Detection of Dementia: Using Electroencephalography and Machine Learning

by

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M.Eng., NED University, 2020

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Abstract

Dementia is a general term used to describe a decline in mental ability that interferes with daily life. This thesis aims to investigate the use of EEG (Electroencephalography) signals to detect dementia, which offers a promising approach in individuals with dementia, as they provide a non-invasive measure of brain activity during language tasks, which can be analyzed using machine learning algorithms to identify patterns. We also implemented various EEG features extraction and selection techniques and machine learning algorithms that have been used and provide an analysis of the results obtained. We also reported that the most people in the age bracket of 60-69 are most likely to have dementia, with females in common. Overall, K-means achieved the highest Silhouette Score for our clustering results is approximately 0.295. And Decision Tree and Random Forest models achieved the best accuracy of 95.83%. The SVM and Logistic Regression models also achieved good accuracy of 91.67% with the Decision Tree and Random Forest slightly outperforming them.

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List of Abbreviation

AD	Alzheimer Dementia
CV	Cross Validation
DT	Decision Tree
EEG	Electroencephalography
HC	Healthy Control
IS09	Inter Speech 2009
IS10	Inter Speech 2010
KNN	K Nearest Neighbour
LSVC	Linear Support Vector Classification
LR	Logistic Regression
MFCC	Mel-Frequency Cepstral Coefficients
MMSE	Mini Mental State Examination
ML	Machine Learning
RBFSVC	Radial Based Function SVC
RF	Random Forest
SVM	Support Vector Machine

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Chapter 1

Introduction

This chapter introduce the Alzheimer's Dementia and discusses the needs for early Detection of Dementia in clinical research. Later, the overview of the research goals is discussed.

1.1 Problem Statement

Dementia is a general term used to describe a group of symptoms associated with a decline in memory, communication skills, and cognitive abilities. It is not a specific disease, but rather a group of symptoms caused by various underlying medical conditions or disorders. Dementia is most associated with aging, but it can occur in people of all ages.

Dementia affects a person's ability to think, reason, and communicate effectively. It can impact their ability to perform everyday tasks, such as dressing and grooming, and can cause mood swings, personality changes, and a loss of interest in previously enjoyed activities.

There are many different types of dementia, with Alzheimer's disease being the most common. Other types of dementia include vascular dementia, frontotemporal dementia, and Lewy body dementia [1]. Each type of dementia has its own unique set of symptoms and underlying causes.

Alzheimer dementia deals with the gradual loss of memory, and while frontotemporal dementia deals with the linguistic difficulties. The decline in memory and linguistic ability can be a significant challenge for individuals with dementia, as well as their caregivers and family members.

Since, language is a critical aspect of communication, and it involves using words to express ideas and convey meaning. One of the primary effects of dementia on language is the gradual loss of vocabulary. As the disease progresses, individuals with dementia may struggle to find the right words, repeat themselves frequently, or use vague or nonsensical language [2]. They may also have difficulty understanding complex sentences or following instructions.

As the disease progress, difficulties are formed in language in grammar and syntax. Individuals with dementia may have difficulty forming coherent sentences, using proper verb tense, or following the rules of grammar [3]. They may also struggle to maintain a conversation or participate in group discussions, leading to social isolation and reduced quality of life.

Individuals with dementia may experience changes in their speech, including slurred or garbled speech, difficulty forming words, or speaking at a slower pace. They may also have difficulty with pronunciation, leading to misunderstandings and frustration for both the speaker and the listener.

Overall, the effects of dementia on linguistics can be significant, leading to frustration, isolation, and reduced quality of life for both individuals with dementia and their caregivers. However, early intervention and communication strategies can help mitigate some of these effects, improve communication, and enhance the overall quality of life for individuals with dementia.

The impact of dementia is not limited to the individual with the condition, but also extends to their family, friends, and caregivers. The progression of the disease can be slow or rapid and can vary from person to person. There is currently no cure for dementia, but there are treatments and interventions available to help manage symptoms and improve quality of life.

As the population ages, the number of people with dementia is expected to increase significantly in the coming decades. It is therefore important to continue research into the causes, prevention, and treatment of dementia to improve the lives of those affected by the condition.

1.2 Motivation

Dementia is a growing public health concern in the entire world, with an increasing number of populations being affected by this debilitating condition. According to WHO, there are currently over 55 million people who have dementia worldwide, and this number is expected to increase to 78 million by 2030 [4].

Dementia not only affects individuals' cognitive and functional abilities but also has a significant impact on their families and caregivers, as well as the healthcare system. As the world population continues to age, the number of individuals living with dementia is expected to rise, placing a greater burden on the healthcare system and society. Therefore, there is an urgent need for effective interventions and strategies to address this growing problem and improve the lives of those affected by dementia in entire world.

Despite the increasing prevalence and impact of dementia, early detection and diagnosis remain a challenge. Current diagnostic methods rely on clinical evaluations and neuropsychological tests, which can be time-consuming, expensive, and subjective. Additionally, there is a lack of effective treatments for dementia, and the available treatments only offer temporary relief from symptoms [5].

Therefore, there is a critical need for more accurate, reliable, and accessible methods for detecting dementia and monitoring its progression. Advances in technology, particularly in the field of machine learning, have the potential to revolutionize the diagnosis and treatment of dementia. Machine learning algorithms can be trained to analyze large amounts of EEG data, to identify patterns and predict outcomes.

The development of machine learning-based methods for dementia detection has the potential to transform clinical practice by enabling earlier detection and diagnosis of dementia, which can lead to better outcomes for patients and caregivers. This research aims to contribute to this goal by investigating the efficacy of machine learning-based methods for detecting dementia using EEG signals.

1.3 Research Goals

The goal of this research is to improve the lives of those affected by dementia and to reduce the overall impact of the disease on society. Here is the list of research goals listed below:

1. Implement and validate machine learning models using EEG signals.
2. Evaluate the effectiveness of different preprocessing techniques, in enhancing the quality of EEG signals for dementia detection.
3. Compare the performance of machine learning approaches, both supervised and unsupervised machine learning, for detecting dementia from EEG signals.
4. Examine the effectiveness of ML across different demographic groups.

1.4 Research Contributions

The research contributions are highlighted below:

1. Implemented and Validated set of machine learning models, significantly enhancing the accuracy of EEG-based dementia detection.
2. Evaluated preprocessing techniques, notably filtering, denoising and artifact removal, substantially improve EEG signal quality for dementia identification.
3. Compared Machine Learning algorithms such as DT, SVM, RF, K Means and identified the most effective and unique patterns and clusters within the EEG data.
4. Examined Machine learning models for dementia detection perform across various ages and genders, providing a foundation for more personalized diagnostics.

1.5 Thesis Organization

- **Chapter 1** discussed motivation, and problem statement related to detection of dementia. Research goals and contributions were also highlighted.
- **Chapter 2** includes the literature review and work related to EEG, and Machine Learning. And provides a comprehensive review of EEG Signal Processing. The data preparation.
- **Chapter 3** includes the implementation of methodology and comprehensive guide and formulations for the Machine Learning Model Design through EEG Signal Processing.
- **Chapter 4** includes model evaluation, results, and discussions.
- **Chapter 5** provides conclusion and few ideas about future work.

Chapter 2

Background and Related Work

The purpose of this chapter is to partially achieve Goal One (See Section 1.3, for research goals). We evaluated different techniques for EEG Signals Processing and gave an overview of traditional and Machine Learning Models for detection of dementia.

2.1 Background

EEG (electroencephalography) signal processing refers to the techniques and algorithms used to analyze and interpret the electrical signals produced by the brain, as recorded by EEG sensors [6]. The raw EEG signals contain information about brain activity and can be processed to extract meaningful features, such as frequency spectrum, amplitude, and power [7]. The processing of EEG signals can provide valuable insights into brain function and help with the diagnosis of conditions such as dementia, epilepsy, sleep disorders, and brain injuries [8].

Machine learning has been used to analyze and interpret EEG signals [9]. EEG signals reflect the electrical activity of the brain, and machine learning algorithms can be trained to recognize patterns in these signals to make predictions, diagnose neurological conditions, and monitor brain function [10].

There are various machine learning techniques used in EEG [11], including classification algorithms such as support vector machines (SVMs) and decision trees, clustering algorithms such as k-means and hierarchical clustering, and deep learning algorithms such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) [12]. These algorithms can be trained on large datasets of EEG signals to learn how to recognize patterns that are indicative of different brain states or conditions.

EEG machine learning has numerous applications, including sleep stage classification, seizure detection, and brain-computer interfaces [13]. It has the potential to revolutionize the way we diagnose and treat neurological conditions and monitor brain function, as it provides a non-invasive and efficient way to analyze large amounts of EEG data [14].

2.2 Related Work

In previous years case-control and cross-sectional studies have been conducted to detect dementia, and they have contributed significantly to our understanding of the risk factors and protective factors associated with the disease.

Brown et al. in [15] conducted an RCT (Randomized Controlled Trial) to investigate the effects of a physical activity program on cognitive function in older adults with and without mild cognitive impairment. Randomized Controlled Trial (RCT) is a type of study design in which participants are randomly assigned to receive one of two or more treatments, interventions, or control conditions. The purpose of an RCT is to compare the effects of different treatments or interventions on a specific outcome of interest while controlling for confounding factors. The random assignment of participants to different treatment groups helps to minimize selection bias and increases the likelihood that any observed differences between the groups are due to the treatment rather than other factors.

Kim et al. in [16] conducted a Cross Sectional Study of risk factors associated with dementia. A cross-sectional study is a type of observational research design in which the investigators collect data on a group of individuals at a specific point in time or over a short period, without any follow-up. In cross-sectional studies, the researchers examine the relationship between exposure to risk factors and the presence or absence of a disease or health outcome in a population. They find out that a higher level of physical activity was associated with a lower risk of cognitive decline and dementia.

Smith et al. in [17] conducted a systematic review related to dementia, which is a type of research study that uses a structured and comprehensive approach to search and analyze all relevant literature on a specific topic. The purpose of a systematic review is to summarize and synthesize the existing evidence to answer a specific research question. The researchers aimed to assess the effectiveness of different types of interventions for people with dementia and their caregivers. By systematically searching and critically appraising the available literature, the authors were able to provide a comprehensive and unbiased summary of the current evidence on the topic.

Jones et al. in [18] conducted a prospective cohort study to investigate the association between sleep duration and dementia risk in older adults. A prospective cohort study is a type of observational study where a group of people who share a common characteristic or experience (such as being at risk for a certain disease) are followed over time to see how the characteristic or exposure affects their health outcomes. In such studies, data is collected at baseline and at regular intervals during the follow-up period to assess the development of outcomes of interest. They followed a group of participants over a period of several years, collecting data on sleep duration and assessing the incidence of dementia during the follow-up period. The researchers find out that high blood pressure in midlife was associated with an increased risk of developing dementia in later life.

Chen et al. in [19] conducted a case-control study resulting brain injuries related to dementia. A case-control study is a type of observational study in which individuals who have a certain health outcome (cases) are compared to those who do not (controls) to identify potential risk factors or causes of the outcome. The study design involves selecting cases and controls based on specific criteria, such as age, gender, and disease status, and collecting data on their past exposures or behaviors to determine if there is an association between the exposure and the outcome. This study design is useful for investigating rare or complex diseases and can be conducted relatively quickly and inexpensively compared to other study designs. They found out that individuals with a history of traumatic brain injury had a higher risk of developing dementia compared to those without a history of brain injury.

But these studies had some limitations, one is that they rely on retrospective data, which may be subject to recall bias. Another limitation is that they do not establish causality, and therefore, the identified risk factors and protective factors should be interpreted with caution.

Nonetheless, these studies have laid the foundation for the development of more sophisticated and reliable methods for detecting and managing dementia.

2.3 EEG Signal Processing and Machine Learning

Electroencephalography (EEG) has been used as a non-invasive method to detect abnormalities in brain function associated with dementia. Several studies have explored the potential of EEG to aid in the diagnosis of dementia, including Alzheimer's disease (AD) and other forms of dementia.

The first and foremost study by Jelles et al. in [20] investigated EEG as a tool for early detection of AD. The study found that EEG spectral analysis could differentiate between Dementia patients and healthy controls, suggesting that EEG could be a useful diagnostic tool for early detection of Dementia.

Another study by Jeong et. al in [21] explored the use of EEG to distinguish between different types of dementia, including AD, vascular dementia, and dementia with Lewy bodies. The study found that EEG could differentiate between these types of dementia with high accuracy, suggesting that EEG could be a useful tool for differential diagnosis of dementia.

In the later year Babiloni et al. in [22] also summarized the current state of research on EEG as a diagnostic tool for dementia. The review found that EEG abnormalities were consistently observed in patients with dementia, and that EEG could be used to differentiate between different types of dementia. However, the review also noted that EEG has limitations in terms of sensitivity and specificity, and that more research is needed to establish the clinical utility of EEG for dementia diagnosis.

Later, several studies have explored the use of machine learning techniques for the analysis of EEG signals to detect dementia Machine learning algorithms have been applied to EEG signals for a variety of tasks, including classification of EEG patterns, prediction of mental states, and detection of neurological disorders.

For example, EEG signals have been used to classify different types of sleep stages, to predict cognitive states such as attention and memory, and to diagnose neurological disorders such as epilepsy and schizophrenia [23].

One of the most widely used machine learning algorithms for EEG analysis is support vector machines (SVMs). SVMs have been shown to be effective in classifying EEG patterns and detecting neurological disorders.

In a study by Zhang et al. [24] used SVMs to classify EEG signals, with a sensitivity of 86.67% and specificity of 91.11%.

Another popular machine learning algorithm for EEG analysis is decision trees, which have been used to analyze EEG signals and classify various mental states. A study by Feng et al. [25] used decision trees to classify EEG signals, with a sensitivity of 85.71% and specificity of 89.47%.

