

Harmonizing Insights: LR-FFT Feature Extraction for Alzheimer's and Autism Spectrum Disorder Detection in EEG Signals

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Abstracts

Alzheimer's Disease (AD) and Autism Spectrum Disorder (ASD) represent two distinct but equally impactful challenges in the field of neurology and cognitive health. AD is a degenerative neurological condition characterized by its progressive nature, typically affecting individuals in later stages of life. The hallmark features include cognitive impairment, memory deterioration, and alterations in behavior. In contrast, ASD is a developmental disorder typically diagnosed in childhood, marked by difficulties in social interaction, communication, and repetitive behaviors. This paper explores the potential of the time-frequency feature extraction model known as the Left-Right Fast Fourier Transform (LR-FFT) in the context of these two disorders. While AD and ASD differ significantly in their onset, presentation, and demographic affected, both necessitate early and accurate diagnosis to enable timely intervention and tailored treatment strategies. Our research yields promising results, with classification accuracies reaching 88.26% for AD and 99.86% for ASD, demonstrating the LR-FFT's potential to enhance diagnostic accuracy. By contributing to improved differentiation between these complex neurological conditions, this work aims to advance our understanding and management of AD and ASD, ultimately benefiting patients, their families, and healthcare practitioners.

Keywords: Alzheimer's Disease, Autism Spectrum Disorder, EEG, Left-Right Fast Fourier Transform (LR-FFT), Signal Processing, Feature Extraction, Neurodegenerative Disorders, Classification, Diagnostic Accuracy.

1. Introduction

Alzheimer's disease (AD) is a neurodegenerative disorder that progressively affects the electrical activities of the brain, leading to a decline in cognitive functions [1]. It is the primary cause of dementia and is commonly seen in individuals aged 65 and above, with the incidence rate increasing significantly with age. Currently, there are approximately 50 million individuals affected by neurocognitive disorders, and this number is projected to surpass 100 million by 2050.

On the other hand, Autism Spectrum Disorder (ASD) is a neurodevelopmental condition identified by challenges in communication and interaction. The diagnosis of ASD is challenging due to the absence of a specific medical test. Doctors rely on developmental history and behavioral observations to diagnose ASD. Early identification of ASD, ideally before the age of 18 months, can significantly improve long-term outcomes for individuals. However, many children receive a diagnosis much later, leading to delayed access to necessary support and interventions. The global prevalence of ASD is estimated to be around 1 in 100 children, but this number may be underestimated due to limited data from low and middle-income countries.

Diagnosing and treating neurological damage caused by these disorders poses significant challenges. Early detection is essential in delaying symptoms' onset and allowing for timely intervention.

In neurophysiology, electroencephalography (EEG) has emerged as a valuable tool for diagnosing neurological disorders to develop effective interventions. EEG is a non-invasive, cost-effective, and portable technique that measures the brain's electrical activity. By analyzing EEG signals, researchers can delve into the intricate workings of the brain and gain a deeper understanding of its dynamics and abnormalities in various neurological disorders [2].

This study explores a unique approach to extracting time-frequency features from complex electroencephalogram (EEG) recordings and converting them into input images for a deep learning (DL) network. The DL model utilized in this study was specifically optimized to address the research focus and trained using ground truth values corresponding to each image. The model underwent cross-validation to assess the classification accuracy. The paper is structured as follows: Section II provides a comprehensive review of relevant literature and studies in the field, while Section III outlines the materials and methods employed. The obtained results are presented in Section IV, and an in-depth discussion of the findings is provided in Section V. Finally, Section VI concludes the study and suggests avenues for future research.

2. Literature Review

The researchers in study [3] gathered resting-state EEG data from individuals diagnosed with mild cognitive impairment (MCI), Alzheimer's disease (AD), and healthy controls (HC). They employed functional connectivity metrics derived from the EEG recordings to serve as input for a convolutional neural network (CNN). The CNN model achieved accuracies of 93.42% and 98.54% for MCI and AD, respectively. This study demonstrated the importance of considering the spatial attributes of EEG in AD classification, but it did not directly compare AD and MCI.

