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AI-Driven Deep Learning Framework for Robust Multiclass Dementia Classification Using EEG Data

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Abstract

Dementia is a growing public health concern worldwide. Accurately differentiating among its various forms can facilitate earlier clinical assessment and support more effective management strategies. Electroencephalography (EEG) has emerged as a promising tool for dementia assessment because it is noninvasive, inexpensive, portable, easy to administer, and capable of capturing brain activity with high temporal resolution. However, existing EEG-based approaches often rely on manually engineered features, evaluate only a limited number of classification tasks, or employ models with limited generalisability across multiple diagnostic classes. This study proposes a deep learning framework to classify dementia-related conditions from resting-state EEG. The framework integrates systematic signal preprocessing, 5-second multichannel EEG segmentation, and a two-dimensional convolutional neural network to learn hierarchical spatiotemporal representations and distinguish different forms of dementia patients from

healthy controls. The proposed framework was evaluated via a publicly available dataset comprising 88 participants: 36 with Alzheimer's disease (AD), 23 with frontotemporal dementia (FTD), and 29 healthy controls (HC). Performance was assessed using 10-fold cross-validation across one multiclass task (AD vs FTD vs HC) and three binary tasks (AD vs HC, FTD vs HC, and AD+FTD vs HC). The framework achieved an average multiclass accuracy of 98.78% and binary accuracies of 99.21%, 99.40%, and 99.15%, together with consistently high sensitivity, specificity, precision, and F1 scores. These findings demonstrate the potential of combining automated EEG preprocessing with convolutional neural network (CNN) based representation learning to support accurate dementia classification and the development of accessible, cost-effective clinical decision-support tools.

Keywords: Alzheimer's disease (AD), frontotemporal dementia (FTD), healthy control (HC), electroencephalography (EEG), deep learning, dementia classification

1 Introduction

Dementia is a progressive neurodegenerative syndrome characterized by impairments in memory, cognition, language, and activities of daily living, with a substantial burden on patients, carers, and health-care systems. It is one of the fastest-rising global health concerns and a major contributor to disability, loss of independence, and social and economic costs. Among the major forms of dementia, Alzheimer's disease (AD) and frontotemporal dementia (FTD) are particularly relevant because they often overlap in clinical presentation but require separate diagnostic attention and therapeutic options. The World Health Organization (WHO) reported that 57 million people worldwide had dementia in 2021, with nearly 10 million new cases being diagnosed each year. By 2030, this number is estimated to increase to 78 million and reach 139 million by 2050. Someone in the world develops dementia every 3 seconds [1]. In 2026, there were an estimated 446,500 Australians living with dementia. Without significant intervention, the number of Australians living with dementia is expected to increase to more than 1 million by 2065 [2]. According to the WHO, in 2019, the global social cost of dementia was estimated at US$1.3 trillion and is expected to exceed US$2.8 trillion by 2030 [1]. In 2022–23, the Australian government provided almost $126 million to support dementia support programs and initiatives [3].

As the world's population ages, the number of people affected by dementia is increasing, making early and precise diagnosis more critical than ever before. However, the diagnosis of dementia can be performed via a variety of tests, including laboratory tests, medical history review, mental status examination, and, more recently, brain imaging tools such as positron emission tomography (PET), computed tomography (CT), and functional magnetic resonance imaging (fMRI). These conventional diagnostic techniques remain costly, time-consuming, and heavily dependent on the interpretation of specialists, limiting their utility for large-scale or early screening. To overcome these challenges, electroencephalography (EEG) has appeared to be a promising tool for dementia detection because it is noninvasive, relatively low-cost, portable, and capable of capturing brain activity with high temporal resolution. EEG

measures the electrical activities generated by the brain, and the signal reflects functional changes in neuronal activity, making it suitable for identifying abnormalities associated with dementia-related disorders. The recorded signals reflect the patient's physiological state and mental health condition. In particular, EEG signals can also provide clinically useful information that can support the differentiation among healthy controls (HC), AD patients, and FTD patients. Because of these advantages, EEG-based automated classification offers a more practical and affordable option than costly neuroimaging methods do. In recent years, numerous studies have focused on the detection of dementia via EEG signal data.

In recent years, several EEG-based studies have been carried out for detection and classification of dementia including AD, FTD, mild cognitive impairment (MCI), and HC. Section 2 briefly reviews the related machine learning and deep learning approaches [4–20]. From the literature, it is evident that many of these methods have been used to classify dementia, but have not been able to achieve an optimal balance between accuracy and efficiency. They rely on handcrafted features, shallow learning structures, and relatively small datasets. Although more recent deep learning approaches, including long short-term memory (LSTM), transformers, convolutional neural networks (CNNs), and hybrid-based models, have improved performance, several studies still report limitations in generalizability, interpretability, or class-wise robustness. This study evaluates systematic preprocessing and a two-dimensional convolutional neural network (2D CNN) within a common framework for multiclass and binary classification of HC, AD, and FTD EEG recordings.

To address the current deficits, this study proposes a new AI-driven deep learning framework involving a robust multiclass dementia classification task to distinguish among HC, AD, and FTD subjects with improved performance. The framework uses a preprocessing pipeline consisting of bandpass filtering, artifact rejection via automatic subspace reconstruction (ASR) and independent component analysis (ICA)-based rejection, and segmentation of the EEG values into epochs of 5 seconds. The preprocessed epochs are then used to train a CNN architecture to learn hierarchical spatiotemporal feature representations from the EEG data. The use of 5-second epoch segments captures informative EEG dynamics and ensures that the model remains computationally efficient and robust. Furthermore, the suggested framework is not only confined to three-class classification but also assesses its diagnostic capacity in clinically important binary classification scenarios. This strategy combines multiclass classification of HC, AD and FTD with binary classification tasks, namely, AD+FTD vs. HC, AD vs. HC and FTD vs. HC, making the proposed approach effective in detecting dementia-related abnormalities from EEG signals. The contribution is a common preprocessing and CNN evaluation framework spanning one multiclass and three binary tasks, together with an architectural ablation study; it does not establish a new convolutional operation.

The study provides several significant contributions, including the following:

- A 2D CNN-based deep learning model was built for the automatic classification of dementia-related EEG signals via cleaned multichannel EEG segments.

- Evaluation of a single EEG-based CNN framework on one multiclass and three binary classification tasks with the same preprocessing pipeline and validation protocol.
- This study evaluates the proposed framework using 10-fold cross-validation and reports its performance alongside published EEG-based dementia classification results.
- Improved classification accuracy over additional EEG-based dementia diagnosis methods.

