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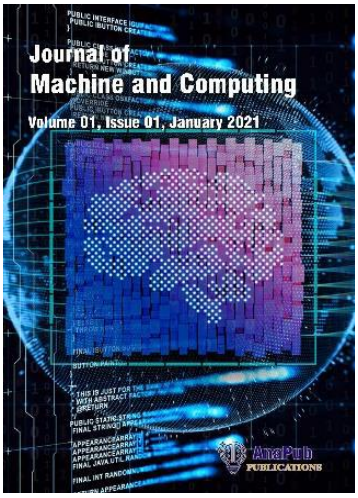

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A Novel EEG-Based Alzheimer's Classification Framework Using Multi-Stage Feature Fusion and Domain Adaptation

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Abstract - Alzheimer's Disease (AD) and Mild Cognitive Impairment (MCI) are neurodegenerative disorders that require early and accurate diagnosis for effective intervention. Electroencephalography (EEG) is a non-invasive tool for detecting cognitive decline, but subject variability poses a significant challenge in classification models. This work proposes Neurological Domain Adaptation with Transformer (NDAT), a multi-input Transformer-based framework that incorporates Instance Normalization (IN) and Adversarial Domain Adaptation (ADA) for subject-independent EEG-based classification of AD and MCI. The model extracts features from 1D EEG signals using a Transformer encoder and from 2D EEG spectrograms using a Custom Convolutional Neural Network (Custom CNN). A fusion network aligns these multi-modal features for final classification. To mitigate subject-specific biases, Instance normalization is applied to the extracted features. Additionally, ADA is integrated using a Gradient Reversal Layer (GRL), ensuring the model learns domain-invariant representations for robust subject-independent classification. The framework is evaluated on two EEG datasets: one for Alzheimer's disease classification (Normal, Frontotemporal Dementia (FTD), AD) and another for MCI classification (Normal, MCI, AD). To address the class imbalance in the FTD category, augmentation, and resampling techniques are applied to improve generalization. Experimental results demonstrate that NDAT significantly outperforms conventional methods, achieving high accuracy, sensitivity, and specificity in both subject-dependent and subject-independent settings. These findings highlight the effectiveness of deep learning-based feature extraction, domain adaptation, and normalization strategies in enhancing EEG-based neurodegenerative disease classification.

Keywords— Alzheimer's Disease, Mild Cognitive Impairment, Neurological Domain Adaptation with Transformer, EEG Signal, 2D EEG Spectrogram, CNN, Transformer Encoder.

1. Introduction

Alzheimer's Disease (AD) is a progressive neurodegenerative disorder that affects memory, cognition, and daily functioning. It is the most common cause of dementia, accounting for approximately 60–70% of dementia cases worldwide. Mild Cognitive Impairment (MCI) is an intermediate stage between normal aging and AD, where individuals exhibit cognitive decline greater than expected for their age but do not yet meet the criteria for dementia. According to the World Health Organization (WHO), over 55 million people worldwide suffer from dementia, with nearly 10 million new cases reported annually. AD remains incurable, and early detection is crucial for timely intervention and slowing disease progression [1]. Electroencephalography (EEG) is a non-invasive and cost-effective neuroimaging technique that captures electrical activity in the brain. EEG-based analysis has shown promise in identifying neurological abnormalities associated with AD and MCI, as these conditions are linked to disruptions in brain connectivity, power spectral density changes, and altered rhythmic activity. Compared to MRI and PET scans, EEG offers high temporal resolution, affordability, and portability, making it an attractive modality for early-stage AD diagnosis [2].

Despite its advantages, EEG-based AD classification faces several challenges. Subject-specific variability affects EEG signals due to individual differences in brain structure, noise interference, and recording conditions. Feature representation limitations arise when traditional methods fail to capture both temporal (1D) and spatial (2D) features, leading to suboptimal classification performance. Additionally, deep learning models trained on EEG data often struggle with domain shifts, making generalization difficult in real-world clinical applications [3]. To address these challenges, we propose a multi-modal EEG-based AD and MCI classification framework that integrates 1D temporal feature extraction using a Transformer-based model and 2D spatial feature extraction from EEG spectrograms using a Custom CNN. The extracted features are fused, and domain adaptation techniques such as Instance Normalization and Adversarial Domain Adaptation using a Gradient Reversal Layer are applied to enhance the model's ability to learn subject-invariant representations, improving classification accuracy across different EEG datasets. The key contributions of this paper are as follows:

(i) First, we propose a dual-stream feature extraction approach that extracts temporal (1D) features from raw EEG signals using a Transformer encoder and spatial (2D) features from EEG spectrograms using a Custom CNN-based model.

(ii) Second, we introduce a concatenation-based feature fusion strategy, followed by Instance Normalization and Adversarial Domain Adaptation (ADA) with a Gradient Reversal Layer (GRL) to mitigate subject-specific variations and improve generalization.

(iii) Third, we develop a robust Deep Neural network-based classification framework that accurately classifies EEG signals into Normal, MCI, and AD, ensuring reliable diagnosis.

The rest of the paper is structured as follows. Section 2 discusses related works in EEG-based AD and MCI classification. Section 3 describes the proposed methodology, including EEG preprocessing, feature extraction, fusion, domain adaptation, and classification. Section 4 reports the results and analysis, and finally, Section 5 provides the conclusion and future research directions.