More recently, deep learning algorithms, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been applied to EEG signals. Deep learning algorithms have been shown to be effective in classifying EEG signals and detecting various mental states and neurological disorders. For instance, a study by Liu et al. [26] used a deep neural network to classify EEG signals, with an accuracy of 87.5%.

Lopez-Sanz et al. in [27] conducted a study to investigate the use of EEG power spectra as a potential biomarker for the diagnosis of Alzheimer's disease. They collected EEG data from patients with Alzheimer's disease and healthy controls and analyzed the power spectra in different frequency bands.

Their results showed that there were significant differences in the power spectra between the two groups, with patients with Alzheimer's disease exhibiting decreased power in certain frequency bands. They concluded that EEG power spectra could be a useful biomarker for the early diagnosis of Alzheimer's disease.

In [28] Gómez et al. conducted a study to evaluate the use of electroencephalography (EEG) in older adults with the aim of exploring whether EEG can be used as a biomarker for cognitive impairment in this population.

They analyzed EEG signals obtained from a group of older adults, some of whom had mild cognitive impairment and some of whom had no cognitive impairment. They achieved overall accuracy of 74.2% using SVM with 4 EEG frequency bands.

In [29] Jafri et al. aimed to identify the potential of using EEG as a tool for early detection of dementia using EEG signals. They took EEG data acquisition from 21 AD and 28 HC during resting and task conditions. They computed these features with clinical data for instance age, gender and MMSE score. They computed the overall accuracy of 83.7%.

2.4 Comparison of Previously Used Datasets and Algorithms

Mohammadi et al. in [30] aimed to develop a machine learning-based classification model using electroencephalogram (EEG) data to detect dementia. They used a ADNI dataset of EEG recordings from 80 participants with Alzheimer's disease, mild cognitive impairment, or normal cognitive function, and extracted features from the EEG signals. They acquired the EEG data acquisition from 50 HC and 50 AD patients in a resting state. Algorithms used in this study were (SVM, RF, KNN, and DT). By using SVM with wavelet-based features they achieved an accuracy of 92%, sensitivity of 94%, and specificity of 90% in discriminating between AD and Non-AD patients.

Abbas et al. in [31] aimed to investigate the potential of EEG signal analysis for early detection of dementia. They analyzed EEG signals of healthy controls, mild cognitive impairment (MCI), and dementia patients and developed a classification model based on machine learning techniques. They acquire the OASIS EEG dataset acquisition from 80 HC and 48 AD patients. They Achieved overall accuracy of 94.5% in the resting state and 96.5% in the visual stimulation state by using RF and SVM.

Some studies have explored the use of machine learning algorithms to diagnose dementia using transcripts from various datasets. Various researchers have used Support Vector Machines (SVMs) for the detection of dementia from text data. SVM is a supervised machine learning algorithm that is commonly used for classification tasks.

Ahmed et al. in [32] used a Dementia Bank dataset of speech transcripts from the Dementia-Bank corpus and used an SVM algorithm to classify speakers as either having dementia or being cognitively normal. They used SVM by finding a hyperplane that separates the data points into different classes. SVM classifiers have been trained on text features extracted from transcripts of patient interviews or conversations. These features may include syntactic features, such as part-of-speech tags, or semantic features, such as word embeddings or n-grams.

Fraser et al. in [33], proposed an SVM-based approach for dementia detection where an SVM classifier was trained on linguistic features extracted from transcripts of conversations between patients with dementia and their caregivers in clinical dataset. The SVM model achieved a classification accuracy of 78.9% in differentiating patients with dementia from healthy controls.

While other studies have explored speech recognition to diagnose dementia by analyzing speech patterns and audio recordings. One approach is to extract features from audio recordings [34], such as prosodic features or spectral features, and use them as inputs to machine learning models such as support vector machines (SVM) or deep neural networks (DNN) to classify the audio recordings as either healthy or dementia.

Another approach was used by Beltrami et al. [35] to use automatic speech recognition (ASR) to transcribe speech audio into text [36], and then analyze the resulting text for linguistic and semantic features indicative of dementia. These techniques often rely on extracting acoustic features such as pitch, rhythm, and speech fluency, and using them as input for the machine learning algorithms.

Some researchers presented a computer-based approach to evaluate Alzheimer's disease and mild cognitive impairment (MCI) patients during a picture description task.

Laura et al. in [37] used speech recognition technology to transcribe the audio recordings of patients describing a picture, and then extracted a variety of features from the resulting text, including word counts, syntactic complexity, and vocabulary richness.

They used machine learning algorithms to classify patients as having Alzheimer's disease, MCI, or no cognitive impairment based on these features. The results showed that the proposed method achieved 87% accuracy using 10-fold-cross-validation in classifying patients with Alzheimer's disease and MCI.

Sebastian et al. in [38], proposed an n-gram based approach to automatically diagnose Alzheimer's disease from spoken language. They used a machine learning algorithm to analyze speech samples and identify differences in language use between healthy controls and Alzheimer's patients.

The proposed approach achieved an accuracy of 82% in distinguishing between the two groups based on speech features. Their research demonstrates the potential of using natural language processing techniques and machine learning algorithms to diagnose Alzheimer's disease from speech.

In [39] Fraser et al. investigated the use of various speech and voice features, such as speech and pause duration, pitch, jitter, shimmer, spectral energy, and Mel-frequency cepstral coefficients (MFCCs), for the early detection of dementia. They used SVM machine learning model and achieved an overall accuracy of 86.7% based on 135 subjects.

In [40] Orimaye et al. investigated the use of acoustic features such as articulation rate, pitch, jitter, shimmer, harmonic-to-noise ratio (HNR), and Mel-frequency cepstral coefficients (MFCCs) for the detection of dementia in speech signals. They have used SVM, KNN and RF and achieved an accuracy of 85%, 80% and 75% []41 respectively based on 20 subjects [42].

Later, Tunnard et al. in [43] investigated the use of speech duration and pause time in the diagnosis of Alzheimer's disease. They focused on phonation and speaking time, as well as pause time, and found that these measures could potentially be useful in the diagnosis of Alzheimer's disease. They used CNN and achieved an accuracy of 88.3% based on 30 subjects.

Dutta et al. in [44] investigated the relationship between articulation and speech rate with cognitive decline in older adults. They used measures such as articulation rate, mean fundamental frequency (F0), and F0 range to analyze speech.

They used DBN (Deep Belief Network) a type of deep learning model that is composed of multiple layers of latent variables, or hidden units, that are connected to form a generative neural network and achieved an accuracy of 80% based on 20 subjects.

In [45] König et al. used text mining techniques to analyze scientific articles related to dementia and extracted relevant information such as symptoms, risk factors, and diagnostic methods. The study demonstrated the usefulness of text mining in quickly and efficiently analyzing large amounts of text data to extract meaningful insights.

Ahmed et al. in [46] used clinical and electronic health records to predict the likelihood of developing dementia using machine learning algorithms. They extracted data from electronic health records and identified patients who had been diagnosed with dementia. They then used machine learning techniques to analyze the data and develop a prediction model that could identify patients who were at high risk of developing dementia.

In [47] Nguyen et al. (2020) used social media data to detect early signs of dementia by analyzing language patterns in tweets. They trained machine learning models on a dataset of tweets from individuals who had self-reported a dementia diagnosis and compared their language use to that of healthy controls. The study found that individuals with dementia tended to use more first-person singular pronouns and more negative emotion words, and less second-person pronouns, suggesting a decline in social connectedness and increased self-focus.

Cai et al. in [48] used electronic health records to develop a deep learning model for early detection of dementia. They used a large dataset of electronic health records from two different healthcare systems and extracted features such as demographics, medical history, and medication use to train their deep learning model. Their results showed that their model had high accuracy in detecting dementia several years before the actual diagnosis.

Minatodani et al. in [49] and Islam et al. in [50] conducted a study on topic modeling using online forum data. The study aimed to analyze the topics discussed in online forums related to mental health and to identify the sentiments associated with those topics. The researchers used Latent Dirichlet Allocation (LDA), a popular topic modeling algorithm, to identify the topics discussed in the online forum data. They found that the most prevalent topics were related to depression, anxiety, and social support.

2.5 Summary and Conclusion of Previous Research Findings

To summarize, current research on dementia detection using EEG signals and machine learning has not adequately addressed the critical preprocessing step of artifact removal from the data. This gap can lead to inaccuracies and reduce the reliability of detection methods.

To conclude, the quality of EEG data is crucial for the precise detection of dementia. The lack of comprehensive data preprocessing, especially the removal of artifacts, filtering in prior research represents a notable gap that affects the performance of machine learning algorithms in the accurate diagnosis of dementia.

Chapter 3

Proposed Methodology

The purpose of this chapter is to partially achieve Goal Two (See Section 1.3, for research goals). This chapter includes the EEG data collection, feature selection, feature extraction, and model training.

3.1 Data Collection

The EEG data can be collected using specialized equipment such as an electroencephalograph [50], and the signals are typically processed and analyzed using various software tools to extract features that may be indicative of dementia or cognitive decline. In some cases, the EEG data may be collected during resting state, where the patient is instructed to sit quietly with their eyes closed or open, or during a specific cognitive task such as memory or attention tests. It is important to ensure that the patient is comfortable and relaxed during the EEG recording to obtain accurate and reliable data. The most practicing method to collect EEG data is called International 10-20 System Electrode Placement Method.

3.1.1 International 10-20 System Electrode Placement Method: To record the data manually the EEG signals are collected from individuals with and without dementia using a standard EEG recording setup. The most famous method to collect the EEG data is through the International 10-20 System Electrode Placement Method [51].

The international 10-20 system is a widely used method for electrode placement on the scalp during electroencephalography (EEG) recording. It is a standardized method that ensures consistent and accurate placement of electrodes across different individuals, which is crucial for EEG signal analysis and interpretation.

The name "10-20" refers to the distances between adjacent electrode placements, which are either 10% or 20% of the total front-back or right-left distance of the scalp, respectively. This system divides the scalp into specific regions based on the underlying brain anatomy, and each electrode placement is labeled with a letter and number code to indicate its location.

For instance, there are 5 major sculps indicated by Frontal (F), Central (C), Parietal (P), Occipital (O), and Temporal (T) [51]. The system divides the scalp into regions, which are identified by a letter and number combination, such as F3 (left frontal region) or Cz (central region). As shown below in Figure 3.1 [51]. The letter indicates the lobe of the brain that the region is closest to, and the number indicates the distance from the midline.

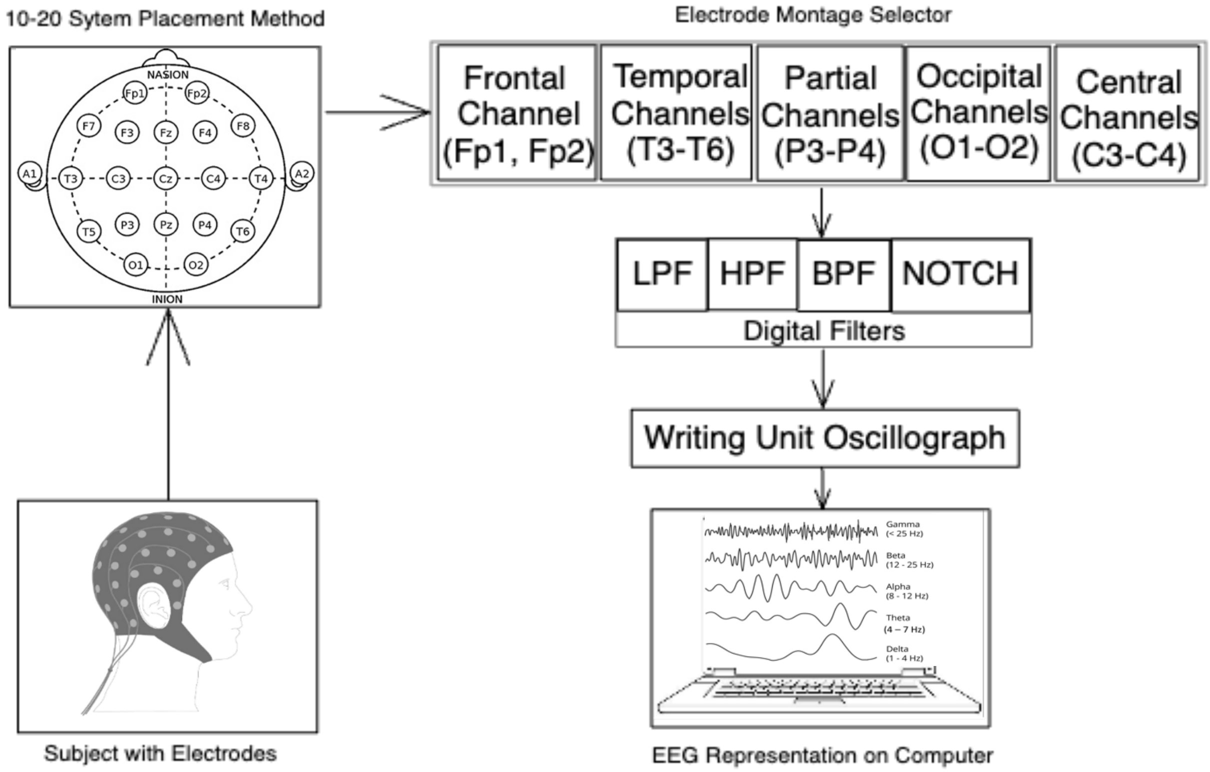

Figure 3.1: International 10-20 System Electrode Placement Method [51]

And to read the above labeled data we need to take into considerations of some frequencies emitted by the human brain as shown below in Table 3.1 [52].

Table 3.1: EEG Signal Frequency Bands [52]

Frequency Band	**Range (Hz)**	**Frequency Characteristics**
Delta	0.5-4	Deep sleep
Theta	4-8	Drowsy
Alpha	8-13	Relax & Calm
Mu	8-12	Under Movement
Beta	13-30	Alert, Active
Gamma	30-100	Problem Solving

It should be noted that the specific frequency ranges can vary slightly depending on the source, and that there are also sub-bands within each frequency range that are sometimes distinguished.