The remainder of the paper is structured as follows. Section 2 presents a concise survey of the literature on current methods for dementia classification detection on the basis of EEG signals. The proposed methodology, analysed data, preprocessing steps, model architecture, and evaluation strategy are described in Section 3. Section 4 includes the experimental setup, results, and comparison with existing methods. The classification performance, ablation study, limitations and future directions are discussed in Section 5. The paper ends with the conclusion in Section 6.

2 Related Work

In the past few years, many studies have focused on the detection of dementia-related disorders from EEG signals, including those of AD, MCI, and FTD patients and healthy controls [4–20]. Various feature extraction and classification techniques have been used in these studies, such as lifting wavelet transform (LWT) decomposition, Hilbert–Huang transform (HHT), principal component analysis (PCA), empirical mode decomposition (EMD), intrinsic mode functions, Katz fractal dimension, sample entropy, spectral and entropy features, functional connectivity, Hjorth parameters, spatial filtering, independent component analysis (ICA)-based feature selection, relative band power and graph-based EEG features [5, 8–10, 13, 16, 18–20]. These features have been integrated with several machine learning (ML) and deep learning (DL) models, such as k-nearest neighbors (kNN), support vector machines (SVMs), long short-term memory (LSTM), recurrent neural networks (RNNs), CNNs, transformer-based models, fuzzy RNNs, temporal convolutional networks–long short-term memory (TCN-LSTM), and graph-based classifiers [4–20].

In 2023, Alvi et al. [4] proposed a deep learning framework based on an LSTM model. Their method can effectively discriminate MCI patients, an early stage of AD, from healthy controls. In the same year, Ravikanti and Saravanan [5] proposed an optimized transformer-based attention long short-term memory (OTA-LSTM) model for EEG-based AD detection, which consists of LWT decomposition, an RNN, a multiscale dilated CNN, and an optimization algorithm for feature weighting. The model performed better than the CNN, RNN, SVM, and attention long short-term memory (A-LSTM) methods did, but the small number of AD subjects limited its performance. Chaabene et al. [6] classified amnestic MCI (aMCI), nonamnestic MCI (naMCI), and healthy control (HC) individuals during a verbal fluency task (VFT) with EEG data. A transformer-based MCI detection method is proposed, which achieves an accuracy as high as 94.78%.

In 2024, Siuly et al. [7] applied the LSTM to find the optimal EEG rhythms and channels for diagnosing AD. Pallathadka et al. [8] used 19-channel EEG data from 131 subjects and extracted features of the Katz fractal dimension and sample entropy. The framework extracts the Katz fractal dimension and sample entropy features and employs a kNN classifier with hold-out validation. Gopu et al. [9] developed an EEG-based MCI detection approach using data collected from 68 subjects, including 23 healthy controls and 45 MCI patients. Their approach employed HHT, PCA, EMD, and intrinsic mode functions with a kNN classifier under 10-fold cross-validation and obtained 98.60% accuracy. Faghfouri et al. [10] used two EEG datasets for MCI classification and extracted spectral and entropy-based features via parallel factor analysis (PARAFAC) and statistical complexity measures. They achieved 93.96% accuracy on DB1 and 78.65% accuracy on DB2 via SVM. Nour et al. [11] proposed a deep ensemble model that uses five EEG frequency bands and a 2D-CNN classifier. Their method obtained 97.9% accuracy with 5-fold cross-validation. Tawhid et al. [12] proposed a CNN-based framework to identify exact frequency band biomarkers for MCI diagnosis. Hasoon et al. [13] explored EEG functional connectivity to differentiate stable MCI and converting MCI. Altered EEG connectivity in the alpha and beta bands of patients converting to dementia can be useful for early prediction. Kachare et al. [14] proposed a CNN-based model named STEADYNet for dementia detection via multichannel spatiotemporal EEG signals. Their model achieved a high classification performance of 98.24% accuracy, which demonstrates the effectiveness of CNN-based feature learning for EEG-based dementia detection. Amer and Belhaouari [15] proposed a forward–backwards Fourier transform (FBFT)-based CNN model to improve EEG visualization for brain disorder classification. The model achieved accuracies of 85.1%, 99.82%, 100% and 95.91% for murmur, epilepsy, mental stress and AD, respectively, and the eye-naked classification method achieved accuracies of 78.6%, 71.9%, 82.7% and 91.0% for epilepsy, AD, murmur and mental stress, respectively.

In 2025 and 2026, Lee et al. [16] proposed an EEG time-domain method based on Hjorth parameters for distinguishing AD, FTD and cognitively normal (CN) subjects. They reported accuracies of 92.5% for AD&FTD vs. CN, 88.6% for AD vs. CN and 96.0% for FTD vs. CN, suggesting that time-domain EEG features are useful for dementia classification. Sreedhar et al. [17] proposed a fuzzy RNN-based model for the classification of AD, dementia and healthy control subjects using EEG signals and achieved 97.82–98.82% accuracy with high sensitivity and specificity. Similarly,Escobar-López et al. [18] developed an EEG-based framework for AD and MCI detection via spatial filtering, ICA-based noise removal and feature selection. Twenty-six important features were selected from the 133 extracted features, and the method achieved more than 95% accuracy in most of the experiments. Khan et al. [19] proposed a lightweight TCN-LSTM with modified relative band power (RBP) features based on 6 EEG bands and achieved 99.7% accuracy for binary tasks and 80.34% accuracy for multiclass AD, FTD and HC classification. Singh et al. [20] presented a graph-based EEG classification approach based on the angle–relation connection (ARC) rule with a weighted angular irregularity index (WAII) and curvature-based edge feature index (CBEFI) features to capture the irregularity and geometry of the

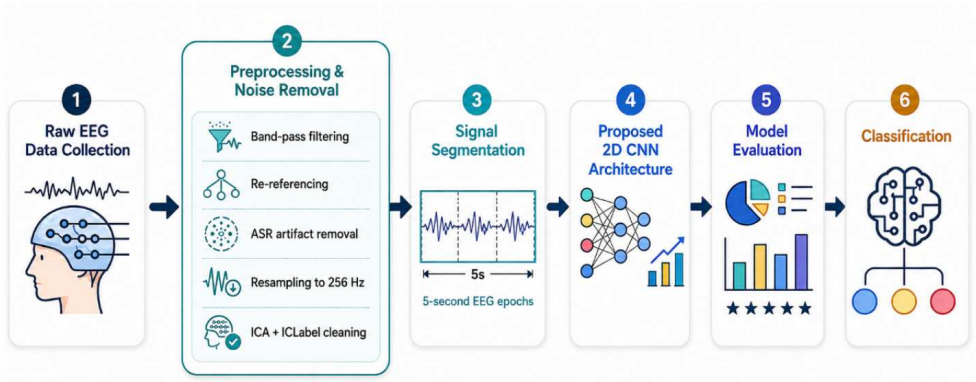


Fig. 1: Overview of the proposed framework for classifying dementia from EEG

signal. They achieved 88.02% accuracy for multiclass AD vs. FTD vs. HC classification and 97.5% accuracy for FTD vs. HC classification by their method.

