Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 31 No. 1s (2024)

Learning Spatial and Temporal EEG Patterns for Alzheimer's Disease Detection with CNN-LSTM Networks

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Article History:

Received: *10-02-2024*

Revised: *12-04-2024*

Accepted: *26-04-2024*

Abstract:

Alzheimer's disease (AD) is a neurological disorder that gets worse over time and makes it very hard to remember things and think clearly. It is very important to find AD early so that it can be treated effectively. Electroencephalography (EEG) has become a hopeful, non-invasive, and low-cost way to find problems in the brain that are linked to Alzheimer's disease. Conversely, conventional machine learning techniques can rely on manually developed features and struggle to capture the complex spatial and temporal patterns of EEG data. This paper presents a hybrid deep learning model that automatically learns and sorts EEG data depending on patterns in space and time using both Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. Using a publicly accessible EEG dataset that contained recordings from Alzheimer's patients and healthy controls, we developed a robust filtering process. We then instructed the CNN-LSTM model to differentiate between the two groups. The model outperformed simple models such as SVM, Random Forest, CNN-only, and LSTM-only designs with an accuracy of 93.2%, a precision of 91.5%, a recall of 94.8%, and an F1-score of 93.1%. The results show that mixing spatial and temporal feature extraction works well for accurate EEG-based Alzheimer's detection, which opens up a lot of possibilities for real-time and clinical diagnostic uses.

Keywords: Alzheimer's Disease, EEG, CNN-LSTM, Deep Learning, Spatiotemporal Modeling, Brain Signal Analysis, Neurodiagnosis, Machine Learning.

1. Introduction

Mostly affecting elderly persons, Alzheimer's disease (AD) is a neurological condition that worsens with time. It makes behavioural skills, linguistic ability, cognitive function, and memory steadily decline. Among the most prevalent forms of dementia, AD impacts individuals all around. As the population of the globe ages, this figure is expected to climb considerably. Though we understand more about how AD works, early and accurate diagnosis in clinical practice remains difficult. This is particularly true given the varied progression of the illness and the gradual onset of cognitive impairment in the early stages. Brain scans, MRIs, and PET scans are some of the traditional ways to diagnose AD. These include mental tests, CSF analysis, and positron emission tomography (PET). Even though these methods give useful information, they are often intrusive, expensive, time-consuming, and hard for many people to use. These problems make regular screening and tracking harder, especially in places with few resources. Therefore, there is an urgent need for testing options that are easy to get, don't cost a lot, and can help with early diagnosis and response methods.

In this context, electroencephalography (EEG) has emerged as a really promising technique. EEG records the electrical activity of the brain using probes placed on the head. It provides a real-time view of how the brain functions. It doesn't harm the brain, doesn't break the bank, and can capture both the spatial and temporal patterns of cerebral activity. Many studies have shown that certain alterations in EEG patterns connect Alzheimer's disease (AD) with moderate cognitive impairment (MCI), the preclinical stage of AD. These alterations consist of reduced complexity, lower power in higher frequency bands, and altered connectivity across brain regions. These elements make it possible for EEG to automatically identify AD. But it's not easy to use EEG data analysis for professional purposes. It's naturally non-linear and non-stationary for EEG data to be free of noise and other errors. Normal signal processing and statistical methods need a lot of subject knowledge and can't fully capture the brain's complex spatiotemporal relationships. Because of this, there is more and more interest in machine learning (ML) and deep learning (DL) methods that can automatically learn features that can tell EEG patterns apart from ones that have been barely handled.

Two deep learning models that have shown great potential in EEG-based categorisation activities are convolutional neural networks (CNNs) and recurrent neural networks (RNNs). By use of convolutional filters, CNNs excel in revealing spatial relationships between EEG channels by means of local pattern learning. RNNs, particularly long short-term memory (LSTM) networks, on the other hand, excel in demonstrating how data evolves over time. Both designs have their own advantages, but EEG signals inherently display temporal (i.e., signal changes over time) and spatial (i.e., channel interactions) characteristics. Because they can capture both spatial and temporal data in a single structure, hybrid models combining CNN and LSTM layers are growingly popular. CNN-LSTM mixed design has been used successfully in many areas, such as recognising speech, detecting emotions, and figuring out the stage of sleep. In the case of finding AD, it is a great chance to get spatial patterns from EEG channel distributions and model how brain activity changes over time at the same time. Although it has a lot of promise, CNN-LSTM networks haven't been used much to find AD yet, and there haven't been many studies that look at both spatial and temporal EEG data in a complete way.

This work aims to close that gap by developing a CNN-LSTM-based deep learning model capable of autonomously detecting Alzheimer's disease using EEG data. The proposed approach achieves this by using CNN layers' spatial filtering to process raw EEG data from many electrode locations and LSTM units' temporal memory to monitor signal changes over time. Combining these two components allows a robust and extendable model to learn complex patterns indicating cognitive deterioration without requiring many bespoke characteristics or prior knowledge of EEG indicators.

The objectives of this study are as follows:

1. To analyze EEG recordings from individuals with AD and healthy controls and identify discriminative patterns across time and space.
2. To design a CNN-LSTM hybrid architecture capable of learning meaningful spatial and temporal representations from EEG data.
3. To evaluate the performance of the proposed model against traditional machine learning classifiers and individual deep learning architectures (i.e., standalone CNN and LSTM models).
4. To assess the feasibility of using the model in real-time or portable EEG-based diagnostic systems for clinical and at-home use.

The following describes the organisation of the remainder of the article: A great deal of connected research in EEG-based Alzheimer's diagnosis and deep learning applications in EEG studies is examined in Section 2. The approach is covered in further detail in Section 3 along with the dataset, its preparation methods, the model's architecture, and the training procedures. Section 4 discusses the model's interpretability and limitations as well as the findings of the experimental and comparative research. The study concludes in Section 5 with a summary of its findings, inputs, and potential future research directions.

