SSPNet: Towards Feasible Spatio-Spectral Portraits-Based Deep Learning Framework for Neurodegenerative Disease Multi-Classification

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Abstract. Early diagnosis of neurodegenerative diseases is crucial for effective intervention and treatment planning. However, conventional screening tests such as Mini-Mental State Examination (MMSE) often produce false-negative issues. While electroencephalogram (EEG) signals contain valuable neurophysiological information, multi-class classification remains challenging due to subtle differences between conditions, with existing methods achieving around 50-60% accuracy. Therefore, we propose SSPNet, a novel deep learning framework for multi-class classification of neurodegenerative diseases using spatio-spectral portraits derived from EEG signals. Our approach extracts spatio-spectral images that maximize neurophysiological differences between Alzheimer's disease, frontotemporal dementia (FTD), and cognitively normal subjects, utilizing minimal frequency bands encoded through specialized asymmetric convolutional blocks and attention mechanisms. To our knowledge, this represents the first attempt to use EEG spatio-spectral portraits for multi-class classification of neurodegenerative diseases. The proposed SSPNet significantly improves accuracy to 72.22% compared to existing EEG-based methods for multi-class classification. It also demonstrates notably lower false-negative rates for FTD patients compared to MMSE, thus accelerating practical clinical application.

Keywords: Spatio-Spectral Portraits · Neurodegenerative Disease · Multi-Classification · Asymmetric Convolution · Attention Mechanism · Electroencephalography (EEG)

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1 Introduction

The prevalence of neurodegenerative diseases is expected to increase in most countries as life expectancy rises[13]. Dementia represents a major cause of disability, institutionalization, and mortality, with global costs reaching US$ 1 trillion[26]. Previous research indicates that Alzheimer's disease (AD) is the most common neurodegenerative disease, accounting for 60-70% of dementia cases[30], with early-onset Alzheimer's disease (EOAD) comprising 5-10% of reported cases[8]. Notably, early-onset dementia typically progresses more rapidly than senile dementia[7], resulting in relatively shorter survival periods for EOAD patients[4]. Additionally, frontotemporal dementia (FTD), a primary cause of early-onset dementia, progresses faster than AD while exhibiting similar mortality risk[23],[25]. Therefore, early diagnosis and therapeutic intervention are critical factors in determining the prognosis of these conditions[7].

In clinical settings, the diagnosis of neurodegenerative diseases typically encompasses screening, diagnostic testing, and differential diagnostic processes, achieved through comprehensive evaluation utilizing neuropsychological assessments, neurological examinations, and neuroimaging. Among these, screening tests serve as gatekeepers at the early stage of evaluation. The Mini Mental State Examination (MMSE)[10] is the most widely adopted cognitive screening tool globally[19], encompassing tests in various cognitive domains and demonstrating high acceptability among clinical professionals[1]. Despite these advantages, numerous studies have shown that the MMSE inadequately evaluates frontal/executive function[2],[15], with various studies reporting false-negative and false-positive issues[18],[27]. Behavioral variant FTD often maintains normal scores on standard cognitive tests in the early disease stages[29] and is often classified as normal on MMSE[32]. Furthermore, existing screening tests are limited to reflecting cognitive behavioral characteristics without adequately representing neurophysiological characteristics.

Electroencephalogram (EEG) offers advantages of non-invasiveness and portability, enabling widespread utilization even in settings with limited healthcare accessibility, thereby facilitating early detection of neurodegenerative diseases and mediating timely intervention. Recent studies combining EEG with artificial intelligence (AI) have demonstrated effective binary classification performance between AD-cognitively normal (CN), AD-FTD, and FTD-CN [24],[28],[21], suggesting potential for complementing existing screening protocols. Despite these promising results, clinical environments require solutions for more complex and diverse disease classification problems. Accordingly, another study reported the feasibility of classifying AD, HC, and mild cognitive impairment (MCI) with potential for progression to dementia[16]; however, multi-class classification of EEG-based neurodegenerative diseases and neurocognitive disorders incorporating actual dementia subtypes remains challenging. One previous study[14] showed approximately 55% accuracy in 3-class classification of AD-FTD-CN using various artificial intelligence models. Another study[31] demonstrated 54.28% accuracy using a convolutional neural network (CNN)-based model. Thus, multi-class cognitive impairment classification using EEG remains a difficult problem.

