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Deep Learning for the Detection of Dementia by Using Brain Mapping Images

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***Abstract*—Dementia, a progressive neurodegenerative condition manifesting in various forms, impacts a considerable portion of the population, particularly the elderly. Electroencephalography (EEG) has been used as a promising instrument for the prompt identification and categorization of dementia types, offering substantial advantages through its fast diagnostic capabilities. Despite its inherent benefits, the use of EEG for dementia classification as well as its performance are still not satisfactory compared to its extensive application in other domains. This study aimed to build a Deep Learning (DL) framework for the classification of Alzheimer's disease (AD) and frontotemporal dementia (FTD) with a healthy control (HC) group by using resting-state scalp EEG signals. For this, pre-processed EEG recordings were divided into 4-second periods, and power-based features from each EEG frequency band were extracted using the Welch method. Following the statistical analysis of the five frequency bands, the three bands showing the most significant differences were selected. Then, colorful 2-D brain mapping images were constructed using these features via the Azimuthal equidistant projection (AEP) technique. The generated image datasets were used for classification through the MobileNetV2 model. The achievement of a 97% success rate through the AD/HC classification, as well as a 96% success rate through the AD/FTD classification, possesses promise within the context of the numerous successful studies documented in the literature.**

***Index Terms*—Dementia, EEG, Transfer Learning, AEP**

I. Introduction

Neurodegenerative diseases are caused by structural and functional degeneration or death of nerve cells [1]. Dementia, one of these diseases, is a general name given to many diseases with different varieties that occur with anamneses. It comprises a variety of subtypes and is commonly observed in the elderly demographic [2]. According to World Health Organization information, there are more than 55 million cases of dementia worldwide, which continues to increase every year [3]. This highlights the importance of early diagnosis and intervention.

AD is the most common cause of dementia characterized by senile plaques, neuritic tangles, and progressive neuronal loss, which causes impairment in cognition and memory, and progressive deterioration in the ability to perform daily living activities [4]. FTD is a type of dementia characterized by progressive deficits in behavior, executive function, or language, and can be confused with many psychiatric disorders due to its distinctive behavioral features [5]. FTD is also frequently misdiagnosed as AD [6]. There are several available neuroimaging instruments to possibly detect dementia, however, these instruments' high costs indicate a major drawback. Furthermore, disorders like AD and FTD cannot be detectable before visible deterioration takes place in the brain. EEG has become the most common method used in measuring brain activity due to its easy applicability, accessibility, and affordability [7]. EEG reflects electromagnetic waves produced by cortical neuron interaction. EEG can be used to study neuron populations indirectly [8]. Anomalies such as slowing down of EEG rhythms, loss of synchronization between pairs and electrodes, and loss of complexity can be observed in the EEG signals of dementia patients. In particular, it has been observed that AD slows down EEG signals [9]. As a result of such studies, it has been revealed that EEG signals can be an important tool in distinguishing types of dementia.

The growth of diverse medical data modalities has engendered the widespread adoption of computer-assisted systems. Several studies are presented for the classification of dementia diseases that may help doctors with early diagnosis. Numerous Machine Learning (ML) studies are noticeable when the use of EEG for the classification of dementia, particularly AD and FTD, is investigated. In the field of ML research, there are different feature extraction discoveries such as time-frequency analysis [9], statistical feature analysis [10], connectivity features analysis [11], as well as discoveries that offer new methods for feature extraction [12].

