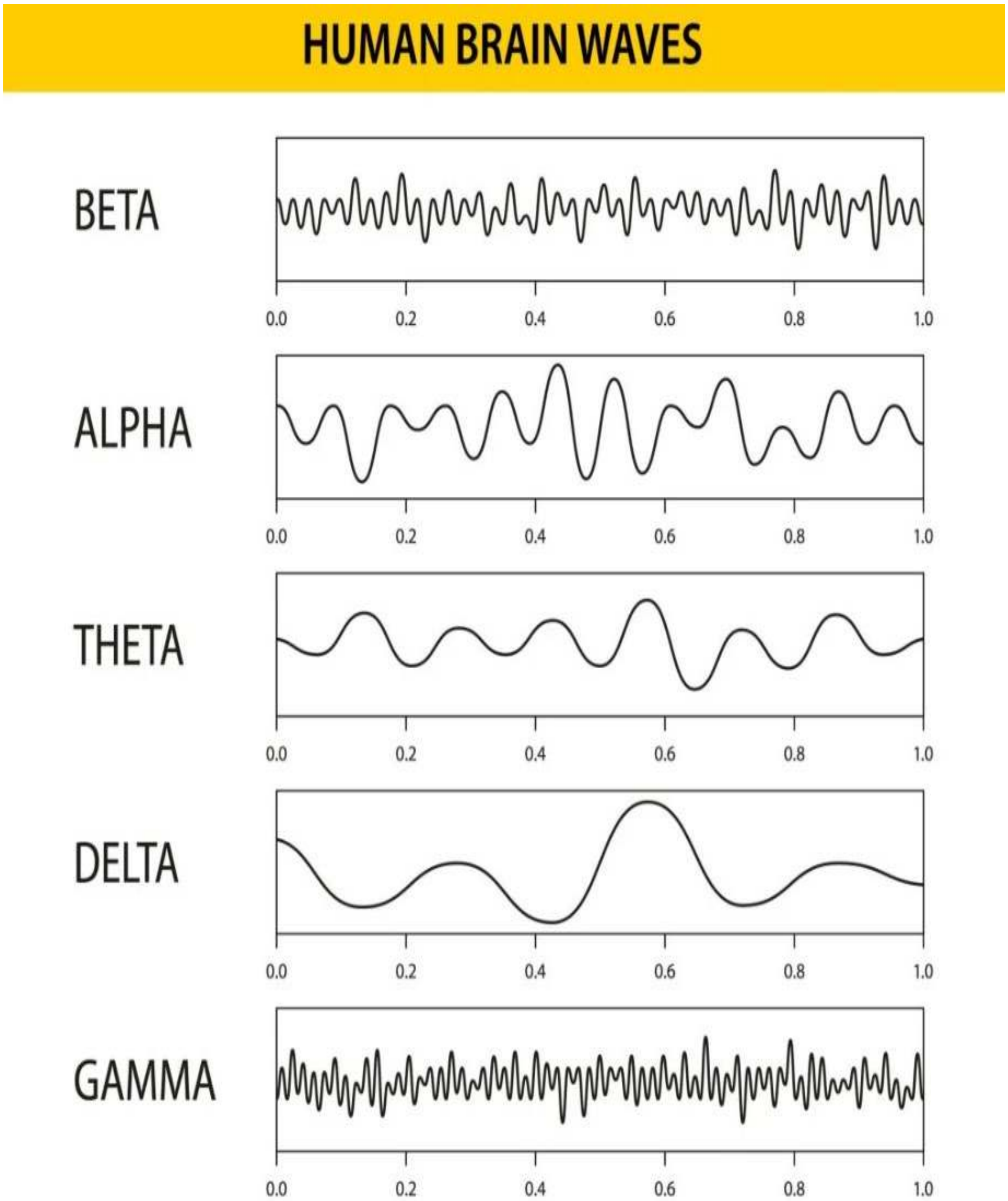

Figure 1.3. Brain waves (Georgieva et al., 2014)

1.5. Brain Computer Interface and Motor Imagery (MI)

The convergence of neuroscience and technological advancements has paved the way for integrating Brain-Computer Interface (BCI) technology which serves as a widely recognized, unidirectional conduit linking the human brain with external devices (Aggarwal and Chugh, 2022).

This synthesis offers a promising avenue for understanding the neural underpinnings of motor cognition and expanding applications in human-machine interaction. Motor imagery, which involves the mental simulation of movement without physical execution, serves as a focal point for examining the complex interplay between cognitive processes and neurophysiological activity. Utilizing EEG as a primary investigative tool, researchers are delving into the neural foundations of MI, focusing on the sensorimotor cortex's role and the manifestation of movement-related cortical potentials (MRCPs) during mental motor tasks(Abiri et al., 2019; Wang et al., 2022). This neuroimaging approach elucidates cortical dynamics associated with MI, shedding light on how the brain encodes and processes imagined movements.

BCI systems, when combined with motor imagery, enable the decoding of neural patterns associated with mental tasks using machine learning algorithms. These algorithms are employed to interpret the unique neural signatures arising from MI, transforming them into actionable commands that can control external devices (Wu et al., 2023).

During the training phase, users engage in MI tasks to develop a reciprocal relationship with the BCI system, allowing it to discriminate and translate neural representations of motor intentions into real-world outputs. This technology has significant implications beyond the laboratory, particularly in neurorehabilitation, where MI-BCIs can help individuals with motor impairments control assistive devices such as prosthetics or exoskeletons through mental commands. Such applications highlight the potential of MI-BCIs to restore mobility and autonomy, underscoring the translational potential of BCI technology in addressing real-world challenges associated with motor disabilities (Brusini et al., 2021).

However, implementing MI-BCIs is not without challenges. Variability in individual neural patterns, the accuracy of decoding algorithms, and the cognitive load associated with maintaining sustained BCI control present significant obstacles .Current research efforts aim to address these limitations by refining decoding methodologies, exploring sophisticated signal processing techniques, and integrating alternative neuroimaging modalities, such as functional near-infrared spectroscopy (fNIRS), to enhance the robustness and generalizability of MI-BCIs (Li et al., 2022). These advancements seek to improve system performance and user experience, making MI-BCIs more practical for daily use.

Beyond neurorehabilitation, MI-BCIs have applications in virtual reality (VR) and gaming, where they can elevate human-computer interaction to a new level of experiential immersion. The ability to control virtual environments through mental commands offers an innovative approach to VR experiences, with potential benefits in gaming, training simulations, and educational tools

(Leeb and Pérez-Marcos, 2020). This represents a convergence of technological innovation with cognitive exploration, broadening the impact of MI-BCIs across diverse domains.

The integration of BCI technology with motor imagery presents a multidisciplinary frontier, bridging neuroscience, engineering, and rehabilitation sciences. This collaboration holds the promise of advancing our understanding of cognitive processes and translating this knowledge into transformative applications with broad societal implications. BCI systems typically follow a structured framework involving data acquisition, preprocessing, feature extraction, and classification. EEG remains the most widely used modality for recording neural signals due to its high temporal resolution and portability. Feature extraction methods transform raw neural signals into representative features, such as, filter bank common spatial pattern (FBCSP) while classification algorithms interpret these features to identify specific mental states or intentions (Ghumman et al., 2021). Continuous research focuses on optimizing each stage of the BCI pipeline for improved performance, with system architectures adapted to various applications.

Recent studies underscore the importance of refining every component of BCI systems, including feature extraction and machine learning techniques, to enhance their accuracy and robustness (Maiseli et al., 2023). With ongoing advancements, MI-BCIs have the potential to revolutionize fields such as rehabilitation, VR, and beyond, making significant strides in both theoretical and practical domains.

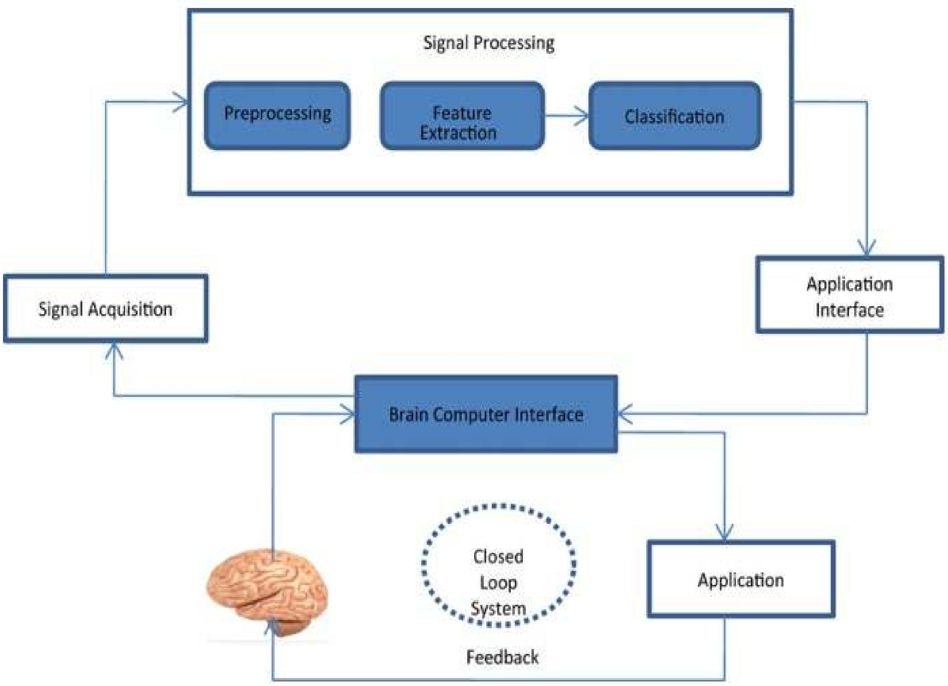

Figure 1.4. Schematic representation of the BCI components(Aggarwal and Chugh, 2022)

EEG signal analysis is central to improving BCIs and diagnosing neurological disorders. The process involves several critical stages: preprocessing, feature extraction, and classification, all of which contribute to the accuracy and reliability of interpreting brain activity. Each stage incorporates advanced techniques that are constantly evolving with research advancements (Aggarwal and Chugh, 2022)

1.6. Research Goals

The thesis contributes significantly to the field of EEG signal classification.

1. Comparison of Feature Extraction Methods for MRCPs:
   The study aims to compare two distinct feature extraction techniques—Hadamard basis with Savitzky-Golay filtering and the Variance-Based MRCP Feature Extraction with Detrending (VB-MFED) method to determine their effectiveness in classifying movement-related cortical potentials (MRCPs) from EEG signals.
2. Evaluation of Classifier Performance Across Configurations:
   The research investigates the performance of four classifiers—SVM, KNN, FLDA, and sLDA—across different EEG channel configurations (4 and 61 channels) and time windows of interest (WOI), focusing on their ability to decode attempted hand movements.
3. Exploration of Feature Extraction Impact on Low-Channel EEG Systems:
   The study explores how different feature extraction methods impact classification performance when fewer EEG channels are used, with the goal of optimizing BCI systems for practical, low-channel, real-time applications in clinical and rehabilitative settings.
4. Development of Efficient EEG-Based BCI Systems:
   The research seeks to enhance EEG-based brain-computer interfaces (BCIs) by identifying optimal combinations of feature extraction methods and classifiers, improving the accuracy and reliability of movement intention detection for individuals with spinal cord injuries (SCI).
5. Novelty:
   Introduction of the Hadamard Basis with Savitzky-Golay Filtering and the Variance-Based MRCP Feature Extraction with Detrending (VB-MFED) method for MRCP classification.The study introduces two methods as novel feature extraction techniques for MRCP classification in EEG-based BCIs. It highlights their ability to capture subtle neural dynamics, offering a more effective approach compared to traditional techniques for enhancing BCI systems intended for real-time clinical applications.

This study is structured as follows: Section 2 presents literature review; section 3 provides description of the materials and methods. Section 4 presents the results and discussions. Section 5 concludes the study.

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2. LITERATURE REVIEW

This section presents a detailed review of studies centered on Movement-Related Cortical Potential (MRCP) in EEG-Based BCI Systems, movement intention detection, EEG classification and feature extraction techniques. By examining the evolution and advancements in these domains, this review provides a comprehensive foundation for understanding the interplay between EEG classification, MRCP analysis, and feature extraction. This exploration also contextualizes the study's methodologies within the broader landscape of neural interfacing, machine learning, and signal processing innovations, setting the stage for further advancements in BCI research.

EEG-based BCIs have become a cornerstone in neural interfacing technologies, facilitating direct communication between the human brain and external devices. These systems are instrumental in applications ranging from neurorehabilitation and assistive technologies to advanced human-computer interaction. A critical aspect of EEG-based BCIs is the classification of brain signals, which involves identifying specific patterns corresponding to user intentions or cognitive states. MRCP, a key neural signature reflecting brain activity linked to voluntary movements plays a vital role in this process. Detecting and leveraging MRCP not only improves the accuracy of movement intention prediction but also enhances the responsiveness and reliability of BCIs (Ofner et al., 2019; Li et al., 2018; Kam et al., 2019).

2.1. Movement-Related Cortical Potential (MRCP) in EEG-Based BCI Systems

EEG has emerged as the predominant non-invasive technique for recording brain activity in BCI systems. Its popularity stems from a combination of factors, including its simplicity, flexibility, affordability, and ease of implementation. Recent advancements in EEG technology, such as the development of dry electrodes and wireless systems, have further enhanced its appeal for BCI applications (Kam et al., 2019).

Despite these advancements, challenges remain in achieving consistently high performance across different BCI applications and user populations. The goal of BCI systems is to achieve high speed and accuracy, necessitating efficient feature extraction and classification techniques. However, as noted by (Lotte et al., 2018), there is no single method for extracting features that consistently provides optimal performance across all BCI applications. This challenge has led researchers to explore and formulate various feature extraction methods tailored to specific BCI applications and user needs.

MRCP represent additive cortical activities associated with voluntary movements, and they can be recorded using non-invasive electrodes placed on the scalp. These potentials are characterized by low-frequency signals ranging between 0 and 5 Hz and exhibit negative shifts in the EEG waveform, with amplitudes typically falling within the range of 5 to 30 µV. Unlike other types of evoked potentials, MRCPs show a unique temporal pattern. Their generation starts well before the actual movement begins, continuing for about 1.5 to 2 seconds prior to the movement stimulus and persisting for an additional 0.5 to 1 second after the movement stimulus. This distinctive behavior is closely linked to the processes of movement planning, preparation, and execution, as MRCPs generally emerge approximately 2 seconds before the onset of voluntary movement (Karimi et al., 2017).

The MRCP signal comprises three distinct components that are believed to represent different stages of movement: planning and preparation, execution, and performance monitoring. These components are referred to as the Bereitschaftspotential (BP), also known as the readiness potential, the motor potential (MP), and the movement monitoring potential (MMP), respectively. The Bereitschaftspotential (BP) reflects the early cortical activity associated with the mental preparation for movement. The motor potential (MP) represents the cortical activity occurring during the actual execution of the movement. Lastly, the MMP is thought to correspond to the feedback and control mechanisms that monitor and adjust the performance of the movement. Importantly, these components of MRCPs are observed not only during the execution of physical movements but also during the mental imagery of movement, showcasing their versatility and potential utility in a variety of applications as shown in Figure (Shakeel et al., 2015).

MRCPs can be influenced by numerous factors, which may alter the signal's components and characteristics. Variables such as the repetition speed of movements, the precision and velocity of the movement, the perceived level of effort required, the applied force, and the complexity or discreteness of the movement all have a significant impact on MRCPs. In addition, these potentials are affected by the processes of learning and skill acquisition, the involvement of specific brain structures, and the presence of neurological injuries or pathological conditions (Shibasaki and Hallett, 2006).

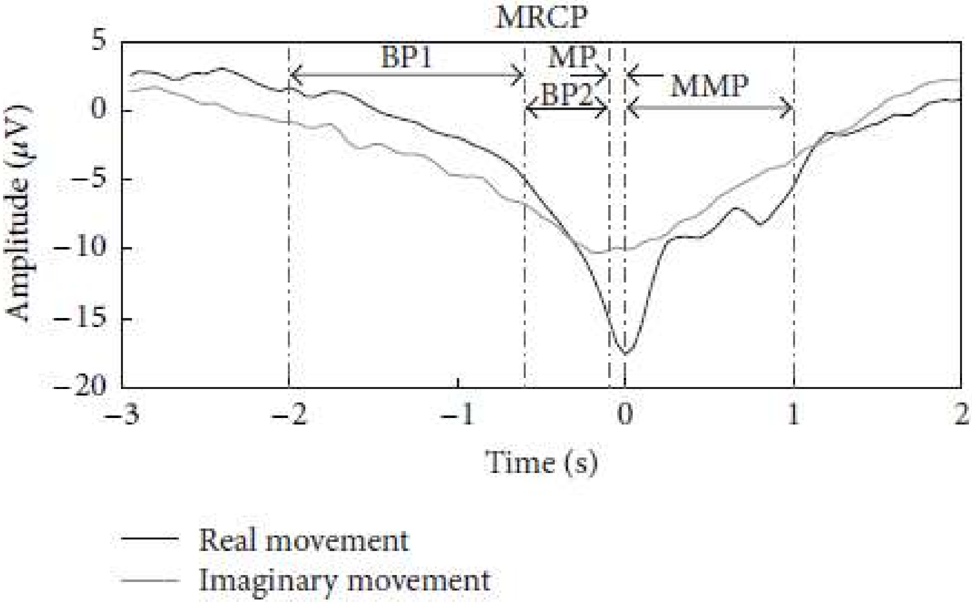

Figure 2.1.MRCPs of a healthy subject during real and imaginary right ankle dorsiflexion(Shakeel et al., 2015).

Differences in MRCP signals have also been noted based on the limb performing the movement and the specific nature of the movement. Furthermore, inter-individual variability and variations across patient populations contribute to the complexity of analyzing MRCPs. The fact that MRCP signals vary depending on the limb and its movements makes them particularly valuable as a control signal in BCI systems. BCIs designed to enable movement-related tasks can utilize these differences to create more precise and personalized control mechanisms .Given the comprehensive information that MRCPs provide about the cortical processes involved in movement, they have become a key focus in neurophysiological research and applications. Their ability to reflect movement-related processes both during physical execution and mental imagery makes MRCPs highly advantageous for developing assistive technologies, such as BCIs, for individuals with motor impairments. The inclusion of these signals in BCI systems could enable users to perform complex tasks by decoding movement intentions directly from brain activity, providing a significant step forward in assistive and rehabilitative technologies(Li et al., 2018; Rashid et al., 2019; Shakeel et al., 2015).

The exploration of MRCPs has paved the way for innovative treatment and rehabilitation strategies in neurology, particularly for individuals with movement impairments. Recent studies indicate that MRCPs can be utilized to develop novel therapeutic approaches. For instance, (Lin et al., 2023) demonstrated that real-time feedback of MRCPs during motor imagery tasks could enhance motor learning and potentially expedite rehabilitation in stroke patients. Furthermore, (Ofner et al., 2017) highlighted the feasibility of using MRCPs to control robotic arms for individuals with spinal cord injuries, presenting a promising avenue for restoring upper limb function. In the context of predictive interventions, (Olsen et al., 2021) investigated the application of MRCPs to predict movement onset in Parkinson's disease patients, suggesting that this could facilitate timely interventions to avert freezing of gait episodes.

Rashid et al., (2019) introduced an automated method for labeling movement-related cortical potentials (MRCPs), which are EEG signals associated with motor planning and execution. Their approach addresses the limitations of manual and semi-automatic methods, which struggle with modeling features like the early and late Bereitschaftspotential (BP1, BP2) and the negative peak (PN). Using segmented regression and a local peak detection method, their method identifies MRCP features, including the onsets, amplitudes, and slopes of BP1 and BP2, and the time and amplitude of PN.The method was evaluated using simulated MRCP datasets and experimental EEG data from 22 participants performing lower limb movements. The bounded segmented regression technique, optimized with particle swarm algorithms, outperformed other regression methods in accuracy and reliability. Compared to expert manual labeling, the automated method achieved comparable or superior performance for BP2 and PN identification. It was validated as a reliable tool for MRCP feature extraction, with potential applications in motor training and neurorehabilitation studies.

Li et al., (2018) investigated MRCPs and event-related desynchronization (ERD) during wrist extension tasks to study brain activity during movement preparation and execution. The study involved 33 healthy, right-handed participants performing unilateral wrist movements in two experimental paradigms: Instruction Response Movement (IRM) and Cued Instruction Response Movement (CIRM). EEG and EMG signals were recorded and analyzed in the time and frequency domains.The results revealed that MRCPs peaked at the central cortex (Cz) during movement execution, indicating bilateral control, whereas mu ERD showed contralateral dominance during movement preparation. EMG onset and peak times were shorter in CIRM compared to IRM due to the visual cue facilitating preparation.Statistical analyses confirmed significant differences in MRCP amplitudes across locations (Cz > C3/C4) and in mu ERD between contralateral and ipsilateral sensorimotor areas. The study highlights the distinct topographical and temporal patterns of MRCPs and ERD, suggesting their potential for improving motor intention detection in brain-computer interface (BCI) systems.