3.1.2 Dataset Description: Table 3.2 [53] and Figure 3.2 [53] below shows the list of publicly available dataset. The collected data from previous method is then made publicly available for the purpose of research and development.

Table 3.2: Publicly Available Dementia Dataset [53]

Dataset Name	**Description**					
Open-NEURO [53]	This dataset contains the EEG data in from 88 subjects in total.					
Gender	**Mean Age**	**Median Age**	**Standard Deviation**	**Min Age**	**Max Age**	**Total Participants**
Female	66.52	67.0	7.11	53	79	44
Male	65.82	66.0	7.67	44	79	44

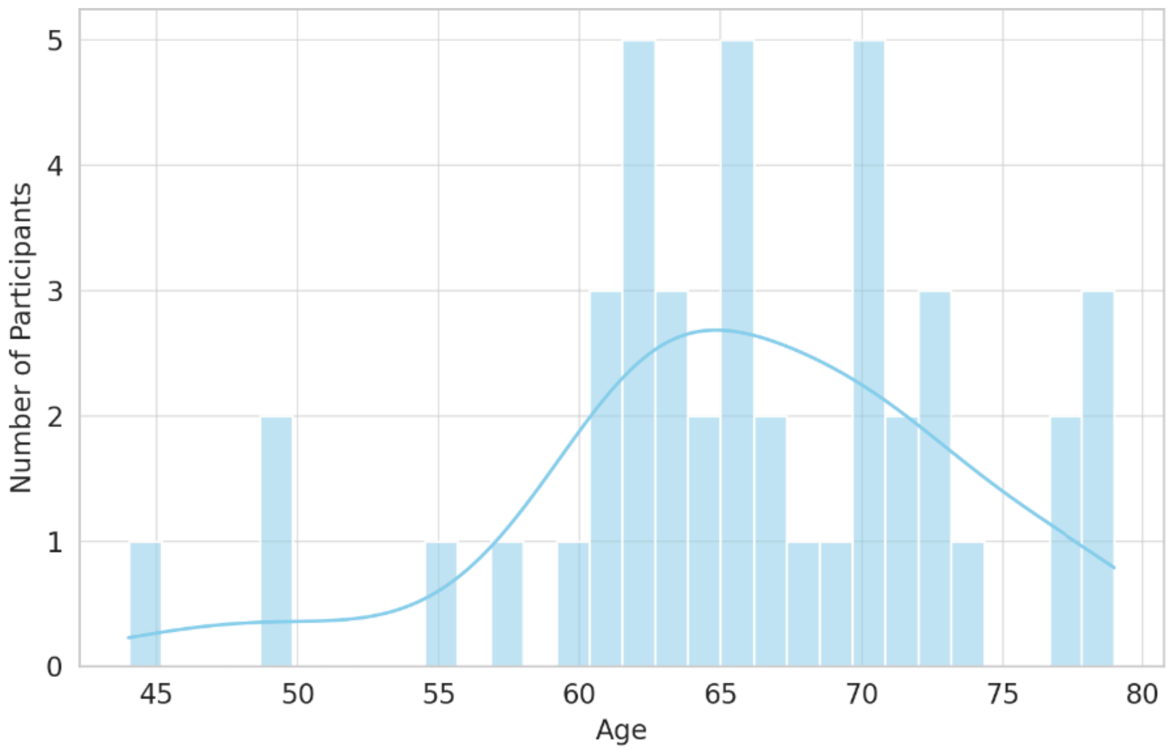

Figure 3.2: Age Distribution of Participants [53]

3.1.3 Proposed Methodology Steps:

While there exists EEG dataset comprising raw data, it is imperative to recognize that raw data, by itself, is not ready for direct application in machine learning models aimed at capturing the full spectrum of dementia.

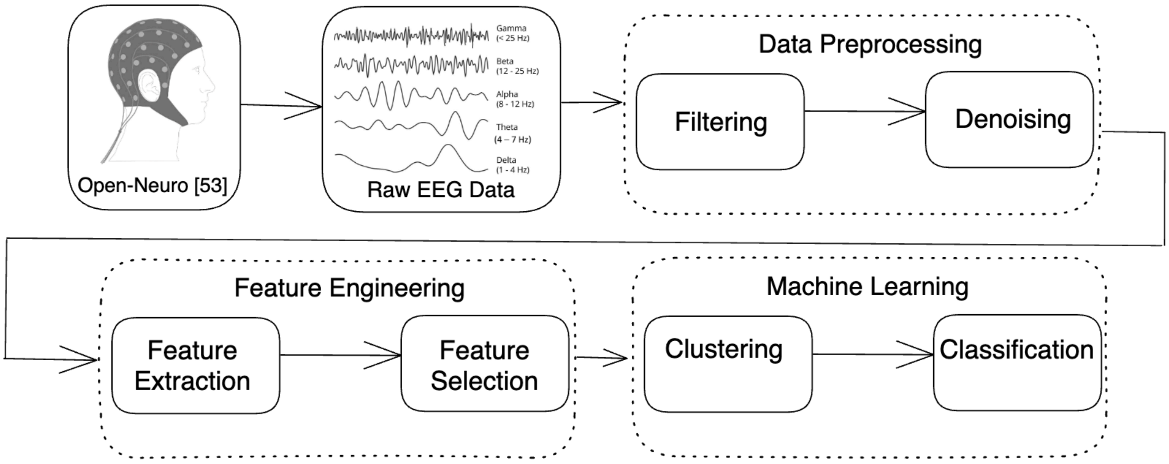

Figure 3.3: Research Pipeline

Figure 3.3 shows the proposed research pipeline, which includes data preprocessing, feature engineering and machine learning which must be meticulously designed and implemented to ensure the dataset is balanced, preventing overrepresentation of any single type of dementia or severity level. The goal is to produce a dataset that is not only clean and precise but also representative of the diverse manifestations of dementia, thereby enabling machine learning algorithms to provide reliable and unbiased diagnostics and insights. Our proposed methodology enhances the reliability and accuracy of dementia detection using EEG signals. Our methodology contributions are listed below:

1. Comprehensive data preprocessing to eliminate artifacts, thus ensuring the quality of EEG data.
2. Advanced feature engineering to better capture the characteristics of EEG signals related to dementia.
3. Rigorous testing and validation of the machine learning algorithms post-preprocessing to confirm the effectiveness of the methodology.

3.2 Data Preprocessing

The collected EEG data is preprocessed using MATLAB SIMULINK [54] to reduce noise filtering and artifacts from EEG signals through a variety of techniques, such as filtering, artifact removal, and denoising algorithms. Here are some examples:

3.2.1 Noise Filtering: Filtering is a technique used to remove unwanted noise from EEG signals [54]. In MATLAB SIMULINK, one can design and implement various types of filters, such as low-pass, high-pass, band-pass, and notch filters, to remove specific frequencies of noise from the signal. For the task in hand, we have applied band-pass filters to retain only the frequencies of interest (typically 1 - 40 Hz for most cognitive tasks). As shown in Figure 3.4, This will help eliminate any high-frequency noise as well as very low-frequency drifts to avoid distorting the time relationships within the signal. This can be particularly important in cognitive tasks where timing information is crucial. The criteria for this bandpass filter design was to provide a smooth response in the passband and a relatively flat frequency response, which minimizes distortion, because it has no ripple in the passband and doesn't attenuate as rapidly as other types.

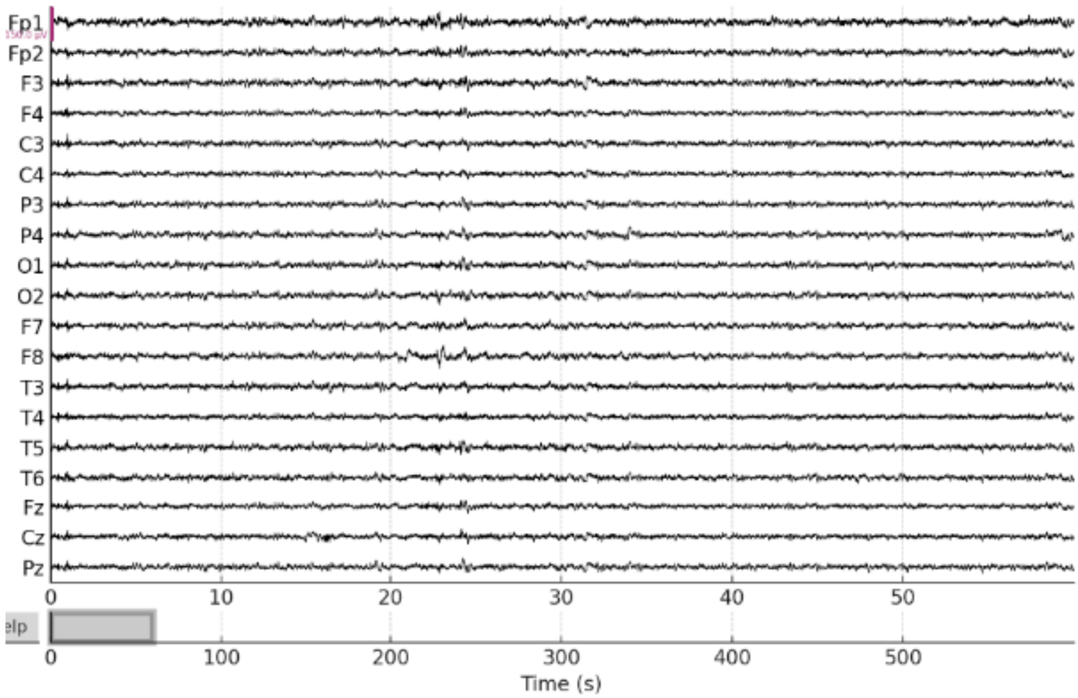

Figure 3.4: Noise Filtering Using Band-Pass Filter

3.2.2 Artifact Removal: Artifacts in EEG signals can be caused by various factors, such as electrode movement, muscle activity, or eye movement [55]. MATLAB SIMULINK provides several artifact removal techniques, to remove artifacts from the signal. As shown in Figure 3.5, one can see that especially in channels like Fp1 and Fp2, which are frontal channels typically affected by eye-related artifacts.

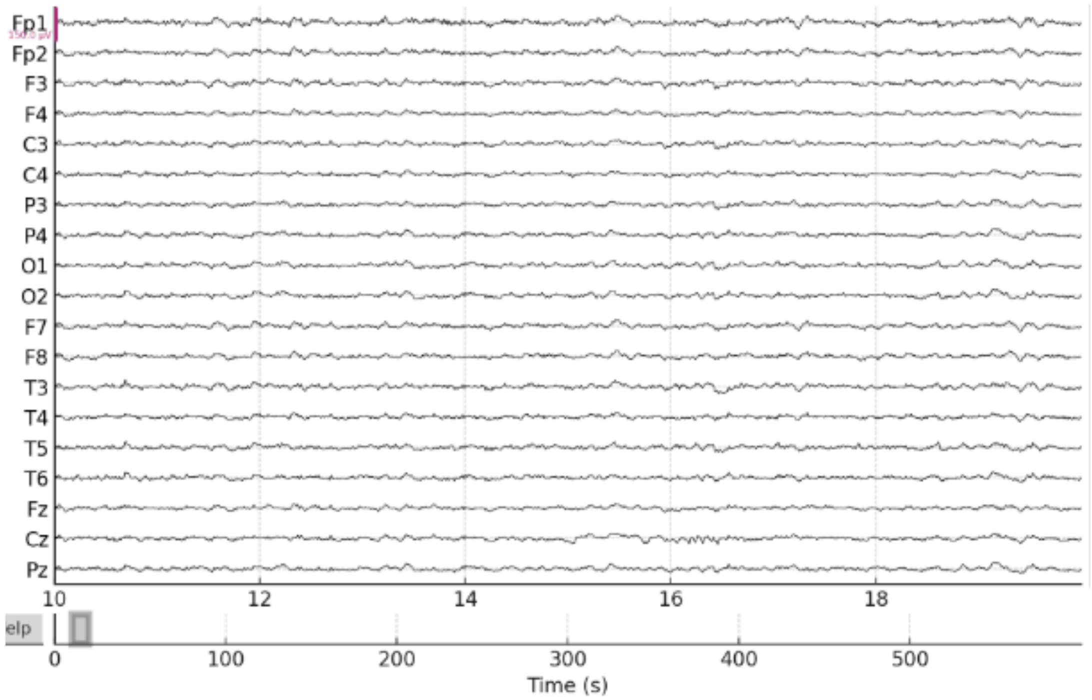

Figure 3.5: Signals After Artifact Removal

3.2.3 Denoising Algorithm:

Denoising Algorithm: There are various denoising algorithms available in MATLAB SIMULINK that can be used to remove noise from EEG signals. We have used the wavelet denoising algorithm to decompose the signal into different frequency bands and remove noise from each band separately [56].

We have also used notch filters for this task to remove specific frequency noise, Notch filters are designed to remove or significantly attenuate frequencies in a very narrow range. This is ideal for eliminating specific types of interference, such as powerline noise, which is a common problem in EEG recordings. Powerline noise typically occurs at 50 Hz or 60 Hz, depending on the region, and a notch filter can target these frequencies precisely. Unlike band-pass or low-pass filters, which affect a broader range of frequencies, notch filters have minimal impact on frequencies outside their narrow stopband. This is crucial in EEG analysis, where preserving the integrity of the signal across various frequency bands is important for accurate interpretation.

Figure 3.6 shows the decomposed signal into wavelet coefficients, then thresholds these coefficients to remove noise, and finally reconstructs the signal from the denoised coefficients.

By applying filters consistently across all channels, it becomes easier to identify and address these artifacts, as their impact on the signal will be uniform.