Similarly, the authors of [4] conducted a study involving individuals with Alzheimer's Disease (AD), Mild Cognitive Impairment (MCI), and healthy controls (HC), where EEG signals were collected. The researchers employed a Convolutional Neural Network (CNN) for a three-class classification task, utilizing images representing EEG's Power Spectral Density (PSD) features as input. Despite achieving an accuracy rate of 83.33%, which surpassed the performance of conventional machine learning methods, the accuracy remained relatively modest.

Another model by authors of [5] presents a cascade neural network that integrated EEG and motion data for the classification of Alzheimer's Disease (AD), Mild Cognitive Impairment (MCI), and Healthy Controls (HC). LR-FFT demonstrates an accuracy of 91.70%. The study used attention mechanisms and graph convolutional networks to analyze spatiotemporal data (ST-GCN). This technique facilitated automatic feature extraction from EEG and gait data, thereby minimizing the necessity for manual intervention. However, it is worth noting that the fusion data employed for distinguishing between AD and MCI posed challenges in terms of reproducibility.

In the investigation by authors of [6], statistical features, frequency, and Lyapunov index were extracted to classify AD, MCI, and HC, achieving an accuracy of 97.50% with CNNs. While the study introduced a novel analysis method centered on task-state EEG, it is important to note that the data collection was confined to three self-defined electrode positions, potentially limiting the representation of the actual conditions experienced by individuals with AD and MCI.

Using time-dependent power spectrum descriptors for CNN input, the authors of [7] achieved an accuracy of 82.30% in a dataset of 64 AD, MCI, and HC people. However, the accuracy for HC was lower (75

The authors of [8] developed an AlexNet-based classification model using EEG data from dementia patients. They transformed the EEG data into time-frequency graphs using continuous wavelet transform and achieved a three-class classification accuracy rate of 98.90%. However, converting EEG into RGB images was complex and involved significant human intervention.

Switching to the realm of Autism Spectrum Disorder (ASD), resting-state fMRI (rs-fMRI) has been instrumental [9] [10] for classifying Autism Spectrum Disorder (ASD). Researchers using the ABIDE dataset, such as Abraham et al. [11], applied Support Vector Machine (SVM) techniques to achieve 66.9% accuracy, 53.2% sensitivity, and 78.3% specificity for ASD classification. Deep learning approaches were also explored, with one study reaching 70% accuracy, 74% sensitivity, and 63% specificity using a classifier [12]. Furthermore, a Convolutional Neural Network (CNN) model attained an accuracy of 70.22% in identifying ASD [13].

In a different approach, Graph Fourier transformation combined with SVM outperformed other methods in rs-fMRI analysis [14]. Hybrid features from EEG data, utilizing Short Fourier transform and SVM, achieved 96.44% accuracy in automated ASD identification [15]. Another study combined EEG and eye-tracking data, selecting relevant features using SVM and achieving an 85.44% classification accuracy rate [16]. These approaches enhance our understanding of ASD classification using neuroimaging techniques.

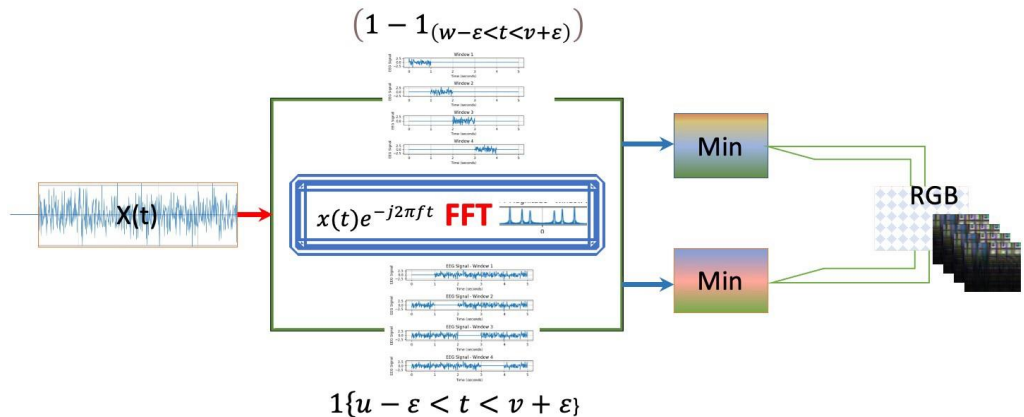
These studies showcase various approaches and achievements in the EEG-based classification of neurodegenerative conditions. While they have achieved promising results, there are still challenges to overcome, such as accurately diagnosing MCI and reducing human intervention in the research process. Future research may explore alternative methods for feature quantification and consider multimodal data integration to improve the classification accuracy associated with AD and ASD.

