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DETERMINATION AND ANALYSIS OF CHARACTERISTICS OF DYSPHAGIA DISEASE FROM EEG SIGNALS

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SUBMITTED TO THE DEPARTMENT OF ELECTRICAL AND
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AND THE GRADUATE SCHOOL OF ENGINEERING AND SCIENCE
OF ABDULLAH GUL UNIVERSITY
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
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By

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ABSTRACT

DETERMINATION AND ANALYSIS OF CHARACTERISTICS OF DYSPHAGIA DISEASE FROM EEG SIGNALS

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Ph.D. in Electrical and Computer Engineering
Advisor: Prof. Bülent YILMAZ
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Dysphagia is a swallowing disorder that is usually associated with neurological diseases and negatively affects the quality of life, especially in elderly individuals. This study investigates the neurophysiological analysis of swallowing and motor imagery processes using EEG data and how this data can be used in dysphagia rehabilitation. Different experimental paradigms, such as natural swallowing, induced saliva swallowing, induced water swallowing, and induced tongue protrusion, were used in the experiments conducted on 30 right-handed individuals. Techniques such as Independent Component Analysis (ICA), Empirical Mode Decomposition (EMD), band-pass filtering, and Common Spatial Pattern (CSP) analysis were applied in the preprocessing of the data. These preprocessing methods provided a more accurate analysis by reducing the noise in the EEG data. The differences between the resting and imagery stages were clearly separated in the classification tasks performed with traditional machine learning techniques and deep learning methods. In addition to ensemble-based algorithms such as Random Forest, AdaBoost, and Bagging, Convolutional Neural Networks (CNN) from deep learning methods were also applied. In addition, the multi-scale spatial attention network (MS-SAN) model distinguished neurophysiological differences between motor imagery and resting states, especially in delta and theta frequency bands, with high accuracy. The results show that detecting motor imagery and resting stages with EEG data has great potential in dysphagia treatment and motor rehabilitation applications. This study highlights the potential of EEG-based brain-computer interface (BCI) technologies, machine learning, and deep learning methods in dysphagia rehabilitation. It reveals the importance of research in this area for clinical applications.

Keywords: Electroencephalography, Machine Learning, Deep Learning, BCI, Swallowing

ÖZET

EEG SİNYALLERİNDEN DİSFAJİ HASTALIĞININ KARAKTERİSTİKLERİNİN BELİRLENMESİ VE ANALİZİ

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Disfaji, genellikle nörolojik hastalıklarla ilişkilendirilen ve özellikle yaşlı bireylerde yaşam kalitesini olumsuz yönde etkileyen bir yutma bozukluğudur. Bu çalışma, EEG verileri kullanılarak yutma ve yutmayı hayal etme süreçlerinin nörofizyolojik analizini yapmayı ve bu verilerin disfaji rehabilitasyonunda nasıl kullanılabileceğini araştırmaktadır. Otuz adet sağ elini kullanan birey üzerinde gerçekleştirilen deneylerde, doğal yutma, indüklenmiş tükürük yutma, indüklenmiş su yutma ve indüklenmiş dil dışarı çıkarma gibi farklı deneysel paradigmlar kullanılmıştır. Verilerin ön işlenmesinde Bağımsız Bileşen Analizi (ICA), Empirik Mod Ayrıştırma (EMD), bant geçiren filtreleme ve Ortak Uzamsal Desen (CSP) analizi gibi teknikler uygulanmıştır. Bu ön işleme yöntemleri, EEG verilerindeki gürültüyü azaltarak daha doğru bir analiz sağlamak amacıyla kullanılmıştır. Geleneksel makine öğrenmesi teknikleri ve derin öğrenme yöntemleriyle yapılan sınıflandırma görevlerinde, dinlenme ve hayal etme evreleri arasındaki farklar belirgin bir şekilde ayrılmıştır. Random Forest, AdaBoost ve Bagging gibi topluluk tabanlı algoritmaların yanı sıra, derin öğrenme yöntemlerinden Konvolüsyonel Sinir Ağları (CNN) da uygulanmıştır. Ayrıca, çok ölçekli mekânsal dikkat ağı (MS-SAN) modeli, özellikle delta ve teta frekans bantlarında hareketi hayal etme ile dinlenme durumları arasındaki nörofizyolojik farkları yüksek doğrulukla ayırt etmiştir. Sonuçlar, hareketi hayal etme ve dinlenme evrelerinin EEG verileriyle tespit edilmesinin disfaji tedavisinde ve motor rehabilitasyon uygulamalarında büyük bir potansiyel taşıdığını göstermektedir. Bu çalışma, EEG tabanlı beyin-bilgisayar arayüzleri (BBA) teknolojilerinin, makine öğrenimi ve derin öğrenme yöntemlerinin disfaji rehabilitasyonundaki potansiyelini vurgulamakta ve bu alandaki araştırmaların klinik uygulamalar açısından önemini ortaya koymaktadır.

Anahtar kelimeler: Elektroensefalografi, Makine Öğrenmesi, Derin Öğrenme, BBA, Yutkunma

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LIST OF ABBREVIATIONS

ANOVA	Analysis of Variance
AR	Autoregressive
AUC	Area Under the Curve
BCI	Brain Computer Interface
BMI	Brain Machine Interface
CAR	Common Average Reference
CSP	Common Spatial Pattern
CWT	Continuous Wavelet Transform
DWT	Discrete Wavelet Transform
ECG	Electrocardiogram
ECoG	Electrocorticography
EEG	Electroencephalography
EMG	Electromyography
ERD	Event-Related Desynchronization
ERPs	Event-Related Potentials
ERS	Event-Related Synchronization
FFT	Fast Fourier- Transform
FN	False Negative
FP	False Positive
ICA	Independent Component Analysis
ITR	Information Transfer Rate
KNN	K-Nearest Neighbors
LDA	Linear Discriminant Analysis
MEG	Magnetoencephalography
MI	Motor Imagery
MRPs	Motor-Related Potentials
ROC	Receiver Operating Characteristic
STFT	Short-Time Fourier Transform
SVM	Support Vector Machines
TN	True Negative
TP	True Positive



To my lovely family

Chapter 1

Introduction

1.1 Motivation

1.1.1 Dysphagia

Dysphagia is defined as difficulty swallowing and is often associated with neurological diseases, including stroke, Parkinson's disease, cerebral palsy, and head and neck cancer [1], [2]. This condition manifests itself with symptoms such as difficulty swallowing food or liquids, choking, and coughing. It can lead to serious complications such as malnutrition, dehydration, immunosuppression, airway obstruction, and pneumonia [2]. Dysphagia is particularly common in the elderly and individuals with neurological diseases and is responsible for more than 60,000 deaths each year [3]. Dysphagia treatment also increases healthcare costs, including additional charges such as using feeding tubes. Dysphagia costs the healthcare system billions of dollars annually. This section will examine the neurological sources of dysphagia, the effects of various diseases, and treatment options [4].

1.1.2 Neurological Factors

Dysphagia is a condition that many different factors can cause, and genetic defects and factors play an important role. Neurological communication can affect the coordination and reflexes of the swallowing muscles, leading to dysphagia [5]. For example, it develops because of damage to brain tissue due to lack of oxygen and nutrition, and the swallowing centers in the brainstem can be affected, causing loss or delay of the swallowing reflex. The subsequent negativities, adverse effects of living conditions, prolonged feeding time, and increased risk of aspiration are important problems [6]. Similarly, Parkinson's disease, as a progressive treatment disease, narrows the coordination of the swallowing muscles; this leads to the weakening of tongue

movements and pharyngeal reflexes during swallowing. Dysphagia in Parkinson's patients is common, with the risk of food escaping from the airway, which can be changed [7]. The characteristics of motor forces lead to the weakening of muscle strength in amyotrophic lateral sclerosis (ALS), disrupting the function of the swallowing muscles and causing dysphagia. In ALS patients, the risk of the swallowing reflex weakening and the food escaping from the airway increases, and the progression of dysphagia symptoms, can lead to serious nutritional problems [8].

Multiple sclerosis (MS) is a disease that develops with discharge in the central nervous system, and this can affect the swallowing muscles and cause dysphagia. Muscle spasms and coordination problems are frequently seen in MS patients during swallowing, swallowing reflexes increase, and difficulties are experienced in the passage from the mouth to the pharynx [9]. Traumatic brain injuries can affect the swallowing reflex by causing damage to the brain tissue. Dysphagia after these injuries can usually occur due to damage to the swallowing centers and may require nutritional support due to loss of swallowing abilities[10].

Therapeutic regression and motor control problems such as Alzheimer's disease can also disrupt swallowing reflexes and lead to difficulties in swallowing food safely, leading to difficulties in swallowing food [11]. Other neurodegenerative diseases can also cause dysphagia in a similar way. This type of disease affects the infection through swallowing and causes dysphagia in individuals, which can cause serious health problems.

1.2 Anatomy and physiology of swallowing

1.2.1 Swallowing Process

Swallowing is presented as a complex neuromuscular process that starts from the mouth and continues to the stomach. This process requires much anatomical care and coordination of cranial nerves and simultaneous control of voluntary and involuntary stages [12]. For swallowing to occur successfully, perfect harmony is required between the mouth, throat, esophagus, and these structures' existing muscle groups and nerves. The swallowing process consists of three main stages: oral, pharyngeal, and esophageal phases. The swallowing process begins with preparing food in the mouth into a suitable swallowing bolus. In this stage, it is a voluntary presentation in which it is chewed and turned into a bolus [13]. Chewing occurs with the up-down and sideways movement of

the mandible (lower jaw). These movements are provided by the temporomandibular joint (jaw joint). The tongue has a central role in the sources of the bolus and in pushing it towards the oral features. The tongue, especially in the posterior part, is essential in directing the bolus to the pharynx. This process is coordinated by the tongue muscles controlled by the hypoglossal nerve (CN XII). The salivary glands (parotid, submandibular, and sublingual glands) secrete saliva to soften the bolus and provide lubrication during chewing. Exhalation also plays a role in the initial phase of digestion. The cheek muscles and the orbicularis oris muscle ensure that the food remains between the teeth and is chewed properly in the mouth. These muscles are controlled by the facial nerve (CN VII). At the end of the oral phase, the back of the tongue pushes the bolus upwards and backward together with the palate, sending it to the pharynx [14], [15], [16]. Here, the swallowing reflex is initiated, and the involuntary phases come into play. The most complex phase of swallowing, the pharyngeal phase, begins with transmitting the bolus to the pharynx and is completely reflexive. This phase is managed by the swallowing centers in the medulla oblongata. The soft palate closes the nasal cavities, preventing sweetness from escaping from the nose. This movement is controlled by the vagus nerve (CN X). The epiglottis (laryngeal valve) prevents food from escaping the respiratory tract by closing the upper part of the larynx. This movement protects your clothes by avoiding the risk of aspiration. The muscles of the pharynx, especially the pharyngeal constrictor muscles, contract to push the bolus from the pharynx into the esophagus. These contractions are controlled by the glossopharyngeal nerve (CN IX) and the vagus nerve (CN X). During the pharyngeal phase, breathing temporarily stops. This coordination between breathing and swallowing is achieved by close communication between the respiratory and swallowing centers of the brain. Correct regional timing during this period, opportunities such as the aspiration complex [17], [18], [19]. The final stage of the swallowing process, the esophageal phase, was involuntary, in which the bolus was transported from the esophagus to the stomach [20]. During this stage, the peristaltic movements of the muscles in the esophagus ensure that the bolus moves toward the stomach. The esophagus is a muscular tube approximately 25-30 cm long [21]. There are separated muscles in the upper part and smooth muscles in the lower part. These muscles contract rhythmically to continue the bolus into the stomach. The flaps of the esophagus are closed by sphincter muscles. The upper esophageal sphincter (UES) allows the bolus to open from the pharynx to the esophagus, while the lower esophageal sphincter (LES) allows the bolus to reach the stomach and prevents the stomach contents from

escaping into the esophagus. The esophageal phase is controlled by the autonomic nervous system. In harmony with the central nervous system, peristaltic movements in the esophagus allow the bolus to advance toward the stomach. The opening and closing of the LES at the right time prevents stomach acid from escaping into the esophagus [22], [23].

1.2.2 Regulation of Swallowing Process in the Brain and Nervous System

The swallowing process is a complex neuromuscular process controlled by the perfect coordination of the central and peripheral nervous systems. Both cortical and brainstem structures play an active role in different stages of swallowing [24]. During swallowing, voluntary and involuntary movements are realized by the coordinated work of brain regions. Among these structures, especially the motor cortex, somatosensory cortex, basal ganglia, brainstem (medulla oblongata), and various cranial nerves play critical roles [25]. While swallowing is provided by precise control of these structures, possible disorders can lead to clinical problems such as dysphagia. The beginning of the swallowing process is controlled voluntarily, and the cortex comes into play at this stage. The initiation of swallowing is carried out, especially by cortical structures and motor centers in the brain. The primary motor cortex (M1) controls the voluntary movements of the mouth, tongue, and pharynx muscles [26]. The motor cortex contains neurons that manage the muscle groups that initiate swallowing. Here, the motor neurons of the muscles critical for swallowing, such as the lips, tongue, and jaw, are located. These motor commands are transmitted to the muscles via cranial nerves [27], [28]. The premotor and anterior cingulate cortex are critical in planning and initiating swallowing. The premotor cortex provides timing and regulation of motor movements, while the anterior cingulate cortex is known as an area that manages the initiation of motor activity. The somatosensory cortex processes sensory input from the mouth, tongue, and pharynx. This increases the sensitivity of swallowing reflexes and helps the bolus pass safely into the esophagus [29]. The brainstem (medulla oblongata) and pons play a critical role in the involuntary stages of swallowing, especially in the pharyngeal and esophageal phases. The brainstem is the center that regulates the involuntary stages of swallowing, which occur reflexively. These stages begin with the swallowing reflex and are completed in a very short time. Swallowing centers located in the brainstem ensure the timed contraction and relaxation of the correct muscle groups during swallowing. The swallowing center located in the medulla oblongata controls muscle groups via cranial nerves and initiates

the involuntary swallowing reflex. This center is a region where involuntary muscle movements from the mouth to the esophagus are controlled. This center in the brainstem processes afferent (sensory) and efferent (motor) signals, ensuring that the swallowing reflex is performed precisely [19], [25]. The Nucleus Tractus Solitarius (NTS) is the center where sensory information is collected to initiate the pharyngeal and esophageal phases. The NTS receives sensory information from the cranial nerves and transmits it to the motor neurons in the medulla oblongata. It is considered the most critical structure that initiates and regulates the reflex stages of swallowing [30]. The Nucleus Ambiguus (NA) is the region where the motor neurons that control the contractions of the pharyngeal muscles are located. The sensory inputs the NTS receives are transmitted to the NA, and the pharyngeal muscles contract with the motor commands coming from here. The brainstem also ensures that respiration and swallowing work are in harmony. During swallowing, respiration stops for a short time (apnea period), preventing the bolus from escaping into the respiratory tract [31]. Cranial nerves play a decisive role in the swallowing process. The trigeminal nerve (CN V) is important for the motor fibers controlling the chewing muscles and the transmission of sensory inputs in the mouth. The facial nerve (CN VII) controls the muscles around the mouth and ensures the functioning of the salivary glands [32]. The glossopharyngeal nerve (CN IX) transmits sensory information from the back of the tongue and the pharynx region and controls the contraction of the pharyngeal muscles. The vagus nerve (CN X) regulates the pharyngeal and esophageal phases. The vagus nerve initiates contractions in the pharynx and esophagus, ensuring the bolus is directed correctly to the stomach. This nerve also governs the transition between breathing and swallowing [17], [33].

1.3 Management and Treatment Approaches for Dysphagia

Dysphagia can seriously affect an individual's health, nutrition, and quality of life. Dysphagia treatment requires an individual approach to the patient's condition and is usually carried out by a multidisciplinary team [34].

Swallowing therapy is one of the most important components of dysphagia treatment and includes methods such as exercises, technical modifications, and sensory stimulation to strengthen the swallowing muscles of individuals. In addition, strategies

such as changing the head position or using audible stimuli can be applied to improve swallowing skills [35], [36]. Dietary modification aims to make the swallowing process safer by adjusting the consistency of food and drinks. Changes in consistency, such as pureed foods, liquid diets, or gelled drinks, reduce the risk of aspiration and facilitate the swallowing process [37].

Nutritional support is important to prevent malnutrition, especially in individuals whose swallowing ability is severely affected. In some cases, enteral feeding methods (nasogastric or PEG tubes) may be required [38]. For the effectiveness of the treatment process, it is necessary to create a nutrition plan that will adapt to the individual's needs and preferences. In addition, neurological rehabilitation processes also help develop motor skills and strengthen the muscles that affect the swallowing process. Methods such as physical therapy and occupational therapy offer strategies to improve swallowing skills by increasing the overall functionality of individuals [39]. Finally, in some cases, drug therapy can help improve swallowing function with muscle relaxants or medications for neurological disorders [40]. However, medication use should be customized for everyone and supervised by a doctor. A multidisciplinary teamwork consisting of speech therapists, nutritionists, physical and occupational therapists, and doctors is necessary for a successful treatment process in dysphagia management [41].

1.4 Techniques for Studying Neurological Origins of Swallowing and Dysphagia

Swallowing is a complex motor action requiring multiple muscles and nerves to work harmoniously. Dysphagia is an impairment in swallowing ability and is often associated with neurological diseases. Techniques used to understand the neurological origins of swallowing and dysphagia are critical for both the evaluation of these processes and the development of treatment strategies [5]. Different imaging and electrophysiological methods are used to understand the neurological mechanisms associated with swallowing and dysphagia. Functional magnetic resonance imaging (fMRI) is a safe and non-invasive technique to examine how the human cerebral cortex processes information during specific tasks. It is based on the effects of changes in blood flow, blood volume, and oxygenation on the magnetic resonance signal. Increased oxygen consumption in active brain regions reduces deoxyhemoglobin levels, and these changes

can be visualized. It offers high spatial resolution (2 mm or less) and allows detailed analysis of cortical brain structures. However, it has limitations such as being expensive, difficulty monitoring short-term swallowing movements, and the magnetic field causing side effects in some individuals. This method examines the neurological basis of swallowing and evaluates the effects of treatment interventions [42], [43].

Positron emission tomography (PET) is an imaging method that indirectly measures brain activity using radioactive tracers. It detects changes in local blood flow or glucose metabolism in the brain and evaluates cortical activation, assuming that neural activity is related to energy consumption. However, it is invasive because it requires intravenous radioisotope injections, carries a risk of radiation exposure, and has access limitations due to its high cost. It is an effective tool for mapping brain regions active during swallowing and monitoring recovery processes after dysphagia treatment [44], [45].

Magnetoencephalography (MEG) is a method that evaluates neural activity by measuring magnetic fields produced by the brain. It detects magnetic fields created by the electrical activity of cortical pyramidal cells. It offers high-time resolution (at the millisecond level) and real-time analysis. It is also a non-invasive and radiation-free method. However, due to its high cost and limited ability to measure activity in deep brain structures, there are difficulties in its widespread use [46]. MEG, which allows monitoring of cortical activity during the swallowing process at the millisecond level, is quite effective in understanding the neurological basis of fast and short-term motor actions such as swallowing [47].

Near-infrared spectroscopy (NIRS) is a non-invasive technique that measures changes in oxyhemoglobin (oxy-Hb) and deoxyhemoglobin (deoxy-Hb) concentrations. It uses light absorption at different wavelengths to determine changes in cortical blood flow. It has the advantages of being portable, cost-effective, and usable in the home environment. However, its limitations include its low spatial resolution and inability to measure activity in deep brain structures [48]. It evaluates cortical activity by measuring oxyhemoglobin (oxy-Hb) and deoxyhemoglobin (deoxy-Hb) concentration changes in cerebral vessels during swallowing [49].

Electromyography (EMG) measures the electrical activity of muscles and evaluates neuromuscular functions. It detects the electrical activity resulting from motor neurons' stimulation of muscle fibers. Surface EMG measures the activity of superficial muscles with electrodes placed on the skin; needle EMG is applied with the help of electrodes placed inside the muscle to examine deep muscle activity. While needle EMG can cause

discomfort due to its invasiveness, surface EMG is insufficient to measure deep muscles. It provides information about the functioning of the muscles and nervous system by measuring the electrical activity of the muscles during swallowing. EMG measures the onset time of the swallowing reflex and determines muscle dysfunctions caused by dysphagia.

Electroencephalography (EEG) is an electrophysiological method that monitors real-time brain activity. It records the brain's electrical activity via electrodes placed on the scalp. During different tasks, certain EEG wave frequencies become dominant. EEG is widely preferred in clinical research due to its high time resolution and low cost. It offers the opportunity to monitor the electrical changes occurring in cortical regions during swallowing with high resolution. While it provides important information in understanding the neurological processes of swallowing, it has disadvantages, such as low spatial resolution and sensitivity to environmental factors. Each of these methods provides an important basis for understanding the neurological origins of swallowing and dysphagia processes. The combined use of the methods allows for more comprehensive and effective results in both diagnostic and therapeutic processes [50], [51].

1.5 Review of Recent Studies on Dysphagia and Swallowing Mechanisms

Dysphagia is a condition that usually occurs due to neurological diseases, traumatic injuries, or aging and can seriously affect the quality of life of individuals. Recent studies aimed at understanding the physiological and neural processes of swallowing show that this complex process is organized at both cortical and subcortical levels and is shaped by environmental factors. EEG (electroencephalography), NIRS (near-infrared spectroscopy), and other neuroimaging methods are frequently used to examine the details of swallowing mechanisms. Considering these studies, current findings on swallowing mechanisms and dysphagia are summarized below: Swallowing is a complex motor process that requires coordination of cortical centers, the brainstem, and the peripheral nervous system. Huckabee et al. (2003) identified the early Bereitschaftspotential (BP) component reflecting motor planning and execution during voluntary swallowing [52]. Studies have shown that swallowing is associated with bilateral cortical activity and that this process has no obvious lateralization. Similarly,

Hiraoka (2004) demonstrated differences in neural activity between dry and water swallowing tasks, demonstrating a pattern of brain activity that varies according to the type of swallow [53].

Whether swallowing is voluntary or commanded has a significant effect on neural activity. Nonaka et al. (2009) found significant differences in cortical potentials (CNV and BP) between volitional and commanded swallows. Volitional swallowing produced an earlier onset and higher amplitude cortical activity [54]. These findings indicate that voluntary swallowing requires greater motor control and planning.

A study by Cuellar et al. (2016) found a significant sensorimotor integration in cortical control of pharyngeal and esophageal stages during repetitive swallowing tasks. Event-related desynchronization (ERD), especially seen in the mu and beta bands, indicates that cortical activity is intensified during swallowing [55].

During swallowing, bolus viscosity, volume, and head position significantly affect cortical activity and brain network organization. A series of studies by Jestrovic et al. (2014, 2015, 2016) have shown that fluid viscosity and head position (neutral or chin-tuck) cause changes in brain networks with small-world characteristics during swallowing. For example, the fact that more neural effort is required during swallowing honey-like liquids has been proven by stationarity analyses of EEG signals. Furthermore, changing head positions led to significant changes in brain network structures during swallowing [56], [57], [58], [59].

Koganemaru et al. (2021) examined cortico-muscular coherence during swallowing with water and found significant connections in theta, alpha, and beta bands in frontal and parietal regions [60]. These findings emphasize the importance of cortical and muscle activity coordination during swallowing.

Motor imagery (MI) and neurofeedback stand out as innovative strategies for dysphagia rehabilitation. Kober et al. (2015b) showed that NIRS-based neurofeedback training improved cortical activation, especially by increasing oxygenated hemoglobin (Oxy-Hb) levels. Kober et al. (2015a) reported that patients with dysphagia showed different hemodynamic responses than healthy individuals in motor execution and motor imagery tasks [61], [62]. The high activity observed in the inferior frontal gyrus suggests that the brain activates compensatory mechanisms during dysphagia. EEG-based brain-computer interface (BCI) systems have become an important tool in understanding the neural activities of swallowing control. Studies by Yang et al. (2012-2015) developed models that can classify between motor imagery and motor execution. These models

successfully detected and classified swallowing-related signals in both healthy individuals and patients with dysphagia [63], [64], [65], [66], [67], [68], [69], [70]. These studies have great potential for developing supportive technologies, especially for individuals with neurological damage. In recent years, how brain networks are organized and changed during swallowing has also been a research subject. Jestrovic et al. (2018) examined the relationship between the frequency bands (Delta, Theta, Alpha, Beta, Gamma) of brain networks during swallowing of different volumes of water [71]. The results show that distractions and different bolus volumes during swallowing cause significant changes in brain networks.

Recent studies have revealed how complex and multidimensional the swallowing process is. The study of cortical mechanisms and brain networks shows that swallowing is not just a simple reflex but rather requires a high level of motor control and sensorimotor integration. Research in this area aims better to understand the effects of individual differences and environmental factors, develop new rehabilitation strategies, and integrate technologies such as BCI into clinical practice. In the future, it is expected that these studies will be further adapted to the clinical field and individual-focused treatments will be developed.

1.6 Directions and Goals

Dysphagia is a health problem that usually originates from neurological causes and seriously complicates the daily lives of individuals. Swallowing is a critical function that directly affects nutrition, respiration, and quality of life [72]. However, the diagnosis and treatment of dysphagia are challenging due to the limitations of current methods. Therefore, EEG is believed to be a valuable technique for analyzing a person's swallowing. In addition to identifying the brain regions involved in swallowing activity, the interactions between brain regions during swallowing and their investigation with different signal processing approaches can provide important information about the neurological origins of swallowing using EEG [64]. Currently, limited studies have been conducted on EEG data during swallowing. Therefore, many questions remain and need to be answered to provide a better understanding of brain activity during swallowing using different swallowing experimental paradigms and signal-processing approaches. For example, what are the stationarity characteristics of EEG signals in various swallowing experimental paradigms? How can signal processing methods help? How effective are

time-frequency characteristics in understanding swallowing intention? What are the differences between various swallowing brain networks? How do topological features differ among these networks? How can information extraction methods be developed to understand swallowing intention? Answers to these questions will provide a basic roadmap for identifying and analyzing neurophysiological features associated with dysphagia from EEG signals.

