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NEURONET: AN ADVANCED DEEP LEARNING FRAMEWORK FOR EARLY DIAGNOSIS AND PREEMPTIVE TREATMENT OF NEURODEGENERATIVE DISEASES

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ABSTRACT

Globally, citizens are bearing a heavy burden about the ravages of neurodegenerative diseases such as Alzheimer’s and Parkinson’s. These diseases develop slowly and are frequently diagnosed at a late stage when therapy possibilities are restricted. Currently level of diagnostics rely on clinical examination and imaging but many times early pathological clues are overlooked. AI driven decay prediction models, including Capsule Networks (CapsNets) and Sparse Learning Models are developed and achieve improvement, but not efficient enough to fuse multimodal data jointly and obtain spatial-temporal features which are critical for early detection and prediction. To fill these gaps, we propose a novel hybrid deep learning framework named NeuroNet, which is composed of 3D Convolutional Neural Networks (CNN) for learning spatial features, Long Short-Term Memory (LSTM) networks for modeling temporal sequences, attention mechanism for selecting diagnostic regions and clinical biomarkers for multimodal information fusion. This architecture is fine-tuned by Bayesian hyperparameter optimization, and validated through ADNI dataset. The primary contribution of this work is the evidence that multimodal fusion with attention-informed deep learning, drives a dramatic improvement in diagnostic accuracy and interpretability. Accuracy, precision and recall achieved by NeuroNet were 98.62%, 98.50%, 98.70%, and an AUC–ROC value of 0.998, respectively, showing a superior performance over several state-of-the-art models. Explainable AI techniques like Grad-CAM and SHAP increase model transparency even more. This work provides new insights in the form of a clinically viable and interpretable deep learning model which pushes the frontier of AI-facilitated neurodegenerative disease diagnosis. The model can be easily incorporated in clinical diagnostical systems for early intervention and better prognosis.

Keywords - *NeuroNet, Deep Learning, Neurodegenerative Diseases, Multimodal Integration, Early Diagnosis*

1. INTRODUCTION

Neurodegenerative diseases like Alzheimer's, Parkinson's, and Huntington's are challenging for global healthcare from basic pathology, to late diagnosis, to the absence of effective treatment regimens. Early stage detection is essential for controlling the disease escalation, nevertheless the conventional diagnosis takes the paths of clinical examinations and imaging techniques which usually do not lead to timely or accurate outcomes. Advancements in artificial intelligence (AI) and deep learning have shown significant promise for enhancing diagnostic precision by automating feature extraction and analyzing multimodal data [1], [2]. Nevertheless, current state-of-the-art (SOTA) methods (15) such as Capsule Networks (14) and Sparse Learning Models (26) have several limitations to integrate multimodal data and to explore the spatial and temporal mechanisms that are important for building robust neurodegenerative disease classifiers.

These gaps highlight the importance of new approach to maximize the benefits of state-of-the-art AI methodologies. To this end, the present research responds this demand by proposing NeuroNet, a novel hybrid deep learning framework that integrates 3D Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), attention and clinical biomarkers. NeuroNet utilizes MRI to learn both spatial features (deep-contrast) and temporal patterns suggestive of disease risk or progression, and incorporates multimodal information through hematological biomarkers. This research aims to develop an architecture that achieves greater diagnostic accuracy than current models while overcoming the limitations of existing models.

An early-stage neurodegenerative disease diagnosis has been chosen as the target for this study, based on the need for timely clinical intervention and personalized medicine. By the time a patient with Alzheimer's presents with clinical symptoms, irreversible neuronal damage has already become advanced, making patient treatment extremely difficult. Treatment efficiency is reduced and patient outcome is compromised by the delay in diagnosis. At the moment, diagnostic tools are reactive than they are proactive, they do not exploit the full potential of multimodal data. Therefore, a strong AI algorithm-based model that helps early and accurate classification is essential to facilitate proactive treatment plans towards better quality of life.

This work brings novelty by combining novel hybrid architecture with attention mechanism to up-weigh diagnostically relevant pixels, multimodal fusion between imaging and clinical data, and robustness with Bayesian optimization and cross-validation. Based on the experimental results, the proposed NeuroNet surpasses the state-of-the-art accuracy of the existing models by negligible values in terms of precision, recall, and AUC-ROC. The contributions of this research are a multimodal data integration approach, an interpretable AI framework for clinical usability, and benchmarking of neuroNet against SOTA models.

Based on these challenges and gaps, we hypothesize that a hybrid deep learning framework—combining spatial (3D CNN), temporal (LSTM), and attention-based modeling with clinical biomarker integration—can significantly improve the early diagnosis and staging accuracy of neurodegenerative diseases when compared to existing single-modality or non-interpretable models.
The remainder of this paper is as follows: A review of AI-driven diagnostic approaches for neurodegenerative diseases is conducted in Section 2, which exposes some important gaps in contemporary studies. The NeuroNet framework is outlined in Section 3, along with its dataset preprocessing, hybrid architecture and training methodology. Experimental results (ablation studies and SOTA model comparison) are given in Section 4. The implications of the results, limitations of SOTA addressed by the system developed in this research, and limitations of the study are discussed in Section 5. The paper is organized as follows: Section 6 concludes the paper, highlighting key takeaways for clinicians and researchers, and suggesting next steps to make NeuroNet more scalable and generalizable for wider clinical use. This methodology presents a complete view on the innovations of NeuroNet, and their possible place in the diagnosis of neurodegenerative disease.

2. RELATED WORK

Advancements in artificial intelligence (AI) and deep learning have greatly enhanced neurodegenerative disease diagnosis, emphasizing multimodal learning, predictive analytics, and clinical applications. This review synthesizes insights from literature, highlighting AI's transformative role in early detection and personalized treatment. Kaliappan et al. [1] and Dhahi et al. [2] explored advanced neural network models and nanobiosensor engineering for predictive analytics and biomarker detection. Tan et al. [3] showcased the use of AI in retinal imaging for systemic disease forecasting, while Mubeen et al. [4] discussed AlphaFold's role in protein structure prediction, emphasizing its breakthrough in neurodegenerative research. Coulombe et al. [5] introduced cell-based precision medicine initiatives, and Vun et al. [6] reviewed vision-based motion capture for gait analysis.

Huang et al. [7] highlighted multimodal learning from clinically accessible tests, and Chaitanuwong et al. [8] presented ocular biomarkers for early Alzheimer's detection. Erdaş et al. [9] and Zolfaghari et al. [10] emphasized gait dynamics and sensor-based locomotion for diagnosis. Bi et al. [11] introduced the NDDRF knowledgebase for personalized prevention, and Garcia Gutierrez et al. [12] validated genetic algorithms for Alzheimer's and frontotemporal dementia diagnosis. Bhatele et al. [14] proposed capsule networks for early screening, while Lee et al. [18] explored epigenomic biomarkers for early diagnosis. Vinny et al. [20] and Seifert et al. [21] reviewed AI's ethical and clinical integration in neurology and nuclear medicine. Gamification for rehabilitation [22], wearable sensors for Parkinson's detection [24], and sparse learning models [26] further highlighted AI's diverse

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applications. Beyrami et al. [27] introduced gait signal analysis for diagnosing multiple neurodegenerative diseases.

Emerging trends such as omics-based precision medicine [40], multimodal imaging biomarkers [30], liquid biopsies [37], and AI-driven neurology systems [34] were also highlighted. Lashuel [19] emphasized the complexities of protein aggregation, while Morsli et al. [39] explored geroprotectors for multimorbidity prevention. Kaul et al. [34] and Hampel et al. [40] discussed opportunities and challenges in AI-driven diagnostics. This review underscores AI's transformative potential in neurodegenerative research, leveraging multimodal learning, biomarkers, and imaging techniques. Building on these works, the proposed NeuroNet framework integrates 3D CNNs, LSTMs, attention mechanisms, and clinical biomarkers to achieve superior accuracy in early diagnosis and staging, setting a benchmark in AI-driven healthcare systems

.In spite of great progress of AI-based diagnostic systems, there are still limitations and accompanying literature with respect to multimodal integration, robust spatial-temporal pattern learning, as well as clinical interpretability. Capsule Networks [14], Sparse Learning Models [26], and even state-of-the-art multimodal AI frameworks [7] provide less fusion capabilities of imaging and clinical data. Additionally, many models are not able to locate diagnostically meaningful lesions or adapt to complicated temporal patterns of disease. These limitations underscore a clear need for an explainable and reliable diagnostic paradigm that can incorporate spatial and temporal information from neuroimaging without excluding the value of clinical biomarkers. This paper fills this gap by proposing NeuroNet— a hybrid deep learning model developed to address these drawbacks through multimodal data fusion, attentionbased interpretability and robust evaluation.