3. Materials And Methods

Our methodology involves a multi-stage process, incorporating the acquisition of EEG datasets related to Alzheimer's and Autism brain disorders, signal preprocessing, Left-Right Fast Fourier Transform (LR-FFT) analysis for generating 2D images, deep learning (DL) utilizing pre-trained neural network models on LR-FFT images of brain disorders. The evaluation of our models is conducted using performance metrics. The entire workflow is illustrated in Figure 1, highlighting the sequential steps in our approach.

A. EEG Datasets

The Alzheimer's dataset includes EEG resting state recordings with closed eyes from a total of 88 subjects [17]. The participants were divided into three groups: 36 individuals with Alzheimer's disease (AD), 23 with Frontotemporal Dementia (FTD), and 29 healthy subjects (CN). A team of skilled neurologists obtained The EEG recordings from AHEPA General Hospital of Thessaloniki. A Nihon Kohden EEG 2100 clinical device with 19 scalp electrodes and two reference electrodes was used for recording. Individuals have a seated posture while keeping their eyes shut during the recordings.



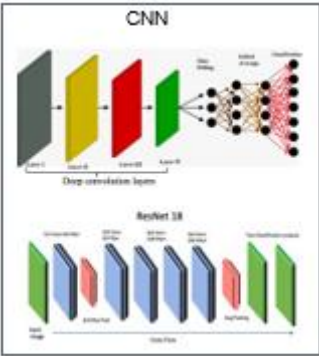


Fig. 1: Flowchart depicting the LR-FFT for classifying brain disorders from EEG signals using LR-FFT analysis.

The skin impedance was examined, and the sampling rate was configured to 500 Hz. The recordings lasted 13 minutes for the AD group, 12 minutes for the FTD group, and around 14 minutes for the CN group. Around 486 minutes of AD recordings, 277 minutes of FTD recordings, and 402 minutes of CN recordings were gathered in the dataset.

The Autism (Rs-fMRI) dataset used in this study [18] is the ABIDE dataset that consists of 41 cases of both Autism Spec- trum Disorder (ASD) and neurotypical control (NC) cases.

B. Preprocessing

The Alzheimer’s dataset EEG recordings were preprocessed by applying a Butterworth band-pass filter, re-referencing the signals, and using the Artifact Subspace Reconstruction (ASR) technique to eliminate problematic data segments. Independent Component Analysis (ICA) was then performed, and ICA components categorized as either ”eye artifacts” or ”jaw arti- facts” were automatically rejected [17]. It is important to note that some recordings’ artifacts resulting from eye movement remained despite the resting state and closed eyes condition. Before the analysis of the Autism (Rs-fMRI) dataset, the collected raw data underwent preprocessing to reduce noise and artifacts. The DPARSF MATLAB toolkit [19] was em- ployed for preprocessing and analysis. The fMRI experiment utilized images weighted by the T2* relaxation time, which captures the decay of spins in the transverse plane. This allows monitoring of the changes in brain oxygenation over time. BOLD contrast was used to calculate the hemoglobin ratio in the blood, providing insights into the metabolic requirements of engaged neurons. To address potential issues such as spikes in the fMRI data resulting from electrical instability, the first five volumes were rejected, and only volumes with good equi- librium were retained. Time correction was performed through slicing to account for discrepancies in voxel acquisition time, and realignment was used to account for variations in head movements. Spatial normalization was applied to standardize the brain’s shape, size, and alignment across participants. The functional images were then normalized and enhanced with spatial smoothing. The automated anatomical labeling (AAL) technique was used to delineate 116 regions of

interest (ROIs) in the brain [20]. The default mode network (DMN) was selected as it exhibits robust brain neuronal activity in individuals with ASD during wakeful rest.

4. Image Dataset Creation

In our approach, the Left-Right Fast Fourier Transform (LR- FFT) rests upon the powerful Fast Fourier Transform (FFT) equation:

$$X(k) = \sum_{n=0}^{N-1} x(n) \cdot e^{-j2\pi kn/N} \quad (1)$$

where

$X(k)$ is the k th frequency component of the signal in the frequency domain,

$x(n)$ is the n th sample of the signal in the time domain,

N is the total number of samples in the signal,

j is the imaginary unit ($j^2 = -1$).