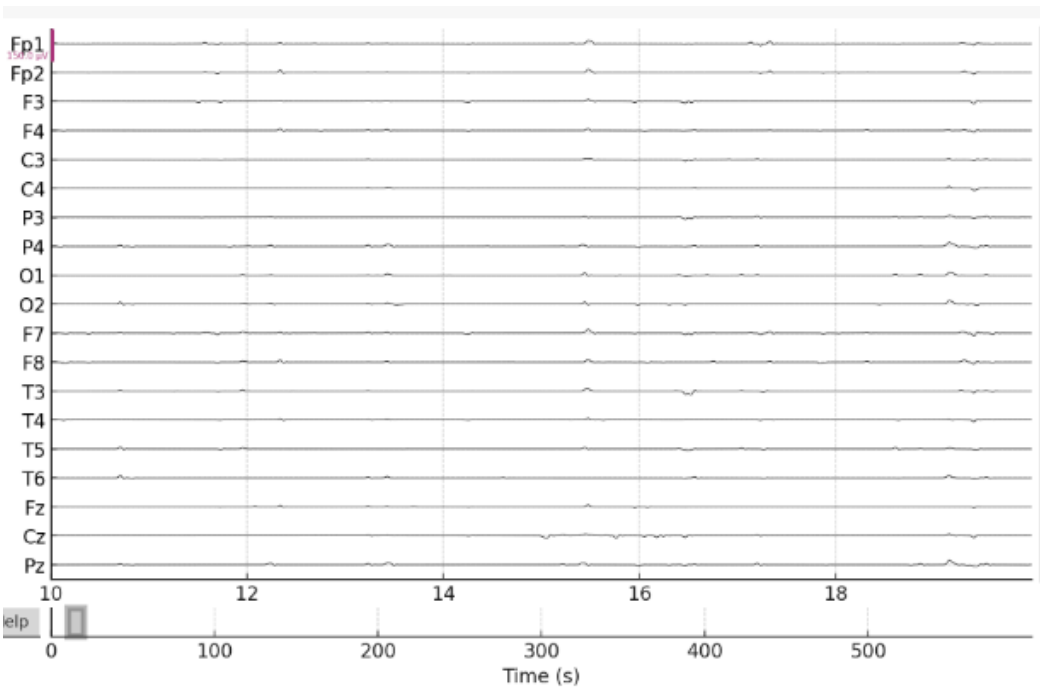

Figure 3.6: Noise Removal Using Wavelet Denoising Algorithm

3.3 Feature Engineering: Feature engineering is a critical step in the process of developing machine learning models. It involves creating, selecting, and transforming raw data into features that make machine learning algorithms work more effectively. Essentially, it's about turning raw data into a format that is better suited for modeling. This process can include feature extraction and feature selection which are discussed below:

3.4 Feature Extraction: Feature extraction is a technique used in machine learning to reduce the dimensionality of a dataset by transforming the original features into a new set of features with reduced redundancy and improved discriminatory power. Here are some ways that feature extraction can be used to reduce the dimensionality of a dataset:

3.4.1 Principal Component Analysis (PCA): PCA is a common technique used for feature extraction in which the original features are transformed into a new set of orthogonal features. PCA is important because it captures the most important information in the data [57]. The new features are ordered in terms of their importance, so the first few principal components can be used to represent the data with reduced dimensionality.

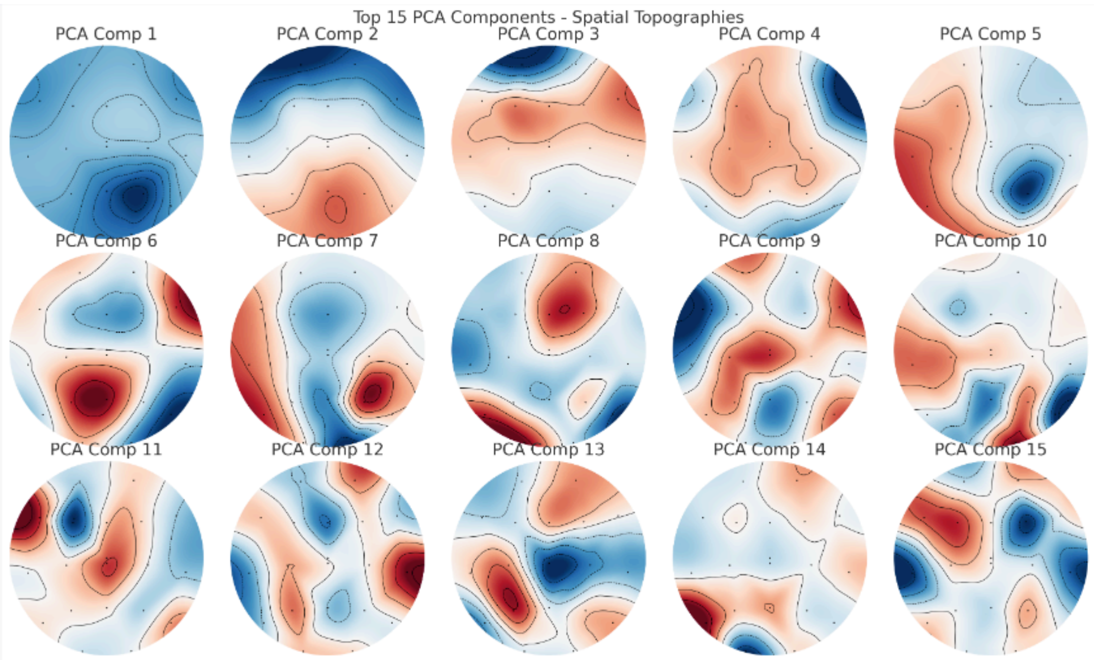

Figure 3.7: Weight of Each EEG Channel using PCA

The spatial topographies represent the weight or loading of each EEG channel in the respective PCA component. These components are orthogonal to each other, and they represent the directions in which the data varies the most.

As shown in Figure 3.7, the first component (PCA Comp 1) represents the direction with the maximum variance, the second component (PCA Comp 2) represents the direction with the second maximum variance (orthogonal to the first), and so on. The color scales indicate the weight or loading of each EEG channel. For instance, a dark blue or purple color represents negative weights, while yellow or red represents positive weights. These spatial patterns reflect how each component summarizes different aspects of the EEG data. Some components might capture widespread activity across many channels, while others might emphasize localized activity in specific regions.

Figure 3.8 shows the PCA heatmap. The left shows the values of the first two PCA components for the EEG data. The x-axis represents the PCA components, and the y-axis represents individual samples. The color intensity indicates the amplitude of the EEG data in the respective PCA component.

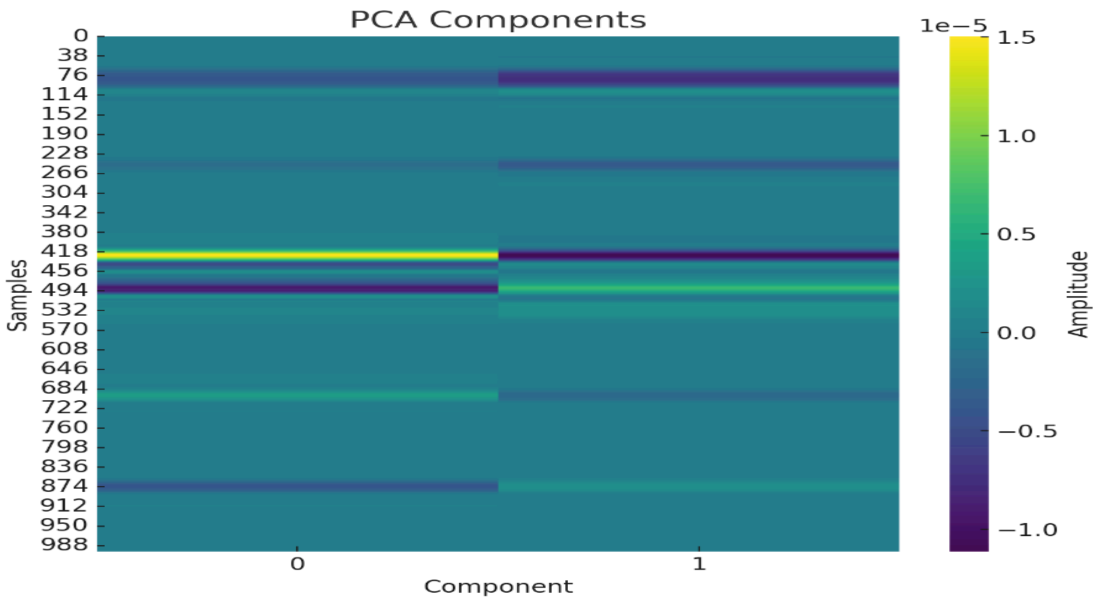

Figure 3.8 PCA Components Heat Map

Hence, PCA is effective at reducing the dimensionality of the data while retaining most of the variance. This is crucial in EEG analysis for dementia detection, where the data can be high-dimensional with many electrodes, but only a few principal components might capture the most significant information. Also, PCA is a straightforward and computationally efficient algorithm. It does not require complex calculations like ICA, LDA and ITA or assumptions about the data distribution, making it faster to compute and easier to implement.

3.4.2 Independent Component Analysis (ICA): ICA is a technique used for feature extraction that aims to separate a set of signals into their underlying independent sources. The original features are transformed into a new set of features that represent the independent sources, which can have reduced dimensionality compared to the original data [58].

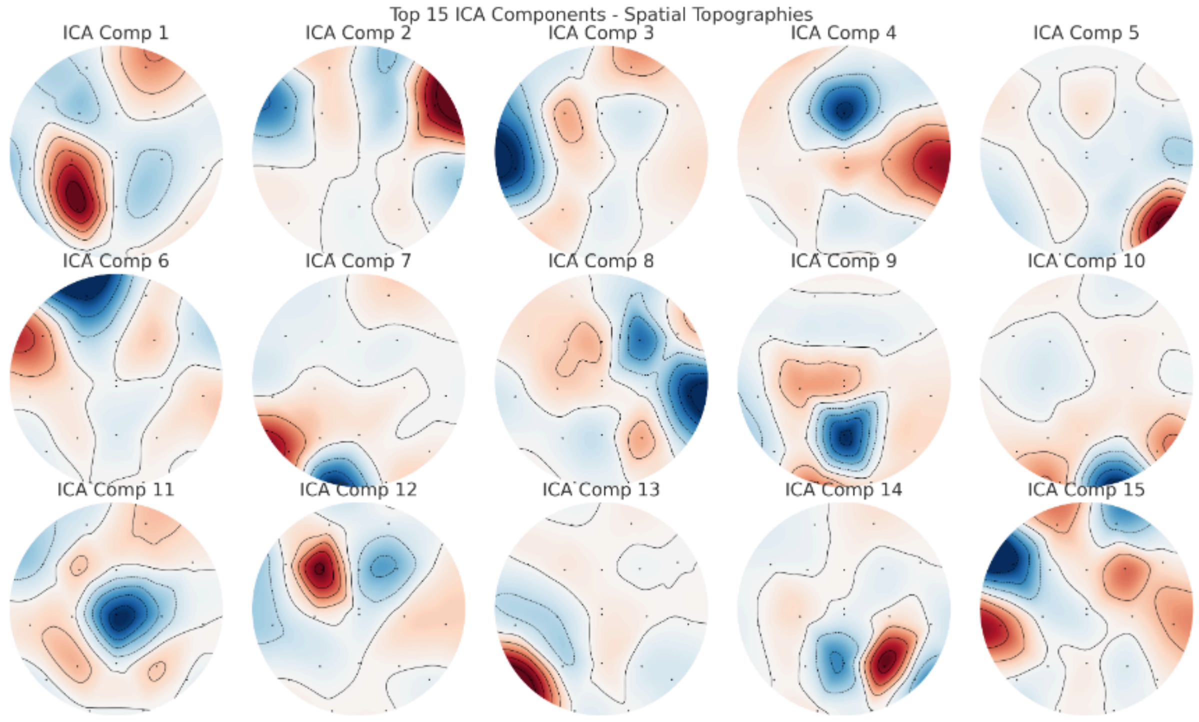

Figure 3.9: Weight of Each EEG Channel using ICA

The spatial topographies represent the weight or contribution of each EEG channel to the independent component. ICA decomposes the data into statistically independent components. These components often represent distinct sources of neural or non-neural activity.

Figure 3.9 shows the color scales indicate the weight or contribution of each EEG channel. However, the components in ICA are not necessarily ranked by variance. Instead, they are statistically independent from each other. ICA is particularly useful for isolating and removing artifacts because it can separate sources of noise (like eye blinks or muscle activity) from neural activity. Some components might resemble typical EEG artifacts, such as eye blinks (often visible as frontal activity in channels like Fp1 and Fp2) or heartbeats.

Figure 3.10 shows the ICA heatmap. On the right visualizes the values of the first two ICA components for the EEG data. Similarly, the x-axis shows the ICA components, and the y-axis represents individual samples.