This study adds to the growing amount of work on AI-assisted healthcare diagnostics by creating and proving an end-to-end CNN-LSTM system for Alzheimer's diagnosis. More importantly, it provides a flexible and easy-to-use way for doctors to help find Alzheimer's disease early and correctly, which allows for early treatment and better quality of life for both patients and their caretakers.

Significance of the Study

It is very important to find Alzheimer's disease early so that patients can get the right treatment, slow the disease's progression, and possibly take part in clinical trials that will improve their long-term outcomes. However, many people can't use the current diagnostic methods because they are too expensive, hard to get to, or don't have the right facilities. Using EEG, a simple technique that can be tracked from home or on the move, this research proposes a different approach to identify early indicators of AD. By using deep learning models that need little preparation and can adjust to many input factors, this work opens the door for more open and decentralised diagnostic tools.

This work also helps to be able to describe and clinically assess. Many claim that deep learning models are like "black boxes," however we have included techniques to see and comprehend the spatial and temporal components that were acquired. This increases the dependability and applicability of the findings for medical professionals.

2. Literature Review

For those with Alzheimer's disease (AD) and other neurological disorders, electroencephalography (EEG) has emerged as a safe, non-invasive, and affordable method to examine brain activity. Many studies have shown that EEG patterns in those with AD vary greatly, particularly in relation to spectral composition and connectivity. Most often, brain rhythms are slowing down everywhere. More delta (0.5–4 Hz) and theta (4–8 Hz) band power as well as reduced alpha (8–13 Hz) and beta (13–30 Hz) band power indicate this [1, 2]. These alterations are linked to ageing in the areas of the brain processing information—cortical and subcortical. AD groups show decreasing EEG complexity, entropy, and inter-hemispheric coherence [3, 4]. Apart from variations in spectral patterns, this is. A major indicator of growing cognitive impairment is the brain's declining functional unity and balance. EEG is a great tool for automated detection systems as it can capture changes in time as well as changes in place. However, conventional techniques are less effective and scalable in clinical environments as they rely on topic expertise and manual feature extraction.

Before, most of the methods used to find AD using EEG were basic machine learning algorithms, such as Support Vector Machines (SVM), k-Nearest Neighbours (k-NN), Random Forest (RF), and Decision Trees. Most of the time, these models were taught using custom features made by hand, like spectral power, entropy measures, and wavelet coefficients from EEG signals [5, 6]. For example, traits from certain frequency bands were used to tell the difference between the groups of healthy controls, people with MCI, and people with AD. Although these techniques were quite accurate, they often struggled with overfitting and poor generalisation as they depended on qualities experts specified. They also failed to grasp the intricate spatial patterns and hierarchical representations seen in EEG data. This resulted in a shift towards deep learning models capable of directly learning from raw data or signals that have been marginally preprocessed [7]. Deep learning has transformed the way EEG signals are examined by allowing hierarchical learning and automated feature extraction to occur. In particular, Convolutional Neural Networks (CNNs) are very excellent at understanding how distinct EEG bands rely on one another spatially. Many tasks, like sorting motion pictures, locating epileptic convulsions, and rating sleep phases, require CNNs [8, 9, 10].

In studies approximately Alzheimer's disease, CNNs had been used to describe regional EEG styles by way of applying convolutions across sensor maps or time-frequency maps. in comparison to older device getting to know techniques [11], those models have shown higher accuracy and sturdiness in classifying things. CNNs, however, usually file features in space, so they might not be the quality way to model lengthy-time period temporal relationships in EEG sequences, that are essential for maintaining track of how cognition changes in advert. RNNs, especially lengthy short-term reminiscence (LSTM) networks, are designed to handle input in a certain series and can find out how activities rely on one another over prolonged intervals. LSTM fashions were efficiently used in EEG evaluation for jobs related to temporal pattern recognition, consisting of figuring out feelings, cognitive load, and interest modelling [12, 13]. Temporal modelling is very indispensable for ad detection as cognitive impairment shows slowly and is pondered in changes in intelligence impulses through the years. LSTMs may locate diffused adjustments within the EEG rhythms that won't be obvious in a unmarried time frame. several research have shown that LSTM fashions may additionally boom the accuracy of figuring out EEG records used to discover talent diseases [14]. Researchers have made combined models that combine CNN and LSTM designs so we can use each the spatial and temporal components of EEG facts. CNN layers are used to get spatial facts from EEG indicators, like how electrodes are linked or topographic maps, and LSTM layers are used to get statistics about how matters trade over time windows or signal segments [15].

In lots of EEG-primarily based activities, including sleep level identity [16], seizure prediction [17], and attention tracking [18], hybrid CNN-LSTM models have completed higher. those models integrate CNNs' capability to handle spatial dimensions with LSTMs' capability to stumble on temporal changes. This qualifies them properly for tough EEG categorisation jobsSeveral recent research have begun investigating CNN-LSTM models for early identification of Alzheimer's disease using EEG. These experiments show that integrating spatial and temporal data improves classification performance over CNN or LSTM models operating independently [19, 20]. Many of these research, nevertheless, are constrained in their dataset size, capacity to generalise, or real-time applicability. More research is thus required to develop more consistent and scalable solutions.