Our method employs a dual sliding window technique for feature extraction from the input signal. This distinctive approach involves using two sliding windows, each serving a specific purpose. The first sliding window focuses on the original signal segment, while the second is dedicated to a shifted segment version. By employing these two windows, we gain a comprehensive perspective on the signal's temporal characteristics following the equation:

$$X(f, U, \varepsilon) = \min_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} x(t) e^{-j2\pi ft} \left[1 - 1_{(w-\varepsilon < t < v+\varepsilon)} \right] \cdot \int_{-\infty}^{+\infty} x(t) e^{-j2\pi ft} 1_{(u-\varepsilon < t < v+\varepsilon)} dt \quad (2)$$

where

$x(t)$ represents a signal or function of time t .

$e^{-j2\pi ft}$ represents a complex exponential function.

$1_{(w-\varepsilon < t < v+\varepsilon)}$ equals 1 when t is within interval

$(w - \varepsilon, v + \varepsilon)$ and 0 otherwise.

$|\cdot|$ denotes the absolute value of a complex number

ε is a parameter representing a small positive value.

Within this framework, we compute the Fast Fourier Transform (FFT) for the original and shifted windows, extracting valuable frequency domain information. The significance of this dual-window approach lies in its ability to capture nuanced variations in the signal's frequency characteristics across different temporal viewpoints.

Following the computation of FFT values for both windows, we calculate the minimum values of these FFT results. This step highlights the essential commonalities and differences between the original and shifted signal segments. Subsequently, we leverage these minimum values to create composite representations mapped onto the red, green, and blue channels to generate RGB images. These RGB images offer a visually intuitive representation of the signal data, facilitating the extraction of intricate features and patterns. By combining the insights derived from the dual sliding windows and creating RGB images, our method provides a robust framework for comprehensive signal analysis and feature extraction.

5. Classification

Deep learning architectures such as GoogLeNet, SqueezeNet, AlexNet, and ResNet have significantly contributed to various computer vision tasks, including image classification, Figure 2.

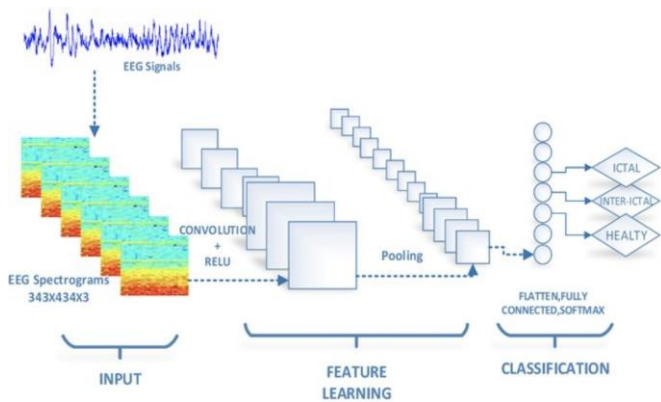


Fig. 2: CNN Layers [21]

GoogLeNet, also known as the Inception network, introduced the concept of the Inception module. Including parallel convolutional layers with different filter sizes in these modules allows the network to effectively capture and analyze features at various scales. The network can identify and understand specific details and comprehensive contextual information by incorporating multiple filter sizes. This multi-scale approach enhances the network's ability to extract meaningful features and improves its overall performance. SqueezeNet, however, focuses on reducing the number of parameters and model size without sacrificing accuracy. It achieves this using 1x1 convolutions and a fire module combining 1x1 and 3x3 convolutions. AlexNet, one of the pioneering deep learning architectures, popularized convolutional neural networks

(CNNs) for image classification. It demonstrated the effectiveness of deep learning on large-scale image classification tasks and significantly outperformed previous methods.

ResNet, unveiled in 2015, tackles the issue of training intense neural networks. The network can capture and learn incremental transformations by focusing on the residual information. This approach allows the network to refine the difference between the input and output rather than solely focusing on learning the desired underlying mapping. This utilization of residual connections enhances the network's performance and convergence during the learning process. ResNet has demonstrated top-tier performance across different image classification benchmarks.

