EEG-SSM: Leveraging State-Space Model for Dementia Detection

Xuan-The Tran[1] , **Linh Le**[1] , **Quoc Toan Nguyen**[1] and **Thomas Do**[1]
Chin-Teng Lin[1*]

[1]University of Technology Sydney (UTS), Faculty of Engineering and Information Technology, GrapheneX-UTS Human-centric AI centre, Sydney, New South Wales, 2007, Australia

Abstract

State-space models (SSMs) have garnered attention for effectively processing long data sequences, reducing the need to segment time series into shorter intervals for model training and inference. Traditionally, SSMs capture only the temporal dynamics of time series data, omitting the equally critical spectral features. This study introduces EEG-SSM, a novel state-space model-based approach for dementia classification using EEG data. Our model features two primary innovations: EEG-SSM temporal and EEG-SSM spectral components. The temporal component is designed to efficiently process EEG sequences of varying lengths, while the spectral component enhances the model by integrating frequency-domain information from EEG signals. The synergy of these components allows EEG-SSM to adeptly manage the complexities of multivariate EEG data, significantly improving accuracy and stability across different temporal resolutions. Demonstrating a remarkable 91.0% accuracy in classifying Healthy Control (HC), Frontotemporal Dementia (FTD), and Alzheimer's Disease (AD) groups, EEG-SSM outperforms existing models on the same dataset. The development of EEG-SSM represents an improvement in the use of state-space models for screening dementia, offering more precise and cost-effective tools for clinical neuroscience.

1 Introduction

Dementia, a cognitive decline that impairs memory and functional abilities, affects approximately 45 million people globally [Nichols *et al.*, 2019], with numbers expected to increase due to longer lifespans and an aging population. Alzheimer's disease (AD), the most common form of dementia, accounts for 60-80% of cases [Association and others, 2018], affecting 1 in 9 individuals over 65 [Rajan *et al.*, 2021]. It is a progressive neurological disorder characterized by beta-amyloid accumulation and tau tangles, leading to neuronal death, brain atrophy, and symptoms like memory loss, confusion, and behavioural changes. Frontotemporal degeneration (FTD), another form of dementia, leads to social, behavioural, and motor deficits due to the deterioration of frontal and temporal lobes. FTD typically affects individuals aged 45-60 and represents a significant portion of dementia cases, especially in those under 65 [Hogan *et al.*, 2016]. These dementia present significant healthcare challenges with substantial impacts on people with dementia (PwD) [Beerens *et al.*, 2014] and society, underscoring the need for advancements in accurate screening methods.

The standard screening approach for dementia typically involves cognitive tests like the Mini-Mental State Examination (MMSE) [Folstein, 1975], the Montreal Cognitive Assessment (MoCA) [Julayanont and Nasreddine, 2017], the Mini-Cog test [Borson *et al.*, 2000], and the Addenbrooke's Cognitive Examination III (ACE-III) [Bruno and Schurmann Vignaga, 2019]. These tests are advantageous due to their simplicity and quick administration. However, their effectiveness can be compromised by factors such as the patient's educational background, emotional state, and test reiteration. Neuroimaging techniques like MRI and PET scans offer greater detecting accuracy but are hampered by high costs and the necessity for extensive expert analysis [Sun *et al.*, 2024]. Electroencephalography (EEG) serves as a practical alternative, being cost-effective, non-invasive, and highly portable while providing direct, high-resolution monitoring of brain activity. The development of AI-based detecting models using EEG data can potentially yield more accurate detection and reduce the burden on healthcare professionals.

The quest for effective AI-based detection models for brain disorders has led to the exploration of various machine-learning techniques using EEG data. Traditional machine learning models typically utilize temporal, spectral, and spatial features extracted from EEG signals for classification tasks. A notable study by McBride et al. [McBride *et al.*, 2014] employed a support vector machine (SVM) to distinguish between healthy controls (HC), mild cognitive impairment (MCI), and PwD, achieving an accuracy rate of 85.4%. Deep learning approaches have also been investigated for this purpose. Ieracitano et al. [Ieracitano *et al.*, 2019] used a multilayer perceptron (MLP) model incorporating wavelet EEG features to classify the same groups, achieving an 89.2% accuracy. Another innovative study applied

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a Boltzmann machine to spectral images from EEG channels, achieving an impressive accuracy of 95%. Ensemble learning methods, which combine multiple machine learning models, have shown promising results. For instance, Sun et al. [Sun *et al.*, 2024] leveraged an ensemble approach using Adaboost to differentiate between HC, mild cognitive impairment (MCI), and dementia groups with an accuracy of 93.3% across a dataset including 75 HC, 99 with MCI, and 78 with dementia. Kim et al. [Kim *et al.*, 2023] extended this approach with an ensemble deep learning model validated on a substantial dataset of 1379 EEG recordings from 1155 PwD.

