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Deep Learning for Electroencephalography (EEG) Signal Analysis in Cognitive Decline Studies

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Master of Applied Statistics and Data Science

by

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ABSTRACT OF THE THESIS

Deep Learning for Electroencephalography (EEG) Signal Analysis

in Cognitive Decline Studies

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Master of Applied Statistics and Data Science

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Professor Ying Nian Wu, Chair

Electroencephalography (EEG) is a non-invasive technique that records brain activity with high temporal resolution and is cost-effective compared to other neuroimaging methods. It can detect subtle neural activity changes before clinical symptoms appear, enabling early intervention and treatment. This study aims to develop deep learning models capable of classifying EEG recordings from healthy individuals, Alzheimer's disease (AD) patients, and frontotemporal dementia (FTD) patients. EEG data and participant metadata (age, gender, cognitive scores) are integrated to enhance model prediction accuracy. Three approaches are evaluated: a Multilayer Perceptron (MLP) trained on power spectral density (PSD) features, a ResNet1D (One-Dimensional Residual Network), and a custom convolutional neural network (CNN) with an attention mechanism. The models were evaluated using leave-one-participant-out (LOPO) cross-validation. ResNet1D achieved the highest accuracy (84.41%), outperforming the MLP with feature extraction (76.14%) and CNN with attention (83.35%), with all models demonstrating balanced precision and recall.

The thesis of Smruthi Meesala is approved.

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LIST OF ABBREVIATIONS

Abbreviation	Full Term
EEG	Electroencephalography
AD	Alzheimer’s Disease
FTD	Frontotemporal Dementia
HC	Healthy Control
MLP	Multilayer Perceptron
PSD	Power Spectral Density
ResNet1D	One Dimensional Residual Network
CNN	Convolutional Neural Network
MMSE	Mini Mental Score Examination
LOPO	Leave One Participant Out
EDA	Exploratory Data Analysis
SVM	Support Vector Machine
KNN	K-Nearest Neighbors
RNN	Residual Neural Network
LSTM	Long Short-Term Memory
ReLU	Rectified Linear Unit
SGD	Stochastic Gradient Descent
AR	Autoregressive
ICA	Independent Component Analysis
LDA	Linear Discriminant Analysis
PCA	Principal Component Analysis
MCI	Mild Cognitive Impairment

CHAPTER 1

Introduction

Electroencephalography (EEG) is a non-invasive technique that records electrical activity in the brain through small electrodes attached to the scalp. These electrodes capture minuscule electrical pulses generated when neurons communicate, revealing patterns of brain activity. The recorded patterns of brain waves help doctors diagnose conditions such as epilepsy, sleep disorders, cognitive disorders and brain tumours. Due to its exceptional temporal resolution, EEG provides crucial real-time insights into neural dynamics, making it an indispensable tool in clinical diagnostics and neuroscience research.

Neurodegenerative diseases, such as Alzheimer's disease (AD) and frontotemporal dementia (FTD), poses a significant public health challenge as the global population ages. The lifetime risk of developing dementia in the US after age 55 is estimated at 42%. The number of US adults projected to develop dementia annually is expected to reach 1 million by 2060, almost double the number in 2020 [6]. Early and accurate diagnosis is crucial for effective intervention and management, but differential diagnosis remains difficult in the early stages due to overlapping clinical symptoms and gradual disease progression. Conventional neuroimaging techniques, while informative, are often expensive and not easily scalable for widespread screening. In contrast, EEG offers a cost-effective and accessible alternative that may enable earlier detection of cognitive impairment before structural brain changes become apparent.

The primary objective of this research is to develop deep learning models capable of classifying EEG recordings from healthy individuals, participants with AD, and participants with FTD. This research aims to improve classification accuracy and strengthen EEG-based diagnostic capabilities by leveraging deep learning approaches tailored for time-series data.

This study utilized EEG data from the publicly available dataset hosted on OpenNeuro [13]. Following the dataset creators' recommendation, the preprocessed data from the derivatives folder was used, eliminating preliminary signal preprocessing steps. Participant metadata—such as age, gender, and mini mental state examination scores (MMSE) were integrated with EEG signals to enhance predictive performance. Three modeling approaches will be explored: a Multilayer Perceptron (MLP) trained on extracted power spectral density (PSD) features from the EEG signals, a one-dimensional convolutional neural network based on the ResNet architecture (ResNet1D), and a custom convolutional neural network (CNN) enhanced with an attention mechanism. Data augmentation techniques and regularization methods were implemented to strengthen model robustness. At the same time, leave-one-participant-out (LOPO) cross-validation was used to test how well the model generalizes to new participants.

The potential impact of this study lies in demonstrating that EEG when combined with deep learning techniques, can serve as a powerful tool for the early detection of cognitive decline. By contributing to the established research in this area, our work aims to validate these methods further and address the remaining challenges in their implementation.

Successful outcomes could strengthen the evidence base supporting these techniques in early diagnosis, informing clinical decision-making, and ultimately improving the quality of life for individuals at risk of developing neurodegenerative diseases.

CHAPTER 2

Literature Review

The classification of EEG signals can be challenging due to the complex and noisy nature of the data, as well as the high variation between individuals' brain activity patterns. To address these challenges, various machine learning and deep learning models have been employed to extract relevant features and classify EEG signals with high accuracy [11]. This section provides an overview of the most commonly used models and methodologies in EEG classification tasks.

Traditional machine learning algorithms were widely used in the early stages of EEG classification research [9]. These models typically relied on feature extraction from the raw EEG signals, such as spectral, statistical, or time-domain features. A study used Discrete Wavelet Transform for EEG feature extraction and demonstrated that a Random Forest classifier achieves 98% accuracy for epilepsy diagnosis on the Bonn dataset [3]. Another paper presented an unsupervised approach for automatic epileptic seizure detection using k-means clustering combined with Ensemble Empirical Mode Decomposition, a feature extraction method to isolate meaningful patterns and frequency components [2]. Another approach involved extracting features using an autoregressive (AR) model, followed by dimensionality reduction with Independent Component Analysis (ICA), Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA), and then classifying using a support vector machine (SVM) [8].