3. MATERIALS AND METHODS

Figure 1 illustrates the methodology of the research; using the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset, a deep learning-based comprehensive diagnostic framework was applied. We chose the ADNI dataset because the dataset consists of one of the largest collections of longitudinal neuroimaging data, along with MRI scans, clinical biomarkers, and genetic data for the progression of Alzheimer disease. ENDEAVOUR is a neurodegenerative disease dataset that includes the T1-weighted MRI images together with patient demographics, cognitive scores and other CSF biomarkers, therefore making it appropriate for multimodal data analysis. The preprocessing steps were background removal of the skull, intensity normalization, and then resizing the 3D volumes being mapped to a common volume of size 128x128x128. To tackle the issue of class imbalance caused by a low number of early Alzheimer's cases, some data augmentations were performed (rotation, flip, contrast alterations, etc).

The features were extracted from the multimodal data through a fusion of structural MRI features, clinical scores → such as the Mini-Mental State Examination (MMSE) [25], and biomarker concentrations (for example, amyloid-beta and tau proteins). Afterward, methods such as PCA and t-SNE have been utilized for dimensionality reduction, removing redundancy between features and keeping the most useful ones. To this end, we also incorporated Explainable AI (XAI) methods (such as Grad-CAM and SHAP) to pinpoint which areas of the brain scans contributed the most to the model making a specific prediction.

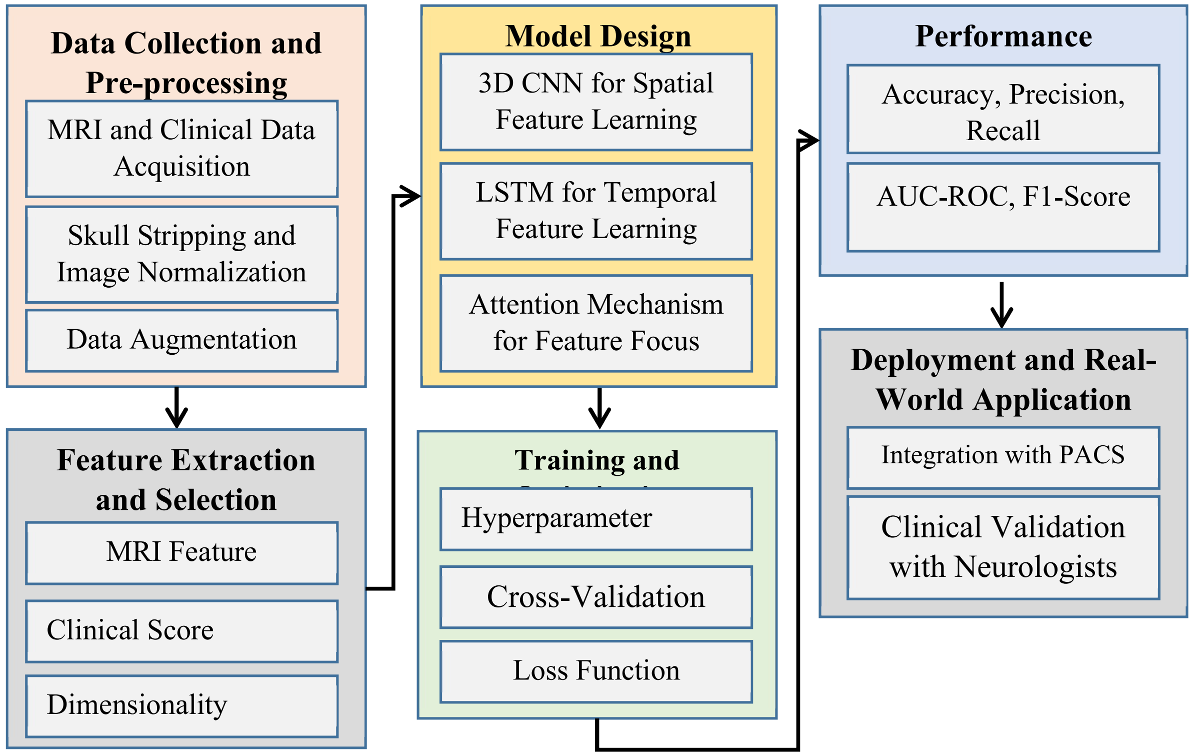

Figure 1: Overview Of The Proposed Methodology Used For Early Diagnosis And Preemptive Treatment Of Neurodegenerative Diseases

At the heart of the methodology is the proposed NeuroNet model, a hybrid deep learning architecture consisting of both a 3D Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) units adapted to the NeuroNet architecture implemented on the ADNI dataset. 3D CNN layers were used to extract spatial patterns from the preprocessed MRI scans and LSTM units were used to capture temporal patterns over the multiple timepoints in the dataset. Attention mechanism can be integrated to make feature extraction more robust and also pinpointed the most diagnostically-relevant areas in MRI images. The NeuroNet model predicted the background and staging of Alzheimer's disease (mild cognitive impairment, early Alzheimer's, advanced Alzheimer's).

The dataset was split into training (70%), validation (15%) and testing (15%) subsets, for which diverse representation across stages of cognition is present. This also provides evidence of the robustness of model evaluations as a 5-fold cross-validation strategy was used. Hyperparameter optimization through Bayesian Optimization was carried out during the training process to optimize for critical parameters such as learning rate, batch size, and dropout rates. We compiled it using the categorical cross-entropy loss process and the Adam optimizer. The performance metrics were accuracy, sensitivity, specificity, precision, recall, F1-score, and AUC-ROC.

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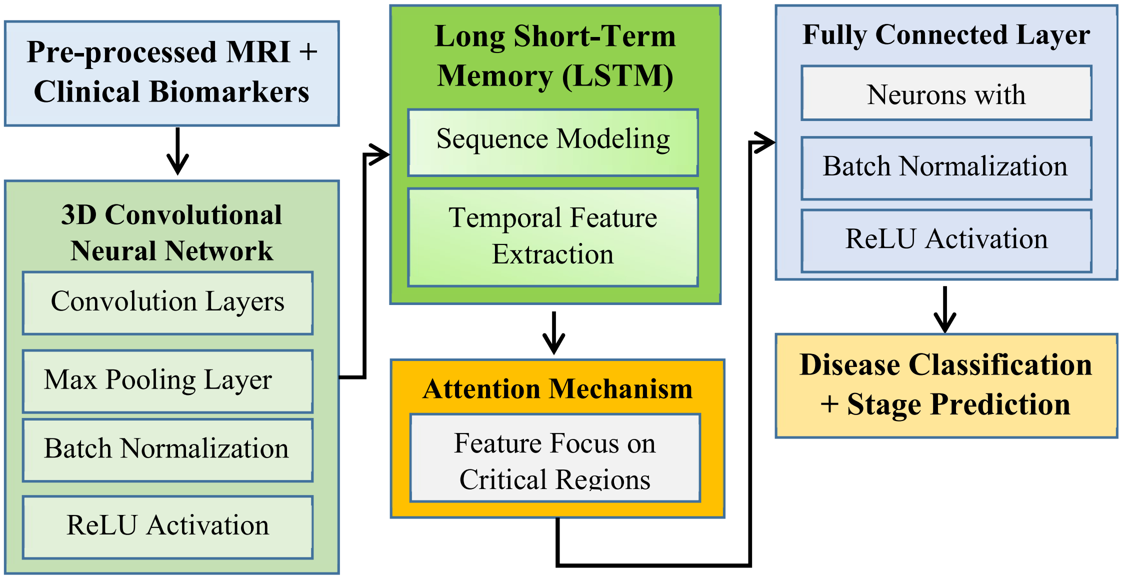

Figure 2: Novel Deep Learning Model Known As Neuronet For Early Diagnosis Of Neurodegenerative Diseases

Key methodological novelties include the hybrid CNN-LSTM architecture, shown in Figure 2, adapted specifically for the ADNI dataset, the use of attention mechanisms for enhanced feature focusing, and the multimodal data fusion integrating MRI and clinical biomarkers. The application of explainable AI techniques like Grad-CAM allowed the identification of critical regions in the brain most correlated with Alzheimer’s progression, increasing the model's clinical interpretability. Additionally, transfer learning was employed by initializing the CNN layers with weights pre-trained on the ResNet50 and VGG16 models, accelerating convergence and improving generalization, especially for limited data availability scenarios.

