Journal of Information Systems Engineering and Management
2025, 10 (1)
e-ISSN: 2468-4376
https://jisem-journal.com/

Research Article

EEG-Based Alzheimer's Diagnosis Using Hybrid Convolutional and Recurrent Neural Networks

Sharyu Ikhar, Dr. Priya Vij

Research Scholar, Department of Computer Science and Engineering
Kalinga University Raipur
Department of Computer Science and Engineering
Kalinga University Raipur

ARTICLE INFO

Received:26 Oct2024
Revised : 01 Nov 2024
Accepted:07 Nov2024

ABSTRACT

Alzheimer's disease (AD) is a neurological disorder that gets worse over time and has a big effect on brain function. It is important to get a correct diagnosis as soon as possible so that treatment can be effective. EEG, which records brain activity without touching the brain, is non-invasive, cheap, and can show activity in real time. It has become a hopeful way to find AD. By exploiting their spatial and temporal characteristics, this paper proposes a hybrid deep learning technique combining Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to better analyse EEG data. The CNN component removes spatial-frequency characteristics from time-frequency representations of EEG data; the LSTM component determines temporal dependence of EEG sequences on one another. The combined CNN-RNN architecture outperforms both conventional machine learning models and single deep learning systems in terms of accuracy, F1-score, and stability. Using standard EEG datasets for experiments shows that the proposed model can accurately classify things while still being easy to program. This means it can be used in clinical settings. The current state of EEG-based Alzheimer's detection is improved by this method, which also lays the groundwork for smart, real-time diagnostic tools.

Keywords: Alzheimer's Disease, EEG, Deep Learning, CNN, LSTM, Hybrid Neural Network, Time-Frequency Analysis, Medical Diagnosis.

I. INTRODUCTION

Alzheimer's disease (AD), a neurodegenerative disorder that gets worse over time, is now one of the main causes of cognitive decline and dementia in older people around the world. AD symptoms include memory loss, confusion, language problems, and changes in behaviour. It is important to find and diagnose AD early so that it can be treated effectively. Though often costly, intrusive, or unavailable in regular clinical environments, traditional diagnostic techniques such neuroimaging and cerebrospinal fluid (CSF) analysis are helpful. On the other hand, electroencephalography (EEG) is a non-invasive, affordable, real-time method to record brain electrical activity [1]. EEG signals are complicated, non-linear, and susceptible to noise and artefacts, thus they require advanced and dependable computer techniques for feature extraction and classification.

Deep learning has changed many fields in recent years, especially biological signal analysis, because it can instantly learn hierarchical models from raw input data. There are many designs that can be used, but Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have shown a lot of promise for understanding patterns in time and space. CNNs are very good at finding local relationships and spatial structures in data [2]. This implies they may be used to extract characteristics from time-frequency representations of EEG data or spectrograms. Conversely, RNNs—especially Long Short-Term Memory (LSTM) networks—are excellent at simulating long-term associations and temporal processes, which are very crucial for comprehending how the brains of Alzheimer's patients evolve over time. Both CNNs and RNNs have advantages that may be used to create hybrid systems that are effective for examining sequential biological data including EEG.

This study offers a hybrid deep learning framework for the automated diagnosis of Alzheimer’s disease using EEG inputs that combines CNN and LSTM models. Using the CNN component to capture spatial dependencies and patterns within the EEG spectrograms, one may successfully filter out unneeded noise and maintain necessary information [3]. The LSTM component then forecasts the temporal dynamics of the recovered features, therefore detecting the progression of brain abnormalities across time. By incorporating spatial and temporal parameters, this combination increases classification accuracy, hence allowing a more full understanding of EEG data. Apart from improving diagnostic performance, the proposed approach provides a scalable and generalisable framework that may be used to various EEG-based neurological disease categorisation tasks.