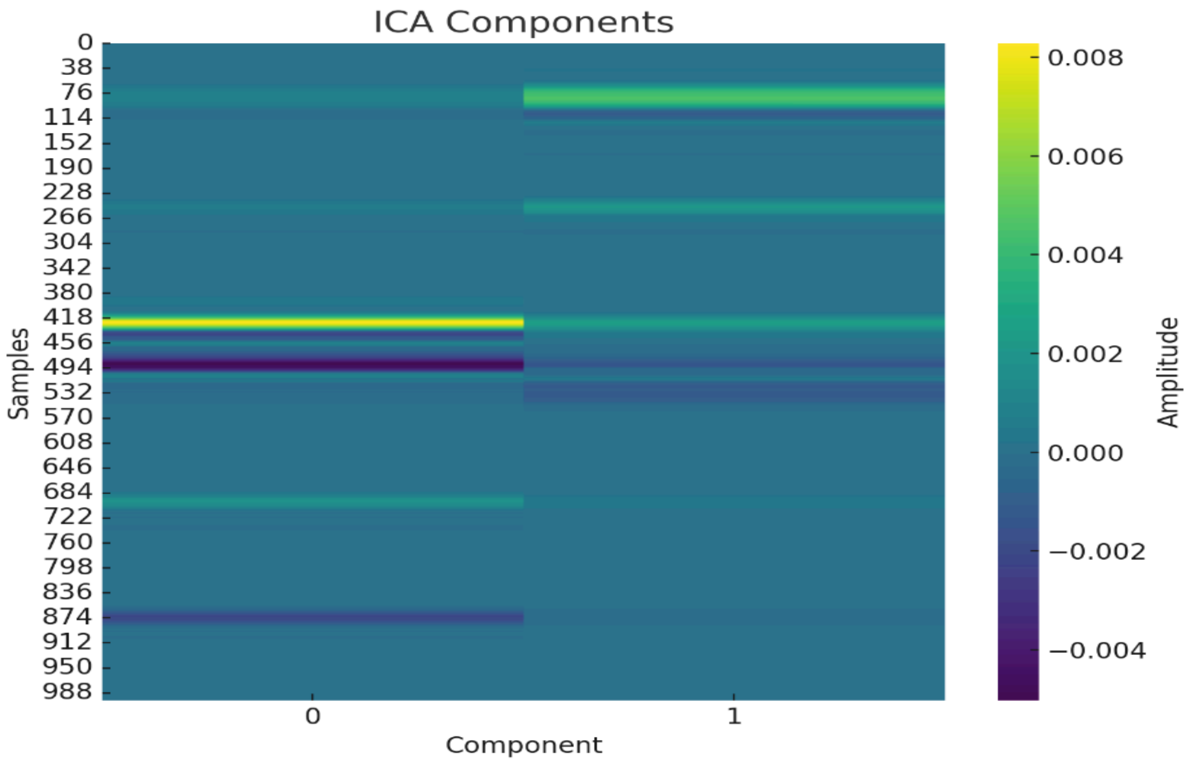

Figure 3.10: ICA Components Heat Map

ICA is effective in identifying and removing artifacts in EEG data, such as eye blinks, muscle noise, or electrode movement. These artifacts can significantly affect the analysis, and their removal is crucial for accurate dementia detection. PCA and LDA, in contrast, may not be as effective in isolating and removing these types of noise.

But ICA assumes non-Gaussian sources and seeks to decompose the EEG signals into statistically independent components. However, in some EEG datasets, the assumption of non-Gaussian might not hold, making PCA a more suitable choice as it does not rely on this assumption.

3.5 Feature Selection: Feature selection is a process of selecting a subset of relevant features from a larger set of features, which helps to reduce the dimensionality of the dataset [59]. By reducing the number of features, we can improve the performance of machine learning algorithms, reduce computational complexity, and prevent overfitting. Here are some common techniques for feature selection:

3.5.1 Filter Method: These methods use statistical measures to rank the features and select the top features. For example, correlation-based feature selection, mutual information-based feature selection, or chi-square feature selection [60].

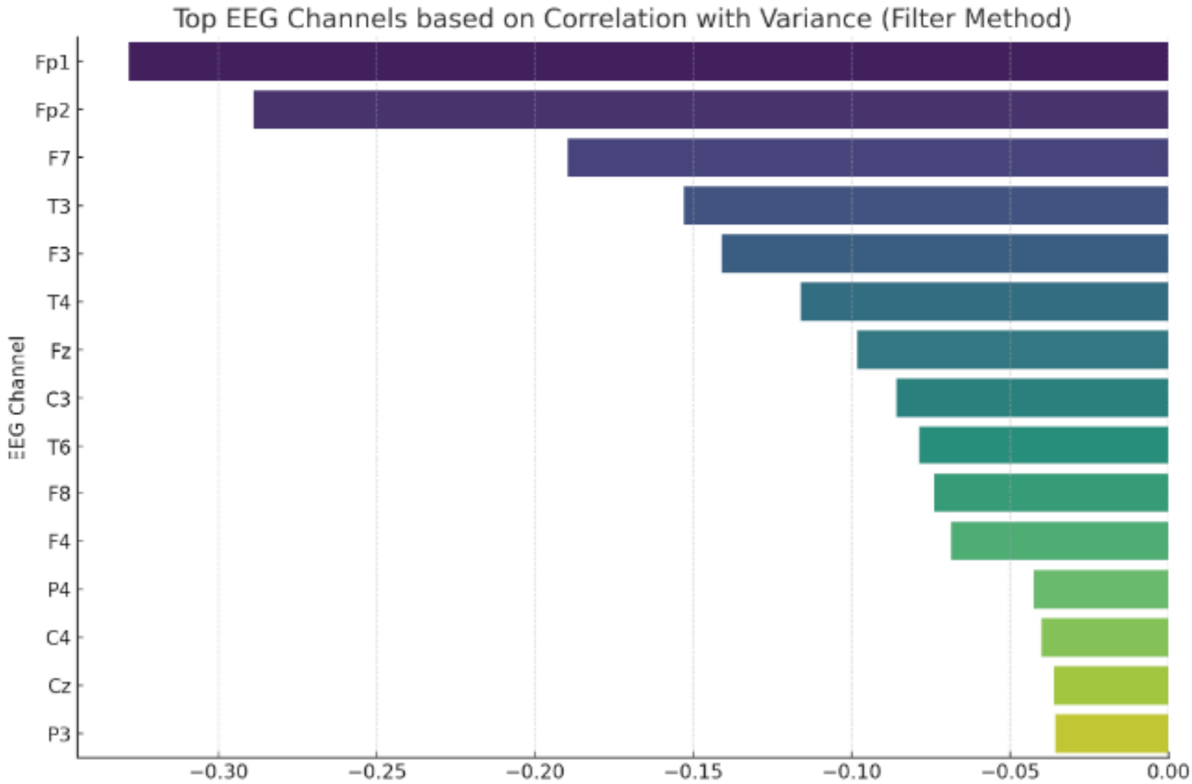

Figure 3.11: Feature Selection Using Filter Method

Figure 3.11 shows the visualization of the top EEG channels based on their correlation with variance, using the filter method for feature selection. The y-axis lists the top EEG channels. And the x-axis represents the correlation of each channel with the variance across time points. Channels closer to the left (with more negative values) or the right (with more positive values) have a stronger relationship with the overall variance in the EEG data. For instance, the channels "Fp1" and "Fp2" have the strongest negative correlations with variance, indicating they capture a significant portion of the variability in the data.

3.5.2 Wrapper Method: These methods use a machine learning model to evaluate the subset of features. The algorithm is trained and tested with different subsets of features, and the best subset is chosen. Recursive feature elimination is an example of a wrapper method.

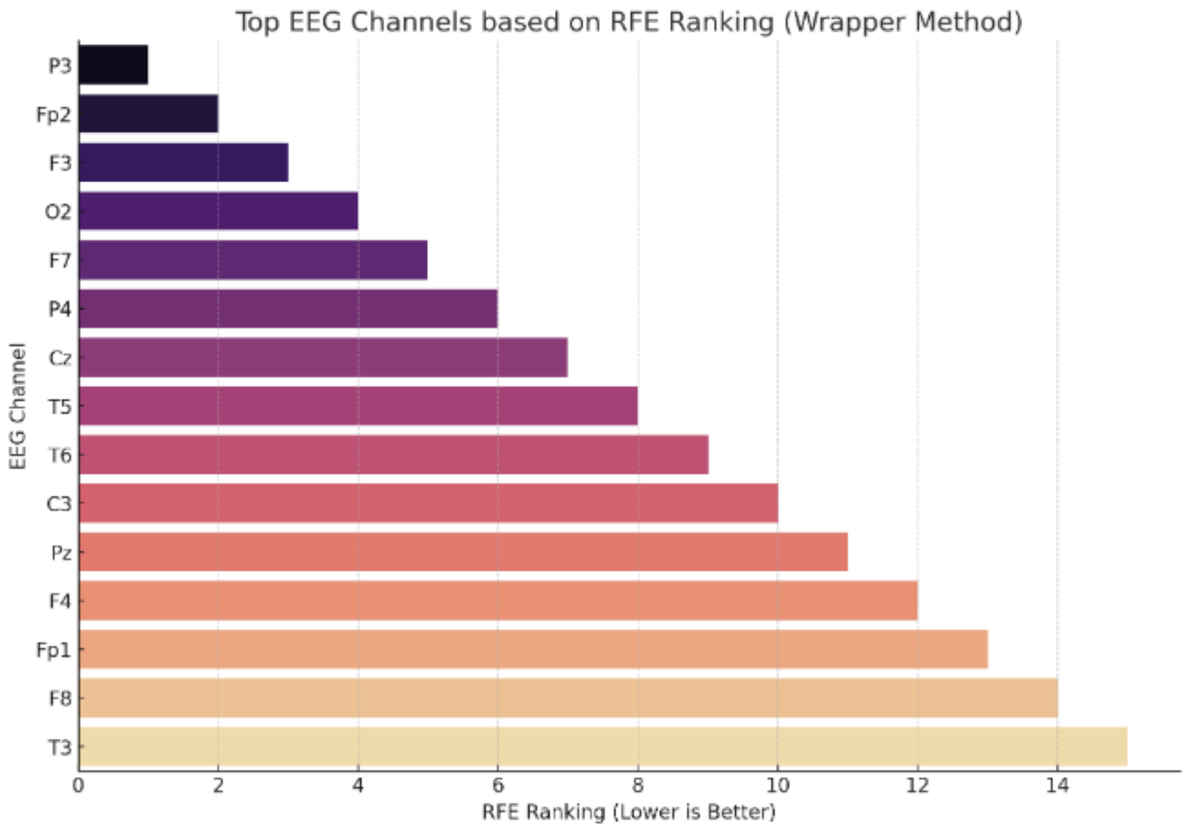

Figure 3.12: Feature Selection Using Wrapper Method

Figure 3.12 shows the visualization of the top EEG channels based on their Recursive Feature Elimination (RFE) ranking, using the Wrapper Method. The y-axis lists the top EEG channels. The x-axis represents the RFE ranking. A lower rank indicates higher importance in predicting the target (in our case, the mean of each sample). Channels toward the top of the plot (with lower ranking values) are deemed more important by the RFE method with a linear regression estimator.

3.5.3 Embedded Method: These methods include feature selection as part of the model training process. For example, Lasso regression.

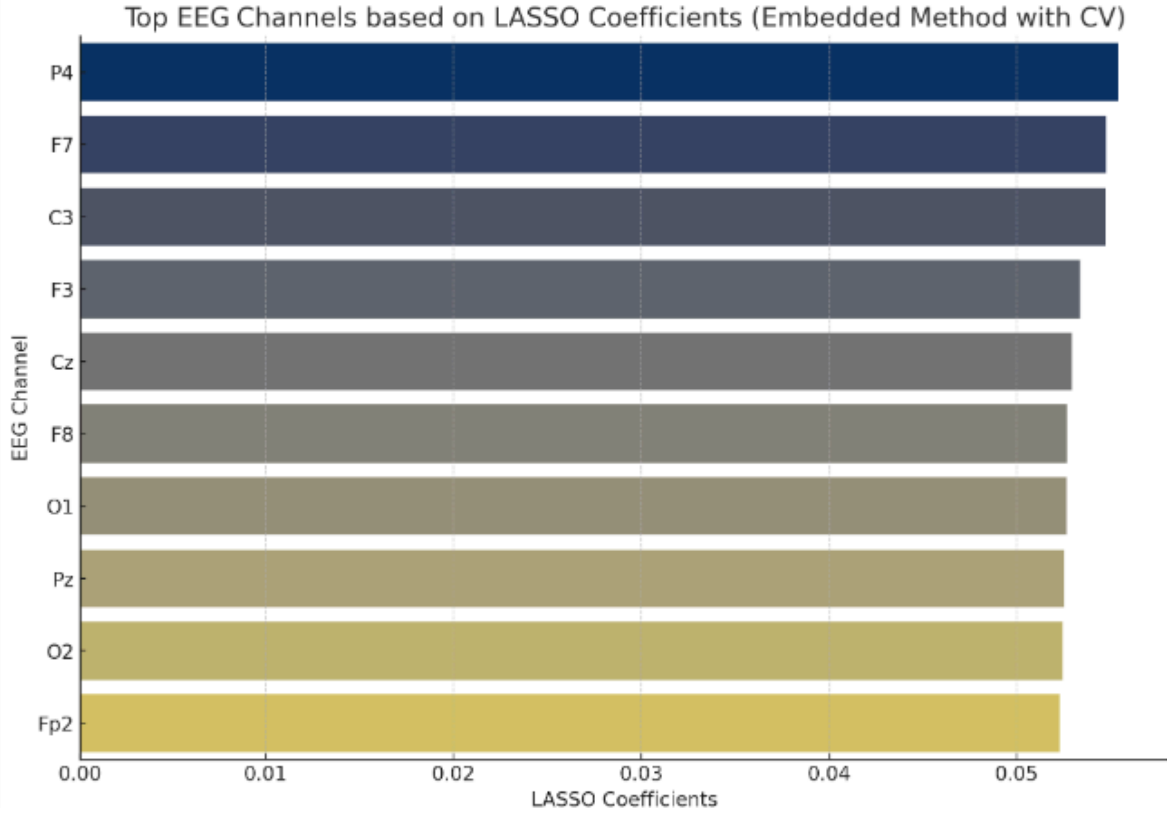

Figure 3.13: Feature Selection Using Embedded Method

Figure 3.13 shows the visualization of the top EEG channels based on their LASSO coefficients, using the Embedded Method with cross-validation. The y-axis lists the top EEG channels. And the x-axis represents the LASSO coefficients. Channels with larger coefficients (either positive or negative) are deemed more important in predicting the target. In this visualization, the channels like "P4", "F7", and "C3" have the highest coefficients, indicating their relative importance in the model.