2. Related Works

Various studies have explored EEG-based Alzheimer's disease and Mild Cognitive Impairment (MCI) classification using traditional machine learning and deep learning techniques. Xia et al. (2023) used EEG data from 100 subjects (49 AD, 37 MCI, 14 HC) and applied a modified Deep Pyramid CNN (DPCNN) with data augmentation using overlapping sliding windows. Their model achieved an accuracy of 97.10% in classifying AD, MCI, and HC [4]. Acharya et al. (2025) reviewed EEG-based deep learning models for Alzheimer's and MCI detection, analyzing state-of-the-art techniques. They highlighted the dual classification of MCI [illegible] and identified high-performing deep learning approaches [5]. Malik et al. (2024) imply that while machine learning methods like SVM, ANN, and ensemble learning are widely used for Alzheimer's diagnosis, challenges remain in optimizing classification techniques. They highlight the need for integrating multi-modal data, improving feature selection, and refining ANN-based models to overcome local minima issues [6]. Chedid et al. (2022) used EEG data from 41 subjects (14-channel montage) to develop an automated ML pipeline for Alzheimer's diagnosis. They employed logistic regression with power spectral density (PSD)-based feature selection, achieving 81% accuracy [7]. Sen et al. (2024) used EEG data to classify Alzheimer's dementia using intrinsic time-scale decomposition (ITD) and a 1D CNN. The ITD-based method achieved the highest accuracy of 94.00% in Quartile 1 (Q1). Raw EEG segment classification with 1D CNN reached 88.40% accuracy in Quartile 2 (Q2) [8]. Chen et al. (2023) used the OpenNeuro database for EEG-based Alzheimer's disease prediction. They proposed a Dual-Branch Feature Fusion Network (DBN) combining CNNs and Visual Transformers (ViTs) with attention mechanisms. Their method achieved 80.23% accuracy in distinguishing AD, Frontotemporal Dementia (FTD), and Normal Control (NC) subjects [9]. Aviles et al. (2024) highlight the increasing significance of machine and deep learning in EEG-based Alzheimer's diagnosis, emphasizing the necessity of careful data selection, preprocessing, and classifier tuning for enhanced accuracy. They discuss the challenges of generalizing models due to variations in genetics, lifestyle, and environmental factors, which may impact the applicability of findings. The study underscores the value of advanced feature extraction methods, such as nonlinear and multifractal approaches, in capturing complex brain activity [10]. Kim et al. (2023) introduced the CAUEEG dataset, which includes well-annotated EEG data for normal, mild cognitive impairment (MCI), and dementia cases. They proposed CEEDNet, an end-to-end deep learning model for automatic EEG diagnosis. CEEDNet achieved ROC-AUC scores of 0.9 on CAUEEG-Dementia and 0.86 on CAUEEG-Abnormal, outperforming traditional methods [11]. Dara et al. (2023) explored machine learning approaches for Alzheimer's diagnosis, emphasizing models like SVMs, decision trees, and ensemble methods. They highlighted the influence of genetics, stress, and nutrition on disease progression and the significance of neuroimaging and non-image biomarkers. They suggested focusing on feature selection and optimization techniques to improve diagnostic accuracy. Methods like whale and gray wolf optimization were recommended for selecting the most relevant MRI features [12]. Al Rahbani et al. (2024) proposed a deep learning-based approach for Alzheimer's disease detection using MRI data from ADNI and OASIS datasets. Their method integrates ResNet and EfficientNet CNN models with a post-processing algorithm, achieving accuracies of 98.97% on ADNI and 99.41% on OASIS [13]. Roncero-Parra et al. (2024) propose a CNN-based deep learning model for detecting moderate and advanced Alzheimer's disease using EEG data. Their study, conducted on a multi-hospital dataset of 668 volunteers, achieved classification accuracies of 97.45% for moderate AD and 97.03% for advanced AD. The model effectively extracts time-domain features while reducing data redundancy, demonstrating its potential for accurate and scalable AD diagnosis [14]. Huggins et al. (2021) developed a deep learning model using resting-state EEG signals to classify Alzheimer's disease (AD), mild cognitive impairment (MCI), and healthy aging (HA). The study utilized EEG data from 141 subjects (52 AD, 37 MCI, 52 HA), preprocessed with continuous wavelet transform and transformed into topographical images for analysis. Using an AlexNet-based CNN and tenfold cross-validation, the model achieved an accuracy of 98.9%, demonstrating its effectiveness in distinguishing between the three conditions [15]. Zhao and He (2014) applied deep learning to EEG-based diagnosis of Alzheimer's disease, leveraging unsupervised feature learning for early detection. Using EEG data from 15 AD patients and 15 healthy individuals, signals from 16 electrodes were processed and classified with a deep learning model combined with SVM. The approach achieved 92% accuracy, with incremental learning further improving performance by 0.5% [16]. Zhang et al. (2023) developed a deep learning model using contrastive representation learning for EEG-based AD detection. Evaluated on a dataset of 23 subjects (12 AD, 11 control) with 663 EEG trials, their model achieved an F1 score of 99.35% in a patient-dependent setup and 86.45% in a patient-independent setup. The approach demonstrated superior generalization ability, outperforming existing baselines by over 20% in the more challenging patient-independent scenario [17]. Patil et al. (2022) conducted a comprehensive review of early AD detection using machine learning, focusing on the ADNI dataset. Their analysis highlights that an 18-layer convolutional neural network (CNN) achieved 98%

accuracy, outperforming a 3D CNN in classification performance. The study underscores the potential of deep learning in improving early diagnosis and treatment strategies for AD [18].

Toshkhujaev et al. (2020) proposed a machine learning-based method for classifying Alzheimer's disease (AD) and mild cognitive impairment (MCI) using cortical thickness and subcortical volume features from T1-weighted MRI scans. Their approach, which utilized a radial basis function support vector machine (RBF-SVM) classifier with principal component analysis for dimensionality reduction, achieved high accuracy, with cortical thickness-based classification reaching 97.37% (GARD dataset) and 95.24% (NACC dataset) for AD versus healthy controls [19]. Mohi ud Din Dar et al. (2023) proposed a deep learning framework for classifying different stages of Alzheimer's disease (AD) using MRI images and CNN. Their approach leveraged the MobileNet model with transfer learning, achieving an accuracy of 96.22% for multi-class AD stage classification [20]. Saroja et al. (2023) proposed a deep transfer learning approach for classifying MCI using EEG-based Scalogram images generated via Continuous Wavelet Transform (CWT). They utilized pre-trained models such as ResNet50, VGG16, InceptionV3, and Inception_ResNetV2, with fine-tuning improving classification accuracy. The study found that ResNet50 and InceptionV3, when fine-tuned with a low learning rate, achieved the highest accuracy in distinguishing MCI from HC [21]. Roberts and Knopman (2013) reviewed the classification and epidemiology of MCI, highlighting its role as an intermediate stage between normal cognition and dementia. They discussed the prevalence, incidence, and progression of MCI, emphasizing the need for improved diagnostic methods, including imaging and biomarkers [22]. Adarsh et al. (2024) proposed a novel diagnostic framework combining CNNs with the Multi-feature Kernel Supervised within-class-similar Discriminative Dictionary Learning (MKSCDDL) algorithm for classifying Alzheimer's disease, Mild Cognitive Impairment (MCI), and Cognitively Normal (CN) individuals. Using the ADNI dataset, their model achieved an accuracy of 98.27%, incorporating LIME and CAM for enhanced interpretability [23]. Santos Toural et al. (2021) introduced a novel EEG-based classification method for distinguishing Healthy, MCI, and AD subjects. Using resting-state EEG data, their approach combined wavelet entropy's Pearson correlation coefficient, theta relative power, and P300 biomarkers, achieving an accuracy of 94.44%. The study highlights the potential of this method as a diagnostic support tool and a predictor for MCI-to-AD progression [24]. Basaia et al. (2019) developed a deep learning model using CNN to classify AD, converters from Mild Cognitive Impairment (c-MCI), and stable MCI (s-MCI) based on a single MRI scan. Trained on the ADNI and an additional dataset (totaling 1,638 subjects), the model achieved 99% accuracy in AD vs. Healthy Control (HC) classification and 75% in distinguishing c-MCI from s-MCI. The study highlights the potential of CNNs for automated, generalizable AD diagnosis without prior feature engineering [25].

3. Materials and Methods

The proposed Neurological Domain Adaptation with Transformer (NDAT) framework is developed for EEG-based classification of Alzheimer's Disease (AD) and Mild Cognitive Impairment (MCI) while addressing subject variability through Instance Normalization (IN) and Adversarial Domain Adaptation (ADA). The methodology consists of data preprocessing, feature extraction, feature fusion, domain adaptation, and classification, as shown in Fig. 1. In the preprocessing stage, EEG signals undergo artifact removal, segmentation, and augmentation to ensure high-quality input for feature extraction. Wavelet Transform-Based Artifact Removal is applied using Discrete Wavelet Transform (DWT) to remove artifacts such as eye blinks, muscle movements, and cardiac noise. The EEG recordings are then segmented using a sliding window approach, with 2-second windows and 50% overlap to preserve temporal dependencies. To address class imbalance, particularly in the Frontotemporal Dementia (FTD) category, Gaussian noise addition and time warping are applied as augmentation techniques. Additionally, Synthetic Minority Oversampling Technique (SMOTE) is used to resample the dataset and balance class distributions. Feature extraction follows a multi-input approach, where 1D raw EEG signals and 2D EEG spectrograms are processed separately to capture both temporal and spatial characteristics. For 1D EEG feature extraction, a Transformer Encoder is employed, consisting of an embedding layer, multi-head self-attention mechanism, and feedforward network, enabling the model to capture long-range dependencies in EEG sequences. For 2D EEG spectrogram feature extraction, Short-Time Fourier Transform (STFT) is used to convert EEG signals into time-frequency spectrograms, which are then processed by a Custom Convolutional Neural Network (Custom CNN). The CNN architecture consists of three convolutional layers with 3×3 kernels and ReLU activation, followed by batch normalization and max-pooling operations to extract spatial features. The extracted temporal (1D) and spatial (2D) features are fused using a concatenation-based feature fusion approach. To mitigate subject-specific variability, IN is applied to the fused features, ensuring consistency across different subjects. To further enhance domain-invariant feature learning, ADA is implemented using a Gradient Reversal Layer (GRL), helping the model learn features that generalize well across subjects. The final fused and domain-adapted features are passed through Deep Neural network which includes a fully connected classifier with Softmax activation for classification. The NDAT framework effectively improves EEG-based neurodegenerative disease classification by integrating deep learning-based feature extraction, domain adaptation, and normalization strategies.