3 Methodology

The proposed framework employs a two-dimensional convolutional neural network (2D CNN) to classify dementia-related conditions by resting-state EEG signals. Its primary objective is to provide a robust pipeline for distinguishing among participants with Alzheimer's disease (AD) or frontotemporal dementia (FTD) and healthy controls (HC). The raw EEG signals were processed via Butterworth bandpass filtering, rereferencing, automatic subspace reconstruction (ASR), independent component analysis (ICA)-based artifact removal, and resampling to 256 Hz. The preprocessed signals were then divided into 5-second epochs. The proposed 2D CNN was trained to learn hierarchical spatial and temporal features automatically for one multiclass task (AD vs. FTD vs. HC) and three binary tasks (AD vs. HC, FTD vs. HC, and AD+FTD vs. HC). A softmax classification layer was used to estimate the probability of each diagnostic category and generate the final prediction. Fig. 1 presents the overall workflow of the proposed framework, including EEG data acquisition, preprocessing, signal segmentation, feature learning via the 2D CNN, model evaluation, and classification. To ensure consistency and reproducibility, the same preprocessing pipeline and evaluation protocol were applied to all multiclass and binary classification tasks.

3.1 EEG data collection

This study utilized a publicly available EEG dataset [21] comprising recordings from 88 participants at the Department of Neurology, AHEPA General University Hospital of Thessaloniki. The dataset included 36 AD patients (13 male, 23 female; age 66.4±7.9 years; Mini-Mental State Examination (MMSE) score 17.75 ± 4.5), 23 FTD patients (14 male, 9 female; age 63.6 ± 8.2 years; MMSE 22.17 ± 8.22), and 29 age-matched HC (11 males, 18 females; age, 67.9 ± 5.4 years; MMSE score, 30 ± 0). EEG signals were acquired via 19 electrodes positioned according to the international 10–20 system.

Table 1: Summary of the dataset used for validating the proposed framework

Group	Subjects	Male/Female	Age (Mean ± SD)	MMSE (Mean ± SD)	Avg. Duration
HC	29	11 / 18	67.9 ± 5.4	30.00 ± 0.00	13.8 min
AD	36	13 / 23	66.4 ± 7.9	17.75 ± 4.50	13.5 min
FTD	23	14 / 9	63.6 ± 8.2	22.17 ± 8.22	12.0 min

with A1/A2 references, recorded at 500 Hz during the eyes-closed resting state with average durations of 13.5 minutes (AD), 12 minutes (FTD), and 13.8 minutes (HC).

The dataset is openly accessible online, and all participants provided informed consent for the use of their anonymized data. As no personally identifiable information was included, additional ethical approval was not required for this study. Demographic and clinical characteristics are summarized in Table 1, demonstrating balanced age distributions across groups with expected cognitive score variations reflecting diagnostic criteria.

3.2 Preprocessing and noise removal

The raw EEG signals underwent a series of preprocessing steps to enhance signal quality and remove artifacts. First, a Butterworth bandpass filter with a frequency range of 0.5–45 Hz was applied to suppress noise outside the typical EEG bandwidth. The signals were then rereferenced to the average of electrodes A1 and A2 to ensure consistency across recordings.

An ASR algorithm [22] was subsequently used to detect and eliminate transient, high-amplitude artifacts. Specifically, signal segments exceeding a standard deviation threshold of 17 within a 0.5-second window were classified as artifacts and removed [23].

To further refine the data, independent component analysis (ICA) was performed via the RunICA algorithm, which decomposes the 19-channel EEG signal into 19 independent components. Artifact-related components, such as those corresponding to ocular and jaw movements, were automatically identified and rejected via the ICLabel plugin within the EEGLAB environment [24]. Finally, the cleaned EEG data were resampled to 256 Hz to standardize the sampling rate across all the recordings.

3.3 Signal segmentation

For subsequent analysis, the preprocessed EEG signals were segmented into shorter, informative time windows. This segmentation process involves dividing the continuous EEG recordings into discrete fragments, which are then normalized to retain the amplitude characteristics of the original signals. This approach not only increases the number of data samples but also maintains a balanced class distribution across the dataset.

In this study, we segmented the filtered EEG signals into 5-second (5 s) epochs, which were aligned with prior research findings [25]. The use of 5-second segments

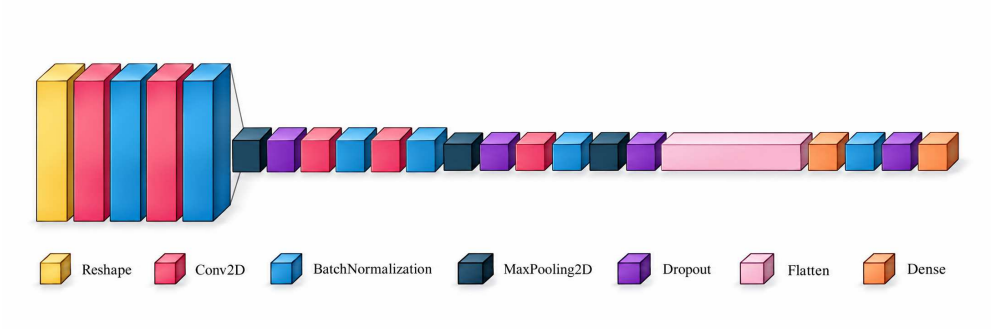


Fig. 2: Architecture of the proposed two-dimensional CNN for EEG classification

provides several benefits: it enhances computational efficiency and preserves critical temporal and spectral features and improves the accuracy and robustness of classification models [25].

3.4 Proposed 2D CNN architecture

Compared with traditional feature engineering approaches, CNNs have demonstrated superior performance in EEG signal classification, offering three key advantages. First, CNNs automatically learn task-relevant spatiotemporal features through hierarchical representation learning, thereby reducing the need for manual feature extraction and selection [26, 27]. Second, their translation-equivariant structure supports the consistent detection of local patterns across spatial and temporal positions within EEG data [26]. Third, weight sharing substantially reduces the number of trainable parameters compared with fully connected networks, which may improve generalizability when working with limited EEG datasets [27]. These characteristics make CNNs particularly effective for identifying subtle neurological patterns associated with AD and FTD in resting-state EEG signals.

In this study, we developed a CNN model to perform classification on the input EEG data. Here, each input EEG signal segment has dimensions of 19×1280, where 19 is the number of channels and 1280 is the 5-second signal segment multiplied by 256 Hz. This produces a total of 1280 sampling points for each channel. An architectural overview of the proposed CNN model is given in Fig. 2.

