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Deep Learning For EEG Signals Analysis While Listening To Quran

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Abstract

This study aims to develop an accurate and objective method for classifying EEG signals recorded during Quran listening. The research question addressed is whether EEG signals can be effectively utilized to classify the response of individuals while listening to Quran recitation. The findings demonstrate the feasibility of utilizing EEG signals for classification and provide insights into the performance of SVM and CNN models in this context. The study contributes to the development of an objective method for detecting and classifying responses to Quran recitation using EEG signals and suggests potential future research directions.

Key-words : Electroencephalogram (EEG), Brain-Computer Interface, classification, Machine Learning, Deep Learning, EEG Signal.

Résumé

Cette étude vise à développer une méthode précise et objective de classification des signaux EEG enregistrés lors de l'écoute de Quran. La question de recherche abordée est de savoir si les signaux EEG peuvent être utilisés efficacement pour classer la réponse des individus tout en écoutant la récitation du Coran. Les résultats démontrent la faisabilité de l'utilisation des signaux EEG pour la classification et donnent un aperçu des performances des modèles SVM et CNN dans ce contexte. L'étude contribue au développement d'une méthode objective de détection et de classification des réponses à la récitation du Coran à l'aide de signaux EEG et suggère de futures directions de recherche potentielles.

Mots-clés : Électroencéphalogramme (EEG),Interface cerveau-ordinateu, classification, ap-prentissage automatique, Apprentissage profond, signaux EEG.

Contents

List of Figures

List of Tables

Introduction

Brain-Computer Interface (BCI) technology has rapidly developed as an exciting area of research, enabling direct communication between the human brain and a computer. This technology has the potential to revolutionize the way we interact with computers, particularly in improving accessibility for people with disabilities and enhancing cognitive tasks. In this context, this study focuses on the application of BCI technology for EEG signal classification to detect responses to auditory stimuli, particularly Quran recitation.

The motivation for this study stems from the significance of the Quran in Islam, where its recitation can evoke profound reactions in listeners. However, objective methods for measuring and classifying these responses are lacking. Therefore, this study aims to develop an accurate and objective method for detecting and classifying responses using EEG signals.

The research question addressed in this thesis is whether EEG signals can be used to accurately classify the responses of individuals while listening to Quran recitation. To achieve this goal, the study sets the following objectives: 1) Investigating the feasibility of using EEG signals for classification during Quran recitation by studying different sets of features, and 2) Comparing the performance of two machine learning techniques, support vector machines (SVM) and convolutional neural networks (CNN), for EEG signal classification.

The thesis is structured into five chapters. Chapter 1 provides an introduc- tion to the study, outlines the research question and objectives, and presents the theoretical background of BCI technology, including its history, evolution, components, and brain signal acquisition techniques such as EEG. Chapter 2 reviews the relevant literature on EEG signals and Quranic recitation. Chapter 3 presents the methodology used in the study and the techniques employed for EEG sig- nal analysis. Chapter 4 focuses on machine and deep learning. Finally, Chapter 5 specifically focuses on the dataset used, preprocessing of EEG signals, fea- ture extraction, and the classification process using SVM and CNN models. The chapter presents the study's findings, including the accuracy of the classification and a comparison between SVM and CNN. It also includes implementation details, discusses the implications of the findings, and suggests future research directions.

Chapter 1

Brain Computer Interface

1.1 Introduction

An electroencephalography (EEG)-based brain–computer interface (BCI) is a system that provides a pathway between the brain and external devices by interpreting EEG.[1] In fact, EEG-based BCI applications were initially developed for medical purposes, but nowadays they are widely used in various applications. First of all, we present in this chapter the concept of the brain-computer inter-face and its applications in the aspect of sensory perception, its types, and how it works. We also explain the brain structures and signals recorded by the EEG.

1.2 Brain computer interface (BCI)

A brain-computer interface (BCI) is a technology that receives, analyzes, and transfers the signals generated from the brain into output commands in the real world to accomplish a particular task. [2] In other words, we can say that it is a system that translates a measure of a user‘s brain activity into messages or commands for an interactive application. [3] BCI does not read the mind accurately but detects the smallest of changes in the energy radiated by the brain when you think in a certain way. A BCI recognizes specific energy frequency patterns in the brain.

1.2.1 History and evolution of BCI

BCIs have their roots in early experiments in the 1920s that showed that the electrical activity of the brain could be measured using electrodes placed on the scalp (Hans Berger) [4]. However, the idea of using this activity to control external devices was not fully realized until the development of computers and advanced signal-processing techniques in the latter half of the 20th century.

The first demonstration of a BCI that could control a cursor on a computer screen was reported in 1973 by E. Donchin and colleagues [5]. This early BCI used a signal called the P300, which is a positive waveform that occurs in response to rare and unexpected stimuli, to control a cursor on a screen [6]. However, the signal was weak and the system was slow and unreliable.

In the 1980s and 1990s, advances in signal processing, machine learning, and computer technology led to the development of more sophisticated BCIs. One key breakthrough was the development of algorithms that could decode the signals from multiple electrodes on the scalp to accurately predict the intended movement of the user. Another important development was the use of implanted electrodes, which can provide much more accurate and reliable signals than surface electrodes. For instance, implanted electrodes in the brain of a man who was paralyzed, enabling him to manipulate a computer cursor through his thoughts. Since then, BCIs have continued to evolve, with researchers exploring new methods for recording brain activity, new algorithms for decoding signals, and new applications for the technology. Today, BCIs are used for a wide range of applications, including restoring mobility to paralyzed individuals, helping people with neurological disorders communicate and even enhancing cognitive performance in healthy individuals.

1.2.2 Application of BCI

BCI is a technology that enables direct communication between the brain and an external device, such as a computer or a robotic limb. Here are some of the applications of BCI:

Medical Rehabilitation: BCI can be used to help individuals who have suffered from strokes or spinal cord injuries regain mobility. By connecting their brain signals to a robotic limb, they can learn to control it and regain some independence [7], BCI technology can also be used for the early detection of abnormal brain structure and functions Therefore, this contributes to the prediction and identification of pathological conditions, such as space-occupying lesions (e.g. brain cancer, encephalitis), abnormal neuronal discharge (seizure), and disorders related to sleep. Indeed, for brain tumor detection, BCI technology can be a cheap, easy, low-risk, and an early detection tool as a secondary alternative or addendum to CT scan or MRI[8][9][10].

Assistive Technology: BCI can be used to create devices that help individuals with disabilities, to communicate with the world, such as ALS (Amyotrophic Lateral Sclerosis) or cerebral palsy. By using brain signals, individuals can con-trol a keyboard or a speech synthesizer, so they can communicate more easily[3].

Gaming: BCI can be used to create immersive gaming experiences. Players can use their brain signals to control characters or objects in a game, making the experience more immersive and engaging[11].

Mental Health: BCI can be used to monitor and treat mental health conditions such as depression and anxiety. By monitoring brain activity, clinicians can gain insights into a patient's condition and develop personalized treatment plans[12].

Education and Research: BCI can be used to study the brain and how it works. Researchers can use BCI to study brain activity during various tasks or to develop new therapies for neurological conditions[12].

Military Applications: BCI can be used to control unmanned aerial vehi- cles (UAVs) or other military equipment, allowing soldiers to operate equipment without the need for physical controls[13]. These are just a few examples of the many potential applications of BCI. As technology advances, we are likely to see even more innovative uses in the future.

1.2.3 Components of a BCI

The primary objective behind designing BCI is to sense and evaluate features of signals in the user's brain, that indicate their intentions. These features are then transmitted to an external device which performs, executes actions in response to the user's intention [14]. To accomplish this aim, a BCI-based system has to follow a sequent process of 4 components from signal acquisition to final decision [15][16].

1. signal acquisition: This consists of placing electrodes on the subject's scalp to capture the electrical signals produced by the neurons of the brain.
2. preprocessing: involves cleaning, filtering, and amplifying the recorded raw electrical signals. This step aims to eliminate artifacts that can affect the signal quality and amplify EEG signals so that they can be analyzed accurately.
3. Feature extraction: involves the conversion of electrical signals into information understandable to researchers or users. This can be achieved by using signal processing algorithms to extract specific characteristics from EEG signals, such as frequencies or amplitudes, which can be used to identify specific brain activity patterns associated with cognitive or emotional tasks.
4. device output or feedback: is the information that the device sends back to the user based on their brain activity. This feedback is designed to help the user modify their brain activity in real-time to achieve a specific goal. The device output or feedback can take different forms, such as a visual display, an audible signal, or electrical stimulation.

More information regarding the Components of BCI can be found in the following chapter.

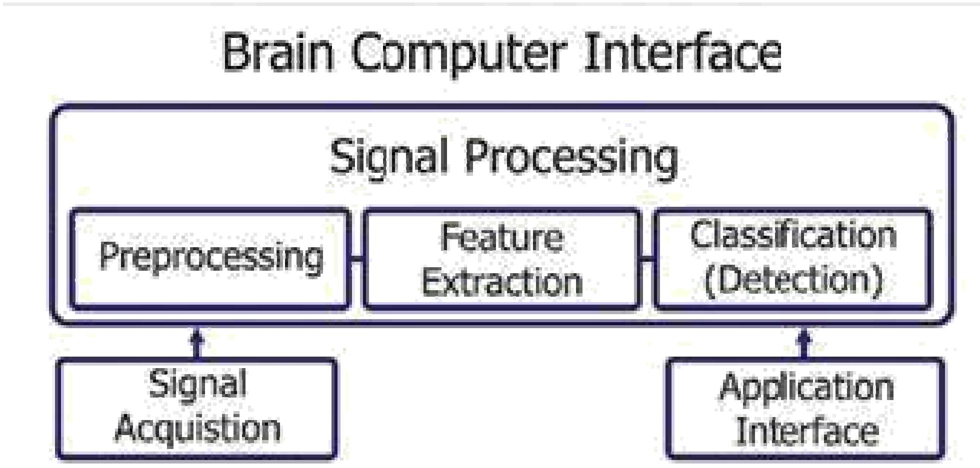

Figure 1.1 – Components of BCI in an illustration of transmission of a signal between input and output with a sequence of processing steps in between[17].

1.2.4 Types of BCI

1.2.4.1 Invasive

Intracortical microelectrode arrays implanted in the cerebral cortex of the brain provide extremely high spatial and temporal resolution. Scientists have demonstrated its potential for use in numerous BCI studies. Studies by Collinger et al [18]. Hochberg et al.[19] have shown that tetraplegics (paralysis of all four limbs usually caused by spinal cord injury) can learn to control a robotic arm with 7 degrees of freedom. The main disadvantage of intracortical electrodes is that they require surgery and can be recognized by the brain as a foreign body, often leading to inflammatory reactions such as ”glial scars” [20].

1.2.4.2 Semi-Invasive

Semi-invasive electrodes for measuring ECoG are also called injectable electrodes, which are less invasive than intra-parenchymal microelectrodes. Inject-ing the net-shape electrodes into a specific position of brain tissue will decrease pain and improve the quality of the recording signal. The mesh structure makes the electrode softer than traditional structures such as paper, needle arrays, and so on. As a result, the electrodes can adhere more closely to the brain tissue [21][22][23][24]. Semi-invasive electrodes overcome some disadvantages of invasive electrodes; they are less invasive and cause less inflammation. As a result, they are more suitable as a means of long-term ECoG recording. However, their special structure brings out some specific problems. The rheological characteristics of semi-invasive electrodes have been studied, but still not in-depth. Some problems such as the fluidity of the mesh in the needle and the entanglement of the whole structure after injection still hinder the practical application. Moreover, even minimally invasive surgery also scares users[25].

1.2.4.3 NON-Invasive

Non-invasive BCIs monitor scalp potentials from the head's surface. Electrodes placed on the scalp are utilized to acquire EEG signals. Signal extrac- tion involves the coordinated activation of thousands or millions of cortical neu- rons [26], mostly because EEG scalp potentials become distorted as they move through the brain, skull, and scalp tissues. Typically, scalp electrodes are positioned in accordance with the 10-20 system [27]. There are several non-invasive techniques used to study the brain, where EEG is the most commonly used because of the cost and hardware portability.[28] We can find for example :

- MEG magnetoencephalography.
- PET positron emission tomography.
- fMRI functional magnetic resonance imaging.
- fNIRS near-infrared spectroscopy.
- EEG Electroencephalography.

1.3 Brain signal acquisition

Brain signal acquisition is the first part of the BCI system, which senses and measures the signals of the brain. This component is mainly accountable for receiving and registering the signals generated by neuronal activity and transferring these signals to the next component of BCI(preprocessing part) for signal improvement and electrical noise attenuation.[12][29][30] [31].

1.3.1 Brain structure

The brain is made up of 100 billion neurons that form a network of very fine wires, and these neurons communicate with each other through electrical signals called nerve impulses. Each neuron is made up of a cell body, extensions called dendrites, and axons. These establish connections with other neurons through synapses. The image below shows an illustration of a biological neuron.