The main research question of this study is, "How can the neurophysiological features of dysphagia be identified and analyzed using EEG signals?" To answer this question, a detailed examination will be conducted on how EEG signals reflect brain activities during swallowing. The research will focus on converting EEG data into meaningful results and how these data can contribute to diagnosis and treatment processes. EEG signals provide the opportunity to directly record motor and sensorimotor activities that occur in the brain during swallowing. This study aims to detect brain activity patterns that occur during swallowing in healthy individuals through EEG signals.

EEG is less costly compared to other methods, such as fMRI and PET, and since it has high time resolution, it can capture brain activities during swallowing more accurately. This study aims to examine brain activity related to swallowing using EEG signals and, as a result, to provide a more accurate diagnosis of dysphagia patients. In addition, it aims to develop effective treatment methods by deepening the neurophysiological understanding of the swallowing process. The intention to swallow is associated with activity observed in certain brain regions before swallowing begins. EEG signals can be used to detect brain activity in the early stages of swallowing intention. Different experimental paradigms will be designed in this direction, and different signal-processing methods will be discussed. In addition, EEG signals will be analyzed using machine learning and deep learning algorithms, and the best classification methods will be determined. Studies will be carried out on how EEG data can be used in the early diagnosis of dysphagia patients and in monitoring their treatment processes.

1.7 Dissertation Organization

This thesis is divided into 7 chapters. Chapter 2 deals with EEG-based BCI (Brain-Computer Interface) technology that examines the applicability of EEG systems to detect movement intentions in individuals with motor disorders. That is, it provides the necessary background information on the basics of EEG and the research done on EEG

studies related to swallowing. Chapter 3 covers the experimental paradigms used in swallowing. Chapters 4-6 present the results and discussions of the studies done on the experimental paradigms detailed in Chapter 3:

- Chapter 4 deals with the in-depth study of swallowing experimental paradigms with EEG signals using statistical analysis and traditional machine learning methods.
- Chapter 5 focuses on applying different preprocessing methods and classifying EEG signals using the deep learning model by performing time-frequency transformation.
- Chapter 6 focuses on obtaining topographic images of EEG signals and a custom designed deep learning model.

Finally, Chapter 7 will summarize the findings and conclusions of the thesis and provide suggestions for future work.



Chapter 2

Background

2.1 Introduction to Brain-Computer Interfaces

Brain-computer interfaces (BCIs) are advanced technology systems that aim to create a direct communication path between the human brain and external devices. These systems interpret the brain's neural activity, allowing users to control devices or software without using traditional neuromuscular pathways in their bodies. This technology is a major revolution in terms of interacting and communicating with their environment, especially for individuals with severe physical disabilities such as amyotrophic lateral sclerosis (ALS), spinal cord injuries, or paralysis [73]. The development of Brain-Computer Interfaces began in the 1960s and 1970s. During this period, pioneering researchers such as José Delgado conducted important studies using brain implants and electrical stimulation to control animal behavior [74]. In the 1970s, Vidal and Wolpaw pioneered studies showing that brain signals could be used for communication and control using EEG [75]. The 1980s and 1990s were years of progress with the development of simple EEG-based BCIs. These systems provided basic applications such as writing and cursor control, especially for disabled individuals. In the 1990s, studies on invasive BCI technologies gained momentum and focused on improving signal quality by placing electrodes inside the brain [76].

In the early 2000s, projects such as BrainGate became a turning point in this field by allowing paralyzed individuals to control computer cursors and robotic arms. In addition, uses for gaming and artistic applications have also developed [77].

Recently, methods such as functional near-infrared spectroscopy (fNIRS) and magnetoencephalography (MEG) have been investigated as alternatives to non-invasive methods. These technologies have expanded their application areas by offering more options for users [78], [79]. In addition, with the introduction of consumer-friendly EEG devices, BCI technologies have begun to be used in everyday applications such as gaming

and relaxation [73]. Companies like Neuralink, founded by Elon Musk, stand out with their high-bandwidth BCI development work. These studies offer a wide range of potential uses in both medical and non-medical applications.

BCI systems, as a field fed by disciplines such as neuroscience, computer engineering, biomedical engineering, and psychology, offer innovative solutions with features such as real-time interaction and adaptive learning. These systems analyze users' neural activities, convert brain signals into meaningful commands, and enable communication with external devices through these commands.

BCI systems work through four main processes:

1. Signal Collection: Electrical activities from the brain are collected via electrodes or sensors.
2. Signal Processing: The collected data is filtered, and meaningful components are obtained.
3. Classification of Commands: The processed signals are converted into commands representing user intentions.
4. Interaction with Environmental Devices: These commands are used to control external systems such as prosthetics, robotic devices, or software.

The application areas of brain-computer interfaces are quite wide. In the medical field, applications such as neuroprosthetics that restore movement functions, rehabilitation systems after strokes, and communication devices for individuals with speech impairments come to the fore. In non-medical fields, innovative solutions such as enriching the user experience in gaming and virtual reality systems, developing cognitive tools that increase focus, and optimizing decision-making processes in the military are offered [80].

The potential offered by these technologies also brings with it some challenges, such as the reliability of the signals, user adaptation to the system, and ethical issues. In addition, the need for portable and affordable systems is among the factors that prevent BCIs from becoming available to a broader audience. However, with the continuation of interdisciplinary research, it is anticipated that the impact of BCIs on both technology and human life will increase even more.

The future of BCI technologies will be shaped by innovations aimed at increasing the sensitivity of signals, improving ease of use, and reducing costs. BCIs, which have the potential to revolutionize many areas, from assistive technologies to neurological

research, will continue to be an important tool in improving the quality of life of individuals and learning more about the human brain.

2.2 Signal Acquisition

In Brain-Computer interface (BCI) systems, the signal collection process refers to the methods used to perceive and measure brain activities. In this process, brain signals are recorded by devices and form the basis of the system's operation. The techniques used vary depending on invasiveness level, spatial, and time resolution criteria.

- **Non-invasive Methods**

Non-invasive techniques measure signals from the outside without intervening in the brain tissue and prioritize user comfort:

- **Electroencephalography (EEG):**

EEG records electrical activities on the brain surface through electrodes placed on the scalp. It is widely preferred because of its high portability and low-cost advantages. However, signal quality is limited, and the signal-to-noise ratio (SNR) is low.

- **Functional Near-Infrared Spectroscopy (fNIRS):**

fNIRS measures brain regions' blood flow and oxygenation changes by sending near-infrared light through the scalp. This method offers a low-cost and minimally invasive option, but its time resolution is limited.

- **Functional Magnetic Resonance Imaging (fMRI):**

fMRI indirectly measures brain activity and detects blood flow and oxygenation changes in areas where neuronal activity is present using Blood-Oxygen Level Dependent (BOLD) signals.

It offers high spatial resolution, creating a detailed map of brain functions. It has low time resolution and can usually be used in a laboratory setting with fixed, costly devices.

- **Magnetoencephalography (MEG):**

MEG measures the brain's magnetic field changes and provides high spatial and temporal resolution. However, it has limited use due to the high cost of the device and portability issues.

- **Invasive Methods**

Invasive techniques aim to increase signal quality by placing electrodes directly into the brain tissue. These methods, which require surgical intervention, provide higher sensitivity:

- **Electrocorticography (ECoG):**

ECoG measures brain activity with electrodes surgically placed on the brain's surface. It offers higher spatial and temporal resolution than EEG and is preferred in clinical research.

- **Intracortical Electrodes:**

Microelectrodes are placed directly into the brain tissue and can detect individual neuron activities. They are used in advanced applications due to their high sensitivity but carry high surgical risks.

The quality of the collected signals directly affects the accuracy and performance of the BCI system. Although non-invasive methods are user-friendly, their signal resolution is limited. In contrast, invasive methods provide high resolution but are risky because they require surgical intervention [81].

Significant advances have been made in signal collection processes with the development of portable devices and the widespread use of minimally invasive techniques. These developments make it possible to spread BCI technologies to a wider range of applications and improve the user experience.

2.2.1 Electroencephalogram

Electroencephalography (EEG) is a method used to record the brain's electrical activity over time. EEG measures neuronal electrical activity via electrodes placed on the scalp, representing the sum of the excitatory and inhibitory potentials originating from the brain's cortical surface [82], [83]. EEG measurements are usually performed using the 10-20 international electrode placement system, which allows the electrodes to be placed in a standard manner. This method provides a reliable basis for creating a topographic map of the brain. One of the most important features of EEG is that it responds directly to changes in brain metabolism, which allows immediate observation of metabolic activity in the brain. EEG is widely used in many different areas for clinical and research purposes. In clinical applications, it is an important tool in the diagnosis of epilepsy, sleep disorders, changes in consciousness, coma, and neurological diseases [84]. At the same time, EEG allows the detection of neural disorders while they are still reversible. In the

field of research, it is used to examine cognitive processes, sensory perceptions, and motor functions. For example, movement-related cortical potential (MRCP), which examines cortical activity associated with motor movements, and event-related potentials (ERP) triggered by specific stimuli are examples of research uses of EEG [85], [86].

The main advantages of EEG are:

- **Noninvasive and Cost-Effective:** Since EEG is a noninvasive technique, it is comfortable for patients and is less expensive than other neuroimaging methods.
- **High Time Resolution:** EEG has a time resolution of milliseconds, which allows detailed monitoring of the brain's electrical activity over time.
- **Portability:** Thanks to developing technology, portable EEG devices have become available for research and clinical applications.

EEG signals occur in different frequency ranges controlled by the brain's homeostatic systems [87]. These frequencies are associated with certain brain states:

- **Delta Waves (0.5-4 Hz):** Delta waves have the lowest frequency and are generally dominant during deep sleep.
- **Theta Waves (4-8 Hz):** Theta waves are usually observed during light sleep, meditation, and daydreaming.
- **Alpha Waves (8-13 Hz):** Alpha waves are usually observed in awake and relaxed individuals.
- **Beta Waves (13-30 Hz):** Beta waves occur during a focused and active mental state.
- **Gamma Waves (30-150 Hz):** Gamma waves are associated with higher levels of cognitive processing and conscious awareness.

2.2.2 Types of Neurophysiological Signals in BCI Systems

Event-related potentials (ERPs) are voltage changes observed in EEG waveforms associated with cognitive or sensory-motor events. ERPs are generated by averaging continuous EEG signals corresponding to specific stimuli or events. These waveforms provide important information about broad neural activities such as attention, perception, and motor activity. ERP components are usually determined by polarity (positive or negative) and latency (measured in milliseconds) [88]. For example, a positive polarity ERP seen around 130 ms may be called a P1 and classified as a P310 when classified in latency.

ERP components are usually defined by peak amplitude and latency (stages of cognitive processing). Three distinct time windows are used to detect these peaks, reflecting different stages of cognitive processing. Specific ERP components may vary depending on the experimental design, stimulus type, and cognitive task performed.

Motor-related potential (MRCP), especially EEG signals such as Bereitschaftspotential (BP), are important components reflecting cortical activities associated with motor responses [89]. BP, defined by Kornhuber and Deecke, is a negative potential observed 1–2 seconds before a voluntary motor movement. This potential can be recorded on the skull, and its amplitude varies depending on the motor demands of the task [52]. BP consists of two components: the first component is observed symmetrically in both cerebral hemispheres approximately 1–1.5 seconds before the onset of the movement, while the second component occurs approximately 0.5 seconds before the onset of the movement and is observed in a region opposite to the hemisphere controlling the movement. The first component of BP is thought to be generated in the supplementary motor area (SMA), while the second component is associated with the primary motor cortex. MRCP includes the BP and negative bias components and is used to study cortical activations, especially during motor activities (e.g. swallowing). The high signal-to-noise ratio in EEG signals allows MRCPs to be analyzed effectively and provides valuable information about motor planning and execution.

Also, contingent negative variation (CNV) is another cortical potential observed with EEG [90]. This potential represents a slow negative decay observed between two consecutive tasks or stimuli. MRCPs are associated with motor planning and execution, while CNVs are associated with the prefrontal cortex.

As a result, EEG provides important information for understanding brain activities and is an important tool for examining cortical potentials associated with cognitive and motor processes. The study of components such as ERPs, MRCPs, and CNVs helps us better understand the brain's responses to sensory, cognitive, and motor tasks and offers potential applications for clinical diagnosis and therapeutic interventions.

2.3 Signal Pre-Processing

EEG (Electroencephalography) signals are low-amplitude and low-frequency biological signals. However, these signals are unsuitable for raw analysis due to device

limitations and environmental noise. Various preprocessing techniques are first applied to extract meaningful information from EEG signals [91].

2.3.1 Filtering

Filtering aims to increase analysis accuracy by eliminating unwanted components in EEG signals. Noise, device-induced distortions, and non-physiological signals in the signal are largely eliminated by the filtering process [92]. The types of filters frequently used in EEG analysis are as follows:

Low-Pass Filters

Low-pass filters suppress high-frequency components above a certain cutoff frequency. Since EEG signals generally contain meaningful information between 0.1 Hz and 100 Hz, components above 30-40 Hz are mostly considered noise. These filters effectively eliminate high-frequency noise (e.g., electromagnetic interference) and fast artifacts (e.g., signals resulting from muscle movements) [93].

High-Pass Filters

High-pass filters suppress low-frequency components below a certain cutoff frequency. Low-frequency components in EEG signals are usually caused by the drift effects of devices or environmental slow-varying noise. These types of filters clean low-frequency noise while preserving the basic structure of the signal [94].

Band-Pass Filters

Band-pass filters pass signals within a specific frequency range and suppress components outside this range [95]. They are frequently used in EEG analysis to examine frequency bands such as delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz) and gamma (>30 Hz).

Band-Stop Filters

Band-stop filters suppress a specific frequency range while passing other frequencies. A narrow band stop filter (notch filter) eliminates power line noise,

especially at 50 Hz (or 60 Hz in some countries). This is a common method to prevent EEG devices from being affected by power line interference [96].

2.3.2 Artifact Removal and Data Reliability Enhancement Techniques

Removing unwanted noise (artifacts) from EEG signals and increasing the reliability of the data are critical for accurate analysis. The following methods are the main techniques used to achieve these goals:

Independent Component Analysis (ICA)

ICA removes artifacts from brain activity by separating independent components in EEG signals. This method isolates and removes artifacts such as eye blinks, muscle movements, and environmental effects by demixing the signals [97], [98], [99].

Empirical Mode Decomposition (EMD)

EMD separates the signal into components and allows each mode (intrinsic mode function - IMF) to be analyzed. This technique can be especially effective in removing low-frequency and transient artifacts by separating the signals into nonlinear and time-varying components [100], [101], [102].

Notch Filtering (Narrow-Band Filtering)

Electrical noise (e.g., 50/60 Hz power line noise) can interfere with EEG signals. Notch filters are used to eliminate such noise [103], [104]. It effectively suppresses unwanted components in specific frequency ranges.

Common Spatial Pattern (CSP)

CSP is a technique to distinguish different brain activities, especially motor imagery or movement. This method increases classification accuracy by separating brain waves associated with motor activities from EEG signals [105], [106], [107].

Epoching (Division into Time Intervals)

Since EEG signals are large data sets, they must be divided into short periods (epochs) for analysis [108], [109]. Epoching allows for a more detailed examination of brain activities in certain periods.

Normalization

Normalization techniques are applied to reduce the effect of amplitude changes in EEG signals. This process provides analysis consistency by bringing the signals to a certain reference level [110], [111], [112].

Time-Frequency Analysis

EEG signals have a structure that changes over time and contain different frequency components [113], [114]. Time-frequency analysis analyzes the change of different frequency components in the signal over time and better separates temporary signals.

Signal-to-noise ratio (SNR) Enhancement

SNR enhancement techniques increase the reliability of the signal by minimizing the noise components in the signal. This allows for a cleaner and more accurate EEG signal analysis [115].

2.4 Feature Extraction

EEG signals are an important tool for analyzing brain activities, and the information that can be obtained from these signals can be examined under four main analysis categories: time domain, frequency domain, non-linear features, and autoregressive model parameters. These analyses allow us to understand different aspects of the EEG signal, and each method provides in-depth information about brain functions and neurological conditions. Detailed explanations of these four categories are given below:

2.4.1 Time Domain Features

Time domain analysis is a technique for understanding how the EEG signal changes over time and follows certain trends. This type of analysis is often used to describe the

general structure of the signal. Time domain features provide important information about the amplitude and shape characteristics of the signal [116].

The time domain features include minimum, maximum, and median values. While minimum and maximum values indicate the amplitude limits of the signal, the median value determines the central tendency of the signal. It provides a more robust measure, especially in non-symmetrical data distributions. Variance and standard deviation indicate how widespread the signal amplitude changes are [117]. These features help us understand how the EEG signal fluctuates over time and how variable it is. The arithmetic mean shows the general trend of the signal and is also used to understand long-term changes in the signal.

Among more complex measurements, the logarithmic root of the total variability is an important feature that emphasizes the magnitude of small changes in the signal. Teager energy provides non-linear energy measurement and is especially used in detecting events such as epileptic seizures [118]. In addition, features such as curve length and normalized differences allow us to understand the shape properties of the EEG signal [119], [120]. Kurtosis and skewness analyze the intensity at the extreme values of the signal distribution and whether it is symmetric or not [121], [122], [123]. These measurements are used to determine the signal's broader distributions and central features.

Hjorth parameters are important time domain features that measure the signal's activity, mobility, and complexity. Activity defines the signal's overall energy, mobility defines the rate of change in the signal's frequency, and complexity defines the irregularity and complexity of the signal. These parameters provide important information in examining the low and high-frequency components in the EEG signal [124], [125].

The autoregressive (AR) model is a powerful method, especially for analyzing time series data, and plays an important role in understanding EEG signals. The AR model is a technique used to predict future values from past observations. Since EEG signals have complex dynamics that change over time, the AR model models these dynamics. AR parameters allow future values to be predicted based on past values of the signal. EEG signals are usually time-dependent, so the AR model provides information about the future states of the signal. These parameters are used to analyze the short-term predictions and behaviors of the signal [126], [127], [128]. AR model parameters are especially helpful in studying the model's short-term dynamics and behaviors in the EEG signal analysis.

2.4.2 Frequency Domain Features

Frequency domain analysis is a technique that examines the energy distribution in specific frequency bands, not the changes in the EEG signal over time. Brain activities are associated with specific frequency bands, and each frequency band represents different brain functions. Frequency domain features allow us to understand at which frequencies brain activities are concentrated [129], [130], [131].

One of the most used features in frequency domain analysis is the delta band power (0.5-4 Hz), which is associated with deep sleep and relaxation. Theta band power (4-8 Hz) is associated with sleep, meditation, and memory, and the increase in power in theta band plays an important role, especially in deep thinking and remembering processes. Alpha band power (8-12 Hz) is more pronounced during relaxation, rest, and open-eyed relaxation, while beta band power (12-30 Hz) is associated with mental alertness, focus, and active thinking. Gamma band power (30-150 Hz) is associated with higher cognitive functions and information-processing processes [132], [133].

Among these frequency bands, the alpha/beta ratio can be used to distinguish between relaxation and stress states. For example, alpha power increases during relaxation, while beta power increases during stressful situations. Power Spectral Density (PSD) measures the energy density of the EEG signal at different frequencies, which helps determine which frequency components of the signal are dominant. Various techniques are used to calculate PSD, such as the Welch method and the Burg method, and each offers certain advantages for measuring the strength of the signal's frequency components [134], [135], [136].

2.4.3 Non-Linear Features

Non-linear features are a special type of analysis aimed at examining the complexity and irregularity of EEG signals. Since EEG signals often exhibit non-linear behavior, non-linear analyses allow us to understand the signal more deeply. Such analyses play a critical role in understanding the complexity of brain activities [137], [138].

Entropy-based measurements come first in non-linear analyses. Renyi entropy measures the uncertainty and irregularity of the signal, while Shannon entropy shows the degree of randomness and irregularity in the signal [139], [140]. Tsallis entropy is considered a generalization of Renyi entropy and is especially useful in complex systems

[141], [142]. These entropy measurements are effective tools used to understand irregularities in the signal.

Fractal dimensions are also an important method for understanding the complexity of EEG signals. Petrosian fractal dimension measures the complexity of the signal and is especially used to understand the structural features of the signal [143], [144]. Higuchi fractal dimension is another method used to analyze the complexity of the signal over time and long-term memory effects. Lempel-Ziv Complexity (LZC) involves analyzing signals that have been segmented and binarized to measure the complexity of the signal and examines the "connectivity" and "structure" properties of the signal [145].

2.4.4 Time-Frequency Domain Features

Time-frequency domain analysis is a method that allows the properties of EEG signals to be examined in both time and frequency dimensions. This analysis approach plays a critical role in understanding the dynamic nature of EEG signals. Because EEG signals have a complex structure that constantly changes over time and contains different frequency components. Time-frequency domain analysis offers powerful tools to evaluate these signals' time and frequency properties simultaneously [146], [147]. Time-frequency domain analysis is used primarily to detect short-term events and frequency changes frequently encountered in EEG data. This approach is widely applied in areas such as examining neurological disorders and understanding cognitive processes.

The basic principle of this method is to analyze which frequency components are present in a specific time interval by representing the signal in both time and frequency planes [148], [149]. While traditional time or frequency analysis examines only one dimension, time-frequency analysis provides a more comprehensive evaluation by combining these two dimensions.

One of the main methods used in time-frequency analysis is spectrogram [150]. The spectrogram visualizes the energy density that changes over time by calculating the frequency distribution of the signal in short time windows. This method is suitable for examining the frequency responses of the brain in different activities. For example, in a motor imagination task, it can be seen through the spectrogram that frequencies are active in various periods.

Another standard method is Wavelet Transform. Wavelet analysis allows examining the components of the signal at different scales (and therefore frequencies). Wavelet transform is mainly used in the study of short-term signal changes. It is often

preferred in applications such as the detection of epileptic seizures or the examination of short-term motor activities[151].

Another prominent method in time-frequency domain analysis is the Hilbert-Huang Transform. This transform analyzes the nonlinear and time-varying frequency components of the signal [152]. As an adaptive method, it can be used effectively in complex biological data such as EEG signals.

As a result, time-frequency domain analysis is a comprehensive tool for understanding and interpreting the complex structure of EEG signals. Evaluating time and frequency components simultaneously allows for a better understanding of the dynamic nature of signals, and this feature is used in a wide range of applications from neuroscience to medical diagnostics.

2.4.5 Spatial Features

It is an important type of analysis that examines the spatial characteristics of brain activity by analyzing how EEG signals are distributed between electrodes on the brain surface. These features are usually extracted from topographic maps obtained from EEG and allow detailed analysis of spatial variations of brain activity. Spatial power distribution is obtained by calculating the power densities in a specific frequency band for each electrode, and this distribution allows visualization of activity intensities in different brain regions. Spatial features also play a critical role in determining functional connections between brain regions by analyzing electrode correlations [153], [154], [155], [156]. The frequency bands used in this analysis are generally physiologically meaningful ranges such as delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz) and gamma (30–150 Hz).

2.5 Statistical Analysis

In the analyses performed on EEG signals, the correct selection of statistical tests is determined by the distribution characteristics of the obtained data, the sample size, and the number of groups compared. The Shapiro-Wilk test was applied to determine whether the data were suitable for normal distribution. The main purpose of this test is to test the degree of conformity of the data in the sample to normal distribution. The conformity of the data to the normal distribution is evaluated according to the obtained p-value. If the

p-value is less than 0.05, it is accepted that the data deviates from normal distribution, and in this case, non-parametric tests are preferred. Otherwise, if the p-value is 0.05 or greater, the data are assumed suitable for normal distribution, and parametric tests are selected for use. Parametric tests are generally applied in cases where the data are normally distributed, and the variances are equal. These tests are used especially for the purpose of comparing the means between groups. Single-group tests are tests aimed at comparing the meaning of a sample with a specific reference value. In this context, the sample size is classified according to certain criteria: If the sample size is less than 30, the Single Sample T-test is used, while if the sample size is 30 or more, the Z Test is applied. In comparisons between two groups, the Independent Samples t-test can be used. This test tests the difference between the means of two independent groups and is valid, especially provided that the normal distribution and equal variance assumptions are met. If the variances are unequal, the test may need to be performed with the unequalized (unpooled) variance option. In the case of paired data, the Paired Samples t-test is preferred. This test compares measurements made on the same individuals under different conditions. The One-Way ANOVA test is applied in comparisons between three or more groups. The ANOVA test evaluates whether the mean differences between the groups are significant. If the test result detects a significant difference, post-hoc tests (e.g., Tukey test) can be performed to determine which groups this difference is between. Non-parametric tests are preferred if the data does not show a normal distribution or if a ranking-based analysis is required. These tests are based on comparing the medians of the data and can be used in cases where the assumption of normal distribution is not met or where there are outliers. Single-group non-parametric tests test the sample median against a specific reference value. For this purpose, tests such as the 1 Sample Wilcoxon Sign Test and the 1 Sample Sign Test can be applied. The Mann-Whitney U Test can be used in comparisons between two groups. This test is intended to compare the medians of two independent groups and is suitable for cases where the data does not conform to a normal distribution. The Mood's Median and Kruskal-Wallis Tests evaluate median differences between three or more groups. While the Mood's Median Test is preferred, especially in cases with outliers, the Kruskal-Wallis Test can be applied in cases where the variances are equal and there are no outliers. Each of these tests is selected in accordance with the distribution characteristics of the data and the purpose of the hypothesis test. As a result, choosing the right tests in the analyses performed on EEG signals allows for statistical evaluations appropriate to the characteristics of the data. Parametric or non-parametric

tests are applied according to whether the data are normally distributed, sample size, and number of groups. Parametric tests are suitable for data that meet the assumptions of normal distribution and equal variance. In contrast, non-parametric tests are preferred for data that do not meet the assumption of normal distribution. Both types of tests allow the researcher to determine significant differences between the data and reach accurate results [157], [158], [159]. Therefore, choosing the right tests at each analysis stage is critical regarding the results' validity.

2.6 Classification

2.6.1 Machine Learning

Classification of EEG data plays an important role in better understanding neurological processes and developing motor imagery-based brain-computer interfaces (BCI). There are different machine learning algorithms for classifying EEG data. Each of these algorithms has demonstrated its effectiveness according to the features of EEG data and their classification accuracy [160].