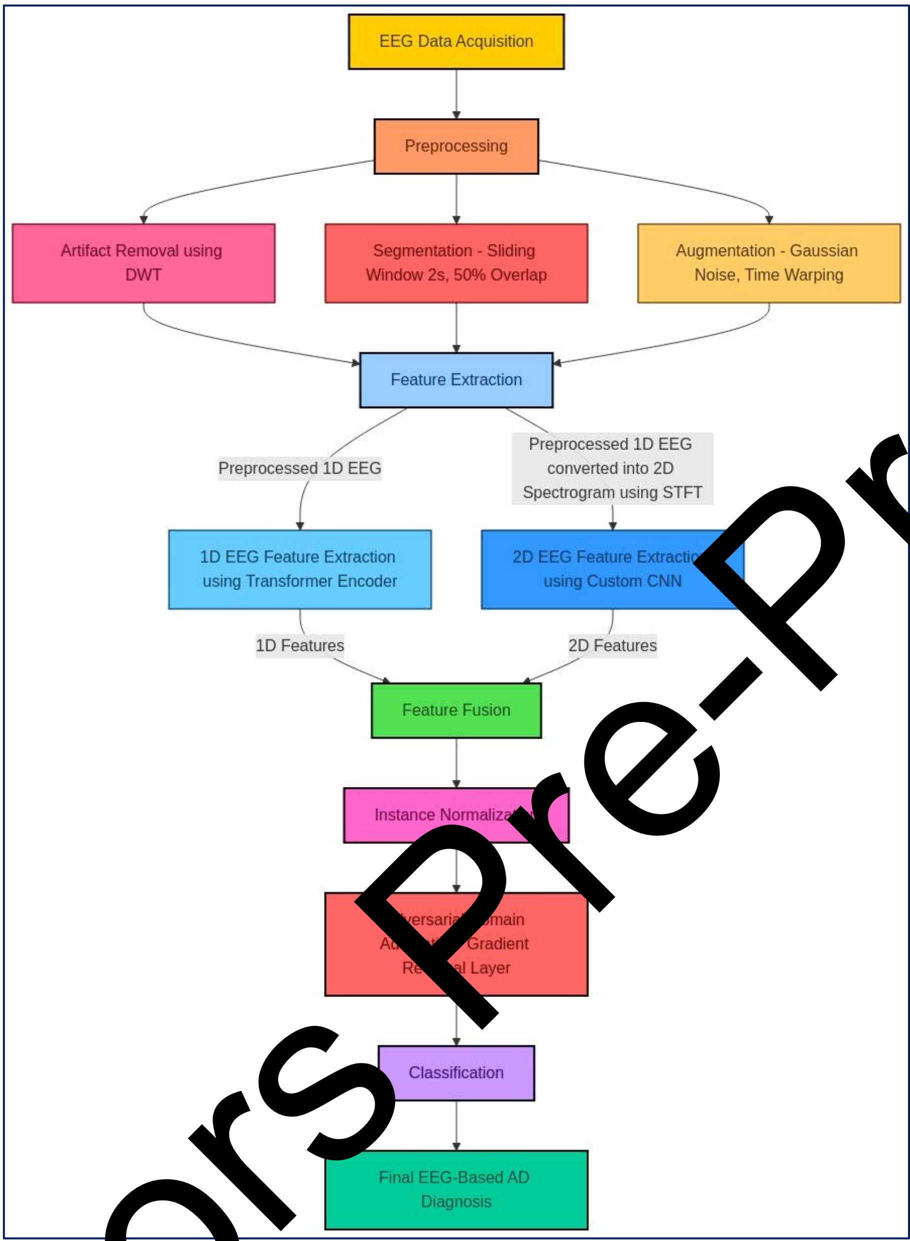

Fig. 1. Overall proposed workflow for Alzheimer's disease diagnosis using proposed Neurological Domain Adaptation with Transformer (NDAT) framework.

3.1. Material

This work utilizes two publicly available EEG datasets (https://doi.org/10.3390/data8060095 and https://data.mendeley.com/datasets/sgzbgwjfkr/5) for Alzheimer's disease classification. The first dataset consists of resting-state EEG recordings from 88 participants, including 36 Alzheimer’s Disease (AD) patients, 23 Frontotemporal Dementia (FTD) patients, and 29 cognitively normal (CN) individuals. The cognitive assessment was conducted using the Mini-Mental State Examination (MMSE), with lower scores indicating greater cognitive decline. The average MMSE scores were 17.75 (AD), 22.17 (FTD), and 30 (CN). EEG recordings were acquired using a Nihon Kohden EEG 2100 clinical device with 19 scalp electrodes (10-20 system) and two reference electrodes (A1, A2). The sampling rate was 500 Hz, and the recording durations averaged 13.5 minutes for AD, 12 minutes for FTD, and 13.8 minutes for CN, totaling 485.5 minutes (AD), 276.5 minutes (FTD), and 402 minutes (CN). The second dataset includes EEG recordings from an olfactory oddball perception task, involving 35 participants categorized into 15 healthy controls (Normal), 7 Mild Cognitive Impairment (MCI) patients, and 13 Alzheimer’s Disease (AD) patients. Originally, 44 participants were recruited, but 6 were excluded due to EEG recording issues, stroke history, or traumatic brain injuries. Additionally, individuals with olfactory dysfunction were excluded. The final participant demographics were as follows: Healthy (Normal): 15 participants, mean age = 69.27 ± 6.65, 53.33% female; MCI: 7 participants, mean age = 66.57 ± 6.85, 51.14% female; AD: 13

participants, mean age = 75.31 ± 9.90, 61.54% female. This combination of resting-state EEG and olfactory-stimulus EEG datasets enables a comprehensive investigation of Alzheimer's disease and cognitive impairment through diverse neural activity patterns.

3.2. Preprocessing

To ensure high-quality input for feature extraction, EEG signals undergo multiple preprocessing steps, including artifact removal, segmentation, and augmentation. These steps enhance signal quality, maintain temporal dependencies, and address class imbalance for robust classification.

(i) Wavelet Transform-Based Artifact Removal

Artifacts such as eye blinks, muscle movements, and cardiac noise are removed using Discrete Wavelet Transform (DWT). DWT decomposes the EEG signal into approximation (S) and detail (R) coefficients at different frequency bands. The noisy components are identified in high-frequency detail coefficients and eliminated through thresholding. The DWT decomposition process is given by:

$$S_x[k] = \sum_i n(i) \cdot g[2k - i] \quad (1)$$

$$R_x[k] = \sum_i n(i) \cdot h[2k - i] \quad (2)$$

where, $S_x[k]$ and $R_x[k]$ are the approximation and detail coefficients at level x, $g(i)$ is the low-pass filter, $h(i)$ is the high-pass filter, $n(i)$ is the EEG signal.

After thresholding, the signal is reconstructed using the inverse DWT (IDWT), ensuring that useful neural activity is preserved while eliminating artifacts.