In the dataset leveraged for our research, Miltiadous et al. reported an accuracy of 83.28% for Alzheimer's disease versus Control (AD-CN) and 74.96% for Frontotemporal Dementia versus Control (FTD-CN) using a Convolution-Transformer Architecture known as DICE-Net [Miltiadous *et al.*, 2023a]. A separate method by Chen et al., which integrated Convolutional Neural Networks (CNNs) with Visual Transformers (ViTs), attained an accuracy of 76.37% [Chen *et al.*, 2023a]. Our results will be juxtaposed with these findings for a comprehensive comparison.

The burgeoning computational power and the advent of transformer-based deep learning methods have ushered in new opportunities for EEG data analysis. With their parallel computation abilities and self-attention mechanisms, transformers are well-suited for capturing the intricate temporal patterns within EEG signals that extend over long durations [Vaswani *et al.*, 2017]. However, despite their advantages, transformers are not without their challenges. They often necessitate substantial computational resources, and their performance tends to wane as sequence lengths grow [Gu and Dao, 2023]. This is a significant concern for EEG data characterized by complex and prolonged temporal dynamics. To surmount the inherent limitations of transformers, a novel approach known as the State Space Models with Selective Scan, or Mamba models, has been introduced [Gu and Dao, 2023]. These models strive to synergize the sequential processing strength inherent in traditional state space models (SSM) [Hamilton, 1994] with the parallel processing and long-term memory retention proficiencies of transformers. Mamba models are thus poised to capitalize on the best of both worlds, offering a promising new direction for enhancing EEG data analysis and expanding the potential for AI-based screening in neurology. Several variations of the Mamba model have been successfully applied in both the vision [Zhu *et al.*, 2024; Liu *et al.*, 2024b; Ma *et al.*, 2024; Liu *et al.*, 2024a] and medical fields [Guo *et al.*, 2024], yielding promising results.

In this study, we propose an improved Mamba model by adapting it to varying temporal resolutions of multivariate EEG data. Our adaptation, termed EEG-SSM temporal, demonstrates the model's versatility in handling different EEG segment sequence lengths. Furthermore, we have developed EEG-SSM spectral, a novel approach that enables the Mamba model to integrate spectral information from EEG signals. By merging EEG-SSM temporal and EEG-SSM spectral, we formulate EEG-SSM combined, a hybrid model that leverages the strengths of both temporal and spectral domains to achieve enhanced accuracy and stability, even as EEG segment length increases. Crucially, EEG-SSM spectral addresses individual variability in EEG signals by determining the optimally weighted contributions of various EEG frequency bands for each subject's segment data. Our integrated approach not only showcases the adaptability and efficiency of EEG-SSM models but also lays the groundwork for developing more precise and computationally economical detection tools in clinical neuroscience.

2 Method

Our EEG-SSM model aims to harness the strengths of SSM in conjunction with multivariate EEG segmentation, as detailed in Figure 1. This section begins with an introduction to the key principles underpinning SSMs. It then delves into the technique used to divide EEG data into multivariate segments, each defined by specific feature categories: temporal and spectral features (frequency). The section concluded by presenting *a novel optimization strategy (Opt-W)* designed to efficiently encode EEG wavelet bands, showcasing the innovative integration of SSM with EEG data analysis.

2.1 Preliminaries - SSM

The SSM functions by mapping the input vector $x \in \mathbb{R}^{1 \times D}$ to a higher-dimensional latent space $h \in \mathbb{R}^{1 \times N}$ (where $N > D$), subsequently computing a mapping from h to the output $y \in \mathbb{R}^{1 \times D}$. The following set of equations formalizes the SSM:

$$h'(t) = Ah(t) + Bx(t) \tag{1}$$

$$y(t) = Ch(t) + Dx(t) \tag{2}$$

where $A \in \mathbb{R}^{N \times N}$, $B \in \mathbb{R}^{N \times 1}$, $C \in \mathbb{R}^{1 \times N}$, and $D \in \mathbb{R}^{1 \times 1}$ represent the learned parameter matrices of the model. Equations 1 and 2, initially in continuous form, are not directly applicable for deep learning tasks. To adapt these for use, they were converted to a discrete form using the Zero-Order Hold (ZOH) method [Pohlmann, 2000]. Following this transformation, a global convolution operation was applied to the discretized form, rendering it suitable for input into the Mamba Encoder.

$$K = \begin{pmatrix} C\tilde{B} & CA\tilde{B} & \cdots & CA^{M-1}\tilde{B} \end{pmatrix}, \tag{3}$$

$$y = x * K, \tag{4}$$

where M signifies the length of the input sequence x, and K is an $\mathbb{R}^M$ - dimensional structured convolutional kernel.