K-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) offers a nonparametric approach to classification. This algorithm looks at the classes of the nearest K neighbors to determine the class of a data point. In this approach, the distances between the data are calculated, and the class labels of the closest neighbors are considered [161]. While KNN can provide fast results in small data sets, the computational load can increase in large data sets, and the disadvantage is that the model is sensitive to noise. KNN also does not require independence between features, which increases its flexibility. However, the processing power requirement in large data sets and its sensitivity to noisy data can affect the model's accuracy [162], [163].

Support Vector Machine (SVM)

Support Vector Machine (SVM) projects data into a higher dimensional space using kernel functions to classify nonlinear data sets. This method searches for a hyperplane that maximizes the margin between classes and provides high accuracy even in nonlinear

data. Although SVM is particularly effective in modeling nonlinear relationships, kernel selection and hyperparameter optimization require attention. In large data sets, the computational power requirement is high, and choosing the right kernel function is critical for the model to work correctly [164], [165], [166].

Decision Tree

Decision Tree performs classification by separating data into decision nodes and branches. A feature is selected in each node, and the data is divided according to this feature. As a result, each leaf node is associated with a class label. Decision trees attract attention with the visualizability and understandability of the model. However, decision-making tree models tend to overfit. Therefore, the depth of the model should be limited, and pruning techniques should be used [167], [168]. The most important advantage of the decision tree is that the model is easy to visualize and present to the user. Still, in complex data sets, the accuracy of the decision tree may be limited.

Naive Bayes

Naive Bayes works based on Bayes' theorem and performs classification assuming that each feature is independent of each other [169]. This algorithm provides fast results, especially in small data sets. In classifications based on biological data such as EEG, Naive Bayes performs classification by modeling the probability relationship of each feature with the class label. However, the independence assumption of this algorithm is generally not valid for real-world data, which can limit the accuracy of the model [170], [171]. Nevertheless, the biggest advantage of Naive Bayes is that it works quickly and obtains efficient results with low computational cost, especially in large data sets.

Kernel

Kernel Methods are methods used for nonlinear data and transform the data into a higher-dimensional space through kernel functions. Kernel functions project the data to a new space, making it linearly separable. This method provides high accuracy in complex data, but the correct kernel function and parameter optimization selection are important. Kernel methods provide effective results in high-dimensional data, while the model's training time and processing power requirements are also quite high. In addition, the

wrong selection of the kernel function can negatively affect the model's accuracy [172], [173], [174].

Random Forest

Random Forest is an ensemble learning method and consists of many decision trees. The final class is determined by combining the results of each tree [175], [176]. This method creates diversity by training each tree on different examples of the data set, thus increasing the generalization power of the model. Random Forest provides high accuracy by reducing the risk of overfitting, but the interpretability of the model may be weak. In addition, the processing power requirement and the stability of the model in large data sets may also create some disadvantages while making Random Forest a strong classifier [177], [178].

AdaBoost

AdaBoost creates a strong classifier by combining weak classifiers. Each weak classifier tries to correct its errors by learning from previous classifiers. AdaBoost is strong in creating correct classifiers but is sensitive to noisy data. It may lose its performance in unbalanced data sets. However, the biggest advantage of AdaBoost is that it is a powerful algorithm that improves accuracy and generally provides good integration between classifiers.

Bagging (Bootstrap Aggregating)

Bagging (Bootstrap Aggregating) increases the stability of the model by creating multiple models from random subsets of the dataset. Bagging combines the predictions of each model and determines the final class by majority vote or averaging. This method reduces the variance of the model and provides a more stable classification. While Bagging generally works effectively on large datasets, the interpretability of the model can be poor, and the processing power requirement is high [179], [180]. These disadvantages may lead to more powerful hardware requirements for the model to work more efficiently.

2.6.2 Deep Learning

Deep learning is an artificial intelligence technique developed specifically for analyzing large data sets and complex relationships. EEG (electroencephalogram) signals are time series data that measure the brain's electrical activity, and deep learning models are highly effective in learning patterns in such data. Analysis of EEG signals plays an important role in various neurological applications such as motor imagery, seizure detection, and sleep stage classification [181].

Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNN) is a deep learning architecture widely used especially in image and signal data. CNN processes data in layers. Each layer learns the features of the input data and creates more complex representations. In sequential data such as EEG signals, CNN can extract important features by combining time and frequency information [182]. EEG signals are usually analyzed at the time-frequency level and converted into 2D representations such as scalograms or spectrograms. In this way, EEG signals can be processed like a type of image. CNN learns local features using a specific filter on each input data. These filters are applied with convolutional layers to identify patterns in the input data. CNN also uses max-pooling layers to reduce the size of the data and extract more distinct features [183].

CNN is quite powerful in learning local patterns in data. Since EEG data creates strong local patterns at the time-frequency level, CNN can effectively extract such patterns. In addition, the fact that CNN does not require feature engineering allows the model to learn the data automatically. In this way, the model can combine time and frequency information more effectively and make high-accuracy classifications [183], [184]. Training CNNs on large data sets usually requires much computational power. When deep networks are used, the risk of overfitting the model can be increased. In addition, when very deep networks are trained, the training process can become complex and time-consuming [185].

Recurrent Neural Networks (RNN)

Recurrent Neural Networks (RNN) is a structure that processes time series data. While processing each step of the data, RNN makes predictions based on previous information thanks to the feedback mechanism. Since EEG signals have a structure that

changes over time, RNN is extremely suitable for learning these dependencies. RNN models make more accurate predictions using information from previous steps while processing the data at each time step [186].

The biggest advantage of RNN is that it learns by considering the order of time series data and can combine current data with past data. Since EEG signals change over time, RNNs can learn future information associated with past data. This allows the model to make more accurate predictions [187], [188]. However, RNNs can have difficulty learning long-term dependencies. This occurs due to the vanishing gradient problem, making the learning process difficult in deep networks. In addition, RNNs can generally be inefficient on extensive data sets and may require long training times [189].

Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is an RNN structure for learning long-term dependencies. LSTM controls the information at each time step with input, forget, and output gates. These gates filter the information, ensuring that only important data remains in the network and that unnecessary information is forgotten. This feature is important for better learning long-term dependencies. The biggest advantage of LSTM is that it can learn long-term relationships in time series data and solve the vanishing gradient problem. LSTM can provide effective results in EEG data, especially in analyzing long-term processes such as motor imagery. However, LSTMs usually require large computational power and can take training time. In addition, the complex structure of LSTM models can increase the risk of overfitting the model and require high training time [190], [191].

Autoencoders

Autoencoders are a deep learning model that tries to learn low-dimensional representations by compressing data. Autoencoders pass the input data to an encoding layer and then reconstruct this representation by decoding it. This process is used especially for feature extraction and data size reduction [193].

Autoencoders are especially powerful in data compression and size reduction processes and can also be used to clean noise in EEG data. The advantage of autoencoders is that they extract more meaningful and representative features by reconstructing the data. However, the disadvantage of this model is that they are usually not powerful enough to perform classification alone, and their generalization capacity may be limited.

In addition, the training process of the model can be time-consuming, and the hyperparameters must be adjusted correctly [194], [195].

Generative Adversarial Networks (GANs)

Generative Adversarial Networks (GANs) consist of two networks, a generator and a discriminator. The generator produces fake data, while the discriminator network classifies this data as real or fake. GANs are used especially for the purpose of augmenting data and producing more training data. When EEG data is limited, GANs can increase the model's accuracy by producing new and diversified data [196].

GANs are powerful in augmenting data and can increase the generalization capacity of the model by producing more data when there is limited data. They also increase the diversity of the data and enable the model to learn more robustly. They are beneficial for increasing the diversity in EEG data. However, training GANs is usually difficult and requires unsupervised learning. This can weaken accuracy in an unsupervised environment. The training process can be time-consuming, and the model needs to be trained with the right parameters [197].

Transformer Models

Transformer models have revolutionized the field of natural language processing (NLP) in recent years and are also effectively used in studies with time series data [198], [199]. Transformers are especially successful in learning long-term dependencies. Using the attention mechanism, this model assigns different weights to each part of the data and thus learns better the relationship of each data point with others. Unlike traditional methods such as RNN and LSTM, transformer architecture can provide parallel access to data and thus work faster and more efficiently. The biggest advantage of Transformer models is that they can successfully learn long-term relationships in data. In addition, thanks to their parallel processing capability, they can work more efficiently with large data sets [200]. Transformer architecture enables the training of large and complex models, and the attention mechanism allows them to make more precise predictions by considering the context of each piece of data. However, Transformer models require large computational power, and hyperparameter optimization is usually more complex. In addition, a careful regularization strategy may need to be applied during model training [201], [202].

2.7 Performance Evaluation

Evaluating the effectiveness of machine learning and deep learning models is critical to understanding the model's accuracy, reliability, and suitability for application purposes. Several metrics are used to evaluate the performance of the model. These metrics offer different ways of measuring model success in classification problems [203].

Accuracy:

Accuracy refers to the ratio of the number of examples the model correctly predicts to the total number of predictions (equation 2.1). Although a high accuracy rate indicates the overall success of the model, it can be misleading in imbalanced data sets. For example, suppose a class has many more examples. In that case, the model can achieve high accuracy by predicting only that class, but this does not accurately reflect the model's true performance [204].

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FN+FP} \quad (2.1)$$

TP (True Positive): Examples where the model correctly predicts the positive class.

TN (True Negative): Examples where the model correctly predicts the negative class.

FP (False Positive): Examples where the model incorrectly predicts the positive class.

FN (False Negative): Examples where the model incorrectly predicts the negative class.

Sensitivity / Recall:

Sensitivity or Recall indicates the rate at which the positive class is correctly predicted (equation 2.2). This metric is especially critical for situations where false negatives (FN) are unacceptable, i.e., positive classes should not be missed [205], [206]. For example, detecting all patient cases when diseases are detected correctly in health diagnostic systems is desirable. Therefore, high sensitivity is generally preferred.

$$\text{Sensitivity/Recall} = \frac{TP}{TP+FN} \quad (2.2)$$

It is used in the same sense as Recall, but in some cases, the term Recall may be preferred when evaluating the overall success of the model.

Specificity:

Specificity indicates the rate at which the negative class is correctly predicted. High specificity refers to the ability of the model to keep false positive predictions (FP) to a minimum (equation 2.3). The specificity metric can be critical, especially when false positives are important [207], [208]. For example, in disease diagnosis, false positives (identification of healthy individuals as patients) can lead to unnecessary treatment processes, so it is preferable to have high specificity.

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (2.3)$$

Precision:

Precision shows how many examples the model classifies as positive are true positives (equation 2.4). This metric is used especially when false positives are important and false positives are to be penalized [209]. For example, in e-mail filtering systems, it may be desired to reduce false positives, i.e., the model is expected to mark only e-mails that are truly spam as "spam".

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2.4)$$

F1-Measure (F1-Score):

F1-Measure or F1-Score is the harmonic means of the Precision and Recall metrics (equation 2.5). It measures the overall success of the model by considering both metrics. Especially in imbalanced data sets, finding a balance between Precision and Recall is important to obtain accurate results. A high F1 score indicates the model's ability to make true positive predictions and avoid false positive and false negative predictions [210], [211].

$$F - \text{measure} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (2.5)$$

G-Mean (Geometric Mean):

G-Mean is a metric that considers the model's sensitivity and specificity (equation 2.6). This metric rewards models that provide balanced performance across classes and is beneficial on imbalanced datasets. A high G-Mean indicates that the model performs in a balanced manner and reliably across all classes [212], [213].

$$G - \text{Mean} = \text{Sensitivity} * \text{Specificity} \quad (2.6)$$

AUC (Area Under the Curve):

AUC (Area Under the Curve) measures explicitly the area under the ROC (Receiver Operating Characteristic) curve. The ROC curve represents the model's ability to distinguish between positive and negative classes [214]. AUC summarizes the model's performance from zero to one score and takes a value between 0.5 and 1. AUC close to 1 indicates that the model has strong discrimination power and successfully makes correct classifications. The advantage of AUC is that it evaluates the model's overall performance without being sensitive to the class imbalance [215].

Cohen's Kappa:

Cohen's Kappa is a metric that measures the consistency of the predictions made by two classifiers (or models) on the same data (equation 2.7). It is used primarily to evaluate observer disagreements between classifiers [216]. Kappa considers the level of accuracy that classifiers can reach by chance and more accurately measures proper consistency (i.e., non-random accuracy). Cohen's Kappa takes a value between -1 and 1:

Kappa = 1: Completely perfect agreement.

Kappa = 0: Classifiers produce the same result by chance.

Kappa < 0: Negative agreement, i.e., disagreement, between classifiers.

It is calculated mathematically as follows:

$$Kappa = \frac{\text{Observed Agreement} - \text{Expected Agreement}}{1 - \text{Expected Agreement}} \quad (2.7)$$

Observed Agreement: True observed accuracy.

Expected Agreement: Accuracy expected by chance.

Cohen's Kappa value usually provides a more reliable performance evaluation by measuring the accuracy of the classifier not only with observation but also with random predictions. This metric is used primarily in cases where consistency is expected between classifiers. For example, Cohen's Kappa is used to see the consistency between correct predictions in EEG-based brain-computer interfaces.



Chapter 3

Experiments

3.1 Participants

EEG data were collected from 30 healthy volunteers (15 male, 15 female, age range 18-56). Participants were selected from right-handed individuals and were independent of each other. Individuals who did not have any neurological or psychiatric disorders that could affect EEG data were included in the study. The Erciyes University Clinical Research Ethics Committee approved the study on July 12, 2023, with approval number 2023/461. Participants were given detailed information about the study participation process, and all participants signed the informed consent form.

3.2 Experimental Setup and Equipment

The experiments were conducted in a quiet, comfortable laboratory environment free from external stimuli that could distract the participants.

Our experiments used a 16-channel Nautilus research-grade wearable EEG headset device (g.tec medical engineering, Schiedlberg, Austria) to obtain EEG signals. Thanks to the wearable nature of the headset, the headset with dry electrodes was comfortably placed on the participant's head. EEG electrodes were positioned according to the international 10-20 system. A sampling frequency of 500 Hz was used for the signal acquisition. The positions of the electrodes placed on the skull of the subjects can be seen in Figure 3.1. We recorded the EEG data in the 0.5-200 Hz range via MATLAB 2017 Simulink using the Windows operating system.

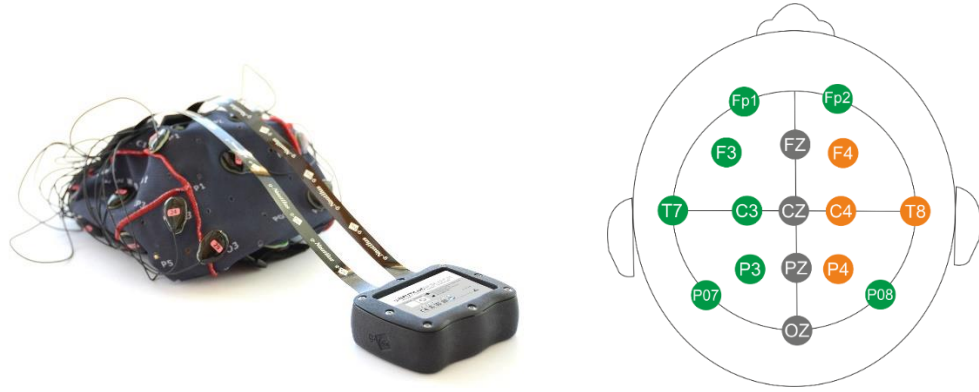


Figure 3.1 Left panel: Nautilus research-grade wearable EEG headset, and right panel: international 10-20 electrode placement system

In this study, we avoided attaching devices or sensors to the neck or other body parts to detect swallowing. Instead, we conducted the entire study based on EEG signals. Our focus extended beyond the swallowing event to analyze brain activities associated with swallowing. We incorporated additional scenarios, such as periods of rest before swallowing and the mental imagery of swallowing, into our experimental protocols. This comprehensive approach allowed us to gain insights into the act of swallowing and the broader spectrum of influencing brain activities. By exploring various conditions, we aimed to provide a better understanding of the neural processes associated with swallowing.

3.3 Experimental Paradigms

3.3.1 Experimental Paradigm 1: Natural Water Swallowing

After the participants were given detailed instructions about the purpose of the experiment and the process, the experiment was started. The participants were asked to act according to the commands shown on the computer screen. As shown in Figure 3.2, a bottle of water was placed in front of each participant, and they were asked to drink water using a straw without moving only when the relevant command was given. The experiment started with a beep sound, and each trial lasted 10 seconds. No separate imagination command was given to the participants during the experiment. At the beginning of the experiment, a beep sound was used to provide a standard starting signal. This sound signaled the participants to act right before starting the experimental process. The researcher observed the participants so they would not be affected by possible

movements during the experiment and ensured accurate data collection. The participants were reminded to avoid unnecessary movements while drawing water from the straw and drinking water only when the command was given. The design of the experiment ensured that the participants drank water stably by taking a position where the straw should be appropriately used to prevent excessive movement. This arrangement provides an ideal structure for analyzing the natural imagination process of swallowing.

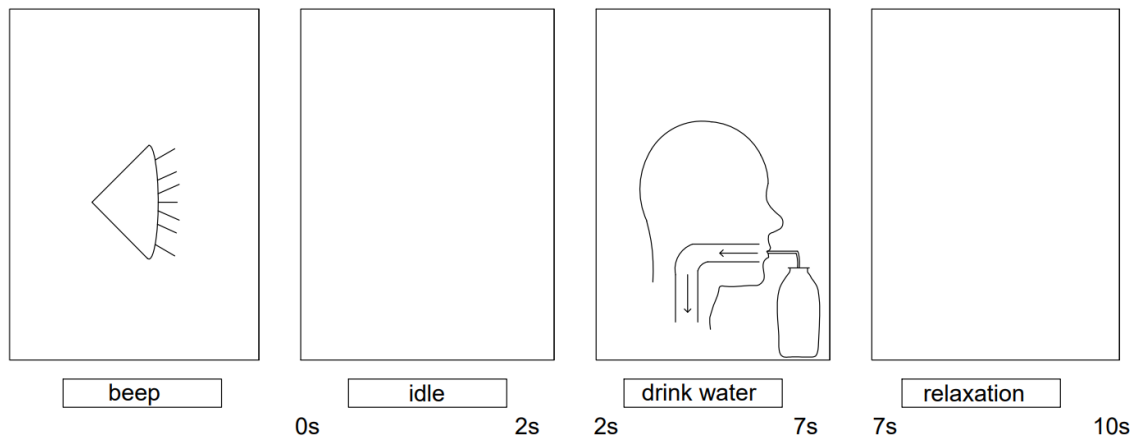


Figure 3.2 Natural Water Swallowing Experimental Paradigm

3.3.2 Experimental Paradigm 2: Induced Saliva Swallowing

Experimental Paradigm 2 was designed to investigate the saliva-swallowing processes of the participants. Each trial lasted 9 seconds, and in each trial, the participants were expected to move in different phases in a particular order (see Figure 3.3). In the first phase of the experiment, the rest phase was initiated. The participants were instructed to focus on the plus sign shown on the computer screen. This process is necessary to ensure that the participants focus and relax, and it constitutes the starting point of the experiment.

The second phase is the imagination phase. In this phase, the participants were asked to imagine swallowing their saliva. The fact that the participants thought about the act of swallowing is an essential phase for the analysis of EEG data. It is a mental reflection of the natural swallowing process. In this phase, the participants were allowed to focus on their cognitive processes and imagine their motor skills.

The next phase is the movement and swallowing phase, in which the participants were instructed to swallow their saliva. In this phase, the participants took action to

swallow their saliva. This is the central part of the experiment because the effect of motor imagery and real swallowing movement on EEG signals was observed in this phase.

Finally, the relaxation phase was applied. In this phase, the participants received no command and only rested. This allowed the participants to relax after the previous activities and before moving on to the next phase of the experiment.

During each trial, a particular phase was passed from one to another for 9 seconds, and the participants were ensured to perform these processes correctly. The experiment was designed to measure the different brain activations and the differences between motor imagery and real movement during these repeated tasks for each participant.

This structure was applied under the same conditions for all participants to increase the reliability and consistency of the experiment. The guidance of the participants during the experiment was carefully controlled to ensure accurate and effective data collection. This experiment is an essential step towards a deeper understanding of the swallowing processes and the neural basis of motor imagery.

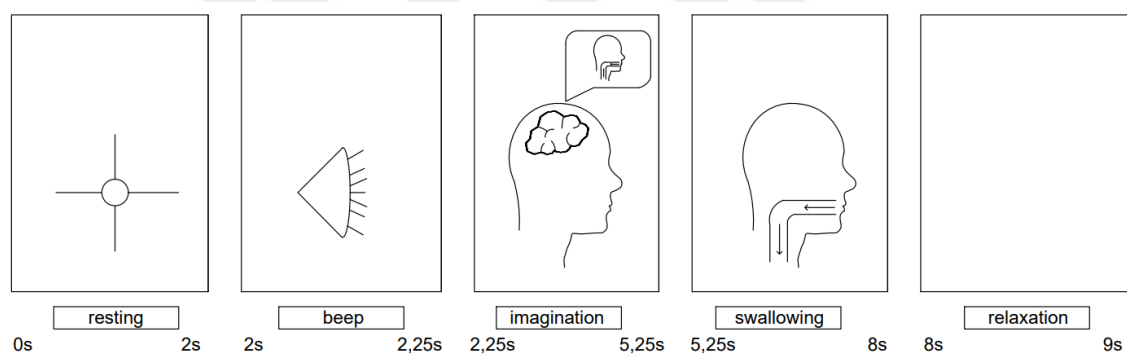


Figure 3.3 Induced Saliva Swallowing Experimental Paradigm

3.3.3 Experimental Paradigm 3: Induced Water Swallowing

In this paradigm each participant was given a bottle of water and a straw. As shown in Figure 3.4, detailed information about the purpose and procedure of the experiment was provided to the participants before the experiment began. The experiment was started by asking the participant to take a sip of water. At this stage, the participants were told not to swallow the water in their mouths. This instruction was given to observe the effect of the induced imagination process, which was carried out by holding the water in the mouth during the imagination phase. Only the impact of mental processes was examined by ensuring the participant did not make an actual swallowing movement.

The next phase of the experiment was the rest phase. In this phase, the participants were instructed to focus on the circle in the middle of the plus sign. This focus was necessary to ensure that the participants were relaxed and focused. This phase aimed to allow the participants to rest before starting the swallowing imagination and to move on to the subsequent phases of the experiment mentally.

The second phase was the imagination phase. In this phase, the participants were asked to imagine swallowing the water in their mouths. Imaginative swallowing of water triggered the motor imagery process, enabling the analysis of EEG signals. This phase allows participants to think about the process before performing the actual movement.

Finally, the movement/swallowing phase came. In this phase, participants were instructed to swallow the water in their mouths. In this phase, the effects of the differences between motor skills and mental imagery on the EEG were observed. When participants swallowed the water, valuable information about brain activity and motor control processes was obtained.

At the end of the experiment, a relaxation phase was applied. Participants were given free time without any command. This process allowed the participants to relax at the experiment's end and detach from previous activities. Observations are used to analyze better the effects of the movement and imagery phases on EEG data.

Each trial lasted 13 seconds. This allowed for the collection of sufficient data to examine in detail the processes of mentally imagining the action of drinking water and performing the actual movement of each participant.

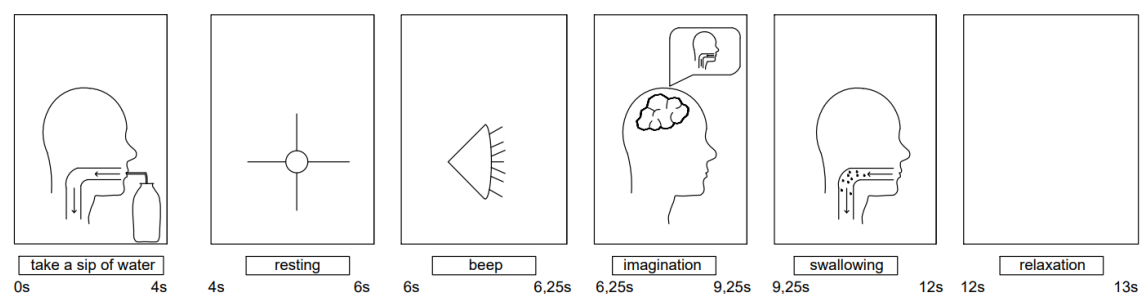


Figure 3.4 Induced Water Swallowing Experimental Paradigm

3.3.4 Experimental Paradigm 4: Induced Tongue Protrusion

The relationship between tongue protrusion and swallowing was specifically designed to determine them. Previous studies have used this paradigm to surrogate model swallowing processes and examine motor control, particularly in dysphagia

rehabilitation. The experiment aimed to explore the neurological and motor relationships between tongue protrusion and swallowing movements.

Figure 3.5 shows that the experiment began with a beep sound followed by a rest phase. During the rest, participants waited, relaxed, and prepared to focus on the following experiment stages.

In the imagination phase, participants were instructed to imagine that they were sticking out their tongues. This phase allowed participants to simulate the tongue movement mentally through motor imagery. This phase of participants' imagination is critical to more clearly analyze the neural processes of the tongue protrusion movement. After the imagination phase, participants moved on to the movement phase, where they stuck out their tongues. This movement triggered the actual motor action and allowed the collection of EEG signals. The participants must perform this movement to observe the connections between motor skills and brain activities.

At the end of the experiment, a relaxation phase was applied, and the participants were shown a blank screen. This phase allows the participants to mentally relax and separate from the previous movements at the end of the experiment.

The experimental process lasted 135 seconds, with each trial of 9 seconds. This experimental design aims to collect sufficient data to examine the neurological relationships between tongue protrusion movement and swallowing.