EEG typically exhibits nonlinear dynamical characteristics[11] that can be considered across time-frequency-spatial domains. However, existing classification models have limitations in comprehensively considering EEG characteristics and utilizing features that are representative of each cognitive impairment.

Therefore, this paper proposes a spatio-spectral image based deep learning framework (SSPNet) to overcome limitations in multi-class classification of neurodegenerative diseases. In the present study, we utilized a dataset containing MMSE scores and clinical diagnostic labels, with the objective of complementing existing screening processes for neurodegenerative diseases and supporting diagnostic procedures. Our approach extracts EEG topographic images that maximize differences between neurophysiological features. Specifically, we extract spatio-spectral features from EEG topographic images by selecting minimal frequency bands based on neurophysiological evidence, then encode and classify this information using specialized asymmetric convolutional blocks (ACB)[9] and attention mechanisms. The main contributions of this work are: (i) We propose a novel deep learning framework utilizing spatio-spectral image features from EEG topographic images for multi-class classification of neurodegenerative diseases. To our knowledge, this is the first attempt to utilize EEG topography-based spatio-spectral features in multi-class classification of neurodegenerative diseases. (ii) We utilize representative features based on prior neurophysiological evidence, demonstrating robust classification performance with minimal EEG frequency bands(delta: 0.5-4 Hz, alpha: 8-12 Hz). (iii) By employing ACB and attention mechanisms specialized for each spatio-spectral image, we can extract frequency-specific spatial features while effectively preserving channel and spatial information. (iv) Our performance evaluation on public datasets significantly improves the accuracy of existing EEG-based methods for multi-class classification of neurodegenerative diseases and demonstrates notably lower false-negative rates for FTD patients compared to conventional screening methods (MMSE), accelerating potential clinical application.

2 Method

2.1 Dataset

This study utilized a public EEG dataset[22]. This dataset consists of 36 individuals in the AD group, 23 individuals in the FTD group, and 29 individuals in the CN group. Additionally, all subjects have recorded scores from the MMSE. All subjects' recordings were performed during a resting state with eyes closed. The recording lengths by group were as follows: AD group (min=5.1, max=21.3), FTD group (min=7.9, max=16.9), CN group (min=12.5, max=16.5). The dataset was preprocessed using a Butterworth band-pass filter with a range of 0.5–45 Hz, Artifact Subspace Reconstruction (ASR), and Independent Component Analysis (ICA).