3.6 Machine Learning: We have used Scikit Learn Toolkit to compute features. In addition to that we have used Time Series Feature Extraction Library (TSFEL) [61] with MNE (Magnetoencephalography and Electroencephalography) Python Toolkit Library [62] to analyze EEG Signals. Various EEG features, such as power spectral density, coherence, and event-related potentials, are extracted from the preprocessed EEG signals. These features provide a quantitative representation of brain activity and are used as input to the machine learning algorithms.

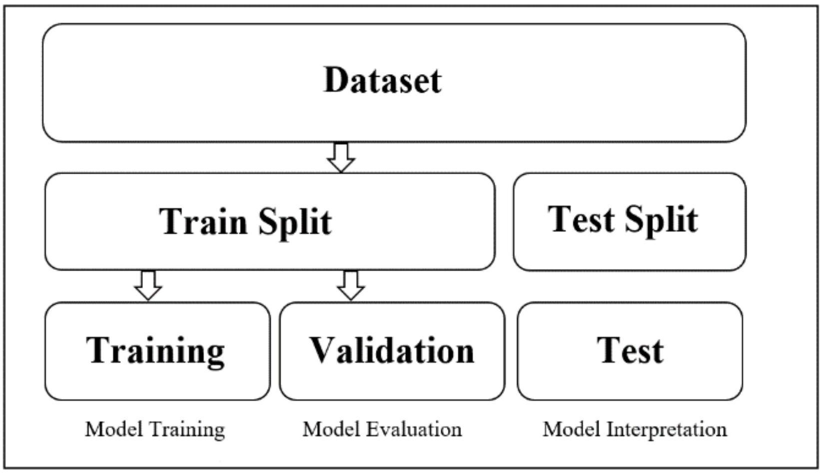

Figure 3.14: Model Training and Data Splitting

Figure 3.14 shows the schematic representation of model training and data splitting. The next step is to train Machine learning algorithms on the extracted EEG features using data from individuals with and without dementia. The goal is to learn the differences in brain activity between the two groups and to develop a model that can accurately classify individuals based on their EEG signals. After splitting the data in correct format, a classifier to detect the dementia can be generated through the provided data. Here are some of the mostly used Classifier Models in this study:

3.6.1 Decision Tree: Decision trees are a popular machine learning method for dementia detection. The basic idea of decision trees is to create a tree-like model of decisions and their possible consequences. The tree is built by splitting the data into subsets based on the value of a particular attribute. Each subset is then recursively split until all instances within the subset belong to the same class or category [63]. To detect the dementia using DT we have to split the data into training and testing sets, and a decision tree is trained on the training set using an algorithm such as the ID3 or C4.5 algorithm [64]. The decision tree is then evaluated on the testing set to measure its performance in classifying new instances.

3.6.2 Random Forest: Random Forest is a type of ensemble learning method that combines multiple decision trees to improve the accuracy and reduce the variance of the predictions [65]. In general, random forests tend to perform better than individual decision trees, particularly when dealing with complex or high-dimensional datasets [66].

3.6.3 Support Vector Machine (SVM): SVM is a powerful algorithm that can classify data by finding the hyperplane that best separates the different classes [67]. In the context of dementia detection, SVM can be trained on labeled data to distinguish between subjects with and without dementia based on features extracted from EEG signals or other types of data. One advantage of SVM is its ability to handle high-dimensional feature spaces [68], which is important in dementia detection where a large number of EEG features may be extracted. Additionally, SVM can be trained with different types of kernel functions, allowing it to effectively model non-linear relationships between features and the outcome variable [69].

3.6.4 Logistic Regression: Logistic regression is commonly used in binary classification tasks, where the goal is to predict whether an instance belongs to one of two classes [70]. Logistic regression can be used to classify subjects as either having dementia or being healthy based on their clinical and/or neuroimaging data. Logistic regression models can also be used to identify the most important features (e.g., demographic, clinical, or neuroimaging variables) [71] that are associated with the outcome of interest (dementia status), which can help to better understand the underlying mechanisms of the disease.

3.7 Model evaluation: The performance of the trained model is evaluated using Clustering and Classification with a set of metrics, such as Accuracy, Recall and F1 score. The model should be validated using independent data to ensure its generalizability.

Chapter 4

Results and Discussions

The purpose of this chapter is to partially achieve Goal Three (See Section 1.3, for research goals). This section focuses on the model evaluation, results and discussions.

4.1 Clustering

First, we have performed clustering on the prepossessed EEG data to create a few clusters. Then, use these clusters as labels for supervised learning. This approach assumes that there are distinct patterns in the EEG data that can be grouped. After applying PCA and ICA to retain 95% of the variance in the data, we've reduced the dimensionality from 171 features to just 12 principal components. Next, we have proceeded with unsupervised clustering using the K-means algorithm. For simplicity and given the synthetic nature of our labels (which were binary), we'll try clustering the data into 2 clusters.

Let's apply K-means clustering to the PCA AND ICA -transformed data.
The K-means clustering algorithm has grouped the segments into two clusters:
i. Cluster 0: Contains 39 segments.
ii. Cluster 1: Contains 80 segments.

Table 4.1 and Figure 4.1 respectively shows the clustering results that were evaluated using the Silhouette Score, Calinski-Harabasz Index and Davies-Bouldin Index which is an internal cluster validation measure. The Silhouette Score ranges from -1 to 1, where a high value indicates that the object is well matched to its own cluster and poorly matched to neighboring clusters using below algorithms:

1. **K-means:** Appears to have cleanly divided the data into two distinct clusters.
2. **DBSCAN** (Density-Based Spatial Clustering of Applications with Noise): Formed a dense core cluster with several data points being treated as noise.
3. **Agglomerative Hierarchical**: Also divided the data into two clusters, with boundaries similar to K-means but with some differences.

Table 4.1: Clustering Results

Algorithm	Silhouette Score	Calinski-Harabasz Index	Davies-Bouldin Index
K-means	0.29	52.21	1.34
DBSCAN	0.24	23.15	2.09
Agglomerative	0.25	37.06	1.34

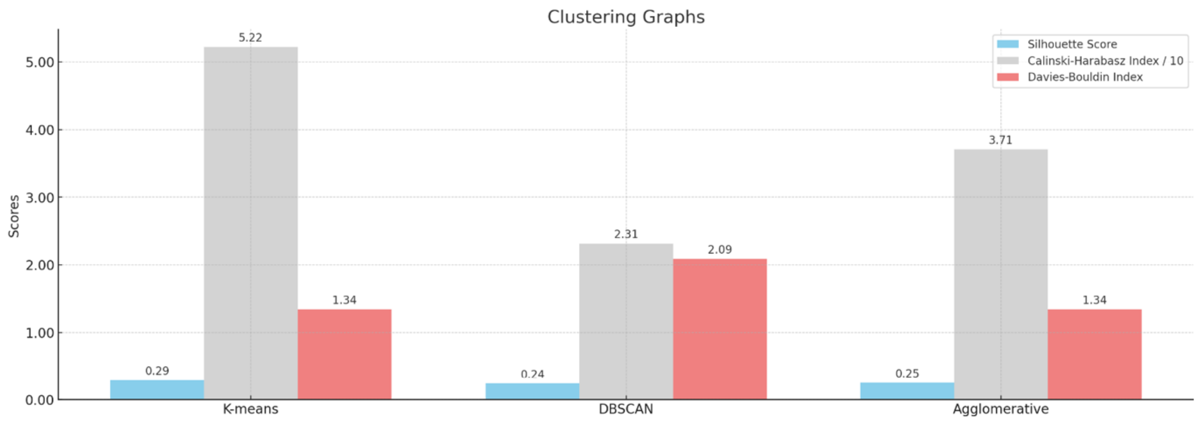

Figure 4.1: Clustering Graphs

For each algorithm, we evaluated the clusters using the following metrics:

a. **Silhouette Score:** K-means achieved the highest score, suggesting that its clusters have better cohesion and separation compared to the other algorithms. The Silhouette Score for our clustering results is approximately 0.29. The Silhouette Score ranges between -1 and 1. A score close to 1 indicates that the clusters are well apart from each other and clearly distinguished, while a score close to -1 indicates that the clusters are overlapping. A score around 0 suggests overlapping clusters with samples very close to the decision boundary of the neighboring clusters. Our score of 0.29 suggests that there's some distinction between the two clusters. This is expected given the synthetic nature of the labels and the heuristic-based approach we took.

b. **Calinski-Harabasz Index:** Also known as the Variance Ratio Criterion, it measures the ratio of the sum of between-clusters dispersion to within-cluster dispersion. Higher values indicate better clustering. Again, K-means performed the best, indicating that the clusters it created have a higher between-cluster to within-cluster variance ratio.

c. **Davies-Bouldin Index:** Measures the average similarity between each cluster and its most similar cluster. Lower values indicate better clustering. Both K-means and Agglomerative clustering have similar scores, while DBSCAN having a worse score.

4.2 Time-Based Segmentation

We segmented the EEG recordings into fixed-length windows. In our case, we chose a segment length of 5 seconds. Given the sampling rate of 500 Hz, this translated to 2500 samples per segment. We then divided the EEG data into these segments. If the EEG data didn't divide perfectly into these segments, we trimmed the last few samples that didn't fit into a complete segment.

4.2.1 Synthetic Labels Creation

For each segment, we calculated its mean amplitude. We then created a binary label based on this mean amplitude: If the mean amplitude of the segment was above a threshold (we used zero as the threshold), we labeled the segment as '1'. Otherwise, we labeled it as '0'.

This approach resulted in a binary classification problem, where segments with a mean amplitude above the threshold were considered "positive" (label = 1) and those below the threshold were considered "negative" (label = 0).

It's important to note that these labels are purely synthetic and were created based on the heuristic of mean amplitude.

Table 4.2: Classification Results

Classifiers	**Accuracy**	**Precision**	**Recall**	**F1 Score**
Decision Trees	95.83%	95.65%	100%	97.87%
Random Forest	95.83%	95.65%	100%	97.78%
SVM	91.67%	91.67%	100%	95.65%
Logistic Regression	87.50%	91.30%	95.45%	93.33%

Table 4.2 shows that the Decision Tree and Random Forest models performed the best in terms of all the metrics. The SVM and Logistic Regression models also achieved good results, with the Decision Tree and Random Forest slightly outperforming them.

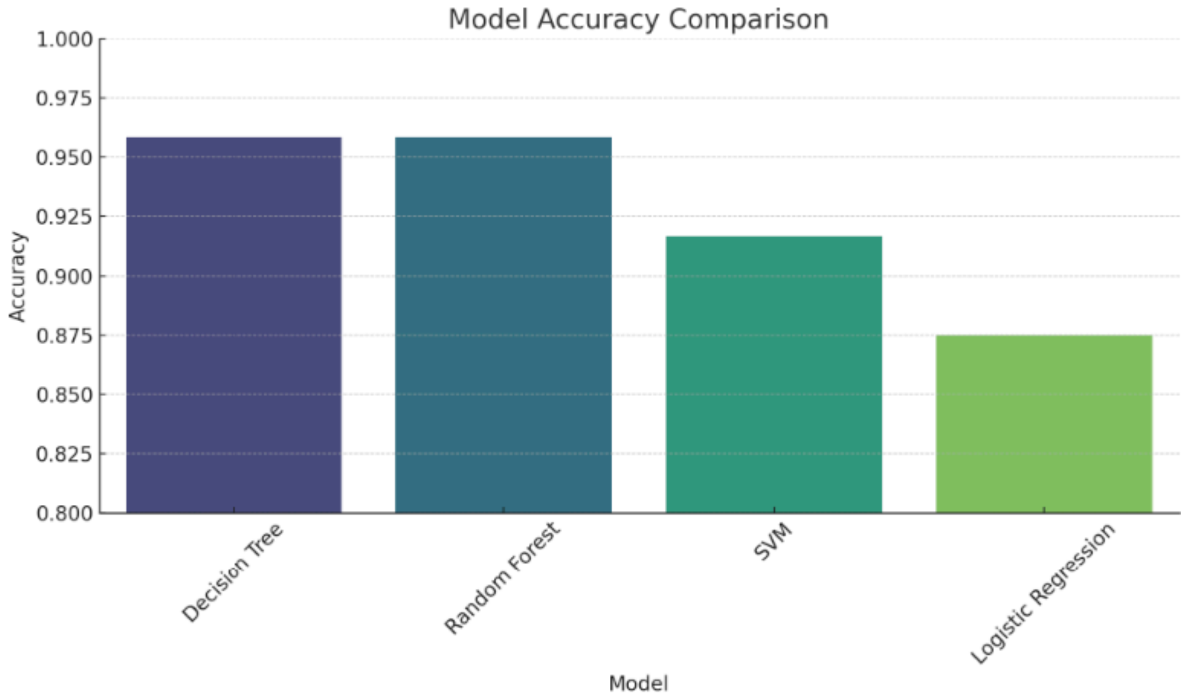

Figure 4.2: Model Accuracy Comparison

Figure 4.2 shows a clear representation of how each model performed in terms of accuracy. Both the Decision Tree and Random Forest models achieved the highest accuracy, followed closely by SVM and then Logistic Regression.