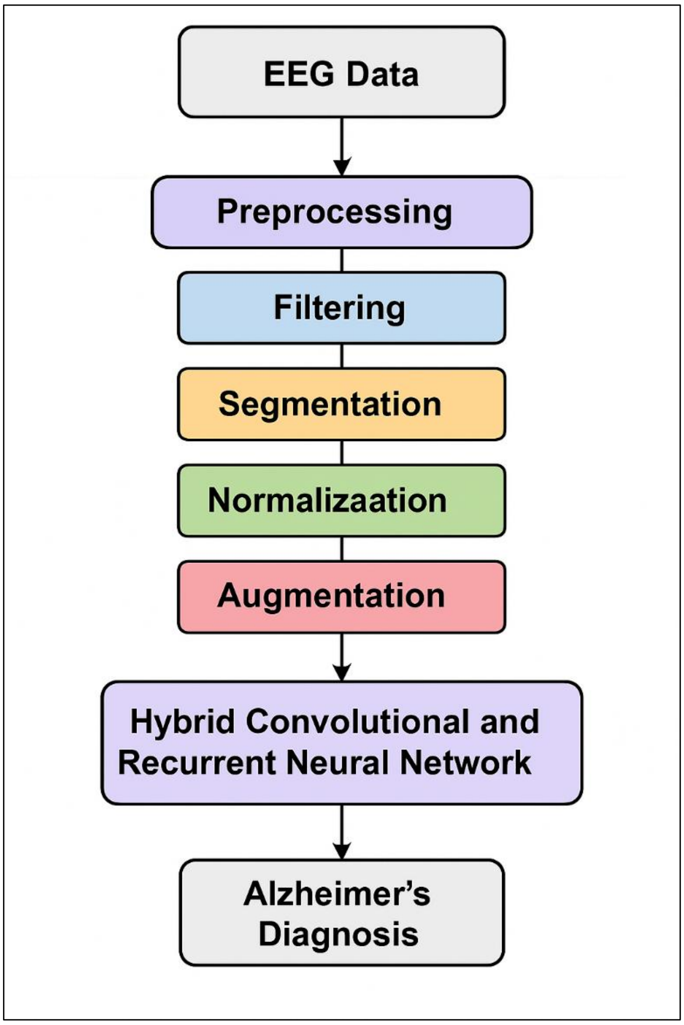

Figure 1. Hybrid model for Alzheimer’s Diagnosis

The idea behind using EEG to find Alzheimer's is that it can show changes in functional connections and brain rhythms, both of which are often messed up in people with AD. Several studies have found changes in EEG rhythms, mainly in the alpha, beta, and theta bands, as well as less coordination and coherence between brain areas. Though tiny, if documented and examined properly these changes could serve as precise indicators for early-stage AD. Some of the most usual machine learning techniques that have been successfully used to EEG data include Support Vector Machines (SVM), k-Nearest Neighbours (k-NN), and Random Forests [4]. These techniques, nevertheless, have limitations as they cannot be used across several people or sessions since EEG patterns varies from individual to individual.

They also often rely on manually created characteristics. On the other hand, deep learning models like CNNs and RNNs have shown promise in automatically learning features that separate things from raw or slightly preprocessed data [5]. CNNs have been used in the past to process 2D EEG images like spectrograms or geographic maps, and the results were promising for classifying AD [6]. Similarly, RNN-based algorithms have been used to identify patterns in the timing of EEG data played one after another. Standalone models, on the other hand, often neglect the spatial and temporal richness of EEG data. A fair approach that results in improved performance and readability is thus a CNN-RNN model using CNNs for spatial encoding and RNNs for sequential modelling [7].

Three main goals are at the heart of this work. First, to prepare and change the raw EEG data into time-frequency representations that deep learning models can use effectively. Second, create and train a CNN-LSTM system capable of learning from EEG spectrograms both spatial and temporal data. Third, evaluate the performance of the model using publicly accessible EEG datasets and compare it to the best F1-score, accuracy, sensitivity, and specificity techniques. This paper also investigates model explainability using saliency maps and attention mechanisms. The aim is to assist physicians determine which brain areas and frequency bands are most relevant for their diagnosis. The study uses a strong experimental process with cross-validation, subject-independent tests, and ablation studies to make sure that the results are applicable to other people and are useful in clinical settings. To overcome the challenges resulting from limited EEG datasets, data enrichment techniques are applied; normalisation and artefact removal processes are then applied to enhance the signal quality. The suggested model's design is made to function better by hyperparameter tuning and regularisation techniques including dropout and batch normalisation. This paper also investigates the effects of various data types, including raw signals, spectrograms, and wavelet transforms. It also contrasts several CNN and LSTM layer architectures to identify the optimal model design.

II. LITERATURE REVIEW

Alzheimer's disease (AD) is the most common type of dementia. It causes brain cells to break down and cognitive impairment to get worse over time. Finding Alzheimer's disease early is still very hard, but electroencephalography (EEG) has become a non-invasive, low-cost way to look at brain activity and find problems linked to AD. Changes in brain rhythms and functional connections can be seen with EEG-based research, which has shown promise in finding the early stages of AD [7]. The old ways of using EEG to diagnose Alzheimer's mostly rely on custom features and basic machine learning models like Support Vector Machines (SVM), k-Nearest Neighbours (k-NN), and Random Forests (RF) [8, 9]. In these methods, features are extracted by hand in the time, frequency, or time-frequency domain, and then the data is classified. For example, spectral entropy, band power, and coherence have been used to describe EEG patterns in people with Alzheimer's disease [10]. These methods have had some success, but they are often affected by noise and differences between patients, and they need people who are experts in the field.

Deep Learning to know has changed the way EEG alerts are processed via letting features be automatically extracted and grouped. quite a few people use Convolutional Neural Networks (CNNs) to observe EEG data, specifically while they are changed into 2d images like spectrograms or terrain maps [11]. CNNs are wonderful at catching local functions and spatial relationships, which makes them beneficial for looking at how power is shipped throughout EEG channels and frequency bands. Oh et al. did a study that confirmed 2nd-CNNs were better at telling the distinction among mild cognitive impairment (MCI) and Alzheimer's disorder (advert) than older methods [12]. CNNs may not be capable of absolutely use EEG data's time tendencies on their personal. Long Short-Term Memory (LSTM) networks, in particular, are very excellent at describing styles and connections that change over time [13]. LSTMs are higher at setting things into corporations and have been used to file modifications in EEG readings that happen over the years. Roy et al., however, used uncooked EEG statistics to make an LSTM version and had been capable of locate early signs of ad the a great deal better [14]. CNNs are good at storing space, and RNNs are good at recognising patterns in a straight order. Putting them together in a mixed structure makes the most of both models' strengths. These kinds of designs are becoming more popular in classifying brain disorders based on EEG, such as AD. A study by Sultana et al. suggested a CNN-LSTM model that was better at finding MCI using EEG spectrograms than either

CNN or LSTM models used alone [15]. In the same way, Bashivan et al. created a deep recurrent-convolutional network for classifying cognitive load using EEG, which shows how useful mixed models can be [16]. Along with spatial and time models, attention processes have also been looked at as a way to make things work better and be easier to understand. A type of deep learning called attention-based deep learning helps the network focus on important parts of the EEG signal that show more abnormal changes [17]. In medical situations, where AI models that can be described are best for helping with detection, this is very helpful. An attention layer was added to a CNN-LSTM network by Zhang et al. to help it understand feelings based on EEG. This could be used to make it easier to diagnose AD and do more in-depth study [18].