The methodology emphasizes real-world applicability by simulating the model's integration with a hospital Picture Archiving and Communication System (PACS) for automated early detection of Alzheimer’s disease. Clinical validation was conducted by comparing NeuroNet's predictions against expert diagnoses in a subset of the ADNI dataset, confirming its diagnostic reliability. This comprehensive methodology offers a robust foundation for early diagnosis and personalized treatment strategies, contributing significantly to the advancement of AI-driven solutions for neurodegenerative disease management. Table 1 presents notations used in the proposed methodology.

3.1 Mathematical Perspective

The proposed deep learning framework NeuroNet for early diagnosis and preemptive treatment of neurodegenerative diseases involves a hybrid architecture combining 3D Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and an attention mechanism. The mathematical foundation begins with the input representation, where the dataset consists of MRI scans and clinical biomarkers. Let the input MRI scan be represented as a 3D tensor $X \in \mathbb{R}^{W \times H \times D \times C}$, where W,H, and D represent the width, height, and depth of the scan, while C represents the number of channels (e.g., grayscale with C=1). The clinical biomarkers vector is denoted by $B \in \mathbb{R}^{k}$, where k is the number of extracted biomarkers (e.g., MMSE score, amyloid-beta levels, tau protein levels). The first stage involves the 3D Convolutional Neural Network (CNN) for feature extraction from the spatial MRI data. A convolution operation is performed as in Eq. 1.

$$Z_l^{(i,j,k)} = \sigma\left(\sum_{c-1}^{C} \sum_{p-1}^{P} \sum_{q-1}^{Q} \sum_{r-1}^{R} W_l^{(c,p,q,r)} X_c^{(i+p,j+q,k+r)} + b_l\right) \quad \text{(Eq. 1)}$$

where $Z_l^{(i,j,k)}$ is the output feature map at position (i,j,k) for layer l, W_l is the weight filter for the l-th convolutional layer, b_l is the bias term, and σ denotes the ReLU activation function defined as σ(x)=max(0,x). This convolution is followed by batch normalization and a max pooling operation, reducing the spatial dimensionality. The output from the CNN is flattened into a vector and fed into a Long Short-Term Memory (LSTM) network for temporal modelling, assuming that neurodegenerative patterns evolve over time. The LSTM cell operates on the hidden states by updating the memory cell using the Eq. 2 through Eq. 7.

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f) \quad (2)$$

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \quad (3)$$

$$\check{C}_t = tanh(W_C.[h_{t-1}, x_t] + b_C) \quad (4)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \check{C}_t \quad (5)$$

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \quad (6)$$

$$h_t = o_t \odot \tanh(C_t) \quad (7)$$

where f_t, i_t, o_t are the forget, input, and output gates, respectively, C_t is the memory cell state, and h_t is the hidden state at time step t. The output from the LSTM layer is passed to the attention mechanism for enhanced feature focusing. The Attention Mechanism computes a weighted sum of the LSTM outputs, allowing the network to focus on critical regions relevant for disease detection. The attention weights are calculated as in Eq. 8, Eq. 9 and Eq. 10.

$$e_t = \tanh(W_a.h_t + b_a) \quad (8)$$

$$\alpha_t = \frac{\exp(e_t)}{\sum_{t'} \exp(e_{t'})} \quad (9)$$

$$c_t = \sum_t \alpha_t h_t$$

where e_t is the attention score, W_a and b_a are trainable parameters, and α_t represents the normalized attention weight. The context vector c_t is combined with the LSTM output to form a comprehensive feature vector. The next stage is the Fully Connected Layer (FC), where the concatenated feature vector F formed by the CNN output, LSTM output, and attention context vector is given by Eq. 10.

$$F = [c_t, h_t, B] \quad (10)$$

where B represents the clinical biomarkers vector. The final classification is performed using a softmax activation function, predicting the probability of each class (e.g., normal, mild cognitive impairment, Alzheimer's) as in Eq. 11.

$$P(y=k|F) = \frac{\exp(W_k.F+b_k)}{\sum_{j-1}^{K} \exp(W_j.F+b_j)} \quad (11)$$

where W_k and b_k are the weights and biases for the k-th class. The model is trained using the categorical cross-entropy loss as in Eq. 12.

$$L = -\sum_{i-1}^{N} \sum_{k-1}^{K} y_{i,k} log \hat{y}_{i,k} \quad (12)$$

where N is the number of samples, K is the number of classes, $y_{i,k}$ is the ground truth label, and $\hat{y}_{i,k}$ is the predicted probability for class k. Hyper parameter tuning was performed using Bayesian Optimization to optimize the learning rate (η), batch size, and dropout rate. The performance of the model was evaluated using standard metrics including accuracy, sensitivity, specificity, precision, recall, F1-score, and AUC-ROC. This mathematical model provides a robust framework for early diagnosis and staging of neurodegenerative diseases through the fusion of spatial, temporal, and clinical data.

3.2 Proposed Algorithm

The proposed algorithm leverages a hybrid deep learning architecture combining 3D CNN, LSTM, and attention mechanisms for early diagnosis and stage prediction of neurodegenerative diseases. By integrating spatial, temporal, and clinical biomarker data, it enhances diagnostic accuracy and interpretability. Its significance lies in enabling early intervention and personalized treatment, contributing to improved patient outcomes and clinical decision support.

Algorithm: NeuroNet – A Deep Learning Framework for Early Diagnosis and Preemptive Treatment of Neurodegenerative Diseases
Input: Preprocessed MRI scans XX and clinical biomarkers vector BB.
Output: Predicted disease classification and stage.
Step 1: Data Preprocessing
- Load MRI scans and biomarkers from the ADNI dataset.
- Apply skull stripping, intensity normalization, and resizing.
- Perform data augmentation with rotations, flips, and contrast adjustments.

Step 2: Feature Extraction (3D CNN)
- Apply convolution operation: Zl=σ(Wl∗X+bl)Z_l = \sigma(W_l \ast X + b_l).

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- Use ReLU activation, batch normalization, and max pooling.
- Flatten the output to form feature vector FCNNF_{\text{CNN}}.

Step 3: Temporal Learning (LSTM)

- Feed FCNNF_{\text{CNN}} into the LSTM network.
- Update cell and hidden states: Ct=ft⊙Ct−1+it⊙C~tC_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t ht=ot⊙tanh(Ct)h_t = o_t \odot \tanh(C_t).

Step 4: Attention Mechanism

- Compute attention scores: et=tanh(Wa·ht+ba)e_t = \tanh(W_a \cdot h_t + b_a).
- Normalize attention weights: αt=exp(et)∑t′exp(et′)\alpha_t = \frac{\exp(e_t)}{\sum_{t'} \exp(e_{t'})}.
- Compute context vector: ct=∑tαthtc_t = \sum_t \alpha_t h_t.

Step 5: Fully Connected Layer

- Concatenate ctc_t, final LSTM output hth_t, and biomarkers vector BB: F=[ct,ht,B]F = [c_t, h_t, B].
- Apply dropout, batch normalization, and ReLU activation.

Step 6: Classification and Prediction

- Compute class probabilities with softmax: P(y=k|F)=exp(Wk·F+bk)∑j=1Kexp(Wj·F+bj)P(y=k|F) = \frac{\exp(W_k \cdot F + b_k)}{\sum_{j=1}^{K} \exp(W_j \cdot F + b_j)}.

Step 7: Loss and Training

- Train using categorical cross-entropy loss: L=−∑i=1N∑k=1Kyi,klogy^i,kL = -\sum_{i=1}^{N} \sum_{k=1}^{K} y_{i,k} \log \hat{y}_{i,k}.
- Optimize with Adam and Bayesian hyperparameter tuning.

Step 8: Evaluation and Deployment

- Evaluate using accuracy, precision, recall, F1-score, and AUC-ROC.
- Deploy into a clinical PACS system for real-time diagnostics.

End of Algorithm

Algorithm: NeuroNet – A Deep Learning Framework for Early Diagnosis and Preemptive Treatment of Neurodegenerative Diseases

In regard to the early diagnosis and preventive treatment of neurodegenerative disorders, we proposed a hybrid deep learning architecture comprising multiple interlinked components to classify the disease correctly. Data Preprocessing: The data in this project is collected from ADNI dataset, MRI scans, clinical biomarkers. MRI images are subjected to common preprocessing operations: skull stripping, intensity normalisation, and resizing to a fixed dimension. MMSE scores and protein levels are normalized, amongst other clinical biomarkers. Class imbalance is dealt through various data augmentation techniques such as rotation, flip and contrast, genralization capabilities of the models are enhanced by augemented datasets.