2.2. Movement Intention in EEG Signals

Movement intention, encompassing both attempted movement and motor imagery, has emerged as a powerful paradigm for manipulating EEG signals in BCI systems. Recent studies have demonstrated that both imagined and attempted movements elicit synchronized fluctuations in EEG signals, particularly within the delta frequency band (below 4 Hz).

These fluctuations, known as MRCPs, play a crucial role in decoding signals related to movement intention, thereby enhancing the efficacy of BCI systems (Ofner et al., 2019; Kokate et al., 2021).

In (Ofner et al., 2019) conducted a groundbreaking study exploring the detection of multiple hand and arm attempted movements using low delta band EEG signals from individuals with spinal cord injury (SCI). Their offline paradigm achieved an average accuracy of 45% across ten participants in classifying five distinct movements. In an online experiment featuring three classes (including a rest state), one subject with SCI achieved an impressive accuracy of 68%. This study not only demonstrated the feasibility of decoding multiple movement types in SCI patients but also highlighted the potential of low-frequency EEG signals for BCI applications.

Benzy et al., (2020) developed an EEG-based BCI to decode imagined hand movement directions in stroke patients, aiding neurorehabilitation. The method uses Phase Locking Value (PLV) features extracted from EEG signals, combined with Event-Related Desynchronization/Synchronization (ERD/ERS) analysis to identify motor imagery (MI) tasks. EEG data were recorded during calibration and feedback sessions, with feedback controlling a motorized arm support to mimic imagined movements. The system was evaluated on 16 stroke patients, achieving 74.44% classification accuracy during calibration and 68.63% during feedback. This approach demonstrated feasibility for active neurorehabilitation, enhancing movement recovery through motor imagery-based interventions.

Kokate et al., (2021) proposed a method for classifying upper arm movements using EEG signals, focusing on both motor imagery and execution tasks. The study used a publicly available EEG Motor Movement/Imagery dataset with data collected from 109 subjects across 64 EEG channels. Signals were pre-processed with a notch filter and band-pass filter, and artifacts were removed using Independent Component Analysis (ICA).

2.3. Classification and Feature Extraction

Feature extraction is another essential component of EEG signal processing, enabling the transformation of raw data into meaningful representations that facilitate accurate classification. Various methods, including time-domain, frequency-domain, and time-frequency analysis techniques, are employed to distill critical information from EEG signals. Advanced approaches, such as wavelet transforms and common spatial pattern (CSP) algorithms, have been instrumental in isolating relevant features, boosting classification performance, and ensuring robustness against noise(Saha et al., 2021; Saha et al., 2019). EEG signal classification has experienced substantial advancements, primarily driven by a variety of innovative feature extraction techniques. These methodologies are essential for enhancing both the accuracy and efficiency of brain-computer interface (BCI) applications, which hold significant potential to transform the interaction between individuals, particularly those with motor disabilities, and technology.

A noteworthy study in this domain was conducted by (Amin et al., 2015), who investigated the application of the Discrete Wavelet Transform (DWT) as a tool for extracting features from EEG signals. This research highlights the effectiveness of DWT in decomposing

EEG signals into multiple frequency components, allowing for the extraction of significant features that accurately represent the underlying neural activity. By employing DWT, the author successfully captures critical information from the EEG data, effectively addressing the complexities associated with analyzing non-stationary signals. Moreover, the integration of evolutionary algorithms for feature selection substantially enhances this approach. These algorithms optimize the feature selection process, ensuring that only the most relevant features are retained for classification tasks. This dual strategy not only improves classification performance but also helps mitigate issues related to noise and irrelevant information, which are prevalent in EEG data.

Recent investigations have increasingly focused on extracting discriminative features from specific EEG frequency bands and channels. For example, research conducted by (Bah and Arica, 2023) extracted features from the delta band of central and frontal EEG channels. This work employed classification techniques such as FLDA and multiclass SVM to enhance the accuracy of movement intention detection. The findings from this study demonstrate the effectiveness of targeting specific frequency bands in improving classification outcomes, thereby contributing to the broader understanding of EEG signal dynamics.

In a parallel study,(Postalcioglu, 2021) conducted a comprehensive examination of wavelet transform methods, further supporting their efficacy in classifying EEG signals. The capacity of wavelet transforms techniques to capture significant patterns within EEG data is particularly noteworthy, as it plays a crucial role in developing robust feature sets tailored for diverse classification tasks. This work emphasizes the transformative potential of wavelet transforms in enhancing the accuracy of classification algorithms across a spectrum of applications, thereby contributing to the ongoing evolution of BCI technology.

Additionally, (Saha et al., 2021) concentrated their research on the CSP technique, specifically its application in the frequency domain for feature extraction from multichannel EEG signals. CSP is widely recognized for its ability to improve the discrimination of motor imagery tasks, which are critical for developing effective BCIs. By directing attention to the spatial patterns that are most relevant for classification, this method enables more precise interpretations of EEG data. The implications of this research are significant, as accurately discerning spatial patterns associated with motor imagery could lead to substantial improvements in the usability and functionality of BCI systems, particularly for individuals seeking to control assistive devices through thought alone.

In a comprehensive literature review conducted by (Jaipriya and Sriharipriya, 2024), the authors presented a thorough overview of various signal processing techniques utilized within BCI applications. This review underscores the pressing need for effective feature extraction and classification methods specifically designed to address the unique challenges posed by motor imagery tasks using EEG signals. By synthesizing key advancements in the field, the authors highlight not only the progress that has been made but also the ongoing challenges and opportunities that researchers face in developing robust BCI systems. This work serves as a valuable resource for guiding future research endeavors, illuminating potential avenues for innovation and refinement in signal processing techniques.

Moreover, the research done by (Saha et al., 2019) introduced a novel frequency domain approach within the context of CSP-based feature extraction. This methodology leverages frequency analysis to identify and delineate distinguishing characteristics of EEG signals, thereby further refining the feature extraction process to enhance classification accuracy. The emphasis on frequency-domain characteristics represents a significant advancement in understanding and interpreting the nuanced behaviors of EEG signals, which is essential for the development of effective BCI systems.

Wang et al., (2021) investigated the decoding of single-hand and both-hand movement directions using EEG signals. MRCPs from 24 EEG channels were analyzed as features, alongside low-frequency power sums. SVM and LDA classifiers were employed. The SVM with temporal features achieved a six-class classification accuracy of 70.29% ± 10.85%. Results showed significant differences in MRCP amplitudes between single-hand and both-hand movements, indicating distinct neural signatures. This study highlights the potential for EEG-based systems in decoding movement parameters for applications in human-machine collaboration.

The study by (Jochumsen et al., 2016) investigated the detection and classification of three hand movements—palmar, lateral, and pinch grasps—using EEG for neurorehabilitation. EEG data were collected from 25 electrodes in 14 healthy participants performing 100 repetitions of each movement. Temporal and spectral features were extracted, with dimensionality reduction achieved using Sequential Forward Selection (SFS) and Principal Component Analysis (PCA). Classification was performed using linear discriminant analysis.The combination of temporal and spectral features achieved the highest accuracy for movement detection (~79%), while spectral features were optimal for movement discrimination, with accuracies of ~76% for pairwise comparisons and 63% for three-class classification. SFS outperformed PCA in feature selection. These results suggest the feasibility of using EEG for movement detection and classification prior to onset, enabling potential BCI applications in neurorehabilitation and prosthetic control.

Liu et al., (2020), investigated the impact of combining sensory motor rhythm (SMR) and MRCP features to mitigate BCI inefficiency. Ninety-three participants completed two experimental sessions involving executed movements (right hand, left hand, and right foot), with EEG recorded using 64 electrodes. SMR features were extracted using Common Spatial Pattern (CSP) and MRCP features via template matching. Linear discriminant analysis classified the features, and a winner-take-all strategy integrated their outputs.Results showed that combining SMR and MRCP improved classification accuracy for the two-class problem (right hand vs. right foot) from 62% to 79% for participants with low SMR performance (<70%). Across all subjects, combining features eliminated inefficiency, achieving 86.8% average accuracy. In the three-class problem, combining features maintained 0% inefficiency. The findings suggest MRCP features provide complementary information to SMR, making their combination a robust solution for improving BCI performance.

The study by (López-Larraz et al., 2018) investigated the effects of EEG artifact removal on ERD and brain-machine interface (BMI) performance in 31 stroke patients attempting hand movements. EEG data were recorded using 16 electrodes, and artifacts such as eye movements, motion, and muscle activity were removed through automated methods involving linear regression and statistical thresholding.Results showed that removing artifacts enhanced cortical activation estimates, with more pronounced alpha and beta ERD during motor tasks. The most restrictive method combining EMG and EEG artifact removal discarded 69.5% of trials for the paretic hand but provided the cleanest signals. However, artifact removal reduced BMI classification accuracy for movement attempts, suggesting artifacts create optimistic bias. The findings highlight the trade-off between accurate brain activity estimation and BMI performance, emphasizing the need for tailored artifact rejection methods in rehabilitation systems.

Bulea et al., (2014) investigated the decoding of sitting, standing, and quiet states from delta-band EEG recorded before movement execution. Ten healthy participants performed 20 sit-to-stand and stand-to-sit transitions under self-initiated and triggered conditions. EEG data were preprocessed using artifact subspace reconstruction (ASR) and bandpass filtering. Movement-related cortical potentials were analyzed through time-embedded features and dimensionality reduced via Local Fisher's Discriminant Analysis. Classification was performed using a Gaussian Mixture Model. Numerical results showed a classification accuracy significantly above chance (33.3%): 78.0% ± 2.6% for self-initiated movements and 74.7% ± 5.7% for triggered movements. No significant difference in overall accuracy was found between paradigms, though motor strip electrodes provided higher accuracy for self-initiated tasks. The study highlights the potential of delta-band EEG for detecting movement intent, suggesting applications in brain-machine interfaces for rehabilitation and motor recovery.

Saka et al., (2016) introduced a Fast Walsh Hadamard Transform (FWHT)-based method for classifying EEG signals recorded during imagined right/left hand movements. Using Data Set III from BCI Competition 2003, with signals from the C3 and C4 electrodes, the study achieved a top accuracy of 88.87% using Artificial Neural Networks (ANN). The dataset included 280 trials, equally split between two classes and training/testing groups. The FWHT-based features, including median and maximum values, demonstrated strong discriminative power. The method also exhibited computational efficiency, requiring only 1.21 milliseconds per trial for feature extraction, making it a promising approach for BCI applications.

Eileen Y.L. Lew (2014) studied single-trial prediction of self-paced reaching directions from EEG signals. The research included three stroke patients and two able-bodied participants performing upper-limb reaching tasks in four directions. EEG signals were processed using slow cortical potentials (SCPs) and Canonical Variate Analysis for feature selection. Linear Discriminant Analysis classifiers were trained and evaluated using 5-fold cross-validation.Results revealed decoding accuracies of 76% for able-bodied participants (dominant arm) and 47% for stroke patients (paretic arm), significantly above the chance level of 25%. Early detection of movement intention occurred up to 687.5ms before onset for able-bodied participants and 625ms for stroke patients. The fronto-parietal network was identified as a key region for decoding. SCPs in the 0.1–1 Hz range provided the best performance, emphasizing the feasibility of SCPs in brain-machine interfaces for stroke rehabilitation.

Schwarz et al., (2020) studied the feasibility of decoding natural reach-and-grasp actions using gel-based, water-based, and dry-electrode EEG systems. The methods involved 45 participants, divided equally across the three systems, performing 80 trials of self-initiated grasping tasks under controlled conditions. EEG data were processed using time-domain and frequency-domain analyses, with key features extracted for classification. The study demonstrated significant MRCPs and event-related desynchronization (ERD) patterns.Results showed comparable decoding accuracies for gel-based (61.3%) and water-based systems (62.3%), while the dry-electrode system performed slightly lower (56.4%). Variability stemmed from electrode count and technical differences. The study highlighted the potential for mobile EEG systems in real-world applications and made the dataset publicly available to encourage further research.

Ofner et al., (2019) developed a method to detect and classify attempted hand movements (hand open and palmar grasp) in a person with a complete cervical SCI. Using MRCPs recorded via EEG with 61 electrodes, the study trained a five-class shrinkage linear discriminant classifier to distinguish movements and rest in a closed-loop setup.The participant performed movement attempts in structured training and self-paced testing paradigms. The classifier achieved an average detection true positive rate of 31.8% with 3.4 false positives per minute, and a classification accuracy of 68.4% (significantly above chance). Topographic EEG analyses confirmed brain-originated signals rather than artifacts.This proof-of-concept demonstrates the feasibility of decoding hand movements in people with complete SCI using MRCPs, suggesting potential applications in motor neuroprosthesis control, though further performance improvements are required for real-life usability.

The study by (Aydın, 2023) aimed to detect Movement-Related Cortical Potentials (MRCPs) from single-trial EEG signals to classify two states: movement and resting, making it a binary classification problem. The method involved using Katz's Fractal Dimension (KFD) for feature extraction, which captures the complexity and self-similarity of EEG signals, and nonlinear Support Vector Machines (SVM) with Gaussian kernels for classification. Preprocessing included band-pass filtering (cut-off frequencies: 0.3–50 Hz) and examining different time windows: pre-stimulus (-2 to 0s), post-stimulus (0 to 1s), and combined (-2 to 1s). Additionally, the study evaluated performance with 3, 9, and 61 electrode configurations.The best results were achieved using the [-2 1] second time window, 61 electrodes, and a 0.3–50 Hz filter, yielding an impressive classification accuracy of 96.47%. The results demonstrate the potential of MRCPs for real-time brain-computer interfaces (BCIs), offering accurate and reliable movement intention detection.

Makouei and Uyulan, (2023) study aimed to classify attempted arm and hand movements in cervical SCI patients using EEG signals. The study involved five classes of movements, including resting states. A hybrid deep learning model combining 1D Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks was employed to extract spatial and temporal features from EEG data. Preprocessing steps included filtering, dimensionality reduction, and standard scaling.

Three feature selection methods—Random Forest, Recursive Feature Elimination, and Chi-Square—were evaluated, with Random Forest providing the best results. The model achieved a test accuracy of 81.25% and a mean F1-score of 0.81, reflecting a balance between precision and recall. Additionally, 10-fold cross-validation was performed, yielding an average accuracy of 75.75%, demonstrating the model's robustness.The study highlighted the efficacy of combining feature selection and deep learning for EEG-based classification, emphasizing its potential for developing assistive devices in SCI rehabilitation. The findings underline the feasibility of using non-invasive EEG technologies to decode neural activity, advancing brain-computer interface (BCI) systems for individuals with motor impairments

Ieracitano et al.,(2022) study proposed an explainable deep learning system for EEG-based brain-computer interfaces (BCIs) to classify motor preparation phases of hand movements. The task involved two classes: hand closing (HC) versus rest (RE) and hand opening (HO) versus rest (RE). The methodology included reconstructing cortical EEG sources through beamforming, followed by classification using a custom deep convolutional neural network (CNN). The CNN received time-source maps of EEG signals as input and performed binary classifications.For interpretability, the study employed occlusion sensitivity analysis to identify which cortical regions contributed most to the classification, supplemented by k-means clustering to map highly salient cortical areas.The proposed model achieved an average classification accuracy of 89.65% ± 5.29% for HC vs. RE and 90.50% ± 5.35% for HO vs. RE. The study highlighted significant activation in the central and right-temporal cortical regions during motor preparation, emphasizing the importance of these areas in planning hand movements. This work advanced the field by combining deep learning accuracy with explainable methods, offering insights into cortical activations for BCI applications.

The study by Aydin, (2022) focuses on classifying forearm movements using MRCPs, particularly pronation and supination. The methodology involves EEG data collected from spinal cord injury patients. Signals were recorded using 61 electrodes and processed through Higuchi Fractal Dimension (HFD) analysis and the k-Nearest Neighbor (k-NN) classification algorithm. The classification accuracy was evaluated under different time windows and stimulus durations.Numerical results indicate that the pronation movement was classified with 70.09% accuracy, and supination achieved 69.22%. The optimal results were obtained using a 3-second post-stimulus window and a 100 ms frame size. The study highlights the potential for enhanced BCI systems, increasing their degree of freedom by recognizing additional movement types with moderate classification accuracy.

Lastly, the work of (Kabir et al., 2024) provided a comprehensive summary of various feature extraction techniques specifically tailored for BCI applications. Their findings underscore the critical importance of employing diverse methodologies in the effective processing of EEG signals. By highlighting the need for varied approaches, this research emphasizes the potential for improved performance in BCI systems.

Whereas the literature highlights the potential of BCIs to transform human-computer interaction, particularly for individuals with motor impairments, studies have demonstrated the critical role of MRCP-based feature extraction in enabling tasks such as motor imagery and device control, highlighting its importance in the classification and interpretation of EEG signals.

The studies emphasized the need for further development in feature extraction methods, which play a pivotal role in improving EEG signal classification. These advancements are crucial for enhancing human-computer interaction, particularly for individuals with disabilities, enabling more intuitive, adaptive, and inclusive BCI systems.

3. MATERIAL AND PROPOSED METHOD

This section discusses the experimental setup, exploratory data analysis, and data preprocessing techniques, including feature extraction for identifying key attributes. It also highlights the machine learning classifiers employed, detailing their suitability for the task, along with the performance metrics used to evaluate their effectiveness. Additionally, an overview of the theoretical framework is provided, contextualizing the methods and their alignment with existing research and study objectives.

3.1. Experimental setup

The dataset was generously provided through the BNCI initiative within the Horizon 2020 framework, as described by (Ofner et al., 2019). The primary goal of this study was to meticulously examine and classify attempted arm and hand movements in individuals with SCI using EEG signals. The classification of these movements is crucial for developing effective BCI systems aimed at enhancing the quality of life for individuals with SCI.

The research was conducted within two distinct paradigms: offline and online. For this thesis work, the primary focus was directed towards the offline paradigm. This decision was made to allow for a controlled environment where the nuances of EEG signal patterns associated with motor imagination could be thoroughly investigated without the additional variables introduced in an online setting. The offline paradigm described by (Ofner et al., 2019) provided a structured framework that facilitated the detailed analysis of brain activity associated with different motor tasks.

In the offline framework, participants were instructed to perform five specific motor imagination tasks. These tasks were carefully chosen to represent a range of arm and hand movements and included: hand open, palmar grasp, lateral grasp, pronation, and supination. Each of these tasks was selected based on their relevance to everyday activities and their potential to be used in practical BCI applications. Figure 3.3 provides a visual representation of these tasks, illustrating the distinct movements participants were required to imagine.

The study involved ten right-handed male participants with SCI, aged between 20 and 69 years. These participants were selected based on specific inclusion criteria to ensure a homogeneous study group. Right-handed males were chosen to eliminate variability in motor imagination tasks due to hand dominance. The age span covered a broad spectrum of adult life, allowing the study to capture data from individuals at different stages of adulthood.

Participants were seated in a comfortable position in front of a computer screen. To ensure that they were able to maintain a stable and relaxed posture, their arms were rested on a pillow placed on their lap. This setup minimized any extraneous movements that could potentially introduce noise into the EEG recordings. The environment was designed to be quiet and free from distractions to allow participants to focus entirely on the motor imagination tasks.

The trials initiated with the appearance of a visual cross on the computer screen, accompanied with a beep sound. This was intended to prepare participants for the upcoming task and to synchronize the start of each trial. The visual cross served as a focal point, helping to retain consistent eye position and reduce artifacts in the EEG data. Participants were then instructed to perform the specified motor imagination task when the class cue appeared on the screen. The appearance of the target cross cue varied randomly in duration, lasting from 1 to 3 seconds, covering the entire 5-second trial period. This randomization was implemented to prevent subjects from anticipating the cue and to ensure that the EEG data captured genuine responses to the stimuli.

A visual cue indicating the class (specific motor task) was shown on screen 2sec following the trial and remained visible for 3sec, as shown in Figure 3.1. During this period, participants were required to engage in the MI task related to the visual cue. The use of visual cues was crucial for ensuring that participants correctly identified and performed the intended motor imagination task.

Figure 3.1.The experiment time course (Ofner et al., 2019)

The experiment was structured into nine sessions, with each session recording eight attempted movements per category. This design allowed for a comprehensive collection of data across multiple instances of each motor imagination task, enhancing the reliability and robustness of the subsequent analysis. The repetition of tasks across sessions also helped in capturing the variability in EEG signals associated with repeated attempts of the same motor imagination activity.

To record the brain signals, 64-channel bio-signal amplifiers were used. These amplifiers captured EEG signals from 61 channels positioned across the frontal, central, parietal, and temporal regions, following the 10/10 electrode positioning system as shown in Figure 3.2. This extensive coverage ensured that the recorded EEG data included signals from all major regions of the brain involved in motor control and imagination. The remaining three channels were allocated for recording EOG signals, which helped in identifying and correcting for eye movement artifacts in the EEG data.