While these traditional methods have achieved good performance, they often rely on feature engineering and may not fully leverage the temporal and spatial dependencies present in the EEG data. With the advent of deep learning, more sophisticated architectures have been proposed for automatically extracting features and classifying EEG signals. These models can learn hierarchical features directly from the raw EEG data, eliminating the need for manual feature extraction. CNNs are widely used for their ability to extract spatial hierarchies from data. A deep CNN with separate temporal and spatial filters, which directly used raw EEG signals from electrode pairs over the motor cortex was used to classify motor imagery tasks [12]. Recurrent Neural Networks (RNNs) and Long Short-Term Memory Networks (LSTMs) are well-suited for sequential data and are particularly effective at capturing temporal dependencies in EEG. A deep learning model using an RNN-LSTM architecture was proposed to diagnose schizophrenia from EEG signals, achieving up to 98% accuracy with the full feature set [15]. Residual Network (ResNet) architectures, adapted from computer vision to time-series analysis, are also very effective as they address a key challenge in deep learning – the vanishing gradient problem. A modified ResNet18 model achieved high accuracy on raw EEG-based emotion classification using the SEED dataset, outperforming the original architecture and reducing parameters by over 50% [5]. Recent studies have used hybrid models like CNN-LSTM on EEG signals to analyze emotional stress and mental health conditions such as Post-Traumatic Stress Disorder [4]. These hybrid models combine the strengths of multiple deep learning architectures like convolutional layers to extract spatial patterns and recurrent layers to model temporal dependencies.

While EEG classification methods have been widely explored in various neurological applications such as epilepsy and motor imagery, recent research has increasingly focused on applying these techniques for the early detection of AD. One study proposed a simple yet effective method of using finite impulse response filtering in the time domain to extract power features from EEG frequency bands and use supervised machine learning methods on these features for early detection of dementia-related conditions like Mild Cognitive Impairment (MCI) and AD from healthy controls (HC) [14].

Another study applied a continuous wavelet transform to convert resting-state EEG signals into topographical images, which were then classified using an optimized AlexNet CNN [10].

Building on these advancements, this study applies deep learning methods to the OpenNeuro dataset consisting of EEG recordings of AD, FTD, and HC subjects. While MLP models have been explored in previous studies, this work explores two approaches namely ResNet1D and CNN with an attention mechanism. By applying these diverse models, the study aims to improve classification accuracy and provide a more comprehensive analysis of EEG patterns across different dementia types.

CHAPTER 3

Data and Preprocessing

3.1 Dataset Overview

The dataset contains EEG recordings of 36 AD patients (Group A), 23 FTD patients (Group F), and 29 healthy control subjects (Group C). The 88 participants were evenly distributed by gender (44F, 44M). The Mini-Mental State Examination (MMSE) score is also reported for each subject. The MMSE is a set of 11 questions used by doctors and health professionals to check for cognitive impairment [7]. It tests different areas of cognitive function, like orientation, registration, attention, calculation, recall, and language. The maximum score is 30. A score of 23 or lower is indicative of cognitive impairment.

3.2 Preprocessing Overview

The EEG recordings included signals from 19 scalp electrodes (Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, and O2) and two reference electrodes, positioned according to the international 10–20 system. They were recorded at a sampling rate of 500 Hz, with a signal resolution of 10 μV per millimeter. In accordance with the dataset creators' guidelines, the preprocessed EEG data located in the derivatives folder was used for this study. As a result, no additional preliminary signal preprocessing was performed. The data was distributed in .set file format (EEGLAB-compatible), and the specific preprocessing steps are detailed in the original paper.

3.3 Feature Extraction for MLP

For the MLP classifier, feature extraction was performed based on spectral power characteristics. Each participant's EEG signal was segmented into 4-second epochs with 50% overlap. For each epoch, the relative power within the five standard frequency bands – Delta, Theta, Alpha, Beta, and Gamma was computed using Welch's method. Table 1 below represents the frequency range of different EEG bands, along with descriptions of the physiological processes they are associated with [1]. The relative power was calculated by normalizing the band-specific power by total power in the 0.5- 45 Hz range. Band power features were then averaged across all epochs to obtain a single feature vector per participant, resulting in five spectral features per subject.

Frequency Band	Range (Hz)	Physiological Significance
Delta	0.5 – 4	Associated with deep sleep, restorative states
Theta	4 – 8	Linked to drowsiness, light sleep, and relaxation
Alpha	8 – 13	Present during relaxed, wakeful states, often with closed eyes
Beta	13 – 25	Observed during active thinking, focus, and problem-solving
Gamma	25 – 45	Cognitive processing and higher mental activity

Table 1: EEG Frequency Bands and their Physiological Significance

3.4 Data Preparation for ResNet1D and CNN

For the ResNet1D and CNN architectures, the continuous EEG recordings were first downsampled from the original 500 Hz sampling rate to 128 Hz to reduce computational load. The downsampled signals were then segmented into overlapping epochs of 4 seconds duration with 50% overlap, creating multiple epochs per participant. The participant metadata, including group label, age, gender, and MMSE score, were appended to each EEG epoch and used as additional input features during model training.

CHAPTER 4

Exploratory Data Analysis (EDA)

4.1 Age Distribution of Participants

The age distribution of participants in the dataset shows that the majority are concentrated in the 60s and 70s. The range of ages from 60 to 65 has the highest count, with 25 participants, followed by the 70 to 75 age range, which includes 21 participants. The 75 to 80 age range has 12 participants, while the younger age groups, 45 to 50 and 50 to 55, have only 2 participants. This distribution indicates that most participants are older, peaking in the 60 to 70 age range, and fewer participants in the younger age groups.