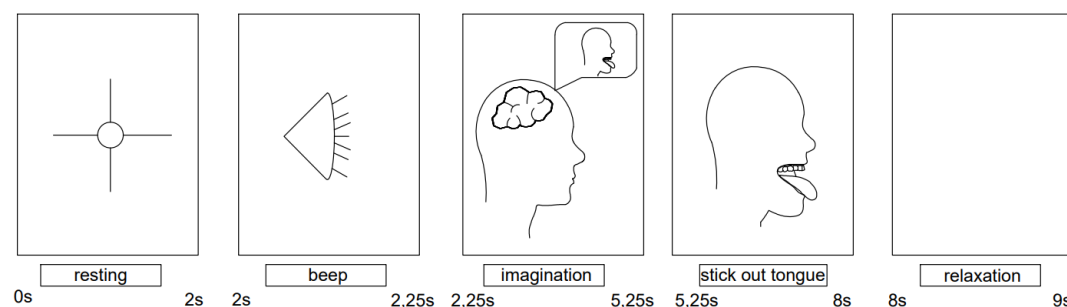


Figure 3.5 Induced Tongue Protrusion Experimental Paradigm

3.4 Data Collection

EEG signals were recorded from each participant for 15 trials. Each trial had recording times determined by the experimental protocol. During the recording, real-time filtering processes were applied on the device to increase signal quality and minimize noise sources:

- **Band-Pass Filter:** The signals were purified from low and high-frequency noise by the device using a band-pass filter in the frequency range of 0.5 Hz - 200 Hz.
- **Notch Filter:** To effectively block network noise (50 Hz), the device applied a notch filter in the 48-52 Hz range.

These real-time filtering processes ensured that the signals were recorded with high quality and reliability before analysis.



Chapter 4

Distinguishing Water and Saliva Swallowing Using Statistical Analysis and Machine Learning Methods

4.1 Motivation

This study uses multichannel EEG signals to explore the intricate relationship between swallowing and brain functions. Employing two distinct experimental paradigms—induced water swallowing and saliva swallowing, we engaged 30 right-handed subjects without speech or swallowing difficulties or neurological diseases. After obtaining 16-channel EEG signals, noise removal, and extraction of frequency- and time-domain features, statistical analysis and classification were performed. The primary objective is to advance our understanding of dysphagia by examining brain signals during swallowing. Employing the Induced Saliva Swallowing Experimental Paradigm and the Induced Water Swallowing Experimental Paradigm, we comprehensively examined EEG data during rest and imagination phases. This involved applying classification and statistical analysis methods to both rest and imagination segments under each paradigm to discern potential variations in imagination phases across different conditions.

The methods employed and the findings obtained contribute to a broader comprehension of how brain signals influence the intricate swallowing process. The utilization of different paradigms elucidates, in detail, the variations in brain signals affecting the swallowing process under diverse conditions. These results not only offer insights into dysphagia treatment and rehabilitation strategies but also pave the way for the adaptation of these strategies to varying circumstances.

4.2 Materials and Methods

The experimental paradigms in this section are based on the induced saliva swallowing protocols applied in Experimental Paradigm 2 and induced water swallowing protocols applied in Experimental Paradigm 3, details of which are provided in Section 3 of this thesis.

In the first stage of this study, a comprehensive filtering process was performed on the data obtained from both experimental paradigms in the Data Analysis section. After filtering, the data were separated into rest and imagination sections. The data obtained from these two sections was subjected to feature extraction. The extracted features were then analyzed in detail using statistical and classification methods.

The Results section evaluated the findings obtained, and the relevant data were presented comprehensively. The study was completed with the Conclusion and Discussion sections, where the results were interpreted and discussed. This systematic approach was meticulously applied at each stage of the research, revealing the scientific value and contributions of the study.

4.2.1 Filtering

EEG data provides essential information in neurological studies. However, this data is often contaminated with noise and unwanted components. Therefore, cleaning EEG data and removing unwanted signals is crucial before conducting data analysis. This section will examine three different filtering methods used for cleaning EEG data acquired during the experimental paradigms.

Empirical Mode Decomposition (EMD) Method

Empirical Mode Decomposition (EMD) is a non-linear method employed to clean EEG data, which allows EEG data to decompose into intrinsic modes or components. This method considers EEG data's complexity and is important due to its non-linear nature. We used the EMD method, particularly to address the complexity of EEG data (equations 4.1 and 4.2).

The basic formula for EMD can be expressed as:

$$X(t) = \sum_{i=0}^n C_i(t) + R_n(t) \quad (4.1)$$

Here:

$X(t)$: Original EEG signal.

$C_i(t)$: Intrinsic mode or component.

$R_n(t)$: Residual component.

In our study, we applied the EMD method to clean EEG data with the following steps:

EMD Application: EEG data was decomposed into 10 intrinsic modes using the EMD method (see Figure 4.1).

Selection Criteria for Intrinsic Modes: We carefully examined the characteristics represented by each intrinsic mode. After a detailed analysis, we selected the first three intrinsic modes that best represent noise-free EEG data.

Signal Cleaning Process: Utilizing the selected first three intrinsic modes, the EEG signal underwent a thorough cleaning to produce a refined output:

$$X_{clean}(t) = C_1(t) + C_2(t) + C_3(t) \quad (4.2)$$

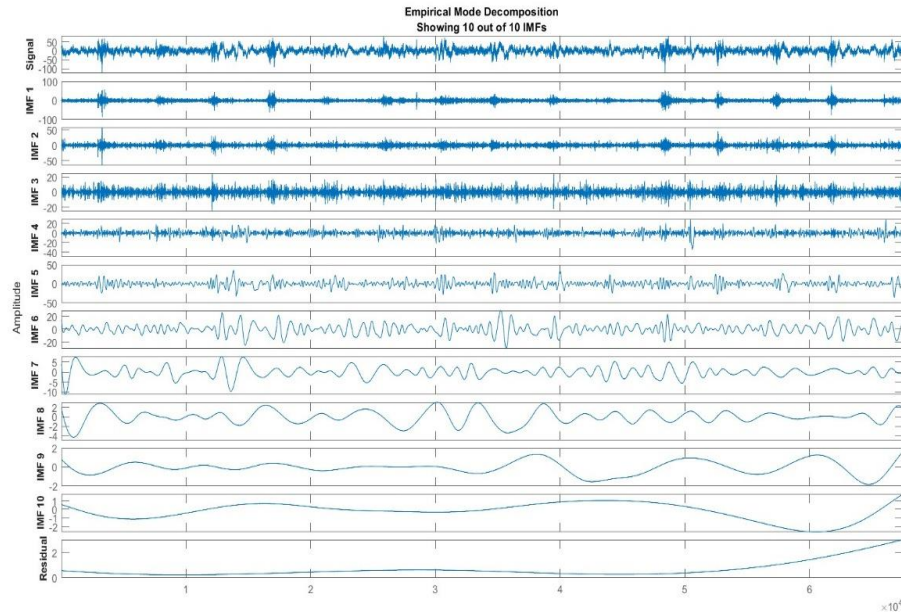


Figure 4.1 EEG signal decomposed into 10 Intrinsic Mode Functions (IMFs) using Empirical Mode Decomposition (EMD)

Band-Pass Filtering (0.5-40 Hz)

Band-pass filtering was applied to EEG data to preserve a specific frequency range (0.5-40 Hz) using the EEGLab toolbox [217]. EEGLab is a powerful open-source tool for

processing EEG data. This method retained the desired frequency components in EEG data while filtering out noise and unwanted components.

Independent Component Analysis (ICA)

Using the EEGLab toolbox, Independent Component Analysis (ICA) was employed to clean EEG data. ICA enables the separation and isolation of different sources within EEG data. Our EEG signal contained signals such as muscle activity and eye movements. Applying ICA to each channel allowed us to decompose our data into independent components, thereby improving our data quality. We could isolate unwanted components with filtering methods, obtaining new noise-free data (see Figure 4.2).

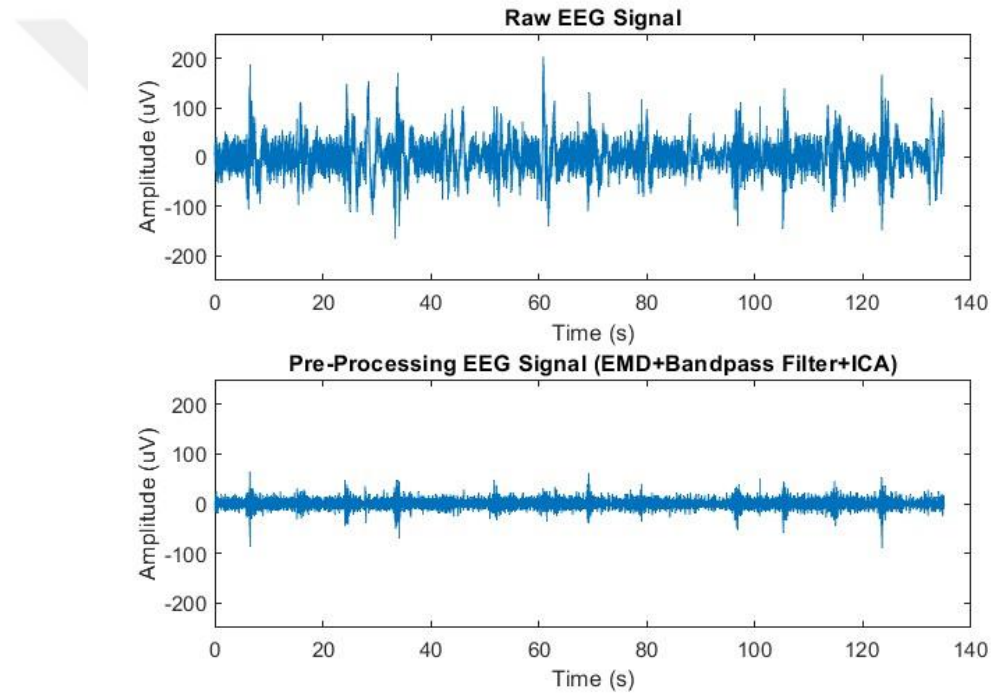


Figure 4.2 Comparison of raw and preprocessed EEG data. (Top) Raw EEG data before preprocessing. (Bottom) EEG data after preprocessing, including Empirical Mode Decomposition (EMD), a 0.5–40 Hz bandpass filter, and Independent Component Analysis (ICA) for artifact removal

4.2.2 Feature Extraction

We extracted 30 frequency- and time-domain features from each EEG channel corresponding to the rest and imagination phases of different swallowing experimental paradigms (see Figure 4.3 and Figure 4.4). The feature extraction approaches employed included the Ratio of Band Power (Alpha to Beta), Band Power Gamma, Band Power Beta, Band Power Alpha, Band Power Theta, Band Power Delta, Hjorth Activity, Hjorth

Mobility, Hjorth Complexity, Skewness, Kurtosis, First Difference, Normalized First Difference, Second Difference, Normalized Second Difference, Mean Curve Length, Mean Energy, Mean Teager Energy, Log Root Sum of Sequential Variation, Tsallis Entropy, Shannon Entropy, Log Energy Entropy, Renyi Entropy, Arithmetic Mean, Standard Deviation, Variance, Median Value, Auto-Regressive Model, Maximum Value, and Minimum Value.

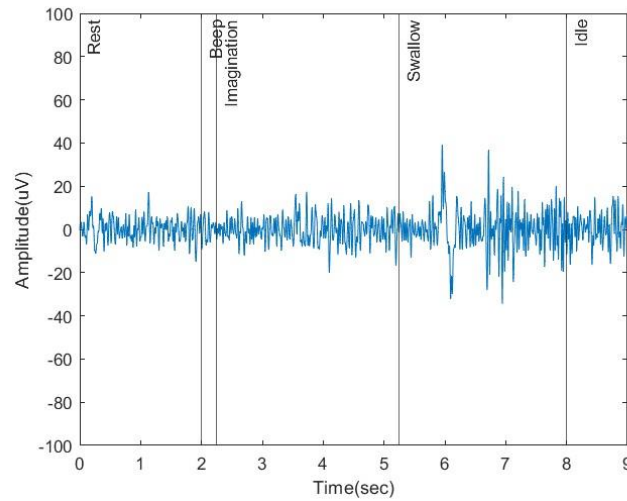


Figure 4.3 An example of preprocessed data from the induced saliva swallowing experimental paradigm shows segmented intervals. The intervals are divided into rest and imagination sections for feature extraction

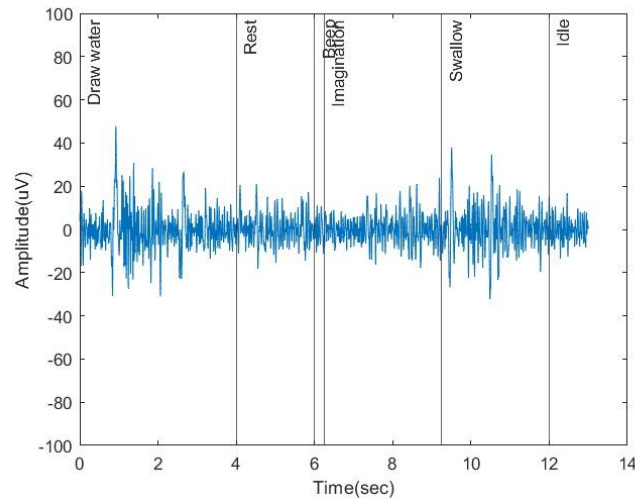


Figure 4.4 An example of preprocessed data from the induced water swallowing experimental paradigm shows segmented intervals. The intervals are divided into rest and imagination sections for feature extraction

These 30 features were extracted from the 16 channels for each imagination and rest segment. Consequently, for each segment, we obtained a total of 480 features (30 x 16).

4.2.3 Statistical Analysis

This phase in our research aimed to assess the significance of differences among these features in various experimental paradigms using appropriate statistical tests. Values with a p-value greater than 0.05 were considered non-significant, indicating no notable difference between groups. P-values less than 0.05 were categorized as significant, those less than 0.01 as very significant, and those less than 0.001 as highly significant. In our study, Bonferroni correction was applied to control for multiple comparisons. In experimental paradigms involving all features, considering 30 different features and conducting 16 trials for each, 480 comparisons were made. Bonferroni correction was employed to maintain the significance level during these multiple comparisons. This method aims to reduce false positive results and ensure statistically reliable outcomes.

It is possible to use various normality tests to reveal whether the feature we are interested in is suitable for a normal distribution. The Chi-Square, Kolmogorov-Smirnov, Lilliefors, and Shapiro-Wilk normality tests are the most well-known tests. We decided to use the Shapiro-Wilk test because it is the most powerful test of normality assumption [218], and we conducted our experimental paradigms with less than 50 subjects. First, with the Shapiro-Wilk test, we determined which features have normal or non-normal distribution among 480 features. Then, we performed a parametric test (paired-sample *t*-test) for normally distributed variables and a non-parametric test (Mann-Whitney U test, also known as the Wilcoxon rank-sum test) for non-normal distribution variables.

4.2.4 Classification

This study employed various classification methods to discriminate between the rest and imagination phases in the Induced Saliva Swallowing and Induced Water Swallowing experimental paradigms using the Leave-One-Subject-Out Cross-Validation (LOSO-CV) method. Additionally, classification was performed on the imagination data from these experimental paradigms to facilitate comparative analysis and gain insights into the distinctive features associated with each paradigm.

During the comparison of classification approaches, careful selection of hyperparameters is crucial. Determining optimal hyperparameters for each classifier is necessary for an objective and reliable comparison. In this context, a detailed hyperparameter optimization was conducted in my study to identify the most suitable hyperparameters for different classifiers. The optimization process involved various methods, and the results were validated through cross-validation. The models demonstrating the best performance, as determined by these methods, were utilized in the study analyses. The following classification methods were applied to conduct these analyses:

The KNN method is an instance-based classification approach that categorizes data points based on similarity metrics. In our analysis, we trained our data using a 3-nearest neighbor classifier. SVM is a supervised learning method to find a hyperplane that best separates data points in one or more dimensions. We utilized an SVM classifier trained with the predictors in the matrix data and the class labels in vector form for two-class (binary) classification. Decision Trees construct a tree structure to classify a dataset based on a sequence of decisions. Our model comprises a fitted binary classification decision tree based on the input variables. Naive Bayes is a probability-based classification method grounded in Bayes' theorem. In our study, we trained our data using predictive data and class labels with a Naive Bayes model. Random Forest is an ensemble learning method that combines multiple decision trees. In our study, we trained a random forest comprising 100 regression trees using the entire dataset. AdaBoost is a boosting algorithm that combines weak classifiers to create a strong classifier. We trained AdaBoost with an ensemble decision tree using 100 learning cycles and the entire dataset. Bagging, employing bootstrap sampling, trains multiple models and aggregates their predictions. In this study, we trained an ensemble of bagged trees using the entire dataset with 100 weak learners. Kernel Classification transforms feature space using kernel functions, often applied in SVM. A binary Gaussian kernel classification model is trained using predictor data.

Performance measurements for each of the above methods were performed for classification accuracy and detailed evaluations. Based on these definitions, the following performance metrics are computed: Precision, Recall, Accuracy, and F1-measure.

The results of these analyses are presented in the following sections, allowing a comprehensive understanding of the effectiveness of each classification approach in

distinguishing between resting and imagination parts for these two experimental paradigms and between imagining parts in the two experimental paradigms.

4.3 Results

4.3.1 Induced Saliva Swallowing Experimental Paradigm Rest and Imagination

As a result of the Shapiro-Wilk Normality test, it was determined that 13 of the 480 features had a normal distribution, while the rest did not comply with the normal distribution. When these 13 features were subjected to a t-test, it was seen that all these features were highly significant.

Table 4.1 Significance test results of the Induced Saliva Swallowing Experimental Paradigm between rest and imagination. The channel-feature is marked with X when there is a statistically significant difference between the features obtained during rest and imagination. rba:Ratio of Band Power Alpha to Beta, bpg:Band Power Gamma, bpb:Band Power Beta, bpa:Band Power Alpha, bpt:Band Power Theta, bpd:Band Power Delta, ha:Hjorth Activity, hm:Hjorth Mobility, hc:Hjorth Complexity, skew:Skewness, kurt:Kurtosis, 1d:First Difference, n1d:Normalized First Difference, 2d:Second Difference, n2d:Normalized Second Difference, mcl:Mean Curve Length, me:Mean Energy, mte:Mean Teager Energy, lrssv:Log Root Sum of Sequential Variation, te:Tsallis Entropy, sh:Shannon Entropy, le:LogEnergyEntropy, re:RenyiEntropy, am:Arithmetic Mean, sd:Standard Deviation, var:Variance, md:Median Value, ar:Auto-Regressive Model, max:Maximum Value, min:Minimum Value

Channel	rba	bpg	bpb	bpa	bpt	bpd	ha	hm	hc	skew	kurt	1d	n1d	2d	n2d	mcl	me	mte	lrssv	te	sh	le	re	am	sd	var	md	ar	max	min
1	x			x															x	x	x	x	x							
2																			x	x	x	x	x							
3																			x	x	x	x	x							
4																			x	x	x	x	x							
5																			x	x	x	x	x							
6																			x	x	x	x	x							
7																			x	x	x	x	x							
8																			x	x	x	x	x							
9																			x	x	x	x	x							
10																			x	x	x	x	x							
11																			x	x	x	x	x							
12																			x	x	x	x	x							
13																			x	x	x	x	x							
14																			x	x	x	x	x							
15																			x	x	x	x	x							
16									x										x	x	x	x	x							

When the 467 features that did not have a normal distribution were subjected to the Mann-Whitney U test, we found that 397 features were not significant (see Table 4.1), 2 features were significant, 1 feature was very significant, and 67 features were highly significant. Table 4.1 shows the significance test results of the Induced Saliva Swallowing Experimental Paradigm between rest and imagination. The Log Root Sum of Sequential Variation, Tsallis Entropy, Shannon Entropy, Log Energy Entropy, and Renyi Entropy features for all channels, where there is a statistically significant difference between the features obtained during rest and imagination.

All 480 features were subjected to 8 classifiers to classify rest and imagination. The results are displayed in Table 4.2. When the results are examined, Random Forest, AdaBoost, and Bagging classifiers distinguish between rest and imagination at a rate of 99%. In addition, new results were obtained by classifying only the channel features with significant features among these 480 features (see Table 4.3). The results are like the features in the results for all features. Random Forest, AdaBoost, and Bagging classifiers provided 99% discrimination between rest and imagination.

Table 4.2 Classification results for all features obtained during Induced Saliva Swallowing Experimental Paradigm between rest and imagination

Classifier	Accuracy	Precision	Recall	F1-measure
KNN	80.4444	96.6667	76.6222	0.8452
SVM	50.0000	100.000	50.0000	0.6667
Decision Tree	98.2222	98.2222	98.4273	0.9824
Naive Bayes	55.1111	16.8889	81.7300	0.6853
Random Forest	99.3333	99.3333	99.3750	0.9932
AdaBoost	99.4444	99.5556	99.3750	0.9945
Bagging	99.3333	99.3333	99.3750	0.9932
Kernel	49.6667	59.5556	50.2000	0.5414

Table 4.3 Classification results for significant features obtained during Induced Saliva Swallowing Experimental Paradigm between rest and imagination

Classifier	Accuracy	Precision	Recall	F1-measure
KNN	78.1111	93.1111	75.8658	0.8186
SVM	75.2222	86.8889	72.7286	0.7759
Decision Tree	98.0000	98.2222	97.9967	0.9801
Naive Bayes	81.0000	66.2222	95.5696	0.7677
Random Forest	99.3333	99.3333	99.3750	0.9932
AdaBoost	99.2222	99.3333	99.1912	0.9922
Bagging	99.3333	99.3333	99.3750	0.9932
Kernel	50.8889	57.5556	51.3340	0.5396

4.3.2 Induced Water Swallowing Experimental Paradigm Rest and Imagination

The Induced Water Swallowing experimental paradigm determined that out of 480 features tested using the Shapiro-Wilk Normality test, 15 exhibited a normal distribution. In contrast, the remaining features did not conform to a normal distribution. Upon subjecting these 15 normal distributed features to t-test analysis, it was observed that 14 features were highly significant, whereas 1 feature did not show significance.

The Mann-Whitney U test was applied for the 465 features that did not follow a normal distribution according to the Shapiro-Wilk test. The results revealed that 362 features were not significant (Table 4.4), 13 features were significant, 10 features were very significant, and 80 features were highly significant.

Table 4.4 Significance test results of the Induced Water Swallowing Experimental Paradigm between rest and imagination. The channel feature is marked with X when there is a statistically significant difference between the features obtained during rest and imagination. The abbreviations of the features are given in Table 1

Channel	rba	bpg	bpb	bpa	bpt	bpd	ha	hm	hc	skew	kurt	1d	n1d	2d	n2d	mcl	me	mte	lrsv	te	sh	le	re	am	sd	var	md	ar	max	min
1																			x	x	x	x	x							x
2											x								x	x	x	x	x						x	x
3											x								x	x	x	x	x						x	x
4						x					x								x	x	x	x	x						x	x
5											x								x	x	x	x	x						x	x
6						x													x	x	x	x	x							x
7																			x	x	x	x	x							x
8						x					x								x	x	x	x	x						x	x
9						x					x								x	x	x	x	x						x	x
10					x						x								x	x	x	x	x						x	
11											x								x	x	x	x	x						x	x
12											x								x	x	x	x	x							
13																			x	x	x	x	x							x
14																			x	x	x	x	x							x
15											x								x	x	x	x	x							x
16											x								x	x	x	x	x							

All 480 features were used to classify rest and imagination for the Induced Water Swallowing Experimental Paradigm. It was subjected to 8 different classifiers: KNN, SVM, Decision Tree, Naive Bayes, Random Forest, AdaBoost, Bagging, and Kernel. Accuracy, precision, recall, and F1-measure results are shown in the table. When the results are examined, it is observed that the Random Forest, AdaBoost, and Bagging classifiers give better results than other classifications between rest and imagination, like the first paradigm. It is seen that these classifications discriminate at an average accuracy rate of 98% (Table 4.5). When only 5 features with significant channel features are

subjected to the classifier, AdaBoost gives 98% accuracy (Table 4.6). The significant features results are similar to the features in the results for all features. Random Forest, AdaBoost, and Bagging classifiers provided 98% discrimination between rest and imagination.

Table 4.5 Classification results for all features obtained during Induced Water Swallowing Experimental Paradigm between rest and imagination

Classifier	Accuracy	Precision	Recall	F1-measure
KNN	81.2222	95.3333	76.9580	0.8445
SVM	51.0000	98.6667	51.3636	0.6696
Decision Tree	97.5556	99.5556	96.5212	0.9783
Naive Bayes	57.5556	23.1111	81.6173	0.5140
Random Forest	98.7778	99.5556	98.8816	0.9916
AdaBoost	98.8889	99.7778	98.3578	0.9896
Bagging	98.8889	99.5556	98.3578	0.9887
Kernel	51.4444	56.2222	49.9153	0.5251

Table 4.6 Classification results for significant features in the Induced Water Swallowing Experimental Paradigm between rest and imagination

Classifier	Accuracy	Precision	Recall	F1-measure
KNN	78.0000	91.1111	75.0256	0.8064
SVM	33.8889	29.5556	29.9507	0.5188
Decision Tree	95.8889	96.8889	95.7491	0.9605
Naive Bayes	74.1111	50.0000	98.0451	0.6429
Random Forest	98.4444	97.7778	99.1912	0.9833
AdaBoost	98.3333	97.9902	98.8889	0.9834
Bagging	98.5556	98.2222	98.9828	0.9849
Kernel	55.0000	59.5556	53.8544	0.5627

4.3.3 Induced Saliva Swallowing Experimental Paradigm Imagination vs. Induced Water Swallowing Experimental Paradigm Imagination

In examining the imagination parts of two experimental paradigms, a preliminary analysis involved the application of the Shapiro-Wilk Normality test to 480 features, revealing that 16 features exhibited a normal distribution. In contrast, the remaining features did not conform to normal distribution. Upon subjecting the 16 features with normal distribution to t-test analysis, it was observed that all 13 features were statistically highly significant, and 3 features were statistically very significant.

For the 464 features not conforming to normal distribution based on the Shapiro-Wilk test, the Mann-Whitney U test was employed. The results indicated that 178 features were not statistically significant (Table 4.7), 18 features were significant, 33 features were very significant, and 235 features were highly significant. Consequently, it was observed that the non-normally distributed features collectively yielded 302 statistically significant outcomes.