2.2 EEG Preprocess

Segmentation

The Mamba architecture, originally tailored for 1-D sequences, has been adapted in this work for multivariate EEG data to encapsulate all EEG feature dimensions, as depicted in Figure 1. The upper module of the architecture processes segmented multivariate EEG data, preparing it for the EEG-SSM encoder block. A key attribute of the Mamba model is its proficiency in managing long sequence data, rendering it particularly apt for resting-state EEG analysis. This attribute allows for EEG data segmentation into various lengths with minimal data information loss.
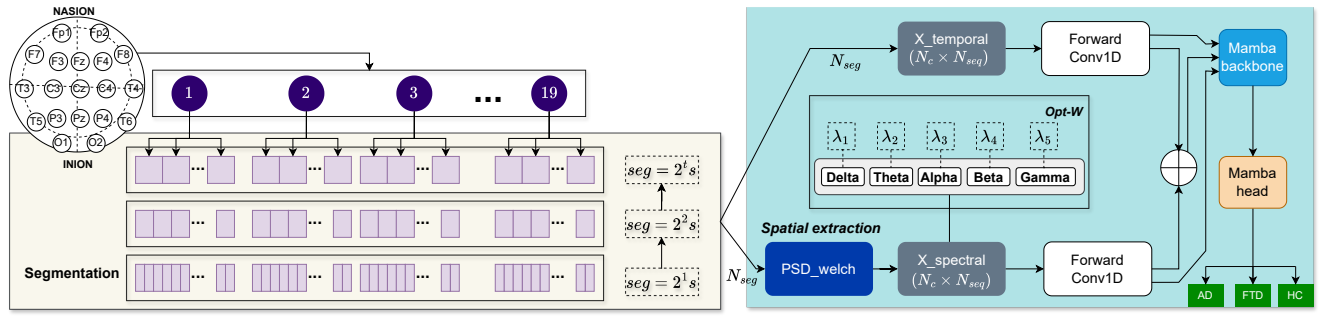
Figure 1: Overview of our proposed framework.

Temporal EEG: To process the multivariate EEG data into blocks suitable for encoder networks, we initiate by converting the 3-dimensional EEG data, denoted as $t \in \mathbb{R}^{N_{seg} \times N_c \times N_{seq}}$, into flattened 2-dimensional patches represented by $x_p \in \mathbb{R}^{N_c \times N_{seq}}$. Here, N_{seg} signifies the number of segments, N_c stands for the number of channels, and N_{seq} denotes the segment length corresponding to the number of time points within a single EEG segment. For instance, a segment with a length of 2 seconds could encompass a sequence ranging from time frame = 0 to time frame = 2s. Subsequently, these 2-D patches x_p are linearly projected onto a vector of size M, which facilitates the extraction of temporal features from the EEG data follows: $T_0 = [t_p^1 S; t_p^2 S; ...; t_p^J S]$ where t_p^j is the *j-th* patch of the original EEG sequence, $S \in \mathbb{R}^{N_c \times N_{seq}}$. The EEG-SSM encoder is used in individual segments, extracting representative EEG features for each segment. Given that Mamba operates on 1D sequences, the temporal domain data, X_{temporal}, retaining the original shape of the EEG segment input, transforms a Forward Conv1D layer into a 1D array as follows:

$$x(t) = [Conv_{1d}(t_p^1 S); ...; Conv_{1d}(t_p^J S)] \quad (5)$$

Spectral EEG

- Wavelet Filter: We employ a Wavelet Filter [Xu *et al.*, 1994], denoted as Ω, to process EEG data for feature extraction. Specifically, we focus on segmenting the EEG signals into distinct frequency bands, each associated with different cognitive states and activities. These bands include the Delta band (0.5– 4Hz), Theta band (4–8Hz), Alpha band (8–12 Hz), Beta band (12–20 Hz), and Gamma band (20–40 Hz), which are utilized to feature the EEG data for subsequent analysis [Sun *et al.*, 2024].

- In the spectral domain, Power Spectral Density (PSD) features are computed using Welch's method [Welch, 1967] to obtain X_{spectral} before its transformation to a 1D array by an additional Forward Conv1D layer follows:

$$x(t) = [Conv_{1d}(\Omega(t_p^1 X)); ...; Conv_{1d}(\Omega(t_p^J X))] \quad (6)$$

Mamba Input In our methodology, the Mamba system is designed with three distinct inputs $x(t)$ (see Equation 1) : one for purely temporal features (Equation 5), another for exclusively spectral features Equation 6), and a third that concatenates both temporal and spectral features, allowing for a comprehensive analysis through separate yet complementary data feature types (see Figure 1).