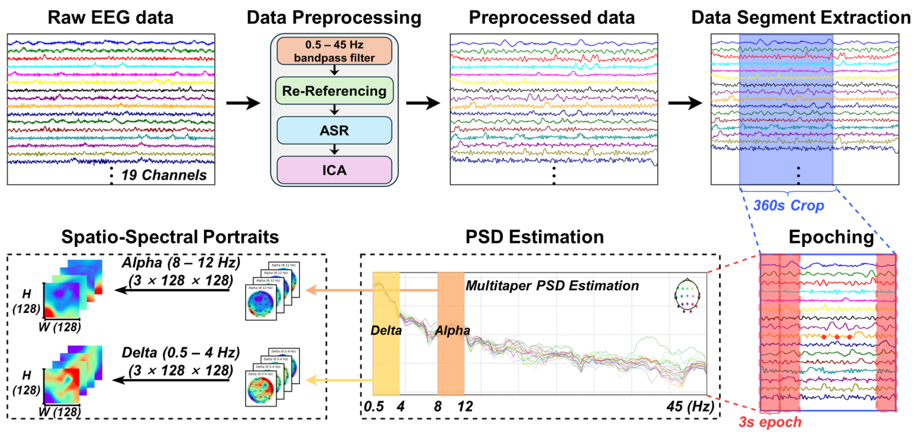

Fig. 1. EEG Processing Workflow and Spatio-Spectral Portrait Features

2.2 Data Processing

EEG Segment Extraction and Epoching: This study involved segment extraction and epoching of EEG data for the training and validation of a deep learning framework. EEG signals from each subject were extracted for a duration ranging from 60 to 420 seconds (a total of 360 seconds) for analysis, in order to mitigate the influence of environmental adaptation and noise that may arise during the initial minute. We established a criterion of a minimum of 6 minutes of EEG data to guarantee data consistency and adequate training material, thereby excluding subject-003, whose total data duration was the shortest at 5.1 minutes. As shown in Fig. 1, the extracted EEG data was segmented into 3-second epochs without overlap, resulting in each subject's EEG data totaling 360 seconds divided by 3 seconds, equating to 120 epochs. The final processed dataset comprised 87 subjects $\times$ 120 epochs, 19 channels, and 1500 time points (3 seconds $\times$ 500 Hz sampling rate).

2.3 Proposed Framework

We propose a deep learning-based framework (Fig. 2) for effective multi-classification of neurodegenerative diseases (AD, FTD, and CN) by extracting minimal frequency-based spatial image features from EEG based on neurophysiological evidence. This framework learns specific patterns of neurodegenerative diseases using spatio-spectral features extracted from EEG topographic images derived from alpha and delta bands of EEG signals as input.

EEG Frequency Band Configurations: The EEG alpha band indicates decreased power spectral density in the parietal-occipital regions in AD, reflecting cholinergic neurotransmission impairment[3]. In contrast, the EEG delta band

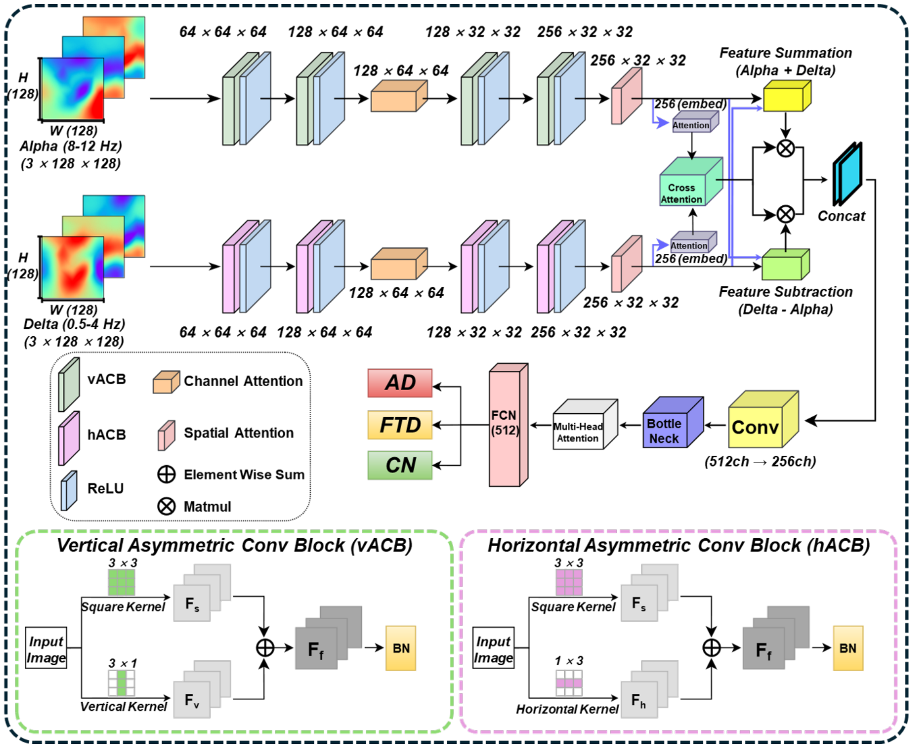

Fig. 2. Spatio-Spectral Portrait Based Deep Learning Framework(SSPNet)

shows increased frontal activity in FTD[17], characterized by left-right asymmetry[12]. Additionally, [5] revealed that EEG frequency characteristics effectively distinguish between AD and FTD, and the alpha/delta ratio enhances disease monitoring and classification[6]. Based on this physiological evidence, we utilized the EEG delta and alpha bands.