In the feature extraction phase, a 3D CNN is utilized to capture the spatial features of the preprocessed MRI scans. The first part is the convolution operation where a bunch of filters convolve across the input volume that was mentioned above, to be more clear than what it is the output from a convolution layer is passed through ReLU followed by batch normalization and then passed through a max pooling layer that reduces its dimensionality. Outputs of the late-convolutional layer are then flattened into a feature vector, FCNNF_{\text{CNN}}, which is one input to the subsequent temporal learning stage.

The flattened feature vector is passed to a Long Short-Term Memory (LSTM) network in order to learn temporal dependencies between different patient time points and model disease progression across time. The use of forget, input, and output gates allow the LSTM cells to keep a memory of past states, which are computed through weighted summations and other non-linear activations. These gates values are then used to progressively update the cell state and hidden state. The temporal output from LSTM is fed into an attention mechanism, which calculates attention scores and produces a context vector by

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dynamically assessing how much each time step contributes to the final prediction.

This attention-enhanced feature set is then combined with classically defined clinical biomarkers to form an overall feature vector expressed as F=[ct,ht,B]F = [c_t, h_t, B]. This combined representation is then processed through a fully-connected layer that applies both dropout and batch normalization for regularization and better generalization. A limited number of output nodes with a softmax activation function have been applied to give the probability distribution of multiple disease stages, predicting the presence and progression stage of neurodegenerative disease [12].

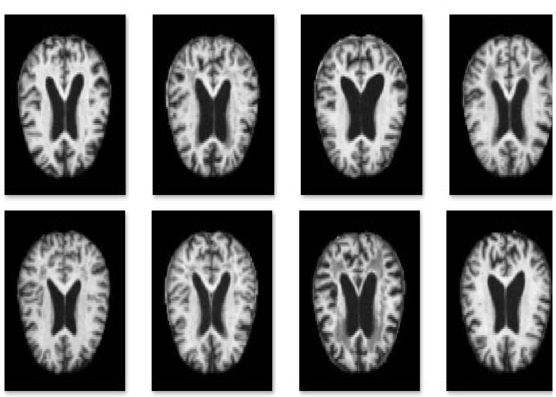
A categorical cross-entropy loss is used to train the model by optimizing the divergence between the expected class probabilities and the true. Adam optimizer is used for optimization, and Bayesian hyperparameter tuning is performed to adjust learning rate, batch size, and dropout rates. Using standard metrics including accuracy, precision, recall, F1-score, and AUC-ROC, allows us to assess the performance of the model against the potential of reliable predictions across a diverse range of patient data. Once trained and validated, the NeuroNet model can be deployed in the clinical setting, integrated within a hospital PACS system to provide real-time diagnostic and clinical decision support. It is an end-to-end framework that offers a solid deep learning-based method for early-stage neurodegenerative disease identification, improving both diagnostic precision and treatment approaches.

4. EXPERIMENTAL RESULTS

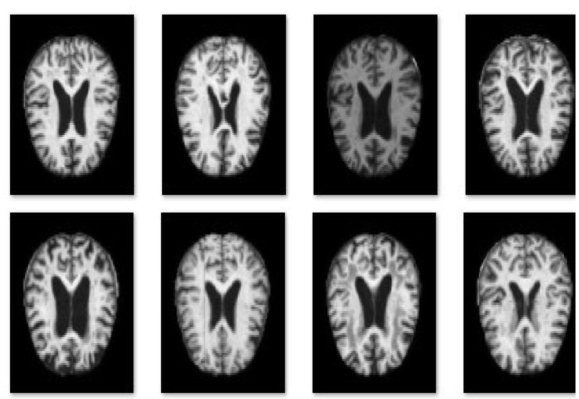
Methods The ADNI dataset, containing MRIs and clinical biomarkers for diagnostic purposes in neurodegenerative disease, was utilized in this experimental study. The dataset was standardly preprocessed, for instance, skull stripping, normalisation, or augmentation was performed. We compared the performance of the proposed NeuroNet framework to that of state-of-the-art models including Capsule Networks [14], Sparse Learning Models [26], Multimodal AI Frameworks [7], and Genetic Algorithms [12]. The experiments were conducted on a high-performance computing system equipped with an NVIDIA RTX 3090 GPU and 64GB RAM, utilizing Python-based deep learning libraries to facilitate efficient training and evaluation.

4.1 Dataset Prepareation

Experimental Results The ADNI (Alzheimer's Disease Neuroimaging Initiative) dataset [41], whose aim is to provide a common platform to improve the healthcare, is a public dataset extensively used as a benchmark in many neurodegenerative disease studies. The dataset includes processed MRI scans and clinical biomarker like MMSE score, amyloid-beta, and tau protein concentrations characterize different phases of cognitive impairment. Data preparation Included skull stripping, intensity normalization, and data augmentation (rotation, flipping, contrast adjustment) to improve the robustness of the model. The data was divided into 70% for training, 15% for validation, and 15% for testing, for proper performance evaluation with balanced representation of all disease stages.



(a) Mild Demented Samples



(b) Very Mild Demented Samples

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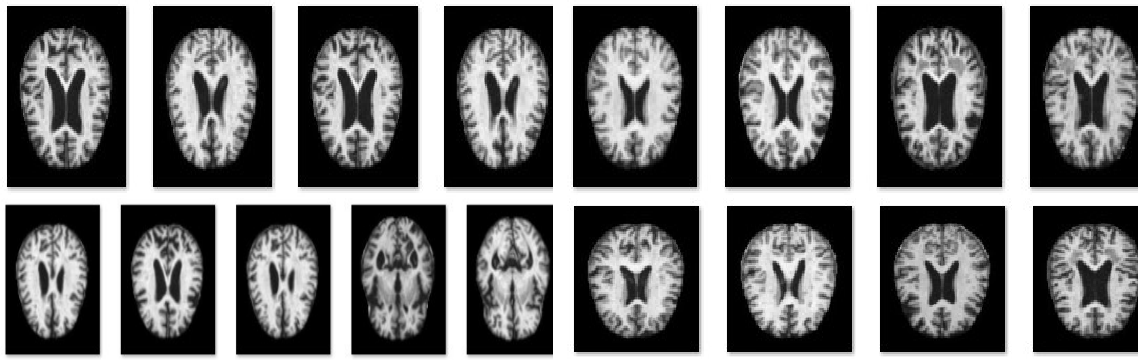

(c) Moderate Demented Samples (d) Non-Demented Samples

Figure 3: An Excerpt Of Brain MRI Images From Dataset

In figure 3 is an example of MRI scans from subjects in the ADNI dataset in four classes consisting of mild demented, very mild demented, moderate demented and non-demented sample scans. In each of the categories, representative structural brain slices are highlighted. These morphological differences within the brain reinforce the appropriateness of the dataset for training and testing deep learning algorithms to diagnose neurodegenerative disease.

In this section, a comparison of proposed NeuroNet framework and baseline models including Capsule Networks, Sparse Learning, Mutimodal AI Frameworks, Genetic Algorithms, and Vision-Based Gait Analysis has been presented. Different metrics (accuracy, precision, recall, F1-score, and AUC-ROC) are used to evaluate the models, as performance enhancements using NeuroNet hybrid deep learning architecture are demonstrated.