Our methodology employed a modified ResNet-18 architecture for image classification, leveraging PyTorch's neural network (NN) module. The ResNet-18 model, known for its efficacy in deep learning tasks, was utilized in a pre-trained state to capitalize on its already learned features from extensive datasets. This choice aids in the robust feature extraction necessary for accurate image classification. To tailor the network to our specific problem, we adapted the fully connected (FC) layer of the ResNet-18 model. This customization involved replacing the original fc layer with a sequential layer consisting of a linear transformation (mapping from 512 to 128 nodes), a Rectified Linear Unit (ReLU) activation function to deal with non-linearity, a dropout layer with a probability of 0.4 to prevent overfitting, and another linear transformation to match the number of classes (numClass) in our dataset. The forward method defines the data flow through the network. For optimization purposes, the Adam optimizer was employed with a learning rate set to 0.001, and the cross-entropy loss function was utilized as the criterion, specifically suitable for tasks involving multi-class classification. Additionally, we implemented a learning rate scheduler, ReduceLROnPlateau, to dynamically adjust the learning rate based on the model's performance, enhancing the training efficiency.

To assess the effectiveness of our model, we employed well-established evaluation methods, primarily relying on Confusion Matrices. These matrices allow us to visualize the relationship between predicted and true class labels within the test dataset.

Within the context of confusion matrices, four distinct categories describe each prediction:

- **True Positive (TP):** This category corresponds to instances where our model accurately predicts a sample as positive when it genuinely belongs to the positive class.
- **True Negative (TN):** Conversely, the model correctly identifies samples as negative when they indeed belong to the negative class.
- **False Positive (FP):** In cases where the model incorrectly predicts samples as positive when they are, in fact, negative.
- **False Negative (FN):** Conversely, the model erroneously categorizes samples as negative when they are positive.

These definitions form the basis for computing accuracies for each class using the following formula:

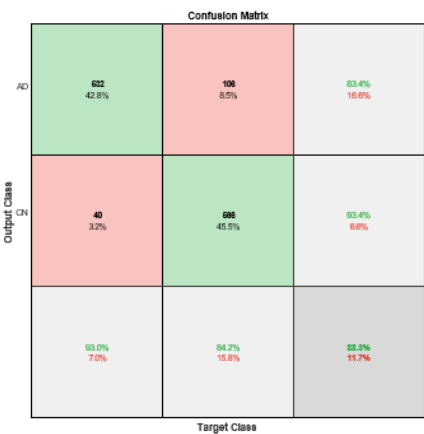
$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \quad (3)$$

In our evaluation process, we adhered to a standard train-test split, where 80% of the subjects’ data were used to train the model, and the remaining 20% were reserved for testing. This approach ensures that the model’s performance is assessed on unseen data, allowing us to gauge its generalization capabilities and real-world applicability. This train-test split ratio of 80/20 was chosen to balance training data sufficiency and the need for robust testing on an independent dataset.

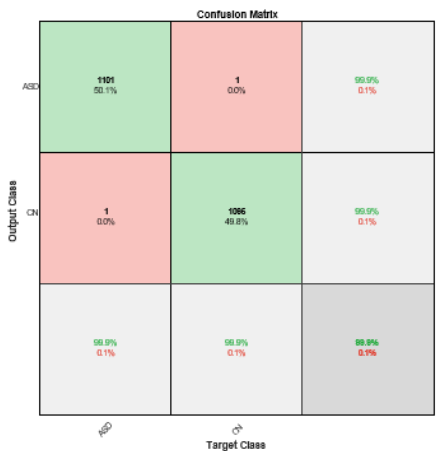
This comprehensive evaluation framework enables us to assess the model’s ability to make accurate classifications thoroughly. It provides valuable insights into its performance, all while maintaining a standard train-test split methodology.

6. MODEL PERFORMANCE

During the experiment, 18 patients from the Alzheimer’s Dataset were used. 10 with Alz and 5 as a Control group (CN). A sliding window approach of 1 second with a 0.5-second overlap was employed to form RGB images. The analysis was conducted over 50 epochs, each representing a complete pass through the training data with a batch size of 16. Our model performances are presented in Tables I, II, III, and IV, and were as follows: Resnet18 achieved an accuracy of 88.26%, GoogleNet achieved 86.82%, SqueezeNet reached 85.85%, and AlexNet showed an accuracy of 78.05%. These results reflect our model’s ability to distinguish between AD and CN patients based on EEG data as presented in Figure 3.