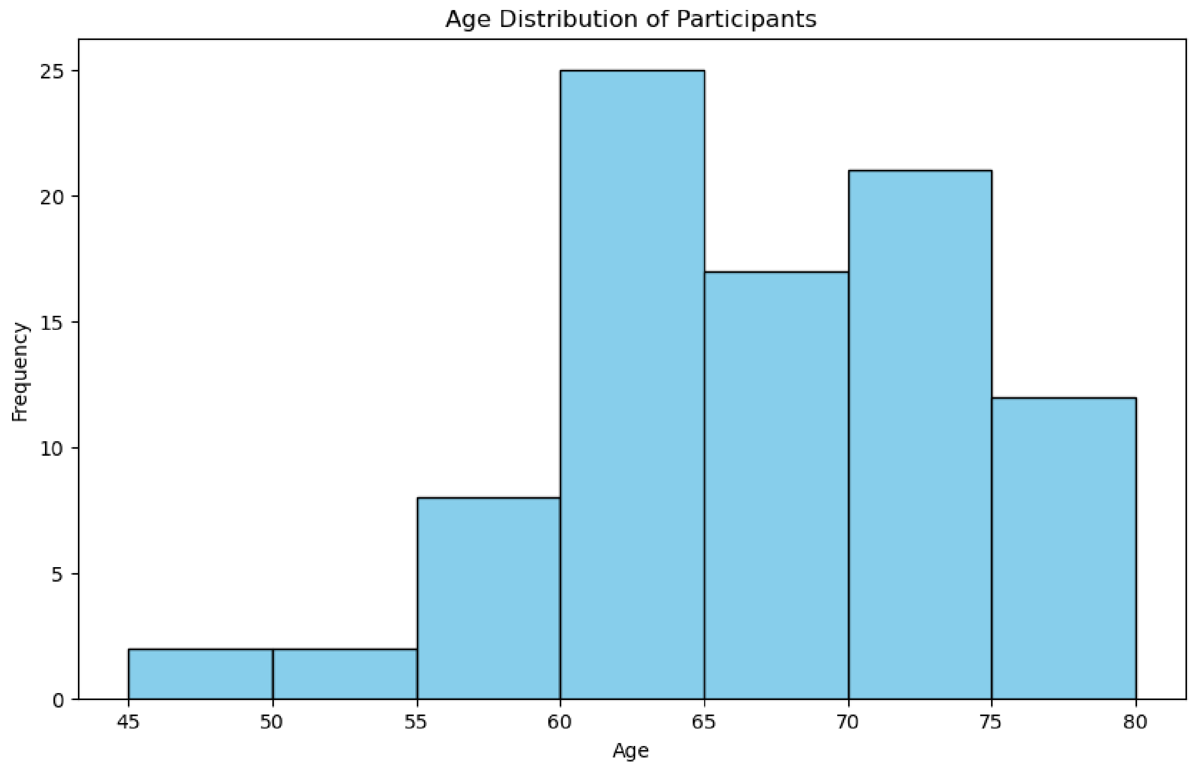

Figure 1: Distribution plot of Age of Participants

4.2 Age Distribution across Groups

The age distribution across the three groups shows some notable differences. Group A has the highest mean age of 66.4 years with a moderate age spread. Group C is slightly older on average at 67.9 years but with a narrower age range. Group F is the youngest group, with a mean age of 63.7 years, but has the broadest age distribution.

Group	Mean	Std Dev	Min	Max
A	66.39	7.89	49	79
F	63.65	8.22	44	78
C	67.89	5.40	57	78

Table 2: Summary of Age Statistics by Group

4.3 MMSE Score Distribution of Participants

The MMSE score distribution shows that most participants score above the threshold typically considered indicative of cognitive impairment (MMSE < 23), with the majority of participants falling in the higher score ranges. However, this distribution may not fully capture early-stage cognitive decline in groups like AD or FTD, where individuals may still score above the impairment threshold. This is where EEG analysis becomes particularly valuable, as it can detect subtle brain activity changes even when MMSE scores remain within normal ranges. While MMSE provides a snapshot of cognitive function, EEG offers a more sensitive and earlier indicator of brain dysfunction, helping to detect and differentiate early-stage dementia more accurately.