Due to DL's ability to extract complex information from various types of data, there is a growing interest in leveraging DL techniques to process and analyze EEG signals related to the onset of dementia. Many methods for extracting information from EEG signals are available in these studies. In addition to studies that extract features from signals through model layers, the extraction of information through handcrafted methods and the use of visual representations of these features have become popular in classification studies. A DL model developed by

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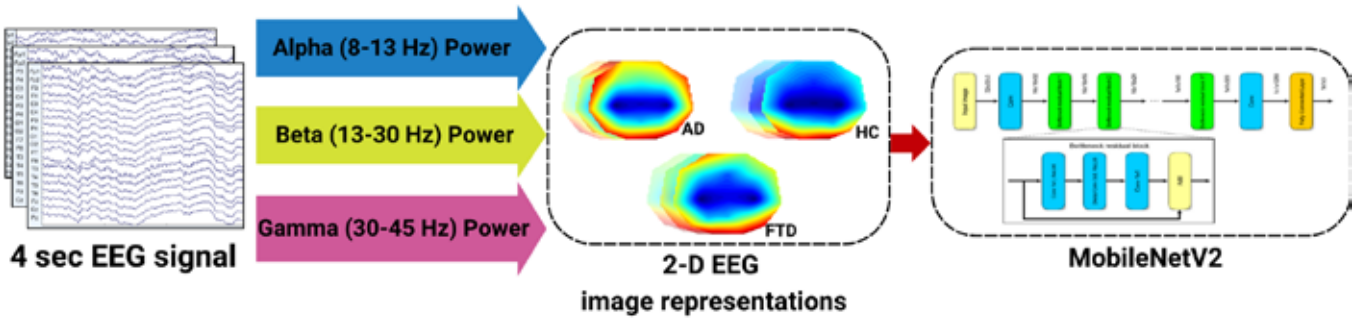


Fig. 1. Flowchart of the proposed method for dementia classification from EEG signals.

Ieracitano et al. [13] was achieved to classify AD, MCI, and HC by utilizing a 19-channel EEG signal. In the data pre-processing step, Power spectral density (PSD) images were generated from signals of EEG channels, and the images were classified with the Convolutional Neural Network (CNN) model. In the DICE-Net model created by Miltiadous et al. [14], AD and FTD were classified separately. Relative Band Power (RBP) and Spectral Coherence Connectivity (SCC) features were used to create image-like representations and an 83% success rate for AD/HC classification was achieved for classification. Using the same dataset and employing image representations of signals with a novel Fourier transform, Amer et al. [15] utilized GoogleNet for classification. As a result of the study, the method was very successful across different datasets, especially in AD/HC classification, where it achieved a 95% success rate. In an alternative DL-based study conducted by Zhou et al. [16], leveraging the EEG-Net model formulated by Lawhern et al. [17], the primary objective was to identify an appropriate data generation approach for AD/HC classification of EEG. The highest success rate as a result of the AD/HC classification model was 93%.

Upon a thorough examination of the literature, particularly regarding research that investigated the classification of FTD, the OpenNeuro dataset [18] was observed to be the most often utilized dataset. Each study employing this dataset differs depending on the feature extraction method used. Moreover, 2-dimensional EEG images derived from different time, frequency, or time-frequency (TF) analyses were used as input for the DL models. Spatial information which includes information such as electrode placement was mostly not considered.

In this study, the Open-Neuro open-source EEG signal dataset [18], which includes AD, FTD, and HC group data, was used. EEG image representations which cover the spatial, spectral, and temporal information of the EEG were generated from the features obtained through the selected three frequency bands as a result of statistical analysis. Then, CNN-based classification models were utilized to accurately detect dementia.

II. Materials and Methods

Our approach is summarized in Figure 1 as feature extraction for dementia types using EEG data, feature analysis for 2-D image generation, and classification tasks using transfer learning with CNN models.

A. Dataset and Pre-processing

The dataset consists of EEG recordings obtained from the 2nd Neurology Department of AHEPA General University Hospital in Thessaloniki [18]. It includes data from 88 individuals, divided into three groups: 36 with AD, 23 with FTD, and 29 with HC. An EEG device with 19 scalp electrodes was used for signal acquisition. All EEG signals were recorded according to the clinical protocol while participants were in a seated position, relaxed, and with their eyes closed. The initial filter setting was 0.5-60 Hz, and the sampling rate was 500 Hz.