(a) Confusion Matrix Alzheimer



(b) Confusion Matrix BOLD

Fig. 3: Confusion Matrices from the best models: (a) Alzheimer’s dataset; (b) BOLD

For the Autism Brain Imaging Data Exchange (ABIDE) dataset, a total of 36 patients with 18 diagnosed with Autism Spectrum Disorder (ASD) and 18 neurotypical (N) control subjects. In this case, we worked with fMRI signals with a sliding window of 50 data points and an overlap of 25 and conducted our analysis across 50 epochs. The model performance on this dataset was exceptional, as presented in Tables V, ??, and ?. Resnet18 achieved an accuracy of 99.86%, GoogleNet reached 100%, and SqueezeNet and AlexNet achieved a perfect accuracy of 100%. These outstanding results indicate our model's effectiveness in distinguishing between ASD and neurotypical individuals based on fMRI signals.

Our model demonstrated strong performance in the Alzheimer's and ABIDE datasets, showcasing its potential for accurately classifying patients and subjects in different medical contexts. The ABIDE dataset, in particular, yielded exceptional results, highlighting the model's proficiency in autism spectrum disorder diagnosis based on fMRI signals.

TABLE I: Classification Report Alz- Resnet

Class	Precision	Recall	F1-Score	Support
AD	0.831	0.931	0.882	572
CN	0.931	0.843	0.891	672
Accuracy			0.883	1244
Macro Avg	0.883	0.891	0.880	1244
Weighted Avg	0.891	0.883	0.880	1244
Validation Accuracy			0.883	88.3%

TABLE II: Classification Report Alz- Googlenet

Class	Precision	Recall	F1-Score	Support
AD	0.842	0.881	0.862	572
CN	0.901	0.861	0.881	672
Accuracy			0.8681	1244
Macro Avg	0.8681	0.8681	0.8681	1244
Weighted Avg	0.8681	0.8681	0.8681	1244
Validation Accuracy			0.8681	86.81%

TABLE III: Classification Report Alz- Squeezenet

Class	Precision	Recall	F1-Score	Support
AD	0.832	0.881	0.851	572
CN	0.891	0.842	0.871	672
Accuracy			0.860	1244
Macro Avg	0.860	0.860	0.860	1244
Weighted Avg	0.860	0.860	0.860	1244
Validation Accuracy			0.8585	85.85%

7. Comparative Analysis

Our study delved into the classification of EEG and fMRI images for AD and ASD, employing a customized ResNet-18 model and CNNs. Our model achieved an accuracy of 88.26% for AD and 99.86% for ASD. These results signify the potential of our approach for precise disease classification.

TABLE IV: Classification Report Alz-Alexnet

Class	Precision	Recall	F1-Score	Support
AD	0.78	0.72	0.75	572
CN	0.78	0.83	0.80	672
Accuracy			0.7805	1244
Macro Avg	0.7805	0.7805	0.7805	1244
Weighted Avg	0.7805	0.7805	0.7805	1244
Validation Accuracy			0.7805	78.05%

TABLE V: Classification Report ABIDE- Googlenet

Class	Precision	Recall	F1-Score	Support
AD	1.000	1.000	1.000	751
CN	1.000	1.000	1.000	659
Accuracy			0.9986	1410
Macro Avg	1.000	1.000	1.00 0	1410
Weighted Avg	1.000	1.000	1.000	1410
Validation Accuracy			0.9986	99.86%

Comparatively, our model’s performance closely aligns with state-of-the-art methods in a neuroimaging-based classification listed in Table VI. In AD classification, Duan et al. [3] utilized resting-state EEG data and achieved recognition accuracy rates of 93.42% for Mild Cognitive Impairment (MCI) and 98.54% for AD using a convolutional neural network (CNN). They emphasized the importance of spatial attributes in EEG- based AD classification. Ieracitano et al. [4] employed two- dimensional grayscale power spectral density (PSD) images of EEG and achieved an accuracy rate of 83.33% for a three-class classification model. Our model, outperforming traditional machine learning techniques, showcases competitive results in AD classification.