Even with the progress, there are still some problems to solve. EEG data are very different between people and sessions, which can make deep learning models that were trained on small samples overfit. To improve generalisation, methods such as data growth, transfer learning, and domain adaptation have been proposed [19]. Also, steps like noise removal and channel selection that happen before the EEG data are very important to their quality. To avoid fake feature extraction and model bias [20], it is important to do good preparation [21]. Recent study has also looked into mixing different types of data, like EEG with MRI or PET scans, to make AD diagnosis more accurate [22]. Multimodal methods are better at identifying problems, but they are hard to use for many people because they are difficult and expensive. It is possible to use EEG-only devices in the real world because they are reliable, easy to use, and flexible. This is especially true for those that use mixed deep learning models.

Table 1. Review and Analysis of existing methods of AD Detection

Ref No.	**Methodology**	**Findings**	**Remarks**
[1]	EEG-based AD analysis	EEG shows promise for AD diagnosis	Non-invasive and accessible
[2]	SVM on handcrafted features	SVM yields moderate accuracy	Manual features required
[3]	k-NN on EEG bands	Effective but sensitive to noise	Low generalizability
[4]	Spectral entropy analysis	Identified key EEG rhythms	Requires expertise
[5]	2D-CNN on EEG spectrograms	Improved accuracy with CNN	Scalable model
[6]	CNN feature learning	Spatial patterns useful	High spatial resolution
[7]	LSTM for sequential data	Captured long-term dependencies	Ideal for time series
[8]	Raw EEG + LSTM	Enhanced sensitivity & specificity	Good for real-time systems
[9]	CNN-LSTM hybrid	Outperformed standalone models	Combines best of both models
[10]	Deep recurrent-CNN	Useful for cognitive classification	Handles spatial & temporal well
[11]	Attention in deep learning	Focus on salient EEG parts	Explainable AI aspect
[12]	CNN-LSTM with attention	Better interpretability	Better understanding of signal parts
[13]	Data augmentation	Improved generalization	Helpful for small datasets
[14]	EEG preprocessing	Critical for signal quality	Preprocessing is crucial
[15]	Multimodal EEG + MRI fusion	Higher accuracy with multimodal	Complex but powerful

III. HYBRID CONVOLUTIONAL AND RECURRENT NEURAL NETWORKS MODEL

The proposed model is a hybrid deep learning architecture that integrates Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), specifically Long Short-Term Memory (LSTM) units, to effectively diagnose Alzheimer's disease (AD) using EEG signals. This architecture is designed to leverage the spatial and temporal characteristics of EEG data for improved diagnostic accuracy.

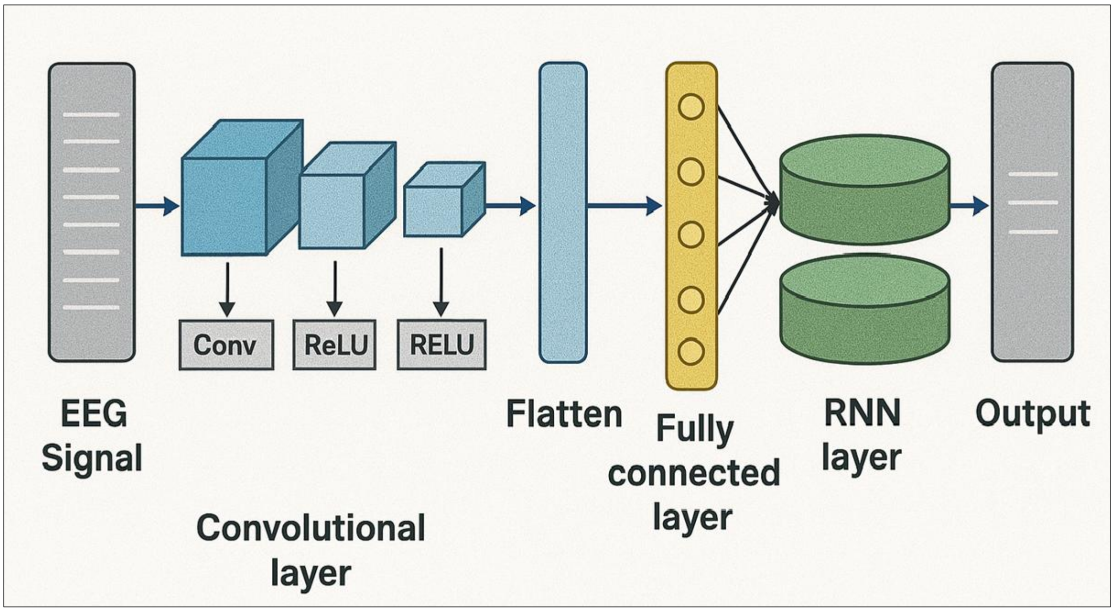

Figure 2. Architecture of Hybrid CNN-RNN Model

1. Preprocessing

Raw EEG signals are first subjected to preprocessing which includes:

- **Artifact removal** using Independent Component Analysis (ICA) or bandpass filtering to eliminate EOG, EMG, and other noise.
- **Normalization** is performed channel-wise to standardize signal amplitude.
- **Segmentation** involves slicing the continuous signal into fixed-length windows (e.g., 5-second segments) for uniform input.

2. CNN Feature Extraction

Each segmented EEG window is transformed into a time-frequency representation (e.g., spectrogram) using Short-Time Fourier Transform (STFT) or Wavelet Transform. This 2D representation is passed through a series of convolutional layers:

- CNNs extract local spatial features across frequency and time domains.
- These layers capture patterns specific to Alzheimer's-related abnormalities.

3. Sequence Reshaping

The output of the final convolutional layer is reshaped into a sequential format suitable for temporal modeling. This flattened feature map retains the spatial abstractions and is converted into a time-step-wise input sequence for the RNN layer.