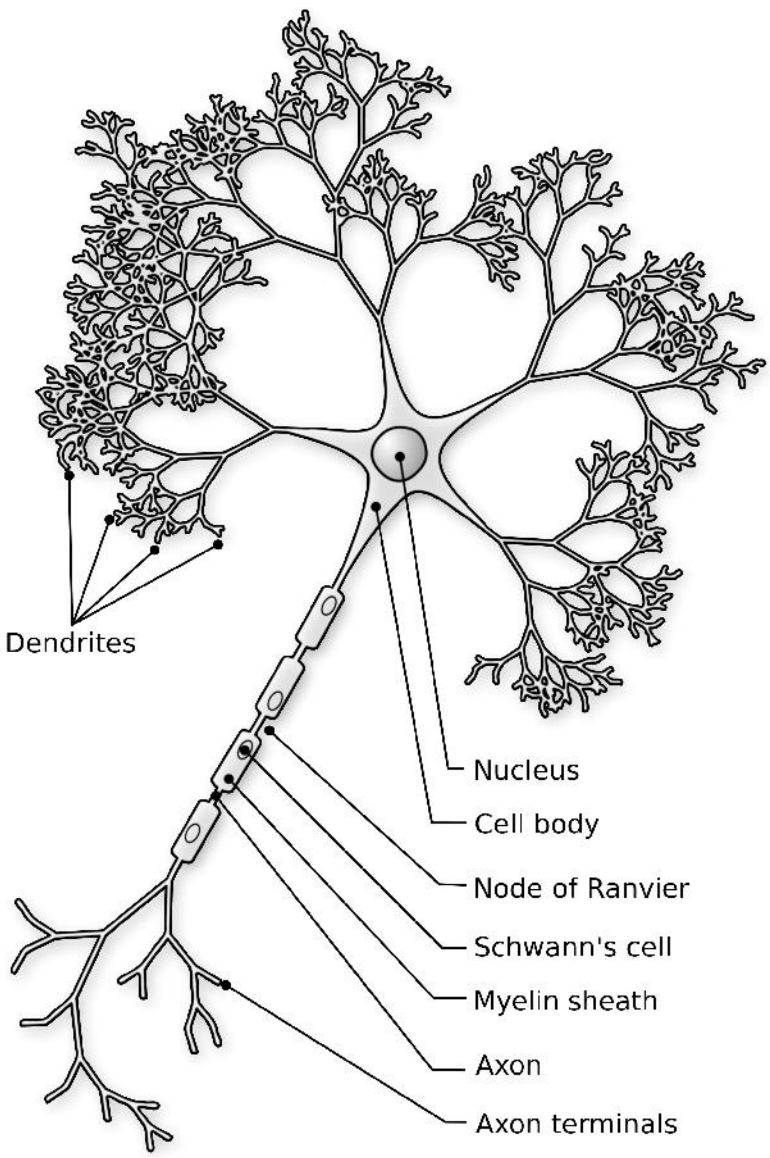

Figure 1.2 – Biological neuron schema[32].

The brain is divided into three parts. The first part is the cerebrum, which is responsible for controlling functions such as language and reasoning. The second part is the brain stem, Which controls visual and auditory functions. The third part is the cerebellum, which controls coordination and movement.

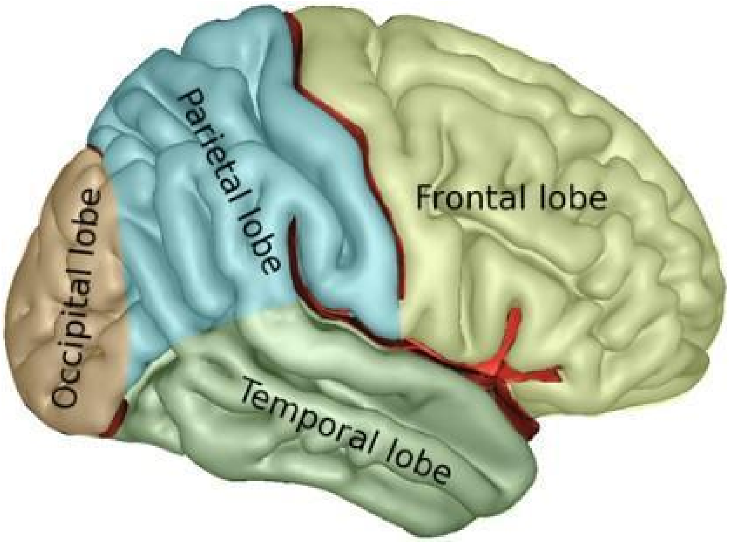

Figure 1.3 – Section of the brain[33].

The brain is also divided into several lobes as shown in Figure number 3. Each lobe controls a different set of functions which we present below and summarize in Figure number 4.

- The frontal lobe: is anterior to the central sulcus and superior to the lateral fissure. The frontal lobe further divides into a superior, middle, and inferior frontal gyrus, primary motor cortex, and orbital area. These areas com- bine to control our executive and motor functions. It controls judgment, problem-solving, planning, behavior, personality, speech, writing, speak-ing, concentration, self-awareness, and intelligence [34].
- The parietal lobe: is posterior to the central sulcus and anterior to the parieto-occipital sulcus. This lobe controls perception and sensation. The primary somatosensory cortex is in the postcentral gyrus and is positioned immediately posterior to the central sulcus. The primary somatosensory cortex controls the sense of touch, temperature, and pain of the contralat-eral body. Mirroring the primary motor cortex, the medial region senses the

lower extremity, the superior-lateral region senses the upper extremity and hand, and the lateral region senses the face. Similar to the primary motor area, the hands, face, and lips take up the majority of the somatosensory area [35].

— The occipital lobe: is posterior to the parieto-occipital sulcus and superior to the tentorium cerebelli. This lobe interprets vision, distance, depth, color, and facial recognition. The occipital lobe receives its information from the contralateral vision field of both eyes (i.e., the left occipital lobe receives and interprets information from the right visual field from both the left and right eye [36].

— The temporal lobe: is inferior to the lateral fissure and further divides into a superior, middle, and inferior temporal gyrus. This lobe controls language comprehension, hearing, and memory. Wernicke's area is responsible for language comprehension, and it is not found in both hemispheres. Sim- ilar to Broca's area, Wernicke's area is in the superior temporal gyrus of the dominant hemisphere, which is usually the left hemisphere. Therefore, the location of Wernicke's area is most commonly in the superior temporal gyrus. The primary auditory cortex is in the superior temporal gyrus and processes most auditory information from the contralateral ear and some from the ipsilateral ear. The temporal lobe communicates with the hippocampus and amygdala to form memories [34].

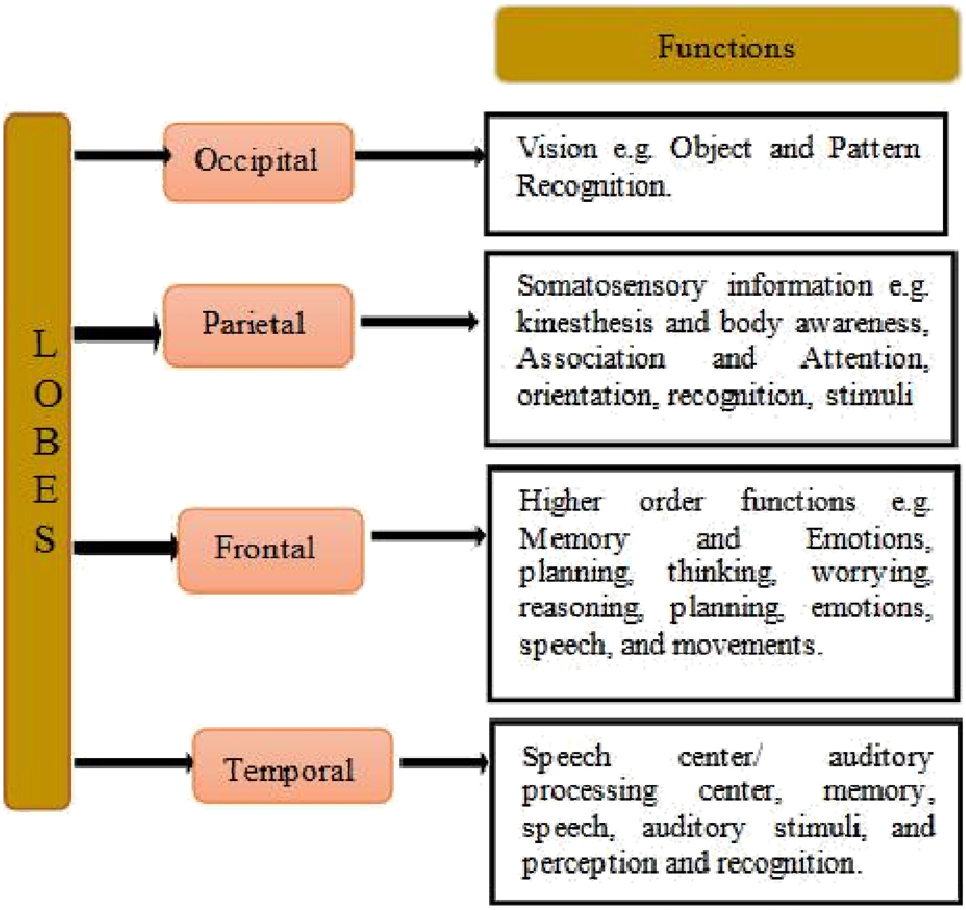

Figure 1.4 – function of brain[37].

1.3.2 Electroencephalography (EEG)

Brain activity produces different types of signals such as electrical and magnetic signals. This activity can be recorded using different types of approaches, invasive and non-invasive. Electroencephalography (EEG) is one of the most commonly used recording methods. EEG is considered a direct, simple, non-invasive recording method of brain electrical activity expressed as voltage fluctuations with currents in neurons of the brain, EEG can be described as signals over time that is recorded from electrodes placed on the scalp above the brain.

1.3.2.1 Principle and functioning of EEG

Electroencephalography (EEG) is an examination based on the measurement of the electrical activity of the brain allowing cerebral exploration. This is done using electrodes placed on the patient's scalp. Generally, this approach is used to diagnose certain diseases such as epilepsy, and insomnia, to differentiate the different types of brain waves and even to study the functioning of the brain of a healthy person.

Comparable to electroencephalography (ECG) which makes it possible to study the functioning of the heart, the EEG is a painless and non-invasive examination that provides information on the neurophysiological activity of the brain over time and in particular of the cerebral cortex either in a diagnostic purpose in neurology or in cognitive neuroscience research. The electrical signal at

Figure 1.5 – EMOTIV EPOC EEG Headset[38].

the base of the EEG is the result of the summation of synchronous post-synaptic action potentials from a large number of neurons. In 1875, Richard Caton detected the presence of electric currents in rabbits and monkeys on the surface of the brain confirmed by the occurrence of oscillations of the needle of a galvanometer[39]. Hans Berger applied this approach to humans and recorded the first EEG in 1929 under permanent variations of potential, recorded with non-polarizable electrodes on an intact skull[39]. With the evolution of technology, EEG amplifiers can support multiple channels up to 512 on some devices[39].

1.3.2.2 The Rhythms

EEG is a measure of voltage as the function of the time. EEG characteristics are highly dependent on the degree of activity of the cerebral cortex[40][39].In general, an EEG signal is a combination of waveforms and is usually classified accordingly. A waveform is characterized by:

1. Frequency
2. Magnitude
3. Wave morphology
4. Spatial distribution
5. Reactivity

The most common classification uses an EEG waveform frequency band. signals can therefore be decomposed within 5 different frequency bands

— Delta waves are found in between the frequency range of 0-4 Hz which are detected during deep sleep or coma. Such waves have higher amplitude and are measured in more than 100 microvolts [39].

— Theta waves range from 4-8 Hz and tends to be more prominent in childhood than adulthood. However, theta re-emerges often in drowsy periods and is the hallmark of some normal findings including rhythmic temporal theta of drowsiness (RMTD) [39]

— Alpha waves are found in between the frequency range of 8-13 Hz. These waves are originated from the occipital lobe of the brain during the state of relaxation and calm. It has also been found that the activity of Alpha rhythm reflects the visual functioning of human beings [39].

— Beta waves are present between 13-30 Hz frequency ranges. These waves are associated with anxious thinking and active concentration, originating from the brain's central area [39].

— Gamma waves are found between the frequency ranges of 30-100Hz Mental state associated with these waves is a multi-tasking and conscious waking state [39].

1.3.2.3 Channels of EEG

EEG channels are recordings of electrical signals produced by neuronal activity in different regions of the brain. The number of EEG channels varies de-

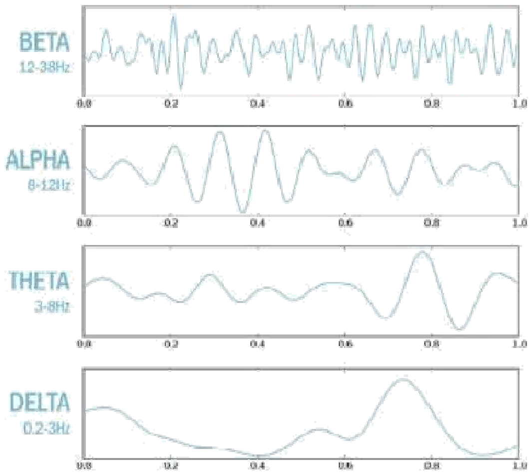

Figure 1.6 – Waves of human brain[41].

pending on the number of electrodes used. Standard EEG systems often have between 8 and 32 channels, but more advanced systems can have hundreds[42]. Each EEG channel records the electrical potential difference between two specific electrodes. When the neurons in the region of the brain located between these electrodes are activated, they produce an electrical signal which is recorded by the EEG channel. EEG signals are amplified, filtered and digitized for computer analysis.[42] EEG channels can be used to study brain activity during various cognitive and emotional tasks. They can be used to study patterns of brain activity associated with different emotions, to assess changes in brain activity that occur when performing specific tasks, and to diagnose certain neurological and psychiatric conditions.

