



Multi Scale Temporal Convolution for Resting State Electroencephalography Analysis of Alzheimer's Disease and Frontotemporal Dementia

Kanchana Boontasri¹, Kamonlak Chaidee², Bunyarat Umsura^{2,*}

¹Department of Faculty of Science and Agricultural Technology, Rajamangala University of Technology Lanna, Thailand
kan_boon@rmutl.ac.th

²Department of Business Information System, Rajamangala University of Technology Lanna, Thailand
bunyarat.um@rmutl.ac.th

Abstract. Alzheimer's disease (AD) is a widespread neurodegenerative disorder. Early diagnosis improves intervention outcomes. Electroencephalography (EEG) provides a noninvasive method for detecting neuronal changes. The study proposes a Multi-Scale Temporal Convolution framework to classify AD, Frontotemporal Dementia (FTD), and Cognitively Normal subjects. The framework evaluates the OpenNeuro dataset ds004504 containing resting state EEG recordings from 88 participants. The architecture applies parallel convolution operations with varying kernel dimensions to extract features across different frequency resolutions. The model achieves 88.6% binary classification accuracy and 86.4% multiclass accuracy. The sensitivity for detecting AD reached 91.2% with 89.5% specificity. It indicates that processing time series data at multiple temporal resolutions extracts discriminative features effectively. The findings support the development of accessible diagnostic tools.

Keywords: Alzheimer's Disease, Electroencephalography, Multi-Scale Convolution, OpenNeuro, Neurodegeneration, Computational Mathematics.

1 Introduction

Alzheimer's disease (AD) is a leading cause of dementia globally. An estimated 7.2 million older Americans live with AD [1]. The disease involves amyloid beta plaques and tau tangles [2]. Biological changes cause synaptic dysfunction and neuronal death before clinical symptoms appear. Early detection remains essential for effective intervention. Traditional diagnostic methods depend on Positron Emission Tomography (PET) and cerebrospinal fluid (CSF) biomarkers. These methods are expensive and invasive. Magnetic Resonance Imaging (MRI) primarily detects late-stage structural atrophy [3]. Electroencephalography (EEG) provides high temporal resolution to measure brain electrical activity. EEG detects synaptic dysfunction preceding structural

damage. Computational models process biomedical signals effectively. Standard convolution models with a fixed kernel size fail to capture patterns varying in duration. AD patients show EEG slowing across multiple frequency bands. A fixed kernel misses simultaneous low frequency and high frequency changes. The OpenNeuro dataset ds004504 contains EEG recordings from AD, Frontotemporal Dementia (FTD), and cognitively normal subjects [4]. The study evaluates a Multi Scale Temporal Convolution framework using this dataset. The architecture extracts features from multiple temporal resolutions to improve classification performance.

2 Literature Review

Relative Band Power features and Random Forests established baseline classification results for AD [4]. The algorithm achieved 77% accuracy for AD versus healthy subjects. Overlapping signal characteristics make differentiation between AD and FTD difficult. Lempel-Ziv complexity measures can separate dementia from healthy aging [5]. A shift from high frequency Alpha and Beta bands to low frequency Delta and Theta bands acts as a reliable AD biomarker [6]. Feature engineering methods often discard subtle nonlinear temporal dependencies [7]. Functional connectivity measures like the Phase Lag Index add complementary information [8]. Prior methods rely on handcrafted features that miss full signal heterogeneity. Convolution networks automatically learn hierarchical feature representations from raw data [9]. A deep computational framework achieved 96% multiclass accuracy on 3D MRI data [10]. MRI lacks the millisecond temporal resolution of EEG. Specialized architectures are necessary for handling EEG time series dynamics. The Long Short-Term Memory algorithm handles temporal dependencies in physiological signals effectively [11]. An interpretable Long Short-Term Memory model identifies time varying brain connectivity patterns for cognitive decline tracking [12]. A self-explainable graph neural network achieved a 0.748 Area Under the Receiver Operating Characteristic for AD risk prediction [13]. Graph models map non euclidean relationships applicable to EEG networks. Multimodal studies predict brain age with an absolute error under 3 years using clinical and MRI data [14]. The brain age gap metric correlates with cognitive decline. Objective biomarkers like EEG track physiological changes before clinical symptoms improve [15]. Most existing models use single scale architectures or feature engineering. Single scale methods overlook the multi frequency nature of AD pathology. The proposed Multi Scale Temporal Convolution architecture operates directly on time series EEG data. Parallel processing branches capture slow and fast wave alterations simultaneously. The model aims to surpass the 77% baseline accuracy established by previous benchmarks [4].