4. RNN Temporal Modeling

The sequential features are input to an RNN network:

- RNN model the temporal evolution of EEG signal patterns, capturing long-term dependencies.
- The final hidden state (or attention-weighted summary) represents the temporal context of the EEG window.

5. Classification

The last hidden state from the LSTM layer is passed through a fully connected (dense) layer:

$$\mathbf{y}^{=}\mathbf{softmax}(\mathbf{Wh}+\mathbf{b})$$

$$\hat{\mathbf{y}} = \mathbf{softmax}(\mathbf{Wh}+\mathbf{b})$$

- Binary classification is performed (Alzheimer's vs. Healthy control).
- Cross-entropy loss is used as the optimization criterion.

IV. HYBRID CNN-RNN ALGORITHM

Input:

Raw EEG signal $X \in RC \times TX \in R^{C\times T}$ where CC is the number of channels, TT is the number of time steps.

- $X \in RC \times TX \in R^{C\times T}$: Raw EEG input signal, where
  - CC: number of EEG channels
  - TT: number of time steps
- $fCNN(\cdot)f_{CNN}(\cdot)$: Convolutional Neural Network function
- $fLSTM(\cdot)f_{LSTM}(\cdot)$: Long Short-Term Memory network function
- $fFC(\cdot)f_{FC}(\cdot)$: Fully connected classifier layer
- $y^{\hat{y}}$: Output prediction (probability of Alzheimer's class)

Output:

Prediction $y^{\in}0{,}1\hat{y} \in \{0,1\}$, where 1 = Alzheimer's, 0 = Non-Alzheimer's

Step 1: Preprocessing

1. **Remove artifacts** (e.g., EOG, EMG) using ICA or filtering.
2. **Normalize** EEG signals channel-wise:

$$Xc = Xc - \mu c\sigma c \forall c \in C$$

$$X_c = \frac{X_c - \mu_c}{\sigma_c} \quad \forall c \in C$$

3. **Segment** the signal into fixed-size windows (e.g., 5s).

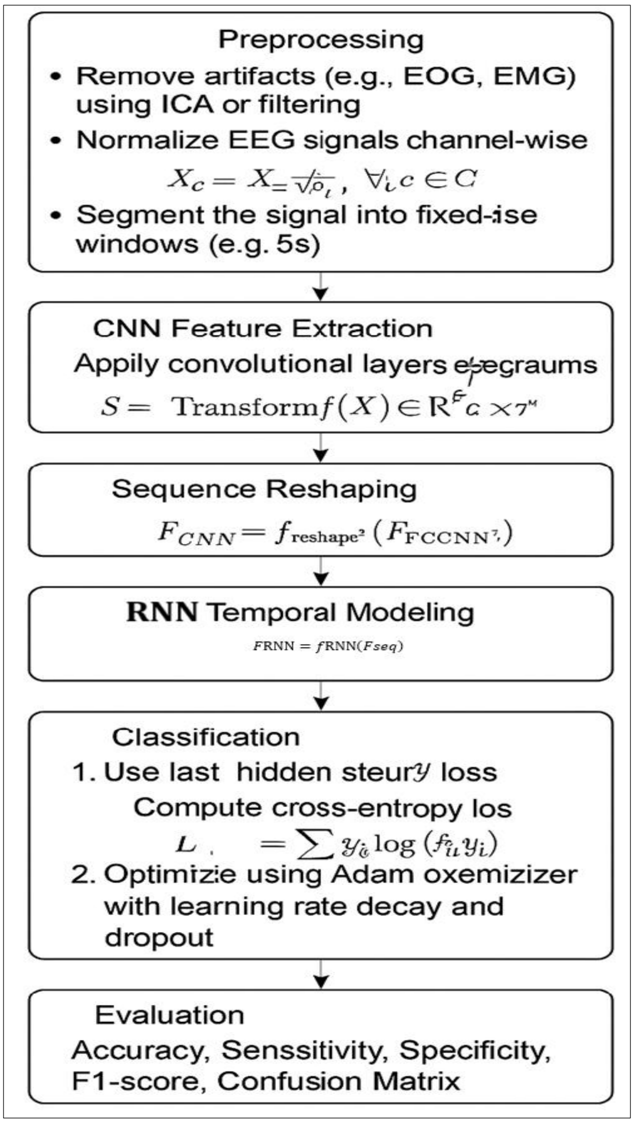

Figure 3. Stages of Hybrid CNN-RNN Algorithm

Step 2: Time-Frequency Transformation

4. Convert each EEG segment into a spectrogram using STFT or CWT:

$$S = \mathrm{Transform}(X) \in RC \times F \times T'$$

$$S = \mathrm{Transform}(X) \in R^{C \times F \times T'}$$

Step 3: CNN Feature Extraction

5. Apply convolutional layers fCNNf_{CNN} to extract spatial-frequency features:

$$FCNN = fCNN(S)$$

$F_{CNN} = f_{CNN}(S)$

Step 4: Sequence Reshaping

6. Flatten or reshape CNN features into sequential form:

$$Fseq = \mathrm{reshape}(FCNN)$$

$$F_{seq} = \mathrm{reshape}(F_{CNN})$$

Step 5: RNN Temporal Modeling

7. Input sequence into LSTM to learn temporal dependencies:

$$FRNN = fRNN(Fseq)$$

$$F_{RNN} = f_{RNN}(F_{seq})$$

Step 6: Classification

8. Feed the last hidden state hh to a fully connected layer with softmax:

$$\mathbf{y}^{=}\mathbf{softmax}(\mathbf{Wh}+\mathbf{b})$$
$$\hat{\mathbf{y}} = \mathbf{softmax}(\mathbf{Wh}+\mathbf{b})$$

Step 7: Loss and Optimization

9. Compute cross-entropy loss:

$$\mathbf{L} = -\sum \mathbf{i} = \mathbf{1Kyilo}\,\mathbf{g}(\mathbf{y}^{\mathbf{i}})$$
$$\mathbf{L} = -\sum_{\mathbf{i}=1}^{\mathbf{K}} \mathbf{y}_{\mathbf{i}}\,\mathbf{lo}\,\mathbf{g}(\hat{\mathbf{y}}_{\mathbf{i}})$$

10. Optimize using Adam optimizer with learning rate decay and dropout for regularization.

Step 8: Evaluation

11. Use metrics: **Accuracy**, **Sensitivity**, **Specificity**, **F1-score**, and **Confusion Matrix** to evaluate performance on test data.