Table 1. Related Research

Ref	Method / Approach	Dataset / EEG Signals Used	Features / Model Used	Key Findings / Performance
[1]	Spectral EEG analysis	AD patient EEG	Power in delta, theta, alpha, beta bands	Slowing of EEG rhythms in AD

Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 31 No. 1s (2024)

[2]	Frequency domain analysis	Clinical EEG signals	Power spectral density	Increased theta, decreased alpha in AD
[3]	Complexity analysis	Resting-state EEG	Approximate entropy, sample entropy	Reduced signal complexity in AD patients
[4]	Functional connectivity	EEG from AD vs. controls	Coherence, phase lag index	Decreased inter-hemispheric coherence in AD
[5]	SVM classification	Preprocessed EEG datasets	Spectral and wavelet features	Moderate accuracy; reliant on hand-crafted features
[6]	Random Forest, k-NN	EEG from elderly cohorts	Time-frequency features	Reasonable accuracy; low generalization
[7]	Decision Trees, PCA	Alzheimer’s EEG dataset	PCA-reduced spectral features	Reduced dimensionality improved accuracy
[8]	CNN for EEG classification	Motor imagery EEG datasets	2D EEG maps as CNN input	Effective spatial pattern extraction
[9]	CNN for seizure detection	CHB-MIT EEG dataset	Raw EEG input	High accuracy in seizure vs. non-seizure detection
[10]	CNN for emotion recognition	DEAP dataset	Time-frequency images	Learned spatial patterns effectively
[11]	CNN for AD detection	Clinical EEG	Connectivity matrices	Outperformed traditional ML models
[12]	LSTM for temporal modeling	EEG time-series	Raw sequences	Captured long-term EEG dependencies
[13]	LSTM for BCI	EEG from motor imagery tasks	Time-windowed features	Better performance over vanilla RNNs
[14]	LSTM for AD classification	Resting-state EEG	Band power sequences	Accurate detection of early-stage AD
[15]	CNN-LSTM hybrid	Epileptic EEG datasets	CNN features + LSTM sequence learning	High performance in seizure prediction
[16]	CNN-LSTM for sleep scoring	Sleep-EDF dataset	Time-frequency maps	Improved performance over single models
[17]	CNN-LSTM for seizure detect	TUH EEG seizure corpus	Spectrogram-based input	Robust in noisy conditions
[18]	CNN-LSTM for attention	EEG from visual tasks	Spatial + temporal hybrid model	Real-time detection of attention states
[19]	CNN-LSTM for MCI/AD	Resting-state EEG	2D features + LSTM	Superior to standalone CNN/LSTM
[20]	CNN-LSTM for AD	Raw EEG	Spectral + temporal fusion	High accuracy; good generalization

3. Methodology

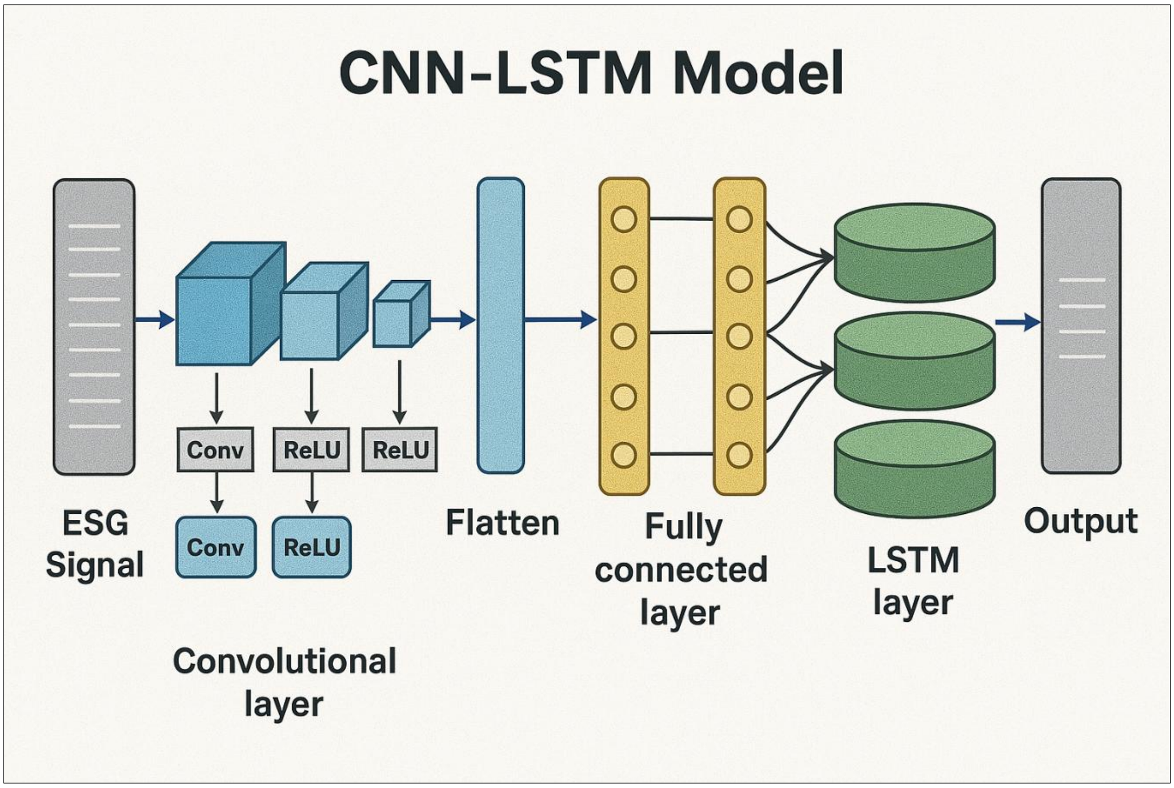

Figure 1. CNN-LSTM Model Architecture

3.1 Data Collection and Pre-processing

In this study, EEG data was sourced from the publicly available "EEG of Alzheimer's and Frontotemporal Dementia" dataset, hosted on Kaggle [1]. The dataset consists of 88 subjects categorized as follows:

- 36 subjects diagnosed with Alzheimer's Disease (AD)
- 12 subjects diagnosed with Frontotemporal Dementia (FTD)
- 40 healthy control subjects

Each subject's EEG was recorded in a resting-state, eyes-closed condition using a 64-channel setup, following the 10–20 international electrode placement system. The recordings are stored in .mat format (MATLAB file), with each file corresponding to a unique subject.