1.3.2.4 10-20 System

This system is standardized and splits the skull into increments of 10% or 20% to place the electrodes, ensuring that each electrode is relatively positioned to all the others and making it possible for every EEG study to be consistent despite peoples' many different head shapes and sizes[43]. In the 10-20 system, each electrode is identified with a letter and a number. The letter corresponds to its region of the brain: F for the frontal region, T for the temporal, P for the parietal, and O for the occipital (the only exception to this is that F7 and F8, while seemingly frontal, are in fact actually over the anterior temporal region).

The number corresponds to the side of the brain–odds on the left, evens on the right–and the particular area of each region. For the midline/central electrodes, instead of a number their letters are clarified with a ”z”[44].

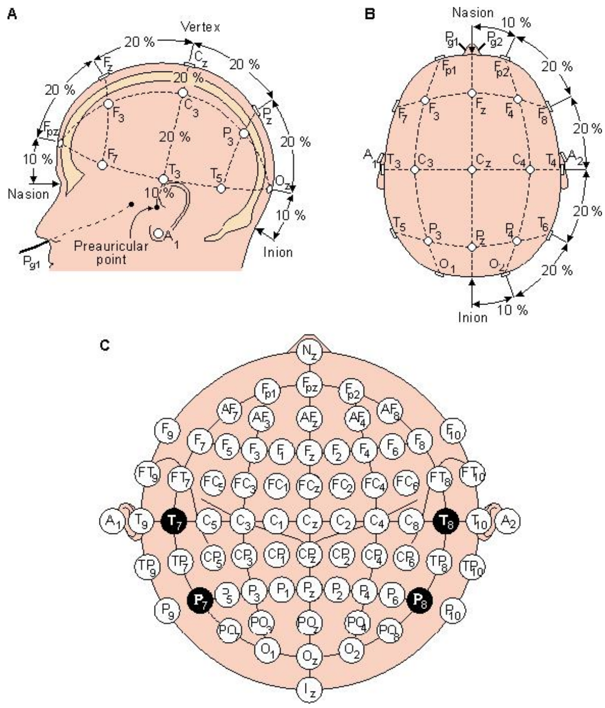

Figure 1.7 – Electrode Positions 10-20[45].

1.4 Brain image techniques

This passage is discussing the categorization of brain-computer interface (BCI) signals, which can be invasive or non-invasive. The different types of non-invasive BCI signals include magnetoencephalography (MEG), functional near-infrared spectroscopy (fNIRS), electrooculography (EOG), functional magnetic resonance imaging (fMRI), and electroencephalography (EEG). EEG signals can be further classified as either spontaneous or evoked potential. Spontaneous EEGs are brain signals recorded in the normal state of the brain without external stimulation, while evoked potentials are brain signals that occur in response to a specific stimulus, such as a visual or auditory stimulus. The latter consists of two other types: Event-Related Potential (ERP) and Steady State Evoked Potential (SSEP). ERP is a type of evoked potential that includes all the potentials that occur after a stimulus presentation at a specific time. ERP includes visual evoked potentials (VEP), auditory evoked potentials (AEP), and somatosensory evoked potentials (SEP). SSEP is another type of evoked potential that occurs in response to a steady-state stimulus which is continuous and rhythmic. SSEP includes steady-state visual evoked potential (SSVEP), steady-state auditory evoked potential (SSAEP), and steady-state somatosensory evoked potential (SSSEP).

In our work, we will focus on evoked potential EEG signals with auditory stimuli. More particularly we will be interested on the Steady State Evoked Potential (SSEP) since we are going to study the auditory perception and brain response of individuals when listening to the Quran.

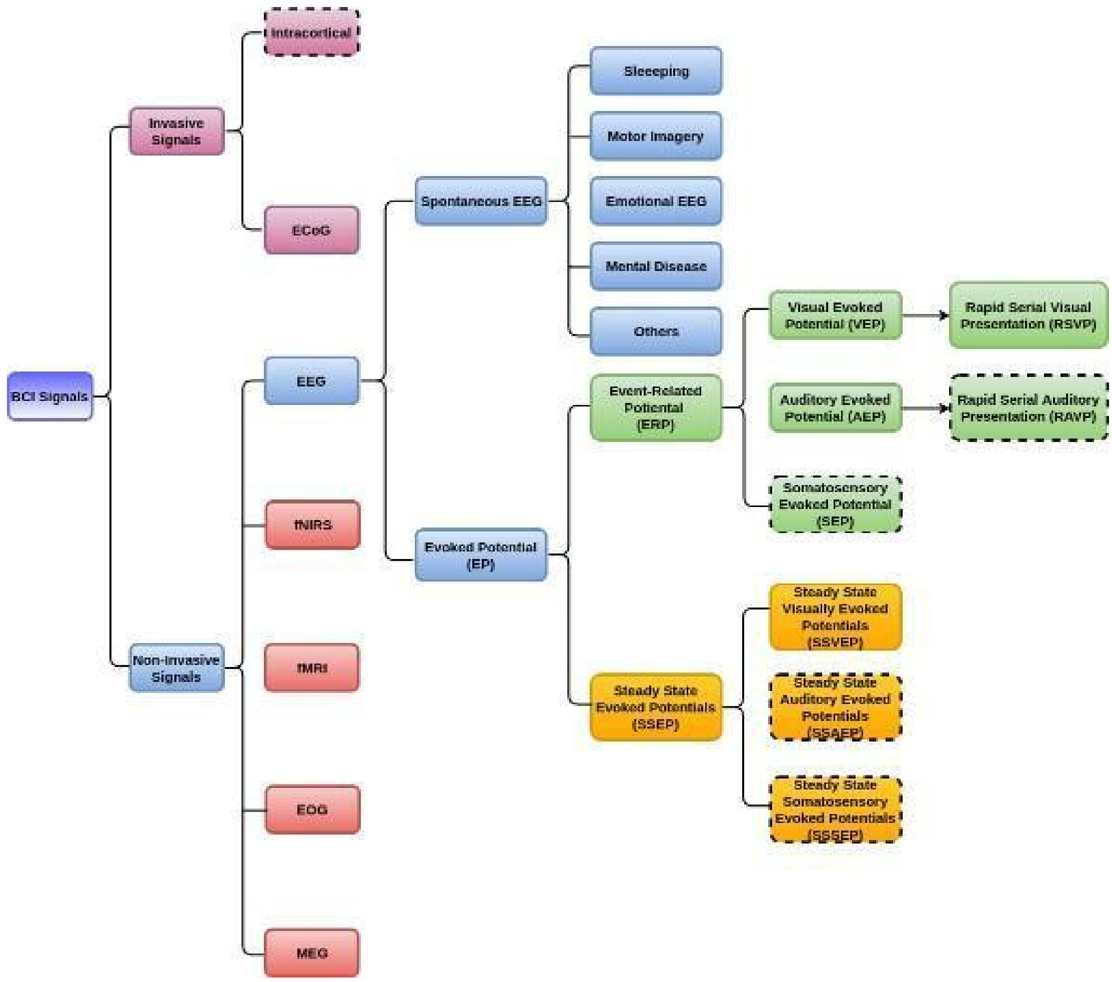

Figure 1.8 – The different types of invasive and non-invasive BCI signals and the hierarchy of classification for EEG signals. This classification includes spontaneous and evoked potential, with evoked potentials further divided into ERP and SSEP[46].

1.4.1 Event-Related Potentials

Event-related potentials (ERPs) are changes in the electrical activity of the brain that occur in response to a specific stimulus or event. ERPs are typically analyzed by averaging the EEG signals across multiple trials in which the same stimulus is presented. By averaging the signals, researchers can isolate the electrical activity that is specific to the stimulus and eliminate other sources of electrical noise. Different types of ERP components have been identified based on the timing and location of the electrical activity in the brain. For example, the P300 component is a positive deflection in the EEG signal that typically occurs 300 milliseconds after the presentation of a stimulus that is relevant to the task being performed.[47] The P300 component has been widely studied in the context of BCI systems because it is associated with attention and decision-making processes. ERPs are useful in BCI systems because they can provide information about a person's cognitive processes and attentional state. By detecting changes in ERP components, a BCI system can infer a person's intention or level of attention and use this information to control external devices, such as a cursor on a computer screen or a robotic arm.

1.4.2 Steady-State Evoked Potentials

Steady State Evoked Potentials (SSEPs) are a type of evoked potential that occurs in response to a repetitive or continuous sensory stimulus such as flickering light or sound. Unlike evoked potentials, which are generated by a single stimulus, and are time-locked to the onset of a stimulus, SSEPs are stable over time[48]. SSEPs are generated by a series of repetitive stimuli that are presented at a specific frequency, such as 40 Hz[49], resulting in a sustained electrical response in the brain. The stimuli used in SSEP testing are typically visual or auditory[48]. The electrical responses generated by these stimuli can be recorded using electroencephalography (EEG) or (MEG) techniques and can be used to study brain activity related to sensory processing, attention, and cognition.

1.5 Conclusion

In conclusion, this chapter has provided an overview of the concept of the brain-computer interface and its applications in the field of sensory perception. We have explored the principle and function of electroencephalography as a widely-used tool for recording and analyzing brain activity. Furthermore, we have discussed various brain imaging techniques, including Event-Related Potentials and Somatosensory Evoked Potentials.

Chapter 2

Sentiment analysis using EEG (Literature review)

2.1 Introduction

This chapter introduces the field of sentiment analysis. It is a field that aims to identify and extract subjective information from textual or auditory data, including opinions, attitudes, and emotions. EEG is widely used as a tool for measuring brain activity associated with emotions. This chapter presents related works in the field of emotion classification in the context of Quran recitation, highlighting the different approaches and methodologies that have been employed. Finally, a discussion and comparative analysis a discussion are provided.

2.2 Sentiment analysis

Sentiment analysis has become one of the most active research areas in natural language processing (NLP) and is widely studied in fields such as data mining, web mining, text mining, and information retrieval[50]. It involves analyzing text, audio, or other types of data to determine the emotional state, opinion, or attitude expressed by the author or speaker[51]. To perform sentiment analysis using EEG signals, several methods can be used, including machine learning, event-related potentials (ERPs). Machine learning involves training a classifier on a dataset of EEG signals and their associated emotional states, and using the classifier to predict the emotional state of new EEG signals. It is important to note that sentiment analysis using EEG signals is a complex and challeng- ing task, as EEG signals are highly variable and subject to noise and artifacts. Additionally, emotions are complex and multifaceted, and may not always be accurately reflected in EEG signals. However, with careful experimental design, data preprocessing, and analysis, it is possible to obtain meaningful insights into the emotional responses of individuals while listening to Quran using EEG sentiment analysis techniques.

2.2.1 Emotions

It is important to investigate emotions experienced by individuals while listening to the Quran using EEG. Emotions can be defined as subjective experiences that involve feelings, physiological changes, and behavioral responses. Emotions are an essential aspect of human behavior and can influence our perceptions, judgments, and actions. Psychologists have identified several basic emotions that can be classified into six categories: happiness, anger, fear, surprise, sad- ness, and disgust.[52] These basic emotions are thought to be biologically based, meaning they are innate and not learned.[53].

Each basic emotion has specific characteristics and can be associated with particular physiological and behavioral responses.

Fear: is a basic emotion that is associated with an instinctive response to danger or threat. Fear can manifest as changes in heart rate, blood pressure, sweating, and other physiological responses.

Anger: is an emotional response to feeling violated, disrespected, or mistreated. It can be associated with feelings of hostility, resentment, and even violence.[54]

Sadness: is a basic emotion that is characterized by a low mood, feelings of failure or loss, and a lack of motivation. It can be associated with feelings of self-pity, loneliness, and depression.

Joy: is a positive emotion that is characterized by feelings of pleasure, contentment, and excitement.[54]

Surprise: is a basic emotion that is triggered by unexpected events or stimuli, and it can cause a temporary interruption in behavior.

Disgust: is an emotion that is elicited by negative stimuli in the environment, such as foul odors or contaminated food.[54]

2.2.2 The Importance of using EEG in the classification of emotions

EEG is a non-invasive neuroimaging technique that measures electrical activity in the brain through electrodes placed on the scalp. EEG has been used in the study of emotions and has proven to be a valuable tool for emotion classification. Studies have described that EEG contains the most comprehensive features that can be utilized for basic emotion classifications such as the power spectral bands. [55] One of the main advantages of EEG for emotion classification is its high temporal resolution. EEG can capture changes in brain activity that occur within milliseconds, making it well-suited for studying fast-changing emotional states. EEG has also been used to identify patterns of brain activity associated with different emotions. By analyzing the electrical signals produced by the brain, researchers have been able to identify distinct patterns of brain activity associated with emotions like joy, anger, sadness, and fear. This information can be used to create algorithms that can accurately classify emotions based on EEG data. Another advantage of EEG for emotion classification is its portability. EEG equipment is relatively small and can be worn by subjects during naturalistic situations, such as while watching a movie or engaging in social interactions. This allows researchers to study emotional responses in real-world contexts, which can provide a more accurate understanding of how emotions are experienced and expressed in everyday life.[56] EEG is a safe and non-invasive technique, which makes it suitable for use with diverse populations, including children and individuals with neurological conditions. It has the potential to provide important insights into the neural basis of emotions, and its use in emotion classification may have practical applications in fields such as mental health, human-computer interaction, and affective computing.