The Induced Saliva Swallowing Experimental Paradigm imagination and Induced Water Swallowing Experimental Paradigm imagination utilize 480 features for classifying between imagination and rest states, employing nine distinct classifiers: KNN, SVM, Decision Tree, Naive Bayes, Random Forest, AdaBoost, Bagging, Kernel, and utilizing all features. Various performance metrics, including accuracy, precision, recall, and F1-measure, were assessed for each classifier. The results reveal that the Random Forest classifier achieves the highest accuracy at 73%, followed closely by Bagging with 72% and AdaBoost with 69% (Table 4.8). When considering only features with significant channel features, the Bagging classifier demonstrates the highest accuracy at 65%, followed by Random Forest at 64% and AdaBoost at 60% (Table 4.9).

Table 4.7 Significance test results of between the Induced Saliva Swallowing Experimental Paradigm Imagination and Induced Water Swallowing Experimental Paradigm Imagination. The channel feature is marked with X when there is a statistically significant difference between the features obtained during rest and imagination. The abbreviations of the features are given in Table 1

Channel	rba	bpg	bpb	bpa	bpt	bpd	ha	hm	hc	skew	kurt	1d	n1d	2d	n2d	mcl	me	mte	lrssv	te	sh	le	re	am	sd	var	md	ar	max	min
1		x	x				x	x			x	x		x		x	x	x	x	x		x	x		x	X		x	x	x
2		x	x	x	x	x	x				x	x		x		x	x	x	x	x	x	x	x		x	X			x	x
3		x	x	x	x	x	x				x	x		x		x	x	x	x	x		x	x		x	X			x	x
4		x	x		x	x	x				x	x		x		x	x	x	x	x	x	x	x		x	X			x	x
5		x	x		x	x	x				x	x		x		x	x	x	x			x			x	X			x	x
6		x	x		x	x	x					x		x		x	x	x	x			x			x	x			x	x
7	x	x	x				x	x	x			x	x	x	x	x	x	x	x			x			x	x		x	x	x
8		x	x	x	x	x	x				x	x		x		x	x	x	x	x	x	x	x		x	x			x	x
9		x	x				x	x				x		x		x	x	x	x			x			x	x		x	x	x
10		x	x	x	x	x	x				x	x		x		x	x	x	x	x	x	x	x		x	x			x	x
11		x									x	x		x		x		x	x	x	x	x	x						x	x
12		x	x			x	x				x	x		x		x	x	x	x	x	x	x	x		x	x			x	x
13		x					x				x	x		x		x		x	x	x	x	x	x		x	x			x	x
14		x	x	x	x	x	x				x	x		x		x	x	x	x	x	x	x	x		x	x			x	x
15		x	x	x	x	x	x				x	x		x		x	x	x	x	x	x	x	x		x	x			x	x
16		x	x	x	x	x	x				x	x		x		x	x	x	x	x	x	x	x		x	x			x	x

Table 4.8 Classification results for all features between Induced Saliva Swallowing Experimental Paradigm imagination and Induced Water Swallowing Experimental Paradigm imagination

Classifier	Accuracy	Precision	Recall	F1-measure
KNN	64.4444	66.0000	64.6330	0.6353
SVM	46.4444	24.4444	50.7814	0.3996
Decision Tree	58.8889	54.6667	60.2739	0.5324
Naive Bayes	57.8889	94.8889	56.3857	0.6983
Random Forest	73.3333	67.7778	80.3911	0.7600
AdaBoost	69.7778	64.4444	77.4227	0.7265
Bagging	72.0000	66.8889	80.6216	0.7435
Kernel	55.1111	58.2222	54.6369	0.5511

Although the results indicate that distinguishing between imagination segments in two different paradigms may not be as explicit as between rest and imagination, they underscore the potential for improvement with enhanced classifier quality. Upon comprehensive examination, Random Forest, AdaBoost, and Bagging classifiers consistently emerge as the top performers across all three paradigms. The robustness of these outcomes suggests that these classifiers hold promise for the discrimination of swallowing-related brain signals, thereby contributing significantly to the comprehension and rehabilitation of dysphagia.

Table 4.9 Classification results for significant features in the between Induced Saliva Swallowing Experimental Paradigm imagination versus Induced Water Swallowing Experimental Paradigm imagination

Classifier	Accuracy	Precision	Recall	F1-measure
KNN	56.8889	51.5556	57.2384	0.5532
SVM	48.1111	56.0000	45.0093	0.5222
Decision Tree	54.5556	54.4444	57.3046	0.5320
Naive Bayes	53.3333	83.7778	54.3741	0.6302
Random Forest	64.2222	57.1111	72.7287	0.6196
AdaBoost	60.6667	66.3556	57.3333	0.6011
Bagging	65.2222	59.7778	70.3423	0.6104
Kernel	50.0000	100.0000	50.0000	0.6667

4.4 Conclusions and Discussion

This study unveils the potential of EEG-based features in understanding and differentiating swallowing-related brain signals. The identified features demonstrate high accuracy in classifying different states of swallowing during induced saliva and water swallowing experimental paradigms. These hold promises for the development of innovative rehabilitation strategies for dysphagia.

The translation of our findings into practical rehabilitation applications could significantly improve the quality of life for individuals with dysphagia. The non-invasive and versatile nature of EEG positions it as a valuable tool for continuous monitoring and personalized treatment plans. As technology advances, the integration of our results into real-world applications has the potential to revolutionize dysphagia rehabilitation, addressing both the physiological and social aspects of this challenging condition.

It is understood that to combat dysphagia, swallowing should also be examined electrophysiologically. Therefore, the study of electrophysiological events allows us to increase our knowledge of controlling swallowing networks and provide a tool to monitor the effects of different treatments on pharyngeal sensory function. Generally, ERPs have

been used in literature to examine the electrophysiological structure of swallowing [219]. ERPs are event-related potential digitally extracted from the EEG and measure time-dependent activity in response to sensory, motor, or cognitive events [220]. The swallowing process appears to involve neural transmission and cerebral integration of oropharyngeal sensory inputs, which can be studied through studies (ERPs) [221], [222]. Other electrophysiological studies on swallowing also provide us with significant information about dysphagia. For example, in a study [223], it was observed that the clinical and electrophysiological findings of dysphagia were like those seen in skeletal muscle diseases. The relationship between MS disease and dysphagia was investigated electrophysiologically in another study [224]. In addition, electrophysiological examination of stroke patients and people with swallowing problems contributed to finding a link between these two diseases. Looking at all these studies, we think that the different electrophysiological features obtained with EEG-based motor imagery may contribute positively to new brain-machine interface applications to be developed for rehabilitating dysphagia patients.

The different electrophysiological connections that occur in motor imagery in the face of other situations, such as the imagination of swallowing water and saliva, show that the determination of EEG-based features can play an important role in rehabilitating patients with dysphagia. Brain regions and effective EEG-based features illustrate the importance of the treatment's relationship with mental practice and physical therapy during motor rehabilitation.

There are many studies on the rehabilitation of swallowing difficulties. However, a few research papers have explored the potential of motor imagery (MI) to improve rehabilitation for swallowing challenges alone. In contrast, current studies suggest that motor imagery can induce a brain response and that mentalizing swallowing-related actions may effectively improve the motor performance of swallowing [225]. Using different experimental protocols, our study focused on the relationship between motor imagery and swallowing. In this way, we observed whether the motor imagery of the swallowing acts differently in different situations. Thus, we aimed to search for practical, cost-effective, accessible applications to increase the effectiveness of active exercises during dysphagia rehabilitation and help patients with swallowing difficulties. Although motor imagery exercise cannot replace active exercise in general, it is recommended to use motor imagery to increase active exercise in motor learning and motor performance, especially after neurological damage [226], [227], [228]. The most effective approach is

when physiotherapy is combined with motor imagery [229]. Moreover, studies in the literature have generally explored different methodologies of swallow motor imagery [61], [62], [70], [230]. This study also aims to conduct a systematic statistical analysis of signals belonging to different experimental paradigms. Furthermore, the observed high accuracy, especially with classifiers like Random Forest, AdaBoost, and Bagging, emphasizes the reliability of EEG-based features in distinguishing between rest and imagination phases during induced swallowing. This achievement holds promise for the development of brain-machine interface applications tailored to the needs of dysphagic patients. The non-invasive nature of EEG, coupled with its ability to record rapid changes in neuronal activity, makes it a powerful tool for exploring the dynamic nature of swallowing processes.

Our findings show promise for developing innovative dysphagia rehabilitation strategies. However, future research must address several limitations to ensure robustness and applicability. The study's sample size and demographic diversity may not be sufficiently representative, and the induced swallowing scenarios might not entirely reflect natural conditions. Additionally, EEG signals are noise-prone, which could affect feature extraction accuracy. Individual variability in motor imagery tasks and the complexity of interpreting EEG-based features also present challenges. Translating these findings into practical rehabilitation tools and brain-machine interfaces may face technological and logistical hurdles, and the long-term efficacy of these strategies requires further evaluation. Comparative studies are needed to assess the effectiveness of EEG-based motor imagery rehabilitation against traditional methods.

Our study aligns with the broader landscape of neurological studies utilizing EEG to analyze brain activities. The cost-effectiveness, patient comfort, and high temporal resolution of EEG make it a preferred method for investigating various conditions, including dysphagia. The significance of our findings lies in their potential applications for dysphagia rehabilitation, addressing physiological and social challenges faced by affected individuals.

While our research focuses on induced swallowing scenarios, the implications could be expanded through further investigations involving diverse swallowing conditions and demographic groups. Incorporating real-time applications and feedback mechanisms into brain-machine interfaces represents a potential avenue for practical solutions, enhancing the daily lives of individuals dealing with dysphagia.

Chapter 5

Distinguishing Resting State from Motor Imagery Using Deep Learning Models

5.1 Motivation

This study aims to investigate EEG signals related to the swallowing process through four different experimental paradigms. The utilization of various experimental paradigms seeks to determine the variability in EEG signals during swallowing, providing insights into multiple aspects of swallowing-related brain activity. Additionally, we evaluate the impact of preprocessing methods, such as Independent Component Analysis, Empirical Mode Decomposition, and bandpass filtering, on the classification performance of EEG signals. We focus on classification results to determine the effectiveness of these methods in the rehabilitation and treatment of individuals with swallowing difficulties.

Furthermore, we investigate the effectiveness of spectrograms and scalograms in visualizing and understanding EEG signals' time-frequency characteristics. We analyze these methods to determine which provides more accurate representations of EEG signals and contributes to a better understanding of swallowing-related brain activity.

Along these lines, this study's proposed approach involves classifying EEG signals to differentiate between imagination and resting processes in the context of swallowing using a deep learning model, Convolutional Neural Networks (CNNs). The results of this study showed that the CNN model can be utilized to accurately classify brain activity associated with swallowing, offering a novel approach for the rehabilitation and treatment of individuals with swallowing difficulties. The findings of this study may contribute to the development of more effective rehabilitation and treatment strategies to enhance the

quality of life for individuals with swallowing difficulties (dysphagia). They may offer a safe, patient-friendly, and affordable way to treat individuals with dysphagia.

5.2 Materials and Methods

In this section, our work is based on all the experimental paradigms detailed in Section 3. Figure 5.1, Figure 5.2, Figure 5.3 and Figure 5.4 show the segmentation sections of the experimental paradigm.

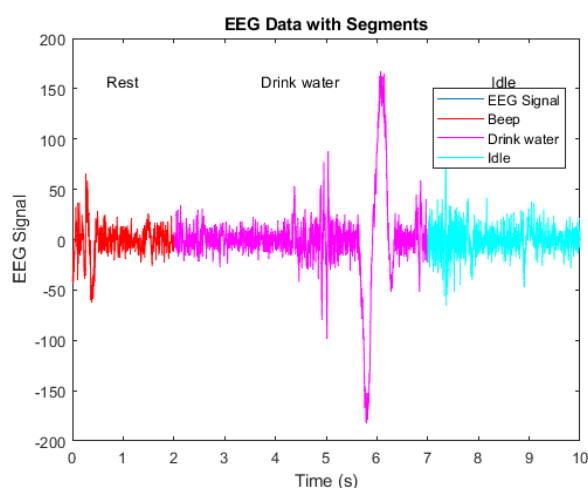


Figure 5.1 EEG data segmentation during Natural Water Swallowing Experimental Paradigm

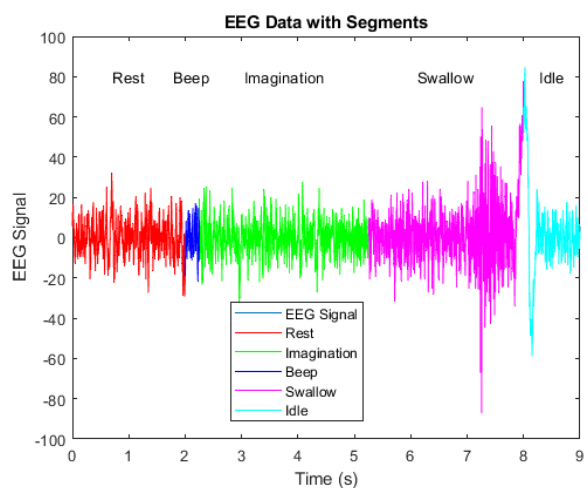


Figure 5.2 EEG data segmentation during Induced Saliva Swallowing Experimental Paradigm

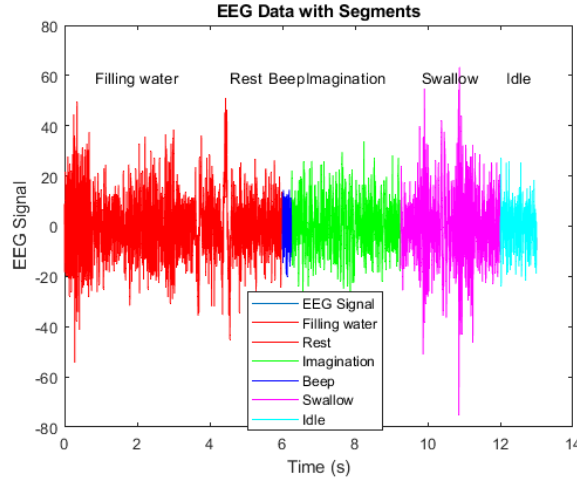


Figure 5.3 EEG data segmentation during Induced Water Swallowing Experimental Paradigm

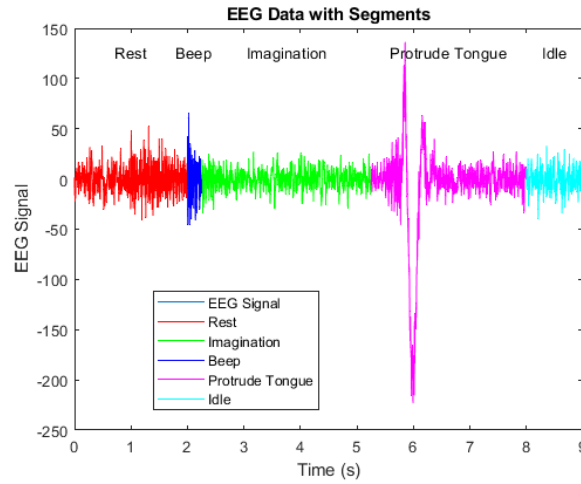


Figure 5.4 EEG data segmentation during Induced Tongue Protrusion Experimental Paradigm

5.2.1 Preprocessing

The analysis of EEG signals is one of the main focal points of this study, and we aim to evaluate the importance of preprocessing steps in this analysis. In this section, four methods for the preprocessing of EEG data were examined: Empirical Mode Decomposition (EMD) Method, Independent Component Analysis (ICA), and Bandpass Filtering (BPF, 0.5-40 Hz), and the hybrid model.

To assess the contribution of preprocessing methods in distinguishing rest and imagination of swallowing, raw data was initially employed in the classification process, and later data underwent preprocessing steps, including EMD, BPF, and the hybrid model, before the classification was performed.

Empirical Mode Decomposition

Empirical Mode Decomposition (EMD) is an effective method for decomposing nonstationary and non-linear data. Using the EMD method to analyze EEG signals, different frequency components contained within the signal have been separated. The aim was to understand the time-frequency characteristics of the signal better. In this study, 10 Intrinsic Mode Functions (IMFs) were obtained from processing EEG signals with the EMD method, and the summation of the first 3 IMFs was selected for further analysis, as depicted in Figure 5.5 and Figure 5.6.

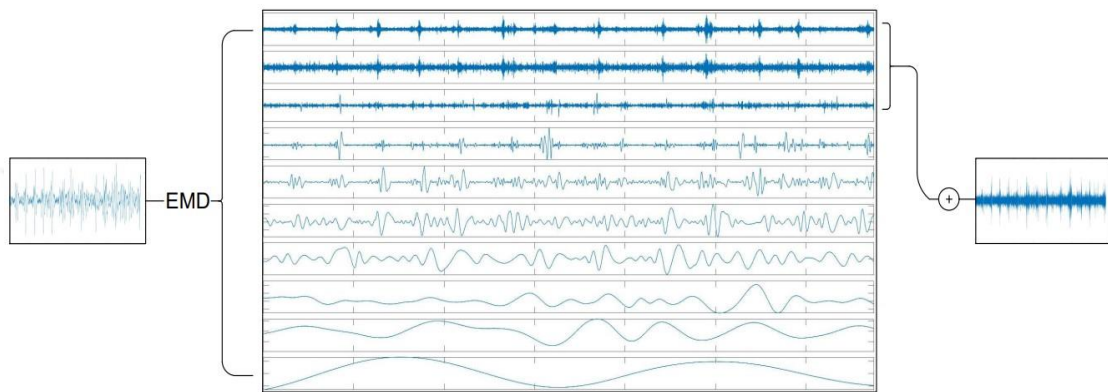


Figure 5.5 Applying EMD to the EEG signal obtained from one channel

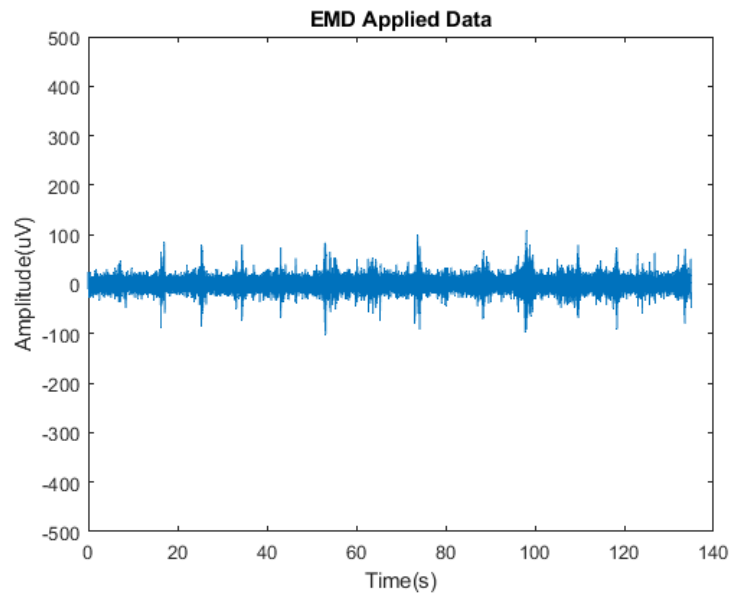


Figure 5.6 The signal obtained by applying Empirical Mode Decomposition (EMD) to the EEG signal from a single channel, selecting the first three Intrinsic Mode Functions (IMFs), and summing them

Our experimental paradigms utilized Independent Component Analysis (ICA) filtering, commonly used in EEG studies, to reduce noise artifacts such as eye blinking, muscle movements, and other physiological interferences. Our goal in applying ICA

filtering is to enhance the accuracy of subsequent analysis and interpretation by ensuring that the resulting EEG data is cleaner and more reliable. Through the application of ICA, we seek to enhance the quality of EEG recordings, which is essential for obtaining robust and reproducible results in neurophysiological research.

Bandpass Filtering

Bandpass Filtering (BPF) is a prevalent technique for eliminating undesired components, such as power line noise and signals beyond the intended frequency range in EEG signals. Since bandpass filtering within the range of 0.5-40 Hz is widely adopted in EEG studies, we implemented filtering within this specified range for our experimental paradigms (see Figure 5.7).

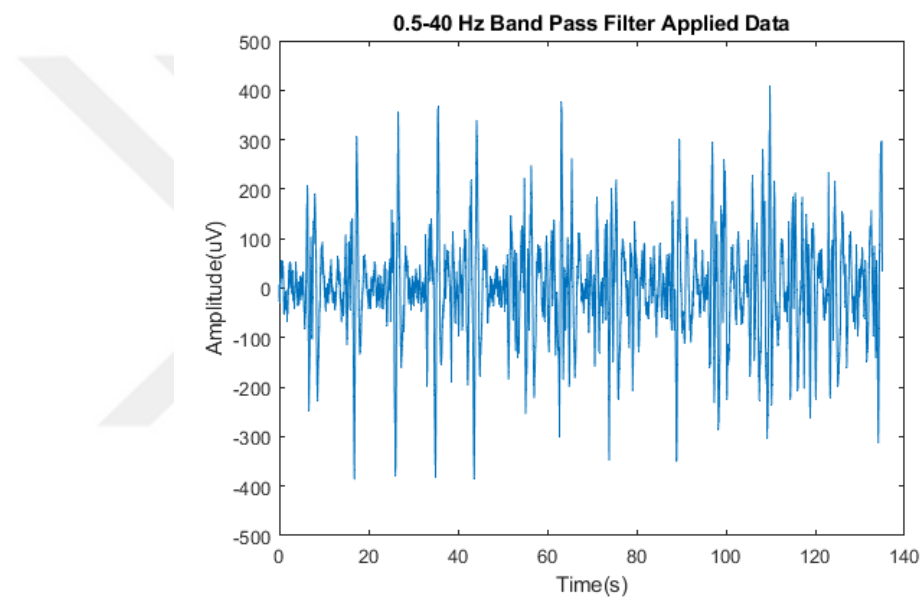


Figure 5.7 The signal was obtained by applying a 0.5-40 Hz band pass filter to the EEG signal from a single channel

Hybrid Model: EMD + ICA + Bandpass Filtering (0.5-40 Hz)

The hybrid model used for the analysis of EEG signals integrates Empirical Mode Decomposition (EMD), Independent Component Analysis (ICA), and bandpass filtering (BPF). Using the EMD method, different frequency components contained within the signal were separated. This study utilized only the summation of the first 3 IMFs out of 10 IMFs. Subsequently, ICA and BPF were applied to the resulting signal using MATLAB and EEGLAB, as shown in Figure 5.8. These steps enabled further EEG data analysis and facilitated removing unwanted components.

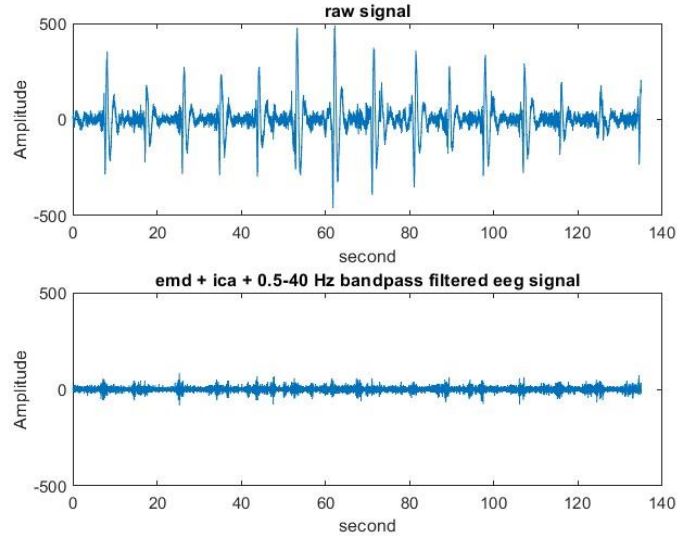


Figure 5.8 Raw and filtered signals from one EEG channel

5.2.2 Generation of Spectral Images

After we performed preprocessing on EEG signals, we were able to work on EEG signals coming from various experimental paradigms that were i) untreated, ii) processed only with Empirical Mode Decomposition (EMD), iii) subjected only to bandpass filtering, and iv) pre-processed with the hybrid model consisting of a cascade of EMD, ICA, and bandpass filter.

We aimed to extract features from these four different signals. Given that EEG signals contain oscillatory and non-stationary frequency components, we applied time-frequency transformation techniques to obtain more information. These techniques help us better understand the relationship between the time and frequency characteristics of the signals. Additionally, various methods were employed to transform EEG signals into the time-frequency domain. The 16-channel EEG signals were combined into a single scalogram, resulting in scalogram images (see Figure 5.9). Subsequently, Short-Time Fourier Transform (STFT) was applied individually to each channel, followed by obtaining scalogram images using Continuous Wavelet Transform (CWT) with different wavelet types for each channel (see Figure 5.10). Using these diverse transformation techniques, scalograms and spectrogram images were obtained for each experimental paradigm. These images were then adjusted to appropriate input dimensions for classification purposes.

This study initially derived black-and-white images from EEG signals, where grayscale values visually represented signal intensities. These grayscale images were

converted into color maps to enhance the interpretability of these signals, making the visualizations more vivid and facilitating an easier understanding of the signal characteristics. Each pixel in these visualizations corresponds to a specific time-frequency representation, where the height and width of each pixel represent a frequency and time interval, respectively. This pixel-based approach enables a comprehensive analysis of frequency changes over time, allowing for frequency-based comparisons across data from different electrodes. Notably, we could have performed normalization across channels, as we aimed to retain the raw data to reflect natural variations inherent in each electrode due to factors such as electrode placement, biological differences, and measurement conditions. This decision allows for preserving natural amplitude differences in the signals, maintaining the biomedical significance of these variations. The signal window size corresponding to each pixel's width was determined by the time-frequency analysis method and sampling rate, optimized to capture frequency changes over time accurately, thus facilitating a precise analysis of both the temporal and frequency components of the signals.