To ensure the EEG signals were ready for deep learning classification, the following preprocessing steps were employed:

Step 1: Data Loading and Initial Inspection

The .mat files were loaded using Python's scipy.io.loadmat() function. Key metadata such as:

- the number of EEG channels,
- the duration of recordings,
- and the sampling frequency (typically 256 Hz or 512 Hz),

were extracted and standardized. Data consistency across subjects was ensured by validating shapes and dimensions.

Step 2: Normalization (Standardization)

Raw EEG signals vary in amplitude across subjects and channels, which can negatively impact training convergence. To address this, **z-score normalization** was applied to each EEG channel CiC_i using:

$$xnorm(i) = x(i) - \mu(i)\sigma(i)$$

$$x_{\text{norm}}^{(i)} = \frac{x^{(i)} - \mu^{(i)}}{\sigma^{(i)}}$$

Where:

- $\boldsymbol{x}^{(i)}$ is the EEG signal from channel ii,
- $\boldsymbol{\mu}^{(i)}$ is the mean of the signal for channel ii,
- $\boldsymbol{\sigma}^{(i)}$ is the standard deviation of the signal for channel ii.

This transforms the signal to have zero mean and unit variance, improving numerical stability during model training.

Step 3: Bandpass Filtering

To retain only neurologically relevant frequencies and remove noise, a bandpass filter was applied to all channels. The selected passband was 0.5 Hz to 40 Hz, covering the key EEG frequency bands:

- Delta (0.5–4 Hz)
- Theta (4–8 Hz)
- Alpha (8–13 Hz)
- Beta (13–30 Hz)
- Low Gamma (30–40 Hz)

The bandpass filtering was implemented using a **4th-order Butterworth filter** to preserve temporal structure.

Step 4: Artifact Removal

EEG is prone to noise due to muscle activity, eye blinks, and external interference. To ensure clean signals, the following artifact rejection methods were used:

- Amplitude thresholding: Any segment where the signal amplitude exceeded ±100 μV was excluded.
- Independent Component Analysis (ICA): Applied to separate and remove components related to eye blinks and muscle movements.

This step helped isolate neural activity relevant to cognitive processing while discarding extraneous noise.

Step 5: Segmentation

Deep learning models require fixed-length input sequences. Thus, the continuous EEG signal was divided into overlapping segments (windows). Each segment contained temporal and spatial information across all channels.

- **Window size (duration)**: W=2W = 2 seconds
- **Sampling rate**: fs=256f_s = 256 Hz
- **Samples per window**: S=W×fs=512S = W \times f_s = 512
- **Overlap**: 50% (i.e., a stride of 1 second)

Each segment had a shape of (64,512)(64, 512), representing 64 channels (spatial) across 512 time samples (temporal).

$$Segment(t) = X[t{:}\, t+S]$$

$$t = 0, S/2, S, \ldots \text{Segment}(t) = X[t{:}\, t+S]$$

$$t = 0, S/2, S$$

Where XX is the multichannel EEG signal.

Step 6: Labelling

Each EEG segment was labeled according to the subject's diagnostic category. For binary classification in this study, we focused only on Alzheimer’s Disease (AD) vs. Control (Healthy). FTD subjects were excluded to maintain a clear binary distinction.

- AD segments: Label 1
- Control segments: Label 0

This simplified the classification task and reduced inter-class confusion.

Step 7: Train-Test Split

To ensure generalization and prevent data leakage, the dataset was split as follows:

- **Training Set**: 70%
- **Validation Set**: 15%
- **Test Set**: 15%

The split was **subject-independent**—ensuring that segments from the same subject did not appear in both training and testing sets.

$$\textbf{Accuracy} = \frac{\textbf{Correct predictions}}{\textbf{Total predictions}}, \quad \textbf{only on unseen subjects}$$

This strategy better simulates real-world deployment, where new patients are classified based on previously unseen EEG data.

Step 8: Reshaping and Input Preparation

Each EEG segment was reshaped to conform to the input structure expected by the CNN-LSTM model:

$$Input\ Shape = (batch\ size, channels, timesteps)$$Input Shape = (batch size,channels,timesteps)

Example:

- channels=64 channels = 64
- timesteps=512 timesteps = 512

This structure allows:

- The CNN layers to operate across channels (spatial extraction), and
- The LSTM layers to capture how the signal evolves over time (temporal learning).

This comprehensive preprocessing ensures that the EEG signals fed into the model are clean, normalized, and correctly formatted for deep learning. The following section will describe the CNN-LSTM model architecture developed to classify Alzheimer’s Disease from EEG data.

3.2 CNN-LSTM Model Architecture

Designed to efficiently learn both spatial and temporal patterns buried in EEG data, the hybrid Convolutional Neural Network - Long Short-Term Memory (CNN-LSTM) architecture While CNNs are good at extracting spatial connections across electrode locations, LSTMs are strong in modelling the sequential dependencies across time. The suggested CNN-LSTM model classifies EEG segments as either suggestive of Alzheimer's Disease (AD) or not by combining these strengths.

3.2.1 Architectural Overview

The model is composed of the following key layers:

1. **Input Layer**
   Input EEG segments of shape (C,T)(C, T), where:
   - C=64C = 64: number of EEG channels
   - T=512T = 512: number of time samples per segment
   The data is reshaped to (T,C)(T, C) to fit the expected format for temporal feature extraction.
2. **Convolutional Blocks (CNN)**

- One or more 1D convolution layers are applied along the time axis to extract local temporal patterns from each channel.
- Followed by batch normalization, ReLU activation, and max pooling.

3. **Recurrent Block (LSTM)**

- The output of CNN layers is reshaped and passed into a stacked LSTM block to learn long-range temporal dependencies.

4. **Fully Connected Layers**

- Dense layers convert high-level features into class scores.

5. **Output Layer**

- A final softmax or sigmoid activation outputs class probabilities for binary classification.