The dataset underwent pre-processing procedures to eliminate a variety of artifacts. Firstly, a Butterworth band pass filter was applied to the raw signals within the frequency range of 0.5-45 Hz. Subsequently, the Artifact Subspace Reconstruction (ASR) routine, which is an EEG artifact correction method, was applied to the signals. Independent Component Analysis (ICA) was performed on the 19 channel EEG signals, transforming them into 19 independent components using the RunICA algorithm. An automatic classification routine called 'ICLabel' in the EEGLAB platform was used to identify and discard ICA components classified as 'eye artifacts' or 'muscle artifacts'. After pre-processing, the signal sampling rate was downsampled from 500 Hz to 250 Hz. The resulting dataset was used for feature extraction and further analysis. Finally, the signals were segmented into 4-second intervals without overlap to yield a greater number of images from each EEG signal. Leveraging the entirety of the data collected from 88 subjects across 19 electrode positions, segments comprising 1000 data points from each subject were extracted for subsequent analysis.

B. Feature Extraction

In classification studies, feature extraction is an important step that ensures obtaining substantial information in the dataset. In our study, as reported in many feature extraction studies, commonly used frequency band features were examined and EEG image representations were created using appropriate features selected as a result of the statistical analysis test.

1) Frequency Band Powers: One prevalent approach for EEG data analysis involves the examination of the signal across distinct frequency bands, including delta (1–4 Hz), theta

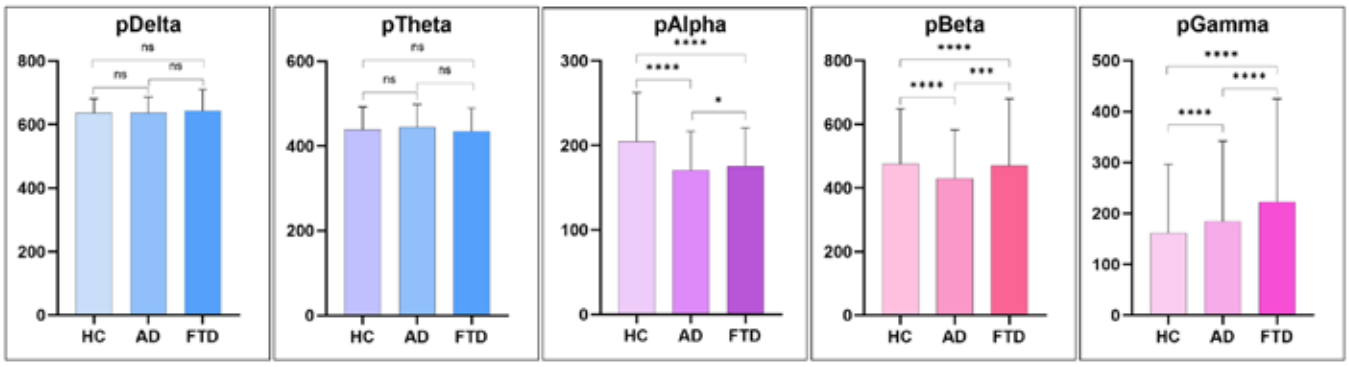


Fig. 2. Feature selection results.

(4–8 Hz), alpha (8–13 Hz), beta (13-30 Hz) and gamma (30-45 Hz). The electrical activity of the brain, which is linked to specific neural processes and cognitive functions, is categorized into frequency subbands. EEG signals are decomposed into several distinct frequency subbands to facilitate the analysis of brain activity related to particular tasks at those frequencies.

Spectral analysis is used in quantifying EEG and extracting power features. PSD is an important method of reflecting the 'frequency content' of the signal, or the distribution of signal power over frequency [19]. The Welch method [20] has found wide application in the analysis of EEG data related to dementia. This entails dividing the time signal into consecutive blocks, creating a periodogram for each block, and subsequently averaging these individual periodograms. Welch method parameters were set to 2500 for the number of DFT points (nfft), 64 for overlapping, and a Hanning window with a 128 window length.