2.3 Auditory stimulus for sentiment analysis

Auditory stimulation refers to any sound-based input that is used to activate or influence the auditory system. This can include a wide range of stimuli, such as music, speech, white noise, and other sounds.

Auditory stimulation can be used for a variety of purposes, including relaxation, stress reduction, cognitive enhancement, and therapeutic interventions. For example, listening to calming music or Quran can help reduce anxiety and promote relaxation, while listening to white noise or nature sounds can help improve focus and concentration.

Auditory stimulation can also be used in clinical settings as a form of therapy. For example, music therapy is a type of treatment that uses music to address the physical, emotional, cognitive, and social needs of individuals.

One common approach to sentiment analysis of auditory stimuli involves using automatic speech recognition (ASR) technology to transcribe spoken words into text. ASR technology uses machine learning algorithms to convert spoken language into text[57]. Once the text has been transcribed, standard sentiment analysis techniques can be applied to the text to determine the sentiment.

Another approach is to use the acoustic features of the audio signal directly to determine sentiment. This approach involves analyzing various characteristics of the sound signal, such as pitch, tone, and rhythm, to infer the speaker's emotional state.

2.4 Related Works

The Quran is the central religious text of Islam, it is the direct word of God as revealed to the Prophet Muhammad over a period of 23 years. It consists of 114 surahs, each containing ayat, that offer guidance on matters of faith, morality, and social justice. It is revered as a source of divine guidance, wisdom, and spiritual nourishment, and is recited and studied or listened to recitations of the Quran by Muslims all over the world as an essential aspect of faith and daily life.

It is known that the Quran brings peace and moral and spiritual comfort to

Muslims because, according to their beliefs, it is the word that comes directly from God who is the creator of all universes. However, in this work, we want to study objectively and scientifically what actually happens in the brain when listening to the Quran and what are the experienced emotions.

EEG-based BCI has been widely studied and used in various fields such as medicine, engineering, and computer science and it has been used to study the emotions and feelings of Muslims while listening to Quran recitation. There has been limited research focusing specifically on the use of EEG-based BCI for sentiment analysis during Quran recitation. However, some studies have looked at the use of an EEG to study brain activity while listening to Quran recitations. Among these studies we mention:

2.4.1 EEG-Based Emotion Recognition while Listening to Quran Recita-tion Compared with Relaxing Music Using Arousal-Valence Model[58]

The study aims to investigate the emotional responses of individuals while listening to Quran recitation and relaxing music using the International Affec-tive Picture System (IAPS) database as stimuli. The study also employs a two-dimensional Arousal-Valence emotion model for emotion classification, and the model is implemented to recognize four basic emotions: Happy, Fear, Sad, and Calm. The findings of the study suggest that both Quran recitation and relaxing music evoke positive emotions in individuals, as they were classified more into positive valence. The average accuracy of emotion recognition using the implemented model was found to be 76.81%. This study provides valuable insights into the emotional effects of listening to Quran recitation and relaxing music, and the use of the IAPS database and the two-dimensional Arousal-Valence emotion model adds rigor to the study. The findings of this study can have implications for the use of Quran recitation and relaxing music in therapeutic interventions for individuals with emotional disorders, and future studies can further investigate the potential benefits of these interventions.

2.4.2 Emotion Detection among Muslims and Non-Muslims While Listening to Quran Recitation Using EEG[59]

The study aims to examine the various human emotions shown by participants while listening to recitations of Quranic verses. The study also analyzes the brain activities of four groups: one group of Muslim participants who under-stand the language of Al-Quran, one group of Muslim participants who do not understand the language of Al-Quran, one group of non-Muslim participants who understand the language of Al-Quran, and one group of non-Muslim participants who do not understand the language of Al-Quran. The study uses EEG devices to record brain waves while participants listen to Quran recitations. The study uses Mel Frequency Cepstral Coefficients (MFCC) and Kernel Density Estima- tion (KDE) as feature extraction techniques to extract features from EEG signals. The Multilayer Perceptron (MLP) is used for classification. The emotions deter-mined from the study will help to provide more information to the medical field for treating stress or depressed patients, both Muslims and non-Muslims. The findings of this study are significant as they provide insights into the potential therapeutic use of Quran recitation in treating stress and depression. The study also provides evidence that individuals who do not understand the language of Al-Quran can also benefit from listening to its recitation. The use of EEG devices to record brain waves adds rigor to the study, and the use of feature extraction and classification techniques helps in the analysis of data.

2.4.3 Analyzing Brainwaves While Listening To Quranic Recitation Compared With Listening To Music Based on EEG Signals[60]

This study aimed to investigate the effects of listening to Quran recitation compared to relaxing music on the calmness and relaxation of subjects. Brainwaves were measured, focusing on the Alpha and Beta bands, using BrainMarker EEG hardware and software. Twenty-five students from the International Islamic University Malaysia participated in the experiment, and EEG was acquired by placing nineteen surface electrodes on the scalp according to the international 10-20 system. The results showed that listening to Quran recitation generated higher alpha magnitudes compared to beta magnitudes, indicating higher levels of calmness and relaxation in the subjects. On the other hand, relaxing music generated almost equal beta and alpha magnitudes, but not as high as Quran recitation. The subjects were also exposed to IAPS stimuli for four emotions (Happy, Fear, Sad, and Calm) combined with suitable music through headphones for one minute each. The findings of this study suggest that Quran recitation can be a useful tool in inducing calmness and relaxation in individuals, as it generates higher alpha magnitudes in brainwaves. The use of BrainMarker EEG hardware and software and the international 10-20 system for electrode placement add rigor to the study.

2.4.4 The Effect of Temporal EEG Signals While Listening to Quran Recitation[61]

This study aimed to investigate the effects of listening to Quran recitation and hard music on the human brain. EEG signals were measured and analyzed during rest and in different cognitive states. A statistical analysis using SPSS software was conducted to test the validity of the obtained data. EEG signals were captured from about 14 subjects using Ag-AgCl surface electrodes placed on the scalp using the 10-20 system electrode placements. The results showed that listening to Quran recitation generated alpha waves, indicating a relaxed state, while listening to hard music resulted in the appearance of beta waves, indicating an excited state. The study also found that listening to Quran recitation induced a more relaxed and calm state compared to rest and listening to hard music. The study faced some difficulties, including the appearance of artifacts that had to be filtered to obtain smooth signals. Overall, the study contributes to the understanding of the effects of religious activities on the human brain and highlights the potential benefits of listening to Quran recitation for inducing relaxation and calmness.

2.4.5 Effects Of Quran Listening And Music On Electroencephalogram Brain Waves[62]

This study aimed to investigate the effect of listening to Quran recitation on generating alpha waves in the human brain and to compare this effect with listening to slow and hard rock music. The study involved 11 healthy students without special musical education, and EEG signals were measured from 3 leads according to the international system. The appropriate electrode for this research is Ag-AgCl surface electrodes applied with electrode paste. The subjects were instructed to rest and listen to soft music, hard music, and Quran recitation for three minutes each while EEG signals were recorded before and after each task. The analysis results showed that listening to Quran recitation can generate al- pha waves, leading to significant relaxation compared to resting and listening to slow and hard rock music. Statistical analysis using t-test correlation, descriptive statistics, and analysis of variance (ANOVA) were performed using GraphPad prism software. The study concluded that the specific effect of Quran recitation on the human heart may lead to the production of certain hormones and chemicals responsible for relaxation, resulting in the significant generation of alpha waves in the brain.

Table 2.1 – Comparison of EEG-based emotion recognition studies

Study	Datasets	EEG Features	Classification Algorithm	Accuracy
Abdullah et al. [2020]	30 participants	Power spec- tral density, complexity measures	Random Forest, SVM, K-NN	73.44% to 98.44%
Alsharif et al. [2021]	N/A	PSD, relative power, asymme- try	CNN	97.67%
Valenzi. [2015]	N/A	Arousal-Valence model	N/A	76.81%
Al-Galal. [2017]	25 students	Alpha and Beta bands	N/A	N/A
Abdullah et al. [2011]	14 subjects	Alpha and Beta waves	ANOVA	N/A
Shekha et al. [2013]	11 healthy stu- dents	Alpha waves	ANOVA	N/A

Based on the table, we can see that Support Vector Machines and Convolutional Neural Networks have been used in some studies and have shown promising results. For example, Alsharif et al achieved an accuracy of 97.67% in EEG-based emotion recognition using a CNN model. Shahid et al also obtained high accuracies ranging from 84.21% to 97.92% using SVM and Random Forest algorithms.

However, it is important to note that the success of these algorithms depends on several factors such as the quality and quantity of data, feature selection, and tuning of hyperparameters. Therefore, it is necessary to carefully design and optimize the models to achieve the best possible performance.

2.5 Conclusion

In conclusion, this chapter has explored the challenges and opportunities in sentiment analysis and emotion classification, highlighting the importance of utilizing EEG and auditory stimulus as tools for measuring and analyzing emotional responses. We have discussed the different approaches and methodologies used in emotion classification and sentiment analysis, and provided a comparative analysis of their strengths and limitations. As the field of sentiment analysis and emotion classification continues to evolve, it is clear that further research is needed to better understand the neural mechanisms underlying emotions and how they can be effectively measured and classified. By utilizing advanced techniques such as EEG and auditory stimulus, we can gain deeper insights into the complexities of human emotions and their impact on various aspects of our lives.

Chapter 3

Methodology

3.1 Introduction

This chapter will provide essential information for creating and implement-ing a brain-computer interface (BCI). We will cover a range of topics includ- ing techniques for recording and processing brain signals, classification methods used in BCI, and the importance of preprocessing techniques such as filtering and artifact removal. Additionally, we will explore the process of feature extrac- tion, which involves identifying and extracting useful information from brain data recordings, and explore different classification techniques that can be used to distinguish between various cognitive states.

3.2 Preprocessing

Preprocessing is an important step in data analysis and machine learning be- cause it can significantly affect the accuracy and efficiency of the final model. By cleaning and transforming the data, through the removal of artifacts which can be removed using methods such as referencing and filtering the data. Sanei and Chambers [63] identify a number of possible artifact sources, including mus- cles (electromyogram, EMG), eyes (electrooculogram, EOG), interference from electrical sources, and cable defect artifacts. To remove artifacts the signal must be amplified and filtered, Another artifact removal technique is thresholding, where a threshold is set for an input signal (e.g. EOG) and epochs where the signal's amplitude exceeds the threshold are deemed to be contaminated and are removed.[33]

3.2.1 Downsampling

Downsampling is a technique used in signal processing and data analysis to reduce the amount of data by lowering the sampling rate[33], EEG recorded at 1000 Hz can be downsampled to 500 Hz by discarding every other sample[33], This reduces the amount of data to process and can help simplify the analysis of large data sets. However, downsampling can also result in loss of information if the removed samples contain important details or features.

3.2.2 Temporal Filtering

Discrete Fourier Transform Filters Discrete Fourier Transform (DFT) is a mathematical tool used to transform a signal from the time domain to the frequency domain (are two different ways of representing a signal or data, The time domain represents a signal as a waveform that changes over time, while the frequency domain represents a signal as a spectrum of frequency components), removing the all-time information of the signal and instead representing it as a sum of sine waves. The DFT filtering of the Xn signal is a three-step process that involves: converting the signal to the frequency domain, setting all coeffi- cients outside the desired range to 0, then converting the signal back to the time domain.[33] DFT filtering can be performed with:

$$X_k = \sum_{n=0}^{N-1} x_n e^{\frac{-2i\Pi}{N} kn}$$

where N is the number of samples, k represents the sine frequency at k/N samples, e is Euler's constant and i is an imaginary number,[33] where $i^2 = -1$

the signal is converted back to the time domain using inverse DFT (IDFT):

$$x_n = \frac{1}{N}\sum_{k=0}^{N-1} X_k e^{\frac{i2\pi kn}{N}}$$

Finite Impulse Response Filters A finite impulse response (FIR) filter is a linear filter. Its output is based on a finite, or limited, number of input samples. The FIR response is calculated from the last M samples of the unfiltered signal s(n).[33] The filtered signal y(n) ends with:

$$y(n) = \sum_{k=0}^{M} b_k\, s(n-k) \qquad (3.2.3)$$

where bk is the vector containing the feedforward filter coefficients, s(n) is the unfiltered raw signal

Infinite Impulse Response Filters Infinite Impulse Response (IIR) filters are digital filters used in digital signal processing. Their output is based on an infinite number of input samples. The IIR response is based on both the last M samples s(n) and the output of the previous P filter operations.[33] The filtered signal y(n) is found from:

$$y(n) = \sum_{k=0}^{M} b_k\, s(n-k) + \sum_{k=1}^{P} axy(n-k) \qquad (3.2.4)$$

where ax is a vector containing the feedback filter coefficients.

3.2.3 Temporal filtering application

High-pass filtering: is a type of signal processing technique that removes or attenuates low-frequency components in a signal while allowing high-frequency components to pass through. Low-frequency signals are often associated with artifacts, such as those that accompany breathing, amplifier drift, and changes in skin resistance due to sweat. Most can be removed by a high-pass filter with a cut-off frequency of around 0.5-1 Hz. Electrocardiogram (ECG) artifacts may also be detectable by EEG [64]however, the effects of this low-frequency signal can also be reduced using a high-pass filter[33].