The architecture reported in Fig.2 contains five convolutional layers, each followed by batch normalization. Three max pooling and dropout layers follow the second, fourth and fifth convolutions. A dense layer with 128 units, batch normalization and 50% dropout precedes the softmax classification layer.

The developed model processes input EEG epochs $X \in \mathbb{R}^{19\times1280\times1}$ (19 channels $\times$ 1280 timepoints $\times$ 1 channel) through three specialized processing stages. The temporal convolution operation:

$$Y_t^{(l)} = \sigma\left(W_t^{(l)} \circledast X + b_t^{(l)}\right) \tag{1}$$

where $W_t^{(l)} \in \mathbb{R}^{1\times 64\times 32}$ represents learnable temporal filters, captures frequency-specific patterns through kernels spanning 64 samples (∼250 ms at 256 Hz). This is complemented by spatial convolution:

$$Y_s^{(l)} = \sigma\left(W_s^{(l)} \circledast Y_t^{(l)} + b_s^{(l)}\right) \tag{2}$$

with $W_s^{(l)} \in \mathbb{R}^{19\times 1\times 32}$ modelling cross-channel dependencies. Batch normalization:

$$\hat{Y}^{(l)} = \gamma\left(Y^{(l)} - \mu\right)\left(\sigma^2 + \epsilon\right)^{-\frac{1}{2}} + \beta \tag{3}$$

stabilizes training by maintaining activation distributions ($\epsilon = 10^{-5}$, γ/β learnable).

The three convolutional blocks use 32, 64 and 128 filters. The pooling sizes are $(1, 4)$, $(1, 2)$ and $(1, 2)$, followed by a 128-unit dense layer. The classification head

$$p(y \mid X) = \text{softmax}\left(W_{d_2}\,\sigma\left(W_{d_1} Y_3 + b_{d_1}\right) + b_{d_2}\right) \tag{4}$$

with dropout ($p = 0.5$) for regularization. The model minimizes:

$$\mathcal{L} = -\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c}\log\hat{y}_{i,c} + \lambda\left\|W\right\|_2^2 \tag{5}$$

($\lambda = 0.001$) via Adam optimization ($\eta = 10^{-3}$), where C denotes the number of diagnostic classes.

3.5 Evaluation strategy

To evaluate the performance of the proposed model, we employed k-fold cross-validation (CV) as the validation strategy. In this method, the dataset is divided into k equal-sized subsets. The model is trained on $k - 1$ subsets and validated on the remaining subset. This process is repeated k times, with each subset serving as the validation set once. The final performance is obtained by averaging the results across all folds, ensuring a robust and unbiased evaluation. For this study, we adopted 10-fold cross-validation, a commonly used configuration that balances bias and variance effectively.

To assess classification performance comprehensively, we calculate the following five standard metrics:

- **Accuracy (Acc)** is the proportion of correctly classified instances among all samples.
- **Sensitivity (Sen)** – also known as the recall or true positive rate; measures the ability to correctly identify positive cases.
- **Specificity (Spec)** – the ability to correctly identify negative cases.
- **Precision (Prec)** is the proportion of true positives among all the predicted positives.
- **F1 score (F1)** is the harmonic mean of precision and sensitivity, providing a balance between them.

These are widely used in medical and machine learning applications to evaluate the discriminatory ability of classification models and to identify optimal threshold values.

4 Results and Analysis

This section outlines the experimental setup, presents the obtained results in detail, and provides a comprehensive analysis of the findings.

4.1 Experimental setup

In this study, we utilized an EEG dataset comprising three distinct subject groups and performed one ternary classification task (HC vs. AD vs. FTD) and three binary classification tasks: AD+FTD vs. HC, AD vs. HC and FTD vs. HC. The EEG signals were segmented into 5-second epochs, following established methodologies in a previous study [28]. After segmentation, the dataset consisted of 5807 signal segments for AD subjects, 3304 signal segments for FTD subjects, and 4808 signal segments for HC subjects.

Each signal segment has dimensions of 19×1280 to match the input requirements of the CNN model. The experiments were carried out on a high-performance computing system equipped with an AMD Threadripper Pro processor, 256 GB of RAM, and 48 GB of GPU memory. The CNN model was trained using a batch size of 32 for 50 epochs.

4.2 Experimental results

In this study, we developed a CNN-based framework to perform both multiclass and binary classification tasks on datasets of AD, FTD and HC subjects. To validate the experimental results, we employed 10-fold cross-validation, ensuring a robust and generalizable evaluation of model performance across all classification tasks. The next two subsections discuss the results of the multiclass and binary classification of the proposed framework.

4.2.1 Multiclass classification

Table 2 presents the foldwise results obtained from the 10-fold cross-validation experiments evaluated for three-class classification (HC vs. AD vs. FTD). The performance is reported via the selected evaluation metrics: accuracy, sensitivity, specificity, precision, and F1 score.

Table 2 shows that the model consistently demonstrates high performance across all the folds, with accuracies ranging from 98.35% to 99.28%. The overall average accuracy across all the folds is 98.78% ($\pm$ 0.30), indicating highly stable and reliable classification performance.

To further illustrate the stability of the multiclass classification results, Fig. 3 shows the foldwise overall accuracy over 10-fold cross-validation. The accuracy is maintained consistently in all folds, which indicates the robustness of the proposed CNN framework.

Table 2: Foldwise performance of the proposed framework for multiclass classification