2.3 EEG wavelet optimization for spectral features (Opt-W)
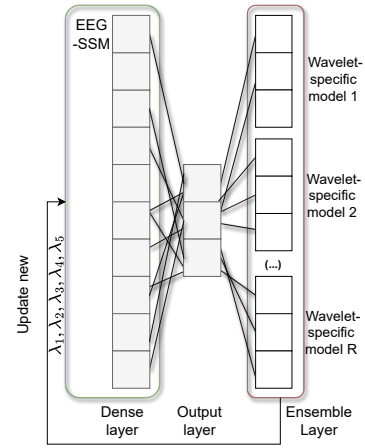

Figure 2: Bottleneck structure for Adaptive EEG Wavelet-Specific Weight Module with three classes and R wavelet-specific models.

Previous research [Swarnalatha and others, 2023; Al-Sharabi *et al.*, 2022; Sedghizadeh *et al.*, 2022] in the field of cognitive impairment and dementia detection has been limited by an inability to automatically optimize the weights among wavelet bands (Delta, Theta, Alpha, Beta, Gamma). The ratio between these bands plays a critical role in identifying various cognitive conditions [Chikhi *et al.*, 2022], underscoring the need for a solution capable of dynamically of each wavelet's importance band according to the specific type of dementia and the patient's condition. Implementing such a system would significantly enhance the accuracy and efficacy of classifying cognitive problems. In this segment, we delineate the ensemble layer, an innovative network layer engineered for the efficacious training of deep neural networks by leveraging features from separate wavelet-specific models to automatically update the weights featuring the combination of different wavelet bands (Delta, Theta, Alpha, Beta, Gamma) for spectral features. The foundational idea is intu-

itive: the ensemble layer assimilates inputs typically designated for the ultimate layer of a deep neural network (such as a softmax layer for classification) and orchestrates a wavelet-specific linkage from this terminal layer to the labels of various wavelet-centric models. This linkage adeptly encapsulates the distinct reliabilities and the biases introduced by specific wavelet bands, transforming the conventional output layer into a pivotal bottleneck layer that is communally utilized by different wavelet-centric models. For illustrative purposes, Figure 2 portrays this bottleneck configuration within a neural network framework tailored for EEG classification challenges, featuring three classes and encompassing R models, inclusive of 5 wavelet-specific models.

The methodology entails employing the labels from a designated wavelet band to disseminate errors throughout the neural network. The ensemble layer meticulously adjusts the gradients emanating from the labels of that particular wavelet band, aligning them with its accuracy through scaling and bias modulation. Consequently, the bottleneck layer of the network aggregates these tailored gradients from the labels of various wavelet-centric models and propels them backward through the network's remaining structure. This orchestration, facilitated by the so-called "ensemble layer", empowers the network to mitigate the influence of unreliable labelers and rectify persistent biases in their labels, all within the traditional backpropagation paradigm.

Formally, let ξ symbolize the output of a deep neural network with an arbitrary architecture. For the sake of simplicity, we postulate that ξ emerges from a softmax layer, with ξ_c denoting the probability of classifying the input instance into category c. The activation for each wavelet-specific model r within the ensemble layer is defined as $m^r = f_r(\xi)$, where f_r signifies a wavelet-specific function, and the output of the ensemble layer is rendered as the softmax of these activations: $\psi_c^r = \frac{e^{m_c^r}}{\sum_{l=1}^{C} e^{m_l^r}}$.

The conundrum then lies in formulating the function $f_r(\xi)$. In the experimental section, we explore various alternatives. For classification endeavors, it is plausible to envisage a matrix transformation such that $f_r(\xi) = W^r \xi$, where W^r represents a wavelet-specific matrix. Given a cost function $E(\psi^r, y^r)$ that juxtaposes the expected output of the rth wavelet-specific model with its actual label y^r, we can ascertain the gradients $\frac{\Delta E}{\Delta m^r}$ at the activation m^r for each model and backpropagate them to the bottleneck layer, culminating in the equation:

$$\frac{\Delta E}{\Delta \xi} = \sum_{r=1}^{R} W^r \frac{\Delta E}{\Delta m^r} \tag{7}$$