Low-pass filtering: are commonly used to eliminate high-frequency noise, typically with a cutoff frequency in the range of 50-70 Hz[63].
Band-pass filtering: are useful for extracting specific frequency bands, such as the mu and beta bands associated with motor imagery. Even BCIs that do not depend on spectral information, like the P300-BCI, are typically filtered prior to detection. In P300-BCI signal detection, band-pass filtering is usually applied within the 0.1-20 Hz frequency range[33].
Notch filtering: are a subtype of band-stop filters that are often implemented with high order. Their primary use is to eliminate line noise at frequencies of either 50 or 60 Hz[33].
Zero-phase filtering: are a type of filter that applies a time reversal to data to avoid phase distortions and signal delay. This is achieved by filtering the data, reversing it, filtering it again, and then reversing it once more. Although zero-phase filtering offers several advantages, it is usually used for offline data because it is non-causal and relies on future inputs, making it unsuitable for real-time ap- plications[33].

3.2.4 Spatial Filtering

Reference Electrodes: In EEG-based brain-computer interfaces (BCIs), reference electrodes are employed to measure the voltage of EEG channels. The voltage, which represents the difference in electrical potential between two points, is determined by placing the reference electrode in close proximity to the scalp and computing the difference. Typically, the mastoid bone (located behind the ear)[65][66] [67]is used as the reference site, but alternative reference placements may offer significant advantages depending on the specific application. By accurately measuring the voltage, reference electrodes play a critical role in EEG-based BCIs, enabling the detection and analysis of brain signals for various purposes, such as communication or control of external devices.

Scalp Reference: Selecting a scalp electrode as a reference can help eliminate noise that is present across a specific region of the brain. This technique has been used in various research studies, such as those involving steady-state visually evoked potential (SSVEP), where references at central and parietal locations [68][69] has been used to isolate SSVEP activity which is typically detected best by electrodes placed above the occipital lobe.

Bipolar Reference: A new bipolar channel, denoted as˜si,j, can be obtained by taking the difference between the signals si and sj from channels i and j respectively.

$$s_{i,j} = s_i - s_j \tag{3.2.5}$$

Common Average Reference: The Common Average Reference (CAR) technique involves subtracting the average signal of all electrodes from each electrode's signal at every time point. This approach effectively reduces noise that is present in all electrodes, such as the 50 or 60 Hz power source noise, and can amplify signals in a limited number of electrodes. However, CAR is not as effective in eliminating noise that is exclusive to a few electrodes, such as EOG or EMG artifacts. Hence, CAR is generally employed alongside other techniques for eliminating other types of artifacts.[33] Applying CAR to an electrode mon- tage with N electrodes uses:

$$s_i = s_i - \frac{1}{N} \sum_{i=1} S_i \tag{3.2.6}$$

where N is the number of channels, and $\tilde{s}_i$ is a single spatially filtered channel.

Surface Laplacian: The Laplacian reference method involves adjusting the signal at each electrode by subtracting the average of its four nearest neighboring electrodes ('small Laplacian')[**empty citation**]or the four next closest electrodes ('large Laplacian')[**empty citation**] This technique is helpful in reducing noise that is specific to a particular region of the scalp or brain

$$s_i = s_i - \frac{1}{4} \sum_{i \in \Theta} s_i \tag{3.2.7}$$

where Θ represents the electrodes of the small or large Laplacian reference. There exist several referencing techniques, and they can be applied separately or, in some cases, in combination. The objective is to use methods that remove as much noise as possible from the signals without eliminating too much relevant information.

Common Spatial Pattern (CSP): CSP is a method used to find spatial filters that optimize the difference in variance between EEG signals from two different conditions. It was first introduced in BCI research by Ramoser et al.[70] and has since been modified [71] and extended for multiclass classification [72]. The method works by identifying spatial filters, denoted as w, that maximize the variance in one condition while minimizing the variance in the other. When the CSP spatial filter is fully trained, the resulting data is arranged in such a way that the activity in the top row is predominantly correlated with one condition, while the bottom row's activity is predominantly associated with the other condition. CSP is particularly useful for separating oscillatory activity in BCIs, such as distinguishing between left- and right-hand motor imagery[33]. To use CSP, the data is initially filtered to a suitable band, such as 8-30 Hz (which includes both the alpha and beta rhythms), and then the normalized spatial covariance of the EEG is calculated by:

$$C = \frac{EE^T}{trace(EE^T)} \tag{3.2.8}$$

The given statement describes the bandpass filtered EEG data represented by E, where E has a size of $N \times T$. Here, N denotes the number of channels, and T denotes the number of samples. The transpose operator is represented by $(\cdot)^T$, and trace$(\cdot)$ represents the sum of the diagonal elements of a square matrix. By taking the average over trials of C for each class within the range of l to r, the spatial covariance C_d can be obtained. Thus, the composite spatial covariance is determined as follows:

$$C_c = \overline{C_l} + \overline{C_r} \tag{3.2.9}$$

C can be expressed in terms of eigenvalues and eigenvectors: (3.2.10)

$$C_c = U_c \lambda_c U_c^T$$

where λ_c is the diagonal matrix of eigenvalues, and U_c is the eigenvector matrix. Next, variances within Uc are equalized using the whitening transform:

$$P = \sqrt{\lambda_c^{-1}}\, U_c^T \tag{3.2.11}$$

By transforming $\overline{C_l}$ and $\overline{C_r}$, so that:

$$S_l = P\overline{C_l}P^T \ and S_r = P\overline{C_r}P^T \tag{3.2.12}$$

It can be shown that S_l and S_r share common eigenvectors. If:

$$S_l = B\lambda_l B^T, \ then S_r = B\lambda_r B^T, \ and \lambda_l + \lambda_r = I \tag{3.2.13}$$

where I is the identity matrix, and B represents the eigenvectors. Two corresponding eigenvalues sum to one, meaning that an eigenvector with a large eigen-value for S_l will have a small eigenvalue for S_r, which gives the CSP algorithm its ability to separate the variances between classes so effectively, the projection matrix $W = (B^T P)^T$ is used to perform the spatial filtering:

$$Z=WE \tag{3.2.14}$$

where Z is the spatially filtered single trial

3.2.5 Source Localisation

The readings obtained from EEG sensors placed on a particular area of the brain may not accurately reflect the activity occurring in that specific region. This is because the electrodes cover a broad area and must pass through layers of bone, skin, and hair. To address this issue, Source Localisation (SL) is a technique that uses multichannel EEG data to create a model of the brain's neural currents in both space and time. This is achieved by mapping the EEG data onto a higher dimensional source grid [73], where individual source activities are represented by dipoles. To perform SL, an MRI image of the user's head is usually required to create an anatomical model, although a standardized model can be adjusted to fit the user's head if an MRI is unavailable. The primary objectives of SL are either to conduct forward modeling, which aims to reconstruct EEG data based on the source activity, or to perform inverse modeling, which aims to determine the current source locations and strengths that generate a specific set of EEG data[33].

3.3 Artifacts removal and Preprocessing methods

3.3.1 Regression Methods

The regression method [74]is a commonly used technique to reduce artifacts in EEG signals. It works by estimating the amplitude relationship of the reference signal and removing any estimated artifacts. To do this, electrocardiogram (ECG) or electrooculogram (EOG) signals are needed to differentiate artifacts from EEG signals. However, a limitation of this method is its dependence on reference channels for eliminating ECG and EOG artifacts[75], despite its simple mathematical basis and low computational requirements, which are the reasons for its widespread use.

3.3.2 Blind Source Separation Methods

Blind source separation (BSS) methods are used to separate signals observed on a multi-channel recording into their original sources without the need for additional reference channels or prior knowledge[76]. BSS techniques include principal component analysis (PCA), independent component analysis (ICA), and canonical correlation analysis (CCA). ICA[77]is a statistical method that optimizes the independence of output components by finding a linear transformation that takes random factors into account. ICA is useful in extracting artifacts such as eyeblinks and heartbeats that are produced by independent sources and are not associated with specific frequencies. PCA[78][79]on the other hand, optimizes the variance of transformed data based on the second-order statistics of covariance [76]and is commonly used for feature dimensionality reduction while preserving their statistical information. CCA is frequently used in SSVEP- based brain-computer interfaces to identify frequency components of EEG that correspond to visual stimulus frequencies[80]. The effectiveness of BSS techniques depends on the statistical independence and non-Gaussian distribution of the original signals, as well as the signal dimensionality exceeding that of the source signal.

3.3.3 Wavelet Transform

The Wavelet transform(WT)[81][82][83][84] is a method used to estimate a signal's frequency and time domains by decomposing it. When applying this technique to EEG data and removing artifacts, it localizes and preserves features by setting a threshold for eliminating noisy signals. Although WT works effectively for non-stationary signal components, it cannot detect artifacts that overlap with spectral features. To address this limitation, hybrid approaches such as wavelet-BSS have been suggested[85].

3.3.4 Filtering Methods

Several methods have been employed for eliminating EEG artifacts and noise, including frequency filtering, adaptive filtering, and Wiener filtering[86].

Adaptive filtering: Adaptive filtering assumes that the EEG signal of inter-est and the artifact are not correlated, and uses a reference signal to estimate the correlated artifact. This estimated signal is subtracted from the source signals to obtain a clean EEG signal[87]. The least mean squares (LMS) technique is commonly used for adaptive filtering, which enhances the weight parameter linearly to evaluate clean signals. The recursive least squares algorithm, an extension of LMS, is another optimization algorithm that provides faster convergence than

LMS[75], but at a higher computational cost. However, adaptive filtering requires extra sensors to supply reference input, which is a disadvantage[87].

Wiener Filtering: Wiener filtering is a statistical method that generates a linear time-invariant filter to minimize the mean square error between the estimated signals and signals of interest[86]. It does not require an extra reference, but the computational process used to estimate the power spectral densities of the EEG signal and artifact signal can be complicated. In addition to the meth- ods mentioned earlier, there are other efficient strategies, such as CCA, empir- ical mode decomposition (EMD), and sparse decomposition methods. Hybrid approaches that combine these preprocessing algorithms with others, such as EMD-BSS, wavelet-BSS, and others, have been used to improve the algorithm's efficiency[88][89].

3.4 Feature Extraction

The primary objective of feature extraction is to select features that describe the user's ongoing activity and express them as a feature vector. The complexity and high dimensionality of EEG data make it difficult to operate a BCI without reducing it. Feature extraction eliminates irrelevant data and preserves data that is important for the BCI to function.

BCI employs various feature extraction techniques, which can be classified into different categories such as time-domain, frequency-domain, and spatial features. Techniques like DFT, IDFT, and FFTs enable the transformation between time and frequency domains, allowing for the analysis of time-dependent phenomena in the time domain, such as the P300 wave that emerges 300ms after stimulus onset. Analyzing EEG signals in the frequency domain provides information about the signal's frequency content, and this can be used to detect SSVEPs, given the appropriate time window.

3.4.1 Amplitude Features

In some cases, the classifier can be trained using the signal's amplitude. For instance, this method can be applied in the detection of the P300 wave when using the P300 speller.

3.4.2 Band power Features

A feature called band power feature can be created by taking the average power of a signal within a specific frequency band. To obtain this, the signal is passed through a bandpass filter, and the absolute value within that band is averaged. By applying the log transform to these features, a new type of feature can be generated, referred to as log-band power features [90]. This log transformation results in an approximation of normal distribution. Both of these types of features can be utilized to train a classifier in BCI applications.

3.4.3 Power Spectral Density Features

Utilizing the DFT to transform a signal into the frequency domain can produce effective features for BCI applications. By squaring the power spectrum and using the values at the desired frequency, Power Spectral Density (PSD) fea-tures can be created to train a classifier. This technique is applicable to various BCI types, including motor imagery and SSVEP[91][92][93].

Canonical Correlation Analysis: CCA is a technique that identifies the correlation between two variables with multiple dimensions. It can be used for unsupervised SSVEP detection in EEG data, as documented in several studies[94][80][95][96][97]. CCA works by determining the weight vectors, $\mathbf{W}_X$ and $\mathbf{W}_Y$, that maximizes the correlation between two linear combinations of the multidimensional variables, $\mathbf{x} = \mathbf{X}^T \mathbf{W}_X$ and $\mathbf{y} = \mathbf{Y}^T \mathbf{W}_Y$. This is achieved by solving an optimization problem:

$$\max_{\mathbf{W}_X, \mathbf{W}_Y} \rho(\mathbf{x}, \mathbf{y}) = \frac{\mathrm{E}[\mathbf{xy}]}{\sqrt{\mathrm{E}[\mathbf{xx}]\mathrm{E}[\mathbf{yy}]}} = \frac{\mathrm{E}[\mathbf{W}_X^T \mathbf{X}\mathbf{Y}^T \mathbf{W}_Y]}{\sqrt{\mathrm{E}[\mathbf{W}_X^T \mathbf{X}\mathbf{X}^T \mathbf{W}_X]\mathrm{E}[\mathbf{W}_Y^T \mathbf{Y}\mathbf{Y}^T \mathbf{W}_Y]}}$$

(3.4.1)

X Y

The expected value of x is denoted as $E[x]$, and ρ represents the correlation value, which is optimized by finding the weight vectors W_X and W_Y. This process helps to determine the canonical correlation between the two multidimensional variables X and Y.