Folds	Classes	Sen	Spec	Prec	F1	Acc
F1	FTD	96.53	99.91	99.67	0.98	**98.92**
	AD	100.00	98.40	97.80	0.99	
	HC	99.20	99.89	99.80	0.99	
	Avg	**98.58**	**99.40**	**99.09**	**0.99**	
F2	FTD	99.09	99.44	98.20	0.99	**98.42**
	AD	98.79	98.77	98.28	0.99	
	HC	97.52	99.34	98.74	0.98	
	Avg	**98.47**	**99.18**	**98.41**	**0.99**	
F3	FTD	97.89	99.34	97.89	0.98	**98.71**
	AD	98.31	99.75	99.66	0.99	
	HC	99.79	99.02	98.12	0.99	
	Avg	**98.66**	**99.37**	**98.56**	**0.99**	
F4	FTD	97.38	99.62	98.82	0.98	**98.35**
	AD	97.78	99.01	98.62	0.98	
	HC	99.78	98.82	97.67	0.99	
	Avg	**98.31**	**99.15**	**98.37**	**0.98**	
F5	FTD	97.75	99.17	97.12	0.97	**98.56**
	AD	98.09	99.26	98.95	0.99	
	HC	99.60	99.44	99.01	0.99	
	Avg	**98.48**	**99.29**	**98.36**	**0.98**	
F6	FTD	97.10	99.45	96.17	0.97	**98.49**
	AD	98.51	98.99	98.67	0.99	
	HC	99.37	99.23	99.79	1.00	
	Avg	**98.33**	**99.22**	**98.21**	**0.99**	
F7	FTD	97.55	100.00	100.00	0.99	**98.92**
	AD	99.45	98.82	98.19	0.99	
	HC	99.23	99.43	99.04	0.99	
	Avg	**98.74**	**99.42**	**99.08**	**0.99**	
F8	FTD	97.44	90.19	99.71	0.99	**98.99**
	AD	99.32	99.01	98.64	0.99	
	HC	99.78	99.47	98.91	0.99	
	Avg	**98.85**	**96.22**	**99.09**	**0.99**	
F9	FTD	99.72	99.71	99.15	0.99	**99.28**
	AD	99.12	100.00	99.47	0.99	
	HC	99.15	99.57	99.15	0.99	
	Avg	**99.33**	**99.76**	**99.26**	**0.99**	
F10	FTD	99.41	99.72	99.11	0.99	**99.14**
	AD	100.00	98.87	98.50	0.99	
	HC	97.83	100.00	100.00	0.99	
	Avg	**99.08**	**99.53**	**99.20**	**0.99**	
Overall Average Accuracy						**98.78 (± 0.30)**

Across folds, the sensitivity (Sen), specificity (Spec), precision (Prec), and F1 score all maintain strong values, typically above 97% for each class. Notably, the F1

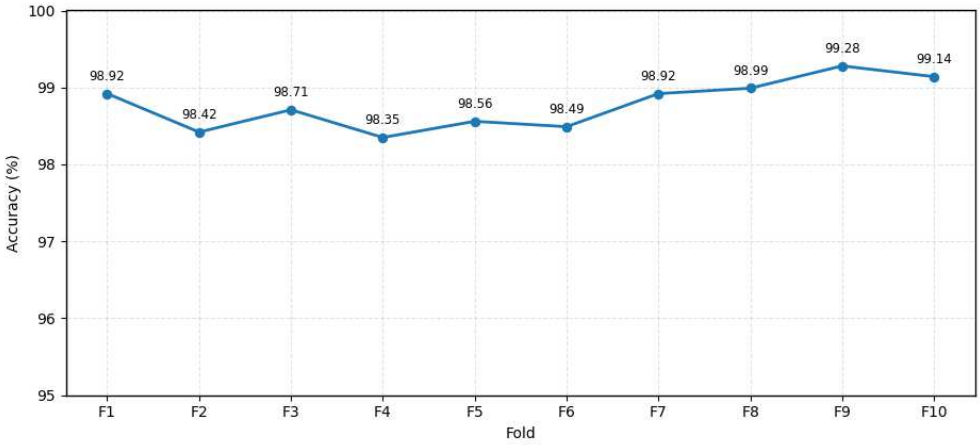


Fig. 3: Foldwise overall accuracy for multiclass classification

scores are consistently approximately 0.98–0.99, confirming that the model balances precision and recall effectively across all classes. The AD class frequently achieves near-perfect sensitivity, with some folds (e.g., F1 and F10) reaching 100%, demonstrating the model's exceptional ability in detecting Alzheimer's disease cases. Similarly, the normal class shows high specificity and precision, often exceeding 99%, ensuring a low false positive rate.

Fig. 4 provides a graphical comparison of performance across the three categories: FTD, AD, and HC. The plot shows that the classifier achieves strong sensitivity, specificity, and precision across all classes, with performance consistently above 98%. Notably, the HC class achieved the highest specificity, while AD and FTD also demonstrated reliable classification performance.

These results collectively demonstrate the model's effectiveness and reliability in classifying EEG signals for distinguishing between FTD, AD, and HC subjects.

4.2.2 Binary classification

To check the performance of the proposed model in binary classification, we have conducted three binary classification tasks: (AD+FTD vs. HC), (AD vs. HC) and (FTD vs. HC). Table 3 shows the fold-wise classification performance of the framework in the three classification tasks.

Table 3 summarizes the 10-fold cross-validation performance of the proposed CNN-based framework for three binary classification tasks: AD vs. HC, FTD vs. HC, and AD+FTD vs. HC. The model achieved consistently high scores across all performance metrics, namely, sensitivity, specificity, precision, F1 score, and accuracy, demonstrating its robustness and effectiveness in distinguishing between subject classes.

The foldwise accuracy for AD vs. HC, FTD vs. HC and AD+FTD vs. HC is displayed in Fig. 5 to compare the stability of the binary classification tasks. The