Hence, the gradient vector at the bottleneck layer amalgamates into a composite of gradients, each weighted according to the labels from the disparate wavelet-specific models. Furthermore, if a wavelet model is predisposed to misclassify class c as class l (indicative of a bias specific to the wavelet model), the matrix W^r can adeptly recalibrate the gradients to accommodate this bias. The weights of the wavelet-specific models, $W^r{}_{r=1}^R$, delineating the transition from the bottleneck layer's output ξ to the wavelet labels $\psi^r{}_{r=1}^R$, can be de-

duced using conventional stochastic optimization methodologies, such as SGD or Adam. Subsequent to the network's training phase, the ensemble layer can be detached, unveiling the bottleneck layer's output ξ, which can subsequently be harnessed for prognostications on novel instances. In our exploration, the individual sensitivities σ^r and specificities δ^r are equated to the prediction probabilities and the biases emanating from the training model, respectively.

3 Experiments

3.1 Dataset

In this study, we utilized a recently published EEG resting state dataset from May 2023, comprising data from 88 subjects across three categories: AD, FTD, and HC [Miltiadous *et al.*, 2023b]. This dataset was selected for its comprehensive data length for each subject and the novelty of its application in research. It features a balanced representation of conditions with 36 AD participants, 23 FTD subjects, and 29 healthy HC. Data were collected using 19 EEG channels (Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, and O2) and 2 reference electrodes, adhering to the international 10–20 system. The recordings offer a resolution of 10 uV/mm at a sampling rate of 500 Hz. Duration varied among groups: AD recordings averaged 13.5 minutes (ranging from 5.1 to 21.3 minutes), FTD recordings 12 minutes (ranging from 7.9 to 16.9 minutes), and HC recordings 13.8 minutes (ranging from 12.5 to 16.5 minutes), totalling 485.5 minutes for AD, 276.5 minutes for FTD, and 402 minutes for HC. Despite the resting state condition with closed eyes, some recordings exhibited eye movement artifacts. To address this, the dataset employed the Independent Component Analysis (ICA) method (specifically, the RunICA algorithm) to transform the 19 EEG signals into 19 ICA components. Artifacts identified as eye or jaw movements were subsequently removed using the "ICLabel" algorithm within the EEGLAB platform [Delorme *et al.*, 2007], ensuring the integrity of the EEG data for analysis.

3.2 Settings

We trained our EEG-SSM model on the dataset previously referenced, setting the model dimension (d-model) to match the number of EEG channels, which is 19. The model distinguishes between HC, FTD, and AD; thus, the number of classes was set to 3. For the optimization process, we employed cross-entropy loss and the Adam optimizer [Kingma and Ba, 2014] with a learning rate of 0.001, iterating the training process over 500 epochs to ensure adequate learning and convergence of the model.

In this study, we trained the EEG-SSM model using a dataset that includes a balanced division into training, testing, and validation sets, each constituting 60%, 20%, and 20% of the data, respectively. The model's efficacy was assessed against established benchmarks, such as a basic Recurrent Neural Network (RNN) and an EEG-transformer model. Consistent across all models, we adhered to a training regimen of 500 epochs to ensure thorough learning and fair comparison.

We use a simple RNN model [Medsker and Jain, 2001] for this classification task. The model, structured with an RNN layer followed by a fully connected layer, is designed to process sequential EEG signals. Configured with an input size of 19 to match the EEG features, the RNN uses 128 hidden units across two stacked layers to enhance learning depth. The forward pass initiates with a zeroed initial hidden state, ensuring the model adapts to the input sequence dynamically. This architecture culminates in mapping the sequential analysis to a predefined number of classes, optimizing for accuracy and computational efficiency. Key hyperparameters, including a learning rate of 0.001 and training over 500 epochs, are fine-tuned to balance performance and speed, making this model a strategic choice for discerning patterns in EEG data relevant to dementia classification.

We also implemented a patched EEG-transformer model inspired by the approach described in Chen et al. [Chen *et al.*, 2023b]. The model utilizes a custom 1-D patch embedding method to project multivariate EEG data into a higher-dimensional space, with a time-len= EEG-segment-length, patch-size=4, embed-dim=1024, and in-chans=19. The encoder consists of depth=24 Transformer blocks, each with num-heads=16, systematically refining the embeddings through self-attention mechanisms to capture complex temporal EEG dynamics.

3.3 Dementia detection results

Benchmark models performance In assessing the performance of various models for classifying resting state neural disorders, Table 1 presents a comparison across different segment lengths ranging from 2s to 256s. The RNN model, with the least number of parameters at 8.6K, shows moderate performance, peaking at 42.7% accuracy for the 32s segment. EEG-Net, with a slightly higher parameter count of 12K, demonstrates improved accuracy, particularly at 4s with 55.6%. The EEG-Transformer, despite a significant increase in parameters to 120K, attains its best performance at a shorter 2s segment with 70.1% accuracy but shows a downward trend as the segment length increases.