During SSVEP detection $X \in \mathrm{R}^{C \times S}$ represents the multidimensional EEG signal with C channels and S samples. $Y_f \in \mathrm{R}^{2Nh \times S}$ is the set of multidimensional reference signals based on stimulus frequency f, which consists of $2Nh$ individual sine waves and S samples, where Nh is the number of harmonics. The sine waves are arranged in a matrix[98].

$$Y_f = \begin{bmatrix} \sin(2\pi f t) \\ \cos(2\pi f t) \\ \vdots \\ \sin(2\pi Nh f t) \\ \cos(2\pi Nh f t) \end{bmatrix} \tag{3.4.2}$$

where t is the time in seconds. By performing CCA on X and Y_f for all f, the stimulation frequency with the maximal canonical correlation value can be identified, which is selected as the estimated SSVEP frequency.

Common Spatial Pattern Features: The technique used to train the spatial filter W was discussed earlier, which is used to filter the EEG data into a spatially filtered signal Z. The rows of Z are arranged such that there is a maximum separation between classes one and two based on variance, and the top m rows are selected for further analysis. To extract log-variance features, we can use the signal $Z_{p=1,\ldots,m}$ using:

$$f_p = \log\left(\frac{\operatorname{var}(Z_p)}{\sum_{i=1}^{2m} \operatorname{var}(Z_i)}\right) \tag{3.4.3}$$

where f_p is the $(1 \times 2m)$ feature vector Using the log transformation provides an approximation of normal distribution, and the features can be used to train a classifier and predict the class of new data.

3.5 Feature Extraction Methods

3.5.1 Principal Component Analysis

PCA is used to reduce dimensionality and is a linear transformation technique. It involves introducing a lower-dimensional vector to simplify the complexity of signals that are dependent on time and space [99]. In addition to identifying and removing artifacts from signals, PCA can also extract useful features while preserving the information[100]. It works by finding a set of orthogonal vectors, known as principal components, that capture the largest variance in the data, The resulting principal components can be used to represent the original data in a lower-dimensional space, which can be useful for visualization, data compression, and other downstream analysis. Although principal components improve signal similarity and data classification performance[101], they are less interpretable than fundamental features. In addition, PCA is inadequate for analyzing complicated data sets[46]. Several variations of PCA, such as kernel PCA[102] and sparse PCA, have been proposed in EEG data processing to counteract these shortcomings.

3.5.2 Autoregressive Mode

The AR model is a technique used in frequency domain analysis to extract features from non-stationary signals like EEG data[99]. It is commonly used for time-series analysis and prediction, where the goal is to predict the future values of a time series based on its past values. Autoregressive models assume that the current value of a time series is a linear combination of its past values, and the model coefficients are estimated using maximum likelihood methods. The model assumes that it can predict genuine EEG signals by using the order and parameters of the approximation model. The order of the model, which ranges from 1 to 12, is an indicator of its performance. However, choosing the appropriate order can be challenging as an incorrect order selection may lead to an incorrect spectrum estimate and increased computing costs. Various AR approaches such as bilinear AAR, adaptive AR parameters, and multivariate AAR have been utilized to process EEG data and help the AR model parameters adjust to non-stationary signals[103]. These strategies lead to improved parameter estimation and reduced prediction error. Using the Kalman filter to evaluate AR parameters in an adaptive AR model can boost classification performance by up to 83%[104]. The AR model has benefits such as its appropriate frequency resolution and ability to estimate the power spectra of shorter EEG data segments. However, it is also susceptible to incorrect parameter selection and ordering[105].

3.5.3 Fast Fourier Transform

FFT is a technique that is suitable for analyzing stationary signals and works by transforming signals from the time domain to the frequency [106] domain to extract features by calculating the PSD using mathematical tools. It is a reli- able and frequently used method, employing non-parametric approaches such as Welch's method[106][107] to estimate PSD for a related band. However, FFT is ineffective when it comes to nonlinear and nonstationary data like EEG sig- nals, and its conclusions can be unreliable. This limitation has prompted the development of novel approaches like the Fourier decomposition method[108], variational mode decomposition (VMD)[109], and the Hilbert-Huang transform (HHT) [110]for analyzing nonstationary signals.

3.5.4 Wavelet Transform

WT is a time-frequency transform that takes into account the unique characteristics of EEG signals in the frequency domain and is entirely localized in the time domain[111]. This method is useful in analyzing irregular and nonstationary signals in windows of varying sizes[112], providing precise frequency and timing information at low and high frequencies. The analysis of high frequen-cies typically involves using a narrow window, while low-frequency evaluation uses a broader window[113][114]. Therefore, WT is suitable for analyzing tran-sient oscillations in biosignal data, which is composed of low-frequency com-ponents with long-time periods and high-frequency components with short-time periods[104]. However, WT is negatively affected by Heisenberg uncertainty, which affects its performance[104]. It examines small wavelets within a spe- cific frequency range for a brief period, starting at 0, with wavelet oscillations growing and then returning to zero[115].

3.5.5 Common Spatial Pattern

CSP is a successful approach for feature extraction in BCI tasks, specifically for motor imagery tasks[116]. It can be used for spatial filtering by dividing the data into temporal segments or by employing the entire data trail. CSP is typically used for binary classification tasks[117] and aims to differentiate between classes by decreasing one class's variance while maximizing the other's variance. Spatial filters are used for each class to carry out this process, resulting in an EEG variance matrix representing class discrimination[118]. CSP's primary advantage is its simplicity and speed of execution[118], but there are limits to this strategy for identifying optimal features from raw EEG data[116]. Some studies have developed optimal spatial feature selection techniques to overcome this issue. Modifying the electrode placements can affect classification performance, and artifacts in the original dataset can also affect CSP's performance[119]. To create an effective CSP algorithm, several characteristics must be addressed, including the frequency band filter, the time segment, and the subset of CSP filters to be utilized. CSSP, CSSSP, spectrally weighted common spatial pattern, sub-band common spatial pattern, and discriminant filter bank common spatial pattern have been proposed to address the issue of identifying the optimal frequency band for CSP algorithms. These algorithms vary in their approach, with some using time delay embedding, noise reduction, and sub-band filtering techniques[120]. The discriminant filter bank common spatial pattern uses the Fisher ratio of single channel band power values[121][122].

3.6 Classification

Classification is a process of categorizing or grouping data, objects, or concepts into predefined classes or categories based on certain criteria. In machine learning and data analysis, classification refers to the process of building a model that can predict which category a given data point or observation belongs to based on the input features. Classification involves using feature vectors generated from feature extraction to make inferences about a user's current state.

There are two main types of classification methods: supervised learning, where an algorithm is trained on labeled samples of each class to identify them later, and unsupervised learning, where the algorithm determines which categories best represent the data given unlabeled data [33]. In our work, to classify emotions while listening to the Quran using EEG, we will use supervised learning because we have labeled the data. Several methods can be used in this case, such as support vector machines (SVMs), decision trees, convolutional neural networks (CNNs), and random forests. However, as mentioned in the previous chapter, SVM and CNN are the two common approaches that have been used for this task.

3.7 Conclusion

The chapter provides a comprehensive overview of the different processes and methods involved in implementing a Brain-Computer Interface (BCI). It highlights the diversity of BCI types and approaches, emphasizing the various techniques used for feature extraction and selection, classification, and translation. Despite the differences in approaches, each has its own strengths and weaknesses. By understanding the underlying processes and methods, researchers and developers can make informed decisions about which approach may be best suited for a particular application.

Chapter 4

Machine and Deep Learning for EEG

4.1 Introduction

In this chapter, we will discuss the application of machine learning and deep learning techniques in EEG-based sentiment analysis. Machine learning and deep learning techniques have been widely used in various fields, including com- puter vision, natural language processing, and speech recognition. These tech- niques have also been applied in EEG signal analysis, which has shown promis- ing results in various tasks, such as emotion recognition, cognitive assessment, and disease diagnosis. In this chapter, we will discuss the application of machine learning and deep learning techniques in EEG-based sentiment analysis.

4.2 Machine Learning Overview

Machine learning is a subset of artificial intelligence that involves the development of algorithms and models that enable computers to learn from data and make predictions or decisions without being explicitly programmed[123].

There is a broad range of tasks that machine learning can accomplish, and they can be classified into two main categories: supervised and unsupervised learning. Unsupervised learning refers to when an algorithm constructs a recog- nition pattern from a dataset that only has inputs and no pre-determined outputs. On the other hand, semi-supervised learning is a type of supervised learning. Both of these types learn from datasets that have known inputs and outputs, with semi-supervised learning having incomplete data sets. Supervised learning is typically utilized in applications involving classification and regression, while unsupervised learning is more suited to feature learning and dimension reduction[124].

Machine learning has a wide range of applications in various fields, includ-ing healthcare, finance, marketing, and engineering. In neuroscience, machine learning techniques are utilized to analyze and interpret diverse types of data, including EEG signals.

4.3 Machine Learning for EEG-Based Sentiment Analysis

Machine learning techniques are frequently utilized in the analysis of EEG signals for a variety of purposes. These algorithms can automatically collect pertinent features for categorization from the incoming data as they learn from it. Machine learning algorithms can be used to categorize EEG data into differ- ent emotional states in the context of EEG-based sentiment analysis. Some of the machine learning techniques that have been applied to EEG-based sentiment analysis include the following:

4.3.1 Support Vector Machine SVM

SVM [125] is a machine learning algorithm that is commonly used for classification tasks and is another supervised classification method. It works by finding the best possible hyperplane that separates the data into different categories. SVM can be used for both linear and non-linear classification by using the (kernel trick)tasks[126]. by implicitly mapping their inputs into high-dimensional feature spaces. draws margins between the classes. The margins are drawn in such a fashion that the distance between the margin and the classes is maxi- mum and hence, minimizing the classification error[123]. SVM has been used in EEG-based emotion recognition, and it has shown promising results.

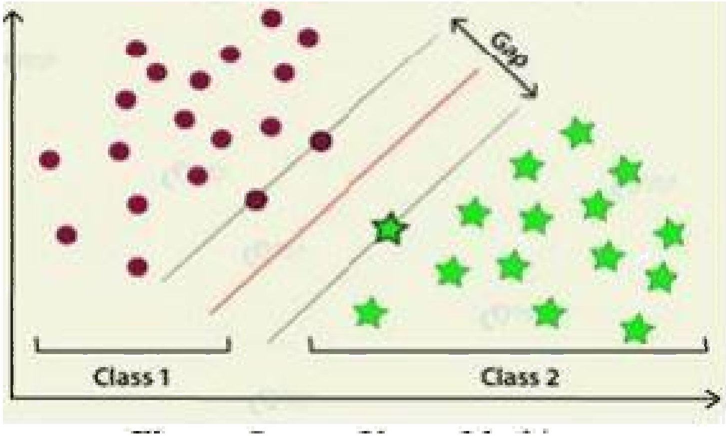

Figure 4.1 – Support Vector Machine. [123]

4.3.2 Linear discriminant analysis LDA

LDA is a supervised learning algorithm that seeks to identify a linear combination of features that can effectively differentiate between two or more groups or classes. It achieves this by projecting the data onto a lower-dimensional subspace while maintaining as much class-discriminatory information as possible. Ultimately, LDA aims to maximize the separation between different groups by identifying a set of discriminant functions[127].

4.3.3 Principal Component Analysis PCA

PCA is a statistical approach that is utilized to decrease the number of dimensions of a dataset while maintaining as much data variance as possible [127]. In simpler terms, PCA is employed to uncover patterns in data that have numerous features by defining a fresh set of variables referred to as principal components, which summarizes the data from the original dataset. These components are formed by linearly combining the initial variables in such a manner that they explain the most substantial variance in the data. PCA is widely employed in machine learning and data analysis to lower the number of features within a dataset, which can improve the efficiency and performance of various algorithms. Additionally, it is often used for data visualization since the principal components can be visualized in two or three dimensions to reveal the underlying structure of the data.

4.3.4 KNN K-Nearset Neighbours

KNN is a widely used machine learning algorithm for classifying and regressing data. It operates by finding the K closest training samples with known class labels to a new sample and using the majority vote of its neighbors to label the new sample. The value of K is a crucial parameter that affects the sensitivity and stability of the classification. KNN is particularly suitable for datasets with small to medium sizes and non-linear decision boundaries, and its simplicity makes it easy to understand and implement. However, KNN's performance can deteriorate significantly as the size of the dataset grows[123], making it computationally expensive.

4.3.5 Naive Bayes

Naive Bayes is a classification technique that utilizes Bayes Theorem while assuming independence among predictors. This means that the presence of a particular feature in a class is considered to be unrelated to the presence of any other feature. This method is commonly used in the text classification industry for clustering and classification purposes, based on the conditional probability of happening.[124] With sufficient preprocessing, this model can compete with more advanced algorithms, such as Support Vector Machines (SVM). However, one shortcoming of this technique is that it treats all feature vectors as independent of one another, despite any actual correlation.[123] One of the primary advantages of the Naive Bayes technique is that it only requires a limited number of training data sets to begin accurately estimating the classification parameters. This technique can be implemented with various models, with the probabilistic model being the most common. Features are represented by vectors, and probabilities are assigned to each instance or result. Event models can be divided into two major categories: Gaussian and Multinomial Naive Bayes. A fair assumption for data collection with continuous values is that it follows a Gaussian distribution. The Bayes technique assigns probability based on the curve using this method. A multi-nomial event model is derived from multinomials, typically shown as a histogram. However, a potential cause for concern is the absence of a feature from the data set, resulting in the multiplication of all estimations being equal to zero. This issue can be rectified with a pseudo count to smooth out data set outliers.[128]

4.4 Deep Learning for EEG-Based Sentiment Analysis

Deep learning has demonstrated outstanding performance In a number of disciplines, including computer vision, speech recognition, and natural language processing. Deep learning techniques are appropriate for EEG-based sentiment analysis because they can automatically learn hierarchical representations from the input data. Some of the deep learning algorithms that have been applied to EEG-based sentiment analysis include the ones listed below.