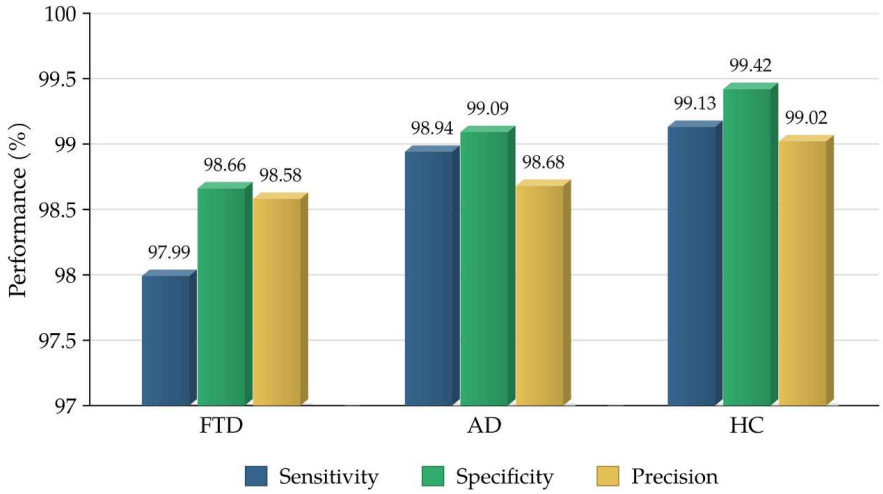


Fig. 4: Average multiclass classification performance of the proposed CNN model

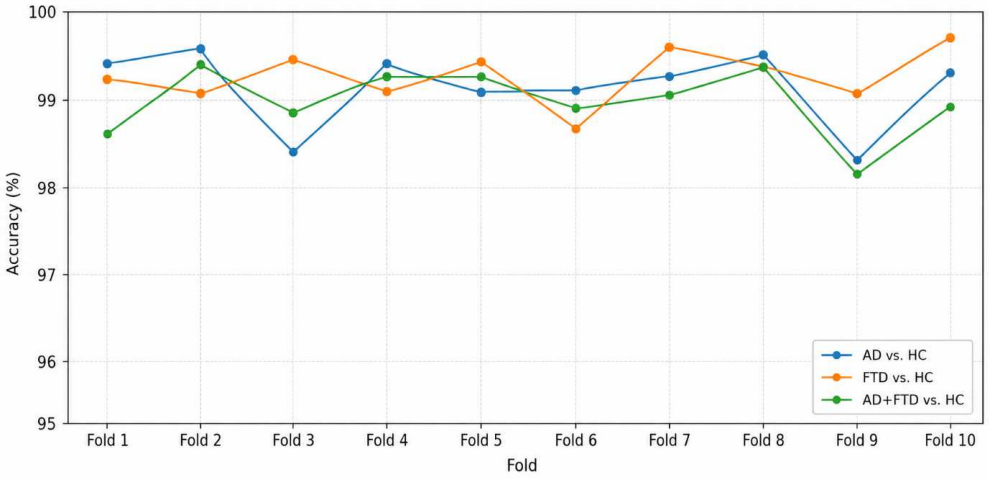


Fig. 5: Foldwise overall accuracy for binary classification

results show that the method has high accuracy for all the folds, showing reliable performance for different diagnostic tasks.

For the AD vs. HC classification, the model achieved an average accuracy of 99.21% (±0.41). The sensitivity was particularly high at 99.40%, indicating the model's excellent ability to detect AD cases. The specificity and precision also remained strong at 98.98% and 99.16%, respectively. The F1 score remained consistent at 0.99–1.00 across folds, suggesting a balanced performance between sensitivity and precision.

In the FTD vs. HC task, the framework yielded an even higher average accuracy of 99.40% (±0.23). Both the sensitivity and specificity averaged 99.41% and 99.40%,

Table 3: Fold-wise performance of the proposed framework for binary classification

Classification	Folds	Sen	Spec	Prec	F1	Acc
AD vs. HC	Fold 1	99.83	99.14	99.33	1.00	99.53
	Fold 2	99.65	99.60	99.65	1.00	99.62
	Fold 3	99.30	97.57	97.92	0.99	98.49
	Fold 4	99.82	99.01	99.11	0.99	99.44
	Fold 5	99.82	98.38	98.61	0.99	99.15
	Fold 6	99.20	99.08	99.36	0.99	99.15
	Fold 7	99.29	99.40	99.47	0.99	99.34
	Fold 8	99.83	99.37	99.49	1.00	99.62
	Fold 9	97.77	99.16	99.30	0.99	98.40
	Fold 10	99.50	99.13	99.33	0.99	99.34
	Average	**99.40**	**98.98**	**99.16**	**0.99**	**99.21**
	STD	0.59	0.56	0.49	0.00	0.41
FTD vs. HC	Fold 1	99.70	99.17	98.79	0.99	99.38
	Fold 2	99.69	98.99	98.45	0.99	99.26
	Fold 3	99.40	99.58	99.40	0.99	99.51
	Fold 4	98.81	99.58	99.40	0.99	99.26
	Fold 5	99.68	99.40	99.05	0.99	99.51
	Fold 6	98.04	99.56	99.43	0.99	98.89
	Fold 7	100.00	99.34	99.16	1.00	99.63
	Fold 8	99.66	99.42	98.99	0.99	99.51
	Fold 9	99.70	98.96	98.50	0.99	99.26
	Fold 10	99.42	100.00	100.00	1.00	99.75
	Average	**99.41**	**99.40**	**99.12**	**0.99**	**99.40**
	STD	0.54	0.29	0.45	0.00	0.23
AD+FTD vs. HC	Fold 1	99.89	96.78	98.24	0.99	98.78
	Fold 2	99.56	99.38	99.67	1.00	99.50
	Fold 3	98.70	99.36	99.67	0.99	98.92
	Fold 4	99.35	99.57	99.78	1.00	99.43
	Fold 5	99.44	99.40	99.66	1.00	99.43
	Fold 6	99.89	97.32	98.59	0.99	98.99
	Fold 7	99.43	98.84	99.31	0.99	99.21
	Fold 8	99.68	99.12	99.57	1.00	99.50
	Fold 9	99.57	97.02	98.50	0.99	98.71
	Fold 10	99.68	97.83	98.93	0.99	99.07
	Average	**99.52**	**98.46**	**99.19**	**0.99**	**99.15**
	STD	0.32	1.05	0.55	0.00	0.29

respectively, while the precision was also high at 99.12%. These results show that the model generalizes well when detecting frontotemporal dementia, with minimal misclassification. The low standard deviations in this task also highlight the stability of the model's performance across folds.

For the AD+FTD vs. HC classification, the model attained an average accuracy of 99.15% ($\pm$0.29). Although the sensitivity remained high at 99.52%, specificity showed slightly higher variability, with a standard deviation of 1.05 and an average of

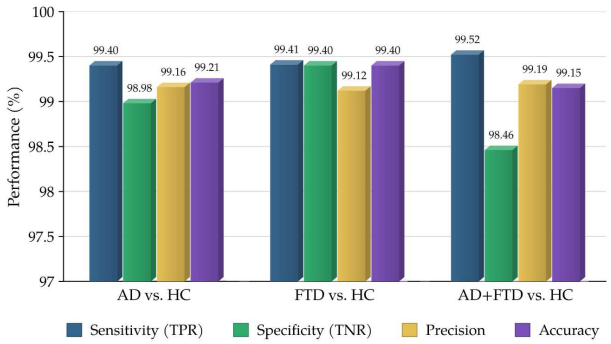


Fig. 6: Average binary classification performance of the proposed CNN model

98.46%. Nonetheless, both the precision (99.19%) and F1 score (0.99) remained consistently high, confirming the model's reliability in distinguishing between normal and pathological cases.

Across all classification tasks, the F1 score remained fixed at 0.99, and in some folds, it even reached 1.00, indicating a near-perfect balance of recall and precision. These findings confirm the effectiveness of the proposed CNN framework in classifying EEG data for both Alzheimer's dementia and frontotemporal dementia with exceptional accuracy and consistency.

In addition to the tabular results, we also provide a graphical comparison of the binary classification performance across different tasks. Fig. 6 shows the average performance (10-fold CV) of the model on three binary classification scenarios: AD vs. HC, FTD vs. HC, and AD+FTD vs. HC. The figure highlights consistently high performance across all the evaluation metrics, with accuracy values exceeding 99% for all the tasks.

5 Discussion

The experimental findings from both multiclass and binary classification tasks highlight the robustness, precision, and reliability of the proposed CNN-based classification framework for EEG-based dementia detection. The model consistently achieved high performance across all the evaluation metrics, demonstrating its ability to distinguish among AD patients, FTD patients, and HC.