The comprehensive setup of this experiment, including the careful selection of participants, structured trial design, and extensive EEG recording, was critical for the accurate classification of motor imagination tasks. This study provided valuable insights into the neural mechanisms underlying MI in individuals with SCI, contributing to the advancement of more efficient BCI systems. By understanding the specific EEG patterns associated with different motor tasks, researchers can enhance the accuracy and reliability of BCIs, eventually enhancing the quality of life for individuals with spinal cord injuries.

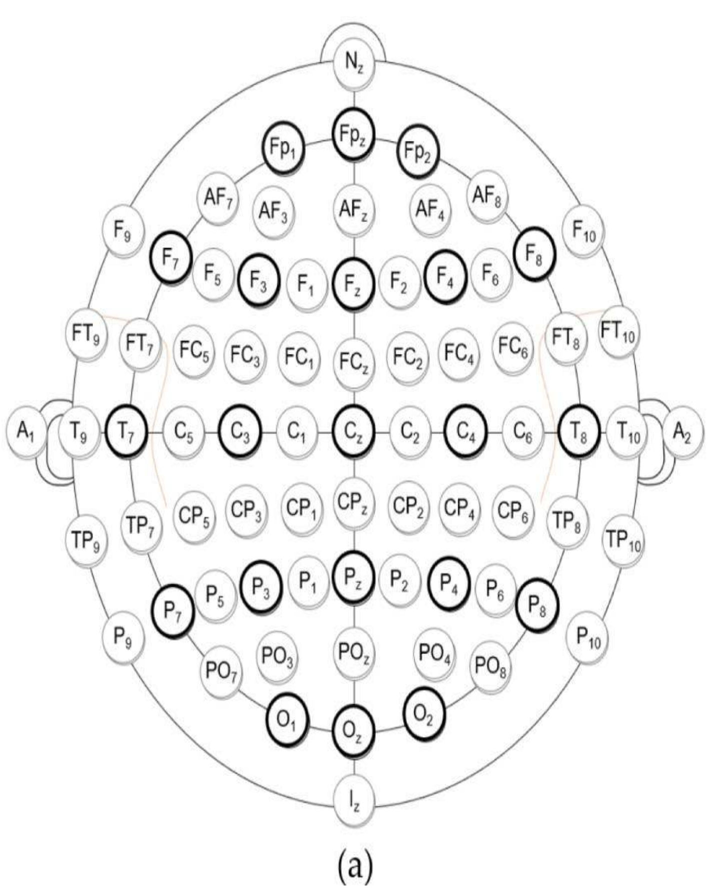

Figure 3.2. (a) This illustrates the conventional 10-20 and 10-10 international electrode positioning systems. Black circles indicate the 10-20 system, while open circles show the 10-10 system, which has more electrode sites for finer measurements (Duffy et al., 2011).

(b) This is a simple brain diagram labeling the major regions: Frontal, Central, Parietal, Occipital, and Temporal.

(c) This highlights specific electrode positions on the scalp, using color-coded circles to represent different groups of electrodes based on their locations. Each group corresponds to different brain regions.

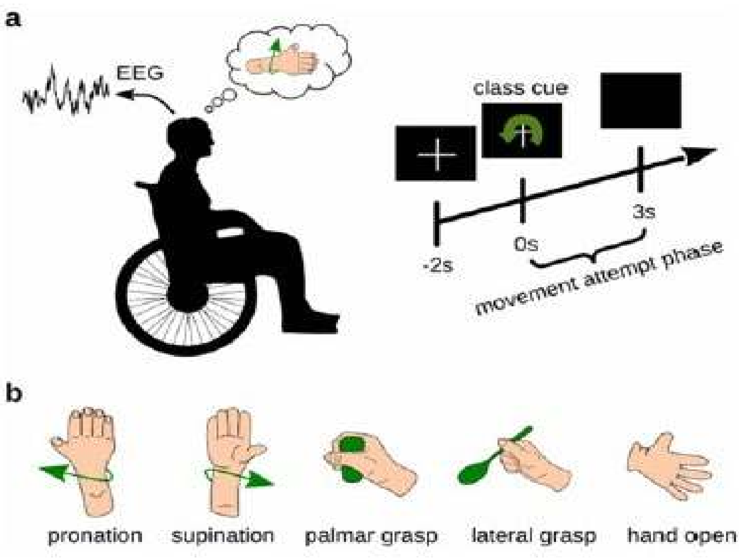

Figure 3.3.Offline Paradigm. (a) Subjects with SCI sat in their wheelchairs and attempted the movement requested on a computer screen. (b) Illustration of the attempted movements (Ofner et al., 2019a)

3.2 . Data Acquisition and Preprocessing

Bio-signals were recorded using a sophisticated setup involving a 61-electrode EEG system in conjunction with a 3-electrode electrooculography (EOG) system. The electrodes were strategically placed to capture data from the frontal, central, parietal, and temporal regions of the brain, as well as from positions above the nasion and below the outer corners of the eyes. The signals were referenced to the left earlobe and grounded at the AFF2h location to ensure accurate and stable recordings.

The data acquisition process employed four 16-channel g.USBamps biosignal amplifiers, integrated with the g.GAMMAsys and g.LADYbird active electrode systems, as depicted in Figure 3.4. The g.GAMMAsys system is specifically created to streamline the setup process for EEG, ECG, EMG, and EOG recordings while making sure high-quality signal acquisition. This system is known for its comfort and ease of use, featuring a cap that holds the electrodes in place. It is compatible with all g.tec amplifiers and supports a variety of both active and passive electrodes.

Figure 3.4. g.GAMMAsys/g.LADYbird active electrode system (Ofner et al., 2019b)

For EEG recordings, electrodes were mounted on the participant's head using the g.GAMMAcap, which can be customized to include electrodes tailored to specific experimental needs, such as the P300 speller paradigm. The g.GAMMAbox acts as an intermediary, connecting the electrodes to the g.USBamp. For other types of recordings like ECG, EMG, and EOG, electrodes can be attached directly to the participant's body. One of the significant advantages of the g.GAMMAcap is that the electrodes remain in place during cleaning, allowing for rapid setup and cleanup, thus enhancing the overall efficiency of the experimental process.

The biosignals were sampled at a frequency of 256Hz and subjected to an 8^{th}-order CF, which provided a BPF range of 0.01Hz to 100Hz. Additionally, a 50 Hz notch filter was employed to eliminate power line noise. All data were stored in the General Data Format (GDF), with each run saved in separate files named according to the participant's code and run number. Each participant completed a total of 15 runs: 9 runs involved attempted movements, 3 runs focused on eye movements, and 3 runs were designated as rest periods. Specific event codes were used to mark different events within the data.

The study included an online component for participant P09, who completed two additional sessions consisting of training and test runs. These sessions collected EEG, EOG, data glove, classifier output, and button press data.

After initial filtering, the EEG signals were processed using the SD as a preprocessing step. This statistical measure, which quantifies the amount of variation or dispersion of the data from the mean, is often used in EEG signal processing to simplify the data while retaining critical information. The application of the standard deviation helps capture the dynamic nature and potential noise within EEG signals. By calculating the standard deviation, the variability of the EEG signal over time is represented, encompassing both temporal and spectral characteristics, which is essential for distinguishing between various brain states or cognitive processes.

Applying SD as a preprocessing technique has been demonstrated to enhance the accuracy and reliability of EEG classification models. The formula for standard deviation, which is a cornerstone of this approach, is given in Equation 3.1. This preprocessing step is crucial as it reduces data complexity, enabling more effective analysis and interpretation of the EEG signals.

$$\sigma_x = \sqrt{\left(\frac{1}{n}\ \sum_{i=1}^{n}(x_i - \overline{x})^2\right)} \tag{3.1}$$

where n is the number of samples, and $\bar{x}$ is the mean value of the samples

3.3. Data Set

3.3.1. Offline Paradigm

The dataset comprises a comprehensive collection of 15 runs for each participant, segmented into various types of activities. Specifically, there are 9 runs that focus on attempted movements, 3 runs dedicated to capturing eye movements, and the remaining 3 runs are designated as rest periods. This structure, illustrated in Table 3.1, provides a balanced representation of different physiological and behavioral states.

Each of these runs is meticulously recorded and saved as an individual file in the GDF. The naming convention for these files incorporates the participant's unique code alongside the specific run number, ensuring precise identification and organization of the data. Within these files, various cues and events are systematically marked using specific event codes. These codes, are detailed in Table 3.2, offer a comprehensive explanation and description of each event, facilitating accurate interpretation and analysis of the data.

The dataset includes a detailed enumeration of the channel labels for the recorded signals, as presented in Table 3.3. These labels correspond to the placement of the EEG electrodes, which are placed according to the 10-5 system, as well as the positions of the EOG electrodes. The 10-5 system, a more detailed variant of the widely used 10-20 system for EEG recordings, provides enhanced spatial resolution, enabling more precise localization of neural activity.

The inclusion of both EEG and EOG channels in the dataset is a notable feature, as it allows for a comprehensive analysis of both brain activity and eye movements across the different types of runs. This dual-modality approach enhances the depth and breadth of the data, supporting more nuanced investigations into the interplay between neural and ocular signals.

In summary, the dataset is structured to capture a wide range of physiological and behavioral states through a meticulously organized series of runs. Each run is carefully documented with specific event codes and channel labels, ensuring that the data is both detailed and accessible for comprehensive analysis. The use of the 10/5 system for electrode placement further enhances the quality and resolution of the EEG recordings, making this dataset a valuable resource for studies in neurophysiology and related fields.

Table 3.1.Run number and types in the offline paradigm(Ofner et al., 2019)

Run Numbers	Run Type
1	eye movements
2	rest
3	attempted movement
4	attempted movement
5	attempted movement
6	attempted movement
7	attempted movement
8	eye movement
9	rest
10	attempted movement
11	attempted movement
12	attempted movement
13	attempted movement
14	eye movement
15	rest

Table 3.1. presents run number and run type, the runs are divided into three distinct types: eye movements, rest, and attempted movement. Runs 1, 8, and 14 are designated as eye movements, where participants likely focus on visual tasks or stimuli. Rest periods are scheduled in runs 2, 9, and 15, allowing participants to relax without performing tasks. The majority of the runs, numbered 3 through 7, 10 through 13, are labeled as attempted movement, during which participants presumably attempt specific motor actions. This pattern ensures a balance between active task performance and periods of rest or passive observation throughout the experiment.

Table 3.2.Event codes in hexadecimal numbers in the offline paradigm(Ofner et al., 2019)

Event Code	Event Description
0x300	trial start
0x311	beep
0x312	fixation cross
0x308	supination class cue
0x309	pronation class cue
0x30B	hand open class cue
0x39D	palmar grasp class cue
0x39E	lateral grasp class cue

Table 3.2 presents the event codes in hexadecimal numbers used in the offline paradigm described by (Ofner et al., 2019).Each event is associated with a specific action or cue during the experiment. The event codes are as follows: 0x300 represents the start of a trial, while 0x311 corresponds to a beep sound. The 0x312 code marks the appearance of a fixation cross. Various class cues are represented by the following codes: 0x308 for supination, 0x309 for pronation, 0x30B for hand open, 0x39D for palmar grasp, and 0x39E for lateral grasp. These event codes are integral to tracking and synchronizing the different phases and actions during the experimental trials.

Table 3.3.Channel numbers and labels in the offline paradigm(Ofner et al., 2019)

Channel	Label	Channel	Label	Channel	Label	Channel	Label	Channel	Label
1	AFz	15	FC1	29	Cz	43	CP2	57	P4
2	F3	16	FCz	30	C2	44	CP4	58	P6
3	F1	17	FC2	31	C4	45	CP6	59	PPO1h
4	Fz	18	FC4	32	C6	46	CPP5h	60	PPO2h
5	F2	19	FC6	33	CCP5h	47	CPP3h	61	POz
6	F4	20	FCC5h	34	CCP3h	48	CPP1h	62	EOG left
7	FFC5h	21	FCC3h	35	CCP1h	49	CPP2h	63	EOG middle
8	FFC3h	22	FCC1h	36	CCP2h	50	CPP4h	64	EOG right
9	FFC1h	23	FCC2h	37	CCP4h	51	CPP6h		
10	FFC2h	24	FCC4h	38	CCP6h	52	P5		
11	FFC4h	25	FCC6h	39	CP5	53	P3		
12	FFC6h	26	C5	40	CP3	54	P1		
13	FC5	27	C3	41	CP1	55	Pz		
14	FC3	28	C1	42	CPz	56	P2		

Table 3.3 presents the channel numbers and corresponding labels used in the offline paradigm described by (Ofner et al., 2019).The table lists a total of 64 channels, each identified by a unique number and its associated label. The channels are categorized by their location on the scalp, with labels indicating the specific regions of the brain being measured, such as AFz, FC1, Cz, CP2, and P4. Additionally, the table includes channels like EOG left, EOG middle, and EOG right, which are likely used to record eye movements. This comprehensive list provides the channel configuration for the EEG setup used in the study, offering a detailed overview of the spatial arrangement of electrodes for analyzing brain activity during the offline paradigm.

3.4 Proposed Methods.

This section employed two distinct and complementary feature extraction methodologies: the Savitzky-Golay algorithm and Hadamard basis and Variance-Based MRCP Feature Extraction with Detrending for EEG signal analysis. These two methods provide unique approaches to deriving meaningful features from raw EEG data, which is a crucial step for improving the accuracy and efficiency of EEG signal classification systems. The effective extraction of features from EEG signals is essential because the complexity and variability of brainwave patterns often obscure the subtle neural activities that are indicative of specific cognitive or motor states. By utilizing these advanced techniques, this thesis aims to enhance the reliability and robustness of EEG classification systems, particularly in applications such as BCIs and neurorehabilitation.

3.4.1. Savitzky-Golay algorithm and Hadamard basis Analysis.

This subsection provides a brief overview of both methods, highlighting their roles in preprocessing and feature extraction for EEG-based classification tasks.

The Savitzky-Golay (SG) smoothing algorithm is a widely used method in signal processing, particularly when dealing with time-series data like EEG signals. Its primary goal is to reduce noise while preserving essential signal characteristics such as peaks and slopes, which are crucial for accurate interpretation and classification. The SG filter achieves this by fitting a polynomial to a window of data points and replacing each point with the value predicted by the polynomial, ensuring minimal signal distortion. This mathematical approach is highly effective in EEG data analysis, where noise from various sources can obscure meaningful neural patterns(Acharya et al., 2016).The SG filter is based on polynomial least-squares fitting. Mathematically, it operates by taking a moving window around each data point in a signal and fitting a low-degree polynomial to the data points within that window. This polynomial is then used to estimate the value of the signal at the center of the window.

On the other hand ,the Hadamard Transform is a linear, orthogonal transform that decomposes a signal into a set of orthogonal basis functions. It can be seen as a generalization of the Fourier Transform, using basis functions consisting of +1 and -1 values, which makes it particularly efficient for digital signal processing(Saka et al., 2016).

The Hadamard matrix $\boldsymbol{H_n}$ of order n is recursively defined as:

$$\mathrm{H}_1 = [1],\ \mathrm{H}_{2^{K}} = \begin{bmatrix} \mathrm{H}_{2^{k-1}} & \mathrm{H}_{2^{k-1}} \\ \mathrm{H}_{2^{k-1}} & -\mathrm{H}_{2^{k-1}} \end{bmatrix} \tag{3.2}$$

Where n must be a power of two .This matrix is composed of +1 and -1, making it an efficient transform .

A .Preprocessing

Clean Data (Remove NaN)

Before conducting the analysis, various strategies were implemented to address missing data in the EEG recordings, including the presence of NaN (Not a Number)values that could disrupt data continuity and pose significant challenges for accurate signal interpretation. These NaN values, if left unaddressed, could skew calculations such as averages, variances, and other statistical measures, potentially leading to misleading feature sets. To mitigate these issues and maintain the integrity of the dataset, NaN values were first filled with zeros to ensure completeness. Subsequently, interpolation techniques were applied to further refine the data and restore any gaps.

$$\mathrm{E}_{\mathrm{filled}}(\mathrm{n}) = \begin{cases} 0, & \text{if } \mathrm{E(n)} \text{ is NaN} \\ \mathrm{E(n)}, & \text{otherwise} \end{cases} \tag{3.3}$$

While this ensured a complete dataset, further refinement was achieved using interpolation techniques. These techniques estimated missing points by considering adjacent values to create smooth transitions:

$$\mathrm{E}_{\mathrm{interpolated}}(\mathrm{n}) = \mathrm{interp}(\mathrm{E}(\mathrm{n}-1), \mathrm{E}(\mathrm{n}+1)) \tag{3.4}$$

This approach guaranteed a consistent dataset, enabling accurate and reliable analysis of the EEG signals, which is crucial for maintaining data integrity and facilitating meaningful interpretation of the results.

Compute MRCPs (Averaging across trials to compute MRCPs)

After obtaining the channel-averaged signal, we then averaged across trials to compute the final MRCP signal for each participant and each movement category. This trial averaging further enhanced the signal-to-noise ratio by reducing random fluctuations across trials, effectively isolating the consistent cortical activity related to movement. The MRCP at each time point t denoted as $MRCP(t)$, is calculated as :

$$\mathrm{MRCP(t)} = \frac{1}{\mathrm{N}} \sum_{\mathrm{k}=1}^{\mathrm{N}} \mathrm{E}_{\mathrm{average}}(\mathrm{t}, \mathrm{k}) \tag{3.5}$$

Where :

$E_{average}(t, k)$ is the channel-averaged signal for the $k-th$ trial at t

N the total number of trials.

The resulting MRCP signal reflects collective cortical activity related to movement, capturing consistent patterns while suppressing random noise and artifacts. This approach is particularly effective in emphasizing the underlying movement-related brain activity, ensuring that the MRCPs are robust and accurately represent the cortical response associated with motor tasks.

Savitzky-Golay smoothing algorithm in EEG preprocessing

The SG filter is applied in EEG preprocessing to smooth the signal while preserving essential features such as peaks and slopes. The workflow of the SG filter implementation is outlined below.

1. **Window Size and Polynomial Fitting**

Let x(t) represent the raw EEG signal, where t denotes the time or sample index. For each point $x(t_0)$, the SG filter considers a window of size W around t_0, such that:

$$W = 2M + 1 \tag{3.6}$$

Here, M is the number of points on either side of the center point t_o and W is the total number of data points in the window. The algorithm fits a polynomial P(t) of degree p to the data points within this window.

The polynomial P(t) is expressed as:

$$P(t) = C_0 + C_1 t + C_2 t^2 + \cdots + C_p t^p \tag{3.7}$$

Where:

$C_0, C_1 \ldots, C_p$ are the polynomial coefficients to be determined,

t is the time index (centered around 0, i.e. $t = t_0 - M$).

2. **Least-Squares Minimization**

To find the polynomial coefficients $C_0, C_1 \ldots, C_p$ the algorithm minimizes the least-squares error between the polynomial and the actual data points within the window. For the set of data points

$\{x(t_0 - M), x(t_0 - M + 1), \ldots, x(t_0 + M)\}$, the error to minimize is: (3.8)

$$E = \sum_{i=-M}^{M} [x(t_0 + i) - P(t_0 + i)]^2 \tag{3.9}$$

The coefficients C_0, C_1 . . .,C_p are chosen such that this error E is minimized.

3. **Smoothing Operation**

Once the polynomial $P(t)$ is fitted, the value of the polynomial at the center of the window t_0 is used to replace the original data point $x(t_0)$. The smoothed value $\hat{x}(t_0)$ is given by:

$$\hat{x}(t_0) = P(t_0) = C_0 \tag{3.10}$$

The window then moves one point forward, and the process is repeated for each point in the signal.

B. Feature Extraction

The Hadamard basis analysis was utilized for feature extraction by transforming EEG data into an orthogonal basis set, thereby simplifying the underlying signal patterns. The detailed workflow of this analysis is outlined below.

1. **Transforming EEG Data with the Hadamard Transform**

The EEG data, stored in a matrix E, is first transformed into the Hadamard domain by multiplying it with the Hadamard matrix H_n

$$G = H_n \cdot E \tag{3.11}$$

Where:

E represents the EEG signal matrix (each column is a channel, and each row is a sample)

H_n is the Hadamard matrix (in this case, $n = 256$, the number of samples)

G is the transformed EEG signal matrix in the Hadamard domain.

This transformation decomposes the EEG signals into orthogonal components, represented by the rows of G. Each row of G contains the transformed data for a specific basis function.

2. **Magnitude Calculation**

The magnitude of the transformed EEG signal is calculated to emphasize the strength of each component:

$$G_{abs} = |G| \tag{3.12}$$

This step ensures that the focus is on the most significant features, as the magnitude reflects the importance of different components of the signal.

3. **Feature Selection**

Next, the components of G_{abs} are sorted in descending order to identify the most important features:

$$t = sort\ (G_{abs}\ , \text{descend}\ ) \tag{3.13}$$

The top w coefficients (i.e., the largest values) are selected, as they represent the most significant features of the signal:

$$A = t(1 : w) \tag{3.14}$$

This selection ensures that only the most important components are retained for further analysis, reducing the dimensionality of the data while preserving the critical features.