4.4.1 Convolutional Neural Networks CNN

CNN is a type of deep learning algorithm that is commonly used in image and video analysis, natural language processing, and speech recognition. CNN is inspired by the organization and functioning of the human visual system, which processes images in a hierarchical and parallel manner[129].particularly suited for analyzing signals with a spatial or temporal structure, such as EEG data. One of the advantages of CNNs is their ability to automatically learn features from raw data, without the need for hand-crafted feature extraction. This makes them suitable for a wide range of applications, where the relevant features are not known in advance. Another advantage is their ability to handle input data with different sizes and resolutions, by using techniques such as padding and pooling [130].

4.4.2 Artificial Neural Networks ANN

An artificial neural network [131] is a computational model inspired by biology, It is made up of interconnected nodes that process information and transmit signals to other nodes in the network. These networks are also known as connectionist models because the connection weights serve as the system's memory. Although a single neuron can perform simple information-processing tasks, connecting neurons in a network enhances neural computations. While the intelligence of artificial neural networks is debatable, they are capable of processing large amounts of data and making accurate predictions. However, they are not intelligent in the traditional sense and may be better described as computer intelligence. It is worth noting that ANNs typically have only a few hundred or a few thousand processing elements, whereas the human brain has billions of neurons, making artificial networks far less complex than the human brain[132]. ANNs are used in a wide range of applications, including speech and image recognition, natural language processing, and predictive modeling. To analyze EEG data, it is necessary to use different techniques depending on the specific application. ANNs can be customized to suit these techniques, such as analyzing long-term or short-term EEG segments, real-time or time-delayed processing, and single or multiple-channel analysis. To accomplish this, different types of ANNs can be chosen for each use case. These types include FeedForward Neural Networks, Radial Basis Function, and Recurrent Neural Networks, and each type operates with its unique architecture.

FeedForward Neural Networks have a simple architecture that allows data to flow in a single direction, starting at input nodes, passing through hidden nodes, and ending at output nodes. This prevents the formation of loops and cycles, ensuring that information can only flow in one direction.

Radial Basis Function uses radial basis functions to determine the output, which is a linear combination of the RBF of the inputs and provided parameters for the neurons. This type of ANN utilizes a specific structure to generate the final output by summing the centers/widths of the points with their corresponding weights.

Recurrent Neural Networks have a more complex architecture with connections between distinct nodes and a defined output flow direction to a particular node. In this case, data flow can form loops and cycles to return data to the intended node, allowing for more flexible processing of information. It is crucial to understand how each type of ANN operates to choose the most appropriate type for a specific use case.

4.4.3 Long Short-Term Memory (LSTM)

LSTM is a type of RNN that can handle long-term dependencies. LSTMs have been used in various applications, including speech recognition, natural language processing, and EEG-based emotion recognition.

4.5 Comparison of machine and deep-learning techniques

Machine learning and deep learning are both widely used approaches for EEG sentiment analysis. The interpretability of machine learning algorithms is one of their key advantages. The categorization decision-making process may be clearly understood thanks to machine learning techniques. Deep learning methods, in contrast, are frequently referred to as ”black-box models” since it is challeng- ing to understand how they operate internally. However, deep learning methods have outperformed machine learning methods in a number of areas, including image identification and natural language processing. This is so that complex patterns and correlations in data that are challenging to identify with conven- tional machine-learning methods can be captured by deep-learning models.

4.6 Hybrid approaches

For EEG sentiment analysis, recent research has concentrated on fusing the benefits of deep learning with machine learning techniques. These hybrid strategies seek to combine the interpretability of machine learning with deep learning’s superior performance. Using a deep learning model to extract features from EEG signals and then feeding those features into a machine learning classifier for sentiment analysis is one example of a hybrid technique. This method combines the interpretability of machine learning models with the capacity of deep learning models to extract complex characteristics. Another illustration of a hybrid strategy is the pretraining of a feature extractor in a machine learning classifier using a deep learning model. In tasks involving EEG sentiment analysis, this strat- egy enhances the performance of machine learning classifiers. The accuracy and interpretability of EEG sentiment analysis models may be enhanced by hybrid methods. These methods can, however, be computationally expensive to create and apply, as well as require a high level of skill.

4.7 Conclusion

In this chapter, we have discussed the application of machine learning and deep learning techniques in EEG-based sentiment analysis. Machine learning and deep learning algorithms have shown promising results in classifying EEG signals into different emotional states.

Chapter 5

Experimental Implementation and Results

5.1 Introduction

This chapter will discuss the experimental setup and the results obtained from the implementation of the proposed EEG signal analysis system. The chapter will start by providing an overview of the dataset used in the study, followed by a description of the experimental setup. The chapter will then present the results obtained from the analysis of the EEG signals using the machine learning and deep learning techniques discussed in the previous chapter.

5.2 Languages and FrameWorks

Google Colab is a cloud-based Jupyter Notebook environment provided by Google. It allows users to write and execute Python code directly in a web browser, which was a helpful and accessible tool for our development tasks. This platform provided us with the ease to access powerful hardware resources such as CPUs and GPUs without any installation or configuration requirements through a web browser. and also offers integration with various Google services like Google Drive, allowing users to easily access and store their data.

Python Python is the primary programming language for our research project due to its versatility and extensive ecosystem of libraries. It is an interpreted high-level object-oriented language with dynamic semantics that supports dynamically typed data structures, making it ideal for developing AI and IoT programs.

TensorFlow is a deep learning platform that is available for free and can be modified by users. The software allows users to develop and teach complex neural networks, and execute computations using graphics processing units, while also offering all-in-one capabilities for implementing and evaluating models.

NumPy We employed NumPy, a crucial Python library for scientific computation, to effectively manage extensive multi-dimensional arrays and carry out numeric operations with speed.

Keras is a sophisticated deep learning model creation and training high-level API under TensorFlow that simplified the process.

5.3 Experimental setup

5.3.1 Data Collection

The data utilized in this study consisted of private data collected from a total of 22 participants who engaged in listening to the Quran, and 18 participants during the rest state.

To capture the electrical signals produced by the participants' brains in real-time, a noninvasive method involving the use of electrodes placed on the scalp was employed. The electrode placement followed the 10-20 international system, which is a widely recognized standard for electrode placement in EEG studies. This system specifies the distance between adjacent pairs of electrodes as 10 or 20 percent of the scalp diameter.

For the EEG recordings, a high-quality Emotiv EPOC+ neuroheadset with 14 sensors and two references was utilized. The EPOC+ neuroheadset is a wireless, multi-channel device that provides a convenient and comfortable experience for the participants. With a sampling rate of 128 Hz, the neuroheadset was able to capture the brain signals in microvolts (V) with high temporal resolution. The recorded signals were transmitted wirelessly to a computer running specialized software for real-time data acquisition.

Prior to the EEG recording, a conductive gel was applied to the participants' scalps at the electrode locations. This conductive gel helps establish a good electrical connection between the electrodes and the scalp, reducing impedance and ensuring accurate readings of the brain signals. The gel was carefully applied to ensure consistent conductivity across all participants and minimize any potential artifacts arising from poor electrode-skin contact.

The data collection process involved capturing continuous EEG signals through-out the listening task. The recorded signals were stored in digital format for subsequent analysis and processing.

During the data collection session, participants were instructed to listen to recitations from the Quran through headphones. The participants were seated comfortably in a quiet and controlled environment to minimize external distractions that could potentially affect their brain activity.

5.3.2 Preprocessing

The collected EEG signals underwent preprocessing to enhance their quality and prepare them for further analysis. The raw EEG data obtained from each participant was loaded into the analysis environment for subsequent processing.

Information about the EEG data, such as channel names, channel types, and sampling frequency, was organized using the MNE-Python library. The channel names adhered to the 10-20 international system, which provides a standardized method for electrode placement. The following electrode channels were used: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4. The channel types were classified as EEG, and the sampling frequency was set to 128 Hz. A standard montage was applied to the EEG data using established electrode lo-cations. This step ensured consistency and comparability across participants.

The raw EEG data underwent bandpass filtering to isolate the desired frequency range. Frequencies below 1 Hz and above 50 Hz were removed to eliminate unwanted noise.

The EEG data was further processed to remove power line noise at 50 Hz using a notch filter. This step minimized interference from electrical sources and improved the signal quality.

Independent Component Analysis (ICA): ICA was applied to identify and remove artifacts caused by eye blinks, eye movements, and muscle activity. This technique allowed for the separation of the underlying brain signals from the contaminating sources. Artifactual independent components identified through visual inspection were excluded from further analysis. These components were associated with non-brain-related activities, ensuring that only relevant brain signals were considered.

The cleaned EEG data were reconstructed by applying the ICA decomposition matrix to the original data, excluding the rejected components. This step yielded the final preprocessed EEG signals ready for subsequent feature extraction and analysis.

5.3.3 Feature Extraction

After preprocessing the EEG signals, comes the step of feature extraction. Our goal is to extract relevant features. To this end, we used three different methods which extract frequency domain and Time-frequency domain features. In fact, it is important to capture meaningful information about brain activity during participants' engagement with the Quran. This represents an important step for further research, especially in sentiment analysis research.

The first two datasets employ Frequency-Domain features. In the first dataset, the features consist of mean Power Spectral Density (PSD) values in the Alpha (8-13 Hz), Beta (13-30 Hz), and Gamma (30-50 Hz) bands for each of the 14 EEG channels.

The second dataset includes features such as Differential Entropy (DE) for each EEG channel, as well as features based on the Differential Asymmetry (DASM) and Ratio Asymmetry (RASM) between specific pairs of left and right channels.

In contrast, the last dataset introduces Time-Frequency features using the Short-Time Fourier Transform (STFT) representation. The features are derived from the magnitudes of the time-frequency representation averaged across channels for each time segment, resulting in a total of 65 features per segment.

The datasets used in the study were organized in Excel files in CSV format. Each dataset had a number of rows and columns, the columns represented features and the rows represent the EEG recording while listening to Quran and the rest stat. Here are the details for each dataset:

Data 1: This dataset consisted of 42 columns and 1136 rows. Data

2: The second dataset contained 21 columns and 2298 rows. Data

3: The third dataset had 65 columns and 4676 rows.

5.4 Classification

5.4.1 SVM model implementation and tuning

We employed a Support Vector Machine (SVM) model with a Radial Basis Function (RBF) kernel for classifying EEG data in order to estimate the accuracy of selected features.

The data were split into training and test sets using an 85 for training and 15 test ratio. To ensure fair evaluation and prevent overfitting, we applied standard scaling to normalize the features in all sets. For the binary classification model, we used two classes: the Quran features class and the rest state features class. The SVM classifier was configured with the RBF kernel, and we performed grid search cross-validation to find the best hyperparameters. The hyperparameter C was set to 550, and gamma was set to ’scale’. The C parameter controls the trade-off between the smoothness of the decision boundary and the classification accuracy. This process allowed us to iteratively train and evaluate the model on different combinations of training and validation sets. The best SVM classifier with the optimized hyperparameters was then fit to the training data.

For the multi-class classification model, we used three classes: Quran features, rest state features, and interstellar features. The SVM classifier with the RBF kernel was trained using hyperparameters C=10 and gamma=0.01. The training and testing data were split using 85 training and 15 test.

Table 5.1 – Binary Classification Model Parameters

Parameter	Value
Kernel	RBF
C	550
Gamma	'scale'
Grid Search Params	{'C': [550]}
Test Size	0.15

Table 5.2 – Multi-Class Classification Model Parameters

Parameter	Value
Kernel	RBF
C	10
Gamma	0.01
Test Size	0.15

5.4.2 CNN model implementation and tuning

Architecture: In the implementation of the Convolutional Neural Network (CNN) model for binary classification between Quran and rest state features, we define a sequential model using the Keras framework. The model comprises multiple layers that progressively extract and transform features from the input data.

The model architecture begins with a Conv2D layer with 64 filters and a kernel size of (16, 11), using ReLU activation. It takes input data of shape (7, 6, 1) and applies padding to maintain the spatial dimensions. Batch normalization is then applied to normalize the feature maps.

Next, a MaxPooling2D layer with a pool size of (2, 2) is added to reduce the spatial dimensions and retain important features. This is followed by another Conv2D layer with 64 filters and a kernel size of (10, 9), again using ReLU activation and padding. Batch normalization is applied after this layer as well.

Table 5.3 – Architecture of the Proposed CNN Model

Layer Type	**Parameters**
Conv2D	Filters: 64, Kernel Size: (16, 11), Activation: ReLU, Padding: 'same'
BatchNormalization	-
MaxPooling2D	Pool Size: (2, 2)
Conv2D	Filters: 64, Kernel Size: (10, 9), Activation: ReLU, Padding: 'same'
BatchNormalization	-
MaxPooling2D	Pool Size: (1, 1)
Conv2D	Filters: 68, Kernel Size: (8, 7), Activation: ReLU, Padding: 'same'
BatchNormalization	-
GlobalMaxPooling2D	-
Flatten	-
Dense	Units: 64, Activation: ReLU, Regularization: L2(0.01)
Dense	Units: 256, Activation: ReLU, Regularization: L2(0.01)
Dropout	Rate: 0.9
Dense	Units: 512, Activation: ReLU, Regularization: L2(0.01)
Dense	Units: 512, Activation: ReLU, Regularization: L2(0.01)
Dense	Units: 2, Activation: Softmax

To further extract features, a Conv2D layer with 68 filters and a kernel size of (8, 7) is included. Batch normalization is applied to normalize the feature maps. Instead of using max pooling, a GlobalMaxPooling2D layer is used to collapse the spatial dimensions and output a feature vector.