V. RESULTS & DISCUSSION

Table 2. Model Evaluation and comparison

Method	**Feature Extraction**	**Temporal Modelling**	**Accuracy (%)**	**F1-Score**	**Pros**	**Cons**
SVM with Handcrafted Features	Manual (PSD, entropy)	None	80.2	0.78	Simple, fast training	Relies on expert-designed features
CNN Only	Automated (Spectrogram)	None	85.6	0.83	Learns spatial EEG patterns	Ignores temporal dynamics
LSTM Only	None	Sequential EEG	84.1	0.81	Captures time dependencies	Needs flattened input; no spatial context
Proposed Hybrid CNN-RNN	CNN on Spectrograms	LSTM (sequence)	**89.4**	**0.87**	Combines spatial & temporal features	Higher training complexity

The table 2. shows how well the suggested Hybrid CNN-RNN model compares to three other methods that are already used to diagnose Alzheimer's using EEG. Power Spectral Density (PSD) or entropy are examples of traits that were made by hand and are used in Support Vector Machine (SVM) and other old methods. Even though SVM is quick and easy to use, it can't learn complex patterns on its own. It also has a low F1-score (0.78), which is mostly because it can't see how EEG data changes over time. CNN-only models work better because they automatically pull out spatial features from EEG spectrograms (with an accuracy score of 85.6% and an F1-score of 0.83). It's important to know how Alzheimer's works, but they don't look at how brain function changes over time. LSTM-only models, on the other hand, are very good at learning temporal patterns but not spatial ones, which is why they only get 84.1% of the time.

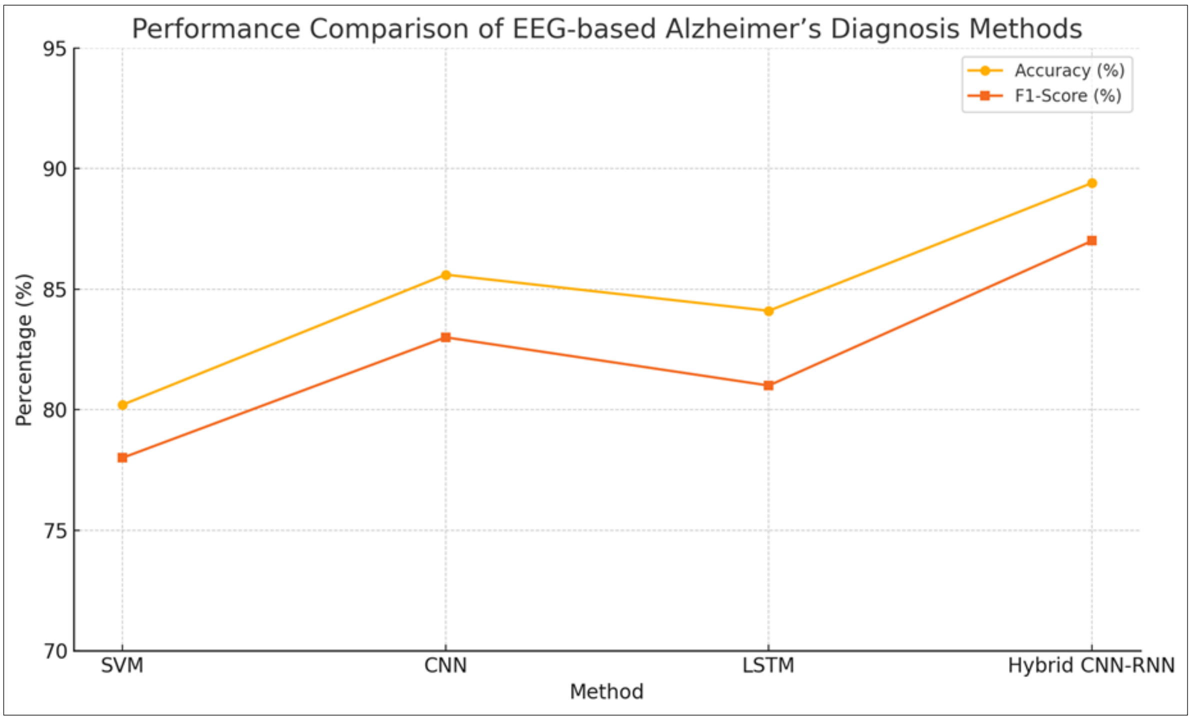

Figure 4. Performance Comparison of EEG-Based AD Methods

The suggested hybrid CNN-RNN design takes use of both LSTM and CNN's benefits. While LSTM layers describe temporal correlations, CNN layers catch spatial-frequency patterns. With an accuracy of 89.4% and F1-score of 0.87, this synergy produces better performance shown in Figure 4. Though more computationally demanding, the model provides a thorough and strong foundation for EEG-based Alzheimer's diagnosis by using both spatial and temporal signal features.