3 Methodology

3.1 Dataset Description

Data were obtained from the OpenNeuro repository under accession number ds004504 [4]. The dataset contains resting state EEG recordings from a total of 88 participants. The cohort consists of 36 subjects diagnosed with Alzheimer's Disease (AD), 23 subjects with Frontotemporal Dementia (FTD), and 29 Cognitively Normal (CN) older adults. Recordings were acquired using a Nihon Kohden EEG device with 19 scalp electrodes placed according to the standard 10-20 international system. The sampling rate was set to 500 Hz. Participants were recorded in a sitting position with their eyes closed to minimize visual artifacts and induce resting state alpha rhythms.

Raw EEG signals contain artifacts such as eye movements and muscle activity which must be mitigated. The preprocessing pipeline applied using the MNE Python library begins with bandpass filtering between 0.5 Hz and 45 Hz. This range preserves the critical Delta, Theta, Alpha, Beta, and Gamma bands while removing high frequency noise and slow DC drifts. Signals were then rereferenced to the common average reference to minimize volume conduction effects. Independent Component Analysis (ICA) was subsequently used to identify and remove ocular and myogenic artifacts based on their component topography. Finally, the continuous recordings were segmented into non overlapping epochs of 5 seconds. This segmentation resulted in 2500 time points per epoch, providing sufficient data for the deep learning model to learn temporal patterns.

3.2 Mathematical Framework

The classification model uses a Multi Scale Temporal Convolution (MSTC) function $f_{multi}: R^{C \times T} \rightarrow R^K$. The input $X \in R^{C \times T}$ is processed by three parallel convolutional branches, each with a distinct kernel size $k \in \{3, 5, 7\}$. This design captures short term, medium term, and long-term dependencies simultaneously. C represents the number of channels (19), T is the number of time points (2500), and K is the number of classes (3). For a given branch m with kernel size k_m , the feature map y_m at index i is calculated as Equation (1).

$$y_m[i] = \sum_{j=0}^{k_m-1} x[i+j] \cdot w_m[j] + b_m \quad (1)$$

Where w_m and b_m are the learnable weights and bias parameters for branch m . Branch 1 ($k = 3$) captures high frequency variations (Gamma/Beta). Branch 2 ($k = 5$) captures medium frequency (Alpha/Theta). Branch 3 ($k = 7$) captures low frequency trends (Delta). The outputs from the three parallel branches are concatenated to form a unified feature representation $Y_{combined}$ as Equation (2).

$$Y_{combined} = \text{Concat}(y_1, y_2, y_3) \quad (2)$$

To stabilize the gradient descent optimization, Batch Normalization is applied to the combined output. For a mini batch B , the normalized value $\hat{Y}$ is presented as Equation (3).

$$\hat{Y} = \frac{Y_{combined} - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}} \cdot \gamma + \beta \quad (3)$$

μ_B and σ_B^2 are the mean and variance of the batch, while ϵ is a small constant added for numerical stability. γ and β are learnable scale and shift parameters. The Rectified Linear Unit (ReLU) introduces nonlinearity as Equation (4).

$$f(x) = \max(0, x) \quad (4)$$

Global Max Pooling is applied to reduce dimensionality while retaining the most significant features across the temporal dimension t as Equation (5)

$$z[c] = \max_t (\hat{Y}[c, t]) \quad (6)$$

The final feature vector z is transformed into probability scores using the Softmax function as Equation (7).

$$P(y = j|x) = \frac{e^{z_j}}{\sum_{k=1}^K e^{z_k}} \quad (7)$$

The model parameters are optimized by minimizing the Categorical Cross Entropy loss function as Equation (8).