EEG topographic Feature: As shown in Fig. 1, we generate EEG topographic images, power values from 19 electrodes were spatially interpolated to create 128×128 pixel images, and a multi-taper PSD method based on seven discrete prolate spheroidal sequence tapers was employed to achieve a balance between frequency resolution and estimation variance.

Spatio-Spectral Portraits Based Multi-Input Structure: The proposed framework employs a dual-branch architecture, processing alpha and delta bands independently to capture distinct spatial characteristics. The alpha band exhibits upper-lower asymmetry, emphasized using an additional vertical kernel($K \times 1$). In contrast, the delta band shows left-right asymmetry, particularly in FTD, which is enhanced using a horizontal kernel($1 \times K$) Here, K represents the kernel size, ensuring effective integration of EEG's physiological properties into feature extraction.

Channel and Spatial Attention Mechanisms: To enhance the most informative spectral components, channel attention is applied, prioritizing critical PSD features in each channel. Additionally, spatial attention refines the representation of spatial asymmetry, enabling the model to focus on key variations associated with neurodegenerative diseases. These attention mechanisms are independently applied to the alpha and delta bands, preserving their distinct spectral and spatial properties.

Cross-Attention Based Feature Fusion: To integrate complementary information, features from the alpha and delta bands undergo cross-attention, refining their representations before fusion. This mechanism captures inter-band relationships by computing complex features (element-wise summation) to extract shared representations and differentiated features (element-wise subtraction) to highlight contrastive patterns. The refined features are then concatenated and fused through convolution, ensuring a robust integration of both shared and distinct EEG characteristics.

Multi-Head Attention Mechanisms: After feature fusion, a bottleneck structure is employed to further refine feature representations, ensuring compact yet discriminative embeddings. To analyze EEG signal interactions from multiple perspectives, a multi-head attention mechanism is applied, capturing intricate relationships between the alpha and delta bands. This multi-faceted analysis enables the model to learn rich and highly discriminative feature representations, ultimately leading to improved classification performance in distinguishing neurodegenerative diseases.

2.4 Majority Voting Strategy and Classification

To enhance classification robustness, each subject's EEG data was segmented into 120 epochs, subsequently transformed into topographic images, with independent classification executed for each individual image. The final classification determination employs a majority voting scheme, selecting the most frequently predicted class across the 120 images. The data were used for training and validation through 5-fold cross-validation. Within each fold, the dataset was further divided into training and validation sets. The model was trained for up to 50 epochs per fold, with early stopping applied when validation loss showed no improvement for 10 consecutive epochs, ensuring stable convergence while minimizing overfitting. To further validate the model's performance, we conducted a comparative analysis using EfficientNet[33] and EEGNet[20], a CNN-based architecture trained under the same experimental conditions.

Table 1. 3-Class Classification Accuracy Comparison

Model	Accuracy	Precision	Recall	F1-Score
LDA[14]	55.69%±9.14%	55.69%±9.14%	55.69%±9.14%	55.69%±9.14%
Linear SVC[14]	57.54%±9.89%	57.54%±9.89%	57.54%±9.89%	57.54%±9.89%
SVM (RBF)[14]	51.35%±9.92%	51.35%±9.92%	51.35%±9.92%	51.35%±9.92%
CNN[31]	54.28%±5.92%	50.41%±14.75%	51.26%±28.45%	49.17%±22.75%
EEGNet (All bands)	44.44%±19.24%	51.00%±15.17%	44.44%±19.24%	43.83%±3.56%
EEGNet (Delta+Alpha)	50.00%±50.00%	39.28%±37.62%	50.00%±50.00%	40.00%±34.64%
EfficientNet	61.11%±53.57%	40.83%±35.38%	61.11%±53.57%	48.80%±42.30%
Proposed	**72.22%±9.61%**	**72.22%±9.61%**	**72.22%±9.61%**	**72.22%±9.61%**

3 Results and Discussions

The results of Experiment 1 and 2 are summarized in Table 1 and Table 2, respectively. To evaluate the general classification performance, we compared our framework with previously published studies that attempted 3-class classification on the same dataset. For Experiment 2, which specifically evaluates the detection of false-negative MMSE cases, we conducted a comparative analysis using EEGNet, EfficientNet, and the proposed framework to assess their ability to identify these challenging cases.