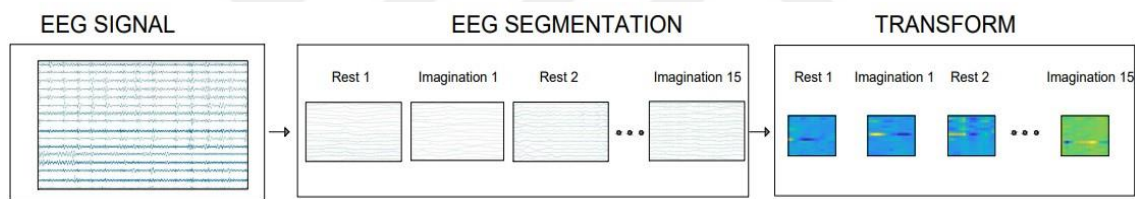


Figure 5.9 Dividing the trials into rest and imagination segments one by one and transforming them into time-channel images

Image Generation from All Channels

The EEG data was visualized to create a composite image of all channels. This method allows for creating an image using the entire color range of the color map. We visualized EEG signal data as a 2-dimensional color map, transforming signal values into color representations where the amplitude is mapped to specific colors, enhancing the understanding of signal strength variations over time and across channels. Each pixel corresponds to an EEG channel (electrode) on the vertical axis and a specific time interval on the horizontal axis, with a 2-second signal window used for visualization; thus, the width of each pixel represents a millisecond change. Notably, normalization across channels was not performed, allowing the signals to retain their original amplitude variations, which enhances the visibility of inter-channel differences and provides more precise insights into signal changes. It enables the representation of different trials, each

containing rest and imagination processes, across different channels within the same visual. Each element in the signal specifies the color of a pixel in the image.

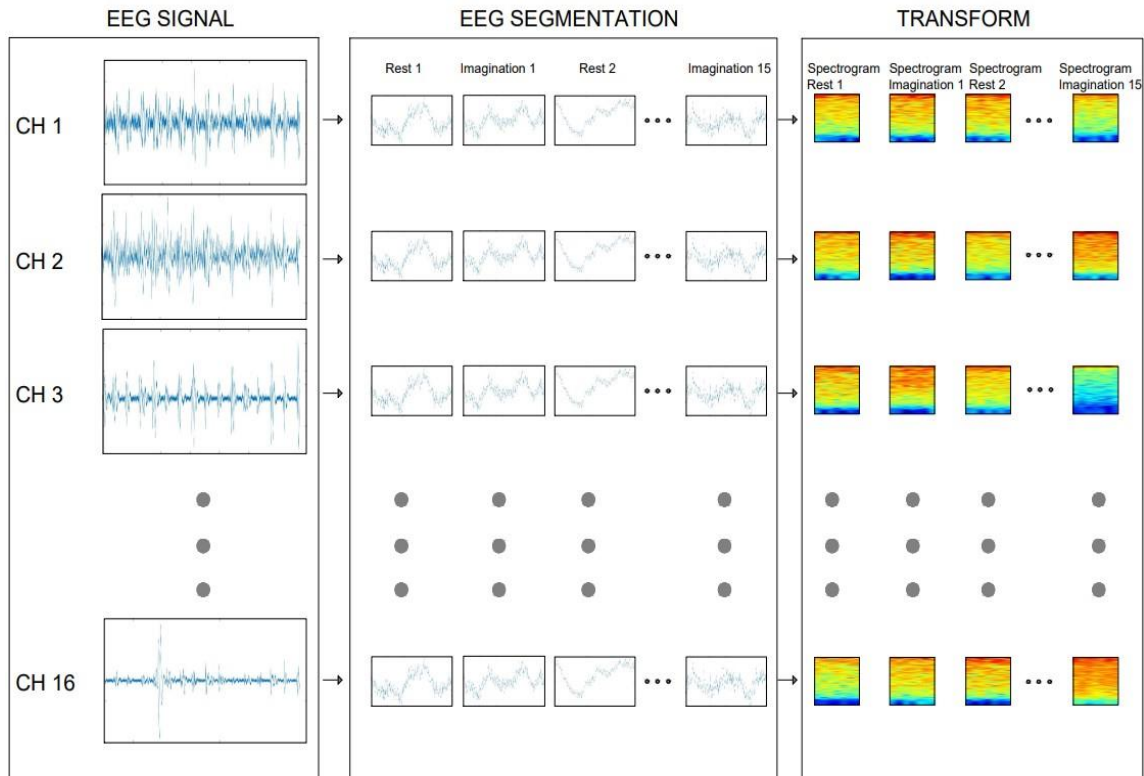


Figure 5.10 Dividing each channel the trials into rest and imagination segments one by one and transforming them into a spectrogram

Each y-axis label represents the electrode positions associated with the EEG (see Figure 5.9). For example, for a 16-channel EEG recording, the y-axis will display 16 different electrode positions.

The visualization demonstrates how signals from different electrode positions change over time. These variations are suitable for classification processes, along with other methods used to examine the time-frequency characteristics of the signal.

Image Generation with Short-Time Fourier Transform

Short-Time Fourier Transform (STFT) is a transformation method to analyze a signal's time-frequency characteristics. Essentially, it is employed to determine how the frequency components of a signal vary over time.

The STFT applies a windowing process to determine the signal's frequency components at different time intervals and calculates the Fourier transform for each window. The resulting image visualizes the time on the horizontal axis, frequency on the vertical axis, and the signal power as color intensity, creating a 2-dimensional image. This image allows for a detailed visualization of the time and frequency characteristics of the

signal (see Figure 5.9). The STFT image mainly provides valuable insights when analyzing frequency components that vary over time.

Image Generation with Continuous Wavelet Transform

Continuous Wavelet Transform (CWT) is another method used to analyze the time-frequency characteristics of a signal. Unlike STFT, which uses fixed-width windows, CWT employs waveforms that can adapt to the local features of the signal in both time and frequency domains.

CWT applies waveforms of varying width and position to analyze the time and frequency characteristics of the signal. This provides a more flexible and detailed analysis compared to STFT. The resulting time-frequency image represents time on the horizontal axis, frequency on the vertical axis, and the magnitude or power of the signal as color intensity. However, the adaptability of waveforms in CWT ensures better localization in both time and frequency domains, depicting the signal's local features more effectively than STFT.

The CWT time-frequency image provides a detailed representation of the signal's time-varying frequency components and offers valuable insights into local features and behaviors. Additionally, this article compares three waveforms – Generalized Morse Wavelet, Analytic Morlet (Gabor) Wavelet (AMOR), and Bump Wavelet – to determine the most suitable waveform for feature extraction in motor imagery. The characteristics of these waveforms can influence their effectiveness in defining and analyzing the time-frequency features of motor imagery signals. The comparison results enable the selection of the most appropriate waveform for extracting the best features from motor imagery signals.

5.2.3 Deep Learning

Deep learning is a subfield of machine learning developed to identify and analyze complex data patterns. This domain has become a significant tool in various fields, such as neuroscience and brain-computer interfaces (BCI).

Deep learning is typically implemented using artificial neural networks with one or more hidden layers. These layers represent input data, taking the previous layer's outputs as inputs. Consequently, the network learns more complex features and patterns [236].

Different architectures exist within deep learning, including Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), Recurrent Neural Networks

(RNNs) [82], [186], [237]. CNN architecture is often preferred when working with EEG data, as it can effectively process time-series data and 2D/3D structures.

CNNs can be highly effective in extracting meaningful features and identifying patterns from complex datasets such as EEG data. CNNs offer distinct advantages, especially when EEG data is visualized as image data. CNNs are particularly adept at capturing local features and neighborhood information robustly. This capability becomes highly beneficial when EEG signals are represented as 2D or 3D structures, such as spectrograms or scalograms. CNNs process features sequentially in a way that helps identify significant patterns within EEG data. Additionally, CNNs are optimized for handling fixed-size inputs and outputs, which enhances their efficiency in processing high-dimensional EEG data. Therefore, in this study, CNN architecture was chosen to classify EEG data. The study evaluated the model's performance in various experimental paradigms and different preprocessing methods applied to the data [238].

Architecture

The dataset has been evaluated using 5-fold cross-validation techniques, where the entire dataset is partitioned into training and validation sets across different folds. Subsequently, labels are added to each dataset. During the creation of the CNN architecture, various layers and parameters were experimented with multiple times. As a result of these experimental paradigms, the layers and parameters that yielded the most successful outcome for the CNN model were identified. The CNN model with the most successful performance was constructed.

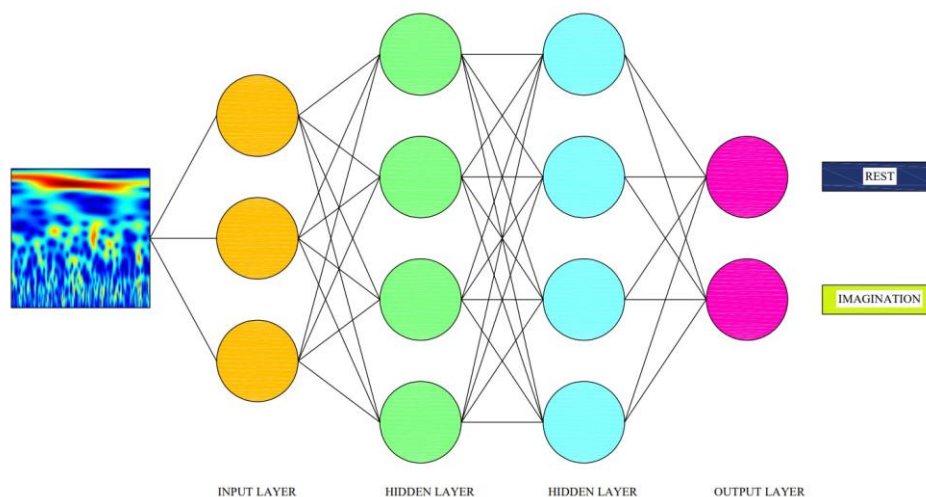


Figure 5.11 Neural network architecture for classifying EEG data into Rest and Imagination states. The model includes an input layer (EEG feature input), multiple hidden layers, and an output layer representing the classification results

The CNN model is sequenced starting from the input layer. The input layer is defined for images of size 343x434 for the first experimental paradigm and 256x256 with 3 channels (RGB) for subsequent 3 experimental paradigms. Convolutional, pooling, normalization, and fully connected layers are defined sequentially (see Figure 5.11 and Figure 5.12). The output layer of the model is a SoftMax layer for classifying two classes (rest and imagination).

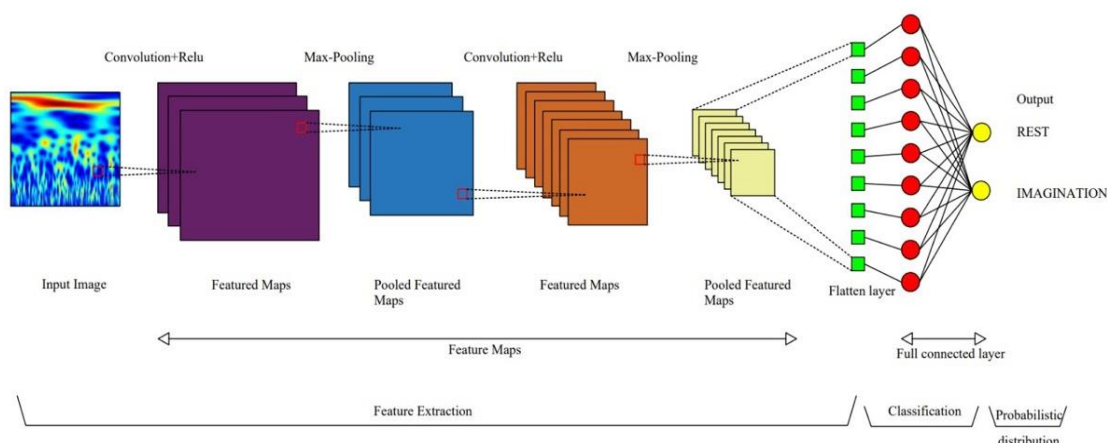


Figure 5.12 CNN architecture

A detailed description of our CNN architecture, comprising 12 layers, is provided in the following Table 5.1.

Table 5.1 Detailed layer-wise description of the CNN architecture

Layer Name	Input Size	Filter Size	Number of Filters	Stride	Padding	Output Size
Input Layer	256x256x3	-	-	-	-	256x256x3
Conv Layer 1	256x256x3	3x3	16	1x1	same	256x256x16
Batch Norm Layer 1	256x256x16	-	-	-	-	256x256x16
ReLU Activation Layer 1	256x256x16	-	-	-	-	256x256x16
Max Pool Layer 1	256x256x16	2x2	-	2x2	[0,0,0,0]	128x128x16
Conv Layer 2	128x128x16	3x3	32	1x1	same	128x128x32
Batch Norm Layer 2	128x128x32	-	-	-	-	128x128x32
ReLU Activation Layer 2	128x128x32	-	-	-	-	128x128x32
Max Pool Layer 2	128x128x32	2x2	-	2x2	[0,0,0,0]	64x64x32
Fully Connected Layer	64x64x32 (flattened)	-	-	-	-	2 neurons
SoftMax Layer	-	-	-	-	-	2 neurons
Classification Output	-	-	-	-	-	2 neurons

- Input Layer: Images of size 256x256x3 with 'zero-center' normalization.
- Convolutional Layers: Processed with 3x3 filters. 'same' padding and [1, 1] stride is used.
- Batch Normalization Layer: Batch normalization is applied.
- ReLU Activation Layer: ReLU activation function is applied.
- Max Pooling Layers: 2x2 max pooling is applied. [2, 2] stride and [0, 0, 0, 0] padding is used.
- Fully Connected Layers: Consists of two fully connected layers.
- SoftMax Layer: SoftMax activation function is applied.
- Classification Output: Classification output is provided using cross-entropy loss.

CNN Model Compilation

The CNN model was compiled using the specified training options. The training was performed using the Adam optimization algorithm. The maximum number of epochs for training was set at 10, and the mini-batch size was set to 20. Shuffling was performed at each epoch; validation was performed every 30 mini-batches. Training stages were not displayed, but training progress was shown graphically.

CNN Model Fit

The training data was fitted to the CNN model using the specified training options. The model weights were updated to adapt to the dataset's characteristics. After completing the training, the model was prepared to evaluate its performance on the test dataset.

Performance Evaluation

The trained Convolutional Neural Network (CNN) model was evaluated on the test dataset. The model was classified using the test data, and these predictions were compared with the ground truth labels. Based on this comparison, the model's accuracy, AUC-ROC, and F1-measure values were calculated, and the results were evaluated.

Accuracy (ACC): This metric indicates the overall correctness of the model by showing the ratio of correctly predicted instances to the total cases. While accuracy is straightforward to understand, it may not be sufficient when dealing with imbalanced datasets.

AUC-ROC (AUC): The AUC-ROC curve represents a model's performance across different classification thresholds.

F1-Measure (F1): The F1-Measure is the harmonic mean of precision and recall, balancing the two.

By using these evaluation metrics, a more detailed understanding of the model's performance is obtained. Accuracy provides a general overview, while AUC-ROC and F1-Measure offer deeper insights into the model's effectiveness, especially in scenarios involving varying decision thresholds. These metrics collectively ensure a robust evaluation of the CNN model, highlighting its strengths and potential areas for improvement. The robustness of the proposed model is demonstrated through several key factors. It generalizes well across multiple paradigms, ensuring applicability in diverse EEG settings. The model incorporates preprocessing steps to mitigate the effects of noise and artifacts, and it has been tested on raw data to assess performance in real-world applications. Additionally, rigorous cross-validation techniques, including k-fold and leave-one-out strategies, were employed to confirm their stability and accuracy. CNN architecture further enhances the model's ability to extract features and classify data effectively, even in the presence of variability and noise.

5.3 Results

In this study, we analyzed electroencephalography (EEG) datasets derived from four distinct experimental paradigms pertaining to both swallowing and the imagination of swallowing. Each dataset encompasses four varieties of EEG data: raw data, data refined through Empirical Mode Decomposition (EMD) or a bandpass filter, and data pre-processed via a sequential application of EMD, Independent Component Analysis (ICA), and bandpass filtering.

Each type of data underwent transformations into images through various techniques. The first method involved converting EEG data from all channels into a single image. The second method used the Short-Time Fourier Transform (STFT) to produce spectrograms of the EEG data. Lastly, Continuous Wavelet Transform (CWT) scalograms were generated using various wavelet types. Figure 5.13 illustrates the diverse EEG data types (raw, ica, emd, bpf, emd+ica+bpf) of the same individual within the same trial, along with different Continuous Wavelet Transform (CWT) visualization techniques representing resting and imagination states. Different visualization methods and data types yield distinct visual representations within the dataset. Furthermore, it is observed that the resting and imagination images within the same trial are also different.

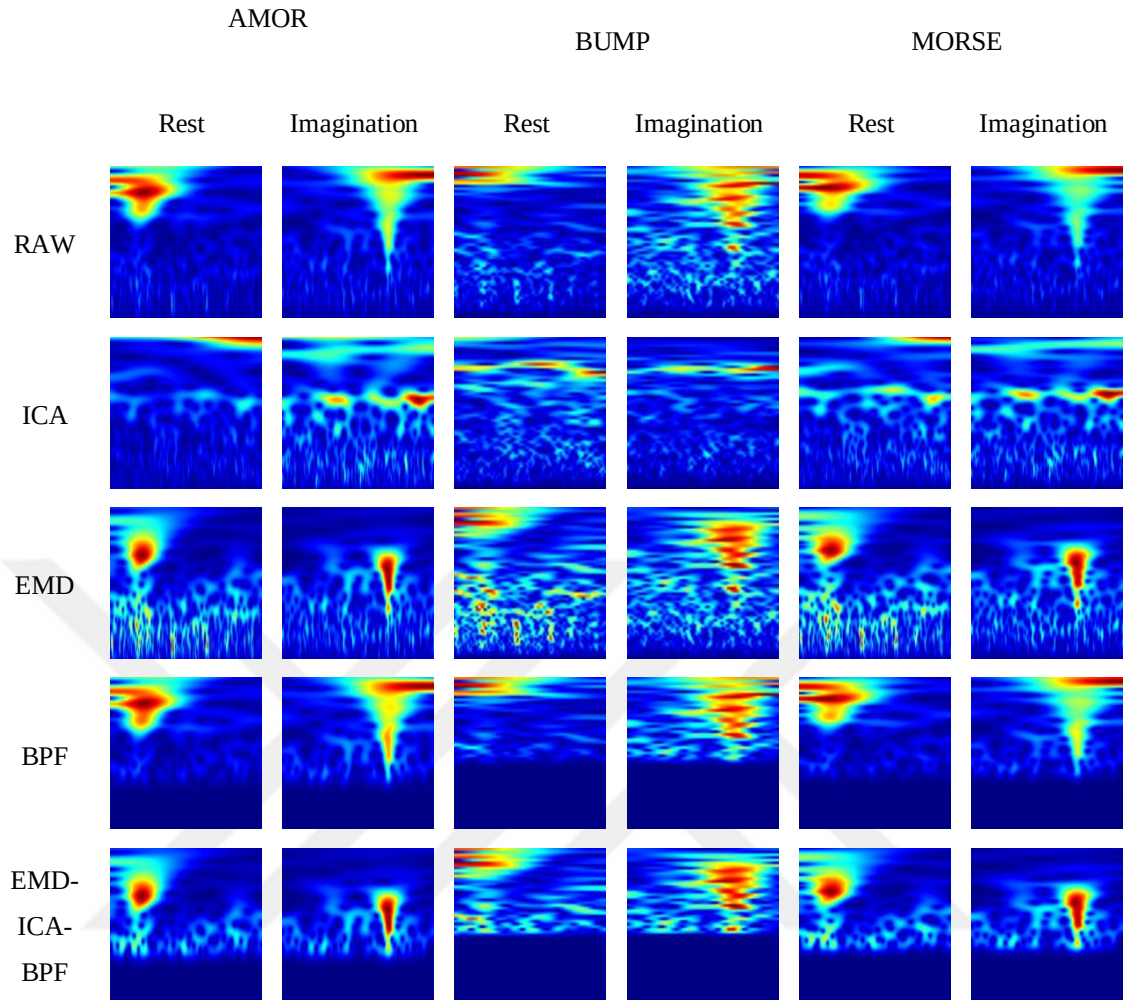


Figure 5.13 Diverse EEG data types and CWT visualization techniques

The results were used to evaluate the classification performance of different EEG data types using each visualization method. This evaluation aimed to determine which preprocessing method(s) and visualization technique(s) provided the best classification results.

In our study, we employed 5-fold Cross-Validation to ensure the reliability and consistency of our model's performance on different data subsets (see Figure 5.14). We divided our dataset into 5 parts to ensure equal representation of each class in the folds. The model was trained on 4 folds and evaluated on the remaining fold, with performance measured using specific metrics for each test fold. This process was repeated by rotating the folds, each used exactly once for testing. Finally, we calculated the average model performance across all iterations. This approach helped guard against overfitting and produced a more generalizable and dependable model.

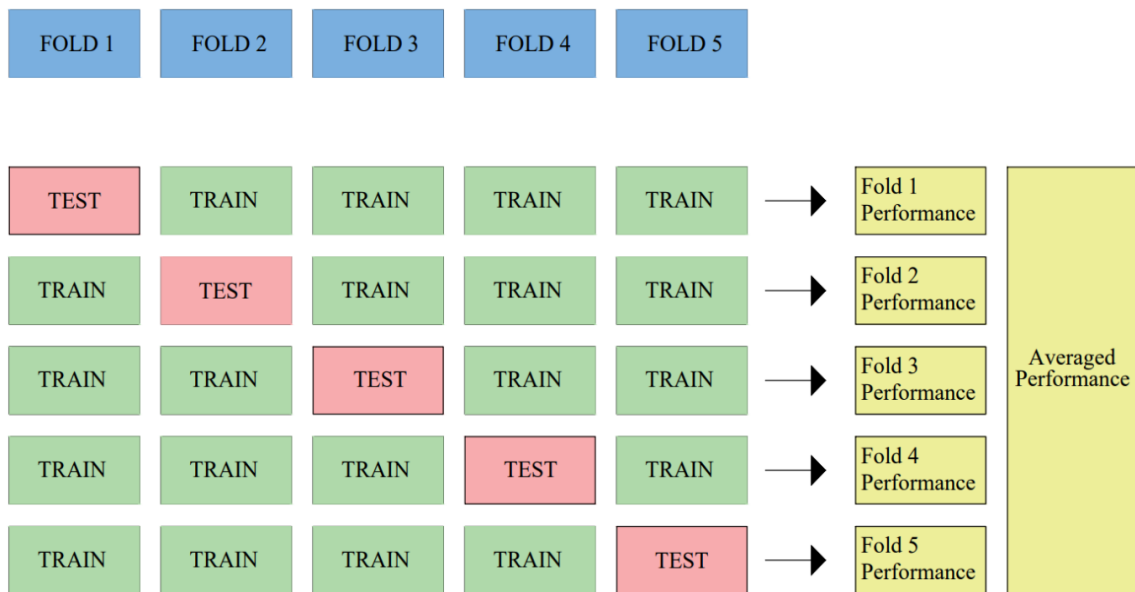


Figure 5.14 5-fold cross-validation

Table 5.2 Natural Water Swallowing Experimental Paradigm classification results

			CWT SCALOGRAM		
	CHANNEL STACK	STFT-SPECTROGRAM	AMOR	BUMP	MORSE
RAW	ACC 0.572 AUC 0.598 F1 0.533	ACC 0.723 AUC 0.798 F1 0.73	ACC 0.839 AUC 0.924 F1 0.841	ACC 0.867 AUC 0.945 F1 0.87	ACC 0.856 AUC 0.936 F1 0.858
ICA	ACC 0.524 AUC 0.554 F1 0.556	ACC 0.719 AUC 0.80 F1 0.73	ACC 0.828 AUC 0.921 F1 0.837	ACC 0.867 AUC 0.943 F1 0.869	ACC 0.8506 AUC 0.933 F1 0.843
EMD	ACC 0.551 AUC 0.571 F1 0.545	ACC 0.754 AUC 0.837 F1 0.755	ACC 0.855 AUC 0.94 F1 0.854	ACC 0.873 AUC 0.947 F1 0.852	ACC 0.864 AUC 0.941 F1 0.862
0.5-40 Hz FILTER	ACC 0.568 AUC 0.587 F1 0.565	ACC 0.572 AUC 0.603 F1 0.571	ACC 0.70 AUC 0.771 F1 0.705	ACC 0.703 AUC 0.776 F1 0.701	ACC 0.707 AUC 0.776 F1 0.706
ICA 0.5-40 Hz EMD FILTER	ACC 0.532 AUC 0.568 F1 0.563	ACC 0.584 AUC 0.620 F1 0.58	ACC 0.711 AUC 0.78 F1 0.709	ACC 0.693 AUC 0.766 F1 0.707	ACC 0.707 AUC 0.775 F1 0.715

Tables 5.2 to 5.5 demonstrate the classification performance of EEG data types and various visualization methods. The classification performance was assessed using three different metrics. It was observed that the accuracy, AUC, and F1 score rates decreased for hybrid models and data with a bandpass filter applied. However, results obtained from experimental paradigms with Raw data, pre-processed data with Independent Component Analysis (ICA), and pre-processed data with Empirical Mode Decomposition (EMD) showed good results for accuracy, AUC, and F1-Measure (F1) metrics. Also, low

accuracy rates were obtained when all channels merged into a single image in the channel stack.

A comparison of spectrograms obtained using Short-Time Fourier Transform (STFT) and scalograms obtained using Continuous Wavelet Transform (CWT) revealed that CWT images outperformed STFT images. The type of success varied among different CWT scalograms based on different preprocessing methods. Despite experimental paradigm variations, the 'bump' type generally yielded the most superior results.