2) Feature Selection: Feature selection is the process of determining the most meaningful and high-information features in the dataset. The segmented data in each group in the dataset was divided into specific frequency bands for feature analysis. The extracted features were analyzed using GraphPad Prism, version 10. The Kolmogorov-Smirnov normality test was used to determine which analysis methods could be used depending on the characteristics of the data. While the features of the delta and theta bands followed a normal distribution, the features of the remaining frequency bands exhibited a log-normal distribution. After conducting the normality analysis, the Kruskal-Wallis test and Dunn's multiple comparison test were applied. $p < 0.05$ was considered statistically significant. The analysis results, shown in Fig. 2, indicate that the alpha, beta, and gamma frequency bands were the most significant according to the statistical analysis.

C. Azimuthal equidistant projection (AEP)

The widely increasing practice involves the utilization of extracted features to generate visual representations, such as scalograms. This study employs 2-D image representations of EEG signals by using the AEP technique which is one of the atlas projection methods. A pivotal phase in this procedure is to interpolate three distinct features onto the cortical surface to allocate values between electrodes [21]. For this purpose, extracted features from each EEG segment were mapped onto a projection plane derived from the 10-20 international system of EEG electrodes. Thus individual features can be represented with a color channel in RGB images while their combinations generate colorful maps. This allows the conversion of cerebral cortex activities carried out by extracted features into a 2-D image format while preserving natural spatial information [22]. Brain Mapping images were generated by AEP using the statistically significance features extracted from alpha, beta, and gamma bands through each segmented EEG block.

D. Transfer Learning

The use of various deep learning (DL) methods is particularly popular for classifying medical data. However, DL methods typically require large datasets. To address the limitations of smaller datasets, transfer learning —where pre-trained models are fine-tuned with new data— has made this process more manageable [23]. The pre-trained MobileNetV2 which is a lightweight CNN architecture designed for mobile and embedded vision applications was adopted. It stands out for its ability to strike an effective balance between model size and accuracy. MobileNetV2's architecture consists of a series of convolutional layers, followed by depthwise separable convolutions, inverted residuals with a bottleneck design, linear bottlenecks, and squeeze-and-excitation (SE) blocks [24]. MobileNetV2's weights were pre-trained on the ImageNet dataset [25], enabling the model to effectively extract features for recognizing various images. In our architecture, L2 regularization was used and one drop-out layer was added to reduce the possibility of overfitting, apart from MobileNetV2 structure. The 'Relu' function was used as the activation function, the Dropout value was set to 0.5 and the regularization parameter was set to 0.01. Also, epoch and batch size were adjusted as 100, and 64, respectively. In our model, 10-fold cross-validation was employed to ensure robust and reliable performance evaluation.

E. Model Evaluation

Four distinct measures were used to evaluate the performance of classification models, including accuracy, precision,