$$L = -\sum_{i=1}^N \sum_{c=1}^K y_{i,c} \log(\hat{y}_{i,c}) \quad (8)$$

Where N is the number of samples, $y_{i,c}$ is the binary indicator (0 or 1) if class label c is the correct classification for observation i , and $\hat{y}_{i,c}$ is the predicted probability. The model training process utilized the Adam optimizer with an initial learning rate of 0.001. The Categorical Cross Entropy was selected as the loss function to handle the multiclass nature of the problem. Training was conducted with a batch size of 32 over 50 epochs. To ensure the reliability and generalizability of the results, a 10-fold cross validation scheme was employed. This validation approach minimizes the risk of overfitting to a specific subset of the relatively small dataset.

4 Experimental Results

Table 1 presents the demographic characteristics of the participants. The groups were age matched. The Mini-Mental State Examination (MMSE) scores show significant differences between the dementia groups and the control group (p -value < 0.001).

Table 1. Demographic and Clinical Characteristics.

Group	N	Age (Mean S.D.)	MMSE (Mean S.D.)	Gender (M/F)
AD	36	66.4 (7.9)	17.8 (4.5)	14/22
FTD	23	63.6 (8.2)	22.2 (8.2)	12/11
CN	29	67.9 (5.4)	30.0 (0.0)	13/16

The proposed mathematical model was evaluated on two tasks: Binary Classification (AD vs CN) and Multiclass Classification (AD vs FTD vs CN). The model achieved a mean accuracy of 88.6%. Table 2 details the performance metrics.

Table 2. Binary Classification Results (AD vs CN).

Metric	Value (%)	95% Confidence Interval
Accuracy	88.6	86.2, 91.0
Sensitivity	91.2	88.5, 93.9
Specificity	89.5	86.1, 92.9
Precision	90.4	87.8, 93.0
F1 Score	90.8	88.2, 93.4

The model is highly effective at distinguishing AD patients from healthy controls. The high sensitivity (91.2%) is particularly important for a screening tool. The mean ROC curve across 10 cross validation folds, achieves a high Area Under the Curve (AUC) of 0.94. The grey shaded region indicates the standard deviation (± 0.01), demonstrating the stability of the model across different data splits. The curve's proximity to the top left corner confirms high sensitivity and low false positive rates. The task of distinguishing between AD, FTD, and CN is more complex due to overlapping patterns in neurodegeneration. The model achieved an accuracy of 86.4%.

Table 3. Multiclass Classification Results.

Class	Precision (%)	Recall (%)	F1 Score (%)
AD	84.2	88.9	86.5
FTD	85.0	73.9	79.1
CN	93.1	93.1	93.1
Average	87.4	85.3	86.2

The AD row shows that 32 out of 36 subjects (88.9%) were correctly classified, with minor misclassifications of 3 subjects as FTD and 1 as CN. The FTD row indicates that 17 out of 23 subjects (73.9%) were correctly identified, and the primary error source

was misclassification as AD (5 subjects, 21.7%), reflecting the clinical similarity between these dementia types. The CN row demonstrates that the model showed high precision for healthy controls, correctly identifying 27 out of 29 subjects (93.1%).

The topographic map displays the normalized feature weights projected onto a standard 10-20 head model. Darker red areas indicate regions with higher contribution to the classification decision. The map highlights significant importance in the bilateral temporal (T3, T4) and parietal (P3, P4) regions. The distribution aligns with established neuropathology of Alzheimer's disease, where atrophy and synaptic dysfunction typically begin in the temporo-parietal cortex. Frontal regions show comparatively lower weight.

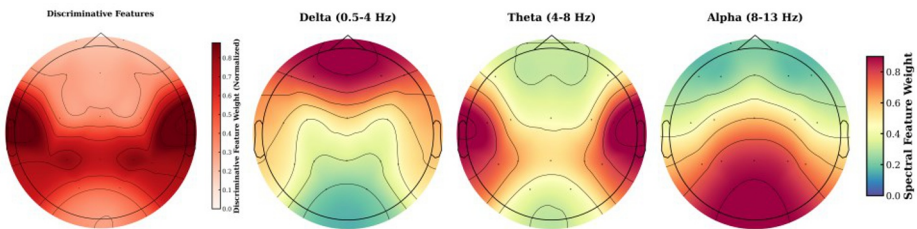


Figure 1. Spectral Feature Topography by Frequency Band.