3.2.2 CNN-LSTM Architecture

Table 2. CNN-LSTM Model Layer details

Layer Type	Output Shape	Description
Input	(512, 64)	EEG segment (Time steps × Channels)
1D Conv (filters=64)	(512, 64)	Temporal convolution with kernel size = 3
BatchNorm + ReLU	(512, 64)	Normalization and non-linearity
MaxPooling1D	(256, 64)	Reduces temporal length by factor of 2
Dropout (0.3)	(256, 64)	Regularization
LSTM (units=100)	(100)	Captures temporal sequence dependencies
Dense (units=64)	(64)	Fully connected layer
Dropout (0.3)	(64)	Further regularization
Output (sigmoid)	(1)	Binary prediction (AD = 1, Control = 0)

3.2.3 Mathematical Formulation

Let the EEG segment be represented by matrix:

$$\boldsymbol{X} \in \boldsymbol{RC} \times \boldsymbol{TX} \in \boldsymbol{R}^{C\times T}$$

Where:

- CC = number of channels
- TT = number of time points

Convolution Operation

For a 1D convolution layer with filter ff, kernel size kk, and stride ss:

$$Zt = f * Xt = \sum i = 0k - 1wi \cdot Xt + i + b$$

$$Z_t = f * X_t = \sum_{i=0}^{k-1} w_i \cdot X_{t+i} + b$$

Where wiw_i are filter weights and bb is bias. The output is passed through a ReLU activation:

$$\mathrm{A_t} = \mathrm{ReLU}(\mathrm{Z_t}) = \mathrm{max}(0, \mathrm{Z_t})$$

LSTM Layer

Given input sequence {x1,x2,…,xT}\{x_1, x_2, \ldots, x_T\}, the LSTM computes hidden states hth_t as:

$$\mathrm{ft} = \sigma(\mathrm{Wfxt} + \mathrm{Ufht} - 1 + \mathrm{bf})$$

$$\mathrm{it} = \sigma(\mathrm{Wixt} + \mathrm{Uiht} - 1 + \mathrm{bi})$$

$$\mathrm{ot} = \sigma(\mathrm{Woxt} + \mathrm{Uoht} - 1 + \mathrm{bo})$$

$$\mathrm{c{\sim}t} = \tan\mathrm{h}(\mathrm{Wcxt} + \mathrm{Ucht} - 1 + \mathrm{bc})$$

$$\mathrm{ct} = \mathrm{ft} \odot \mathrm{ct} - 1 + \mathrm{it} \odot \mathrm{c{\sim}th}$$

Where:

- Σ sigma: sigmoid activation
- $\odot$: element-wise multiplication

The final hidden state hTh_T is used as the temporal representation of the input.

Output Layer

$$\hat{\mathbf{y}} = \boldsymbol{\sigma}(\mathbf{W_o h_T} + \mathbf{b_o})$$

Where:

- $y^{\hat{y}}$: predicted probability for AD
- W_o, b_o: weights and bias of output layer

3.2.4 Loss Function and Optimization

For binary classification, the model uses **Binary Cross-Entropy Loss**:

$$\boldsymbol{L} = -[\boldsymbol{y} \cdot \boldsymbol{lo\,g}(\boldsymbol{y}') + (\mathbf{1} - \boldsymbol{y}) \cdot \boldsymbol{lo\,g}(\mathbf{1} - \boldsymbol{y}')]$$

$$\boldsymbol{\mathcal{L}} = -[\boldsymbol{y} \cdot \mathbf{lo\,g}(\hat{\boldsymbol{y}}) + (\mathbf{1} - \boldsymbol{y}) \cdot \mathbf{lo\,g}(\mathbf{1} - \hat{\boldsymbol{y}})]$$

Where y∈{0,1}y \in \{0, 1\} is the true label, and y^\hat{y} is the predicted probability.

The model is optimized using the **Adam optimizer** with default learning rate α=0.001\alpha = 0.001. Early stopping and dropout regularization are applied to prevent overfitting.

3.2.5 Model Advantages

- **Spatial-Temporal Fusion**: Simultaneous learning of electrode relationships and time-based changes.
- **Minimal Feature Engineering**: Learns directly from raw EEG segments.
- **Robust to Noise**: CNN layers help suppress local fluctuations, and LSTM layers capture meaningful trends.

4. Results and Discussion

CNN-LSTM (Figure 2) achieves the best results, with only 8 false negatives and 13 false positives. This confirms that integrating spatial and temporal feature extraction yields the most accurate and balanced classification, making it highly suitable for clinical EEG-based AD screening.