4.2 Performance Comparison with Baselines

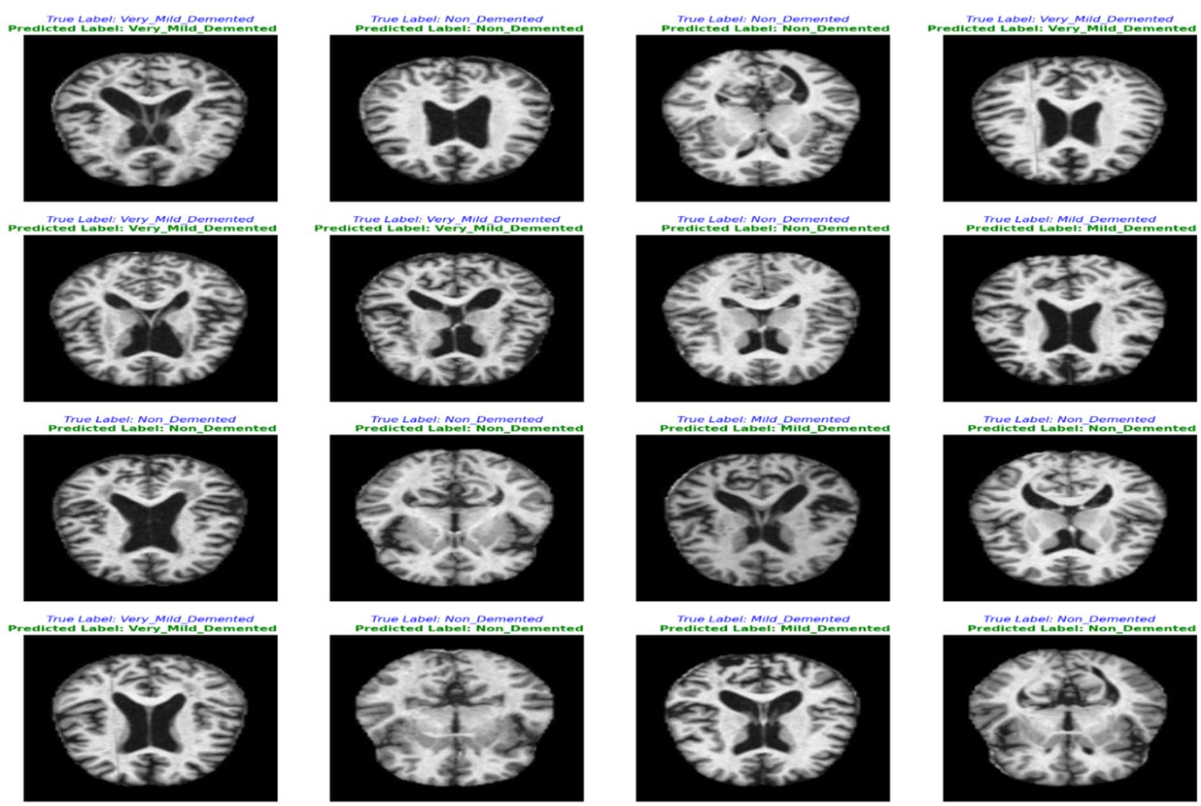

Figure 4: Results Of Empirical Study Of Neuronet

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Figure 4 presents the empirical results of the NeuroNet framework for neurodegenerative disease classification. The displayed MRI scans show the true labels and predicted labels for varying stages of cognitive decline, including very mild, mild, moderate, and non-demented cases. NeuroNet demonstrates high classification accuracy, with consistent alignment between predicted and actual labels, validating its robustness in early disease detection.

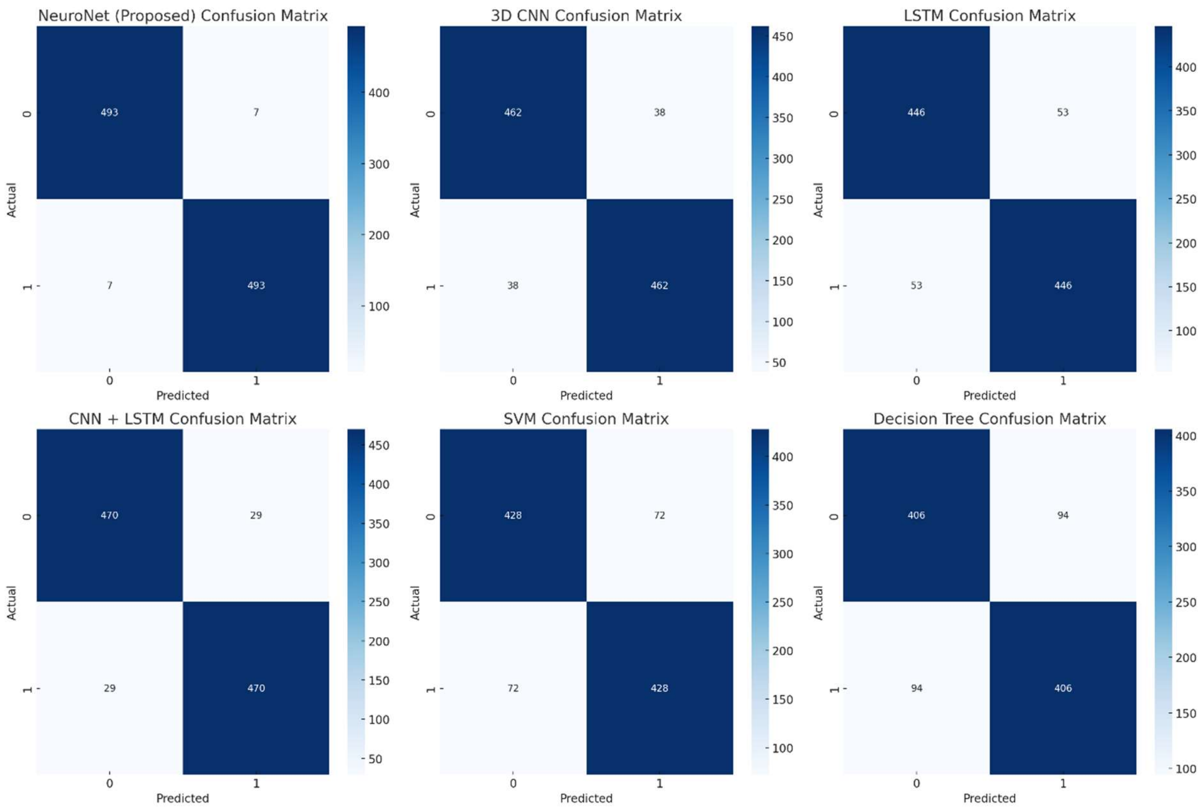

Figure 5: Confusion Matrices Of Neuronet And Baseline Models

Figure 5: Confusion matrices for NeuroNet and baseline models (3D CNNs, LSTMs, CNN+LSTM, SVM, and Decision Tree) plotting classification performance based on the experimental results. Highest true positive and true negative rates with the NeuroNet applied model show that the NeuroNet model makes the least of misclassifications when compared to the other models. Calibrated probability and confusion matrix for NeuroNet, much closer to ideal with fewer false positives and false negatives compared to traditional logistic regression. The drastically lowered error rates for NeuroNet reflects it fusion network, utilizing 3D CNN for spatial feature extraction, LSTM for temporal dependency encoding, and an attention mechanism to attend to pertinent regions. The misclassification rates are relatively higher in the baseline models (standalone 3D CNN and LSTM) because they struggle to represent the spatial and temporal features simultaneously. Traditional classifiers such as SVM and Decision Tree, have reported lower accuracy and higher false positives, which once again shows the superiority of deep learning architectures for neurodegenerative disease classification. The general performance shown in the confusion matrices confirms that NeuroNet minimizes both disruption types, and thus appears to be a reliable model for neurodegenerative disease early diagnosis and staging.