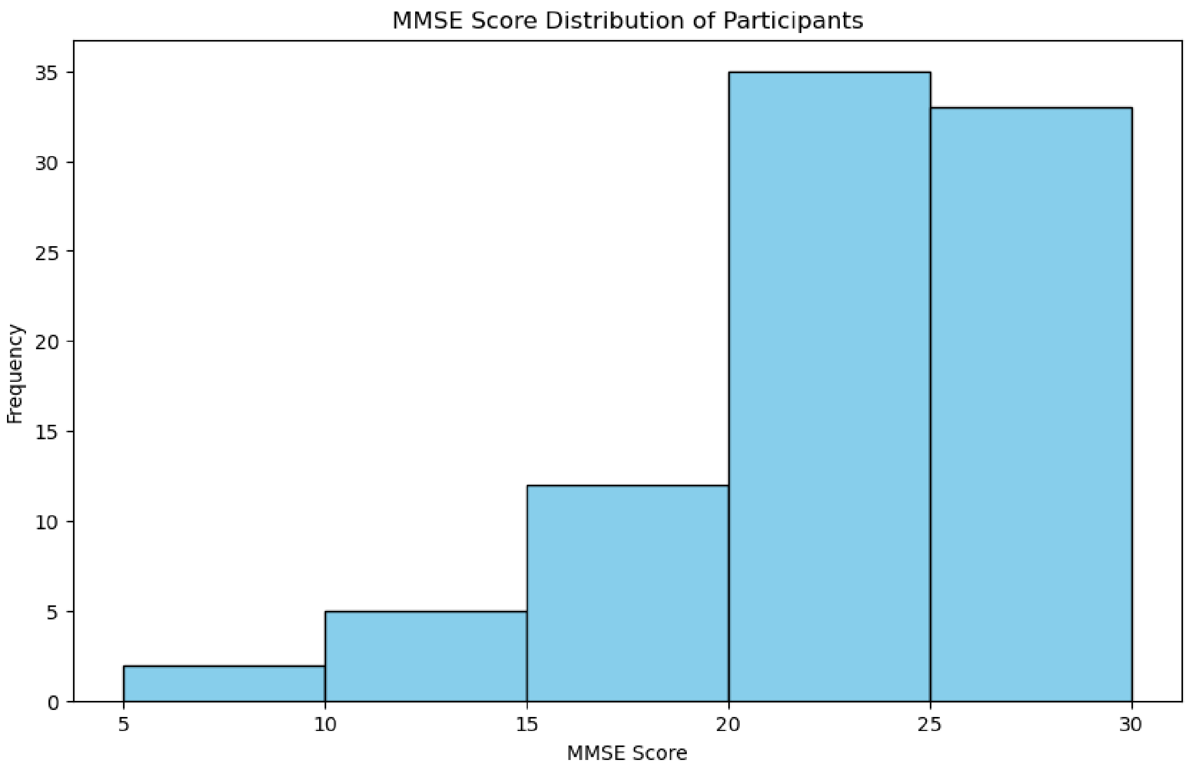

Figure 2: Distribution plot of MMSE scores of participants

4.4 Distribution of MMSE scores across Groups

Table 3 summarizes the MMSE scores across the three groups. Group A showed a mean MMSE score of 17.75, indicating significant cognitive impairment typical of AD. Group F had a mean MMSE score of 22.12, reflecting mild to moderate cognitive impairment. FTD and AD are distinct neurodegenerative disorders affecting different brain regions and have different symptoms. While both are types of dementia, FTD begins with early behavioral changes or language problems, whereas AD typically begins with memory impairment. Group C had an MMSE score of 30 with no variability, suggesting preserved cognitive function among healthy controls.

Group	Count	MMSE Mean	Std Dev	Min	Max
A	36	17.75	4.5	4	23
F	23	22.117	2.64	18	27
C	29	30	0	30	30

Table 3: Descriptive statistics of MMSE scores by Group

4.5 Distribution of MMSE scores across Age

The MMSE scores across age groups generally show mild cognitive impairment, with younger groups scoring higher on average. The 45-50 group displayed relatively preserved cognitive function, while older groups, especially those over 60, showed mild impairment. The scores in the older cohorts varied more, indicating a wider range of cognitive performance, with some individuals showing a more significant decline. Overall, the data suggests that mild cognitive impairment increases with age, particularly in the older participants.

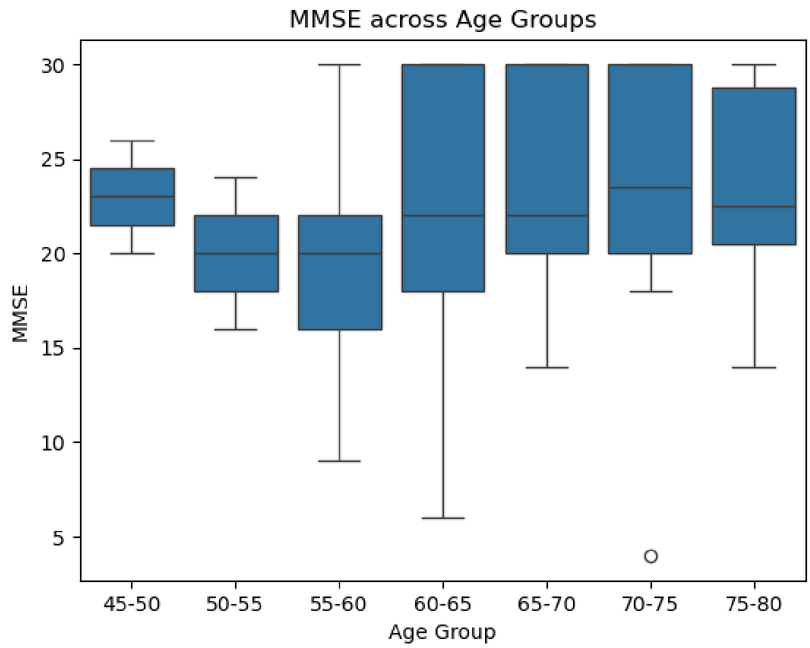

Figure 3: Distribution plot of MMSE across Age Groups

4.6 Distribution of Gender across Groups

Figure 4 shows the gender distribution across the groups. It highlights a higher proportion of females in the AD group, while males are more prevalent in the HC and FTD groups.

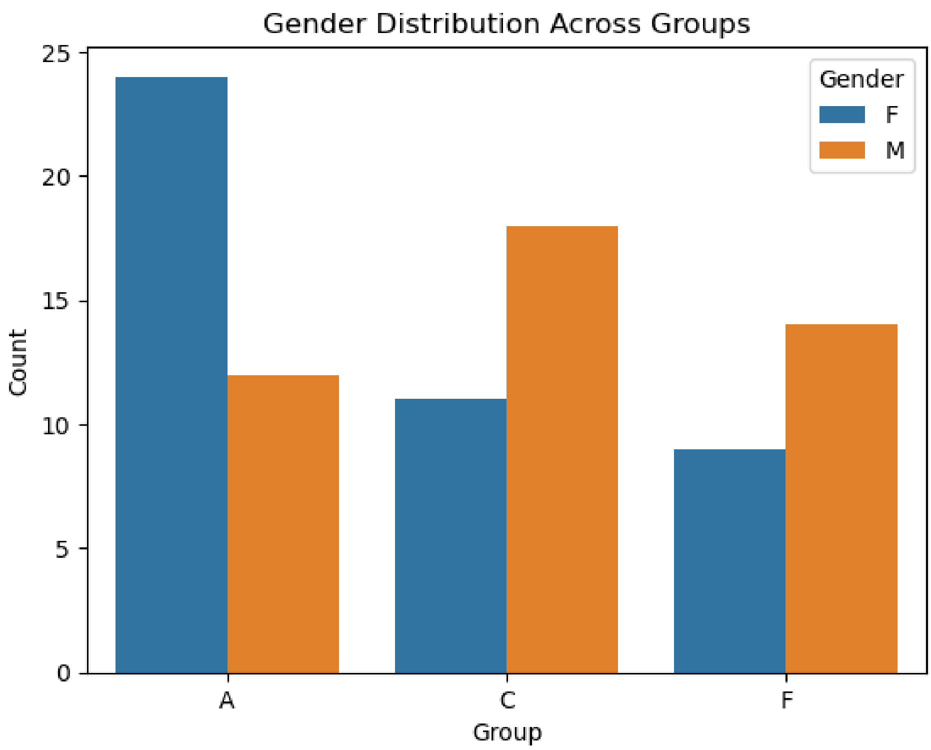

Figure 4: Distribution plot of Gender across Groups

4.7 Analysis of Frequency Band Power across Groups

The box plots for each frequency band (Delta, Theta, Alpha, Beta, Gamma) show the distribution of relative power across the three groups. For Delta and Theta, Group A slightly higher values compared to Groups C and F. Alpha relative power is fairly consistent across all groups. In contrast, Beta and Gamma relative power are slightly higher in Group F, suggesting subtle differences in brain activity. Overall, these differences provide insights into the brain's activity patterns across conditions, which may aid in differentiating between AD, FTD, and HC.