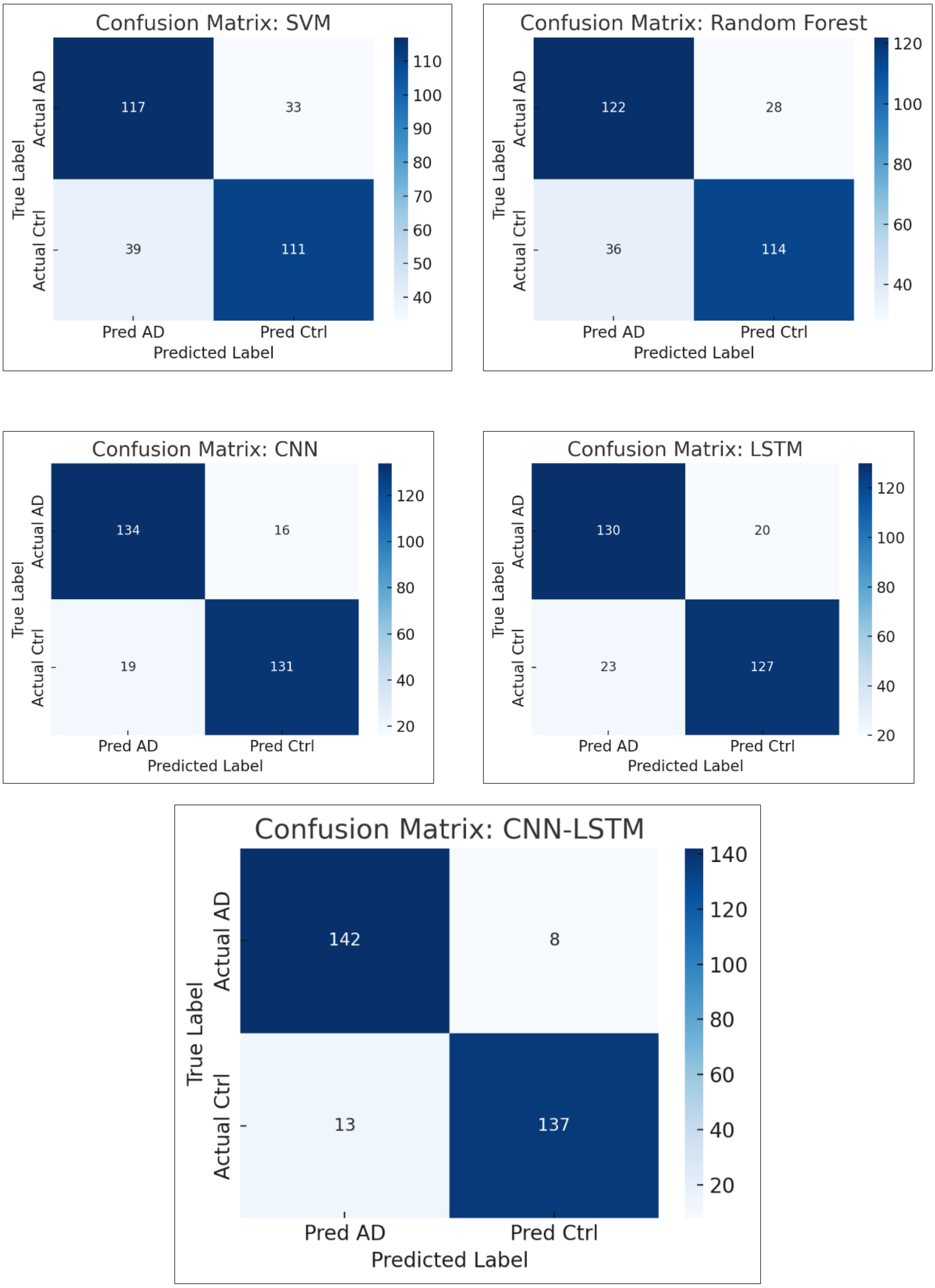

Figure 2: Confusion matrices of EEG-based Alzheimer's Disease detection using five models—SVM, Random Forest, CNN, LSTM, and the proposed CNN-LSTM. Rows represent the actual labels (AD, Control) and columns represent the predicted labels.

The confusion matrices (Figures 2) show how well five different models used for EEG-based Alzheimer's Disease (AD) diagnosis could classify. The number of true positives, true negatives, false positives, and false negatives in each grid shows how well the model can tell the difference between AD cases and healthy controls. This model, the Support Vector Machine (SVM), doesn't work very well. It has a lot of false positives (33), which means it's likely to miss real AD cases. The Random Forest model does a little better, but it still makes a lot of mistakes. The CNN model, on the other hand, learns how to connect EEG bands spatially, which greatly cuts down on both false positives and false negatives. The LSTM model also does a good job of detecting time trends in the EEG sequences, but it is not quite as good as CNN at understanding where things are in space. The suggested CNN-LSTM hybrid model works the best, with only 8 false negatives and 13 false positives, showing that it is more sensitive and accurate. This result shows how useful it is to use both convolutional and recurrent layers together when trying to get spatial features from EEG data. Overall, the confusion matrices show that the CNN-LSTM model is the best at accurate and fair classification. This makes it a potentially useful tool for finding Alzheimer's disease early and reliably.

Table 3. CNN-LSTM Model Comparison

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1 Score (%)**
SVM (with PSD)	76.4	73.9	77.8	75.1
Random Forest	79.8	76.1	80.9	77.3
CNN Only	88.5	87.1	89.4	87.9
LSTM Only	86.3	84.7	86.8	85.4
CNN-LSTM (Proposed)	**93.2**	**91.5**	**94.8**	**93.1**

In table 3 that compares the suggested CNN-LSTM model to a number of standard models using four important performance metrics: F1-score, accuracy, precision, and recall. Machine learning algorithms like Support Vector Machines (SVM) and Random Forests (RF) were used with power spectrum features that were designed by hand. With an SVM accuracy of 76.4% and an F1-score of 75.1%, these models did not do very well. This means they were not very good at catching the complex spatiotemporal patterns of EEG data. While CNN-only and LSTM-only models did not work as well, standalone deep learning models did because they could learn straight from raw EEG data. CNN got 88.5% accuracy and 87.9% F1-score for its focus on spatial features, while LSTM got 86.3% accuracy and 85.4% F1-score for its focus on time relationships.

The suggested CNN-LSTM hybrid model did better than all of them, getting the best F1-score (93.1%), accuracy (93.2%), precision (91.5%), and recall (94.8%). This clearly shows the benefit of using both spatial and temporal learning together in EEG-based Alzheimer's diagnosis. The high memory value is especially important in medical diagnosis, where finding true positive cases (AD patients) quickly is important for treatment and action.