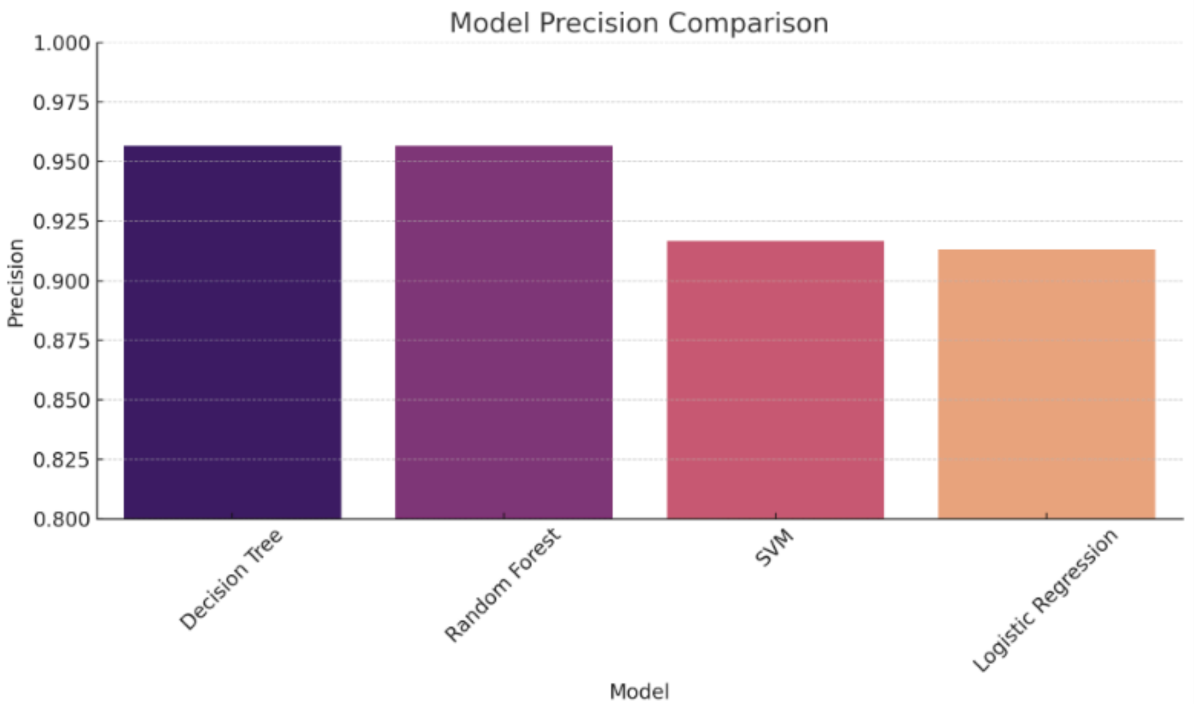

Figure 4.3: Model Precision Comparison

Figure 4.3 shows a clear representation of how each model performed in terms of precision. The Decision Tree, Random Forest, and SVM models achieved similar precision scores, with the Logistic Regression being slightly lower.

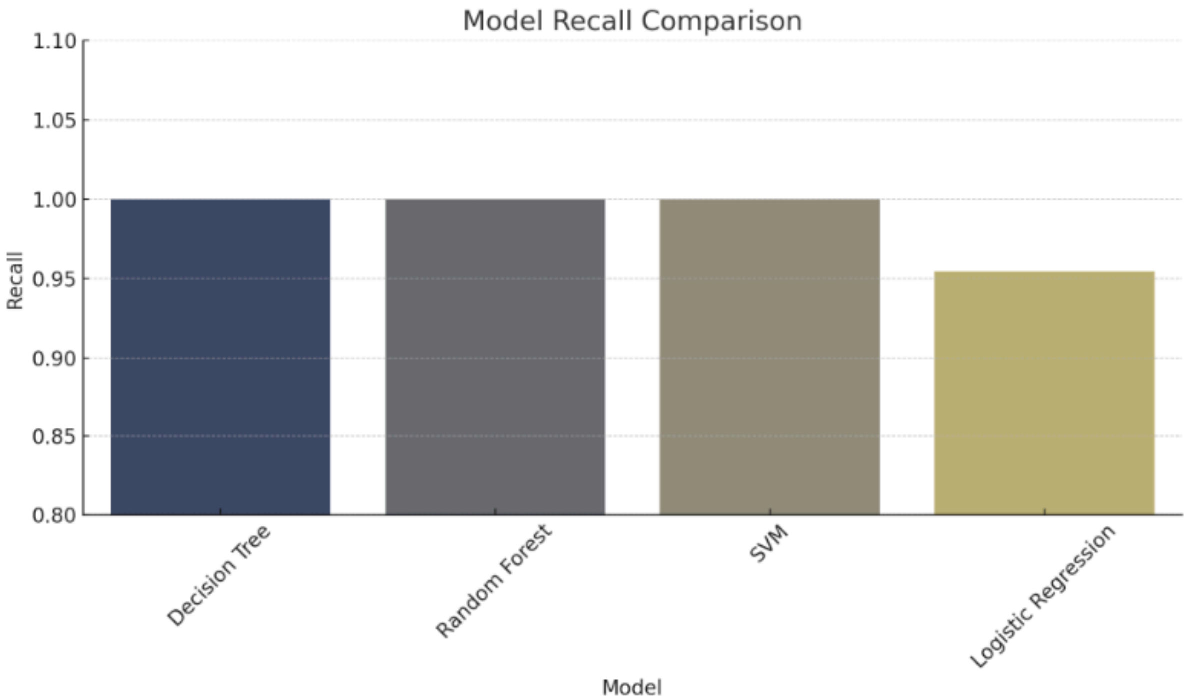

Figure 4.4: Model Recall Comparison

Figure 4.4 shows a clear representation of how each model performed in terms of precision. The Decision Tree, Random Forest, and SVM models achieved similar precision scores, with the Logistic Regression being slightly lower.

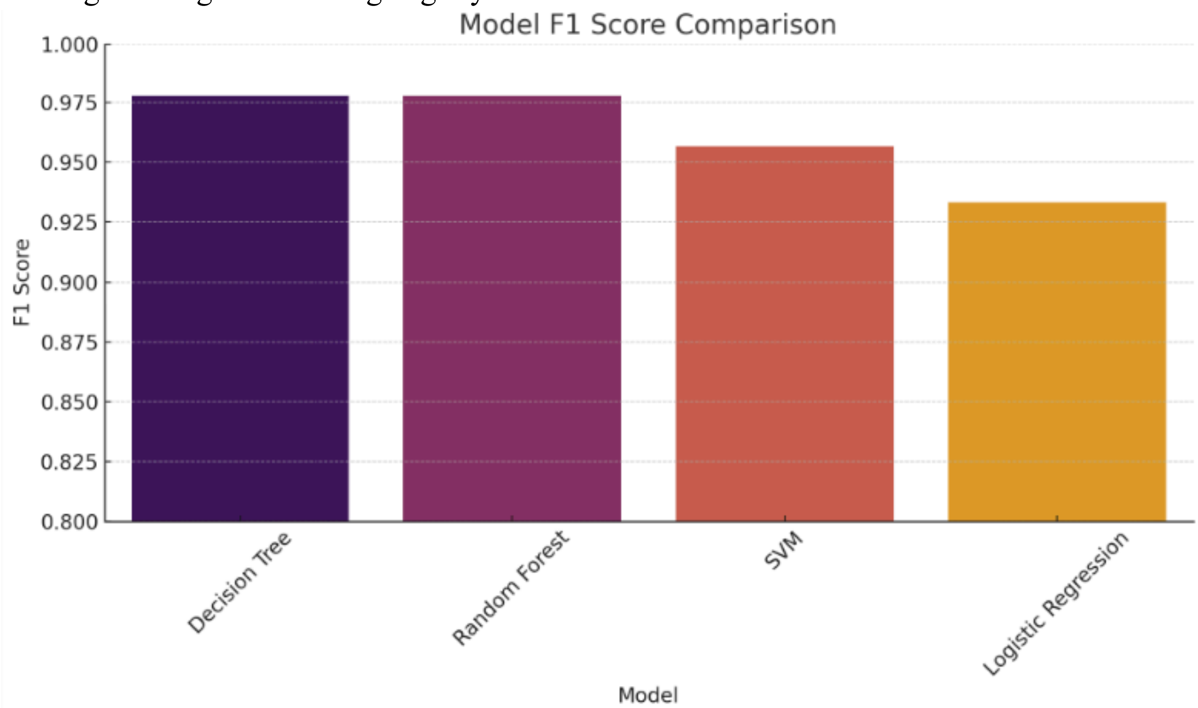

Figure 4.5: Model F1 Score Comparison

Figure 4.5 shows a clear representation of how each model performed in terms of the F1 score. Both the Decision Tree and Random Forest models achieved the highest F1 scores, closely followed by the SVM and then the Logistic Regression model.