EEG-SSM performance The EEG-SSM model exhibits superior performance across all variants when compared to the RNN and EEG-Net, with the EEG-SSM variant, boasting 4.4K parameters, outperforming other models in longer segments. This variant achieves an impressive 91.0% accuracy at 2s and maintains robust performance as the segment length increases, highlighting its efficacy in handling various temporal resolutions of EEG data. The EEG-SSM $_{temporal}$ and EEG-SSM $_{spectral}$ variants also show strong results, particularly favoring the mid-range segment lengths of 16s to 64s. However, a common trend across all models is a decline in performance at the longest segment length of 256s, with the EEG-SSM $_{temporal}$ variant experiencing the most significant drop to 46.8% accuracy, suggesting a potential trade-off between segment length and model efficacy. The provided confusion matrix, depicted in Figure 3, corresponds to the performance of the EEG-SSM model, which attained an impressive accuracy rate of 91.0% on a test set derived from 2-second EEG data segments. The total number of 2-second segments for all subjects amounted to 35,254, with a data split ratio of

60% for training, 20% for validation, and 20% for testing. The matrix showcases the model's considerable accuracy in correctly identifying 2,751 instances of AD, 2,219 instances of HC, and 1,434 instances of FTD. Misclassifications were recorded with AD misidentified as HC and FTD in 146 and 75 instances, respectively; HC mistaken for AD and FTD in 139 and 74 instances, respectively; and FTD confounded with AD and HC in 124 and 89 instances, respectively. These figures highlight the model's robust performance in distinguishing AD and HC, indicating a need for further refinement in accurately classifying FTD to enhance its discernment from AD and HC conditions.

The role of EEG sampling rate in EEG-SSM model performance Table 2 delineates the performance of the EEG-SSM model variants to the number of EEG channels at two distinct sampling rates, 250 Hz and 125 Hz. When analyzing the results at the higher sampling rate of 250 Hz, the EEG-SSM model stands out with consistently high accuracy across all segment lengths, achieving its peak accuracy of 83.1% at the 2s segment length. The EEG-SSM $_{spectral}$ variant, while slightly lagging behind its counterparts, still maintains a commendable performance, especially at 256s, where it nearly matches the EEG-SSM model with an accuracy of 72.8%.
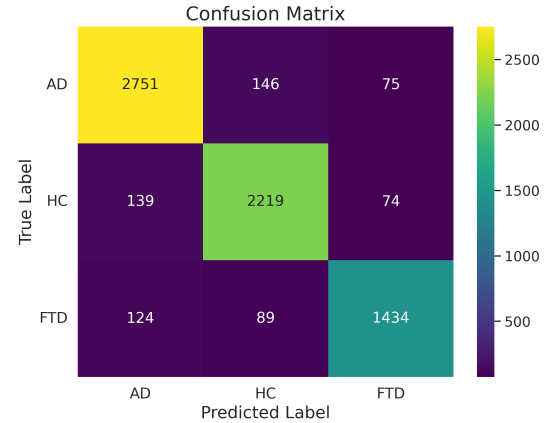

Figure 3: Confusion matrix displaying classification results on the test set using 2-second EEG data segments.

The performance trend alters slightly at the lower sampling rate of 125 Hz. Here, all EEG-SSM model variants generally show a modest reduction in accuracy across the board. Nevertheless, the EEG-SSM $_{combined}$ model demonstrates resilience, maintaining a strong performance with the highest accuracy of 73.6% at 4s. Interestingly, the performance gap between the temporal and spectral variants narrows in the longer segment lengths, indicating a potential dependency of model performance on the interplay between sampling rate and EEG data resolution.

Across both sampling rates, there is a notable trend where accuracy tends to decrease with increasing segment length, affirming the complexity of capturing informative features from extended data sequences. The EEG-SSM $_{temporal}$ variant, in particular, shows a significant decline in performance

Table 1: Model performance (accuracy %) for resting state neural disorder classification (19 channels, sampling rate 500Hz)

Model	Params	2s	4s	8s	16s	32s	64s	128s	256s
RNN	8.6K	41.5	40.5	40.8	40.0	42.7	24.0	37.2	39.6
EEG-Net	12K	50.3	55.6	51.3	53.4	55.6	51.5	48.8	47.5
EEG-Transformer	120K	70.1	65.6	58.3	47.4	38.6	34.5	33.7	30.5
EEG-SSM $_{temporal}$	4.4K	89.1	86.5	82.3	77.4	74.5	64.1	52.5	46.8
EEG-SSM $_{spectral}$	4.4K	80.1	79.5	79.6	79.1	78.4	77.6	77.1	76.8
EEG-SSM	4.4K	91.0	87.5	83.3	79.7	79.4	78.6	78.1	77.8