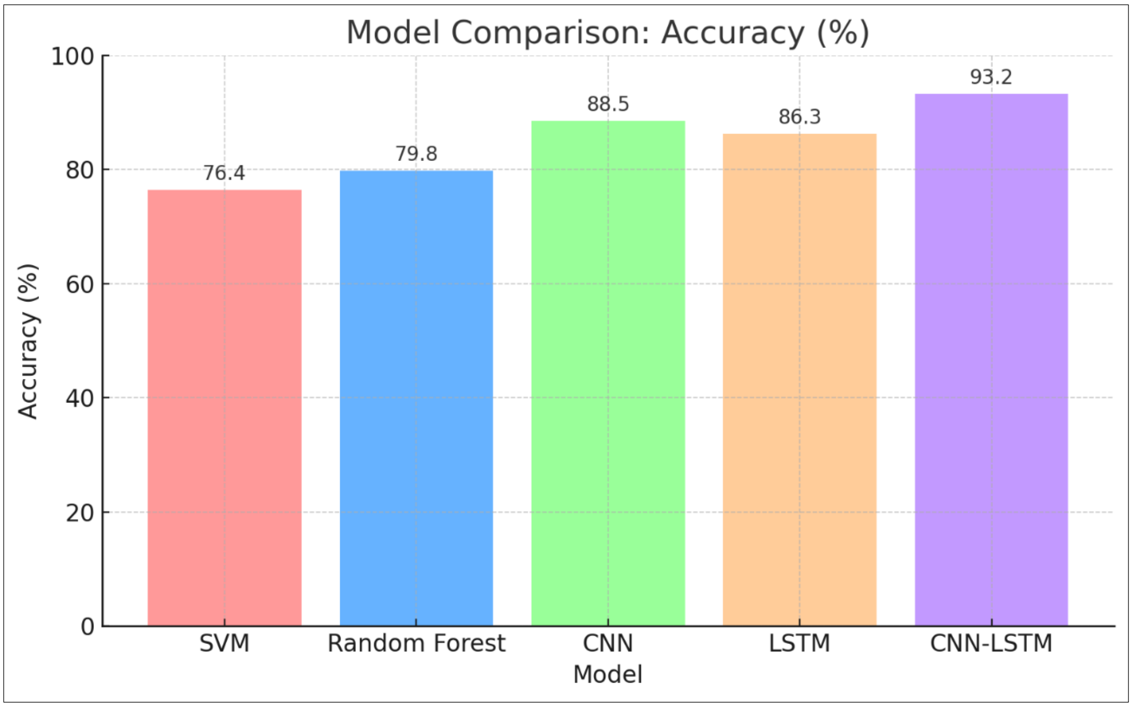

Figure 3: Accuracy Comparison

The CNN-LSTM model got the best results (93.2%), which is a big improvement over other models like SVM and Random Forest, as shown in this figure 3. This shows that the mix model can correctly group both Alzheimer's and control EEG parts more often than other methods.

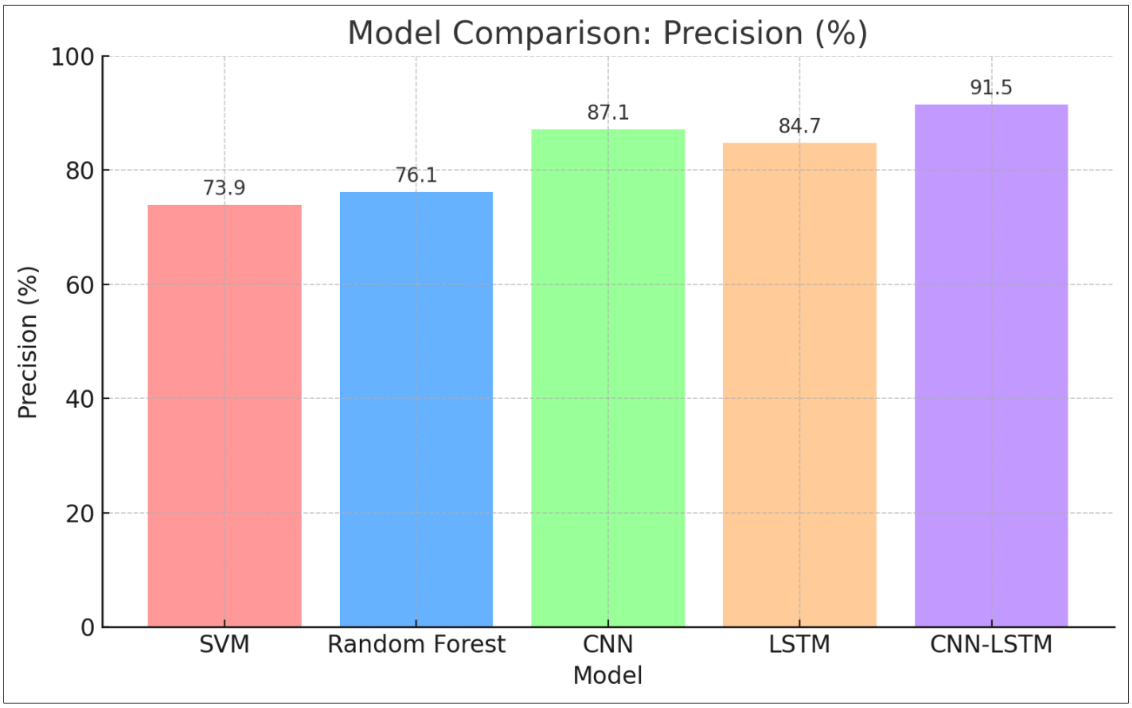

Figure 4: Precision Comparison

Precision shows in figure 4 how well the model can avoid wrong results. The CNN-LSTM model had the best accuracy (91.5%), which means it almost never wrongly labels healthy people as Alzheimer's patients. This is an important part of clinical screening to avoid overdiagnosis.