(ii) Segmentation Using a Sliding Window

The EEG recordings are segmented into 2-second windows using a 50% overlap to retain temporal dependencies. This segmentation ensures that each window contains sufficient information for feature extraction and classification. For a signal $N(t)$, segmentation is performed as:

$$N_y = N(t_y, t_y + \omega) \quad (3)$$

where, N_y is the segmented EEG window, ω is the window length (2 seconds), t_y represents the start time of each window, Overlapping ensures continuity by shifting t_y by 50% of ω.

(iii) Data Augmentation for Class Imbalance

To address class imbalance, particularly in the Frontotemporal Dementia (FTD) category, the following augmentation techniques are applied:

- Gaussian Noise Addition: Random noise is added to the EEG signal to simulate variations while preserving essential patterns:

$$N' = N + \Upsilon(0, \sigma^2) \quad (4)$$

  where, $\Upsilon(0, \sigma^2)$ represents Gaussian noise with zero mean and variance σ^2.

- Time Warping: The EEG signal is stretched or compressed in the time domain using a spline interpolation function:

$$N'(t) = N(\alpha t) \quad (5)$$

  where α is a time-scaling factor.

(iv) Synthetic Minority Oversampling Technique (SMOTE) for Balance Class Distributions

To further balance class distributions, SMOTE is applied to generate synthetic EEG samples for the underrepresented class (FTD). SMOTE creates new samples by interpolating between existing minority class samples:

$$N_{new} = N_y + \lambda(N_x - N_y) \quad (6)$$

where, N_y and N_x are two randomly chosen samples from the minority class, λ is a random number in the range [0,1].

Through these preprocessing steps, the EEG dataset is artifact-free, segmented, and balanced, ensuring high-quality input for further feature extraction and classification.

3.3. Feature Extraction

Feature extraction follows a multi-input approach, where 1D raw EEG signals and 2D EEG spectrograms are processed separately. This method captures both temporal and spatial characteristics of EEG data, improving the robustness of Alzheimer's disease classification.

3.3.1. 1D EEG Feature Extraction Using Transformer Encoder

The Transformer Encoder processes raw 1D EEG signals to capture long-range dependencies in EEG sequences, as shown in Fig. 2. The encoder consists of three key components:

- Embedding Layer: Converts EEG signals into feature representations.
- Multi-Head Self-Attention (MHSA): Identifies relationships between EEG time steps.
- Feedforward Network (FFN): Enhances non-linearity and feature extraction.

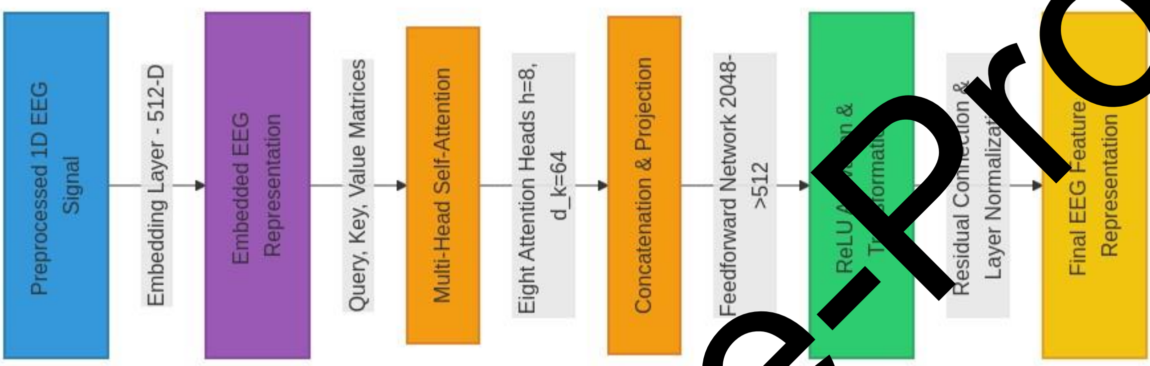

Fig. 2. 1D EEG signal feature extraction using Transformer Encoder.

(i) EEG Signal Embedding

The raw 1D EEG signals are first projected into a higher-dimensional feature space using an embedding layer. Given an EEG sequence $N = [n1, n2, \dots, nT]$ of length T, the embedding operation applies a linear transformation using a learnable weight matrix W_e and bias b_e:

$$Z = NW_e + b_e \tag{7}$$

where Z represents the transformed EEG feature representation. The embedding layer expands the EEG signals into a d_{model}-dimensional space, set to 512 dimensions. This transformation ensures that the signal is in an appropriate format for the self-attention mechanism in the Transformer Encoder.

(ii) Multi-Head Self-Attention (MHSA)

The Multi-Head Self-Attention (MHSA) mechanism allows the model to focus on key EEG time points by computing the relationships between different time steps in the sequence. Each attention head processes the EEG embeddings independently using query (Q), key (K), and value (V) matrices, derived through:

$$Q = ZW_q, \quad K = ZW_k, \quad V = ZW_v \tag{8}$$

where W_q, W_k, W_v are trainable projection matrices. The attention scores are computed as:

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{9}$$

where d_k is the scaling factor (d_k=64) to stabilize gradients. Eight attention heads (h=8) are used, each capturing different aspects of EEG dependencies. The outputs from all heads are concatenated and transformed using another learnable weight matrix W_o:

$$MHSA(Z) = concat(head1, \dots, head8)W_o \tag{10}$$

(iii) Feedforward Network (FFN)

After self-attention, the feature representation passes through a fully connected FFN, which applies non-linearity to enhance feature extraction. It consists of two linear layers with a ReLU activation function:

$$FFN(Z) = \sigma(ZW_1 + b_1)W_2 + b_2 \tag{11}$$

where, W_1 and W_2 are learnable weight matrices, b_1 and b_2 are bias terms, σ is the ReLU activation function.

The FFN expands the input dimension to four times the model size (2048 for a model size of 512) and then reduces it back to the original dimension. This helps in capturing non-linear relationships in the EEG data.

To enhance training stability and prevent vanishing gradients, residual connections and layer normalization are applied:

$$Z' = LayerNor(Z + FFN(Z)) \tag{12}$$

This ensures that the final feature representation retains temporal dependencies while being more robust to noise in EEG signals. The output is then fed into the next processing stage for feature fusion with 2D spectrogram representations.

3.3.2. 2D EEG Feature Extraction Using Custom CNN on Spectrograms

To effectively extract spatial and frequency domain features, the 1D EEG signals are first transformed into 2D spectrograms using the Short-Time Fourier Transform (STFT). These spectrograms serve as input to a Custom Convolutional Neural Network (Custom CNN), which captures discriminative patterns across different frequency bands and time intervals. The CNN extracts high-level spatial features by applying multiple convolutional layers, batch normalization, and pooling operations.

3.3.2.1. Time-Frequency Representation Using STFT

The STFT is applied to convert raw EEG signals into time-frequency representations. Given an EEG signal $n(x)$, the STFT is computed as:

$$ES(t, f) = \sum_x n[x]\omega[x - t]e^{-b2\pi fx} \tag{13}$$

where, $ES(t, f)$ represents the spectrogram, containing both temporal and spectral information, $n[x]$ is the EEG signal, $\omega[x]$the Hamming window function, which reduces spectral leakage, f represents frequency, and t represents time.

The resulting spectrograms are 2D images, where the x-axis corresponds to time, and the y-axis corresponds to frequency components of the EEG signal. These spectrograms serve as input to the Custom CNN model.