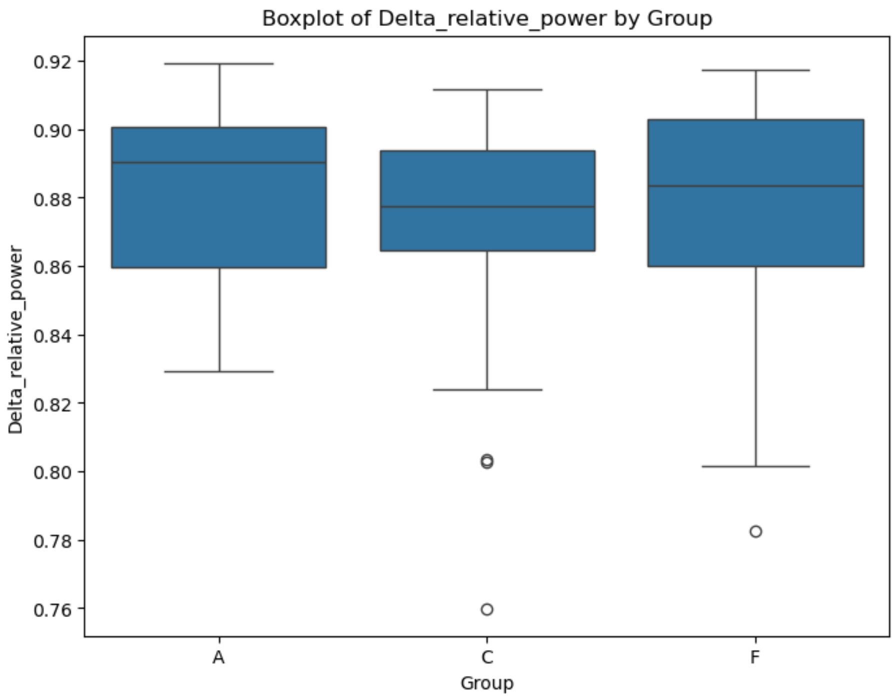

Figure 5: Delta Relative Power across Groups

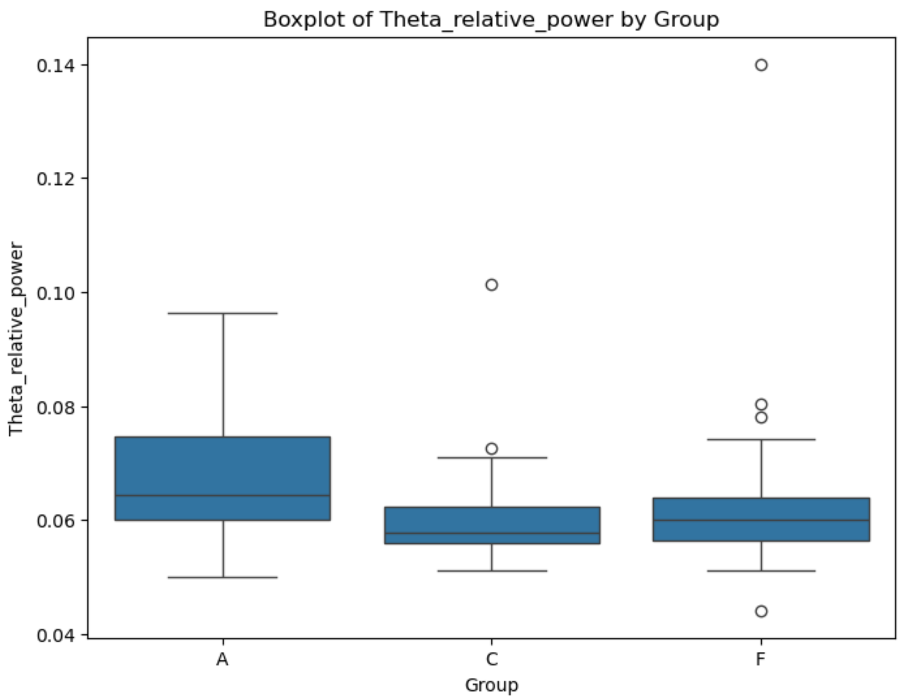

Figure 6: Theta Relative Power across Groups

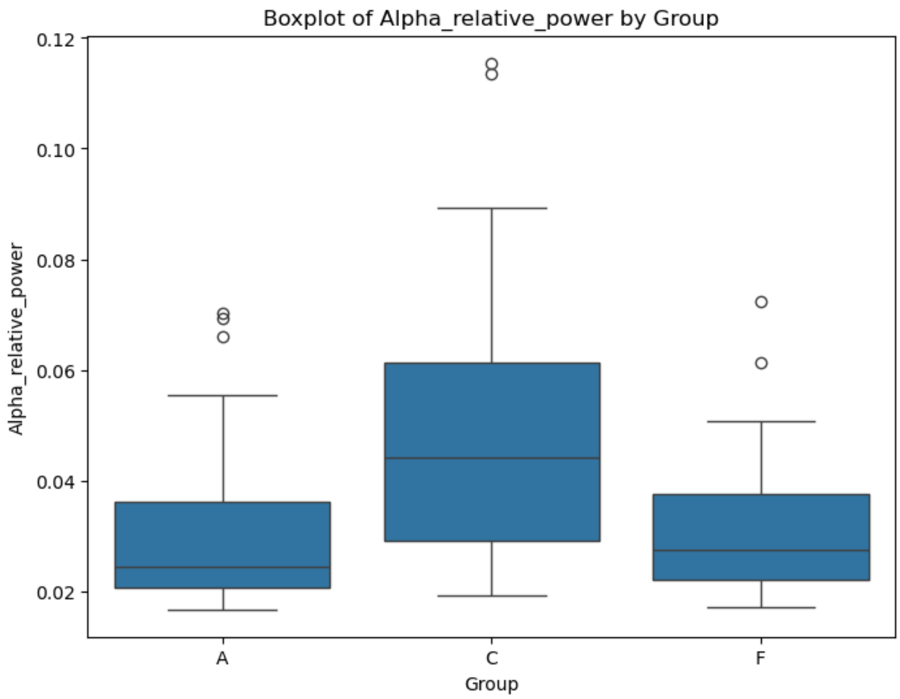

Figure 7: Alpha Relative Power across Groups

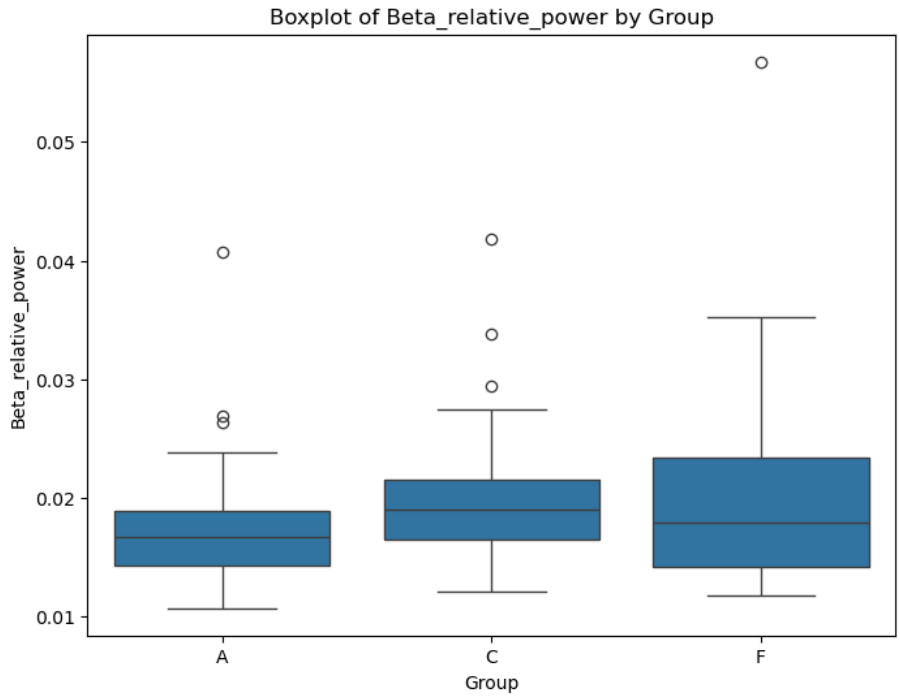

Figure 8: Beta Relative Power across Groups

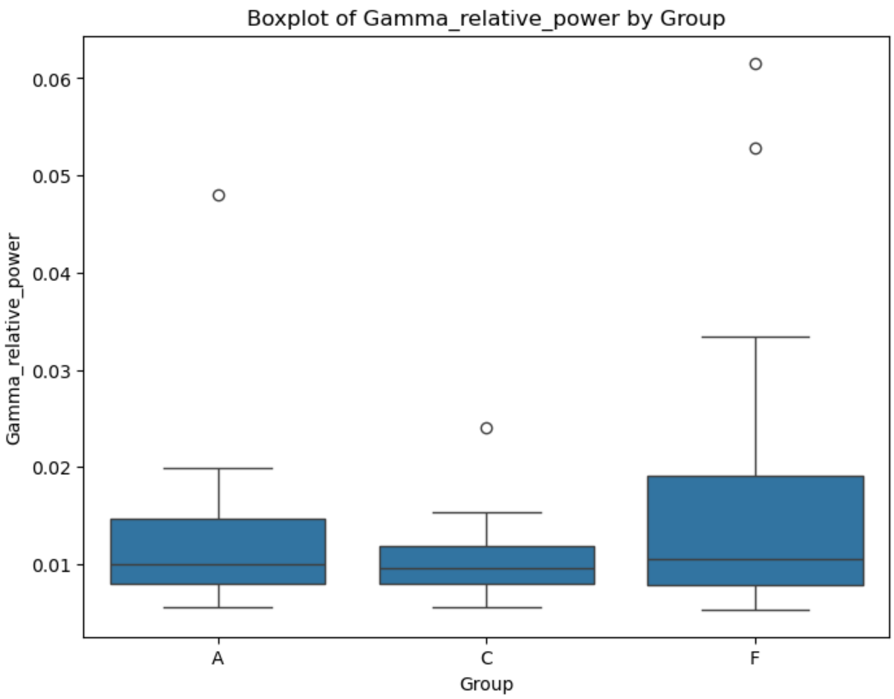

Figure 9: Gamma Relative Power across Groups

CHAPTER 5

Methodology

5.1 Multilayer Perceptron (MLP) Architecture

The MLP was chosen for its ability to model complex, non-linear relationships in spectral power features and participant-specific metadata. Additionally, MLPs offer flexibility in tuning hyperparameters and are computationally efficient for relatively smaller datasets.

The input to the MLP consisted of extracted spectral band power features and participant metadata information – age, gender, and MMSE score. Before model training, the gender variable was one-hot encoded, and other input features were standardized using z-score normalization. The target labels corresponding to the participant groups (A, F, and C) were label encoded into numerical values.

The MLP architecture had a single hidden layer with 200 neurons, utilizing the Rectified Linear Unit (ReLU) activation function. The model was optimized using stochastic gradient descent (SGD) with a learning rate of 0.005, momentum of 0.95, and an L2 regularization coefficient of 0.01 to prevent overfitting. The model was trained for a maximum of 1000 iterations to achieve convergence stability.