The feature vector is then flattened using the Flatten layer, converting it into a 1D vector. Two fully connected Dense layers are added with 64 and 256 units respectively, both using ReLU activation. Regularization is applied to the first dense layer using L2 regularization with a regularization rate of 0.01. Batch normalization is applied after each fully connected layer.

Table 5.4 – Hyperparameters of CNN Model

Hyperparameter	**Value**
Number of Epochs	100
Batch Size	64
Learning Rate	0.001
Dropout Rate	0.9
Optimizer	Adamax
Loss Function	Categorical Crossentropy
Regularization	0.01
Train Set	85%
Test Set	15%

To mitigate overfitting, dropout regularization is employed. A dropout layer with a rate of 0.9 is inserted after the second fully connected layer. This layer randomly sets a fraction of input units to zero during training, aiding in the prevention of overfitting.

For model compilation, the Adamax optimizer is utilized with a learning rate of 0.001. The model is compiled with the categorical cross-entropy loss function and accuracy as the evaluation metric.

To prevent overfitting, early stopping is used with patience of 5, and the best weights are restored. The training data is reshaped to have the appropriate dimensions and the model is trained using the fit function, with 100 epochs and a batch size of 64.

5.5 Result and Analysis

5.5.1 SVM model results

The performance of the SVM model was assessed using precision and re- call metrics. Precision refers to the proportion of correctly predicted positive instances out of all instances predicted as positive, while recall represents the proportion of correctly predicted positive instances out of all actual positive instances.

The First Dataset For the binary classification model, the SVM achieved an accuracy of 90.06%. The precision score was 81.13%, indicating that a significant percentage of instances predicted as positive were indeed classified correctly. The recall score was 86.00%, suggesting that the model was able to correctly identify a substantial proportion of the actual positive instances. The F1-score, which is a harmonic mean of precision and recall, was calculated as 83.50%. These results demonstrate that the SVM model can differentiate between the ”Quran” and ”Rest State” classes.

In the case of the multi-class classification model, the SVM achieved an accuracy of 82.99%. The precision score was 85.34%, indicating that a high percentage of instances were correctly classified for each class. The recall score was 76.34%, indicating that a substantial proportion of actual positive instances were identified by the model. The F1-score, which combines precision and recall, was calculated as 79.72%. These results highlight the effectiveness of the SVM model in accurately differentiating between the ”Quran” and ”Rest State” classes Overall, these results demonstrate that the SVM model achieved a reasonable level of performance in classifying Quran recitation based on EEG features.

The Second Dataset The SVM achieved an accuracy of 82.32%, indicating that it classified 82.32% of instances correctly. The precision score was 75.34%, meaning that a significant percentage of instances predicted as positive were indeed classified correctly. The recall score was 56.12%, suggesting that the model was able to correctly identify 56.12% of the actual positive instances. The F1-score, which is the harmonic mean of precision and recall, was calculated as 64.33%. These results demonstrate that the SVM model shows promise in differentiating between the ”Quran” and ”Rest State” classes.

The third data set The SVM achieved an accuracy of 70.23%, indicating that it classified 70.23% of instances correctly. However, the precision score was 75%, meaning that 25% of instances predicted as positive were actually false positives. The recall score was 1.42%, suggesting that the model could only identify a very small proportion of the actual positive instances. The F1-score, which is the harmonic mean of precision and recall, was calculated as 2.79%. These results indicate that the SVM model struggled to differentiate between the ”Quran” and ”Rest State” classes, resulting in poor performance overall.

Dataset	Accuracy	Precision	Recall	F1-Score
First Dataset	90.06%	81.13%	86.00%	83.50%
Second Dataset	82.32%	75.34%	56.12%	64.33%
Third Dataset	70.23%	75.00%	1.42%	2.79%

Table 5.5 – Comparison of the binary classification Results of SVM for the Three Datasets

Analyzing the results, it is clear that the first dataset has the best overall accuracy with a precision of 81.13%, a recall of 86.00%, and an F1-Score of 83.50%. This indicates that this dataset was able to extract more meaningful features to differentiate the ”Quran” and ”Rest State” classes.

In contrast, the second dataset showed slightly lower performance, with an precision of 75.34%, a recall of 56.12%, and an F1-Score of 64.33%. This suggests that features extracted from this dataset are less discriminating for classification.

Finally, the third data set gave the weakest results, with a precision of 75.00%, a recall of 1.42%, and an F1-Score of 2.79%. These results indicate that the features extracted from this dataset are not representative enough to differentiate the classes significantly.

5.5.2 CNN model results

The First Dataset: The model achieved an accuracy of 92.40%. This indicates that the model performed well in distinguishing between the Quran and rest state features. The precision score, which measures the ability of the model to correctly identify positive samples (Quran), is 83.33%. This indicates that out of all the samples predicted as Quran, 83.33% were actually Quran. The recall score, which measures the ability of the model to identify all positive samples (Quran) correctly, is 85.36%. This indicates that the model was able to correctly identify 85.36% of the Quran samples.

```
6/6 [==============================] - 0s 21ms/step - loss: 1.1446 - accuracy: 0.9240
6/6 [==============================] - 0s 22ms/step
Precision: 0.8333333333333334
Recall: 0.8536585365853658
```

Figure 5.1 – CNN Validation test

The second Dataset: The model achieved an accuracy of 88.70%, indicating that it performed well in distinguishing between the Quran and rest state features. Additionally, the precision score of 96.20% reflects the model's ability to correctly identify positive samples (Quran), where 96.20% of the predicted Quran samples were indeed Quran. Furthermore, the recall score of 67.85% indicates that the model was able to correctly identify 67.85% of the Quran sam- ples. These results highlight the model's effectiveness in accurately classifying engagement with the Quran based on the extracted features.

The Third Dataset: The accuracy score of 0.6895 indicates that the model correctly classified only 68.95% of the samples. This suggests that there is room for improvement in distinguishing between the Quran and rest state features. However, it is important to note that the precision score is reported as "nan," which stands for "not a number." This suggests that the precision metric could not be calculated due to the absence of true positive predictions. Additionally, the recall score of 0.0 indicates that the model failed to correctly identify any of the Quran samples. Overall, these results indicate that the model struggled to classify engagement with the Quran based on the extracted features.

Dataset	Accuracy	Precision	Recall
First Dataset	92.40%	83.33%	85.36%
Second Dataset	88.70%	96.20%	67.85%
Third Dataset	68.95%	N/A	0.0%

Table 5.6 – Comparison of the binary classification Results of CNN for the Three Datasets

5.6 Discussion

5.6.1 Comparison of SVM and CNN model performance

In this study, we wanted to distinguish between the Quran and rest state features, using the SVM and CNN model. We evaluated and compared the performance of each one of the models. SVM and CNN models were assessed using precision and recall metrics.

For the binary classification model, the SVM achieved an accuracy of 90.06%. The precision score was 81.13%, indicating that a significant percentage of instances predicted as positive were correctly classified. The recall score was 86.00%, suggesting that the model was able to identify a substantial proportion of the actual positive instances. The F1-score, which is the harmonic mean of precision and recall, was calculated as 83.50%. These results demonstrate that the SVM model performed well in classifying Quran recitation based on EEG features.

In contrast, the CNN model achieved an accuracy of 92.40%, indicating its success in distinguishing between Quran and rest state features. The precision score, measuring the model's ability to correctly identify positive samples (Quran), was 83.33%. This indicates that out of all the samples predicted as Quran, 83.33% were actually Quran. The recall score, measuring the model's ability to identify all positive samples (Quran) correctly, was 85.36%, indicating that the model correctly identified 85.36% of the Quran samples.

Dataset	Model	Accuracy	Precision	Recall	F1-Score
First Dataset	SVM	90.06%	81.13%	86.00%	83.50%
	CNN	92.40%	83.33%	85.36%	
Second Dataset	SVM	82.32%	75.34%	56.12%	64.33%
	CNN	88.70%	96.20%	67.85%	
Third Dataset	SVM	70.23%	75.00%	1.42%	2.79%
	CNN	68.95%	N/A	0.0%	

Table 5.7 – Comparison of SVM and CNN Results for Three Datasets

Based on these results, the best method appears to be CNN when considering both accuracy and precision. It consistently outperformed the SVM in terms of accuracy for the first and second datasets.

5.6.2 Comparison of The Three Datasets

In terms of features, the best features varied across the datasets. For the First Dataset, the CNN with Frequency-Domain features achieved higher accuracy and precision compared to the SVM with Frequency-Domain features. For the Second Dataset, the CNN with Frequency-Domain features again outperformed the SVM with Frequency-Domain features, particularly in precision. Finally, for the Third Dataset, both methods yielded low performance, but the SVM with Time-Frequency features performed slightly better in terms of accuracy.

In summary, the frequency domain features outperformed the time-frequency domain features in terms of accurately classifying the rest state and Quran. Specif-ically, the frequency domain features provided more accurate and reliable results compared to their time-frequency domain counterparts.

5.7 Limitations and future directions

Despite the positive results obtained in this study on EEG using both the SVM and CNN models, some limitations should be noted. These constraints present potential for future research and advancements in this subject.

One of the constraints is the availability of a small dataset. The models were trained and tested on a single dataset, which may not accurately represent the diversity and complexity of real-world settings. Collecting a larger and more diverse dataset might aid in enhancing the models' generalizability and robustness. EEG signals are highly varied and can be affected by a variety of factors including electrode location, noise, and individual variances. Future research could concentrate on sophisticated preprocessing approaches and feature extrac-tion methods to better handle signal variability, resulting in improved model performance. While the SVM and CNN models performed well in categorizing EEG signals, their decision-making processes may be difficult to understand. Investigating strategies to increase model interpretability would allow for a bet-ter understanding of the underlying EEG patterns linked with various emotions during Quran reciting.

Integrating domain knowledge and expert insights into the model creation process can improve the performance of the models. To improve the models' accuracy and interpretability, domain-specific features or priors relating to Quran recitation and sentiment analysis might be included.

Comparing the SVM and CNN techniques for EEG signals analysis during Quran recitation to other machine learning algorithms and models can provide insights into their respective strengths and drawbacks. Investigating various architectures and methodologies, such as recurrent neural networks (RNNs) or attention mechanisms, could potentially give better outcomes. sentiment analysis techniques could be an interesting perspective for future work.

5.8 Conclusion

This chapter details the language and framework aspects employed in our study, along with an outline of how EEG data were obtained during Quran recitation. The cleaning and preparation techniques utilized on collected EEG data are also mentioned. Moreover, we examine different approaches implemented to extract distinguishing features that can aptly represent emotional patterns when reciting from the Quran. The SVM and CNN models were implemented and tuned, taking into consideration the specific requirements of our task. We described the methodology used and the parameter tuning process to optimize the SVM and CNN model's performance. We presented the results obtained from the SVM and CNN models. Finally, a comprehensive comparison of the SVM and CNN models' performance was conducted, in the context of EEG signals classification during Quran recitation.

Conclusion

This study focused on the EEG signals classification during Quran recitation using SVM and CNN models. The study aimed to explore the feasibility of using EEG signals to classify and enhance the understanding of emotional experiences during Quranic recitation. Through rigorous experimentation and analysis, sev-eral key findings and contributions have been made. Firstly, the SVM model demonstrated strong performance in binary tasks. The model achieved high ac-curacy, precision, and recall, indicating its effectiveness in classifying EEG sig-nals during Quran recitation based on EEG features. These results highlight the potential of SVM as a reliable and robust algorithm for classifying EEG signals in this specific domain. Secondly, the CNN model showcased its capability in distinguishing between Quran and rest state features. With a high accuracy rate, the model successfully identified and classified Quran features from the EEG signals. This outcome underscores the model's effectiveness in capturing the unique patterns associated with Quran recitation and differentiating them from other states. Furthermore, the study investigated the impact of various hyper-parameters on model performance. The CNN model's parameters, such as the number of epochs, batch size, learning rate, dropout rate, optimizer, loss func-tion, regularization, and the train-test split ratio, were fine-tuned to optimize the model's accuracy and robustness. The SVM model also employed kernel selec-tion, regularization, and grid search parameters to achieve optimal performance. Despite the success achieved in this study, certain limitations and opportunities for future research have been identified. These limitations include the availability of a limited dataset, the variability of EEG signals, the interpretability of model decisions, the incorporation of domain knowledge, and the need for comparative studies. Addressing these limitations and exploring these areas of future research will further advance the field of EEG sentiment analysis during Quran recitation. In summary, this thesis contributes to the growing body of knowledge in the field of EEG signals analysis and its application during Quran recitation. The findings underscore the potential of SVM and CNN models in accurately classifying EEG signals and differentiating Quran features based on EEG signals. This research opens avenues for further exploration and development of advanced algorithms and techniques in this domain, leading to a deeper understanding of emotional experiences during religious recitation and potential applications in related fields.

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