3.3.2.2. Custom Convolutional Neural Network (Custom CNN) for 2D EEG Spectrograms Feature Extraction

The spectrograms are processed using a five-layer CNN to extract spatial features that capture essential EEG characteristics across different frequency bands, as depicted in Fig. 3. The CNN architecture consists of five convolutional layers, each designed to progressively learn more complex patterns in the EEG spectrograms. Each convolutional layer employs 3×3 kernels, a stride of 1, and padding to maintain the spatial dimensions of the feature maps. The first convolutional layer uses 32 filters to capture basic edge and texture patterns. As the network deepens, the number of filters increases to 64, 128, 256, and 512, enabling the model to learn high-level spatial structures and complex spectral representations. To stabilize training and accelerate convergence, batch normalization (BN) is applied after each convolutional layer, ensuring that feature distributions remain stable throughout training. Additionally, ReLU activation is used after each convolutional operation to introduce non-linearity and enhance feature learning. To progressively reduce spatial dimensions while preserving important features, max-pooling is applied after every convolutional layer using a 2×2 pooling window with a stride of 2. This operation helps to downsample the feature maps, making the model more translation-invariant and robust to variations in EEG spectrogram patterns. The final convolutional layer outputs a feature map that is flattened and concatenated with the Transformer-extracted 1D EEG features, ensuring a comprehensive multi-modal representation of the EEG data for Alzheimer's disease and MCI classification.

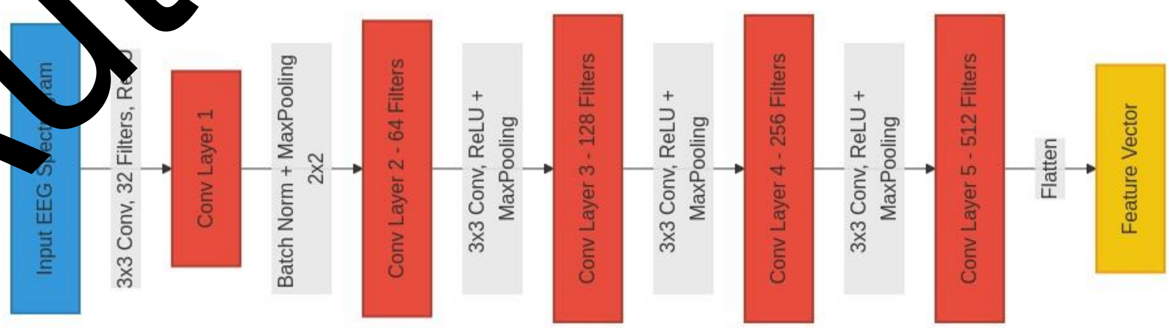

Fig. 3. 2D EEG spectrograms feature extraction using Custom CNN.

3.4. Feature Fusion and Domain Adaption

The extracted temporal (1D) and spatial (2D) features are fused using a concatenation-based feature fusion approach, which combines the strengths of time-domain dependencies and frequency-domain representations for improved EEG-based Alzheimer's Disease (AD) classification. Given the 1D feature vector $F_{1D} \in \mathbb{R}^{d1}$ extracted using a Transformer encoder and the 2D feature map $F_{2D} \in \mathbb{R}^{h \times w \times c}$ obtained from a CNN-based spectral analysis, apply global average pooling (GAP) to flatten F_{2D} into a 1D vector $F'_{2D} \in \mathbb{R}^{d2}$. The fused feature representation is then computed as:

$$F_{fused} = Concat\left(F_{1D,} F'_{2D}\right) \in \mathbb{R}^{(d1+d2)} \tag{14}$$

where Concat(·) denotes the concatenation operation, effectively merging both feature modalities into a unified representation.

To mitigate subject-specific variability, Instance Normalization (IN) is applied to the fused features. Instance normalization ensures consistency across different subjects by normalizing the feature statistics independently for each instance:

$$\hat{F}_{fused} = \frac{F_{fused} - \mu}{\sigma} \tag{15}$$

where μ and σ represent the mean and standard deviation computed across the instance's feature dimensions. This normalization step helps reduce inter-subject variability, improving generalization across different EEG recordings.

To further enhance domain-invariant feature learning, Adversarial Domain Adaptation (ADA) is implemented using a Gradient Reversal Layer (GRL). The GRL facilitates adversarial training by reversing the gradient of the domain classification loss, forcing the feature extractor to learn subject-independent features. The domain adaptation process involves optimizing two objectives:

1. Minimizing EEG classification loss $\mathcal{L}_{cls}$, where the model predicts the correct class labels y for EEG samples x:

$$\mathcal{L}_{cls} = -\sum_i y_i log\hat{y}_i \tag{16}$$

2. Maximizing domain confusion via domain classification loss $\mathcal{L}_{domain}$, where the model is trained to prevent the discriminator from distinguishing source and target domains:

$$\mathcal{L}_{domain} = -\sum_j d_j log\hat{d}_j \tag{17}$$

where d represents the domain labels. The GRL scales the domain loss gradient by a negative factor $-\lambda$, reversing the gradient:

$$\theta_f \leftarrow \theta_f - \eta\left(\frac{\partial L_{cls}}{\partial \theta_f} - \lambda \frac{\partial L_{domain}}{\partial \theta_f}\right) \tag{18}$$

where θ_f are the parameters of the feature extractor, η is the learning rate, and λ controls the strength of domain adaptation.

By integrating feature fusion, instance normalization, and adversarial domain adaptation, the proposed framework ensures that EEG-based Alzheimer's Disease classification is robust, domain-invariant, and generalizable across different subjects, significantly enhancing its clinical applicability.

3.5. Classification

The final fused and domain-adapted features are passed through a Deep Neural Network (DNN)-based classifier for AD diagnosis. The classifier is designed to distinguish between AD, FTD, CN and Normal, MCI, AD classes based on the learned feature representations. The DNN classifier consists of multiple fully connected layers that progressively refine and transform the extracted features for optimal classification. A Softmax activation function is applied in the final layer to assign probabilities to each class, ensuring that the model outputs a confidence score for each possible diagnosis. The network is trained using a cross-entropy loss function, which minimizes the difference between the predicted and true class labels. By integrating deep feature extraction, domain adaptation, and a deep neural network classifier, the proposed approach ensures robust and accurate EEG-based classification of Alzheimer's Disease and Mild Cognitive Impairment.

4. Results and Discussions

This section presents the experimental results and provides an in-depth analysis of the proposed Neurological Domain Adaptation with Transformer (NDAT) framework for EEG-based Alzheimer's Disease (AD) and Mild Cognitive Impairment (MCI) classification. The model's performance is evaluated on two datasets, and a comparative analysis is conducted against existing state-of-the-art approaches. The impact of feature extraction, feature fusion strategies, instance normalization, and adversarial domain adaptation is systematically analyzed. Classification performance is assessed using standard evaluation metrics, including accuracy, precision, recall, F1-score, area under the ROC curve (AUC-ROC), false acceptance rate (FAR), and false rejection rate (FRR). The experimental results demonstrate that the proposed dual-stream feature extraction framework, coupled with adversarial domain adaptation, significantly enhances classification accuracy and robustness across different subjects. The improvements indicate that the NDAT framework effectively learns domain-invariant EEG features, making it a promising approach for clinical EEG-based diagnosis of AD and MCI.

$$Accuracy = \frac{TP_{AD}+TN_{AD}}{TP_{AD}+TN_{AD}+FP_{AD}+FN_{AD}} \tag{19}$$

where, TP_{AD} is the true positive; TN_{AD} is the true negative; FP_{AD} is the false positive; FN_{AD} is the false negative.