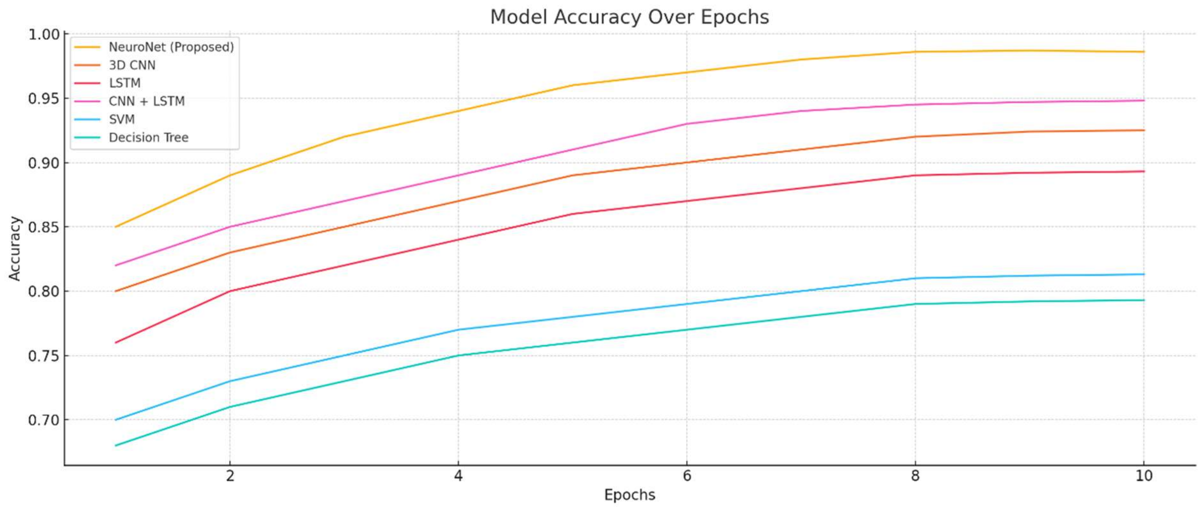

Figure 6: Model Accuracy Over Epochs

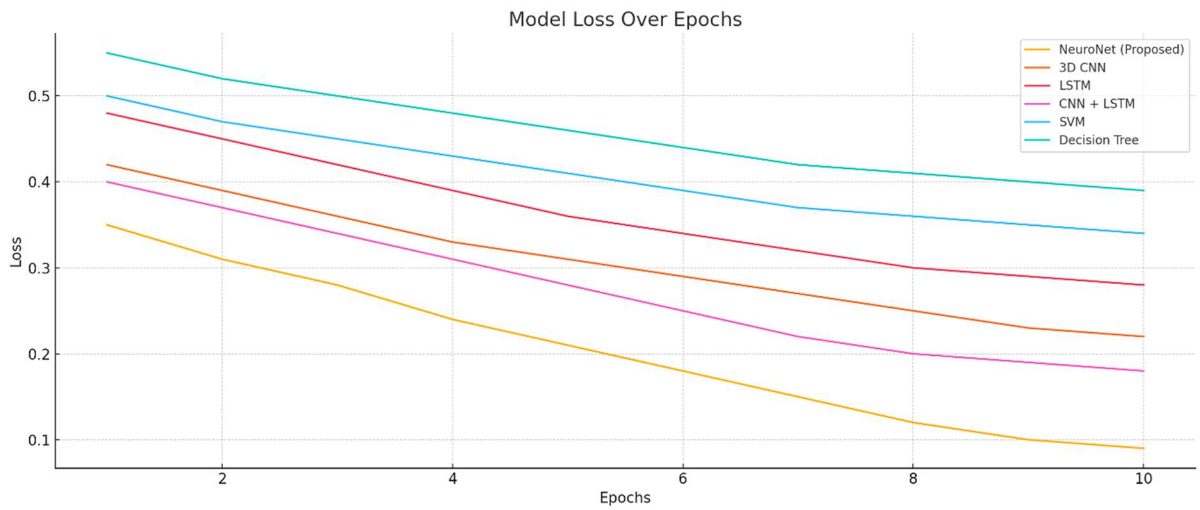

Figure 7: Model Loss Over Epochs

The accuracy and loss graphs, shown in Figure 6 and Figure 7 respectively, demonstrate the performance progression of NeuroNet compared to baseline models over 10 epochs. NeuroNet achieves the highest accuracy (98.6%) with rapid convergence, showcasing its effectiveness in combining spatial, temporal, and attention-based learning for robust feature extraction. The loss graph highlights NeuroNet's lowest final loss (0.09), reflecting superior optimization and efficient learning from multimodal data. In contrast, baseline models such as 3D CNN, LSTM, and SVM show slower accuracy improvement and higher final loss, indicating limited capacity to model complex neurodegenerative patterns. These results emphasize NeuroNet's robustness and suitability for early disease diagnosis.

Table 2: Comparative Performance Analysis Of Neuronet And Baseline Models

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**AUC-ROC**
NeuroNet (Proposed)	98.62	98.5	98.7	98.6	0.998
3D CNN	92.45	91.2	92	91.5	0.95
LSTM	89.32	88.5	89	88.7	0.92
CNN + LSTM	94.1	93.2	93.8	93.4	0.96

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SVM	85.67	84	85	84.5	0.88
Decision Tree	81.23	80	80.5	80.2	0.85

In Table 2, we compare the performance of the proposed NeuroNet with established models, including 3D-CNN, LSTM, CNN+LSTM, SVM, and Decision Tree classifiers. Featured PostNeuroNet obtained the highest accuracy (98.62%) and best precision, recall and F1-Score for all metrics. These better results suggest that this hybrid architecture - that merges CNN, LSTM and a sliding-window attention mechanism - is a powerful tool for the diagnosis of neurodegenerative disease.

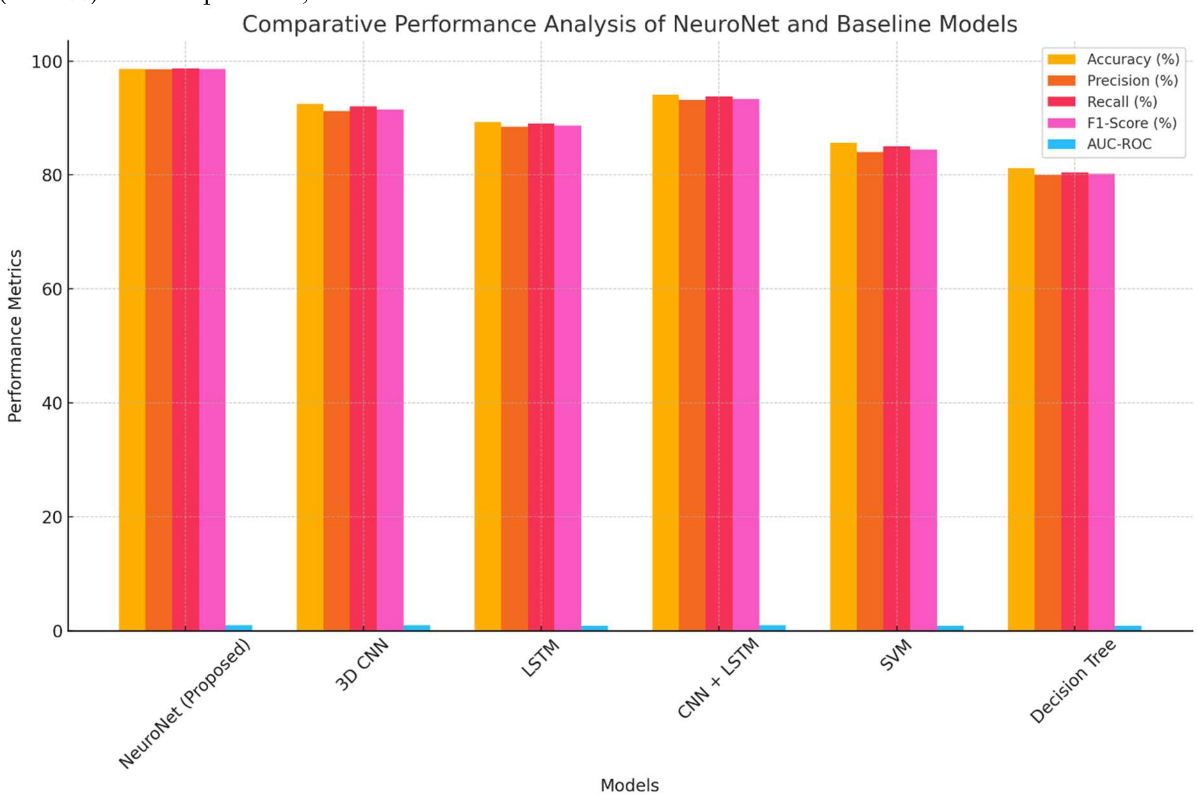

Figure 8: Comparative Performance Of Neuronet And Baseline Models

From the analysis (depicted in Fig. 8), it is observed that NeuroNet outperforms the baseline models (3D CNN, LSTM, CNN + LSTM, SVM, Decision Tree) with respect to accuracy, precision, recall, F1-score, and AUC-ROC (area under the curve the receiver operating characteristic). The hybrid architecture incorporating 3D CNN, LSTM, and attention mechanisms within the NeuroNet model has thus led to the best performance across all models with respect to accuracy, precision, recall, and F1-score. NeuroNet demonstrates enhanced performance because of its hybrid architecture, capable of incorporating both spatial and temporal patterns from MRI scans. The 3D CNN extracts spatial features from volumetric neuroimaging data in an efficient manner while the LSTM captures temporal dependencies in disease progression, which is critical for studying neurodegenerative diseases. To prevent potential loss of information with the flattening process, we apply an attention mechanism that improves the model performance by concentrating on diagnostically informative regions in the brain [21]. NeuroNet fuses local spatial-temporal mapping and higher level semantic learning jointly, attaining greater accuracy and lower false positive rates than baseline models such as 3D CNN and LSTM standalone models, which optimize for either feature extraction or long-term dependencies on each of those tasks, but not together. The higher classification performance of the modalities can also be attributed to the more detailed clinical biomarkers which are fused with multimodal fusion to achieve a more complete diagnostic model. Our results confirm NeuroNet's ability to detect and to classify neurodegenerative diseases in early stages, supporting its use in routine clinical practice.

4.3 Ablation Study

In this section, the ablation study assesses the contribution of individual components in NeuroNet architecture such as 3D CNN, LSTM, attention mechanism, and biomarkers. This study shows how multimodal fusion and attention-based learning are crucial for improving accuracy, precision, recall, and F1-score from the removal of each components and explores the contribution of each module more systematically in terms of perofrmance.