Table 2: Model performance (accuracy %) by sampling rate

Model	Sampling rate	2s	4s	8s	16s	32s	64s	128s	256s
EEG-SSM $_{temporal}$	250	82.4	80.5	75.8	72.5	69.4	62.6	50.3	42.9
EEG-SSM $_{spectral}$	250	77.1	76.5	75.9	75.4	74.8	74.2	73.1	72.8
EEG-SSM	250	83.1	81.6	76.7	75.7	75.4	74.6	73.4	73.0
EEG-SSM $_{temporal}$	125	76.7	72.5	69.8	65.6	61.7	57.3	50.4	46.7
EEG-SSM $_{spectral}$	125	69.7	68.5	67.8	67.2	66.4	64.1	62.7	60.8
EEG-SSM	125	77.0	73.6	70.3	68.5	66.7	64.7	63.1	61.2

Table 3: Model performance (accuracy %) by number of channels

Model	Channels	2s	4s	8s	16s	32s	64s	128s	256s
EEG-SSM $_{temporal}$	6	68.4	66.7	61.2	57.4	53.2	48.4	43.1	38.8
EEG-SSM $_{spectral}$	6	60.6	59.5	58.3	57.7	56.4	55.7	54.1	53.8
EEG-SSM	6	69.2	67.5	61.3	58.1	57.4	56.8	55.1	54.2
EEG-SSM $_{temporal}$	12	76.7	74.5	72.1	68.7	63.4	61.9	52.7	44.6
EEG-SSM $_{spectral}$	12	77.1	76.8	76.6	75.7	75.2	68.7	67.1	65.9
EEG-SSM	12	78.4	77.5	77.3	76.8	75.4	69.6	67.3	66.8

at the longest segment of 256s across both sampling rates, which may suggest limitations in the model's ability to process temporal features over extended periods. Conversely, the robustness of the EEG-SSM $_{combined}$ model across varied segment lengths underscores its effectiveness in integrating multiple feature domains for neural disorder classification, even as the sampling rate varies.

The role of EEG channels in EEG-SSM model performance In Table 3, we assess the EEG-SSM model's performance across different numbers of EEG channels, specifically examining various combinations of 6 and 12-channel configurations across various segment lengths ranging from 2 seconds to 256 seconds, the highest accuracy of 6 and 12-channels combination is selected to report. The EEG-SSM $_{temporal}$ model, which focuses on temporal features, shows a performance boost when the number of channels is increased from 6 to 12, with accuracy improving from 68.4% to 76.7% for the 2s segment length. This trend of improved performance with more channels is consistent across all segment lengths for the temporal model, although the accuracy decrement with longer segments remains evident.

The EEG-SSM $_{spectral}$ model, which relies on spectral features, also benefits from increased channels. With 6 channels, the spectral model peaks at 60.6% accuracy at the 2s segment, while the 12-channel configuration sees a notable jump

to 77.1% accuracy for the same segment length. The spectral model retains higher accuracy rates with increasing segment lengths when more channels are utilized, suggesting that additional channels provide a richer spectral representation that the model can leverage for classification.

The EEG-SSM $_{combined}$ model, which integrates both temporal and spectral features, achieves the highest accuracy across both channel configurations. For the 6-channel setup, the combined model's best performance is at 4s segment length with 67.5% accuracy, while the 12-channel configuration sees its peak performance of 78.4% at the 2s segment length. This model's accuracy is superior at shorter segments and remains relatively stable across longer segments, highlighting the combined model's robustness and ability to utilize a more comprehensive feature set effectively.

The overall trend observed in Table 3 suggests that the performance of all EEG-SSM model variants is influenced by the number of EEG channels and the segment length. There is a clear pattern where the combined model consistently outperforms the individual temporal and spectral models, indicating that a multifaceted approach to feature integration can yield more accurate neural disorder classification across various EEG data resolutions.

4 Discussion

In our exploration, we delve into the capabilities of the Mamba model, tailoring it to effectively process multivariate EEG data across a spectrum of temporal resolutions. This endeavor led to creating the EEG-SSM temporal variant, highlighting the model's adaptability to diverse EEG segment lengths. Additionally, we introduced the EEG-SSM spectral variant, an innovative methodology that facilitates incorporating spectral data from EEG signals into the Mamba framework. The fusion of these two approaches culminates in the EEG-SSM combined model, which highlights the advantages of both temporal and spectral analyses to deliver superior accuracy and robustness against variations in EEG segment lengths.