$$Precision = \frac{(TP_{AD})}{(TP_{AD}+FP_{AD})} \tag{20}$$

$$Recall = \frac{(TP_{AD})}{(TP_{AD}+FN_{AD})} \tag{21}$$

$$F1\ Score = 2 \cdot \frac{Precision \cdot Recall}{Precision+Recall} \tag{22}$$

$$FAR = \frac{(FP_{AD})}{(FP_{AD}+TN_{AD})} \tag{23}$$

$$FRR = \frac{(FN_{AD})}{(FN_{AD}+TP_{AD})} \tag{24}$$

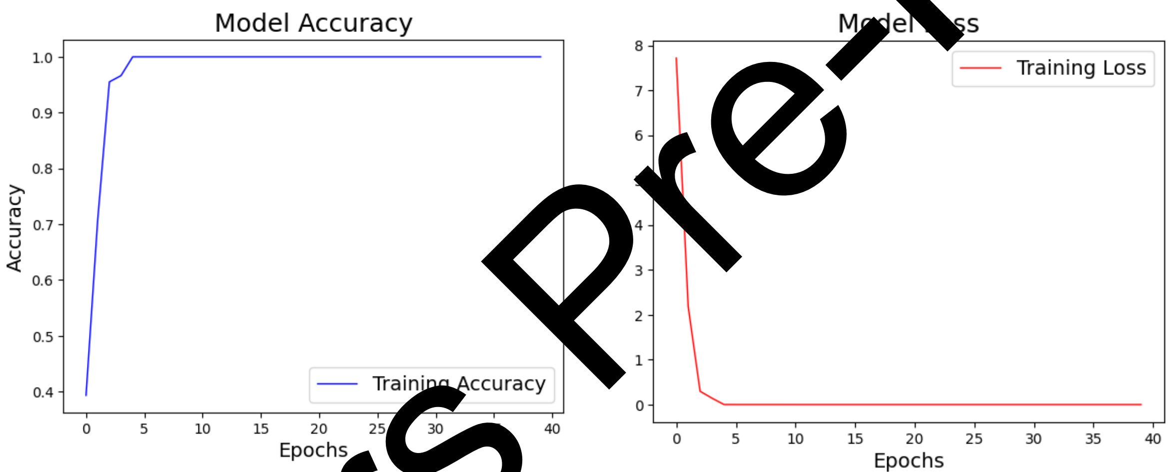

Fig. 4. Training process performance analysis for Dataset 1.

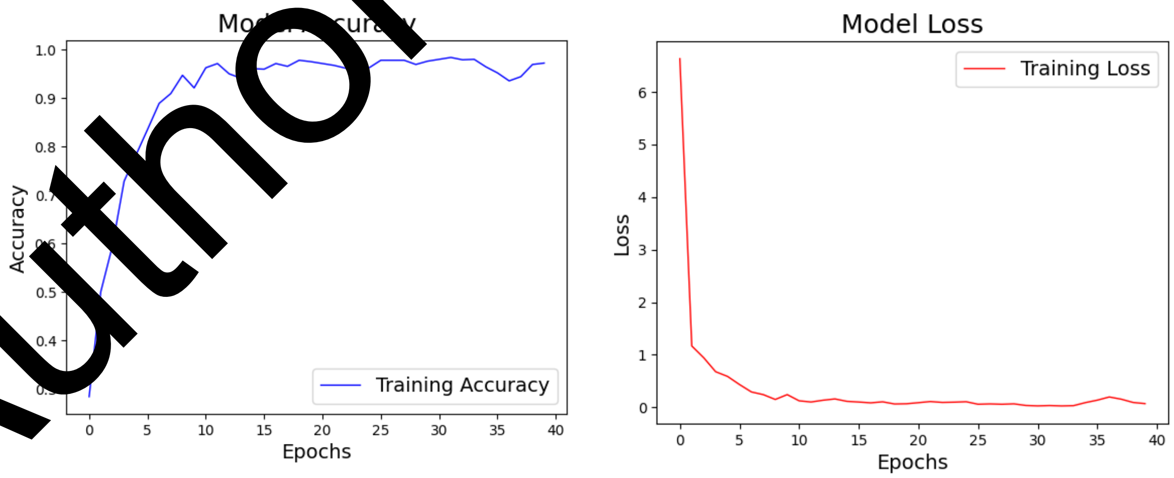

Fig. 5. Training process performance analysis for Dataset 2.

During the training of the Neurological Domain Adaptation with Transformer (NDAT) framework, the model's learning process was analyzed using training accuracy and loss curves. Figs. 4 and 5 illustrate the convergence behavior of the training process for Dataset 1 (AD, FTD, CN) and Dataset 2 (Healthy, MCI, AD), respectively. The training accuracy consistently increases while the loss decreases, indicating effective learning and optimization of the model. The stable convergence of the loss function suggests that the framework successfully avoids overfitting and generalizes well to unseen data. The results show that NDAT effectively extracts both temporal (1D) and spatial (2D) features from EEG signals, and the feature fusion mechanism further enhances classification performance. These enhancements contribute to achieving high classification accuracy for both datasets. The training accuracy curves confirm that the dual-stream feature extraction strategy enables the model to learn discriminative patterns efficiently. Meanwhile, the loss curves highlight the stability of the NDAT framework, demonstrating that the proposed method can effectively differentiate between normal, MCI, AD, and FTD conditions based on EEG data.

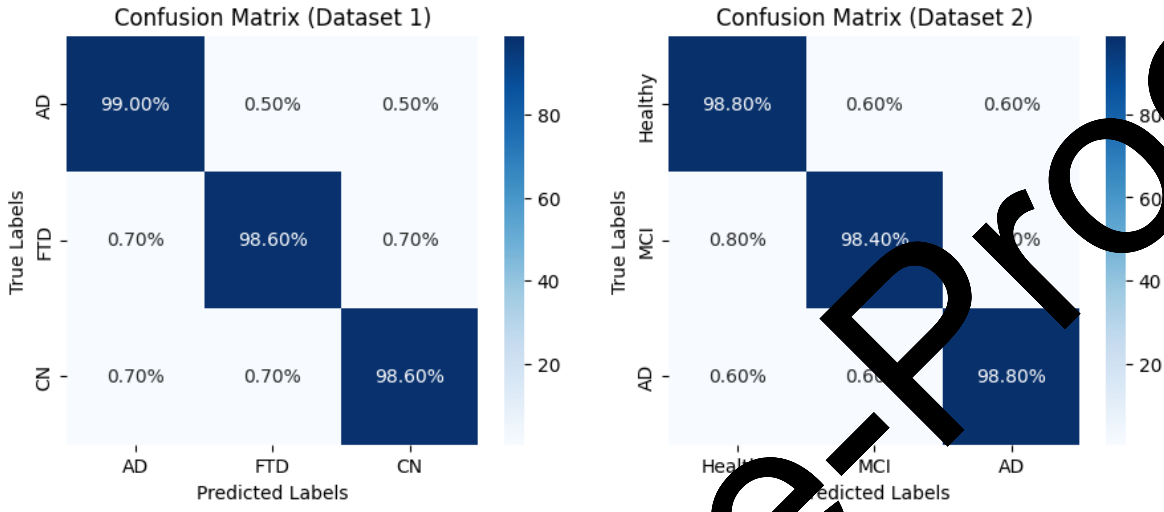

Fig. 6. Confusion matrices of NDAT for both datasets.