C. Feature Construction

1. Construction of the Feature Matrix

After selecting the most significant components, the corresponding rows of the Hadamard matrix are chosen to form the reduced Hadamard matrix H_A

$$H_A = H_n(A, :) \tag{3.15}$$

This reduced matrix is then used to approximate the original EEG signals in the lower-dimensional feature space. The approximation is given by:

$$K = H_A^T . H_A . E \tag{3.16}$$

Where:

H_A is the reduced Hadamard matrix (comprising only the selected rows),

E is the original EEG signal matrix,

This approximation retains the essential characteristics of the EEG signals while reducing the complexity of the data.

D. Feature Vectors for Classification

Finally, the reduced features for each trial are stored in a matrix that can be used for classification. For each trial t and category m, the feature vector p is calculated as:

$$p = H_A \cdot E_k \tag{3.17}$$

Where:
E_k is the EEG signal for the selected channels,
H_A is the reduced Hadamard matrix. The extracted feature vectors are then used for training and testing machine learning classifiers, with each row of the feature matrix representing a trial and each column representing a feature.

E.Summary of the feature extraction based Hadamard Basis

The EEG classification research employed the Hadamard Transform to enhance feature extraction, a crucial step in improving classification accuracy and reliability.

Preprocessing began with addressing gaps caused by missing EEG samples, replacing them with zeros to ensure a complete dataset. A finite impulse response (FIR) filter with a cutoff frequency of 64 Hz and an order of 3 was applied to remove noise while preserving relevant signal components.

Feature extraction utilized data from 61 EEG channels, with a focus on four specific channels: F3, F4, C3, and C4. Channels F3 and F4, located in the frontal region, are associated with cognitive functions, whereas C3 and C4 in the central cortex are linked to motor activities, particularly hand and foot movements. This selection was guided by the established roles of these channels in cognitive and motor processes.

Two distinct time windows were selected for analysis: 0.5 to 1.5 seconds and -2 to 3 seconds relative to stimulus onset. The first window captured the brain's immediate response to the stimulus, while the broader second window provided insights into sustained brain activity. This dual-window approach allowed for a thorough exploration of the temporal dynamics associated with cognitive and motor processes.

Movement-related cortical potentials (MRCPs) were computed by averaging EEG signals across multiple trials within the training set, separately for each channel and category. To enhance MRCP quality and reduce noise, the Savitzky-Golay smoothing algorithm was applied using a polynomial order of 3 and a frame length of 47. This method effectively preserved significant signal features while minimizing noise.

The Hadamard Transform was applied to each 1-second epoch, consisting of 256 samples, resulting in a 256 × 256 matrix. The MRCPs from relevant channels were projected onto this matrix, and the eight highest-magnitude coefficients were selected as significant features for classification. The 0 Hz component, representing baseline activity, was excluded to focus on dynamic variations in brain signals. This process ensured that the extracted features captured the most informative aspects of EEG data.

The selected Hadamard bases formed feature vectors used for classification. These vectors highlighted prominent EEG patterns, contributing to a more effective classification system. The study assessed classifier performance across the two time windows and all 61 channels, identifying the most informative channels and evaluating temporal effects on classification accuracy. Classifiers were tested on feature vectors from both time windows, with performance metrics including accuracy, sensitivity, specificity, and Cohen's kappa.

The combination of advanced preprocessing, Hadamard Transform-based feature extraction, and multi-channel analysis provided a robust framework for EEG classification. The dual-window approach and comprehensive channel assessment deepened the understanding of brain activity related to cognitive and motor functions. Figure 3.5 illustrates the preprocessing and feature extraction workflow.

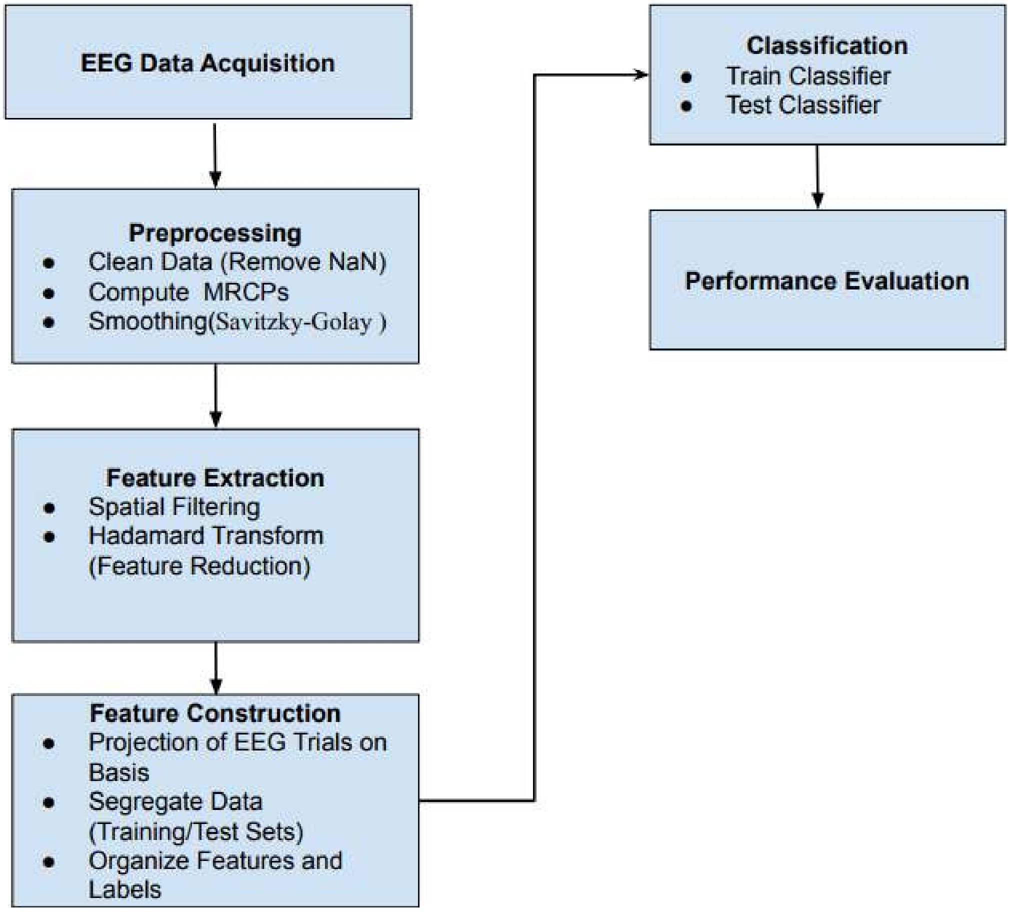

Figure 3.5.Hadamard basis feacture extraction work flow.

3.5. Variance-Based MRCP Feature Extraction with Detrending (VB-MFED) Analysis

Variance-based detection identifies significant transitions in EEG signals, reflecting critical neural events such as motor initiation, cognitive shifts, or state changes. This method operates on the principle that abrupt changes in signal variance correspond to alterations in underlying neural activity. These transitions, or breakpoints, segment continuous EEG signals into meaningful intervals, highlighting regions of notable brain dynamics that are relevant for MRCPs detection(Machavarapu et al., 2014).

MRCPs are slow cortical potentials that emerge several hundred milliseconds before voluntary movements. These potentials are typically characterized by gradual negative shifts in the EEG signal, particularly over motor-related areas such as the C3 and C4 channels. Since MRCPs are closely linked to motor intention, capturing them accurately is critical for applications BCIs, neurorehabilitation, and motor imagery tasks.

The variance-based approach enhances MRCP detection by identifying distinct changes in EEG signal variability that mark the onset of motor preparation and execution. By analyzing variance patterns across relevant EEG channels, this method captures the temporal dynamics of MRCPs, providing valuable insights into neural activity preceding movement events. Breakpoints identified through variance analysis act as markers for key neural transitions, allowing for more focused analysis of EEG intervals rich in MRCP-related information.

EEG signal processing for MRCP analysis involves a comprehensive pre-processing pipeline designed to optimize feature extraction and improve the signal-to-noise (S-to-N) ratio. This optimized pipeline includes adaptive filtering, baseline correction, and variance calculation to enhance the detection of MRCPs while minimizing noise and artifacts.

Adaptive Filtering: Since MRCPs are low-frequency signals, high-frequency noise must be removed to avoid data degradation. Adaptive filtering dynamically adjusts filtering parameters based on signal characteristics, preserving essential low-frequency components for MRCP analysis. Baseline Correction: Signal drift and slow fluctuations unrelated to neural activities can introduce artifacts that obscure MRCPs. Baseline correction addresses these issues by centering the signal on a stable reference point, reducing the impact of drift and improving MRCP detection accuracy.

Variance Calculation: Variance serves as a critical feature in MRCP detection by capturing deviations in EEG signal amplitude that signify neural transitions associated with motor tasks. The difference in variance between the C3 and C4 channels is particularly effective in distinguishing left-hand and right-hand motor imagery tasks. This variance-based feature extraction method enhances the temporal resolution of MRCP detection, making it suitable for real-time BCI applications.

The optimized MRCP processing pipeline ensures that the extracted features, including variance, are precise and relevant for classification algorithms. By leveraging variance as a feature, the system can accurately distinguish between different motor-related brain states, improving the overall performance of MRCP classification. This approach supports real-time applications, where timely detection of movement intentions is crucial for effective BCI operation. The variance method, combined with MRCP-focused pre-processing, provides a robust framework for capturing critical neural events and enhancing the reliability of EEG-based systems.. This is depicted in Figure 3.6.

A. Handling Missing Data

The first step in the EEG analysis was addressing the missing data, which is essential for maintaining the continuity and integrity of the dataset. Missing data in EEG recordings often appear as NaN (Not a Number) values, which disrupt the flow of the signal and present significant challenges for accurate analysis. These gaps can skew essential calculations such as averages and variances, impacting the reliability of derived features. The approach taken involved filling NaN values with zeros:

$$U_{\text{filled}}(n) = \begin{cases} 0, & \text{if } U(n) \text{ is NaN} \\ U(n), & \text{otherwise} \end{cases} \tag{3.18}$$

While this ensured a complete dataset, further refinement was achieved using interpolation techniques. These techniques estimated missing points by considering adjacent values to create smooth transitions:

$$U_{\text{interpolated}}(n) = \text{interp}(U(n-1), U(n+1)) \tag{3.19}$$

B. Sampling Rate Adjustment

Downsampling is the process of reducing the number of samples per second in the signal by selecting every k-th sample, where k is the downsampling factor. The goal is to balance signal fidelity with computational efficiency. Here is how the downsampling is mathematically represented:

$$U_{\text{downsampled}}(n) = U(k.n) \tag{3.20}$$

where :

$U(n)$ represents the original signal at n-th time point

k is the downsampling factor, calculated as:

$$k = \frac{\text{Origninal sample rate}}{\text{New sample rate}}$$

$U_{\text{downsampled}}(n) = U[k.n]$ is the downsampled signal, where only every k-th sample is retained.

C. Noise Reduction: CAR and Chebyshev Type II Band-pass Filters

EEG signals are often contaminated by various types of noise originating from muscle movements (EMG), eye blinks (EOG), and electrical interference. Reducing noise is crucial to extract meaningful cortical signals and improve the analysis of brain activity. In our methodology, noise reduction was achieved using a combination of Common Average Reference (CAR) filtering and an 8th-order Chebyshev Type II band-pass filter. These techniques effectively attenuate unwanted artifacts while preserving essential brain signal components for accurate analysis of MRCPs.

- Common Average Reference (CAR) Filter

The CAR filter is a spatial filter used to reduce common-mode noise by re-referencing each EEG channel to the average signal across all channels. This technique minimizes the effect of artifacts that are shared across channels, enhancing the clarity of the cortical signals.

The CAR filtered signal $U_{CAR}(n, i)$ for the $i-th$ channel at sample n is calculated as:

$$\mathrm{U_{CAR}}(\mathrm{n,i}) = \mathrm{U(n,i)} - \frac{1}{\mathrm{M}} \sum_{\mathrm{j=1}}^{\mathrm{M}} \mathrm{U(n,j)} \qquad (3.21)$$

Where:

$U(n, i)$ is the original signal from the $i-th$ channel at sample n

M is the total number of channels

$\sum_{j=1}^{M} U(n,j)$ represents the sum of the signals from all M channels at sample n

The term $\frac{1}{M}\sum_{j=1}^{M} U(n,j)$ calculates the average signal across all channels for each time point n. By subtracting this average from each individual channel, the CAR filter reduces noise that is present across the entire electrode array, such as electrical interference or general environmental noise. This enhances the ability to detect true cortical signals by making each channel's signal more distinct from global artifacts.

- Chebyshev Type II Band-pass Filter

The Chebyshev Type II band-pass filter was implemented to isolate the low-frequency delta band $0.03H_z$ to $4H_z$which is significant for MRCP analysis. This filter type is known for its sharp roll-off and stopband attenuation, making it effective at removing noise while retaining important low-frequency signal components.

- Filter Transfer Function**:** The transfer function of an $8th\ order$ Chebyshev Type II filter can be expressed as:

$$\mathrm{H(z)} = \frac{\mathrm{B(z)}}{\mathrm{A(z)}} \qquad (3.22)$$

Where :

$B(z)$ and $A(z)$ are polynomials representing the numerator and denominator of the filter, respectively.

$H(z)$ is the frequency response of the filter, which determines how different frequency components are attenuated or passed.

- Polynomial Coefficients for Filter Design

The polynomials $B(z)$ and $A(z)$ can be defined as:

$$B(z) = b_0 + b_1 z^{-1} + b_2 z^{-2} + \cdots + b_8 z^{-8} \tag{3.23}$$

$$A(z) = 1 + a_1 z^{-1} + a_2 z^{-2} + \cdots + a_8 z^{-8} \tag{3.24}$$

Where:

$b_{0,} b_1, \dots, b_8$, are the coefficients of the numerator.

$a_{0,} a_1, \dots, a_8$, are the coefficients of the denominator.

The filter coefficients are determined using design algorithms that specify the passband, stopband frequencies, and the desired attenuation level. For the Chebyshev Type II filter, these coefficients ensure that the filter meets the requirement of a steep roll-off outside the passband with a stopband attenuation of at least 10 dB.

- Filtering Process and Frequency Response

The output of the band-pass filter $U_{\text{fillteredd}}$ (n) is obtained by convolving the input signal U(n) with the impulse response of the filter:

$$U_{\text{fillteredd}}(n) = \sum_{m=0}^{N} h(m).U(n-m) \tag{3.25}$$

Where :

$h(m)$ represents the impulse response of the filter

N is the length of the impulse response.

$U(n-m)$ are the past input values of the original signal.

The filter's steep roll-off ensures that frequency components outside the delta band (above 3 Hz or below 0.03 Hz) are attenuated, maintaining the integrity of the signal within the desired frequency range while removing unwanted noise.

D. Defining the Window of Interest (WOI)

A Window of Interest (WOI) was defined for each trial, spanning from -2 to +3 seconds relative to the movement onset (0 seconds). This WOI included both preparatory neural activity (from -2 to 0 seconds) and movement execution and post-movement effects (from 0 to +3 seconds).

$$\mathrm{WOI} = \{\mathrm{U(t)}|\mathrm{t} \in [-2, 3] \text{ seconds}\} \tag{3.26}$$

This definition allowed for a comprehensive analysis of the brain's activity before, during, and after movement.

E. Channel Selection and Averaging Across Channels

Channels **C3, C4, F3, and F4** were selected due to their known association with the sensorimotor cortex, which plays a significant role in planning, executing, and monitoring motor functions. These channels are situated over or near the central region of the scalp, capturing critical brain activity related to movement preparation and execution(Hall and Hall, 2020).

The averaged signal $U_{normalised}(t, i)$ at a given time t is calculated by taking the mean of the normalized signals across all selected channels. This can be expressed as:

$$\mathrm{U_{average}(t)} = \frac{1}{\mathrm{P}} \sum_{\mathrm{i=1}}^{\mathrm{P}} \mathrm{U_{normalised}\,(t, i)} \tag{3.27}$$

Where :

P is the number of selected channels. This averaging helped highlight consistent movement-related cortical activity while reducing individual channel noise.

F. Normalization for Cross-Subject Comparisons .

Normalization was applied to standardize the signal amplitude across channels and subjects, reducing variability due to individual differences:

$$\mathrm{U_{normalised}\,(n, i)} = \frac{\mathrm{U(n,i)} - \mu_\mathrm{i}}{\sigma_\mathrm{i}} \tag{3.28}$$

Where μ_i and σ_i are the mean and standard deviation for channel i. This step ensured more consistent comparisons across participants.

G. Variance Calculation

Once the signal $U(t)$ is obtained, we calculate its variance using a number of smaple W. For each window i the variance is calculated as:

$$\sigma_i^2 = \frac{1}{W} \sum_{j=1}^{w} \left(U(t_j) - \mu_i\right)^2 \quad \text{where } \mu_i = \frac{1}{W} \sum_{j=1}^{w} U(t_i) \tag{3.29}$$

σ_i^2 : Variance of the $U(t_j)$signal at a point

W : is the number of samples in the segment.

μ_i : is the mean variance.

- **Detecting Change Points Using Variance Threshold**

The change in variance between consecutive point is calculated as:

$$\Delta\sigma_i^2 = |\, \sigma_{i+1}^2 - \sigma_i^2| \tag{3.30}$$

A threshold T is used to detect significant changes:

$$\Delta\sigma_i^2 > T \tag{3.31}$$

T : Variance threshold, defined as $T = k.\overline{\sigma^2}$ where $\overline{\sigma^2}$ is the mean variance over all windows, and k is a user-defined constant $(eg.\, k = 2)$.

- **Breakpoint Detection:**

The time indices t_b where the variance change exceeds the threshold T are flagged as breakpoints**:**

$$t_b = \{\mathbf{t_j} \mid \Delta\sigma_i^2 > T\} \tag{3.32}$$

This method ensures that MRCPs are both smoothed and analyzed for critical transitions, enhancing the detection of neural activity changes while reducing noise.

H. Detrending to Remove Background Trends

To maintain the dynamic characteristics of the MRCPs and remove baseline drifts, a detrending algorithm was applied:

$$U_{detrended}(n, i) = U(n, i) - (a.n + b) \tag{3.33}$$

Where a and b are the coefficients of a fitted linear trend. This ensured that the MRCPs were free from gradual drifts that could otherwise obscure true neural activity.

The processed MRCPs were used to create feature matrices that represented the temporal evolution of the EEG signals across the selected channels.

$$\text{Feature Matrix} = \{U_{\text{detrended}}(t) | t \in \text{WOI}\} \quad (3.34)$$

These matrices, structured by time samples within the WOI, provided the basis for accurate categorization of movement-related states.

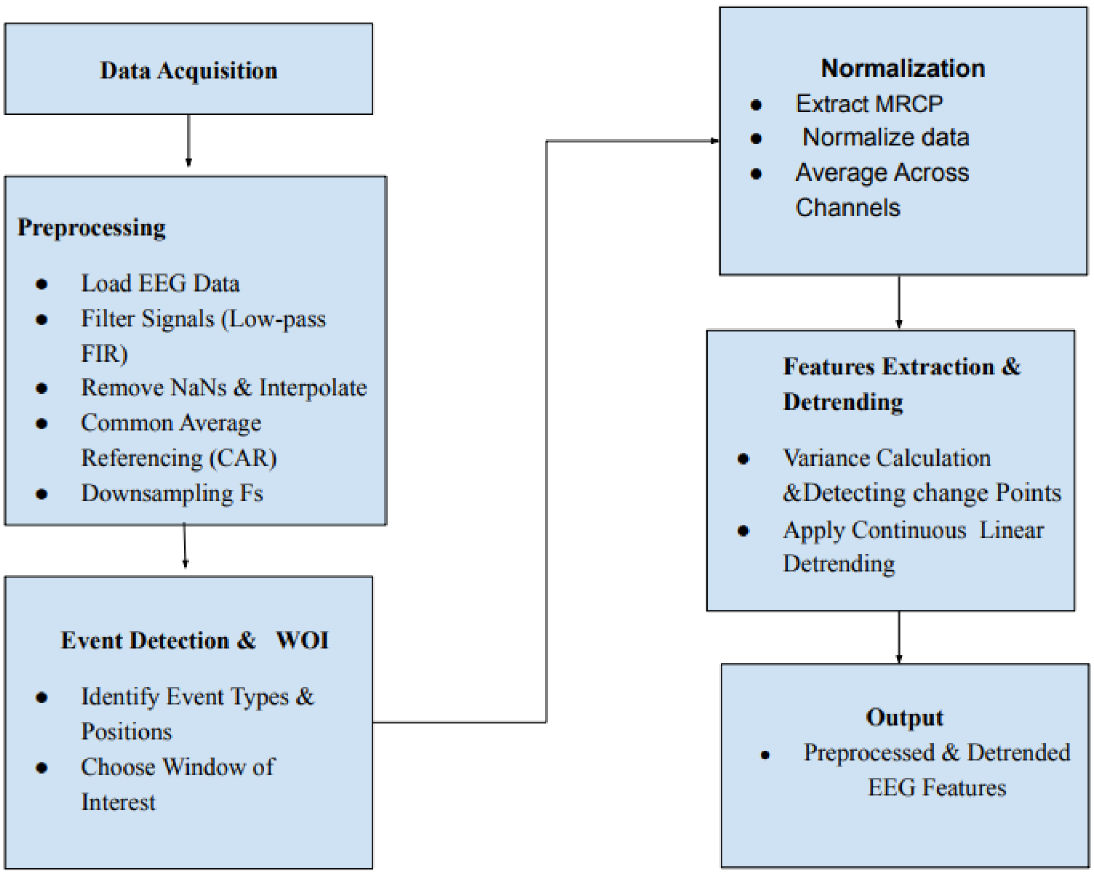

Figure 3.6.VB-MFED for EEG Analysis

3.6. Classification Methods

Classifying EEG signals is a vital process, particularly for the identification of brain condition/state. An effective classification technique is crucial for assessing an individual's mental health by accurately categorizing EEG signals. This classification process involves using sophisticated algorithms to sort unknown observations (referred to as the testing class) into their respective categories based on predefined observations (known as the training class).