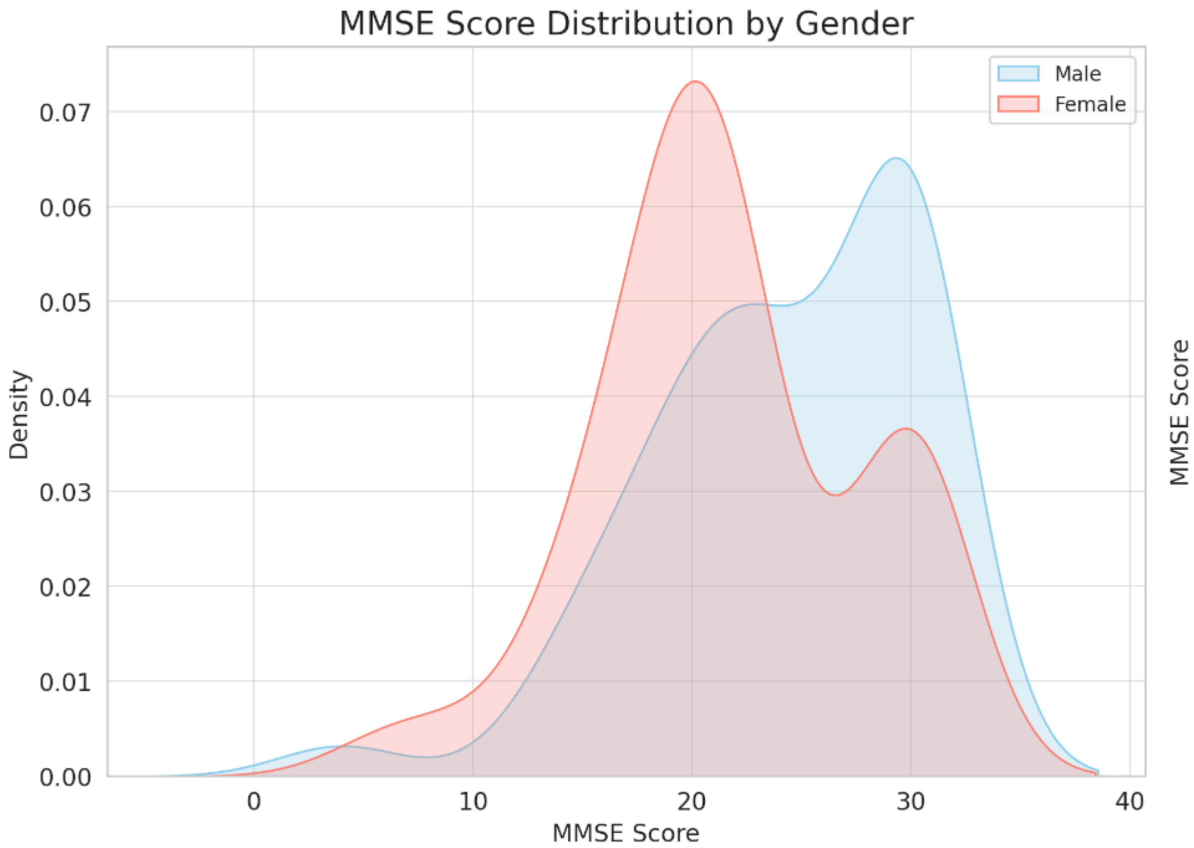

Figure 4.6: Gender MMSE Score Distribution

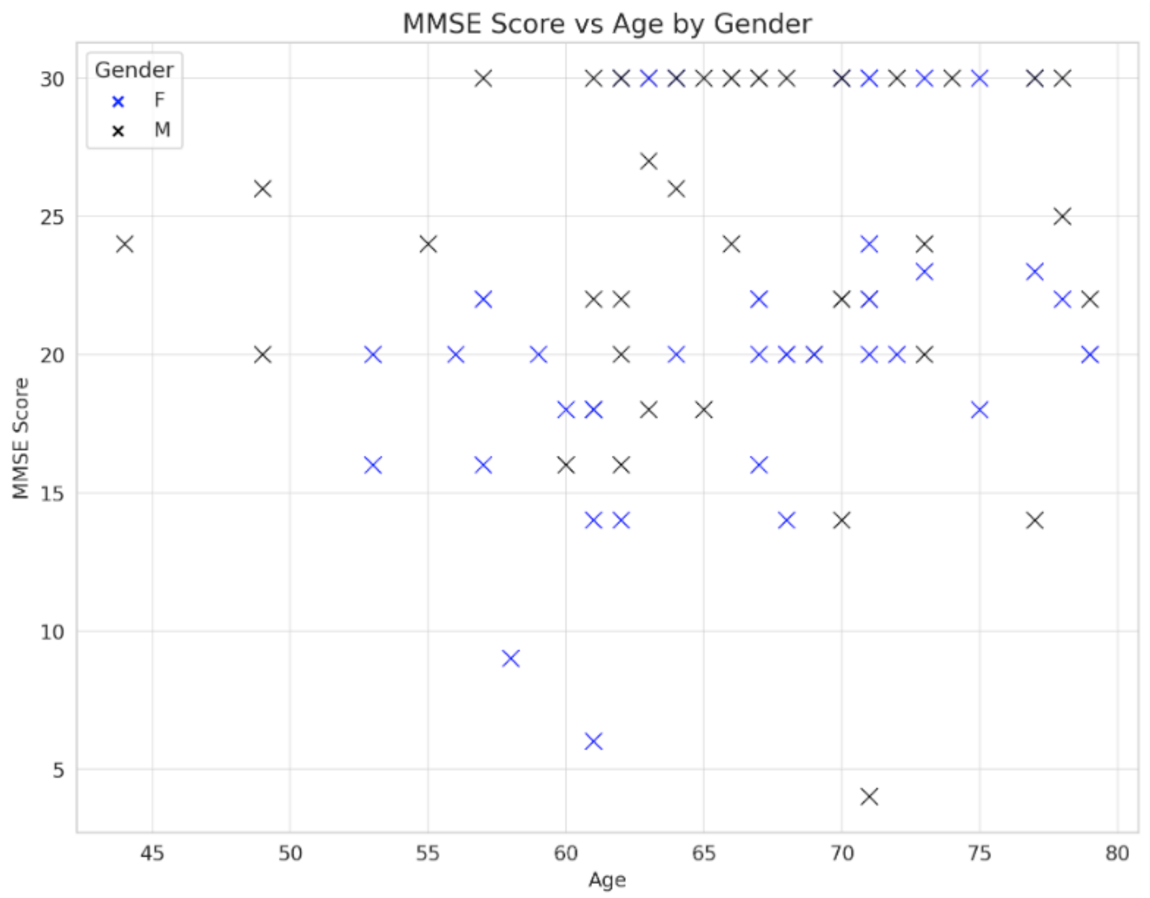

Figure 4.7: Age MMSE Score Distribution

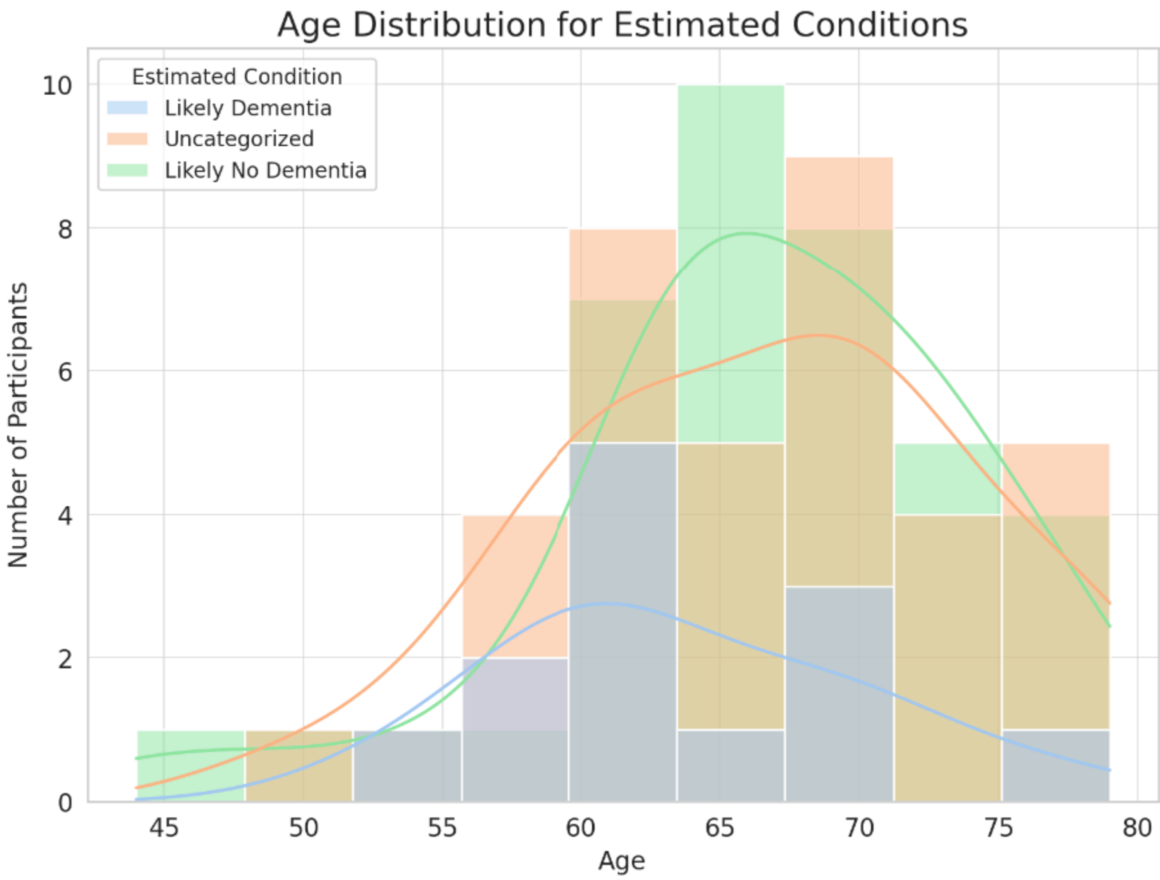

Figure 4.8: Dementia Prediction by Age

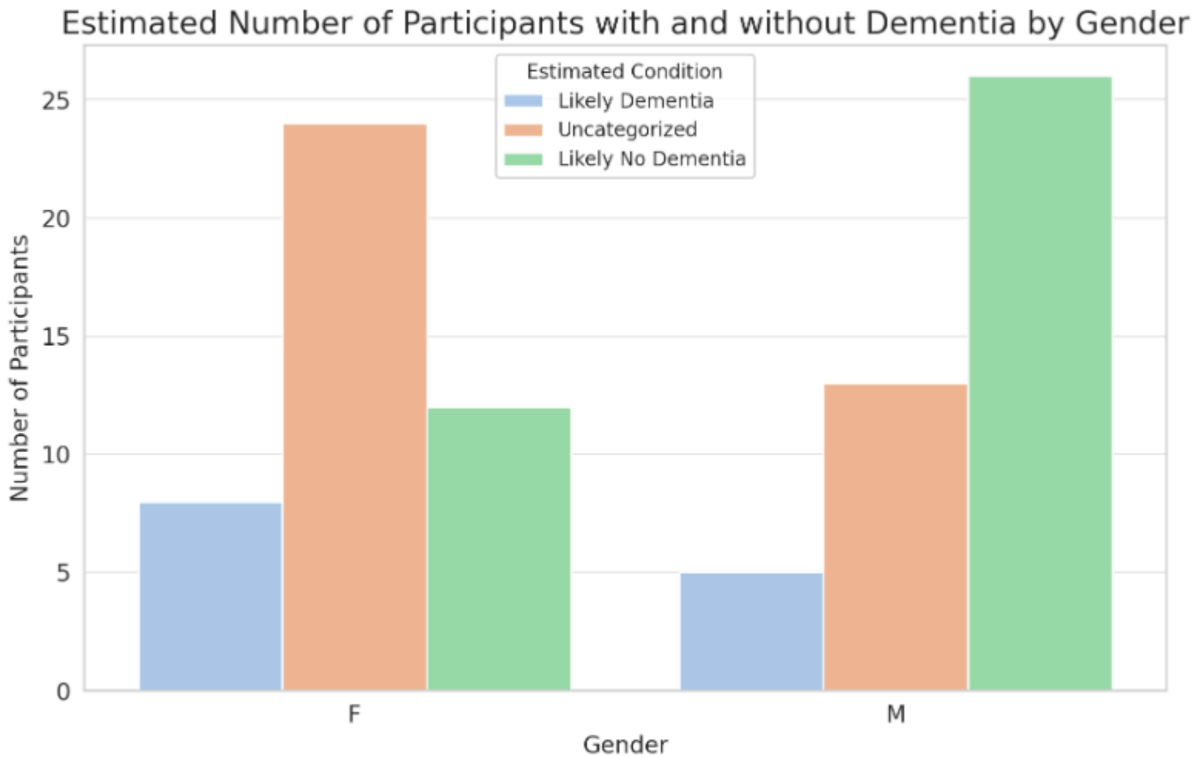

Figure 4.9: Dementia Prediction by Gender

4.3 Comparison of Different Demographic Groups

Figure 4.8 and 4.9 shows the X-axis (Age): Represents the age of participants. The age range observed in the dataset is plotted along this axis. Whereas Y-axis (Number of Participants): Represents the count of participants in each age bin. Pink represents participants who are "Likely No Dementia" (based on MMSE scores between 24 and 30). And blue Represents participants who have "Likely Dementia" (based on MMSE scores between 0 and 17).

The smooth lines (Kernel Density Estimate curves) provide a continuous and smoothed representation of the histogram. These curves can help in visualizing the overall trend in the age distribution for each condition.

Here one can notice that age wise, both conditions (Likely Dementia and Likely No Dementia) are present across a wide age range, but there are certain age bins where one condition might be more prevalent than the other. The peak ages like the pink curve (Likely No Dementia) seems to peak around the mid-60s, indicating a higher concentration of participants in that age range who likely don't have dementia. The blue curve (Likely Dementia) seems more spread out, but there are noticeable peaks, indicating age ranges where dementia is more prevalent. Moreover, there are age ranges where the conditions overlap, indicating that, within those age groups, there are participants who fall into both estimated conditions based on their MMSE scores. Based on the accuracy and MMSE scores results, here's the distribution of participants estimated to have "Likely Dementia" across different age groups:

40-49 years: 0 participants

50-59 years: 3 participants

60-69 years: 7 participants

70-79 years: 3 participants

80-89 years: 0 participants

From the data, the age group 60-69 years has the highest number of participants (7 participants) likely to have dementia based on their MMSE scores.

4.4 Comparison of Results With Other Modalities

Table 4.3: EEG Modality Comparison

Study	Filter	Features	Metrics	Accuracy
Pirrone D [72]	LPF	LDA	K-Fold	DT: 87%, SVM: 89%
Kavita C [73]	LPF	Chi-Square	Voting	DT: 80%, RF: 86%, SVM: 81%
Balea-Fernandz [74]	HPF	PCA	K-Fold	DT: 80%
Giulia Fiscon [75]	DWT/FFT	FT/WT	K-Fold	FDT: 72%, WDT: 83%
Proposed Methodology	BPF/NF	PCA	Clustering	DT: 95%, RF: 95%, SVM: 91%

Table 4.4: IMAGE Modality Comparison

Study	Features	Model	Metrics	Accuracy
Dashtipour D [76]	CNN	Bi-LSTM	K-Fold	83%
Helaly [77]	CNN	SVM	MCC	82%
Aruna & C [78]	ICA	SVM	MCC	79%

Table 4.5: VOICE Modality Comparison

Study	Features	Model	Metrics	Accuracy
Chlasta Wolk [79]	VGGish	CNN	F1 Score	63%
Zhu et al [80]	Wav2vec	BERT	ROC	73%
Weiner [81]	ASR	DNN	ACC	70%

4.5 Discussion

Table 4.3, 4.4 and 4.5 shows different modalities comparison in contrast with proposed methodology. In the EEG modality comparison, the proposed methodology employs a band-pass filter/noise filter (BPF/NF) alongside Principal Component Analysis (PCA) for feature reduction, followed by clustering as a metric. This combination led to remarkable accuracies of 95% for both Decision Tree (DT) and Random Forest (RF), and 91% for Support Vector Machine (SVM). When compared to other studies in the table, the proposed method demonstrates a significant leap in performance. This indicates that the proposed methodology's filter choices and feature extraction techniques are more effective for EEG signal processing and analysis.

The proposed methodology's clustering metric also contributes to its high accuracy. Traditional metrics like K-Fold cross-validation used in other studies are valuable for model validation, but the use of clustering in the proposed methodology likely provides a more nuanced approach to understanding the underlying structure of the data, leading to more accurate model training and prediction.

For voice modality, the table does not specify the features or models used in the proposed methodology, making a direct comparison challenging. However, if we infer that the same innovative approach taken in the EEG modality is applied to voice, the success in EEG suggests that a similar strategy could be highly effective in voice modality as well. The accuracies reported in the voice studies with other methodologies though impressive, but do not reach the high benchmark set by the proposed methodology in EEG.

It is worth noting that the proposed methodology's success also hints at the importance of an integrated approach to data analysis in EEG signal processing. By carefully selecting the filtering method to retain crucial signal components and reduce noise, employing PCA for feature reduction to capture the most significant signal characteristics, and using sophisticated machine learning models, the proposed methodology sets a new standard in the field.

In conclusion, the proposed methodology outperforms traditional methods significantly in the EEG modality and likely has the potential to do the same in the voice modality. Its strengths lie in the strategic combination of advanced signal processing techniques and robust statistical methods, providing a roadmap for future research aimed at developing high-accuracy classification systems in EEG signal processing.

Chapter 5

Conclusion and Future Work

This chapter concludes the work done until now and discusses some future research directions in detail.

5.1 Conclusion

In this thesis, we investigated the potential of using EEG signals and machine learning algorithms to detect dementia. The results suggest that features extracted from EEG signals can be used to classify individuals with dementia and healthy controls with high accuracy.
The use of machine learning models such as SVM, RF showed promising results in differentiating between the two groups. Furthermore, the study highlighted the importance of feature selection and extraction to improve the accuracy of the classification model.
Overall, the findings suggest that EEG signals can be a useful tool in the diagnosis and management of dementia, providing a non-invasive and cost-effective alternative to traditional diagnostic methods. However, further research is needed to validate the findings on a larger and more diverse population, as well as to investigate the generalizability of the models across different types and stages of dementia.

5.2 Limitations

Although this research proposed to use EEG signals to diagnose dementia, there are still some limitations. The majority of methods, for instance, train conventional Machine Learning classifiers by extracting features from signals in which are combined within a single neural network is one significant limitation. In particular, we studies train EEG signals separately and then employ majority voting methods, which significantly increases training time is another significant limitation. Also treating both scenarios and task separately achieve suboptimal performance. We also investigated that despite the fact that EEG have produced cutting-edge results in a number of fields, their potential has not been fully utilized in the process of dementia detection using EEG Data.

5.2 Future Work

- The extraction and analysis of new features that are more likely to help in the diagnosis of dementia disease will be the main emphasis of the future study.
- Duplicate and irrelevant features will also be removed from current feature sets to increase the accuracy.
- Using Digital filters or converting Analog signals to Digital signals will also be the future emphasis of the current study.
- Exploring the effectiveness of incorporating additional modalities, such as EEG and fMRI data, with speech and text data in a multimodal transformer-based approach for dementia detection.
- Investigating the use of different transformer architectures, such as GPT, T5 and XLNet, for dementia detection and comparing their performance.

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