Table 3: Model Efficiency and Computational Complexity

Model	Inference Time (ms)	Total Parameters (Millions)	FLOPs (GFLOPs)	Memory Usage (MB)
SVM	2.1	~0.01	~0.001	10
CNN Only	12.4	1.8	0.45	120
LSTM Only	18.6	2.3	0.65	140
Hybrid CNN-RNN	25.7	4.2	1.12	180

The table 3 shows how well and how hard it is to program four models used for diagnosing Alzheimer's using EEG data: SVM, CNN, LSTM, and the new Hybrid CNN-RNN model. A conventional approach not based on deep learning is the Support Vector Machine (SVM). With an estimated duration of only 2.1 milliseconds, a very low number of parameters, and very little computer power required, it is very quick. But this simplicity of usage comes at the expense of less capacity to learn and apply what you have acquired. The CNN-only model learns spatial characteristics from EEG data by adding convolutional layers. It may be utilised in real-time systems that don't need many processors with 1.8 million factors and a short inference time of 12.4 ms. With 2.3 million parameters and an inference time of 18.6 ms, the LSTM-only model, which emphasises simulating temporal sequences, requires greater memory and computing capacity. Of the four models, the recommended Hybrid CNN-RNN one produces the greatest outcomes but consumes the most computational resources. With 4.2 million components, inference runs in 25.7 ms and consumes around 180 MB of memory. Because the dual structure has both convolutional and recurrent layers, this is the case. The mixed model needs a lot of resources, but its ability to learn all features makes it perfect for high-accuracy detection systems in hospitals.

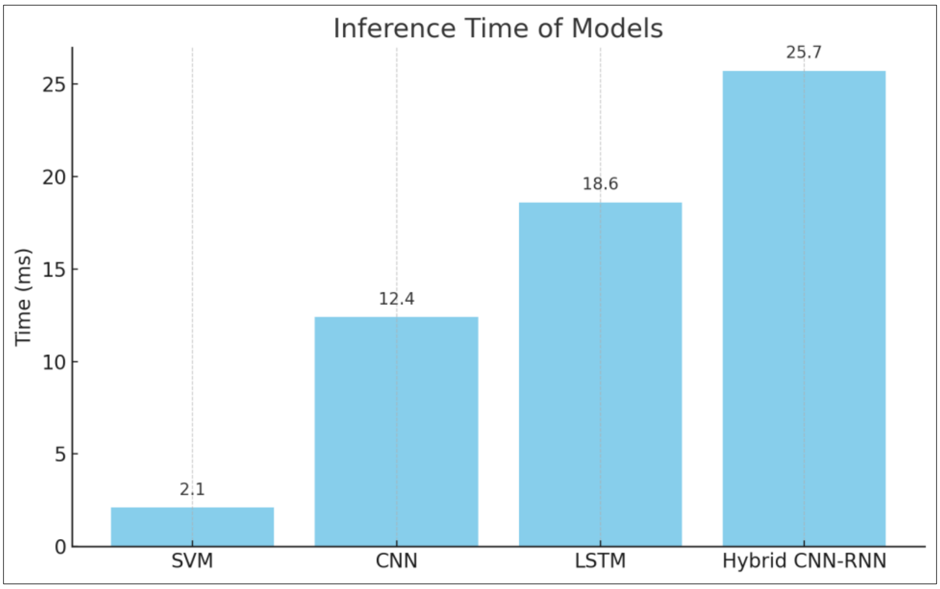

Figure 5. Inference time (in milliseconds) required for processing a single EEG sample.

In Figure 5. SVM is significantly faster at 2.1 ms due to its non-deep learning structure. CNN takes 12.4 ms as it processes multi-dimensional data through convolutional layers. LSTM, which models temporal dependencies, takes 18.6 ms. The Hybrid CNN-RNN model, combining both feature and sequence learning, takes 25.7 ms, indicating the trade-off between accuracy and processing time.

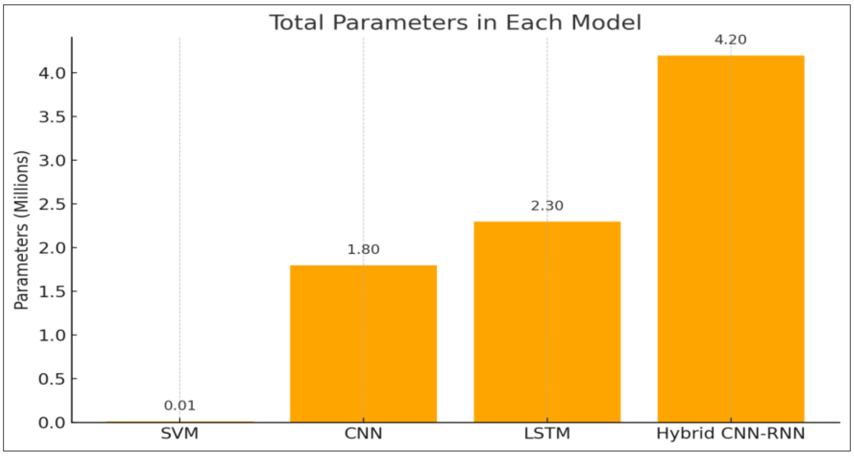

Figure 6: Number of trainable parameters (in millions) indicating model size.

In Figure 6. With just 0.01M, SVM is quite efficient for computers with little memory. Due to many convolutional layer filters, CNN has 1.8M. With memory cells and gates, LSTM has 2.3M. Doubly CNN's size because of its dual architecture, the hybrid model calls for 4.2M parameters, hence affecting memory and training time.