Classification operates through a classifier, which is a mathematical function designed to map input values to their correct classes. This process ensures that the EEG signals are accurately categorized (Siuly et al., 2013). To classify EEG signals efficiently, it is essential to have a deep knowledge of the fundamental properties of these signals.

Features are measurable attributes that quantify specific characteristics of EEG signals. These features are crucial for the classification process. When combined, these numerical features form what is known as a feature vector. This vector , which encapsulates the essential properties of the EEG signals, is then input into the classifier. The classifier uses this information to perform the classification task, determining the correct category for each EEG signal based on the provided data (Siuly et al., 2013).

In essence, the classification of EEG signals is an algorithmic process that transforms raw brainwave data into meaningful categories, aiding in the diagnosis and understanding of various brain condition/state. The success of this process hinges on the accurate identification and quantification of the signals' characteristics, ensuring that the classifier can effectively map these signals to their correct classifications. This meticulous approach is critical for advancing mental health assessments and improving our understanding of neurological conditions.

3.6.1. Fisher Discriminant Analysis (FLDA)

Linear discriminants are fundamental tools in machine learning, particularly valued in EEG applications for their efficiency and efficacy in classifying data. Among these, FLDA stands out for its ability to optimally differentiate between classes by constructing a discriminant vector that maximizes class separability. Initially designed for binary classification, FLDA extends seamlessly to multi-class scenarios, crucially in EEG where multiple distinct brain states or conditions must be distinguished(Machavarapu et al., 2014).

In its basic form for two classes, FLDA operates by projecting d-dimensional feature vectors onto a one-dimensional space defined by a linear combination

$$y = \mathbf{W}^T\mathbf{X} + w_0 \tag{4.1}$$

Where $\mathbf{W}$ denotes the weight vector and w_0 the bias term optimize the ratio of inter-class variance to intra-class variance ensuring that distinct classes are well-separated within the transformed feature space. This is attained by computing mean vectors for each class and overall mean vector for the entire dataset, followed by the calculation of within-class and between-class scatter matrices. The optimal discriminant vectors are then derived through solving a generalized eigenvalue problem, leading to a lower-dimensional subspace where class separability is maximized.

For scenarios involving more than two classes, such as the classification of five distinct EEG patterns, FLDA extends its methodology by computing multiple discriminant vectors (one less than the number of classes) that collectively project the data into a space where class distinctions are optimized. This process involves iterative steps: computing class-specific mean vectors, constructing scatter matrices to quantify intra-class and inter-class variance, and then solving the eigenvalue problem to find discriminant vectors that best discriminate between classes.

3.6.2. Shrinkage Linear Discriminant Analysis(sLDA)

Shrinkage LDA is an extension of the standard LDA that incorporates regularization to improve the estimation of the covariance matrix, especially when the sample size is small compared to the number of features(Ofner et al., 2019b).

- The shrinkage estimator combines the sample covariance matrix S with a structured matrix, typically the identity matrix I.
- The formula is:

$$\Sigma_{\text{shrinkage}} = (1-\lambda)\mathrm{S} + \lambda \mathrm{I} \tag{4.2}$$

  Where λ is the shrinkage intensity parameter.
- λ controls the trade-off: when $\lambda = 0$ it is the standard covariance matrix, and when $\lambda = 1,$ it simplifies to a scaled identity matrix.

3.6.3. K-means Nearest Neighbor classifier (KNN)

The K-NN classifier, offers a straightforward yet powerful approach particularly applicable in EEG signal classification. In the context of EEG analysis, where identifying distinct brain states or patterns is paramount, the KNN method operates effectively by first determining the k nearest EEG signal samples to a given test signal, typically measured using Euclidean distance in the multi-dimensional feature space. This distance metric $d(\mathbf{X_i}, \mathbf{X})$ calculates the dissimilarity between an EEG signal sample $\mathbf{X_i}$ and the test signal $\mathbf{X}$

$$d(\mathrm{X_i}, \mathrm{X}) = \sqrt{\sum_{j=1}^{d}\left(x_{ij} - x_j\right)^2} \tag{4.3}$$

Here, x_{ij} represents the $j-th$ feature of EEG signal sample $\mathbf{X_i}, x_j$ denotes the $j-th$

feature of the test signal $\mathbf{X}$ and d denotes the number of features (e.g., frequency bands, time-domain characteristics).

Once the nearest neighbors are identified, KNN classifier assigns a category label to the test EEG signal based on the majority class among these neighbors. This decision rule is mathematically expressed as:

$$\hat{y} = \mathrm{argmax}_{y} \sum_{i=1}^{k} \mathbf{I}(y_i = y) \tag{4.4}$$

Where y_i denotes the class label of the $i-th$ nearest neighbor $\mathbf{I}(.)$ is the indicator function, and k is the number of nearest neighbors.

KNN method is particularly valued in EEG signal classification due to its ability to handle non-linear decision boundaries and complex patterns inherent in EEG data. It requires minimal assumptions about the underlying data distribution and offers interpretability by directly relating classification decisions to similar historical EEG patterns. However, optimal performance depends significantly on selecting an appropriate k value and refining the feature space representation to enhance discriminative power. Despite these considerations , KNN remains widely utilized in EEG applications, facilitating tasks such as brain state classification, cognitive workload assessment, and anomaly detection. Its simplicity and effectiveness make it a versatile tool in neuroscientific research and clinical diagnostics, where understanding and classifying EEG signals are crucial for advancing knowledge of brain function and pathology(Ramírez-Arias et al., 2022; Saka et al., 2016)

3.6.4. Support Vector Machine (SVM)

The SVM is a robust algorithm extensively applied in EEG signal classification, especially valued for its capability to discern complex patterns and classify data with high-dimensional feature spaces. Initially designed for binary classification tasks, SVM aims to identify an optimal hyperplane that maximizes the separation between EEG signals belonging to different classes (Cortes and Vapnik, 1995; Ramírez-Arias et al., 2022; Saka et al., 2016) .

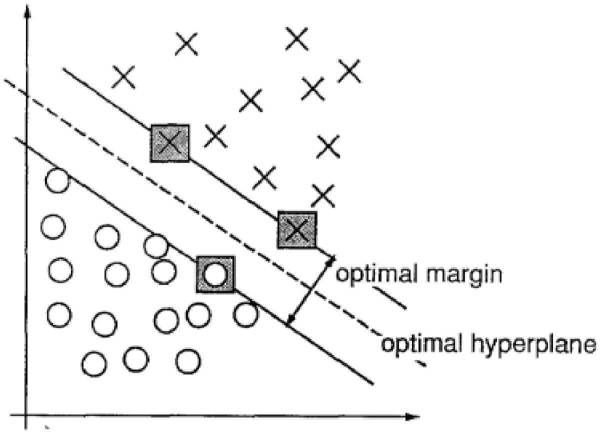

Figure 3.7.Example of two class SVM

In EEG applications, where each data point x_i represents features extracted from EEG recordings and y_i denotes its corresponding class label (e.g., brain state or cognitive task), SVM seeks to find a hyperplane defined by the weight vector w and bias term b
Mathematically, the objective of binary SVM can be formulated as:

$$min_{w,b} \frac{1}{2} \| W \|^2 \tag{4.5}$$

subject to the constraints:

$$y_i (W . X_i + b) \geq 1, \text{ for all } i = 1,2, \ldots \ldots, n \tag{4.6}$$

Here, w represents the vector perpendicular to the hyperplane , b is the bias term, and x_i signifies the feature vector extracted from EEG data.

Expanding SVM to multi-class EEG classification involves strategies like the one-vs-all (OvA) approach, a separate SVM classifier is trained for each class using binary labels: 1 for the current class, 0 for others. This simplifies multi-class classification by breaking it into multiple binary tasks.

3.7. Performance Matrices

Performance matrices task were conducted to evaluate the performance of the model, a critical step in evaluating its performance effectively to novel, unseen data. This evaluation involved employing key metrics that provide comprehensive insights into different facets of the model's predictive performance. These metrics include Accuracy, Precision, Recall (also known as Sensitivity), F1-score, and Cohen's Kappa(Ramírez-Arias et al., 2022)

- **Accuracy:**

This metric evaluates the overall correctness of a classification model to assess the effectiveness by calculating the ratio of accurately predicted instances (including both true positives and true negatives) to the total number of instances of predictions. It offers a broad view of the model's performance but can be misleading in cases of class imbalance.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FN+FP}} \tag{4.8}$$

where :

TP = true positives,

TN = true negatives,

FP = false positives,

FN = false negatives**.**

- **Precision:**

This evaluates the accuracy of positive predictions by computing the proportion of true positives to all cases identified as positive. It is essential in situations where the impact of false positives is substantial as it indicates the model's capacity to deliver trustworthy positive predictions.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{4.9}$$

- **Recall (Sensitivity):**

This gauges the model's ability to identify all true positive cases by calculating the proportion of correct positive predictions relative to the total number of actual positive instances. This measure is crucial in situations where missing positive cases, or false negatives, carry significant consequences.

$$\text{Recall} = \frac{\text{TP}}{\text{TP + FN}} \tag{4.10}$$

- ***F1-score:***

This statistical parameter is a metric that combines precision and recall into a balanced measure, offering a comprehensive evaluation of how well a model performs in terms of both false positives and false negatives. It is particularly valuable in situations with class imbalances, where other metrics might not provide a complete picture.

$$F1 = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4.11}$$

- **Cohen’s Kappa Value:**

This assesses the consistency between predicted and actual classifications, considering the consistency that might occur by chance. It offers a more understanding of the model's accuracy, especially in datasets with uneven class distributions, highlighting the model's performance beyond random guessing.

$$\text{kappa} = \frac{p_o - p_e}{1 - p_e} \tag{4.12}$$

$$p_o = \frac{\sum_a C(a,a)}{\sum_a \sum_b C(a,b)} \tag{4.13}$$

$$p_e = \frac{\sum_b \sum_b C(a,b)\, C(b,a)}{(\sum_a \sum_b C(a,b))^2} \tag{4.14}$$

Where:

Po : stands for the relative observed agreement.

Pe : denotes the agreement expected by chance alone.

C(a,b) represents the counts in the confusion matrix for the predicted and actual labels.

3.8. Cross Validation(KFold)

Cross-validation is a technique used to assess how well a machine learning model generalizes to unseen data.

In this process, the K-fold cross-validation procedure is implemented to evaluate the performance of the classifier across multiple subsets of the dataset. The number of folds is set to 5, meaning the data will be divided into five distinct groups or "folds." For each iteration, the model is trained on four of these folds and tested on the remaining fold. This approach helps assess the model's ability to generalize by ensuring that each portion of the data serves as both training and testing data at different points in the cross-validation cycle.

During each fold, the dataset is split into two parts: one for training and the other for testing. The training set consists of the data points from four of the five folds, while the testing set is made up of the data points from the remaining fold. The features and labels of the training and testing sets are extracted separately to ensure that the model learns from one subset and is then tested on a different, unseen subset. This iterative process helps in providing a more robust estimate of the model's performance and reduces the potential for overfitting, as it tests the model on different data each time. By the end of the cross-validation, the performance metrics from all folds are aggregated to provide an overall evaluation of the classifier's effectiveness in classifying the data. This method is widely used in machine learning to ensure that the model is both accurate and reliable in its predictions across different data sets(Pour and Özbek, 2021).

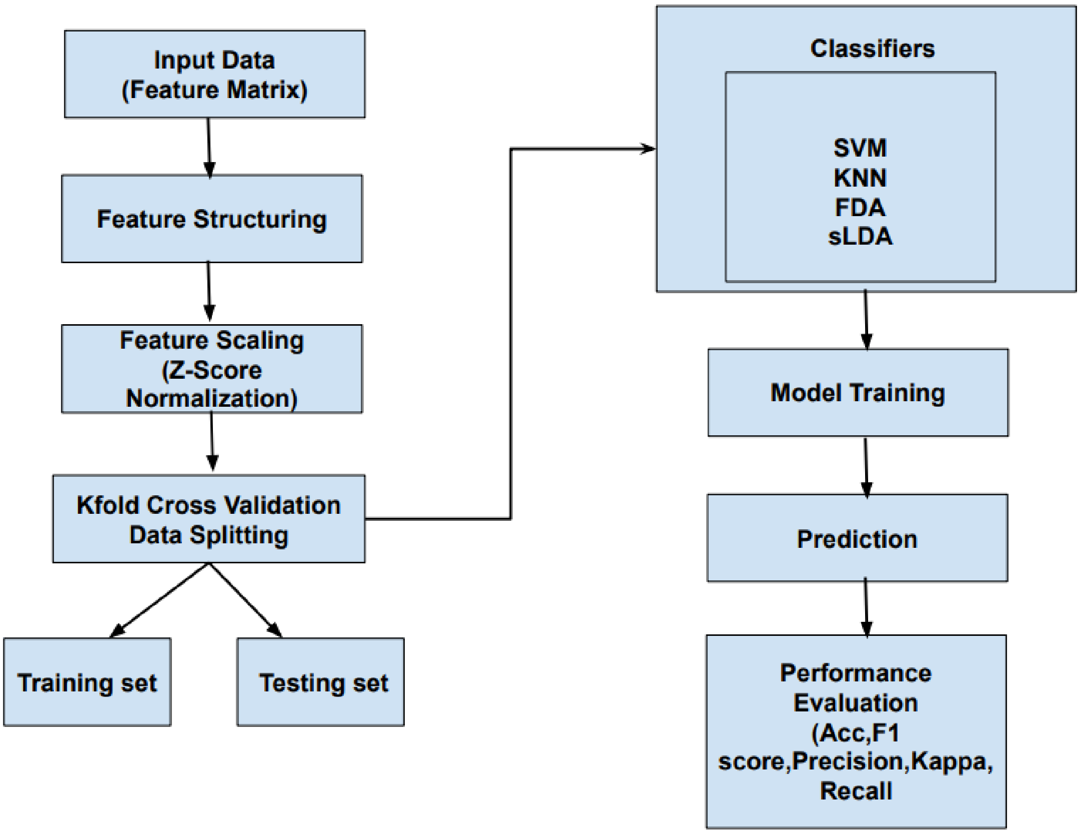

Figure 3.8.Conceptual Framework of the study

4. RESULTS AND DISCUSSIONS

This section reveals and discusses results for classifying EEG data recorded from ten participants with SCI, whose ages range from twenty (20) to sixty nine (69) years. The aim was to evaluate the effectiveness of the proposed algorithms in distinguishing between five (5) different hand and arm movements, specifically pronation, supination, palmar grasp, lateral grasp, and hand opening. To achieve this goal, two distinct feature extraction approaches were employed.

The first approach involves smoothing and feature extraction based on Savitzky-Golay smoothing algorithm and Hadamard basis respectively. The Savitzky-Golay algorithm refined the signals by eliminating noise while maintaining temporal characteristics critical for MRCP classification while Hadamard basis transformation helped in reducing dimensionality or emphasizing key signal components by projecting the data onto an orthogonal basis. This transformation simplified the signal and removed irrelevant information.

The second approach used the Variance-Based MRCP Feature Extraction with Detrending (VB-MFED) for EEG classification. This approach focused on isolating movement-related cortical potentials by targeting a specific frequency range within EEG signals strongly associated with attempted motor actions. A key aspect of this method is the incorporation of linear detrending and normalization step, which ensures that the features extracted from the EEG data are scaled comparably. This normalization enhances the performance of the classification algorithms, providing a more robust foundation for EEG-based analysis.

4.1. Savitzky-Golay algorithm and Hadamard basis transformation results

This study employed four classifiers— FLDA , SVM,KNN and sLDA to assess their effectiveness in categorizing EEG signals. Both classifiers were tested on the same set of feature vectors derived from a novel feature extraction technique that combines the the Savitzky-Golay smoothing algorithm and Hadamard basis transformation.

Before applicatıon of our technique, the results show signals appear noisy and overlapping, with no clear patterns to distinguish the five classes of hand movement. The amplitude fluctuated widely, making it difficult to identify meaningful features for classification. Upon using Hadamard basis transformation wıth Savitzky-Golay smoothing algorithm, the MRCPs are smoothed, revealing distinct patterns for each of the five classes. This is visually depicted in the Figures 4.1, 4.2, 4.3 and 4.4 showing the original and smoothed MRCPs for the C3, C4, F3and F4 channels from subject P05 respectively