5.1 Multiclass classification performance

In the multiclass setting, where the model was tasked with classifying EEG signals into one of three classes (AD, FTD, and HC), the system achieved an overall average

accuracy of 98.78%, with a low standard deviation of ±0.30 across folds. The classwise performance remained consistently strong. For example, AD samples achieved perfect sensitivity (100%) in some folds and consistently high precision and F1 scores. The FTD and HC classes also presented sensitivity and specificity values generally above 97%, indicating that the model's capacity to detect subtle differences in associated EEG patterns with different neurological conditions.

The consistent F1 scores (∼0.98–0.99) across all classes suggest that the model maintains a strong balance between precision and recall, minimizing both false positives and false negatives. This is particularly crucial in medical applications, where misclassification can have significant implications for diagnosis and treatment.

5.2 Binary classification performance

In the binary classification experiments, the model was evaluated across three clinically relevant comparisons: AD vs. HC, FTD vs. HC, and normal vs. abnormal (combined AD and FTD). All three tasks demonstrated exceptional performance:

- AD vs. HC: The average accuracy was 99.21%, with a sensitivity of 99.40%, a specificity of 98.98%, and a very stable F1 score of 0.99. This indicates the model's strong ability to correctly identify Alzheimer's disease cases with minimal false alarms.
- FTD vs. HC: Delivered the highest overall performance, with an average accuracy of 99.40%, and both the sensitivity and specificity were 99.41% and 99.40%, respectively. The model's precision and F1 score were also consistently high, reinforcing its reliability in detecting FTD, a disorder that is often misdiagnosed owing to symptom overlap with other conditions.
- AD+FTD vs. HC: This task yielded an average accuracy of 99.15%, with sensitivity of 99.52%. The slightly lower specificity (98.46%) and relatively greater standard deviation (±1.05) suggest occasional misclassifications of healthy subjects as abnormal. This variability could be attributed to overlapping EEG features between healthy aging and early-stage cognitive decline, emphasizing the need for further refinement in differentiating borderline cases.

The results across both multiclass and binary settings clearly demonstrate the efficacy of combining 5-second signal segments with CNN-based classification. The proposed CNN model captures rich time–frequency dynamics of EEG signals, which are critical in differentiating pathological from normal brain activity. CNNs, in turn, are highly effective in learning these patterns through their hierarchical feature extraction capabilities.

The model's low standard deviations in most metrics across folds indicate strong generalization performance, suggesting that it is not overfitting to specific subjects or recording conditions. The use of 5-second segment durations strikes an effective balance between temporal resolution and computational efficiency.

5.3 Ablation study

Table 4 presents an ablation study evaluating the impact of different CNN block configurations on model performance. The table reports the classification accuracy for Various combinations of convolutional filter sizes, normalization, pooling, and dropout across three convolutional blocks and a dense layer.

The ablation study presented in Table 4 investigates the effects of different architectural configurations on classification performance. The results reveal that the combination of two convolutional layers with 32 filters in the first block, followed by 64 filters in the second block and 128 filters in the third block, achieves the highest accuracy of 98.78%, demonstrating the effectiveness of this balanced hierarchical feature extraction strategy.

When the number of filters is reduced (e.g., starting with 16 filters), the performance slightly decreases to 98.58%, indicating that a lower feature capacity in the initial layers somewhat limits the network's ability to capture fine-grained spectral–spatial EEG information. Conversely, using a deeper configuration with larger filter sizes (64–128–256) also results in a lower accuracy of 98.66%, which may be attributed to potential overfitting and increased model complexity without proportional performance gains.

Notably, configurations that omit the second convolutional layer in the first or second block exhibit a significant decrease in accuracy (≈83%), highlighting the critical role of stacked convolutions in early layers for effective feature learning. Overall, this analysis confirms that a moderately deep CNN architecture with progressive filter scaling (32–64–128) offers the best balance between representational power and generalization for EEG-based dementia classification.

5.4 Comparison with the existing works

Table 5 provides a comparative analysis of the proposed method against existing EEG-based dementia classification approaches. Earlier studies, such as those of Miltiadous et al. [29] and Miltiadous et al. [21], reported relatively modest accuracies (ranging from 73% to 83%) when band power, coherence, and RBP-based random forests were used. Similarly, methods relying on handcrafted features combined with traditional classifiers, such as phase lock values with Gaussian naive Bayes [33] or entropy measures with KNN [31], achieve moderate performance, typically between 84% and 93%.

More recent advancements incorporating deep learning architectures have improved classification accuracy. For example, Chen et al. [30] introduced a dual-branch feature fusion network that combines CNNs and vision transformers with attention mechanisms, achieving accuracies of 87.33% for AD vs. HC and 79.12% in the multiclass scenario. Similarly, Kachare et al. [14] and Jiang et al. [35] demonstrated higher accuracies (84.59%–94.30%) by leveraging STEADYNet and coherence-based CNNs, respectively. Umair et al. [36] improved the multiclass accuracy to 97.10% by employing a hybrid dual-branch EEGNetv4 method. Acharya et al. [37] achieved a multiclass accuracy of 95.70% with a lightweight EEGConvNeXt model applied to CWT spectrogram images, demonstrating the potential of both fusion-based and spectrogram-driven deep architectures.

Table 4: Ablation study of different CNN block configurations and their effects on classification accuracy

1st block	2nd block	3rd block	Dense layer	Accuracy
Conv2D with 32 filter + BatchNormalization + Conv2D with 32 filter + BatchNormalization + MaxPooling2D(1, 4) + Dropout 50%	Conv2D with 64 filter + BatchNormalization + Conv2D with 64 filter + BatchNormalization + MaxPooling2D(1, 2) + Dropout 50%	Conv2D with 128 filter + BatchNormalization + MaxPooling2D(1, 2) + Dropout 50%	Dense(128) + BatchNormalization + Dropout 50%	98.78%
Conv2D with 16 filter + BatchNormalization + Conv2D with 16 filter + BatchNormalization + MaxPooling2D(1, 4) + Dropout 50%	Conv2D with 32 filter + BatchNormalization + Conv2D with 32 filter + BatchNormalization + MaxPooling2D(1, 2) + Dropout 50%	Conv2D with 64 filter + BatchNormalization + MaxPooling2D(1, 2) + Dropout 50%	Dense(128) + BatchNormalization + Dropout 50%	98.58%
Conv2D with 64 filter + BatchNormalization + Conv2D with 64 filter + BatchNormalization + MaxPooling2D(1, 4) + Dropout 50%	Conv2D with 128 filter + BatchNormalization + Conv2D with 128 filter + BatchNormalization + MaxPooling2D(1, 2) + Dropout 50%	Conv2D with 256 filter + BatchNormalization + MaxPooling2D(1, 2) + Dropout 50%	Dense(128) + BatchNormalization + Dropout 50%	98.66%
Conv2D with 32 filter + BatchNormalization + MaxPooling2D(1, 4) + Dropout 50%	Conv2D with 64 filter + BatchNormalization + Conv2D with 64 filter + BatchNormalization + MaxPooling2D(1, 2) + Dropout 50%	Conv2D with 128 filter + BatchNormalization + MaxPooling2D(1, 2) + Dropout 50%	Dense(128) + BatchNormalization + Dropout 50%	83.56%
Conv2D with 32 filter + BatchNormalization + Conv2D with 32 filter + BatchNormalization + MaxPooling2D(1, 4) + Dropout 50%	Conv2D with 64 filter + BatchNormalization + MaxPooling2D(1, 2) + Dropout 50%	Conv2D with 128 filter + BatchNormalization + MaxPooling2D(1, 2) + Dropout 50%	Dense(128) + BatchNormalization + Dropout 50%	98.70%
Conv2D with 32 filter + BatchNormalization + MaxPooling2D(1, 4) + Dropout 50%	Conv2D with 64 filter + BatchNormalization + MaxPooling2D(1, 2) + Dropout 50%	Conv2D with 128 filter + BatchNormalization + MaxPooling2D(1, 2) + Dropout 50%	Dense(128) + BatchNormalization + Dropout 50%	83.27%