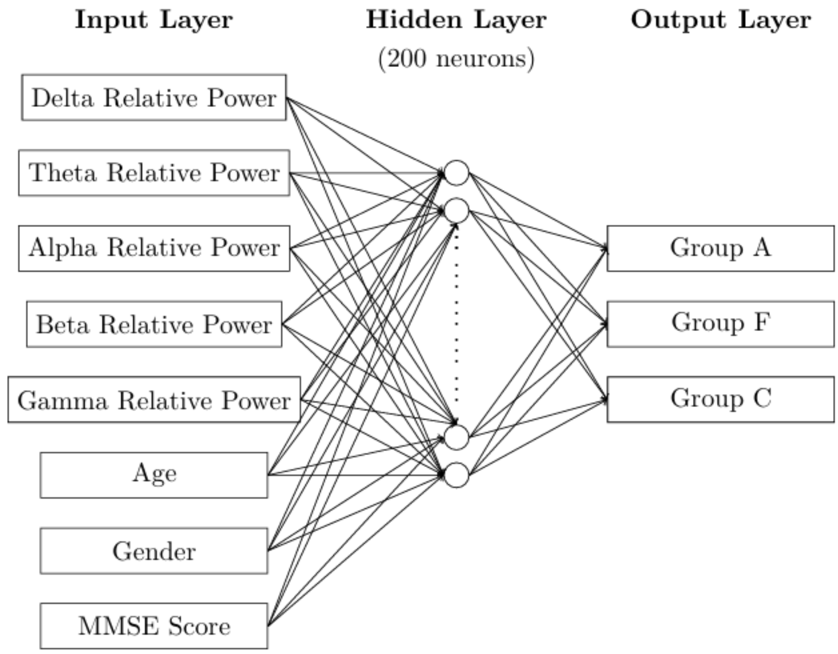

Figure 10: Architecture of MLP model

Model evaluation was performed using LOPO cross-validation, where each participant was systematically used as a held-out test set while the remaining participants formed the training set. This approach provided a reference against which the performance of deeper architectures (ResNet1D and CNN) could be compared.

5.2 ResNet1D Architecture

Pretrained ResNet models are usually designed for image data and cannot be used on EEG data. ResNet1D is a deep convolutional neural network specifically designed for one-dimensional sequential data, making it particularly well suited for EEG signal analysis. It applies convolutional filters that slide over the EEG time series, learning local temporal patterns across channels. These filters capture short-term signal fluctuations, such as oscillatory bursts and transients, which are often clinically significant. By stacking multiple convolutional layers, the model progressively builds more abstract, global representations, enabling the detection of complex patterns across longer time intervals. A key feature of

ResNet1D is its use of residual connections, which bypass one or more layers by directly adding the input of a block to its output. These connections help mitigate the vanishing gradient problem, allowing deeper networks to learn efficiently. For EEG data, which is high-dimensional, noisy, and varies over time, ResNet1D can extract robust temporal features without the need for extensive preprocessing, making it highly effective for identifying and distinguishing between different neurophysiological conditions.

Further preprocessing was done on EEG data where the epochs were flattened and normalized before being reshaped back to their original dimensions (19 channels x 512 timepoints). Age and MMSE scores were standardized independently, while gender was encoded as an integer without scaling. The model was designed with three residual blocks, each containing two 1D convolutional layers with kernel size 3, stride 1, and padding 1, followed by ReLU activations and a residual connection. This design enables the model to retain low-level temporal information across layers and facilitates deeper training without vanishing gradients. Across the residual blocks, the number of convolutional filters increased progressively from 64 to 128 and finally to 256 channels, allowing the network to capture increasingly complex temporal dependencies within the EEG signals hierarchically. A dropout layer with a 50% dropout rate was applied after each residual block to improve generalization and prevent overfitting.

Following the residual blocks, global average pooling was used to summarize each feature map into a single value, creating a fixed-size feature vector that does not depend on the EEG signal's length. The pooled EEG feature vector was then concatenated with the participant's standardized age, MMSE score, and gender information and passed through a fully connected layer with 512 neurons and ReLU activation. Finally, a second fully connected layer projected the 512-dimensional representation into the three output classes corresponding to each group.

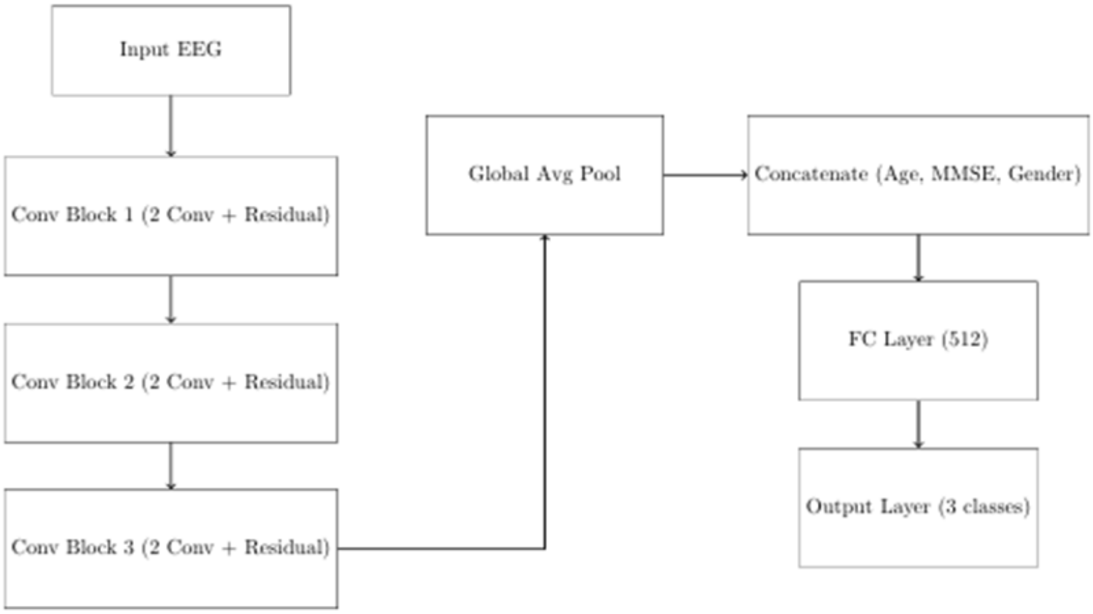

Figure 11: Architecture of ResNet1D model

The cross-entropy loss function was used during training, and the Adam optimizer was employed with a learning rate of 0.001 and weight decay of $1e^{-4}$. Additionally, Gaussian noise (σ=0.1) was added to EEG inputs during training for data augmentation, aiming to improve model generalization. Each LOPO iteration was trained for five epochs with a batch size of 32.