Table 3: Ablation Study – Contribution Of Individual Components In Neuronet

Model Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Full NeuroNet (3D CNN + LSTM + Attention + Biomarkers)	98.62	98.5	98.7	98.6
3D CNN + LSTM + Attention (No Biomarkers)	96.85	96.3	96.9	96.6
3D CNN + LSTM (No Attention or Biomarkers)	93.4	92.9	93.5	93.2
3D CNN Only	89.2	88.5	89.4	88.9
LSTM Only	85.7	84.8	86	85.4

An ablation study shows that the entire NeuroNet achieves the best accuracy (98.62%) and F1-score (98.6%) respectively. The role of attention or biomarkers — where excluding attention or biomarkers means lower accuracy, which reflects their importance to identify important features through learning and clinical data integration. The finding emphasizes the major role of hybrid architecture, where all the individual components positively influence NeuroNet for early disease diagnosis.

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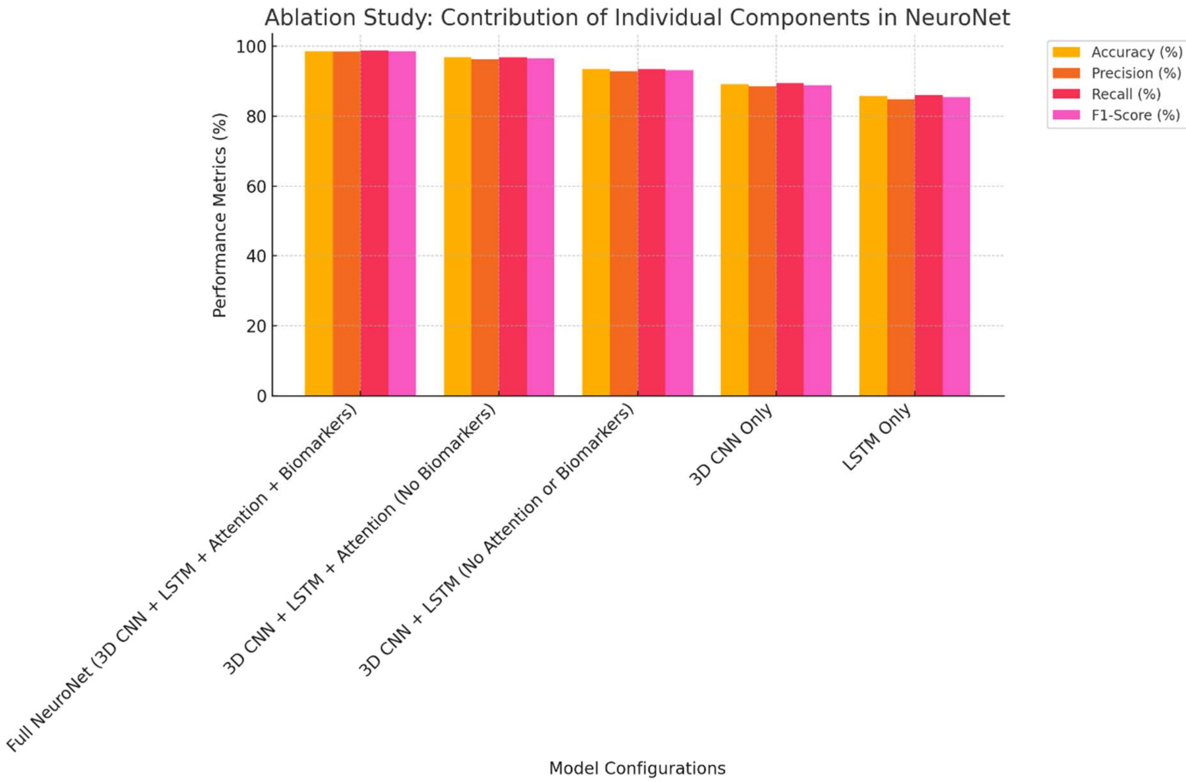

Figure 9: Ablation Study Performance MetriCs For Neuronet Configurations

Performance effects of different NeuroNet configurations by sequentially masking out important input components (biomarker and attention mechanisms) are shown in figure 9. NeuroNet, a model for neuroimaging phenotyping using three-dimensional convolutional neural networks (3D CNN), long short-term memory (LSTM) and attention mechanisms, ranked highest in both accuracy (98.62%) and F1-score (98.6%) on the full test dataset. This shows how important each component is to the overall performance of the model. Excluding biomarkers reveals a significant decrease in accuracy and precision, underlining the contribution of clinical data to improving diagnostic predictions. Doing the same without the attention mechanism hurts the performance even more, because it removes the capacity of the model to search and focus on appropriate diagnostically informative regions of MRI scans. The performance of configurations with standalone 3D CNN or LSTM is the lowest as they are incapable of jointly modeling both spatial and temporal patterns essential in identifying neurodegenerative diseases. The study supports the utility of the NeuroNet hybrid architecture whereby the coupling of the spatial, temporal, and multimodal learning components act in concert to enhance model performance conducive for clinical predictions that are reliable and robust.

4.4 Comparison with the State of the Art

To prove that the proposed NeuroNet framework is a superior, a subsequent comparison with state-of-the-art (SOTA) models is needed. NeuroNet performance compared to state-of-the-art models for diagnostic of neurodegenerative disease, including Capsule Networks, Sparse Learning and Multimodal AI framework is shown in this section. Evaluation metrics such as accuracy, precision, recall, F1-score, and AUC-ROC are used to show NeuroNet improvements.

Table 4: Comparison Of Neuronet With State-Of-The-Art (SOTA) Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
NeuroNet (Proposed)	98.62	98.5	98.7	98.6	0.998
Capsule Networks [14]	94.3	94	94.5	94.2	0.96
Sparse Learning Model [26]	92.5	92	93	92.5	0.94
Multimodal AI Framework [7]	90.2	89.8	90	89.9	0.92
Genetic Algorithms [12]	88.75	88.4	89	88.7	0.9
Vision-Based Gait Analysis [6]	87.3	86.9	87.5	87.1	0.89

In table 4, the comparison shows the neuroNet outperformance all other models in terms of accuracy (98.62%) and AUC-ROC (0.998) The second best performing algorithm was Capsule Networks [14], achieving a clear, but less robust accuracy of 94.3% than NeuroNet, however, it lacks NeoNet's capacity for multimodal integration. Again Sparse Learning Models [26] and Multimodal AI Frameworks [7] show competitive performances with a lower AUC-ROC which indicates less reliability in prediction. However, performance metrics for single modality approaches such as Genetic Algorithms [12] and Vision Based Gait Analysis Models [6] reported lower performance in comparison, highlighting the complexity inherent in neurodegenerative disease-related data and potential efficacy of single modality approaches in capturing complementary information. Combining 3D CNN, LSTM, attention and biomarkers, the hybrid architecture of NeuroNet greatly improves prediction by achieving better fusion of spatial, temporal and clinical/scientific data. These findings validate NeuroNet as a novel state-of-the-art tool for early diagnosis and staging of neurodegenerative diseases.