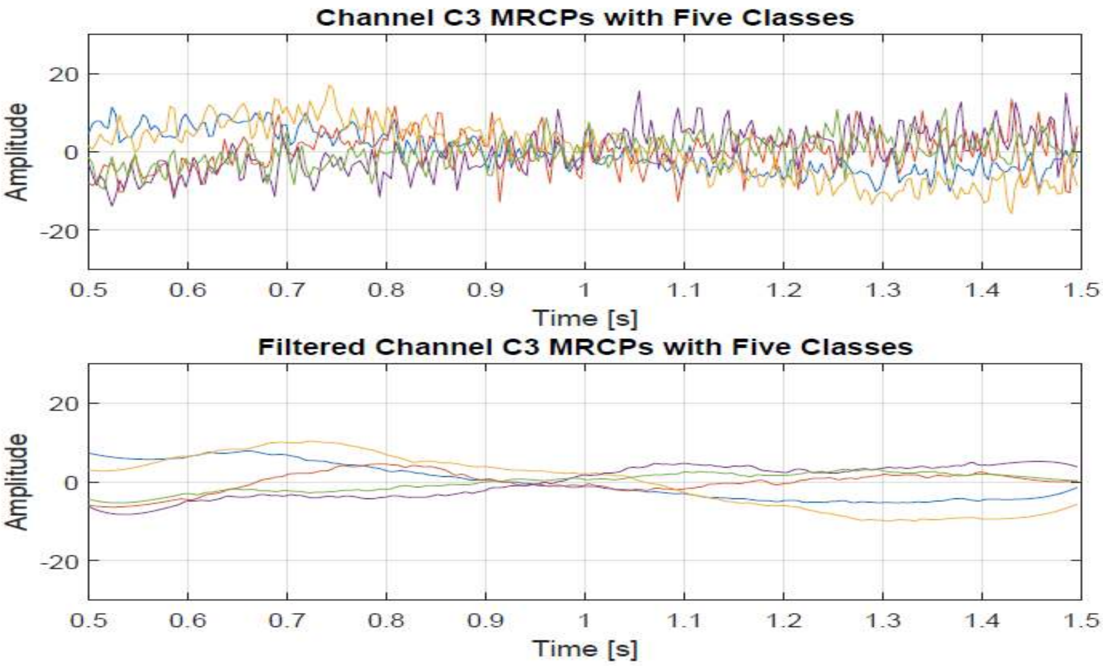

Figure 4.1.Channel C3 MRCPs

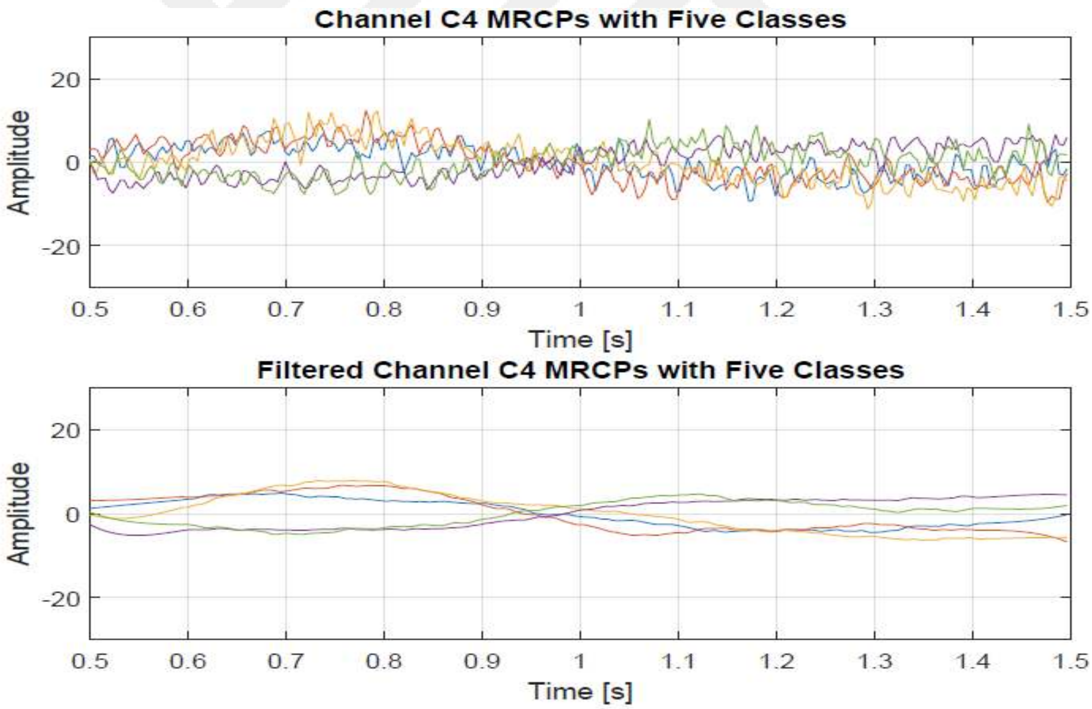

Figure 4.2.Channel C4 MRCPs

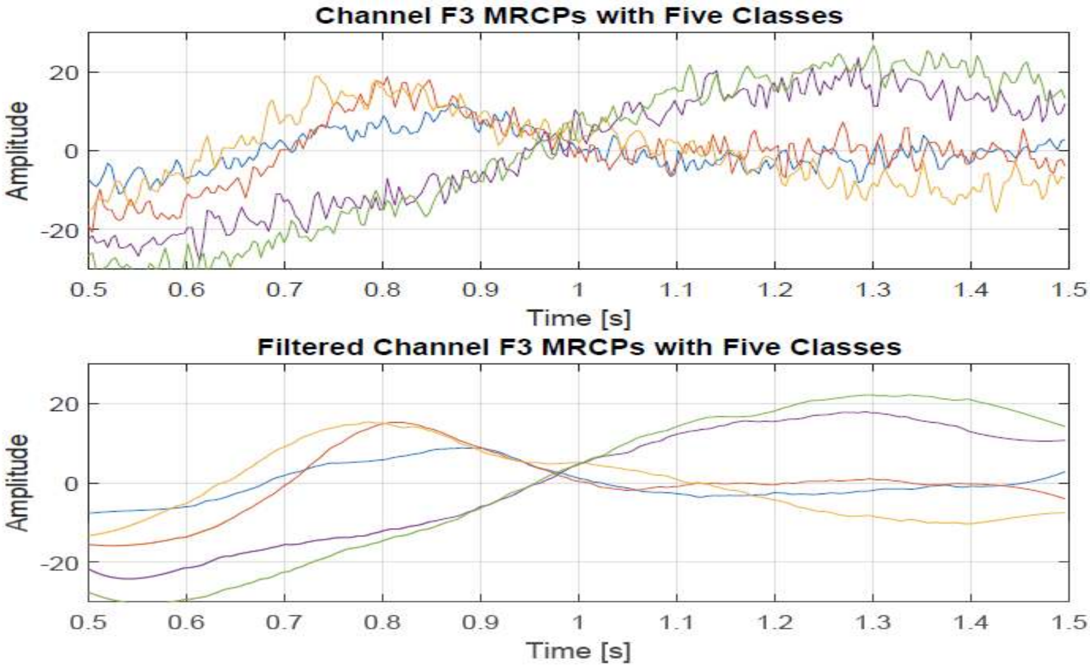

Figure 4.3.Channel F3 MRCPs

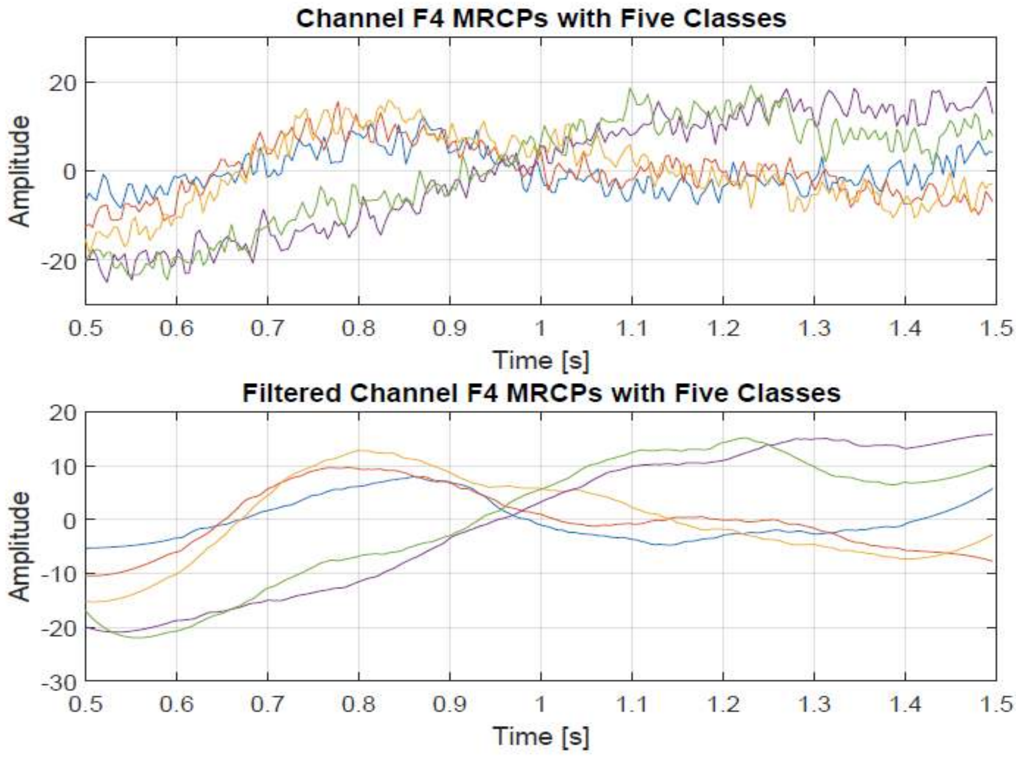

Figure 4 4.Channel F4 MRCPs

4.1.1. The Hadarmard Basis Result Analysis

Tables 4.1, 4.2, 4.3 , 4.4, 4.5, 4.6, 4.7 and 4.8 present the performance metrics of various classification algorithms (SVM, KNN, FLDA and sLDA) in analyzing attempted hand movements using 4 and 61 channels with a time window [WOI = 0.5 1.5 and WO=-2 3]. The metrics include accuracy, kappa, precision, recall, and F1 score across ten participants (P01–P10). The comparison highlights the effectiveness of each model in capturing hand movement patterns, providing insights into their relative strengths in handling the dataset. This summary serves as a foundation for selecting the most suitable classifier

Table 4.1.The Hadamard basis results with attempted hand movement (4 channels WOI =0.5 to 1.5)

Classifiers		P01	P02	P03	P04	P05	P06	P07	P08	P09	P010
SVM	Acc	20.83	24.17	22.92	28.75	32.50	23.33	16.25	21.25	23.75	22.08
	Kappa	0.02	0.06	0.05	0.13	0.17	0.07	0.04	0.02	0.07	0.03
	Precision	19	26	24	29	34	26	15	23	21	21
	Recall	21	24	23	29	33	23	16	21	24	22
	F1 score	19	24	22	26	31	21	15	21	20	21
KNN	Acc	19.17	23.33	25.00	24.17	26.25	27.08	20.00	22.50	27.50	29.17
	Kappa	0.01	0.06	0.08	0.06	0.10	0.10	0.01	0.04	0.11	0.12
	Precision	19	23	27	27	24	26	20	22	30	30
	Recall	19	24	25	24	26	27	20	23	28	29
	F1 score	18	22	23	23	23	25	19	22	27	28
FLDA	Acc	22.5	33.33	26.25	28.33	40.42	25.83	27.50	35.83	21.67	26.25
	Kappa	0.04	0.17	0.08	0.11	0.26	0.08	0.10	0.20	0.03	0.08
	Precision	22	34	25	29	42	26	27	36	21	28
	Recall	22	33	26	28	40	26	28	36	21	26
	F1 score	22	33	25	28	40	26	27	35	21	26
sLDA	Acc	24.58	32.50	30.00	29.17	41.67	26.67	25.00	34.58	29.17	23.75
	Kappa	0.06	0.16	0.13	0.12	0.28	0.09	0.07	0.19	0.12	0.05
	Precision	25	32	30	29	43	27	25	35	29	26
	Recall	24	32	30	29	42	26	25	35	29	24
	F1 score	24	31	29	29	41	27	25	34	28	24

Table 4.1 presents the performance metrics of various classification algorithms (SVM, KNN, FLDA and sLDA, in analyzing attempted hand movements using 4 channels with a time window [WOI = 0.5 1.5]. Its accuracy average values are shown in Table 4.2.

Table 4.2.Hadamard average results of the attempted hand movements for 4 channels[WOI= 0.5 1.5]

Classifiers	**Acc**	**Kappa**	**F1 score**	**Recall**	**Precision**
SVM	23.58	0.07	22.0	23.6	23.8
KNN	24.42	0.07	23.0	24.5	24.8
FLDA	28.79	0.13	28.3	28.6	29.0
sLDA	29.72	0.13	29.2	29.6	30.1

Table 4.2 presents the average classification accuracy of different classifiers using the Hadamard basis for feature extraction to analyze attempted hand movements across four EEG channels (WOI = 0.5 to 1.5 seconds). sLDA achieved the highest accuracy at 29.72%, demonstrating its superior performance. FLDA followed with an accuracy of 28.79%, indicating moderate effectiveness. In contrast, KNN recorded the lowest accuracy at 24.42%, while SVM performed slightly worse at 23.58%, highlighting their limited classification capabilities. These results indicate that sLDA outperforms the other classifiers in terms of accuracy, while SVM and KNN show the least effectiveness. As visually shown in Figure 4.5.

Table 4.3.The Hadamard basis results with attempted hand movement (61 channels and WOI =0.5 to 1.5)

Classifiers		P01	P02	P03	P04	P05	P06	P07	P08	P09	P010
SVM	Acc	20.83	20.00	20.42	20.00	21.67	18.33	18.34	22.92	20.00	21.67
	Kappa	0.18	0.17	0.17	0.19	0.19	0.15	0.16	0.15	0.20	0.15
	Precision	20	19	19	14	18	16	16	22	14	15
	Recall	21	20	21	20	22	18	18	23	20	21
	F1 score	19	18	11	17	15	17	16	18	17	12
KNN	Acc	22.08	24.58	21.67	23.75	26.25	22.08	17.08	26.25	25.00	30.83
	Kappa	0.04	0.07	0.03	0.06	0.10	0.04	0.02	0.08	0.07	0.14
	Precision	25	26	21	24	26	22	18	0.26	24	31
	Recall	22	25	22	24	26	22	17	26	25	31
	F1 score	22	24	20	23	24	21	17	25	23	30
FLDA	Acc	27.08	31.67	31.25	30.42	34.17	21.25	24.17	26.67	28.75	29.17
	Kappa	0.12	0.16	0.16	0.15	0.20	0.04	0.07	0.11	0.13	0.13
	Precision	33	34	32	31	35	23	25	26	35	29
	Recall	27	32	31	30	34	21	24	27	29	29
	F1 score	27	30	29	29	32	20	23	24	27	27
sLDA	Acc	29.58	31.67	26.67	31.67	41.67	28.75	25.00	35.00	28.33	31.25
	Kappa	0.12	0.15	0.09	0.15	0.27	0.11	0.07	0.19	0.11	0.15
	Precision	30	32	26	32	41	28	26	36	29	31
	Recall	30	32	26	32	42	29	25	35	28	31
	F1 score	29	31	26	31	41	28	25	35	28	31

Table 4.3 presents the performance metrics of various classification algorithms (SVM, KNN, FLDA and sLDA, in analyzing attempted hand movements using 61 channels with a time window [WOI = 0.5 1.5]. Its accuracy average values are shown in Table 4.4.

Table 4.4.Hadamard average results of the attempted hand movements for 61 channels[WOI= 0.5 1.5]

Classifiers	**Acc**	**Kappa**	**F1 score**	**Recall**	**Precision**
SVM	20.42	0.17	16.0	20.4	17.3
KNN	23.96	0.07	22.9	24.0	21.7
FLDA	28.46	0.13	26.8	28.4	30.3
sLDA	30.96	0.14	30.5	31.0	31.1

Table 4.4 summarizes the results of applying the Hadamard basis for feature extraction in the classification of attempted hand movements using data recorded from 61 EEG channels, with a WOI set between 0.5 and 1.5 seconds. The results show that the sLDA classifier achieved the highest average accuracy of 30.96%, outperforming the other classifiers in this configuration. The FLDA classifier followed with an accuracy of 28.46%, slightly surpassing KNN, which achieved an accuracy of 23.96%. SVM recorded the lowest average accuracy of 20.42%, highlighting its limited effectiveness in this setup. These are shown in Figure 4.5.

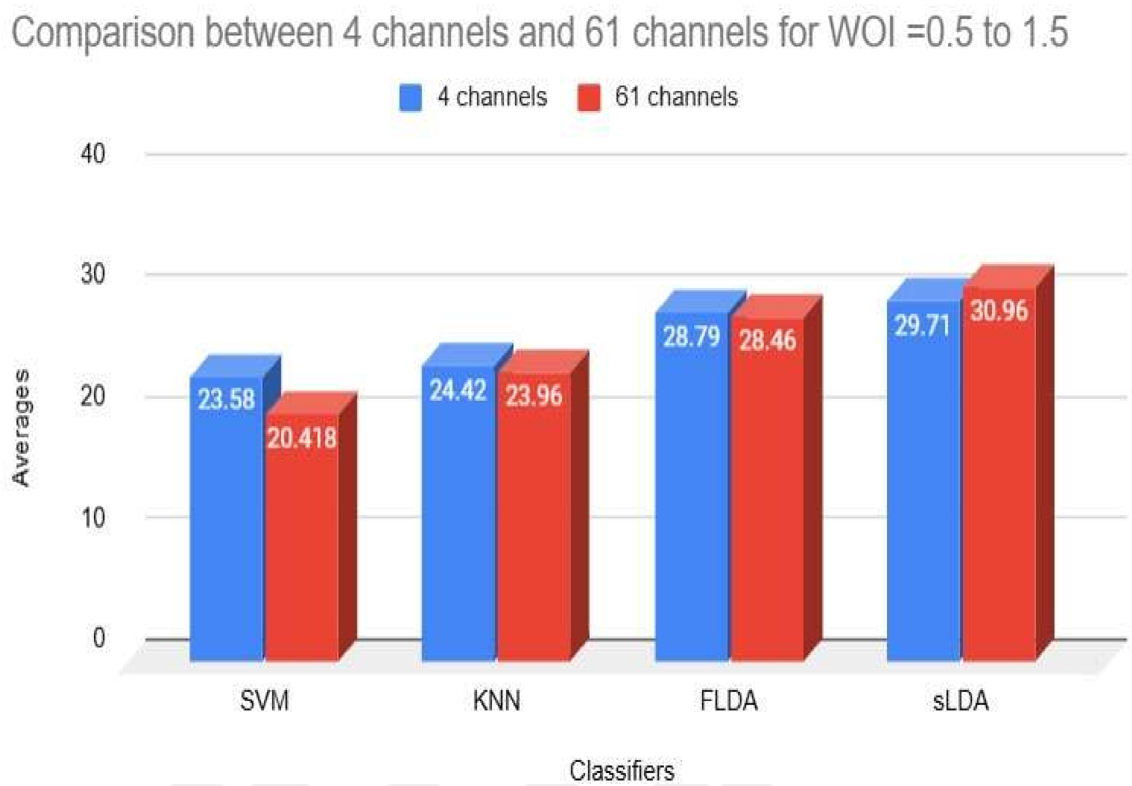

Figure 4. 5. Hadamard average accuracy values of the classifiers[WOI= 0.5 1.5]

Table 4.5.The Hadamard basis results with attempted hand movemen (4 channels and WOI = -2 to 3)

Classifiers		P01	P02	P03	P04	P05	P06	P07	P08	P09	P010
SVM	Acc	22.92	22.92	22.08	27.08	26.25	17.50	22.08	25.83	29.58	21.67
	Kappa	0.09	0.09	0.05	0.13	0.10	0.01	0.08	0.10	0.16	0.05
	Precision	23	23	22	24	24	15	18	29	23	20
	Recall	23	23	22	27	26	18	22	26	30	22
	F1 score	19	19	20	21	23	15	17	24	23	19
KNN	Acc	19.58	26.67	25.00	22.50	26.25	15.83	18.75	23.75	22.08	26.67
	Kappa	0.01	0.10	0.08	0.05	0.09	0.05	0.01	0.05	0.04	0.10
	Precision	21	34	27	24	27	16	19	24	22	25
	Recall	20	27	25	22	26	16	19	24	22	26
	F1 score	19	26	24	22	25	16	18	23	21	24
FLDA	Acc	33.75	33.75	29.58	31.25	29.17	29.18	23.33	29.58	29.58	24.58
	Kappa	0.18	0.18	0.12	0.15	0.12	0.12	0.05	0.12	0.13	0.06
	Precision	34	34	30	30	29	29	25	30	31	24
	Recall	34	34	30	31	29	28	23	30	30	25
	F1 score	33	33	29	30	29	29	23	29	29	24

Table 4.5.The Hadamard basis results with attempted hand movement (4 channels and WOI = -2 to 3 (Continue)

sLDA	Acc	31.25	31.25	26.67	32.08	28.33	24.58	23.33	29.17	29.17	25.42
	Kappa	0.15	0.15	0.09	0.16	0.11	0.06	0.05	0.12	0.12	0.07
	Precision	33	33	29	31	28	25	22	32	29	25
	Recall	31	31	27	32	28	25	23	29	29	26
	F1 score	31	31	27	31	28	24	22	29	28	24

Table 4.5 presents the performance metrics of various classification algorithms (SVM, KNN, FLDA and sLDA, in analyzing attempted hand movements using 4 channels with a time window [WOI = -2 3]. Its accuracy average values are shown in Table 4.6.

Table 4.6.Hadamard average results of the attempted hand movements for 4 channels [WOI= -2 3]

Classifiers	**Acc**	**Kappa**	**F1 score**	**Recall**	**Precision**
SVM	23.79	0.09	20.0	23.90	22.10
KNN	22.71	0.06	21.80	22.70	23.90
FLDA	29.38	0.12	28.80	29.40	29.60
sLDA	28.13	0.11	27.50	28.10	28.70

Table 4.6 summarizes the average results of applying the Hadamard basis for feature extraction in the classification of attempted hand movements using data recorded from 4 EEG channels, with a WOI set between -2 and 3 seconds. The results show that the FLDA classifier achieved the highest average accuracy of 29.38%, outperforming the other classifiers. The sLDA classifier followed with an accuracy of 28.13%, while SVM achieved an accuracy of 23.79%. KNN recorded the lowest average accuracy of 22.71%, highlighting its limited effectiveness in this setup. The average results are shown in Figure 4.6.

Table 4.7.The Hadamard basis results with attempted hand movement (61 channels and WOI = -2 to 3)

Classifiers		P01	P02	P03	P04	P05	P06	P07	P08	P09	P010
SVM	Acc	20.42	21.67	23.33	19.17	29.58	18.75	17.50	22.08	20.00	22.92
	Kappa	0.07	0.15	0.12	0.15	0.20	0.06	0.15	0.14	0.12	0.13
	Precision	16	15	19	12	33	15	15	19	17	28
	Recall	20	21	23	20	30	19	18	22	20	23
	F1 score	15	12	17	16	24	13	17	14	11	17
KNN	Acc	21.25	23.33	24.17	23.33	30.42	20.83	22.08	22.08	20.42	25.42
	Kappa	0.03	0.07	0.07	0.06	0.15	0.02	0.04	0.05	0.02	0.09
	Precision	22	30	23	23	34	19	20	21	22	28
	Recall	21	23	24	23	30	21	22	22	20	25
	F1 score	20	21	22	21	29	19	21	20	18	24
FLDA	Acc	18.33	27.50	34.58	30.00	35.00	30.00	22.50	30.42	33.33	26.67
	Kappa	0.01	0.12	0.20	0.15	0.21	0.14	0.05	0.14	0.20	0.11
	Precision	16	32	36	35	36	31	22	31	35	25
	Recall	18	28	35	30	35	30	23	31	33	27
	F1 score	17	27	33	28	33	28	20	30	29	24
sLDA	Acc	20.83	30.83	35.83	30.00	36.25	27.92	25.00	32.92	37.08	29.17
	Kappa	0.02	0.14	0.20	0.13	0.21	0.10	0.07	0.17	0.22	0.12
	Precision	19	33	37	30	38	29	25	35	37	28
	Recall	21	31	36	30	36	28	25	33	37	29
	F1 score	20	31	35	29	36	28	25	33	36	28

Table 4.7 presents the performance metrics of various classification algorithms (SVM, KNN, FLDA and sLDA, in analyzing attempted hand movements using 61 channels with a time window [WOI = -2 3]. Its accuracy average values are shown in Table 4.8.