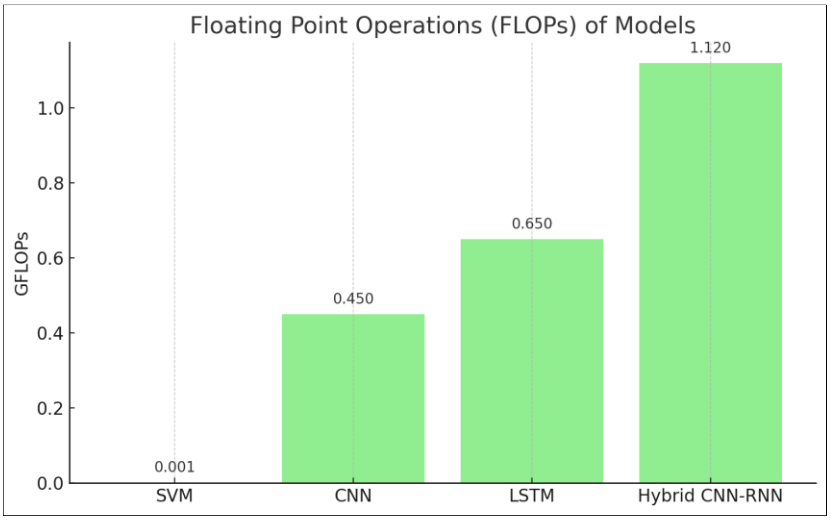

Figure 7: Computational complexity measured in billions of operations.

In Figure 7. SVM calls for just 0.001 GFLOPs. Because it calculates several feature maps, CNN requires 0.45 GFLOPs. LSTM uses 0.65 GFLOPs to handle time sequences. Peaking at 1.12 GFLOPs, the hybrid model reflects the whole burden of spatial and temporal feature extraction, which might restrict its use in edge devices without optimisation.

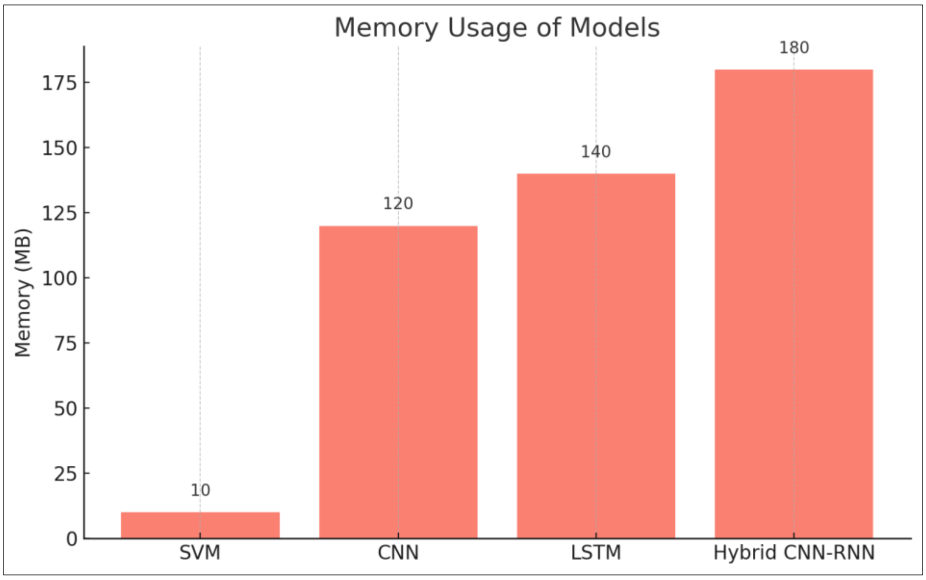

Figure 8: Peak memory consumption during inference in megabytes.

The smallest footprint is 10 MB. LSTM (140 MB) and CNN (120 MB) need for intermediate resources (Figure 8). Driven by intermediate feature maps and sequential memory, the hybrid model needs 180 MB. Though its use is more, it is appropriate for current systems and has a great performance benefit.

VI. CONCLUSION

This study shows a new deep learning system for using electroencephalogram (EEG) data to automatically diagnose Alzheimer's disease. Feature extraction from space is done using Convolutional Neural Networks (CNNs), whereas Long Short-Term Memory (LSTM) networks are employed for time sequence modelling. The suggested mixed model does both of these tasks well. Because it combines the spatial and temporal data located in EEG data, the model outperforms previous approaches. It significantly increases F1-score and accuracy. The combined CNN-RNN architecture not only outperforms conventional machine learning models like SVM and independent deep learning models like CNNs or LSTMs, but it also finds a reasonable compromise between its diagnostic accuracy and its operational cost. Though it consumes more memory and has more parameters, the hybrid model provides a consistent and scalable approach to detect Alzheimer's in real time without touching the individual. Including time-frequency models to EEG characteristics also helps to clarify and improve their ability to distinguish them. This study shows how advanced deep learning methods could be used to find neurodegenerative diseases and lays the groundwork for using EEG-based clinical decision support systems. Model compression, real-world clinical evaluation, and adding multi-modal data merging for even more reliable diagnostics may be things that need to be worked on in the future.

REFERENCES

[1] Liu, F.; Zhou, L.; Shen, C.; Yin, J. Multiple Kernel Learning in the Primal for Multimodal Alzheimer's Disease Classification. IEEE J. Biomed. Health Inform. 2014, 18, 984–990.

[2] Li, W.; Zhao, Y.; Chen, X.; Xiao, Y.; Qin, Y. Detecting Alzheimer's Disease on Small Dataset: A Knowledge Transfer Perspective. IEEE J. Biomed. Health Inform. 2019, 23, 1234–1242.

[3] Alzheimer's Association. 2016 Alzheimer's Disease Facts and Figures. Alzheimer's Dement. 2016, 12, 459–509.