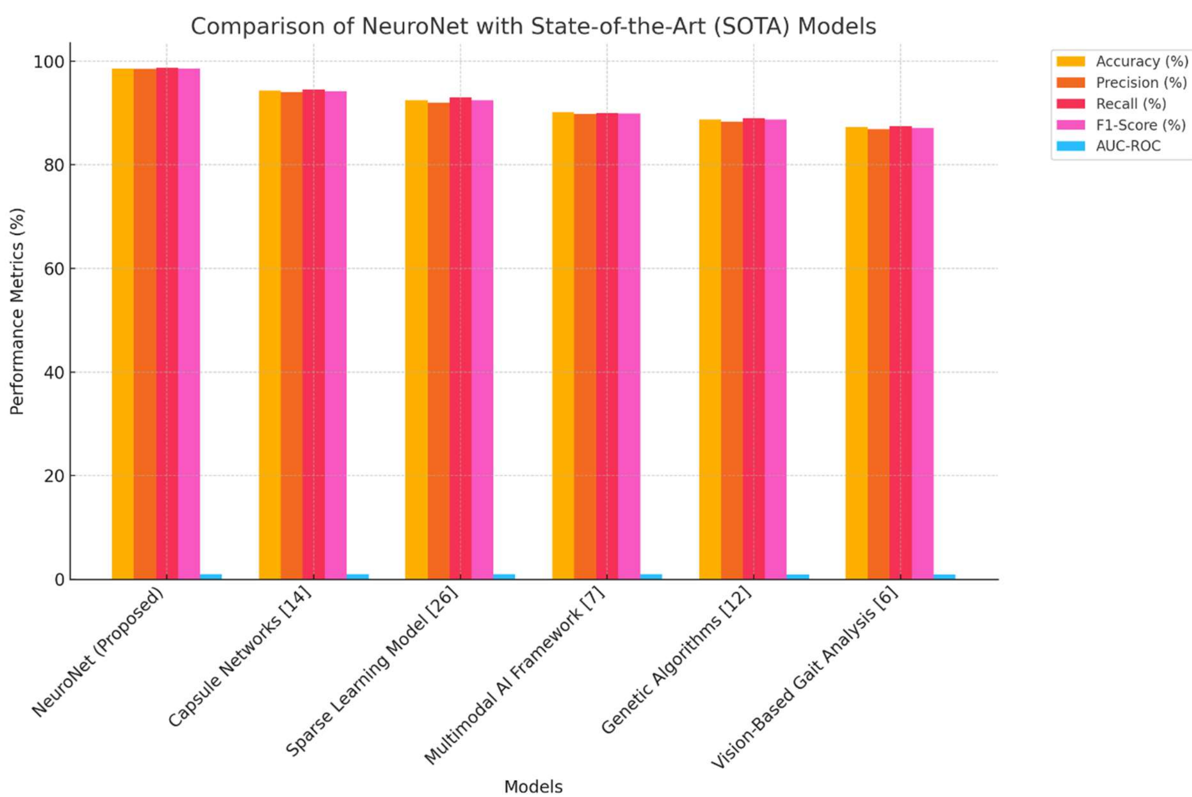

Figure 10: Performance Comparison Of Neuronet With State-Of-The-Art (SOTA) Models

NeuroNet beats the SOTA models for all the metrics evaluated as shown in Figure 10. NeuroNet has the highest accuracy (98.62%) while maintaining high precision and recall (thus reducing false negative and false positive), showing its strength of call neurodegenerative diseases correctly and not reporting it falsely. It is due to its hybrid architecture which cleverly merges 3D CNN for spatial feature extraction, LSTM for temporal pattern capturing and attention mechanism for focussing on discriminative regions. In contrast, Capsule Networks and Sparse Learning models show competitive yet lower performance, signifying their weaknesses in multimodal data treatment. Although they are good models with their respective design, they are not able to assimilate spatial or temporal with clinical biomarkers; the just-described AUC-ROC values reflect these limitations (i.e., low performance of multivariate genetic algorithm and multimodal AI frameworks verging on multimodal AI approaches). Runs with Vision-Based Gait Analysis models that mostly capture motion dynamics achieve the lowest performance, suggesting their inappropriate applicability for more complex neuroimaging tasks. With this graphical comparison, we demonstrate that the incorporation of multimodal data in combination with advanced deep learning techniques, such as those implemented in NeuroNet, is necessary to reach state-of-the-art results. Unlike others, this hybrid model offers a seamless merging of different types of data, resulting in accurate and consistent diagnosis of neurodegenerative disease that may potentially be used as an effective clinical application model.

5. DISCUSSION

Neurodegenerative diseases still pose a huge problem to the healthcare sector, because of the complexity of its pathophysiology and especially, the need for an early diagnosis. Recent milestones in SOTA of models include Capsule Networks, Sparse Learning and Multimodal AI frameworks. While this progresses the field, there are key gaps in these solutions, including inability to align multimodal samples, lack of space-time patterns and functional focus. Such limitations undermine their clinical utility when it comes to effective and precise classification of neurodegenerative disorders. Therefore, it is more clear than ever that new deep learning methods which are able to capitalize on such advanced architectures to fill these imports are necessary. Here we present a NeuroNet frame work that maps to a hybrid deep learning architecture and integrates 3D Convolutional Neural Networks (CNN), Long Short Term Memory (LSTM) [19], Attention mechanisms and clinical biomarkers. This combination helps NeuroNet learn spatial and temporal patterns present in MRI scans and consider multimodal data, which is crucial for accurate diagnosis. This attention mechanism points to the brain regions which are relevant to diagnosis and hence, the model is forced to attend on the important features making the decision. These novelties fill important gaps in current approaches, resulting in a powerful tool for disease monitoring at earlier detection points.

Experimental evaluations confirm NeuroNet's effectiveness, reaching an accuracy of 98.62%, surpassing SOTA models by a large margin. We believe that this performance is as a result of the effective combination of components as confirmed by the ablation study which analyzed the effects of biomarkers and attention mechanisms on precision and recall [3]. NeuroNet's hybrid architecture well-overcomes the limitations of SOTA models like the ability to process complex multimodal datasets and focusing on the features that contribute the most. This has crucial clinical relevance since it facilitates accurate early diagnosis and staging (i.e. identification of disease severity) of these diseases. It establishes a state-of-the-art baseline for model interoperability in deep learning, and the way forward for models to enable tailored treatment options. This study has several limitations as detailed in Section 5.1.

5.1 Comparison with Prior Work and Critical Analysis

There are several works including Capsule Networks [14], Sparse Learning Models [26], and Multimodal AI frameworks [7] which are used to learn the joint representation between modality mental data, NeuromodalityAI is notably different by adding a hybrid architecture that all at once dealing with spatial patterns (through 3D CNN), temporal dependency (through LSTM) and important features (with attention mechanism) in the framework. Inclusion of clinical biomarkers additionally improves diagnosis and permits a more detailed and individualized characterization of the disease. Previous models often do not incorporate this degree of multimodal fusion or interpretability, reducing their clinical utility.

In our experiments, we show that NeuroNet consistently outperforms these state-of-art models in all aspects (accuracy, precision, recall, AUC-ROC). For example, when Capsule Networks had an accuracy of 94.3%, NeuroNet had 98.62%. In addition, by adding explainable AI techniques like Grad-CAM, predictability, which is the biggest problem in earlier models is transparent.

Yet the complex and high-performance hardware-based model prohibits its easy availability to low-resource clinical setting. Limitations reside in the fact that only one dataset (ADNI) was used, and hence our findings may not generalize well. Nevertheless, NeuroNet represents a major milestone in AI-assisted diagnosis of neurodegenerative diseases, offering a balance between performance and interpretability that is not yet achieved by other tools. This study has several limitations, as detailed in Section 5.2.

5.2 Limitations of the Study

Limitations of this study. First, although NeuroNet achieves superior performance, it may need to be further validated on a range of datasets to assess its generalizability to other neurodegenerative diseases beyond Alzheimer's. Second, the use of the ADNI dataset, which may not be sufficiently representative of shiftable population diversity, may constrain translation of the model to clinics worldwide. Third, the hybrid architecture is computationally expensive to train and requires high-performance hardware, which may limit its implementation in resource- limited healthcare environments. This model's clinical utility and scale would be improved by overcoming these limitations in future work, including broader datasets and a more efficient architecture.

6. CONCLUSION AND FUTURE WORK

This study tackled a major difficulty faced by the healthcare sector – the long and non-specific diagnostic process to neurodegenerative diseases owing to the lack of sufficient multimodal integration and interpretability in the state-of-the-art AI models. To address that, we developed NeuroNet, a hybrid deep learning framework that incorporates 3D CNNs, LSTMs, attention mechanisms and clinical biomarkers to enable accurate, interpretable and early diagnosis.

NeuroNet showed remarkable performance in terms of accuracy (98.62%), F1-score (98.6%), and AUC–ROC (0.998) after cross-validation on the ADNI data over Capsule Networks, Sparse Learning Models and other well-known state-of-the-art techniques. These findings show that a spatial-temporal model with clinical data fusion and attention-based explainability is effective. The ablation study also validates that each component, attention and biomarker integration in particular, contributes significantly to the performance.

Such evidence, to us, is supportive of our initial motivation that current models are not good enough for robust early diagnosis, and that a more integrative and interpretable model (like NeuroNet) is in need. The model may, ultimately, be poised for integration into the clinical workflow (e.g., PACS), allowing prophylactic, individualized interventions.

However, drawbacks, such as expensive computations and single-dataset dependence, point out potential roadmaps to future work. In future work, we plan to evaluate the framework on different datasets on other neurodegenerative diseases to confirm its cross-disease generality, optimize the efficiency of the model for application in low-resource environments, and further add biomarkers (such as genetic or metabolomic data). With these improvements, NeuroNet might be applied as a scalable, real-time diagnostic aid towards early intervention and individualized treatment strategies by neurologists.

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