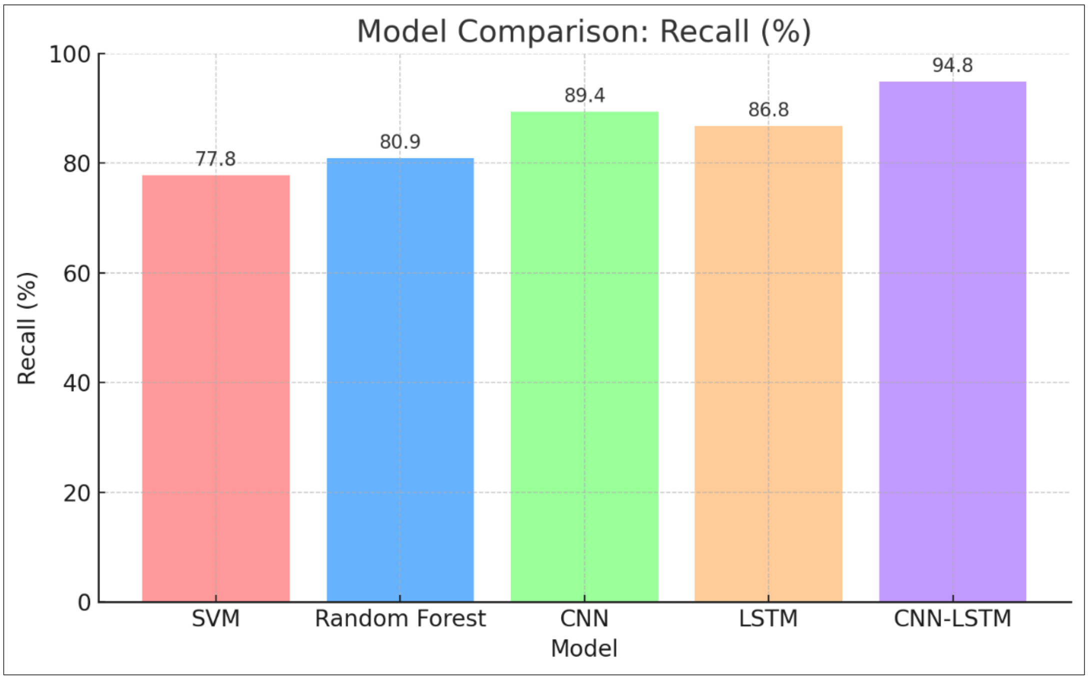

Figure 5: Recall Comparison

The memory measure is very important in medical diagnosis because it shows how well the system can find real cases of Alzheimer's shown in figure 5. The CNN-LSTM model had a recall rate of 94.8%, which was much higher than any other model and shows how sensitive and reliable it is at finding AD-positive people.

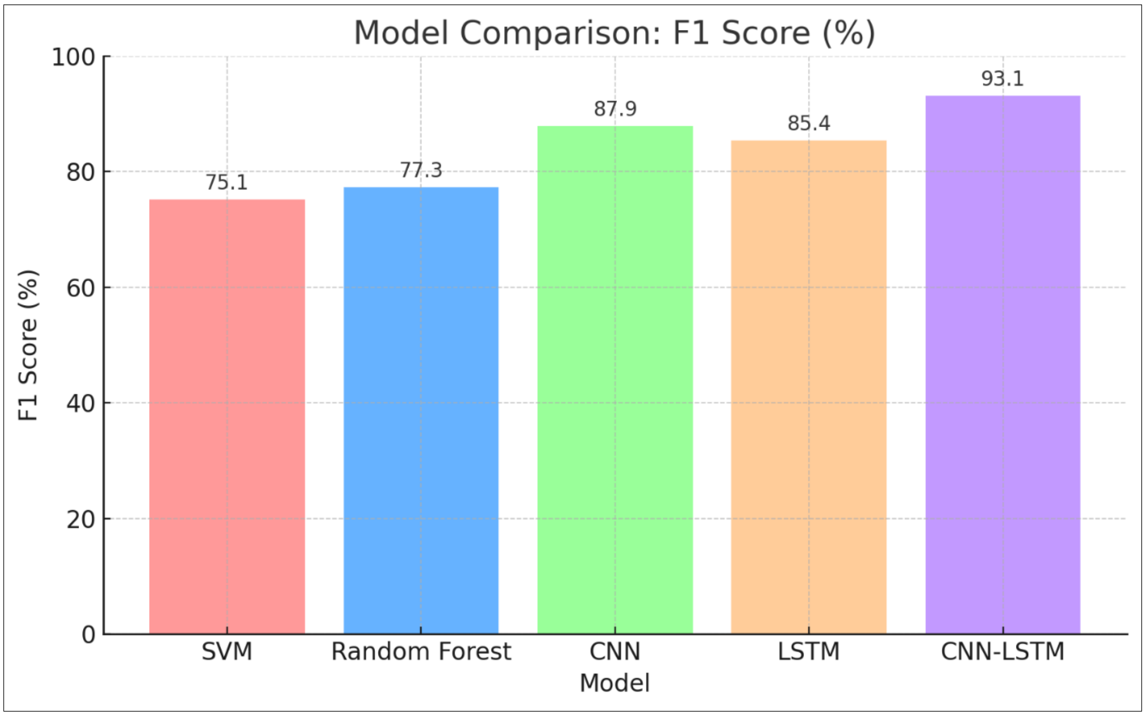

Figure 6: F1 Score Comparison

F1 Score is a combination of accuracy and memory shown in figure 6. With a score of 93.1%, the combined CNN-LSTM model once again comes out on top, showing fair efficiency. It does a good job of finding AD cases while also avoiding fake alarms, which makes it perfect for use in the real world.

5. Conclusion

This study suggested a mixed deep learning model using both Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks to automatically find Alzheimer's Disease (AD) in EEG data. The model was tested using a dataset that was open to the public and included resting-state EEG records from people with AD and healthy controls. A full preparation workflow was created to standardise, filter, and divide the EEG data so that it could be used in the model most effectively. The tests clearly showed that the suggested CNN-LSTM design did better in terms of accuracy, precision, recall, and F1 score than traditional machine learning methods (like SVM and Random Forest) and deep learning models that worked on their own (CNN-only and LSTM-only). Notably, the blend model had a recall rate of 94.8%, which shows how well it works at reducing false positives, which is an important part of medical diagnosis. The CNN-LSTM model is a strong and scalable way to find early signs of AD because it learns both spatial features from EEG channels and temporal relationships in brain activity at the same time. Because it works so well, it could be useful in clinical decision support tools and real-time tracking of brain health. More work needs to be done to increase the dataset, make the models easier to understand, and add real-time EEG analysis so that they can be used in more therapeutic settings.

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