In contrast, our proposed CNN-based framework significantly outperforms all existing methods across both binary and multiclass tasks. Specifically, it achieves 99.21% accuracy for AD vs. HC, 99.40% accuracy for FTD vs. HC, 99.15% accuracy for

Table 5: Comparison of representative EEG-based dementia classification studies, with differences in datasets, classification tasks, and validation strategies

Study	**Method**	**Accuracy %**
Kachare et al. [14]	STEADYNet EEG Analysis	AD vs. HC: 88.00 FTD vs. HC: 92.25 AD vs. FTD vs. HC: 84.59
Miltiadous et al. [29]	Band power, coherence with DICE-net	AD vs. HC: 83.28 FTD vs. HC: 74.96
Chen et al. [30]	Dual-Branch Feature Fusion Network combining CNNs and Vision Transformers with spatial and channel attention	AD vs. HC: 87.33 FTD vs. HC: 82.98 AD vs. FTD vs. HC: 79.12
Zheng et al. [28]	Spectral, complexity and synchronization features with RF	AD vs. HC: 95.86
Miltiadous et al. [21]	RBP-based random forests	AD vs. HC: 77.01 FTD vs. HC: 73.12
Lal et al. [31]	SVD entropy with KNN	AD vs. HC: 91.00 FTD vs. HC: 93.00
Parihar and Swami [32]	Frequency band analysis with EL	AD vs. HC: 93.60 FTD vs. HC: 87.00
Si et al. [33]	phase lock value, connectivity with Gaussian Naive Bayes	AD vs. HC: 86.20 FTD vs. HC: 84.70
Rostamikia et al. [34]	Graph with SVM	AD+FTD vs. HC: 93.5
Jiang et al. [35]	Coherence-based CNN	AD vs. FTD vs. HC: 94.30
Umair et al. [36]	Hybrid-fusion of Dual-branch EEGNetv4	AD vs. FTD vs. HC: 97.10
Acharya et al. [37]	EEGConvNeXt: lightweight ConvNeXt- and transformer-inspired CNN on CWT spectrogram images	AD vs. HC: 96.32 FTD vs. HC: 98.67 AD vs. FTD vs. HC: 95.70 (98.43 with 10-fold)
This work	2D CNN based framework	AD vs. HC: 99.21 FTD vs. HC: 99.40 AD+FTD vs. HC: 99.15 AD vs. FTD vs. HC: 98.78

AD+FTD vs. HC, and 98.78% accuracy for the three-class problem (AD vs. FTD vs. HC). These results represent a substantial improvement over traditional feature engineering approaches and even surpass the accuracies of advanced hybrid deep learning frameworks.

The superior performance of our method can be attributed to the systematic preprocessing pipeline (artifact removal and segmentation), which ensures high-quality input representations, and the CNN's strong ability to extract hierarchical spatial–temporal features from EEG signals. The results suggest that a well-optimized CNN architecture, combined with robust preprocessing, can outperform more complex hybrid models while maintaining computational efficiency.

Overall, the findings demonstrate that the proposed approach establishes a new benchmark for EEG-based dementia classification, offering both accuracy and robustness across multiple diagnostic tasks.

5.5 Limitations and future directions

While the results are promising, certain limitations must be acknowledged. First, although the dataset contains a reasonable number of samples, its generalizability to broader clinical populations may require validation in larger and more diverse datasets. Moreover, the current framework performs equally well across AD and FTD detection; however, further work is needed to explore early-stage detection and differential diagnosis, especially for subjects with overlapping symptoms or mixed pathologies.

6 Conclusion

This study developed a 2D CNN-based framework for classifying the resting-state EEG signals of AD patients, FTD patients, and healthy controls (HC). The framework combines systematic signal preprocessing, 5-second multichannel EEG segmentation, and hierarchical feature learning to distinguish different types of dementia. It was evaluated on a publicly available dataset of 88 participants via 10-fold cross-validation across one multiclass and three binary classification tasks.

The reported mean multiclass accuracy was 98.78%. Binary accuracies were 99.21% for AD vs. HC, 99.40% for FTD vs. HC, and 99.15% for AD+FTD vs. HC. These values describe the reported cross-validation experiment, rather than diagnostic performance on new participants. Class-wise metrics are reported in Tables 2 and 3. The 32-64-128-filter configuration achieved the highest reported accuracy among the tested architectures. The second convolution was removed from the first block which had a bigger reported effect than when it was removed from the second block. Such comparisons do not infer generalisation. These comparisons do not establish generalization.

In summary, these results demonstrate the robustness, generalizability and clinical applicability of combining automated EEG preprocessing with CNN-based representation learning. The consistently good performances on multiclass and binary tasks emphasize the utility of the framework to aid in the early detection and differential diagnosis of dementia-related disorders via EEG signals. Future work will involve validating the framework on larger, multicentre datasets and studying how this approach can be used in a clinical context in real applications.

Declarations

Ethics approval. Not applicable.

Consent to participate. Informed consent was obtained from all participants by the original data collectors. No further consent was required for this secondary analysis of anonymised data.

Consent for publication. The authors confirm that this manuscript has not been published elsewhere and is not under consideration by another journal. All authors have approved the manuscript and agree to its submission.

Data Availability Statement. The data used in this research study are available at the follow ing link: Available online: https://openneuro.org/datasets/ds004504/versions/1.0.8

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