The confusion matrices for both datasets, as shown in Fig. 6, illustrate the classification performance of the NDAT framework across different subject classes. For Dataset 1 (AD, FTD, CN), the model achieves high classification accuracy, with AD being correctly classified 99.0% of the time, while FTD and CN exhibit slightly lower but still strong classification rates of 98.6%. Misclassification rates remain minimal, with only 0.5%-0.7% instances being incorrectly assigned to other categories. Similarly, for Dataset 2 (Healthy, MCI, AD), the framework demonstrates robust classification performance, achieving 98.8% accuracy for Healthy and AD classes and 98.4% for MCI. The confusion matrix confirms the model's ability to accurately distinguish between different neurological conditions, further validating the effectiveness of the proposed dual-stream feature extraction and domain adaptation strategies. The minimal misclassification rates suggest that NDAT efficiently learns domain-invariant representations, ensuring improved generalization across subjects. The performance analysis of the proposed NDAT framework is summarized in Table 1, showcasing its effectiveness in classifying EEG data for both datasets. The model achieves an impressive accuracy of 98.72% for Dataset 1 (AD, FTD, CN) and 98.65% for Dataset 2 (Healthy, MCI, AD). The high precision, recall, and F1-score values across both datasets indicate a strong balance between sensitivity and specificity in classification. Moreover, the AUC-ROC values of 99.21% and 99.14% confirm the model's excellent discriminatory ability. The false acceptance rate (FAR) and false rejection rate (FRR) remain low, demonstrating the robustness of NDAT in minimizing misclassifications. These results validate that the combination of dual-stream feature extraction, instance normalization, and adversarial domain adaptation significantly enhances EEG-based classification for neurological disorder detection.

Table 1: Performance Analysis of the Proposed NDAT Model for Both Datasets

Metrics	**Dataset 1: AD, FTD, CN**	**Dataset 2: Healthy, MCI, AD**
Accuracy	98.72	98.65
Precision	98.65	98.60
Recall	98.89	98.78
F1-Score	98.76	98.70
AUC-ROC	99.21	99.14
FAR	1.13	1.09
FRR	0.89	0.92

Table 2 presents a comparative analysis of different feature extraction methods—1D Feature-Based (Transformer Encoder), 2D Feature-Based (CNN), and Feature Fusion-Based (NDAT)—for both datasets. The results clearly indicate that the feature fusion-based NDAT approach outperforms both individual feature extraction methods across all evaluation metrics. For Dataset 1 (AD, FTD, CN), NDAT achieves the highest accuracy of 98.72%, significantly improving upon the 1D-based (96.55%) and 2D-based (96.92%) approaches. Similarly, for Dataset 2 (Healthy, MCI, AD), NDAT attains 98.65% accuracy, surpassing the 1D-based (96.71%) and 2D-based (97.10%) models. The precision, recall, and F1-score values for NDAT remain consistently high, highlighting its ability to reduce false positives and false negatives compared to the standalone 1D and 2D models. The AUC-ROC scores, which measure the overall classification capability, further demonstrate the superiority of NDAT, achieving 99.21% for Dataset 1 and 99.14% for Dataset 2, outperforming the other approaches. Additionally, NDAT significantly reduces the False Acceptance Rate (FAR) and False Rejection Rate (FRR) compared to 1D- and 2D-based models, confirming that the integration of both temporal and spatial EEG features enhances classification performance. The superior performance of NDAT is attributed to the fusion of temporal (1D) and spatial (2D) features, which effectively capture comprehensive EEG signal characteristics. The Transformer encoder efficiently learns long-range dependencies in EEG sequences, while the custom CNN extracts spatial patterns, and their fusion enhances the model's robustness, leading to improved classification accuracy and reduced error rates. These results validate the effectiveness of the dual-stream feature extraction and fusion mechanism in the NDAT framework, ensuring better discrimination of neurological conditions.

Table 2: Comparison of Classification Performance for Different Feature Extraction Methods on Two Datasets

Metrics	1D Feature-Based (Transformer Encoder)	2D Feature-Based (Custom CNN)	Feature Fusion-Based (NDAT)
Dataset 1: AD, FTD, CN			
Accuracy	96.55	96.92	**98.72**
Precision	96.43	96.85	**98.65**
Recall	96.78	[illegible]	**98.89**
F1-Score	96.60	[illegible]	**98.76**
AUC-ROC	97.21	[illegible]	**99.21**
FAR	1.98	[illegible]	**1.13**
FRR	1.74	1.49	**0.89**
Dataset 2: Healthy, MCI, AD			
Accuracy	[illegible]	97.10	**98.65**
Precision	96.55	97.02	**98.60**
Recall	96.85	97.21	**98.78**
F1-Score	96.69	97.12	**98.70**
AUC-ROC	97.32	97.68	**99.14**
FAR	[illegible]	1.52	**1.09**
FRR	[illegible]	1.38	**0.92**

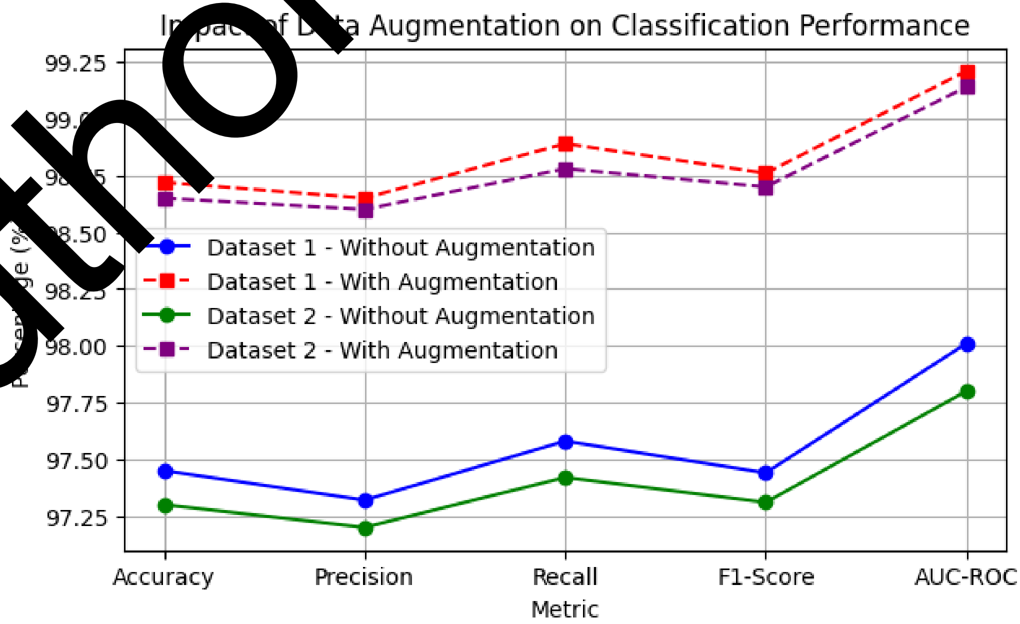

Fig. 7. Impact of data augmentation on classification performance.

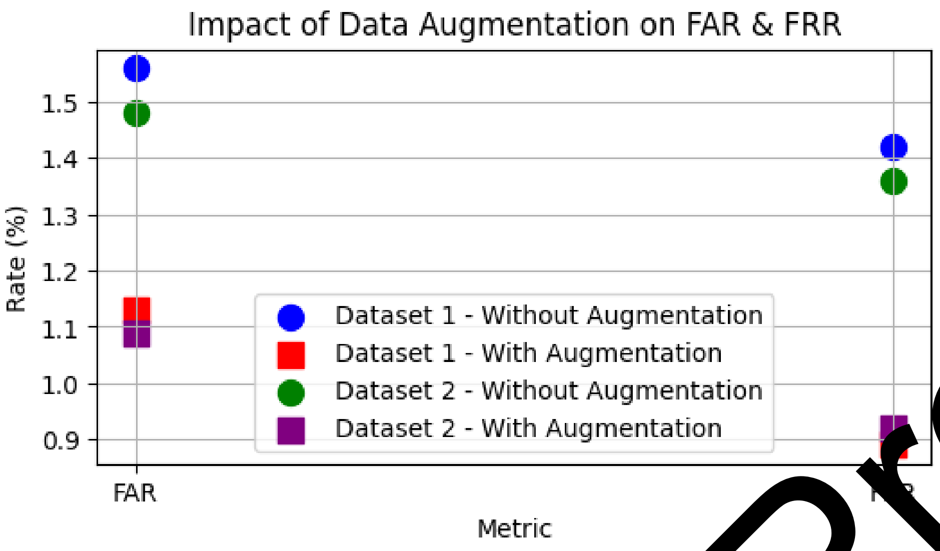

Fig. 8. Impact of data augmentation on FAR and FRR.