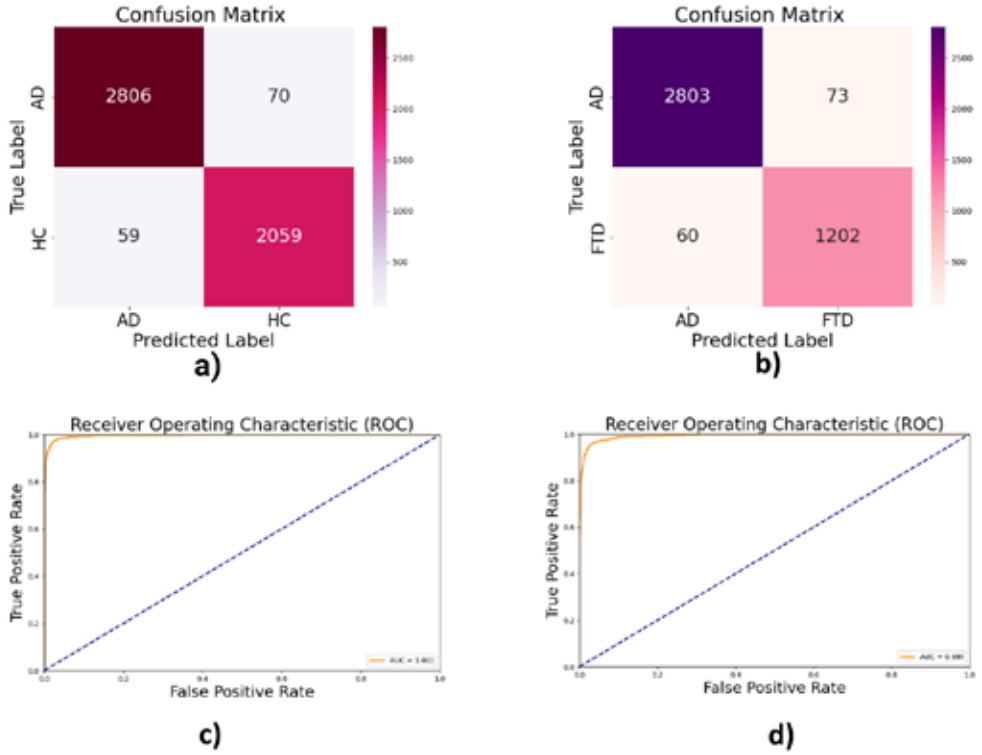


Fig. 3. Confusion matrix for a) AD/HC and b) AD/FTD, and ROC curve for d) AD/HC and e) AD/FTD.

recall, and F1-score, as well as confusion matrices and Receiver Operating Characteristic (ROC) curves, were employed to assess the performance of the models [26]. The relationship between the predicted classes of each image in the test dataset and the actual classes of each image in the test dataset was displayed using confusion matrices. Results on the colored diagonal in the matrix indicate correct predictions, while values outside the diagonal indicate incorrect predictions.

III. Results and Discussion

The use of computer-aided classification models is steadily increasing alongside the growing volume of medical data. Among these domains of research, the classification of data utilized for dementia diagnosis holds particular significance. Notably, the use of EEG data in dementia diagnosis is critical for enhancing time efficiency. In our study, DL classification was performed using the OpenNeuro dataset, which contains 2 dementia classes: AD and FTD along with the HC class. Every data segment derived from the dataset underwent division into five distinct frequency bands through PSD analysis utilizing the Welch method. As a result of the statistical analysis of five frequency bands, three statistically significant frequency band power features were used. This process resulted in the creation of three distinct feature matrices for each class. After the feature matrices were created, 2-D image representations of 19-channel EEG features were obtained with the AEP method. Consequently, a comprehensive dataset that includes a total of 34876 images was compiled. It includes 14550 images of AD, 12041 of HC, and 8285 of FTD to feed the DL-based classification model. Considering the network properties of the MobileNetV2 model 2-D image representations with an original size of 515x385 were resized to 212x212 to reduce computational cost and memory usage. In order to ensure more stable learning of the model, all 2-D images, both test and training, were normalized. The example of 2-D images generated with features is displayed in Fig. 1.

It is important to closely simulate real-world scenarios in disease diagnosis tasks [27]. To achieve this, the image data was split into training and test sets on a subject-by-subject basis. Each subject and their samples were allocated to either the training or testing set, ensuring that samples with the same subject ID appeared in only one of these datasets. For this purpose, we separated 20% of the subjects in the dataset to use only as test data. After this separation, 7 subjects with AD, 5 subjects with HC, and 4 subjects with FTD were used exclusively in the test data. As a result, 28620 images were used for training, while 6256 images were used for testing. To reduce the risk of overfitting, 10-fold cross-validation was used during training. The DL architecture was trained using a

TABLE I
Model Evaluation Results.

Class	Validation Acc.	Test Acc.	Precision	Recall	F1-score
AD/HC	0.97	0.97	0.97	0.97	0.97
AD/FTD	0.96	0.97	0.94	0.95	0.95
FTD/HC	0.77	0.64	0.70	0.73	0.72

transfer learning approach, implemented with the TensorFlow Keras library on a computer equipped with an NVIDIA 3080 Ti GPU.