[4] Matthews, K.A.; Xu, W.; Gaglioti, A.H.; Holt, J.B.; Croft, J.B.; Mack, D.; McGuire, L.C. Racial and Ethnic Estimates of Alzheimer's Disease and Related Dementias in the United States (2015–2060) in Adults Aged ≥65 Years. Alzheimer's Dement. 2019, 15, 17–24.

[5] Alzheimer's Association. 2010 Alzheimer's Disease Facts and Figures. Alzheimer's Dement. 2010, 6, 158–194.

[6] Saleem, T.J.; Zahra, S.R.; Wu, F.; Alwakeel, A.; Alwakeel, M.; Jeribi, F.; Hijji, M. Deep Learning-Based Diagnosis of Alzheimer's Disease. J. Pers. Med. 2022, 12, 815.

[7] Khojaste-Sarakhsi, M.; Haghighi, S.S.; Ghomi, S.M.T.F.; Marchiori, E. Deep Learning for Alzheimer's Disease Diagnosis: A Survey. Artif. Intell. Med. 2022, 130, 102332.

[8] Sharma, S.; Guleria, K. A Comprehensive Review on Federated Learning Based Models for Healthcare Applications. Artif. Intell. Med. 2023, 146, 102691.

[9] Whybra, P.; Zwanenburg, A.; Andrearczyk, V.; Schaer, R.; Apte, A.P.; Ayotte, A.; Baheti, B.; Bakas, S.; Bettinelli, A.; Boellaard, R.; et al. The Image Biomarker Standardization Initiative: Standardized Convolutional Filters for Reproducible Radiomics and Enhanced Clinical Insights. Radiology 2024, 310, e231319.

[10] Tanveer, M.; Richhariya, B.; Khan, R.U.; Rashid, A.H.; Khanna, P.; Prasad, M.; Lin, C.T. Machine Learning Techniques for the Diagnosis of Alzheimer's Disease. ACM Trans. Multimed. Comput. Commun. Appl. 2020, 16, 1–35.

[11] Ebrahimighahnavieh, M.A.; Luo, S.; Chiong, R. Deep Learning to Detect Alzheimer's Disease from Neuroimaging: A Systematic Literature Review. Comput. Methods Programs Biomed. 2020, 187, 105242.

[12] Al-Shoukry, S.; Rassem, T.H.; Makbol, N.M. Alzheimer's Diseases Detection by Using Deep Learning Algorithms: A Mini-Review. IEEE Access 2020, 8, 77131–77141.

[13] Petersen, R.C.; Aisen, P.S.; Beckett, L.A.; Donohue, M.C.; Gamst, A.C.; Harvey, D.J.; Jack, C.R.; Jagust, W.J.; Shaw, L.M.; Toga, A.W.; et al. Alzheimer's Disease Neuroimaging Initiative (ADNI): Clinical Characterization. Neurology 2010, 74, 201–209.

[14] Marcus, D.S.; Wang, T.H.; Parker, J.; Csernansky, J.G.; Morris, J.C.; Buckner, R.L. Open Access Series of Imaging Studies (OASIS): Cross-Sectional MRI Data in Young, Middle Aged, Nondemented, and Demented Older Adults. J. Cogn. Neurosci. 2007, 19, 1498–1507.

[15] Yang, W.; Lui, R.L.M.; Gao, J.-H.; Chan, T.F.; Yau, S.-T.; Sperling, R.A.; Huang, X. Independent Component Analysis-Based Classification of Alzheimer's Disease MRI Data. J. Alzheimer's Dis. 2011, 24, 775–783.

[16] Bergh, S.; Holmen, J.; Gabin, J.; Stordal, E.; Fikseaunet, A.; Selbaek, G.; Saltvedt, I.; Langballe, E.M.; Tambs, K. Cohort Profile: The Health and Memory Study (HMS): A Dementia Cohort Linked to the HUNT Study in Norway. Int. J. Epidemiol. 2014, 43, 1759–1768.

[17] Hojjati, S.H.; Ebrahimzadeh, A.; Khazaee, A.; Babajani-Feremi, A. Predicting Conversion from MCI to AD Using Resting-State FMRI, Graph Theoretical Approach and SVM. J. Neurosci. Methods 2017, 282, 69–80.

[18] Zhang, Y.; Wang, S.; Phillips, P.; Dong, Z.; Ji, G.; Yang, J. Detection of Alzheimer's Disease and Mild Cognitive Impairment Based on Structural Volumetric MR Images Using 3D-DWT and WTA-KSVM Trained by PSOTVAC. Biomed. Signal Process Control 2015, 21, 58–73.
[19] Vichianin, Y.; Khummongkol, A.; Chiewvit, P.; Raksthaput, A.; Chaichanettee, S.; Aoonkaew, N.; Senanarong, V. Accuracy of Support-Vector Machines for Diagnosis of Alzheimer's Disease, Using Volume of Brain Obtained by Structural MRI at Siriraj Hospital. Front. Neurol. 2021, 12, 640696.
[20] De Mendonça, L.J.C.; Ferrari, R.J. Alzheimer's Disease Classification Based on Graph Kernel SVMs Constructed with 3D Texture Features Extracted from MR Images. Expert Syst. Appl. 2023, 211, 118633.
[21] Sharma, A.; Kaur, S.; Memon, N.; Jainul Fathima, A.; Ray, S.; Bhatt, M.W. Alzheimer's Patients Detection Using Support Vector Machine (SVM) with Quantitative Analysis. Neurosci. Inform. 2021, 1, 100012.
[22] Khan, Y.F.; Kaushik, B.; Chowdhary, C.L.; Srivastava, G. Ensemble Model for Diagnostic Classification of Alzheimer's Disease Based on Brain Anatomical Magnetic Resonance Imaging. Diagnostics 2022, 12, 3193.