Table 5.3 Induced Saliva Swallowing Experimental Paradigm classification results

			CWT SCALOGRAM		
	CHANNEL STACK	STFT- SPECTROGRAM	AMOR	BUMP	MORSE
RAW	ACC 0.733 AUC 0.77 F1 0.716	ACC 0.806 AUC 0.887 F1 0.803	ACC 0.856 AUC 0.93 F1 0.855	ACC 0.854 AUC 0.952 F1 0.866	ACC 0.855 AUC 0.936 F1 0.857
ICA	ACC 0.697 AUC 0.773 F1 0.707	ACC 0.797 AUC 0.887 F1 0.797	ACC 0.84 AUC 0.92 F1 0.839	ACC 0.863 AUC 0.949 F1 0.863	ACC 0.855 AUC 0.934 F1 0.856
EMD	ACC 0.569 AUC 0.608 F1 0.499	ACC 0.786 AUC 0.879 F1 0.776	ACC 0.859 AUC 0.937 F1 0.858	ACC 0.872 AUC 0.952 F1 0.87	ACC 0.858 AUC 0.943 F1 0.86
0.5-40 Hz FILTER	ACC 0.714 AUC 0.786 F1 0.698	ACC 0.684 AUC 0.762 F1 0.676	ACC 0.748 AUC 0.824 F1 0.738	ACC 0.733 AUC 0.812 F1 0.731	ACC 0.747 AUC 0.822 F1 0.744
ICA 0.5-40 Hz EMD FILTER	ACC 0.567 AUC 0.606 F1 0.577	ACC 0.603 AUC 0.651 F1 0.62	ACC 0.746 AUC 0.82 F1 0.748	ACC 0.735 AUC 0.809 F1 0.747	ACC 0.744 AUC 0.818 F1 0.747

Table 5.4 Induced Water Swallowing Experimental Paradigm classification results

			CWT SCALOGRAM		
	CHANNEL STACK	STFT- SPECTROGRAM	AMOR	BUMP	MORSE
RAW	ACC 0.636 AUC 0.694 F1 0.637	ACC 0.81 AUC 0.893 F1 0.811	ACC 0.86 AUC 0.937 F1 0.861	ACC 0.898 AUC 0.967 F1 0.902	ACC 0.881 AUC 0.953 F1 0.882
ICA	ACC 0.662 AUC 0.721 F1 0.692	ACC 0.794 AUC 0.89 F1 0.774	ACC 0.847 AUC 0.934 F1 0.847	ACC 0.884 AUC 0.964 F1 0.887	ACC 0.86 AUC 0.947 F1 0.856
EMD	ACC 0.566 AUC 0.612 F1 0.63	ACC 0.819 AUC 0.904 F1 0.826	ACC 0.87 AUC 0.952 F1 0.87	ACC 0.898 AUC 0.967 F1 0.90	ACC 0.889 AUC 0.96 F1 0.893
0.5-40 Hz FILTER	ACC 0.671 AUC 0.728 F1 0.662	ACC 0.70 AUC 0.773 F1 0.722	ACC 0.761 AUC 0.843 F1 0.765	ACC 0.755 AUC 0.839 F1 0.745	ACC 0.753 AUC 0.837 F1 0.756
ICA 0.5-40 Hz EMD FILTER	ACC 0.651 AUC 0.721 F1 0.609	ACC 0.635 AUC 0.696 F1 0.65	ACC 0.759 AUC 0.833 F1 0.764	ACC 0.754 AUC 0.831 F1 0.757	ACC 0.764 AUC 0.838 F1 0.764

Results from experimental paradigms with raw data, data pre-processed with Independent Component Analysis (ICA), and data pre-processed with Empirical Mode Decomposition (EMD) exhibited variations across experimental paradigms. While data pre-processed with EMD performed better in the natural water swallowing, induced saliva swallowing, and tongue protrusion experimental paradigms, raw data results were superior in the remaining experimental paradigm.

Table 5.5 Induced Tongue Protruding Experimental Paradigm classification results

			CWT SCALOGRAM		
	CHANNEL STACK	STFT- SPECTROGRAM	AMOR	BUMP	MORSE
RAW	ACC 0.764 AUC 0.832 F1 0.765	ACC 0.794 AUC 0.889 F1 0.794	ACC 0.854 AUC 0.935 F1 0.861	ACC 0.881 AUC 0.956 F1 0.878	ACC 0.861 AUC 0.943 F1 0.859
ICA	ACC 0.723 AUC 0.797 F1 0.728	ACC 0.794 AUC 0.88 F1 0.802	ACC 0.847 AUC 0.927 F1 0.847	ACC 0.874 AUC 0.951 F1 0.868	ACC 0.854 AUC 0.937 F1 0.86
EMD	ACC 0.592 AUC 0.628 F1 0.617	ACC 0.790 AUC 0.883 F1 0.801	ACC 0.86 AUC 0.942 F1 0.861	ACC 0.873 AUC 0.956 F1 0.864	ACC 0.874 AUC 0.949 F1 0.876
0.5-40 Hz FILTER	ACC 0.708 AUC 0.808 F1 0.713	ACC 0.685 AUC 0.758 F1 0.705	ACC 0.746 AUC 0.833 F1 0.764	ACC 0.741 AUC 0.821 F1 0.751	ACC 0.751 AUC 0.833 F1 0.758
ICA 0.5-40 Hz EMD FILTER	ACC 0.572 AUC 0.608 F1 0.546	ACC 0.620 AUC 0.671 F1 0.633	ACC 0.741 AUC 0.820 F1 0.738	ACC 0.733 AUC 0.819 F1 0.742	ACC 0.742 AUC 0.819 F1 0.74

5.4 Discussion

Brain-computer interface (BCI) technologies, especially methods developed using motor imagery (MI), have significantly advanced in recent years. Motor imagery allows individuals to alter their brain activities by imagining specific movements without physically performing them. These changes are measured through electroencephalography (EEG) and transmitted to and analyzed by computer systems. In this way, physically disabled individuals can control computers, robotic devices, or prosthetic limbs solely with the power of their minds. The development of these technologies holds great potential for medical applications and everyday use [239].

However, there are few approaches aimed at detecting motor imagery swallowing for the rehabilitation of dysphagia patients. Yang et al. conducted comparative studies to detect motor imagery swallowing and imagery tongue movement for post-stroke dysphagia rehabilitation [63], [66], [68], [69], [70]. These studies investigated the following hypotheses: (1) motor imagery swallowing and imagery tongue movement can

be distinguished from the background resting state for use in post-stroke dysphagia rehabilitation, (2) a simple and relevant model for detecting motor imagery swallowing can be developed using imagery tongue movement EEG signals, (3) the accuracy of these hypotheses can be tested by determining classification accuracies across different sessions and modes, and (4) classification accuracies can be determined in a sample of ten healthy volunteers and one chronic stroke patient. Additionally, swallowing and tongue movements share some common brain activation areas, and tongue movements are integral to the swallowing process [63], [70]. Yang et al. conducted a study with six healthy subjects using EEG to classify motor imagery tasks with a Support Vector Machine (SVM), achieving a cross-validation accuracy of 69.96% [63]. Yang et al. continued the study with six healthy subjects, achieving session-to-session accuracies of 74.29% and 72.12% using SVM classifiers and Dual-Tree Complex Wavelet Transform (DTCWT) features [66], [68]. Yang et al. expanded the study to include healthy and dysphagia patients, achieving cross-validation accuracies of 70.89% motor imagery swallowing and 73.79% imagery tongue movement for different motor imagery tasks [70]. Yang et al. analyzed motor imagery correlations using EEG and spectral power analysis, showing significant correlations between different motor imagery tasks in a sample of ten healthy subjects and one stroke patient [67], [69]. Considering these studies, it becomes evident that research on motor imagery of swallowing is relatively scarce and insufficient.

Based on the existing studies, we decided to design four different experimental paradigms. We adopted a careful approach when selecting experimental paradigms for our research. Considering the gaps and needs in the literature, we investigated the relationship between swallowing and motor imagery. Additionally, we aimed to contribute to developing rehabilitation tools by focusing on the specific needs of dysphagia patients. We also examined contemporary preprocessing techniques and imaging methods. Preprocessing techniques are critical for preparing data for cleaning, organizing, and analysis. Methods such as Empirical Mode Decomposition (EMD) and Independent Component Analysis (ICA) are commonly used to separate the components of EEG signals and filter out unwanted noise [240], [241]. Additionally, simple filtering techniques isolate specific frequency intervals in the signal [242]. Visualization techniques are crucial for understanding EEG data's complexity and temporal changes. For example, spectral analysis techniques like Short-Time Fourier Transform (STFT) and Continuous Wavelet Transform (CWT) are used to visualize the temporal distribution of

different frequency components [243], [244]. These visualization techniques aid in better understanding the patterns and changing dynamics of brain activities.

In conclusion, we leveraged technological advancements to enhance deep learning techniques and examined the topic from different perspectives using various experimental paradigms. It also demonstrates the effectiveness of various preprocessing methods and visualization techniques in classifying resting and swallowing imagery and analyzing EEG signals. In evaluating the performance of our model, we opted to utilize three complementary metrics, AUC (Area Under the Curve), F1-Measure, and accuracy, to provide a comprehensive assessment of its effectiveness across different dimensions. AUC is a robust measure of the model's ability to distinguish between the two classes across various decision thresholds. It is beneficial for understanding performance in the presence of class imbalance, which can occur in real-world scenarios. It captures the overall discriminatory power of the model, offering insights into its performance beyond a single threshold. The F1-Measure, on the other hand, harmonizes precision and recall, allowing us to evaluate the model's effectiveness in minimizing false positives and negatives—critical in applications where misclassifications can have significant consequences, such as in medical diagnoses or safety-critical systems. Lastly, accuracy provides an intuitive metric for assessing the overall correctness of the model's predictions. Given our balanced dataset, accuracy reliably indicates how well the model performs in classifying instances. By employing AUC, F1-Measure, and accuracy, we gain a holistic understanding of our model's performance, enabling us to identify strengths and weaknesses in its predictive capabilities. This multi-faceted approach enhances our confidence in the model's effectiveness and guides potential areas for future improvement.

Our current study evaluated performance within each experimental paradigm, ensuring that results were consistent within their specific contexts. Notably, we should have performed cross-experimental paradigm analyses, such as utilizing data from water swallowing to train and classify other swallowing imagery. This independent analysis approach allows for a clearer understanding of each experimental paradigm setup's effectiveness and minimizes potential confounding factors that might arise from integrating data across different contexts. These approaches can help provide a comprehensive and in-depth understanding of the subject. Identifying the limitations and constraints of the study is essential. These limitations include the sample size and diversity. Our study gathered data from 30 right-handed individuals, a sample size often

utilized in EEG research. However, we recognize that this limited sample size may restrict the generalizability and validity of our findings. The study's limited sample size may prevent the results from being more generalizable. While we view this study as a preliminary investigation, we recognize the limitations imposed by our restricted sample size. Moving forward, we plan to expand our participant group to include a more extensive and diverse population. Additionally, we aim to conduct further studies to evaluate the performance of our model across various demographic groups. Additionally, some challenges may arise during data collection when using EEG and brain imaging techniques, affecting the quality of the obtained data and making interpreting the results more challenging. Moreover, standardizing the experimental paradigm conditions used in the study is crucial. Non-standard conditions can affect the consistency of the results and reduce comparability. The absence of individuals with dysphagia in our study is also a limitation.

5.5 Conclusion and Future Work

The primary aim of this study was to assess the classification performance of deep learning models in distinguishing between resting state and motor imagery swallowing, utilizing various preprocessing and data visualization techniques applied to multichannel electroencephalography (EEG) data.

Firstly, the impact of preprocessing techniques on classification accuracy was examined. It was observed that using methods like Empirical Mode Decomposition (EMD) and Independent Component Analysis (ICA) significantly influenced the filtering of EEG data. However, these techniques or their combination did not show the expected performance in some experimental paradigms. Notably, it was noted that bandpass filtering and hybrid models combining EMD, ICA, and bandpass filtering had lower accuracy rates compared to other methods in some instances. These results emphasize the importance of selecting preprocessing methods considering the characteristics of EEG data and the classification tasks.

Secondly, the effects of different visualization techniques on EEG data classification performance were examined. Comparing visualization methods such as visualizing all channels together, individual Short-Time Fourier Transform (STFT) spectrograms and Continuous Wavelet Transform (CWT) scalograms showed that CWT images better capture the time-frequency characteristics. Specifically, it was generally

found that "bump" type CWT scalograms outperform other types and effectively represent complex brain activities.

The effectiveness of these methods is critical in various fields, such as the recognition of EEG-based neurological disorders, rehabilitation, and the development of brain-computer interface technologies. Accurately identifying complex brain activities such as motor imagery and swallowing are vital for early rehabilitation and treatment of diseases.

Additionally, classification performance varies across different experimental paradigms, underscoring the importance of considering different scenarios and contexts in EEG data analysis. While EMD-applied data performs better in specific experimental paradigms, raw data performs better in others, highlighting the need for customized approaches depending on specific tasks and datasets.

In conclusion, this study evaluates the impact of different preprocessing and visualization techniques on the classification performance of EEG data. It offers 4 distinct experimental paradigms for analyzing swallowing events, along with a CNN model that produced superior results in testing existing experimental paradigms. Future research can further explore optimizing preprocessing methods and visualization techniques to enhance the classification performance of EEG data. These findings provide valuable insights for developing EEG-based rehabilitation and therapeutic approaches. They may lead to creating a device specifically designed to effectively interface with the small and complex muscles involved in swallowing events.

For future studies, we aim to work with dysphagia patients to understand better and improve the effectiveness of rehabilitation strategies tailored to this population. Additionally, we can better understand the relationship between swallowing and tongue movements by examining the effects of different motor imagery tasks on brain activity. The increased use of deep learning techniques can make data analysis processes more efficient and yield more precise results. Finally, by investigating the clinical application potential of our findings, we can evaluate how dysphagia patients can benefit in real-world conditions.

Chapter 6

Multi-Scale Spatial Attention Network for Subject-Specific Rest and Imagination Classification

6.1 Motivation

This study aims to obtain topological representations of motor imagery and rest paradigms for different frequency bands and to evaluate the effectiveness of the multi-scale spatial attention network (MS-SAN) architecture in distinguishing between these paradigms in EEG-based swallowing analyses. Motor imagery is mainly associated with motor control and cognitive processes, and EEG data provides a powerful tool to monitor the changes in these processes over time. The study aims to examine the capacity of the MS-SAN model to learn EEG frequency bands and model interindividual variations effectively. CSP (Common Spatial Pattern) filtering was used to extract spatial patterns in EEG signals, and the performance of motor imagery and rest paradigms in different frequency bands (Delta, Theta, Alpha, Beta, Gamma) were evaluated. The topological structures of motor imagery and rest states were mapped for each frequency band using spatio-spectral analysis. With this process, the neurophysiological differences between motor imagery and rest were examined in more detail, and the extent to which the MS-SAN model can accurately distinguish these differences was evaluated. The study aims to test the performance and generalization ability of the model to understand the neurophysiological processes of EEG-based swallowing analyses and to investigate the usability of these techniques in clinical applications.

6.2 Materials and Methods

In this section, our studies were based on the induced saliva swallowing (Experimental Paradigm 2) and induced water swallowing (Experimental Paradigm 3) paradigms detailed in Chapter 3.

6.2.1 Preprocessing

This study preprocessed EEG signals to extract relevant features for subsequent classification using the Common Spatial Pattern (CSP) technique. The preprocessing steps include signal segmentation, data editing for CSP input, and the application of CSP to obtain spatial features that enhance the distinction between different brain states.

EEG signals are divided into two groups: resting state and motor imagery. The segmentation procedure is applied for each participant and trial. The resting state is extracted from the time interval representing the resting mental task. The motor imagery state is extracted from the time interval representing the swallowing mental task. These two segments generate the resting signals as the positive class, and the motor imagery signals as the negative class for input to the CSP algorithm.

The Common Spatial Pattern (CSP) algorithm is then applied to these signals to extract spatial features. CSP is a binary data-driven supervised technique that maximizes the positive class's variance while minimizing the negative class's variance. The algorithm generates a filter matrix W containing spatial filters and eigenvalue lambdas corresponding to each filter. The mixing matrix A is also calculated. After the filter matrix W is trained, the new data can be projected as follows:

$$X_{CSP} = W^T \cdot X \quad (6.1)$$

This projection provides the spatially filtered data, X_{CSP} (equation 6.1), which is then used for further analysis and classification (see Figure 6.1). By applying this preprocessing pipeline, EEG signals are transformed into a feature space more suitable for classification tasks, and the performance of brain-computer interfaces (BCIs) in distinguishing different cognitive states is improved.

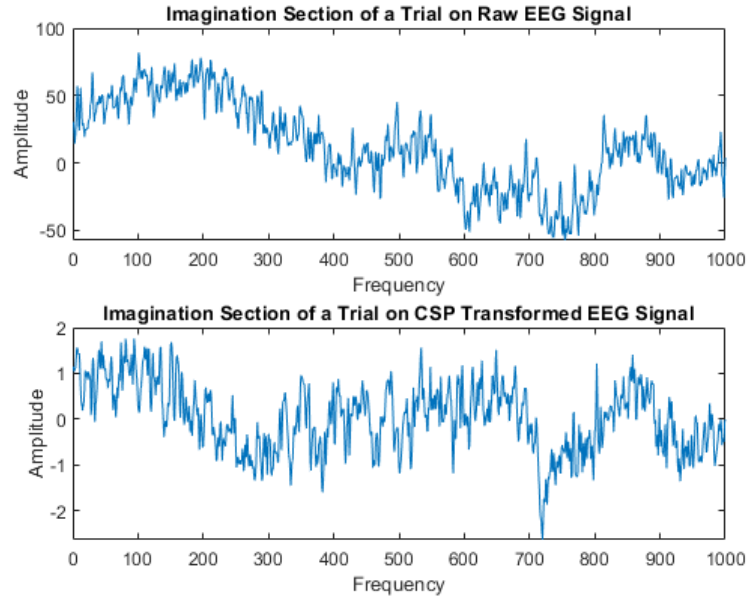


Figure 6.1 Imagination section of a trial on raw EEG signal and imagination section of a trial on CSP transformed EEG signal

6.2.2 Topographical Feature Generation through Spatio-Spectral Analysis

EEG signals are an important source in the analysis of brain activities, and extracting meaningful features from these signals is a critical step for brain-computer interfaces (BCI) and neurological research. This study extracted spatio-spectral features from EEG data, and the relationships between spatial and spectral components were examined. Power distributions in different frequency bands allow a better understanding of brain activities. These obtained features form an important basis for modeling neural mechanisms or BCI applications. In addition, topological maps show which regions the activity on the brain surface spreads to and the changes in these activities over time. In this way, more meaningful inferences can be made from EEG data. In this study, the feature extraction process from EEG data was carried out by calculating the power spectral density (PSD) over certain time windows for each trial. Each trial included rest and imagination periods, and different segments of each period were analyzed by applying the time windows in a shift. In this analysis, which was conducted over 6 different time windows, PSD calculations were made for each window (see Figure 6.2).

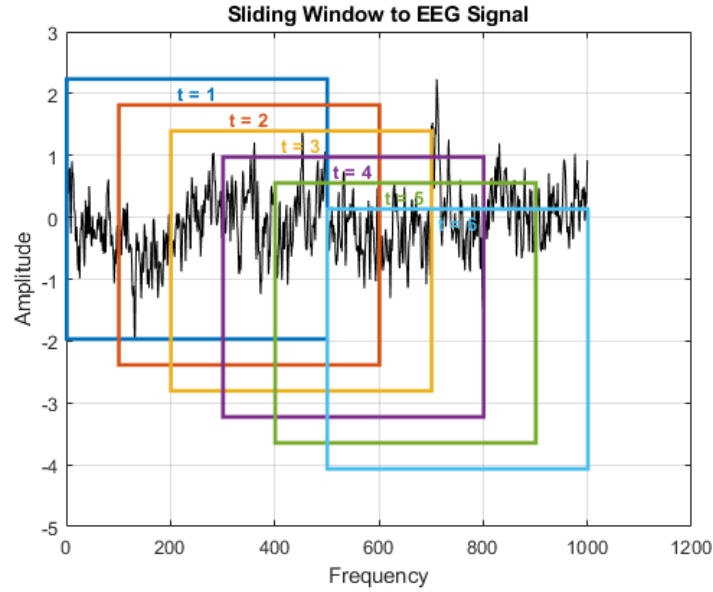


Figure 6.2 Sliding window to EEG signal

A total of five frequency bands were selected within the scope of the study: 0.5-4 Hz (Delta), 4-8 Hz (Theta), 8-13 Hz (Alpha), 13-30 Hz (Beta), and 30-150 Hz (Gamma). These frequency bands represent different brain activities in EEG signals. PSD values corresponding to frequency bands were found in each time window. Then, the general power density of the EEG signal in a specific time period and frequency band was calculated by averaging the power values obtained for each time window and frequency band (see Figure 6.3). This process creates the spatio-spectral features of the EEG signal, which show the distribution of the frequency components in each signal channel over time.

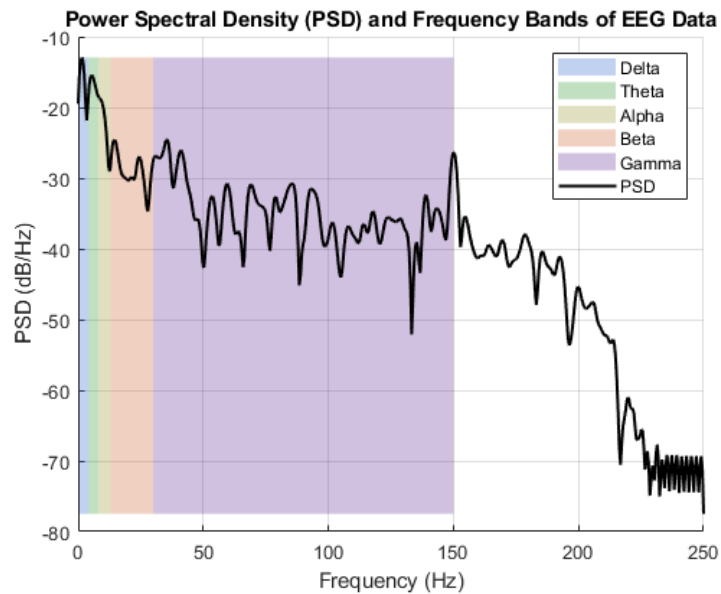


Figure 6.3 Power Spectral Density (PSD) and frequency bands of EEG data

The obtained spatio-spectral features were later converted into topological maps for visualization (see Figure 6.4). Topographic maps were created by assigning the average power values for each frequency band to different areas on the brain surface. These maps visualize the spatial properties of the signal and show activity in specific brain regions. The visualization process reveals the activity of the EEG in different frequency bands. Topological maps are used to study how cognitive states, such as motor imagery, are reflected in brain activity.

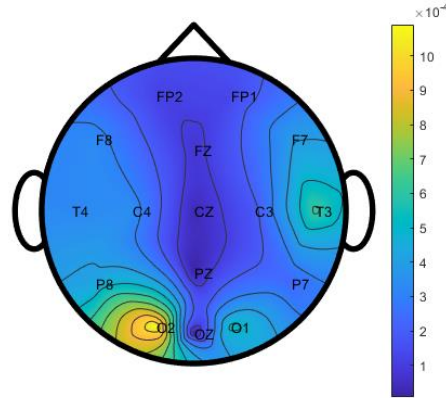


Figure 6.4 Spatial-Spectral transform from EEG signal

6.2.3 Classification

The classification architecture used in this study is a unique convolutional neural network model that integrates multi-scale feature extraction, spatial attention mechanisms, and residual connections, designed to classify EEG-based imagery data into resting and motor imagery swallowing categories (see Figure 6.5 and Figure 6.6). This model accepts $64 \times 64 \times 3$ input images representing topological visualizations obtained from EEG signals and is suitable for processing the signal's spatial and spectral features. The basic building block of the architecture, the multi-scale feature extraction module, uses three parallel paths to capture spatial details at different resolutions:

- Small-scale Path: Uses 3×3 filters to reveal finer details.
- Medium-scale Path: Uses 5×5 filters to capture medium-level features.
- Large-scale Path: Has 7×7 filters to discover larger-scale and general patterns.

The features obtained from these three paths are integrated with the concatenation process, allowing the model to learn information over a wide range of resolutions. In this way, the complex nature of EEG signals is analyzed more comprehensively.

The spatial attention mechanism is another important component that improves the model's performance. This block processes the input feature maps and creates an attention map highlighting important regions. This process has two stages: First, the attention mechanism analyzes the spatial features with convolutional operations and produces an attention map. Then, this map is normalized with the sigmoid activation function and multiplied by the input features. This multiplication process allows the model to focus on critical information while reducing the effect of less important regions.

At a more advanced level, the residual connections in the model solve the gradient vanishing problem, which is especially common in deep networks, and ensure that gradients flow efficiently. These connections both increase the learning capacity of the model and prevent information loss by directly transmitting the information in the previous layers to the subsequent layers.

After these feature extraction processes, spatial dimensions are reduced using a global average pooling (GAP) layer. GAP converts the model output into a compressed representation and transfers it to fully connected layers, thus providing a more compact feature set for classification. Fully connected layers perform the final classification by processing high-level signal representations. In addition, the model applies regularization techniques such as batch normalization and dropout to prevent overlearning.

In the training process, the Adam optimization algorithm was preferred. This algorithm allows the model to converge quickly and stably while reducing the learning rate over time, providing a more stable training process. A low initial learning rate, mini-batch size, and regularization elements were carefully selected as training parameters. This approach increased the model's overall performance and allowed it to distinguish between rest and motor imagery swallowing categories accurately.

Performance Metrics

In this study, various performance metrics were used to evaluate the classification performance of EEG data. The metrics used aim to analyze the model's accuracy, precision, and reliability in a multi-faceted way. The definitions of these metrics and how they are used in the study are detailed below:

Accuracy is the ratio of the model's correctly predicted examples to the total number of examples. It is a fundamental metric that shows the overall success of the model. Sensitivity refers to the ability of the model to predict positive classes correctly. It is a critical metric, especially when false negatives are important. Specificity measures the

ability of the model to predict negative classes correctly. It is useful in situations where reducing false positives is important. Precision is a measure of how accurate positive predictions are. It is a metric used to assess the impact of false positives. F1-Measure is the harmonic mean of Precision and Recall values. GMean evaluates the performance by taking the geometric mean of both sensitivity and specificity in datasets with inter-class imbalance. AUC evaluates the classification performance of the model through the ROC curve. AUC shows the ability of the model to distinguish between positive and negative classes. It takes a value between 0.5 and 1, and the model's performance increases as it approaches 1.