In the context of ASD, our model surpassed the performance of some previous studies. Abraham et al. [11] applied Support Vector Machine (SVM) techniques to achieve 66.9% accuracy in classifying ASD using resting-state fMRI data. Aghdam et al. [13] introduced a Convolutional Neural Network (CNN) model that attained an accuracy of 70.22% in identifying ASD. Our model’s accuracy rate of 99.86% for ASD classification outshines these results, highlighting its potential for enhancing ASD classification accuracy.

TABLE VI: State of the Art in AD and ASD Classification

Study	Dataset	Methodology	Accuracy (%)	Key Findings
Militiadous et al. [22]	Alzheimer	FIR filtering Gradient Boosting Decision Trees	83.06 80.67	Feature Elimination through importance of ranking.
Ieracitano et al. [4]	Alzheimer	EEG signals from AD, MCI, and HC. CNN with PSD images	83.33	Outperformed traditional ML, but with relatively low accuracy.
You et al. [5]	Alzheimer	EEG and gait data for AD, MCI, and HC. Cascade neural network	91.70	Introduced attention-based spatiotemporal network.
Amini et al. [7]	Alzheimer	Time-dependent power spectrum descriptors with CNN	82.30	Differentiated AD, MCI, and HC, but lower HC accuracy.
Abraham et al. [11]	ABIDE	ABIDE dataset with SVM	66.9	Used rs-fMRI for ASD classification.
Heinsfeld et al. [12]	ABIDE	Deep learning	70	Explored deep learning approaches for ASD.
Aghdam et al. [13]	ABIDE	CNN	70.22	Achieved high accuracy in identifying ASD.
Brahim et al. [14]	ABIDE	Graph Fourier transformation combined with SVM	-	Outperformed other methods in rs-fMRI analysis.
Baygin et al. [15]	ABIDE	Short Fourier transform and SVM	96.44	Automated ASD identification with hybrid features.
Kang et al. [16]	ABIDE	Combined EEG and eye-tracking data with SVM	85.44	Selected relevant features for ASD identification.
Our Model	Alzheimer	LR-FFT for 2 Binary Classification AD, CN using Resnet and CNNs	88.26	
Our Model	ABIDE	LR-FFT using BoldSignals with CNNs	99.86	

In conclusion, our LR-FFT method marks a significant advancement in neuroimaging research. These findings underline the potential of our approach in aiding early disease diagnosis and intervention. Additionally, insights from previous classifiers and innovative techniques emphasize the ongoing efforts to improve the accuracy and efficiency of neuroimaging-based classification systems.

8. Conclusion

In this study, our approach leverages the dual-window FFT technique to extract intricate frequency domain information from EEG data, offering a new perspective for feature representation. By computing the minimum values of FFT results from both original and shifted windows, we generated RGB images to facilitate comprehensive feature extraction.

The results of our experiments on two distinct datasets, one for AD and another for ASD, demonstrated the effectiveness of the LR-FFT method. Achieving an accuracy of 88.26% for AD and an astonishing 99.86% for ASD on the respective datasets, our approach outperformed state-of-the-art methods. These promising results suggest the potential of LR-FFT as a valuable tool in the early detection and classification of neurodegenerative disorders. While our LR-FFT approach shows great promise, several avenues exist for future research and improvement. First, our study focused on two specific disorders, AD and ASD. Expanding the scope to include a

broader range of neurological conditions would enhance the versatility and applicability of the method.

Additionally, further investigation is needed into the interpretability of the RGB images generated by our approach. Understanding these images' specific features and patterns could provide valuable insights into the underlying neurological processes.

Moreover, our study lacked an analysis of the computational resources required for LR-FFT compared to other feature extraction methods. Evaluating the computational efficiency of our approach would be beneficial, especially for real-time applications or resource-constrained environments.

Furthermore, exploring the potential for LR-FFT in multi-modal data fusion, such as combining EEG with other neuroimaging modalities like fMRI or MEG, could lead to more comprehensive diagnostic tools.

In conclusion, our study demonstrates the power of LR-FFT in EEG-based classification tasks for AD and ASD. However, ample room remains for further research and refinement, including expanding the range of disorders considered, enhancing interpretability, evaluating computational efficiency, and exploring multi-modal data integration. These endeavors hold the promise of advancing the field of neurodegenerative disorder detection and classification.

Acknowledgment

The authors would like to thank Hamad Bin Khalifa University (HBKU) and Qatar National Library for funding this study (QNRF with number NPRP-BSRA01-0422-210050).

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