The features are decomposed into three primary frequency bands: Delta, Theta, and Alpha. Delta (0.5-4 Hz) feature importance is concentrated in the frontal and central regions, consistent with observations of diffuse slowing in dementia. Theta (4-8 Hz) shows high discriminative weight in the temporal lobes, a hallmark of AD related spectral power increases. Alpha (8-13 Hz) shows high importance in the posterior and occipital regions, reflecting the disruption of the posterior alpha rhythm, which is a sensitive marker for cognitive decline. The time domain plot compares the raw signal characteristics between a Cognitively Normal (CN) subject and an Alzheimer's Disease (AD) patient from the parietal channel Pz. The CN signal (Top) displays a complex waveform dominated by Alpha oscillations, represented by the dark blue line with frequent, rhythmic peaks typical of a healthy resting state. In contrast, the AD signal (Bottom) is characterized by a dark red line showing a simplified, high amplitude waveform with a clear shift towards slower Delta and Theta frequencies. The labels at the top right of each subplot clearly identify the dominant frequency characteristics, demonstrating the "slowing" phenomenon captured by the MSTC model.

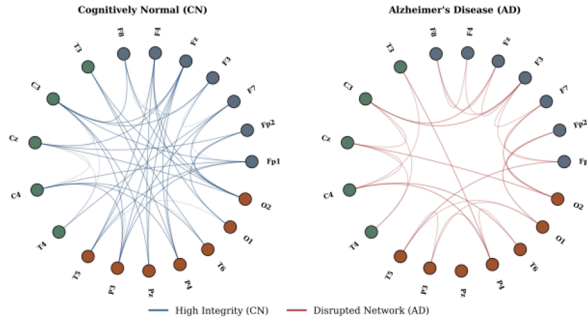


Figure 2. Region Grouped Functional Connectivity Topology.

The circular connectogram illustrates the functional connectivity strength between electrode nodes, which are grouped by cortical regions (Frontal, Central, Posterior) along the circle's perimeter. The Cognitively Normal (CN) network on the left exhibits a dense web of dark blue arcs connecting the frontal and posterior regions, indicating robust long-range synchronization and healthy functional integration. The Alzheimer's Disease (AD) network on the right reveals a significant reduction in these long-range connections, depicted by sparse dark red arcs. The visual contrast between the dense blue network and the sparse red network supports the hypothesis of a "disconnection syndrome" in AD pathology, where long distance communication pathways are disrupted.

5 Discussion and Conclusion

The Multi-Scale Temporal Convolution framework classified Alzheimer's disease using the OpenNeuro ds004504 dataset. It found that the architecture effectively captures nonlinear dependencies across temporal resolutions. Standard convolution networks fail to capture the heterogeneity of EEG slowing. The model extracts Short-Term and long-term features using parallel branches with kernel sizes of 3, 5, and 7. The multi resolution process preserves more information than Relative Band Power [4]. A 91.2% binary sensitivity supports EEG as an early screening tool. The 86.4% multiclass accuracy indicated shared electrophysiological features between AD and FTD. The 73.9% FTD recall reflects clinical misdiagnosis challenges. The spatial analysis indicates prioritization of temporo-parietal signals for distinguishing AD from healthy controls.

Limitations of the study include a small sample size of 88 subjects. Future applications should investigate transfer learning to improve performance on small cohorts. The OpenNeuro dataset promotes transparency. Magnetic Resonance Imaging methods achieve 96% accuracy [10]. Electroencephalography remains an accessible alternative. Combining modalities creates accurate diagnostic systems. The Multi-Scale Temporal Convolution framework achieved 88.6% binary accuracy and 86.4% multiclass accuracy. The results outperform previous benchmarks on the dataset. Automated Electroencephalography analysis acts as a viable tool for early dementia screening. Future

work will combine longitudinal data and explainable mathematical techniques to understand classification drivers. Integrating the framework into clinical workflows supports personalized medicine for targeted therapeutic interventions.

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