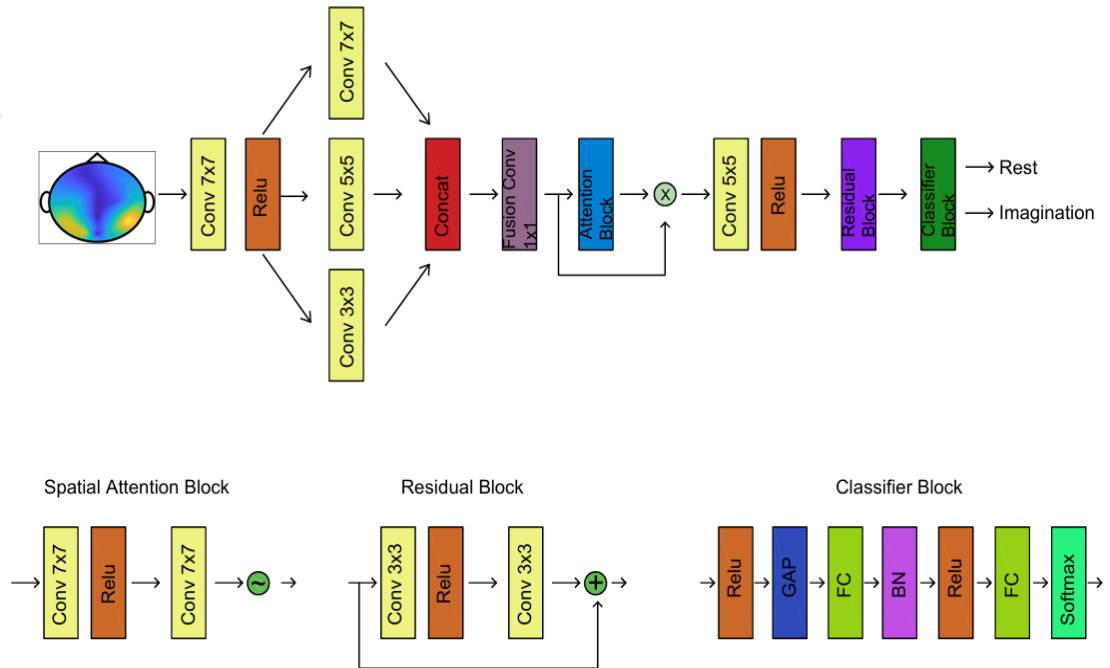


Figure 6.5 Multiscale Spatial Attention Network Model

6.3 Results

Classification performance metrics for different frequency bands (delta, theta, alpha, beta, and gamma) during swallowing experimental paradigms are presented in Table 6.1 and Table 6.2. These experimental paradigms were performed using data sets obtained from 30 individuals containing 15 trials for each individual. The classification process was performed using the leave-one-subject-out cross-validation (LOSO-CV) method. In this method, all data belonging to one individual in each iteration were separated as the test set, and the data obtained from the remaining individuals were used

as the training set. Performance metrics were calculated by averaging the results of all iterations.

This study used a multi-scale spatial attention network (MS-SAN) to increase the classification success. This network design aims to extract more sensitive features from EEG signals by combining spatial and multi-scale attention mechanisms. Spatial attention mechanisms increased the model's classification performance by focusing on important regions of the signals. On the other hand, the multi-scale structure allowed learning a deeper representation by processing information in different frequency bands at different scales.

In the Delta band, excellent classification performance was observed in both experimental paradigms (accuracy, sensitivity, specificity, precision, F1-Measure, GMean, and AUC values were 1.00 ± 0.00). Especially in the Delta band, complete accuracy was achieved for all individuals. These results show that the Delta band has high discrimination power between swallowing experimental paradigms (rest and imagination) and that its generalization ability between individuals is extremely strong. The individual-based classification performances of the bands are visualized in Figure 6.7 and Figure 6.9. The figures clearly demonstrate consistency across all individuals, emphasizing the effectiveness of the Delta band.

In the Theta band, the results were quite high in both swallowing experimental paradigms ($96\% \pm 5\%$ accuracy) and water-induced swallowing experimental paradigms ($96\% \pm 4\%$ accuracy). In addition, the AUC value of $99\% \pm 1\%$ in both cases reveals that the Theta band provides reliable discrimination in this classification task. The fact that the MS-SAN design produces results consistent with high accuracy on the Theta band indicates that the multi-scale attention mechanisms of the model work effectively and that the correct discriminative features are learned for this band.

A slight decrease in performance values was observed in the Alpha band. While the accuracy was calculated as $71\% \pm 7\%$ in the swallowing experimental paradigms, this value increased to $79\% \pm 10\%$ in the water-induced swallowing experimental paradigms. The AUC values for the Alpha band were found to be $80\% \pm 9\%$ and $88\% \pm 8\%$, respectively. These findings indicate that the discriminative power of the Alpha band is at a moderate level. This band can provide limited discrimination between swallowing experimental paradigms due to its sensitivity to the resting state.

Classification performance was found to be low in the Beta and Gamma bands. The accuracy in the beta band was measured as $62\% \pm 9\%$ in the swallowing experimental

paradigms and $64\% \pm 8\%$ in the water-induced swallowing experimental paradigms. In the Gamma band, the accuracy was limited to $54\% \pm 8\%$ and $53\% \pm 9\%$ in both paradigms. Especially in the Beta and Gamma bands, low GMean and AUC values (65% and below) indicate that these bands perform poorly in the classification task. It is evaluated that the direct relationship of these bands with swallowing experimental paradigms is less obvious, and therefore the model can offer low discrimination.

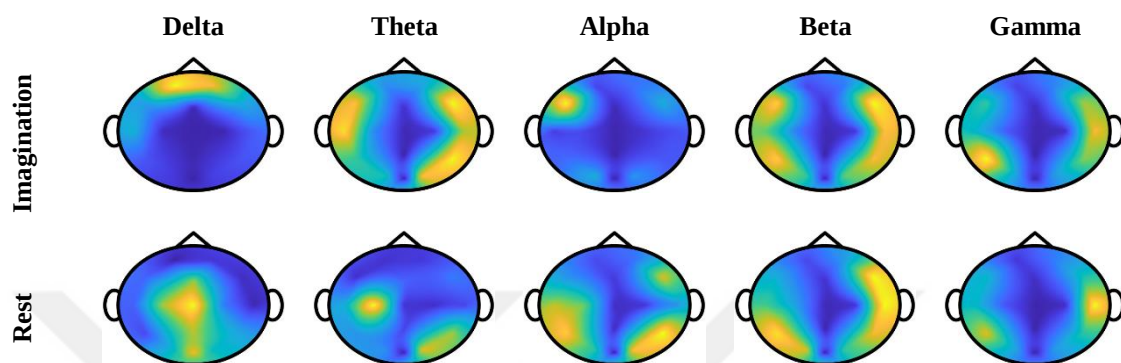


Figure 6.6 Topographical maps from Experimental Paradigm 1 (Induced Saliva Swallowing Experimental Paradigm) for imagination and rest parts of a sample trial for different frequency bands

Experimental Paradigm 1 (Induced Saliva Swallowing) Results

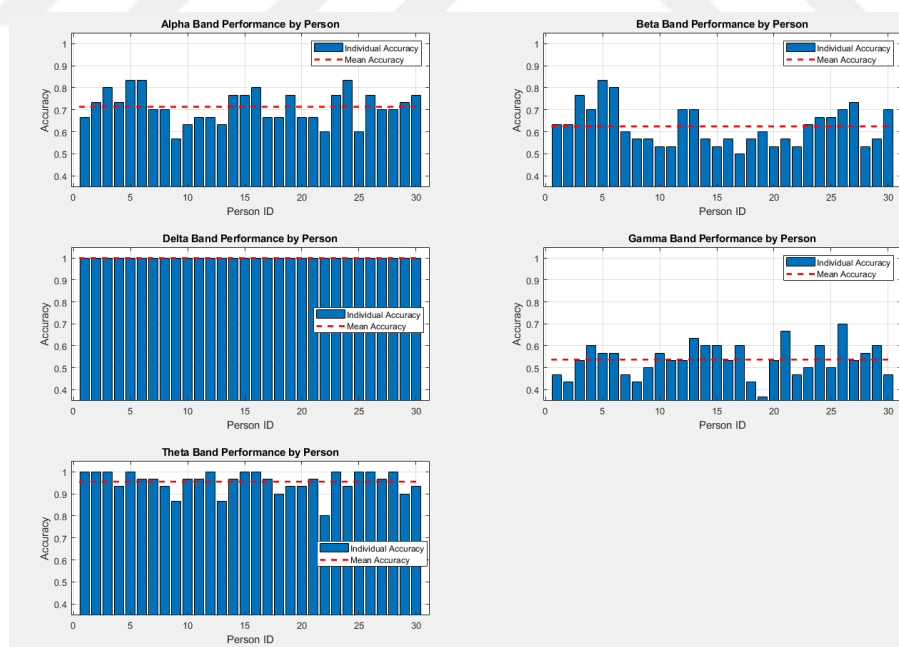


Figure 6.7 Saliva Swallowing Experimental Paradigm: Performance of different frequency bands in accuracy classification by individual

In the Induced Saliva Swallowing Experimental Paradigm, Figure 6.7 presents the classification accuracy performance of different frequency bands for individual

participants, emphasizing the impact of each frequency band on the overall classification results. Figure 6.8 shows the average classification accuracy across different frequency bands in the Induced Saliva Swallowing Experimental Paradigm.

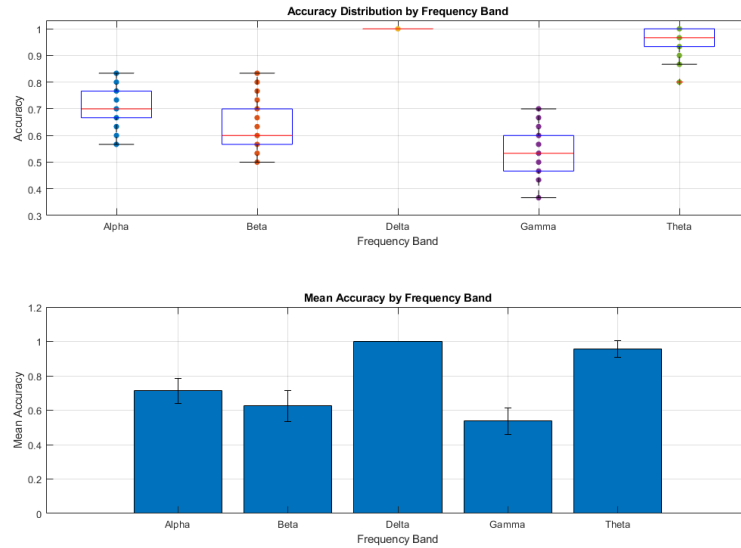


Figure 6.8 Average classification accuracy across different frequency bands in the Induced Saliva Swallowing Experimental Paradigm

Table 6.1 Induced Saliva Swallowing Experimental Paradigm performance metrics results

Band	Accuracy	Sensitivity (Recall)	Specificity	Precision	F1-Measure	GMean	AUC
Delta	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
Theta	0.96 ± 0.05	0.96 ± 0.06	0.95 ± 0.09	0.96 ± 0.07	0.96 ± 0.05	0.95 ± 0.05	0.99 ± 0.01
Alpha	0.71 ± 0.07	0.73 ± 0.13	0.70 ± 0.15	0.72 ± 0.10	0.71 ± 0.08	0.70 ± 0.08	0.80 ± 0.09
Beta	0.62 ± 0.09	0.61 ± 0.18	0.64 ± 0.16	0.63 ± 0.10	0.61 ± 0.13	0.61 ± 0.10	0.65 ± 0.10
Gamma	0.54 ± 0.08	0.52 ± 0.16	0.55 ± 0.16	0.54 ± 0.08	0.52 ± 0.10	0.52 ± 0.08	0.59 ± 0.09

Experimental Paradigm 2 (Induced Water Swallowing) Results

In the Induced Water Swallowing Experimental Paradigm, Figure 6.9 shows the classification accuracy of different frequency bands for individual participants, highlighting the contribution of these bands to overall classification performance. Figure 6.10 shows the average classification accuracy across different frequency bands in the Induced Water Swallowing Experimental Paradigm.

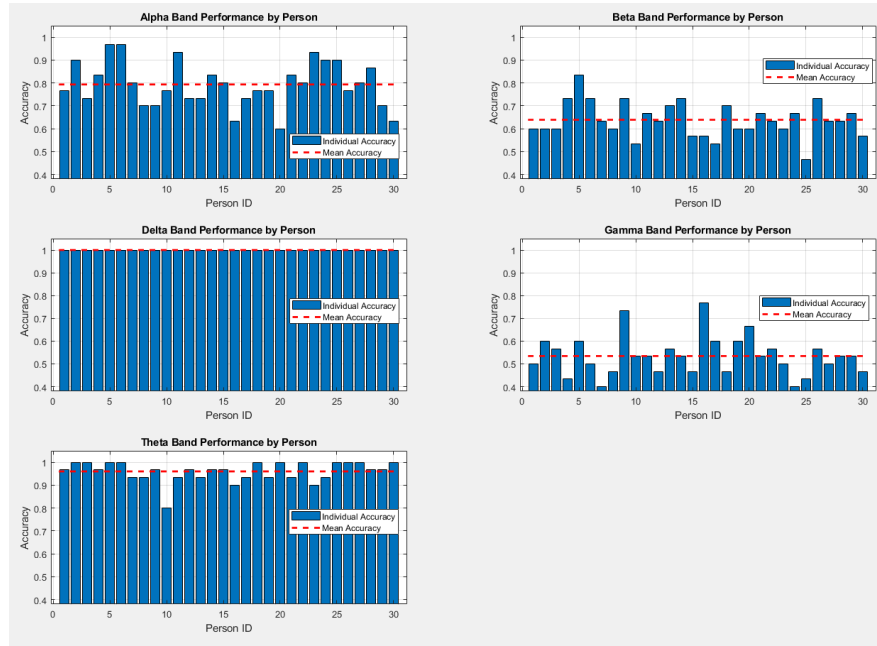


Figure 6.9 Induced Water Swallowing Experimental Paradigm: Performance of Different Frequency Bands in Accuracy Classification by Individuals

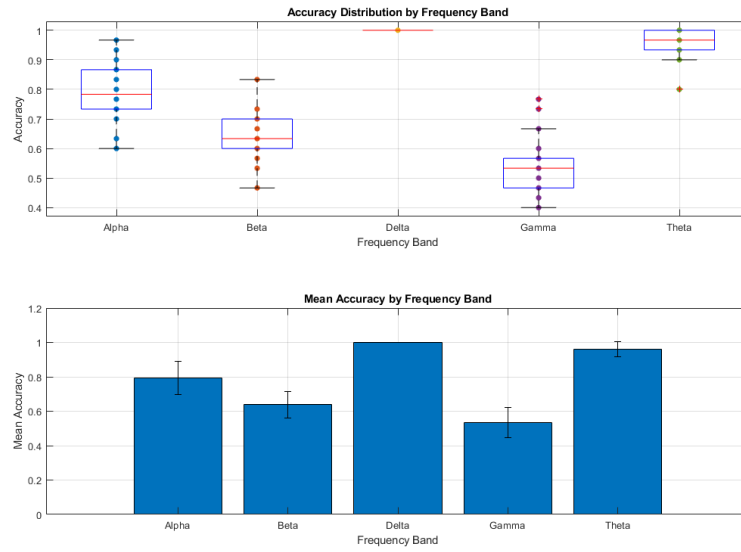


Figure 6.10 Average classification accuracy across different frequency bands in the Induced Water Swallowing Experimental Paradigm

Table 6.2 Induced Water Swallowing Experimental Paradigm performance metrics results

Band	Accuracy	Sensitivity (Recall)	Specificity	Precision	F1-Measure	GMean	AUC
Delta	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
Theta	0.96 ± 0.04	0.97 ± 0.04	0.95 ± 0.07	0.96 ± 0.06	0.96 ± 0.04	0.96 ± 0.04	0.99 ± 0.02
Alpha	0.79 ± 0.10	0.82 ± 0.15	0.76 ± 0.20	0.80 ± 0.13	0.80 ± 0.10	0.78 ± 0.12	0.88 ± 0.08
Beta	0.64 ± 0.08	0.65 ± 0.20	0.63 ± 0.20	0.65 ± 0.10	0.63 ± 0.12	0.61 ± 0.10	0.71 ± 0.10
Gamma	0.53 ± 0.09	0.58 ± 0.22	0.49 ± 0.19	0.53 ± 0.11	0.54 ± 0.14	0.50 ± 0.11	0.57 ± 0.09

6.4 Conclusions and Discussion

This study evaluated the effects of imagination and resting swallowing experimental paradigms on EEG signals. A multi-scale spatial attention network (MS-SAN) architecture was applied to distinguish these conditions. The findings show that EEG frequency bands are influential in revealing the neurophysiological effects of swallowing experimental paradigms. The MS-SAN model effectively achieved this distinction with high classification performance in low and medium frequency bands. Delta and Theta bands generally exhibited high accuracy rates in imagination and resting conditions. The Delta band reached a 100% accuracy rate, demonstrating a strong discriminatory feature related to motor processes. In the literature, it is stated that the Delta band is associated with deep motor processes and provides neurophysiological stability [245], [246], [247]. The Theta band showed a more significant increase in imagination conditions. This is consistent with the activation changes in the Theta band with increasing cognitive load. Since the Alpha and Beta bands are more closely related to motor and mental processes, they performed better in distinguishing imagination and resting conditions, especially in the water-induced swallowing experimental paradigm. Also, the literature shows that swallowing water leaves more consistent neurophysiological traces by increasing cortical activation in motor control processes [248]. On the other hand, the high-frequency Gamma band showed low performance in distinguishing both paradigms. Although the Gamma band is generally associated with perceptual integration and higher-level cognitive processes, it played a limited role in motor-focused tasks in this study. This situation reveals that the neurophysiological effects of the Gamma band on swallowing activities should be examined in more detail. The cross-validation (LOSO-CV) method used in the study played an essential role in learning inter-individual differences and evaluating the generalization ability of the model. This method offers an approach in which each individual is removed from the data set, and the model is trained on the data of other individuals, allowing the effect of individual differences in real-world applications to be examined. The achievement of the MS-SAN architecture in learning differences between individuals demonstrates the model's potential as a generalizable classification method.

In conclusion, Delta and Theta bands performed highly in classifying swallowing experimental paradigms (imagination and rest). While the alpha band showed moderate performance, the contribution of the beta and gamma bands to the classification task was

limited. These findings show that the delta and theta bands are particularly effective for analyzing swallowing experimental paradigms. Thanks to the LOSO-CV method, the model's generalization performance for each individual was reliably assessed. The complete accuracy for all individuals in the delta band emphasizes individual-based reliability. In addition, the differences between the two experimental paradigms are due to the different effects of the swallowing experimental paradigms on the EEG. The alpha and beta bands showed a more significant increase in performance in the water-induced swallowing experimental paradigms and revealed a stronger relationship with motor activities. On the other hand, the delta and theta bands showed similarly high accuracy rates in both experimental paradigms, proving that they have strong discriminatory properties in motor activities. In contrast, the gamma band performed poorly in both experimental paradigms, indicating that this frequency is limited in distinguishing motor activities.

These findings emphasize the effects of swallowing types on the EEG and the success of models such as the multi-scale spatial attention network (MS-SAN) in learning these effects. The high accuracy of Delta and Theta bands indicates that these frequencies have a strong relationship with swallowing experimental paradigms (imagination and rest) and are promising in terms of usability in clinical applications. However, there are some limitations to this study. The limited number of participants may affect the generalizability of the results. Therefore, studying in a more extensive and demographically diverse population is recommended. In addition, only two swallowing experimental paradigms (imagination and rest) were examined. Analysis of swallowing activities associated with different scenarios or cognitive states may expand the scope of the findings. In addition, the 16-channel EEG device may have limited the spatial resolution of the signals. Higher-resolution devices may allow for more prosperous feature extraction but may increase computational costs.

The successful performance of the MS-SAN model in low-frequency bands could not be replicated sufficiently in high-frequency components such as the Gamma band. Future studies will benefit from improvements in model architecture to extract features specific to these bands. Addressing these limitations may provide more sensitive and generalizable results in EEG-based swallowing analyses. In conclusion, this study demonstrates the neurophysiological effects of imagery and resting swallowing experimental paradigms on EEG, demonstrating the success of the multi-scale spatial attention network (MS-SAN) architecture in providing this distinction. These findings

provide a basis for developing more sensitive and practical applications in EEG-based rehabilitation and motor control monitoring systems. In future studies, different modeling techniques and data processing approaches can be evaluated to increase the distinction between Beta and Gamma bands. In addition, testing the generalization performance of the method on different populations will be an essential step in examining the broader applicability of the methodology.



Chapter 7

Conclusions and Future Prospects

7.1 Conclusion

This thesis study focuses on the detection of swallowing intention by analyzing EEG signals and the potential of these signals in biomedical applications. New approaches are needed in the diagnosis and treatment of neurologically based swallowing disorders such as dysphagia. In this context, our study has taken an essential step towards developing an effective system for swallowing intention detection by analyzing EEG data obtained from healthy individuals.

In the study, neurophysiological changes that occur in EEG signals of healthy individuals during swallowing were examined, and the role of these signals in determining swallowing intention was evaluated. The experimental paradigm setup used in the study reduced signal noise with electrodes placed in the antitragus region, allowing cleaner and more stable data to be obtained. This increased the accuracy of the analysis process and improved the performance of algorithms for detecting swallowing intention.

Machine learning and deep learning methods have played an essential role in analyzing and classifying EEG data. The developed models detected swallowing intention with high accuracy and demonstrated the potential for biomedical applications via EEG signals. This success shows that EEG-based analyses can be applied not only in research laboratories but also in clinical settings in the future.

This study has demonstrated that a complex process such as swallowing intention detection can be handled with noninvasive methods and has significantly contributed to the knowledge in this field. The findings obtained can form a basis for analyzing the neurological functions of individuals and developing personalized rehabilitation strategies when necessary. In addition, integrating EEG technology with portable devices and real-time analysis algorithms can provide a wider field of application.

In conclusion, this thesis study has provided an essential methodological framework for detecting swallowing intention using EEG signals. The findings obtained from healthy individuals may shed light on the development of new approaches in the diagnosis and treatment of neurological disorders such as dysphagia in the future. This not only increases the quality of life of individuals but also has the potential to provide sustainable and economical solutions to healthcare systems.

The contributions provided by this study expand the role of EEG-based analyses in biomedical engineering and clinical applications and emphasize the importance of interdisciplinary collaborations. Future studies can further develop this methodology with larger data sets, examination of different neurological processes, and advanced algorithms. This thesis is considered an essential step towards developing innovative solutions in addressing neurological disorders.

7.2 Societal Impact and Contribution to Global Sustainability

The impact of this study on society and its contribution to global sustainability can be evaluated from many perspectives:

Impact on Health and Quality of Life

Dysphagia is a disorder that affects not only the physical health of individuals but also their social and psychological conditions. This study offers a faster and more effective diagnosis and treatment process for dysphagia patients by correctly detecting swallowing intentions. Non-invasive EEG methods provide patients with a more comfortable experience and increase treatment compliance.

Economic and Social Gains

Early diagnosis in dysphagia treatment can significantly reduce treatment costs. Using less invasive methods can shorten the length of hospital stay and increase efficiency in healthcare services. At the same time, these methods can potentially increase the accessibility of healthcare services in developing countries.

Sustainability Perspective

This study contributes to global sustainability by encouraging more efficient use of resources in healthcare systems. Making EEG-based devices portable and affordable allows for broader application of these technologies worldwide. In addition, non-invasive methods reduce the depletion of natural resources and the generation of unnecessary medical waste.

Support for Individuals with Disabilities

Conditions such as dysphagia can severely limit the independent lives of individuals. This study can help individuals with disabilities to integrate more into social life through swallowing intention detection and the development of related technologies. For example, EEG-based human-machine interfaces can control prosthetics or assistive devices.

7.3 Future Prospects

This study has provided an important starting point by demonstrating the applicability of EEG-based approaches in diagnosing and treating dysphagia. However, future studies must focus on different aspects of these methods' wider use and development.

In the future, studies conducted with a more extensive and diverse participant population may increase the generalizability of the findings. Including individuals with different age groups, genders, and dysphagia subtypes will allow for a more detailed understanding of neurophysiological differences in EEG signals. In addition, the development of EEG devices in terms of portability, sensitivity, and ease of use may increase the usability of this technology in both clinical and home environments. Thanks to wireless and economical devices, a wider range of applications can be provided in healthcare systems.

Optimizing machine learning and deep learning algorithms to gain real-time data processing capability will increase the effectiveness of EEG-based diagnosis and treatment processes. This will enable the development of systems that can be directly used clinically, especially in applications such as swallowing intention detection.

Interdisciplinary collaborations can create more innovative solutions in areas such as engineering, medicine, artificial intelligence, and biomedical technologies.

Large-scale validation studies to be conducted in a clinical setting can prove the reliability and effectiveness of EEG-based methods and pave the way for the widespread use of these technologies in the healthcare sector. In addition, the findings obtained can contribute to developing personalized treatment protocols based on individual EEG data. Such approaches can improve treatment outcomes by providing solutions specific to the patient's needs in the rehabilitation process.

EEG-based technologies are not limited to dysphagia alone but can also be applied in the treatment of other neurological disorders such as Parkinson's, ALS, and post-stroke rehabilitation. This broad potential for use can enable EEG signals to assume a more critical role in neurological research and clinical applications. In addition, making such technologies affordable and accessible can reduce global health inequalities by enabling healthcare services to reach wider audiences, especially in developing countries.

In conclusion, it is expected that the EEG-based approach, the foundations of which were laid by this study, will play an important role not only in the treatment of dysphagia but also in the solution of many other health problems, with the support of interdisciplinary collaborations and technological developments in the future. These advances will not only increase the quality of life of individuals but will also contribute to the sustainability of global health systems.

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SELECTED PUBLICATIONS AND PRESENTATIONS

J1) S. G. Aslan and B. Yilmaz, "Distinguishing Resting State From Motor Imagery Swallowing Using EEG and Deep Learning Models," in IEEE Access, vol. 12, pp. 178375-178389, 2024, <https://doi.org/10.1109/ACCESS.2024.3501013>.

J2) S. G. Aslan and B. Yilmaz, "Examining Tongue Movement Intentions in EEG-Based BCI with Machine and Deep Learning: An Approach for Dysphagia Rehabilitation," The EuroBiotech Journal, vol. 8, no. 4, Sciendo, 2024, pp. 176-183. <https://doi.org/10.2478/ebtj-2024-0017>.