Figs. 7 and 8 illustrate the impact of data augmentation, demonstrating notable performance improvements in the NDAT framework. For Dataset 1, accuracy increases from 97.45% to 98.72%, while for Dataset 2, it improves from 97.30% to 98.65%. AUC-ROC also rises significantly, enhancing the model's ability to distinguish between neurological conditions. Additionally, FAR and FRR decrease, indicating improved classification reliability. Data augmentation enables better feature learning, reducing overfitting and enhancing generalization. These results confirm that augmentation strengthens the NDAT framework, leading to more accurate and robust EEG-based classification.

Table 3: Impact of Resampling on FTD Class Performance

Metrics	Without Resampling	With Resampling (FTD)
Accuracy	96.85	**98.72**
Precision	96.70	**98.65**
Recall	96.92	**98.89**
F1-Score	96.78	**98.76**
AUC-ROC	97.30	**99.21**
FAR	2.10	**1.13**
FRR	1.95	**0.89**

Resampling significantly improves the classification performance of the FTD class, as shown in Table 3. Accuracy increases from 96.85% to 98.72%, demonstrating better model generalization. Precision, recall, and F1-score also show noticeable gains, indicating a more balanced classification of the FTD class. The AUC-ROC improves from 97.30% to 99.21%, confirming enhanced discriminatory power. Additionally, both FAR and FRR decrease significantly, reducing misclassification rates. These results highlight that resampling effectively addresses class imbalance, leading to improved performance in distinguishing FTD from other conditions.

Table 4 presents a comparative analysis of the proposed NDAT model with existing state-of-the-art approaches for EEG-based AD and MCI classification. The results indicate that NDAT achieves the highest accuracy of 98.72% on the AD-FTD-CN dataset and 98.65% on the publicly available MCI database, surpassing previous models. Among prior methods, the Deep Pyramid CNN (DPCNN) by Xia et al. (2023) achieved 97.10%, while Romero-Parra et al. (2024) attained 97.45% for moderate AD and 97.03% for advanced AD using a CNN-based approach. The 18-layer CNN by Patil et al. (2022) and the CNN + MKSCDDL approach by Adarsh et al. (2024) achieved 98.00% and 98.27%, respectively, making them the closest competitors to NDAT. Other machine learning-based approaches, such as logistic regression with PSD features (Chedid et al., 2022, 81%) and Dual-Branch Feature Fusion Network (Chen et al., 2023, 80.23%), demonstrated lower classification performance. The Intrinsic Time-Scale Decomposition (ITD) + 1D CNN approach by Sen et al. (2024) attained 94.00% in Quartile 1 and 88.40% in Quartile 2, emphasizing the variability in performance across datasets. The superior accuracy of NDAT highlights the effectiveness of dual-stream feature extraction, multi-modal fusion, and domain adaptation mechanisms in EEG-based neurological disorder classification. The integration of Instance Normalization (IN) improved model generalization by normalizing EEG feature distributions and reducing intra-subject variability. Additionally, the Gradient Reversal Layer (GRL) in the domain adaptation process minimized domain shifts across subjects, enhancing NDAT's robustness for subject-independent classification. These findings validate the potential of NDAT as a state-of-the-art EEG-based model for Alzheimer's disease and MCI detection.

Despite the superior performance of the proposed NDAT model, certain limitations remain. First, the model's computational complexity is relatively high due to the dual-stream feature extraction and fusion mechanism, which may impact real-time processing efficiency. Second, the model relies on labeled EEG data for supervised training, limiting its applicability in scenarios where labeled data is scarce. Additionally, while resampling techniques mitigate class imbalance issues, excessive resampling could introduce synthetic data biases, potentially affecting generalization. For future work, we aim to develop lightweight versions of NDAT to improve computational efficiency for real-time applications. Additionally, self-supervised learning techniques will be investigated to reduce dependence on labeled data, enhancing the model's adaptability to new datasets. Expanding the dataset to include multimodal biosignals (e.g., fMRI, MEG) will also be explored to further improve classification robustness. Finally, real-world deployment and clinical validation will be prioritized to assess the model's effectiveness in practical diagnostic scenarios.

Table 4: Comparison of the proposed model with existing state-of-the-art approaches

References / Year	Input Type	Methods	Dataset	Accuracy (%)
Xia et al. (2023)	EEG	Deep Pyramid CNN (DPCNN)	100 subjects (49 AD, 37 MCI, 14 NC)	[illegible]
Chedid et al. (2022)	EEG	Logistic Regression with PSD features	41 subjects (14-channel montage)	81.00
Sen et al. (2024)	EEG	Intrinsic Time-Scale Decomposition (ITD) + 1D CNN	Q1, Q2 datasets	94.00 (Q1), 88.40 (Q2)
Chen et al. (2023)	EEG	Dual-Branch Feature Fusion Network (DBN)	OpenNeuro database	80.23
Roncero-Parra et al. (2024)	EEG	CNN-based model	668 volunteers (multi-hospital)	97.45 (moderate AD), 97.03 (advanced AD)
Patil et al. (2022)	EEG	18-layer CNN	ADNI dataset	98.00
Santos Toural et al. (2021)	EEG	Wavelet entropy + Pearson correlation + theta power	Resting-state EEG	94.44
Adarsh et al. (2024)	EEG	CNN + MKSCDDL	ADNI dataset	98.27
Mohi ud Din Dar et al. (2023)	MRI	MobileNet with Transfer Learning	MRI dataset	96.22
Toshkhujaev et al. ([illegible])	MRI	RBF-SVM + PCA	GARD, NACC datasets	97.37 (GARD), 95.24 (NACC)
Proposed	**EEG (1D + 2D)**	**Neurological Domain Adaptation with Transformer (NDAT)**	**AD-FTD-CN dataset**	**98.72**
	EEG (1D +2D)	**Neurological Domain Adaptation with Transformer (NDAT)**	**Healthy-MCI-AD dataset**	**98.65**

Conclusion

In this work, we proposed the Neurological Domain Adaptation with Transformer (NDAT) model for EEG-based Alzheimer's disease and Mild Cognitive Impairment (MCI) classification. By leveraging a dual-stream feature extraction approach, NDAT effectively integrates 1D temporal features from a Transformer encoder and 2D spatial features from a Custom CNN, significantly improving classification performance. The model achieves 98.72% accuracy on the AD-FTD-CN dataset and 98.65% accuracy on the publicly available MCI dataset, outperforming state-of-the-art methods. The inclusion of Instance Normalization (IN) ensures robustness against inter-subject variability, while the Gradient Reversal Layer (GRL) enhances domain adaptation, making the model suitable for subject-independent classification. Furthermore, experimental evaluations highlight the effectiveness of feature fusion, data augmentation, and resampling techniques in improving model performance and mitigating class imbalance. Comparative analyses demonstrate that NDAT consistently outperforms existing approaches across multiple performance metrics, including precision, recall, F1-score, and AUC-ROC. Despite its strong performance, NDAT has certain computational constraints, and its reliance on labeled EEG data remains a challenge. Future research will focus on developing a lightweight version of NDAT, exploring self-supervised learning, and integrating multimodal biosignals to enhance diagnostic accuracy. Additionally, real-world clinical validation will be prioritized to assess its effectiveness in practical medical applications. The results of this work establish NDAT as a promising AI-driven framework for early detection and classification of neurodegenerative disorders, paving the way for more accurate and efficient EEG-based diagnostic tools.

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