Table 4.8.Hadamard average results of the attempted hand movements for 61 channels [WOI= -2 3]

Classifiers	Acc	Kappa	F1 score	Recall	Precision
SVM	21.54	0.13	15.6	21.6	18.9
KNN	23.33	0.06	21.5	23.1	24.2
FLDA	28.83	0.13	26.9	29.0	29.9
sLDA	30.58	0.14	30.1	30.6	31.1

Table 4.8 presents the results of using the Hadamard basis for feature extraction in the classification of attempted hand movements, with data recorded from 61 EEG channels and a WOI spanning from -2 to 3 seconds. The analysis reveals that the sLDA classifier achieved the highest average accuracy, with a performance of 30.58%. This was followed by FLDA, which recorded an accuracy of 28.83%, while KNN achieved 23.33%. The SVM classifier obtained the lowest average accuracy of 21.54%, highlighting its limited effectiveness in this setup. These are visually shown in Figure 4.6.

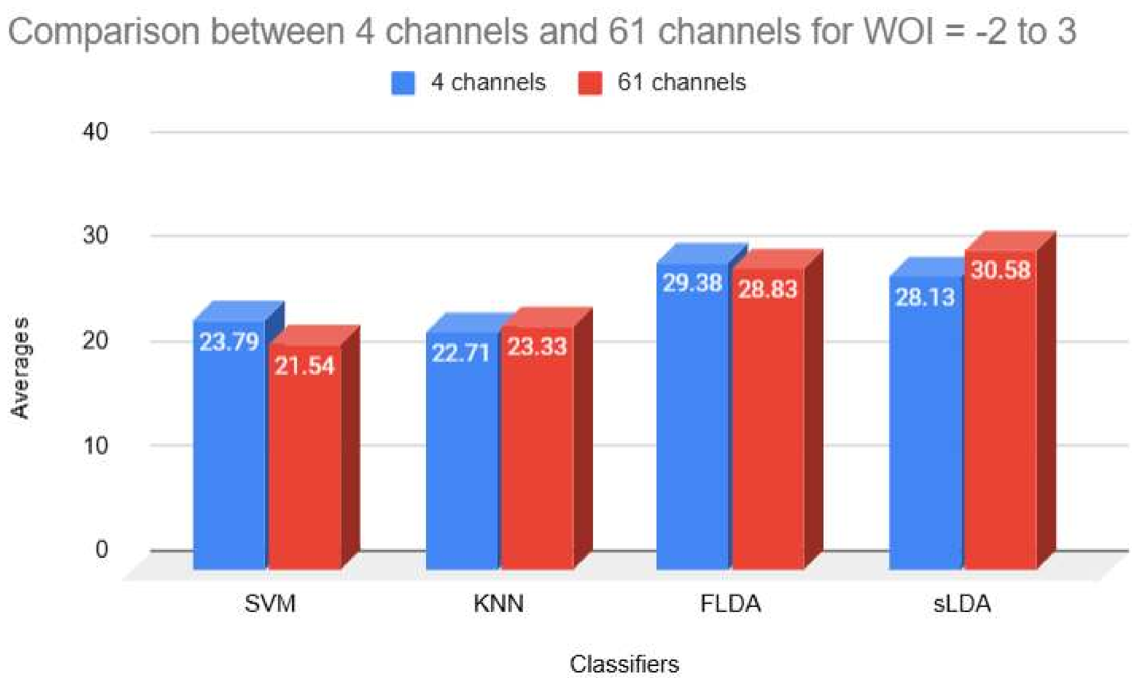

Figure 4. 6.Hadamard average accuracy values of the classifiers[WOI= -2 3]

4.2. Variance-Based MRCP Feature Extraction with Detrending (VB-MFED) Results

In this study, a novel VB-MFED method is employed to extract movement-related cortical potentials. The VB-MFED method effectively highlighted the key moments of change in EEG signal dynamics, offering a powerful preprocessing and feature extraction approach for tasks like MRCP classification in BCI systems. For subject P010 Figures 4.7 and Figure 4.8 shows four channels combined and variance change point and individual channels with variance change point respectıvely. Red dashed lines marked variance change points, indicating significant shifts in brain activity. This visualization aids in analyzing class separability, channel contributions, and event-related changes for EEG-based studies.

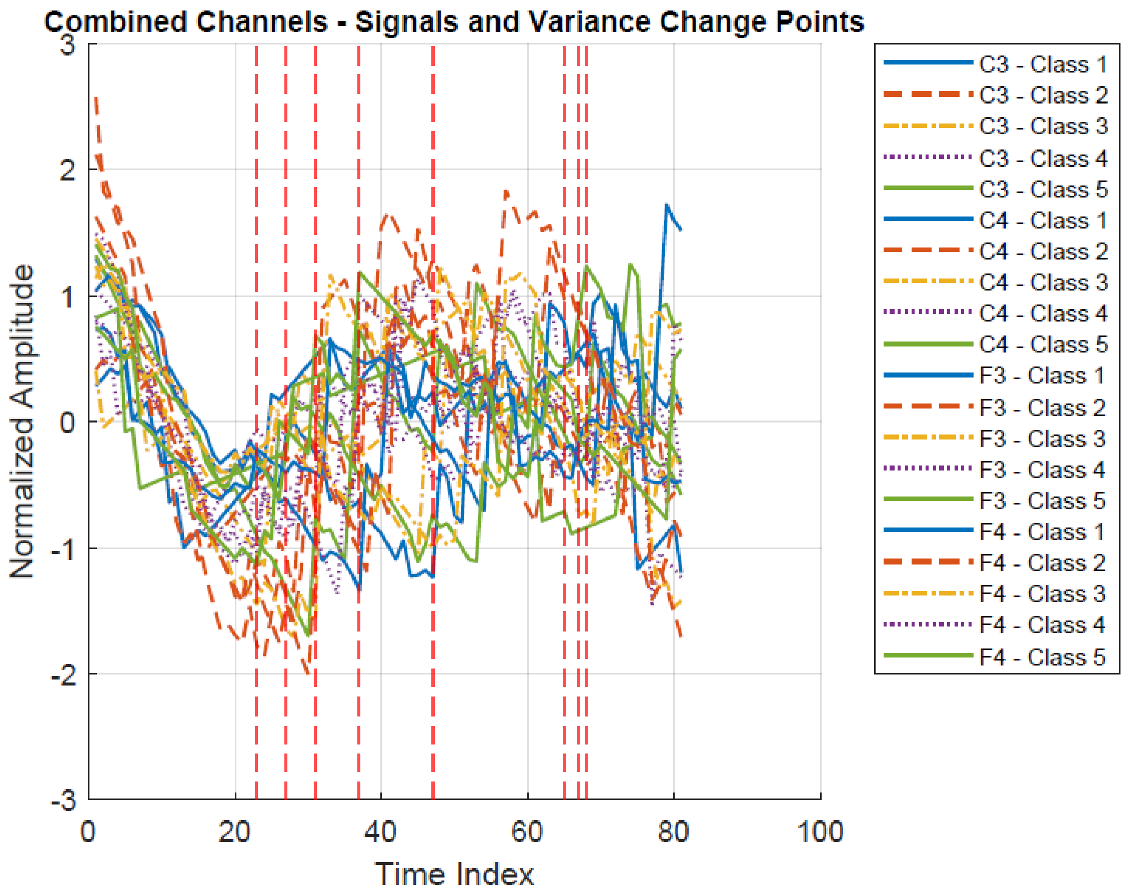

Figure 4. 7.P010 four channels combined and variance change point

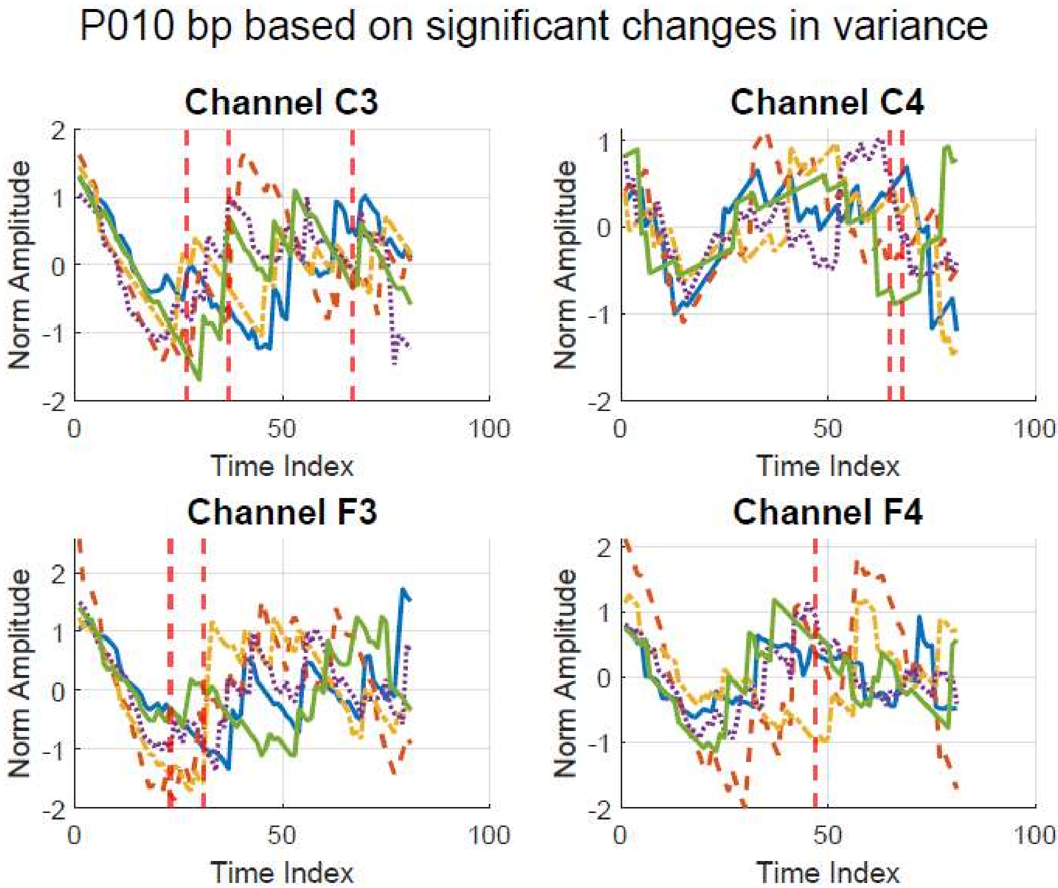

Figure 4. 8 .P010 four channels and variance change point

4.2.1. Result Analysis

Tables 4.9, 4.10, 4.11, 4.12, 4.13, 4.14, 4.15, and 4.16 present the performance metrics of various classification algorithms mentioned in analyzing attempted hand movements using 4 and 61 channels with a time window [WOI = 0.5 1.5 and WOI= -2 3].

Table 4.9. The VB-MFED results of the attempted hand movements for 4 channels[WOI= 0.5 1.5]

Classifiers		P01	P02	P03	P04	P05	P06	P07	P08	P09	P010
SVM	Acc	90.59	48.24	100	96.47	98.82	52.94	75.29	89.41	85.88	94.12
	Kappa	0.88	0.37	1	0.96	0.99	0.42	0.70	0.87	0.82	0.93
	Precision	92	53	100	97	99	56	70	92	89	95
	Recall	90	48	100	96	99	53	75	89	85	94
	F1 score	90	47	100	96	99	51	71	88	85	94
KNN	Acc	81.18	41.18	82.35	95.29	78.82	40.00	70.59	72.94	52.94	65.88
	Kappa	0.77	0.28	0.78	0.94	0.74	0.28	0.64	0.67	0.42	0.59
	Precision	85	45	87	96	85	39	75	77	60	81
	Recall	79	40	82	95	78	40	70	71	53	66
	F1 score	79	40	82	95	77	34	70	70	53	66
FLDA	Acc	91.76	22.35	100	97.65	96.47	50.59	61.18	92.94	81.18	91.76
	Kappa	0.90	0.06	1	0.97	0.96	0.40	0.52	0.91	0.77	0.90
	Precision	93	25	100	98	98	57	61	94	83	93
	Recall	92	23	100	97	96	51	61	92	82	92
	F1 score	91	23	100	97	96	48	60	92	81	92
sLDA	Acc	89.41	21.18	100	97.65	98.82	43.53	63.53	92.95	81.18	88.24
	Kappa	0.87	0.05	1	0.97	0.99	0.33	0.55	0.91	0.77	0.85
	Precision	94	22	100	98	99	47	63	94	84	90
	Recall	90	22	100	97	99	45	64	92	82	89
	F1 score	90	21	100	98	99	41	62	92	81	88

Table 4.9 presents the performance metrics of various classification algorithms of the mentioned classifier in analyzing attempted hand movements using 4 channels with a time window [WOI = 0.5 1.5]. Its accuracy average values are shown in Table 4.10.

Table 4.10. VB-MFED average results of the attempted hand movements for 4 channels[WOI= 0.5 1.5]

Classifiers	**Acc**	**Kappa**	**F1 score**	**Recall**	**Precision**
SVM	83.18	0.79	82.1	82.9	84.3
KNN	68.12	0.61	66.6	67.4	73.0
FLDA	78.59	0.74	78.0	78.6	80.2
sLDA	77.65	0.73	77.2	78.0	79.1

Table 4.10 presents the classification results using the VB-MFED feature extraction method to analyze attempted hand movements across four EEG channels within a WOI from 0.5 to 1.5 seconds. The SVM classifier achieved the highest accuracy at 83.18%, followed by KNN with 68.12%. FLDA recorded an accuracy of 78.59%, while sLDA achieved 77.65%. These results indicate that SVM provides the highest classification accuracy, outperforming the other classifiers. KNN demonstrated the lowest performance in terms of accuracy. The performance trends are visually illustrated in Figure 4.9.

Table 4.11.The VB-MFED results of the attempted hand movements for 61 channels [WOI= 0.5 1.5]

Classifiers		P01	P02	P03	P04	P05	P06	P07	P08	P09	P010
SVM	Acc	94.12	54.12	65.88	69.41	63.53	74.12	31.76	98.82	62.35	48.24
	Kappa	0.93	0.44	0.58	0.62	0.55	0.68	0.19	0.99	54	0.37
	Precision	95	50	74	77	65	74	37	99	68	54
	Recall	93	40	66	70	64	73	32	99	62	48
	F1 score	93	40	65	70	62	72	29	99	61	46
KNN	Acc	72.94	61.18	40.00	43.53	44.71	50.59	29.41	72.94	25.88	35.29
	Kappa	0.67	0.52	0.29	0.33	0.32	0.41	0.16	0.67	0.10	0.21
	Precision	81	67	44	52	44	51	30	80	30	41
	Recall	74	60	40	44	46	51	29	73	27	36
	F1 score	73	61	37	44	43	46	25	73	27	34
FLDA	Acc	88.24	48.24	34.12	58.82	40.00	68.24	20.00	98.82	32.94	31.76
	Kappa	0.85	0.36	0.20	0.49	0.26	0.61	0.02	0.99	0.18	0.18
	Precision	91	48	44	65	40	71	30	99	37	34
	Recall	87	49	34	59	40	67	19	99	34	31
	F1 score	87	47	36	61	39	64	22	99	33	29
sLDA	Acc	80.00	44.71	30.59	63.53	30.59	30.59	17.47	100	25.88	24.71
	Kappa	0.75	0.32	0.15	0.55	0.17	0.17	0.04	1	0.11	0.09
	Precision	82	43	42	65	31	33	22	100	36	28
	Recall	80	45	31	64	32	31	16	100	27	25
	F1 score	79	44	34	64	30	28	15	100	28	23

Table 4.11 compares the performance of SVM, KNN, FLDA, and sLDA in analyzing attempted hand movements using 61 EEG channels within a time window of [WOI = 0.5 to 1.5]. Its accuracy average values are shown in Table 4.12.

Table 4.12. VB-MFED average results of the attempted hand movements for 61 channels[WOI= 0.5 1.5]

Classifiers	Acc	Kappa	F1 score	Recall	Precision
SVM	66.24	0.59	63.7	64.7	69.3
KNN	47.65	0.37	46.3	48.0	52.0
FLDA	52.12	0.41	51.7	51.9	55.9
sLDA	44.81	0.34	44.5	45.1	48.2

Table 4.12 presents the average accuracy results for classifiers analyzing attempted hand movements across 61 EEG channels within a time window of [WOI = 0.5 to 1.5]. SVM achieved the highest accuracy at 66.24%, followed by FLDA at 52.12%, sLDA at 44.81%, and KNN at 47.65%. These results indicate that SVM outperformed the other classifiers, with FLDA showing moderate performance, while sLDA and KNN exhibited lower accuracies. Despite SVM's superior performance, all models demonstrated relatively low accuracy levels , suggesting the need for further optimization to enhance classification accuracy. As visually depicted in Figure 4.9, the performance differences among the classifiers highlight areas for improvement in the overall classification process.

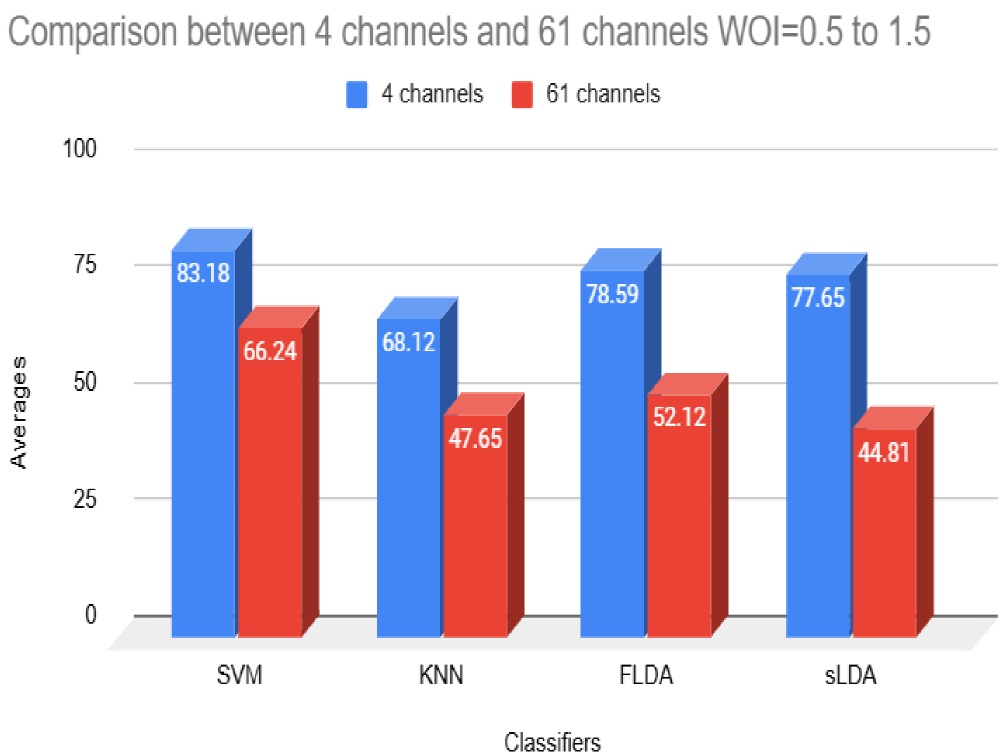

Figure 4.9. VB-MFED average accuracy values of the classifiers[WOI= 0.5 1.5]

Table 4.13 .VB-MFED results of the attempted hand movements for 4 channels [WOI= -2   3]

Classifiers		P01	P02	P03	P04	P05	P06	P07	P08	P09	P010
SVM	Acc	80.25	48.64	72.84	79.51	82.72	76.05	82.96	75.31	81.73	80.25
	Kappa	0.76	0.37	0.66	0.74	0.78	0.70	0.79	0.69	0.77	0.75
	Precision	86	54	76	81	84	80	85	81	83	84
	Recall	80	49	73	80	83	76	83	75	82	80
	F1 score	81	49	73	80	82	76	83	76	82	81
KNN	Acc	94.32	64.94	80.49	82.47	79.01	84.94	86.42	91.36	85.43	83.46
	Kappa	0.93	0.57	0.76	0.78	0.74	0.81	0.83	0.89	0.82	0.79
	Precision	95	71	82	85	82	87	88	92	86	86
	Recall	94	65	81	83	79	85	86	91	85	83
	F1 score	94	66	80	83	79	85	86	91	85	84
FDA	Acc	20.49	22.72	41.73	20.45	50.62	33.58	34.81	29.88	20.48	20.00
	Kappa	0.02	0.04	0.28	0.01	0.39	0.18	0.19	0.13	0.02	0.02
	Precision	29	31	44	28	50	38	34	34	28	29
	Recall	21	23	42	20	51	34	35	30	21	19
	F1 score	23	25	42	22	50	34	34	31	22	22
sLDA	Acc	19.01	21.73	13.83	41.23	50.62	31.11	33.83	28.64	14.81	15.06
	Kappa	0.01	0.03	0.01	0.27	0.39	0.15	0.18	0.12	0.02	0.03
	Precision	23	29	17	44	51	34	34	32	17	24
	Recall	19	22	14	41	50	31	34	29	15	15
	F1 score	19	24	14	42	51	31	34	30	14	15

Table 4.13 presents and compares the performance of SVM, KNN, FLDA, and sLDA in analyzing attempted hand movements using four EEG channels within a time window of [WOI = -2 to 3 seconds]. The average accuracy values for each classifier are shown in Table 4.14.