3.1 Experiment 1: General Classification

In Experiment 1, the performance of the proposed model for multi-class classification of AD-FTD-CN was compared and evaluated, with results summarized in Table1. Previous studies[14] utilized raw EEG signals as features and employed classifiers such as linear discriminant analysis (LDA) and support vector machine (SVM) for classification. However, their reported performance on 3-class classification remained below 55%, highlighting the limitations of traditional machine learning approaches in capturing complex EEG patterns. In contrast, EfficientNet, a CNN-based architecture, achieved an improved accuracy of 61%, outperforming EEGNet and prior research methods. Nevertheless, the proposed framework achieved the highest accuracy of 72.22% among the compared models, demonstrating superior classification performance. This result suggests that incorporating frequency-specific spatial representations and advanced feature fusion strategies enhances the model's ability to distinguish between neurodegenerative conditions.

3.2 Experiment 2: MMSE False-Negative Cases in FTD

Experiment 2 was conducted to minimize the false-negative problem of MMSE, a significant challenge in existing cognitive assessments. Generally, MMSE scores

Table 2. Comparison of Classification Accuracy by Model for FTD Patients with False-Negative Issues through MMSE

Model	Accuracy AD	Accuracy FTD	Accuracy CN	Precision AD	Precision FTD	Precision CN	Recall AD	Recall FTD	Recall CN	F1-Score AD	F1-Score FTD	F1-Score CN
	Overall			Overall			Overall			Overall		
EEGNet (All bands)	100%	0%	0%	33%	0%	0%	100%	0%	0%	50%	0%	0%
	33.33%±57.73%			11.11%±19.24%			33.33%±57.73%			16.66%±28.86%		
EEGNet (Delta+Alpha)	11%	11%	100%	100%	100%	36%	11%	11%	100%	19.9%	19.9%	52.9%
	40.74%±51.32%			78.66%±36.95%			40.74%±51.32%			30.97%±19.02%		
EfficientNet	66%	0%	88%	50%	0%	53.3%	66%	0%	88%	57.1%	0%	66%
	51.84%±46.25%			34.44%±29.87%			51.84%±46.25%			41.26%±36.05%		
Proposed	**66%**	**55%**	**100%**	100%	66%	69.2%	55%	66%	100%	71.4%	66%	81.8%
	74.07%±23.13%			**78.63%±18.55%**			**74.07%±23.13%**			**73.29%±7.74%**		

of 24 or above are classified as normal; however, in the dataset used, the AD group showed 0 cases (0%) of false-negatives among 36 subjects, while the FTD group demonstrated 9 cases (approximately 39%) of false negatives among 23 subjects. Therefore, we evaluated the potential for additional identification of these 9 FTD patient cases with false negatives using the proposed framework (SSPNet). For this purpose, 9 false negative FTD patients were tested alongside 9 randomly selected AD patients and 9 healthy controls. As shown in Table 2, most models, including EfficientNet and other CNN-based architectures, experienced difficulties in FTD classification. Only EEGNet utilizing delta and alpha band features classified a subset of the false-negative FTD cases. However, the proposed framework outperformed all models and effectively classified false-negative FTD subjects. These results emphasize the robustness of the proposed framework and demonstrate its effectiveness in additionally identifying FTD patient cases despite the false-negative issues of MMSE. This suggests enhanced classification reliability in clinical diagnosis.

4 Conclusion

In this study, we propose a novel EEG spatio-spectral portraits-based deep learning framework (SSPNet) to improve existing multi-classification performance in neurodegenerative diseases. The proposed method constructs spatial images from minimal frequency bands that maximize neurophysiological features from EEG. Subsequently, by utilizing specialized ACB and attention mechanisms to effectively extract and classify frequency, spatial, and channel features, our approach demonstrates the potential to overcome the challenges in multi-classification of neurodegenerative diseases. Notably, our framework shows lower false-negative error rates for FTD compared to the commonly used MMSE screening test, demonstrating its possibility to address more complex clinical problems. While validation across diverse datasets should be performed in the future to ensure the generalizability and robustness of the proposed framework, it still demonstrates significant potential to be effectively integrated into real-world clinical workflows.

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