TABLE II
COMPARISON OF STATE-OF-THE-ART DEEP LEARNING STUDIES USING THE SAME DATASET.

Work	Model	Approach	ACC
Miltiadous et al. [14]	DICE-Net	AD/HC	0.83
		FTD/HC	0.74
Zhou et al. [16]	EEG-Net	AD/HC	0.93
Amer et al. [28]	Google-Net	AD/HC	0.95
Kachare et al. [29]	LCADNet	AD/HC	0.93
Shen et al. [30]	GRU (RNN)	AD/HC	0.93
Kachere et al. [31]	STEADYNet	AD/HC	0.88
		FTD/HC	0.92
		AD/FTD	0.89
This Work	MobileNetV2	AD/HC	0.97
		FTD/HC	0.64
		AD/FTD	0.96

The MobileNetV2 was trained with 2-D images generated using alpha, beta, and gamma frequency band powers. In order to generate EEG-representative RGB images, alpha, beta, and gamma powers were assigned to R, G, and B channels, respectively. In this study, among the various models, MobileNetV2 proved to be more successful in identifying hidden patterns in 2-D images. In 2-class classifications, 97% success rate was achieved for AD/HC classification and 96% success rate for AD/FTD classification, while 64% success rate was obtained for FTD/HC classification. Table I provides a comprehensive summary of the outcomes derived from our model. Confusion matrices and ROC curves are shown in Fig. 3. The figure illustrates the model's high success in classification tasks.

The comparison of the presented results with other studies in the literature using the same dataset is shown in Table II. Among studies utilizing the same dataset, the highest success rates are consistently observed in AD/HC classifications, using various DL models and feature extraction methods. After examining the accuracy values in our model, it becomes evident that the AD/HC classification exhibits a relatively high success rate, achieving a commendable accuracy of 97%. With the success rate achieved, our study ranks among the successful models in AD/HC classification. Most studies in the literature have been conducted on a subject-independent basis. Samples from various subjects were randomly mixed and divided into training, validation, and testing sets. The high success rate in AD/HC classification is particularly notable due to its application of a subject-independent approach. In a similar study conducted by Wang et al. [27], the accuracy value for the subject-independent approach in 3 class classification was 53%, which was significantly lower than that of the subject-dependent approach. Our study achieved a significantly higher success rate compared to the lower success reported in this study. This high success rate demonstrates its compatibility with real-world classifications.

Similarly, the AD/FTD classification outcome is a noteworthy achievement, with a rate of accuracy of 96% that compares favorably to many other findings in the literature. It also demonstrates the model's success, particularly in distinguishing AD class. In studies utilizing DL models, the number of studies focusing on AD/FTD classification is relatively small. Among the DL studies that classified AD/FTD, our study achieved significant success according to the highest AD/FTD classification made by Kachare et al. [31].

IV. CONCLUSION

The proposed approach used 4-second EEG segments to extract features via the Welch method. Alpha, beta, and gamma bands, which showed significant differences in statistical analysis, were used to extract power-based features. Afterward, the AEP method was utilized as a 2-D brain mapping approach to represent EEG signals. After separating the test data from the images on a subject-by-subject basis, training was conducted using the MobileNetV2 architecture. Our study has achieved noteworthy success within the existing literature, particularly in the field of 2-class classifications for AD and FTD. The findings presented in this study have significantly contributed to the use of EEG signals for the diagnosis of dementia. Moreover, our study has made a notable contribution to the limited body of research addressing FTD classification using EEG data. This could ultimately help reduce the reliance on resource-intensive and human-dependent methods currently in use, providing a quantitative probability value for a patient's diagnosis. In further research, it is possible to make further contributions by evaluating the brain mapping images using different features, increasing the success rate, especially in 3-class classification.

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