Table 4.14.VB-MFED average results of the attempted hand movements for 4 channels [WOI= -2 3]

Classifiers	Acc	Kappa	F1 score	Recall	Precision
SVM	76.03	0.70	76.3	76.1	79.4
KNN	83.28	0.79	83.3	83.2	85.4
FLDA	29.48	0.13	30.5	29.6	34.5
sLDA	26.99	0.12	27.4	27.0	30.5

Table 4.14 highlights the accuracy of the classifiers in analyzing attempted hand movements using four EEG channels within a time window of [WOI = -2 to 3]. KNN demonstrated the highest performance with an accuracy of 83.28%, followed closely by SVM with an accuracy of 76.03%. FLDA achieved an accuracy of 29.48%, and sLDA recorded the lowest accuracy at 26.99%. These results indicate that KNN outperformed the other classifiers, while SVM showed solid performance. In contrast, FLDA and sLDA displayed significantly lower accuracies, suggesting their limited effectiveness for this task. Overall, KNN and SVM were the most effective methods, with KNN showing a slight edge in performance. The results are visually presented in Figure 4.10

Table 4.15.The VB-MFED results of the attempted hand movements for 61 channels [WOI= -2 3]

Classifiers		P01	P02	P03	P04	P05	P06	P07	P08	P09	P010
SVM	Acc	86.91	69.88	73.09	60.00	69.14	84.94	75.56	76.54	80.25	68.64
	Kappa	0.84	0.63	0.67	0.51	62	0.81	0.70	0.71	0.75	0.61
	Precision	90	75	80	65	72	86	78	84	83	74
	Recall	87	70	73	60	69	85	76	76	81	69
	F1 score	87	70	74	59	69	85	75	76	80	69
KNN	Acc	92.10	79.75	92.11	79.26	78.02	85.93	90.12	81.23	88.89	85.93
	Kappa	0.90	0.75	0.90	0.74	0.73	0.82	0.88	0.77	0.86	0.82
	Precision	93	85	93	81	80	86	92	83	91	87
	Recall	92	80	92	79	78	86	90	82	88	86
	F1 score	92	80	92	79	78	86	90	81	89	85
FLDA	Acc	50.62	31.36	21.23	34.07	21.02	48.64	51.60	21.98	21.00	20.01
	Kappa	0.39	0.15	0.02	0.18	0.02	0.36	0.40	0.03	0.02	0.02
	Precision	64	32	25	35	27	48	53	28	27	28
	Recall	51	31	21	34	19	49	52	22	18	19
	F1 score	54	31	22	34	20	48	52	24	20	22
sLDA	Acc	51.11	31.85	21.23	33.83	14.32	49.14	52.59	25.43	14.57	15.06
	Kappa	0.40	0.15	0.02	0.18	0.02	0.37	0.41	0.08	0.04	0.04
	Precision	65	32	28	34	18	48	54	33	15	19
	Recall	51	32	21	34	14	49	53	25	14	15
	F1 score	54	32	22	33	13	49	53	28	15	15

Table 4.15 presents the analysis of for classifying attempted hand movements using 61-channel EEG data within the time window of [-2 to 3 seconds]. The average values for each classifier are presented in Table 4.16.

Table 4.16.VB-MFED average results of the attempted hand movements for 61 channels [WOI= - 2 3]

Classifiers	Acc	Kappa	F1 score	Recall	Precision
SVM	74.58	0.69	74.4	74.6	78.7
KNN	85.33	0.82	85.2	85.3	87.1
FLDA	32.15	0.16	32.7	31.6	36.7
sLDA	30.91	0.17	31.4	30.8	34.6

Table 4.16 shows the classification accuracy of four classifiers for attempted hand movements from 61 EEG channels within a time window of [WOI = -2 to 3].. KNN achieved the highest accuracy at 85.33%, followed by SVM with an accuracy of 74.58%, demonstrating strong performance in identifying EEG patterns. In contrast, FLDA and sLDA recorded much lower accuracies of 32.15% and 30.91%, respectively, suggesting that these classifiers struggle to capture the complexities of EEG signals. Overall, KNN and SVM proved to be the most effective classifiers for this task, while FLDA and sLDA offered limited utility. These results are visually illustrated in Figure 4.10.

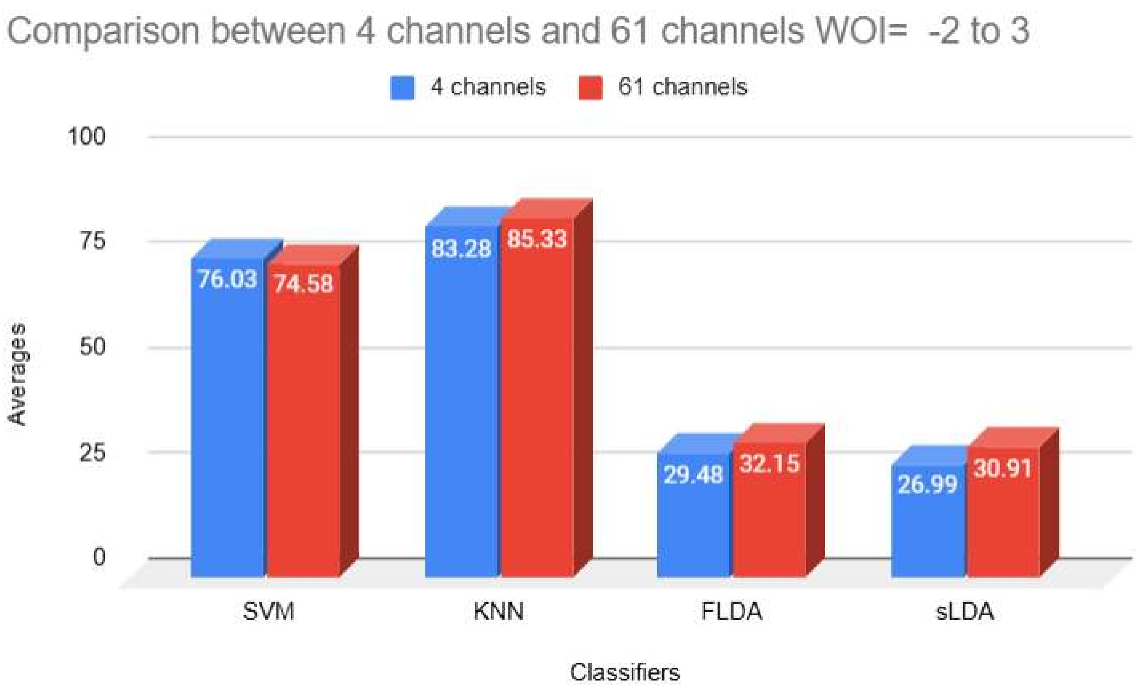

Figure 4.10. VB-MFED average accuracy values of the classifiers[WOI= -2 3]

Table 4.17.Comparative analysis of the same EEG dataset

Study	Methodology	Dataset	Channels &window Size	No. of classes	Accuracy(%)
(Ofner et al., 2019)	sLDA classifier embedded in the discriminative spatial pattern (DSP)	Attempted hand and arm movement dataset	61 Channel, 1.1 seconds	5	**45**
(Ieracitano et al., 2022)	CNN	Attempted hand and arm movement dataset	61 channels, 1second	2	**89.65** (Hand-close/Resting) **90.50** (Hand-open/Resting)
(Aydın, 2023)	KFD+SVM	Attempted hand and arm movement dataset	61 channels, -2 to 1 seconds	2	**96.47**
(Makouei and Uyulan, 2023)	1D CNN + LSTM	Attempted hand and arm movement dataset	32 channels	5	**75.8**
(Aydin, 2022)	HFD+KNN	Attempted hand and arm movement dataset	61 Channels	2	**70.09** for pronation and **69.22** supination
Our Study	Variance-Based MRCP Feature Extraction with Detrending (VB-MFED) + KNN	Attempted hand and arm movement dataset	61 channels and 4 channels -2 to 3 seconds	5	**85.33** and **83.28** respectively

Table 4.17 presents a comparative analysis of studies that utilized the same EEG dataset for classifying hand and arm movements. Ofner (2019) achieved 45% accuracy using sLDA with discriminative spatial pattern (DSP) on five movement classes. Aydin (2022) classified forearm movements using Higuchi Fractal Dimension (HFD) and k-NN, achieving 70.09% accuracy for pronation and 69.22% for supination.Ieracitano (2022) applied CNN, achieving up to 90.50% accuracy in a two-class problem. Aydın (2023) combined Katz's fractal dimension (KFD) and SVM, reaching 96.47% accuracy in a two-class task. Makouei and Uyulan (2023) used a hybrid 1D CNN-LSTM model, achieving 75.8% accuracy on five classes. Our study applied VB-MFED with KNN, achieving 85.33% accuracy on five classes using 61 channels and 83.28% with four

channels. The comparison highlights the impact of feature extraction methods and classifier selection on EEG-based BCI performance.

4.3. Discussions

This study focused on classifying attempted hand movements from EEG signals using two distinct feature extraction techniques: the Hadamard basis with the Savitzky-Golay algorithm and the VB-MFED method. The analysis was performed with 4 and 61 EEG channels, and two distinct time windows: [WOI = 0.5 to 1.5 seconds] and [WOI = -2 to 3 seconds]. The classifiers employed in the study were multi-class SVM, KNN, FLDA, and sLDA, with 10 participants aged 20 to 69 with SCI.

The analysis of various classifiers using the Hadamard basis for feature extraction to classify attempted hand movements across EEG data recorded from four EEG channels, with a WOI from 0.5 to 1.5 seconds, revealed that the sLDA classifier achieved the highest accuracy, demonstrating its superior performance in this configuration. The FLDA classifier followed closely, reflecting moderate effectiveness. In contrast, KNN achieved the lowest accuracy, while SVM performed slightly worse, suggesting limited classification capabilities for these two models.

Further investigation into the Hadamard basis for feature extraction across different EEG channel configurations (61 channels) and WOIs showed notable variations in classification performance. In the configuration with 61 channels and a WOI from 0.5 to 1.5 seconds, sLDA outperformed the other classifiers, achieving the highest average accuracy. FLDA followed closely with slightly higher accuracy than KNN, which obtained the lowest. SVM recorded the lowest average accuracy, emphasizing its reduced effectiveness in this setup. These findings suggest that sLDA consistently performs better in more complex configurations, potentially due to its ability to capture more discriminative features in the data.

An additional analysis of the Hadamard basis for feature extraction in the classification of attempted hand movements using data recorded from four EEG channels, with a WOI spanning from -2 to 3 seconds, revealed distinct classifier performance. FLDA achieved the highest average accuracy, outperforming the other classifiers. The sLDA classifier followed closely behind, while SVM recorded a lower performance. KNN achieved the lowest accuracy. This suggests that FLDA and sLDA classifiers, which rely on linear discriminants, may better capture relevant features within this extended time window, whereas SVM and KNN struggle to identify key movement-related information.

When the analysis was extended to data recorded from 61 EEG channels with the same WOI of -2 to 3 seconds, the sLDA classifier again led with the highest average accuracy.

FLDA followed with a relatively strong performance, while KNN recorded a lower accuracy and SVM performed the worst. These results further highlight the consistent superior performance of sLDA and FLDA in capturing neural activity associated with attempted hand movements, while KNN and SVM demonstrated limited effectiveness in the more intricate 61-channel configuration.

The results indicate that while sLDA and FLDA excel across various EEG channel configurations and time windows, KNN and SVM show reduced effectiveness, especially in more complex setups. This suggests that linear discriminant analysis techniques such as sLDA and FLDA may be more effective for extracting relevant features of attempted hand movements in EEG data, while further optimization may be necessary for KNN and SVM classifiers to improve their performance.

In contrast, the analysis of the VB-MFED feature extraction method for classifying attempted hand movements across four EEG channels within a WOI of 0.5 to 1.5 seconds showed that the SVM classifier achieved the highest accuracy, followed by KNN. FLDA recorded a strong performance, while sLDA performed somewhat lower. These findings suggest that SVM outperforms the other classifiers significantly in this configuration, while KNN, FLDA, and sLDA still perform reasonably well. The performance gap between SVM and the other classifiers indicates that SVM's ability to capture relevant features is significantly stronger in this setup.

When the analysis was extended to 61 EEG channels within the WOI of 0.5 to 1.5 seconds, SVM maintained the highest accuracy, with FDA performing moderately well, followed by KNN and sLDA. These results highlight that while SVM outperformed the other classifiers, all models demonstrated a decrease in accuracy compared to the four-channel configuration. The relatively strong performance of SVM suggests that it is effective in capturing movement-related features, but further refinements in model optimization are necessary to achieve better accuracy.

In a broader analysis of attempted hand movements using a WOI from -2 to 3 seconds, KNN achieved the highest accuracy, closely followed by SVM. FLDA and sLDA recorded significantly lower accuracies. These results suggest that KNN and SVM are more effective at identifying EEG patterns associated with attempted hand movements, especially when extended time windows are considered. In the 61-channel configuration, KNN achieved the highest accuracy, followed by SVM, with FLDA and sLDA recording much lower accuracies. The strong performance of KNN and SVM underscores their suitability for EEG classification tasks, although the limited performance of FLDA and sLDA in complex data configurations calls for further investigation into their limitations and potential improvements.

Overall, these findings suggest that while linear discriminant analysis techniques (sLDA and FLDA) perform well across various EEG configurations, non-linear classifiers such as KNN and SVM show greater potential in more complex setups. Further exploration of feature engineering, signal preprocessing, and hyperparameter tuning could lead to significant improvements in classification accuracy.

The comparison between the Hadamard and VB-MFED feature extraction methods clearly highlights the effectiveness of VB-MFED in enhancing classification performance for attempted hand movements from EEG signals. The Hadamard basis, although effective with SVM, produced moderate classification accuracies that were generally lower than those achieved by the VB-MFED method. The VB-MFED technique, on the other hand, significantly boosted classification accuracy across all classifiers, particularly SVM and KNN. The highest accuracies achieved with the VB-MFED method represented a clear leap in performance, showing that VB-MFED captures more meaningful features from the EEG signals that are highly relevant for classifying attempted hand movements. This study emphasizes the importance of selecting appropriate feature extraction techniques for improving the classification of movement-related brain activity, and it suggests that VB-MFED could be a more effective approach than the Hadamard basis for EEG-based classification tasks.

The classification performance achieved in this study was compared to several recent studies that utilized the same EEG dataset but employed different feature extraction and classification approaches. While our study achieved high accuracy with 4 and 61 channels for a five-class problem, some studies reported higher accuracies in two-class classification tasks.

For instance, Aydın (2022, 2023) achieved 70.09% accuracy for pronation and 69.22% for supination using HFD with k-NN, and 96.47% accuracy with SVM combined with Katz's Fractal Dimension (KFD)., and Ieracitano et al. (2022) reported accuracies of over 90% using a CNN for hand-close versus rest and hand-open versus rest tasks. These higher accuracies reflect the reduced complexity of two-class classification tasks compared to the more challenging multi-class classification problem tackled in this study.

Compared to the five-class classification study by Ofner. (2019), which achieved 45% accuracy using sLDA within a discriminative spatial pattern (DSP) framework, our approach demonstrated a significant improvement. This suggests that MRCP-based feature extraction paired with SVM offers a more effective strategy for multi-class movement classification.

Furthermore, our results outperformed the hybrid 1D CNN-LSTM model proposed by Makouei and Uyulan (2023), which achieved an accuracy of 75.8% for five-class classification, reinforcing the robustness of our method in handling complex EEG datasets.

Although the two-class studies achieved higher accuracies, it is important to note that they addressed simpler classification tasks, such as distinguishing between hand movements and rest, which do not fully capture the complexity of multi-class movement intention decoding.

Our study focused on a five-class problem, which introduces greater variability in EEG signals and presents more realistic challenges for BCI applications. This difference highlights the need for robust feature extraction methods, such as the VB-MFED technique used in this study, to improve classification performance in multi-class scenarios.

The findings of this study align with recent research emphasizing the impact of feature extraction techniques on EEG classification performance. For example, (Kabir et al., 2024), highlighted that feature extraction significantly influences machine learning models' accuracy in EEG-based BCIs.

Similarly, (Machavarapu et al., 2014), demonstrated that advanced feature extraction methods improve the classification of MRCPs, particularly in clinical and rehabilitative applications. Our results further support these conclusions by showing that the VB-MFED method can effectively capture meaningful features from EEG signals, improving multi-class classification performance.

Future research could explore hybrid feature extraction approaches that combine the strengths of multiple methods to further enhance classification accuracy.

Additionally, optimizing classifiers through techniques such as hyper-parameter tuning and ensemble learning could improve their performance further, as highlighted by (Jiang and Wang, 2016).

Overall, our findings of this study underscore the importance of selecting appropriate feature extraction methods and classifiers for EEG-based movement intention detection. While multi-class classification tasks present greater complexity than two-class tasks, they are essential for real-world BCI applications, particularly in rehabilitation and assistive technologies for individuals with motor impairments.

5. CONCLUSION

This study analyzed the classification of attempted hand movements from EEG signals using two feature extraction methods: the Hadamard basis with the Savitzky-Golay algorithm and the VB-MFED method. The evaluation was performed across various EEG channel configurations (4 and 61 channels) and two different time WOI. The findings highlight the importance of feature extraction and classifier selection in EEG-based movement classification.

The results demonstrate that the VB-MFED technique outperforms the Hadamard basis, particularly when paired with non-linear classifiers such as SVM and KNN. The Hadamard basis was effective in simpler configurations, but struggled with complex neural signals, particularly in setups with high-dimensional data and extended time windows. The VB-MFED method, however, consistently provided better feature extraction, leading to higher classification accuracy. SVM, in particular, excelled in handling the high-dimensional feature space produced by VB-MFED.

Linear discriminant analysis techniques (sLDA and FLDA) performed well in simpler configurations with fewer EEG channels and shorter time windows. However, their performance declined in more complex setups, suggesting that these linear classifiers are more effective in lower-dimensional, linearly separable feature spaces. Non-linear classifiers, such as SVM and KNN, showed more robust performance, especially when optimized with the VB-MFED method, indicating their ability to capture complex neural patterns.

The research also explored the impact of different time windows on classifier performance. For shorter windows ([WOI = 0.5 to 1.5 seconds]), linear classifiers like sLDA and FLDA were more effective, while for longer time windows ([WOI = -2 to 3 seconds]), non-linear classifiers like KNN and SVM outperformed the linear ones. This emphasizes the importance of selecting an appropriate time window for EEG-based movement intention classification, as it significantly influences the classifier's ability to capture relevant neural features.

The study underscores the importance of selecting the right feature extraction method and classifier for EEG-based classification of attempted hand movements. The VB-MFED method, combined with non-linear classifiers like SVM, proved to be the most effective combination. The results also suggest that linear classifiers like sLDA and FLDA may not perform well in more complex, high-dimensional setups, highlighting the need for further optimization of non-linear classifiers like KNN and SVM for these configurations.

Future research should explore hybrid feature extraction techniques that combine the strengths of both the Hadamard basis and VB-MFED. Such an approach could help capture a broader range of relevant features from EEG signals, leading to improved classification performance, especially in individuals with spinal cord injuries or other neurological impairments.

The integration of advanced machine learning algorithms, particularly deep learning approaches such as CNNs and Recurrent Neural Networks RNNs, could further enhance classification accuracy. These models can automatically learn hierarchical features from raw EEG signals, potentially eliminating the need for manual feature extraction and improving real-time performance.

Ensemble learning methods, such as Random Forests or Gradient Boosting, could also be explored to improve classification performance by combining the predictions of multiple classifiers. This approach may help mitigate the risk of overfitting while enhancing the robustness and reliability of EEG-based BCI systems, particularly in real-time applications.

Furthermore, optimizing classifier parameters and advancing signal preprocessing and feature engineering techniques will be critical for improving accuracy. Adaptive filtering techniques that account for individual differences in EEG patterns could reduce noise and enhance relevant neural signals, making the systems more effective in clinical applications where variability between patients is common.

Integrating real-time feedback mechanisms into BCI systems is essential for their practical use in neurorehabilitation. By continuously adapting to the evolving neural patterns of users, these systems could improve motor control, providing immediate feedback to individuals with spinal cord injuries or other motor impairments. This could greatly enhance the effectiveness of rehabilitation and improve the quality of life for users.

In conclusion, this study lays the groundwork for future advancements in EEG-based BCI systems by highlighting key factors such as feature extraction, classifier selection, and the impact of time windows. Continued innovation in these areas will be crucial for developing more accurate and reliable systems for individuals with motor impairments, advancing the field of neuroengineering and neurotechnology.

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