EEG Sequence Length Impact The Mamba model has demonstrated exceptional performance in natural language processing (NLP) tasks, effectively handling sequence lengths up to 2^{20} tokens [Gu and Dao, 2023]. However, our findings, as presented in Table 1, reveal a notable performance dip for the EEG-SSM $_{\text{temporal}}$ variant as the EEG sequence length increases. This decrease in accuracy can be attributed to the model treating each EEG timepoint as an individual token, where the timepoint token dimension $(19, 1)$ is significantly smaller compared to typical word token embeddings such as Word2Vec [Church, 2017].

EEG Channel Effectiveness In our experiments with reduced subsets of EEG channels (specifically, using 6 and 12 channels), we observed a decline in accuracy across all EEG-SSM model variants as the number of channels was reduced. This trend likely arises from the unique brain signal information conveyed by each channel in multivariate EEG data, emphasizing the importance of spatial features representing brain connectivity between EEG channels. Despite its success in extracting temporal and spectral features, the current iteration of the EEG-SSM model does not incorporate spatial features, marking a limitation and an avenue for future research. The challenge in integrating spatial features lies in their differing data shape compared to temporal and spectral features. Moving forward, we aim to develop methodologies to incorporate spatial features into the EEG-SSM model, enhancing its screening capabilities by leveraging the comprehensive neural information in EEG data.

Spectral Feature Effectiveness A pivotal aspect of the EEG-SSM spectral variant is its capacity to account for individual differences in EEG signal characteristics, thereby optimizing the contribution of distinct EEG frequency bands to each subject's data analysis. This nuanced approach not only underscores the flexibility and computational efficiency of the EEG-SSM models but also improves the performance of screening methodologies within clinical neuroscience. The sequence length issue of Mamba prompted us to explore the incorporation of spectral EEG features as a means to maintain consistent EEG-SSM performance across different segment lengths. The PSD extraction from EEG segments offers a promising solution, as variations less influence PSD values in segment length, providing a stable feature set for the EEG-SSM model. As evidenced in Table 1, integrating PSD features has resulted in more stable model performance across

various EEG segment lengths, underscoring the effectiveness of spectral information in enhancing the EEG-SSM framework. Upon evaluating the EEG-SSM models across varying sampling rates (Table 2), we observed a uniform decline in performance with the reduction of sampling rates. This outcome is intuitively expected, as lower sampling rates yield fewer temporal data points for model training, resulting in diminished EEG data information. Notably, the performance of the EEG-SSM $_{\text{temporal}}$ model is particularly sensitive to reductions in sampling rate, a vulnerability that becomes more pronounced with longer segment lengths. This sensitivity underscores the critical role of sampling rate in preserving the integrity of temporal information within the EEG data, with lower rates leading to more significant information loss in the temporal domain.

Temporal and Spectral Combination Effectiveness It is crucial to highlight that integrating temporal and spectral features for training with the EEG-SSM model results in higher and more consistent accuracy than training the model with unimodal features. We achieved the peak accuracy of 91.0% when training EEG-SSM with 2-second segments. This performance surpasses that of existing studies utilizing the same dataset. For instance, Miltiadous' approach, utilizing a Convolution-Transformer Architecture named DICE-Net [Miltiadous *et al.*, 2023a], reported accuracies of 83.28% and 74.96% for AD-CN and FTD-CN models, respectively. Additionally, a method combining CNNs and ViTs detailed in [Chen *et al.*, 2023a] achieved an accuracy of 76.37%. These comparisons underscore the efficacy of the EEG-SSM model in dementia detection, highlighting its potential for advancing screening tools in clinical neuroscience.

5 Conclusion

Our study presents a novel method for analysing multivariate EEG data through the novel application of the Mamba model, tailored for varying temporal resolutions. The development of EEG-SSM temporal and EEG-SSM spectral models marks a pivotal step towards leveraging the full spectrum of EEG data, encompassing both temporal and spectral information. This dual approach has demonstrated exceptional performance, notably achieving an accuracy of 91.0% in distinguishing between HC, FTD, and AD subjects, thereby outperforming existing methodologies on the same dataset. Including EEG-SSM spectral is particularly noteworthy for its ability to account for individual variability in EEG signals, ensuring the model's broad applicability and enhanced screening precision. Our findings underscore the potential of EEG-SSM models to improve clinical screening, offering a more accurate, efficient, and cost-effective tool for screening to detect dementia early. This research showcases the versatility and effectiveness of the EEG-SSM framework. It lays a solid foundation for future research in clinical neuroscience, promising improved screening solutions for a spectrum of neurological disorders.

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