5.3 CNN with Multi-Head Attention

EEG data contains subtle, time-dependent patterns, and using attention mechanisms can help capture long-range dependencies that simple convolutions might miss. The model first applied convolutional layers to extract local patterns from EEG signals. Then, instead of limiting the model to capturing only local dependencies, a multi-head attention mechanism is introduced, allowing the model to simultaneously attend to the entire sequence. This helps the model identify the relationship between two distant events – for example, recognizing that a spike at one moment may be linked to a dip several seconds later. Additional convolutional layers are then applied to further extract and refine complex patterns uncovered by the attention process.

The model starts with two convolutional blocks that extract spatial and temporal features from the EEG signals, followed by a multi-head attention layer to capture long-range dependencies in the data. After feature extraction, global average pooling is applied to reduce the dimensionality and retain important information. The model then concatenates the extracted EEG features with normalized metadata, such as age, MMSE, and gender, which are passed through fully connected layers to predict the group classification.

To improve generalization, data augmentation is applied during training by adding random noise to the EEG input, simulating variability in the data and helping the model generalize better to new, unseen examples. The training process utilizes the Adam optimizer with a learning rate of 0.001 and weight decay of $1e^{-4}$ to prevent overfitting.

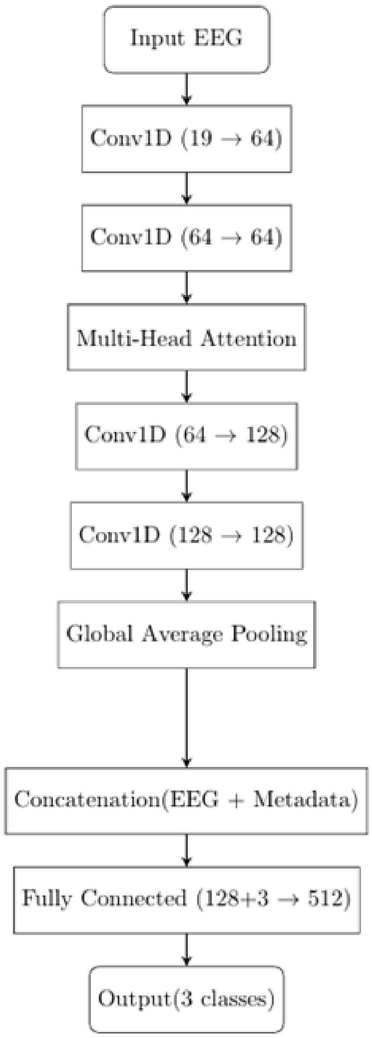

Figure 12: Architecture of Custom CNN with an Attention Mechanism

CHAPTER 6

Model Evaluation and Results

Leave-One-Patient-Out (LOPO) evaluation was employed in this study to assess the performance of the models while minimizing the potential for overfitting and ensuring that the models generalize well to unseen data. In LOPO cross-validation, each participant in the dataset serves as a test case, while the remaining participants' data are used for training. This approach allows for a more robust evaluation, as it simulates real-world scenarios where new, unseen patients must be classified based on the model's ability to generalize from prior training.

The MLP with feature extraction achieved an accuracy of 76.14%, with a good balance between precision and recall. The ResNet1D model outperformed the others, reaching an accuracy of 84.41% and consistently strong precision and recall values around 84%. The CNN with attention also showed strong performance, with an accuracy of 83.35% and good precision and recall scores. The ResNet1D model provided the highest classification performance, though both ResNet1D and CNN with Attention demonstrated strong potential for classifying EEG data.

Model	Accuracy	Precision	Recall	F1-Score
MLP with feature extraction	76.14%	75.66%	76.14%	75.88%
ResNET1D	84.41%	84.13%	84.45%	84.12%
CNN with Attention mechanism	83.35%	83.28%	83.83%	83.40%

Table 4: LOPO Cross-Validation Results

Table 5 presents the classification accuracy of three models across the three groups. The MLP with feature extraction achieved 72.22% accuracy for Group A, 52.17% for Group F, and a perfect classification of 100% for Group C. ResNet1D demonstrated higher overall performance, with accuracies of 86.36% for Group A, 62.43% for Group F, and 98.64% for Group C. Similarly, the CNN model with attention mechanism achieved 86.32% for Group A, 60.87% for Group F, and 96.55% for Group C. Both ResNet1D and custom CNN with attention outperformed the MLP model, particularly in distinguishing AD patients. However, classification performance for the FTD group remained relatively lower across all models, suggesting greater difficulty distinguishing this group based on the available features.

Model	Group A	Group F	Group C
MLP with feature extraction	72.22%	52.17%	100%
ResNet1D	86.36%	62.43%	98.64%
CNN with Attention	86.32%	60.87%	96.55%

Table 5: Classification accuracy of MLP, ResNet1D and CNN models across groups

CHAPTER 7

Conclusion and Future Work

In this study, we explored the application of various deep learning models for classifying EEG data, with a focus on understanding cognitive disorders such as Alzheimer's and frontotemporal dementia. The primary models evaluated include a multilayer perceptron (MLP) trained on power spectral density (PSD) features, a one-dimensional ResNet-based convolutional neural network (ResNet1D), and a custom CNN model incorporating an attention mechanism. Through rigorous training and evaluation, we observed that convolutional architectures, such as the ResNet1D and CNN with attention, provided robust performance in classifying EEG patterns, effectively leveraging both temporal and spatial features of the data. Additionally, including metadata, such as age, gender, and MMSE scores, further enhanced the model's performance.

Overall, the results emphasize the potential of deep learning models in EEG-based classification tasks. These models provide high classification accuracy and offer insight into the underlying structure of EEG data, which is crucial for early diagnosis and monitoring of neurodegenerative diseases.

While the current results are promising, several avenues for future work remain. It was challenging to differentiate between FTD and AD due to overlapping patterns and similar EEG characteristics, so we need more specialized models. One area of improvement could be the exploration of more advanced model architectures, such as transformers or hybrid models combining convolutional and recurrent layers, to capture both spatial and temporal dependencies in the EEG data more efficiently.

Additionally, incorporating other demographic and clinical features like genetic information and neuropsychological tests could improve model generalization and clinical applicability. Lastly, exploring real-time classification systems and testing these models in clinical settings would validate their utility in diagnostic and therapeutic contexts, potentially leading to automated systems for early disease detection and personalized treatment plans.

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