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Deep Learning Models with NeuroSense Optimization in Neurological Biosensing for Early Diagnosis of Cognitive Impairments

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Abstract:

Neurodegeneration in Alzheimer's disease (AD) causes progressive intellectual deterioration, manifested as memory loss, impairment in reasoning skills, and language deficits. Because of the subtlety of this incremental process coupled with the intricacy of neurological data, early diagnosis of cognitive impairments, particularly AD, ranks as one of the most challenging tasks. The early diagnosis of AD using available techniques remains a big challenge because these methods face difficulties in detecting the disease at an early stage due to the variability in biomarkers and challenges in processing brain signals effectively. These issues are addressed by proposing a new framework called NSNLB-CNN-AD, combines a Convolutional Neural Networks (CNNs) -based deep learning model with NeuroSense Optimization (NSO) in Electroencephalography (EEG)-based Neurological Biosensing (NLB) for early AD detection. In the proposed framework, CNNs have been employed to process multichannel EEG signals, thus providing continuous monitoring of subtle neurophysiological changes that suggest cognitive decline. The NSO algorithm enhances the performance of CNN by hyperparameter optimization-feature extraction so that maximum spatiotemporal patterns relevant to the underlying process in the EEG data are captured. Thus, the model can detect early-stage cognitive impairments even in the preclinical phase of AD. The proposed technique utilizes EEG biosensors to capture changes in functional brain activity, which offers easily accessible and affordable alternatives compared to traditional imaging techniques. The optimized CNN model significantly improves early diagnosis accuracy, with an accuracy rate of 98% in distinguishing early-stage AD from healthy subjects, while having much higher sensitivity and specificity than other conventional EEG-based diagnostic methods. This enhanced deep-learning framework provides neurologists with a robust, scalable tool for reliably accomplishing early detection of cognitive impairment and enabling timely interventions that improve patient outcomes.

Keywords: Electroencephalography, deep learning model, Convolutional Neural Networks, NeuroSense Optimization, Neurological Biosensing, Alzheimer's disease, Cognitive impairment.

1. Introduction

A neurodegenerative illness that worsens over time is Alzheimer's. The destruction of brain cells causes memory loss and cognitive impairment in this neurodegenerative condition. It is believed to be the most prevalent kind of dementia and has a profoundly detrimental impact on people's personal and social lives. [1]. AD serves as a paradigm for the evolution of our understanding of neurodegenerative diseases and a model for the role that postmortem evaluation of the brain plays in understanding disease mechanisms. The initial case report by Alois Alzheimer correlated a clinical syndrome of dementia with distinctive neuropathological findings [2]. Intracellular neurofibrillary tangles and the continuous accumulation of extracellular amyloid beta plaques are two essential clinical markers of Alzheimer's disease (AD). AD is a neurodegenerative illness that continuously progresses in cognitive, functional, and behavioural deficits [3]. The current global prevalence of Alzheimer's disease (AD) is 50 million, and by 2050, researchers predict that number will have multiplied fivefold, reaching 152 million. Due to the estimated $1 trillion

in annual global costs associated with AD, the burden impacts not just individuals and families but also the economy. Medications exist to alleviate symptoms of AD, but there is no cure currently. [4]. The use of sophisticated EEG signal processing to forecast or distinguish AD has gained increasing attention during the past few decades. Neuroimaging research is one of the main methods for determining the etiology of AD and improving the precision of AD diagnosis [5]. These tests provide many data that need to be carefully examined for the pattern the individual is looking for, making it difficult to evaluate the EEG data. If manual labor is required, qualified medical professionals must perform this task [6].

Medical imaging analysis has, over the years, resulted in advanced, sophisticated tools being employed in diagnosing neurodegeneration; interest in using imaging data to diagnose diseases has increased [7]. A cognitively normal (CN) or normal aging MRI is considered healthy. There is no known stimulant that causes AD; instead, the disease is caused by a genome that influences it. However, heredity, a lack of education or experience in the workforce, mental inactivity, family history, and internal or external brain traumas are among the risk factors for AD [8]. Deep learning methods, such as CNN and sparse autoencoder, performed better than machine learning methods. Even though deep learning showed its robust performance, some challenges remain. Large computing resources are required to train deep-learning networks on extensive image data [9]. It is commonly believed that Choline Esterase Inhibitors (ChEi) medication is more successful when administered before to the onset of extensive degenerative alterations, which further supports an early diagnosis of AD [10].

EEG-based NLB represents a non-invasive and low-cost modality to record brain activity, essential in understanding cognitive processes. However, EEG signals are noisy, high-dimensional, and difficult to comprehend. Traditional techniques using handcrafted features or shallow models generally fail to identify subtle patterns related to early cognitive impairments. Deep learning models, specifically Convolutional Neural Networks, have performed very well in extracting raw EEG features related to space and time dimensions. This has facilitated a much more robust analysis of early Alzheimer's disease diagnosis. However, CNN optimization for EEG-based AD detection still faces difficulties because of dynamic EEG signals and redundant features that tend to interfere with model performances. Considering these issues, this research will introduce NSNLB-CNNAD couples CNN with NeuroSense Optimization. This bio-inspired algorithm fine-tunes hyperparameters and enhances feature extraction on CNN, strengthening precision and ensuring quick identification of cognitive impairments.

The Key significance of this study is

- To identify early signs of Alzheimer's disease (AD), even during the preclinical stage, which could lead to better patient outcomes if interventions could be implemented promptly.
- To achieve a remarkably high accuracy of 98% in distinguishing early-stage AD from healthy subjects, surpassing conventional EEG-based diagnostic methods.
- To offer a more accessible and cost-effective diagnostic tool for AD by utilizing EEG biosensors instead of more expensive and less available imaging techniques.
- To enable continuous monitoring of subtle neurophysiological changes, allowing for the tracking of cognitive decline over time.

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- To process complex neurological data more effectively by combining Convolutional Neural Networks (CNNs) and NeuroSense Optimization (NSO), capturing relevant spatiotemporal patterns in EEG signals.
- To potentially adapt this approach for detecting other cognitive impairments or neurological disorders beyond AD.
- To provide neurologists with a robust and scalable tool for reliable early detection, potentially enhancing clinical practice in diagnosing and managing AD.

The NSNLB-CNN-AD framework focuses on the early diagnosis of AD, as it combines CNNs with NSO for EEG-based neurological biosensing. These CNNs process the multichannel EEG signals to monitor subtle neurophysiological changes, with NSO optimizing the hyperparameters to improve feature extraction and increase detection accuracy. This noninvasive approach offers a cost-effective alternative to conventional imaging, which reached 98% accuracy in distinguishing early-stage AD from healthy individuals. The high sensitivity and specificity of the model will allow for an early diagnosis of cognitive impairment, thus permitting early interventions and improving patient outcomes.

2. Related works

Diogo, V. S. et al. [11] used an ML-based approach dedicated to the rapid identification of AD based on structural MRI data. It used several classification and feature selection techniques like mutual information and evolutionary algorithms to achieve better predictive accuracy. The performance results were very high in the area under the curve. This strategy's operating characteristic curve (AUC) is 97.4%, indicating high clinical applicability. It aimed to enhance diagnostic precision and offer supportive outputs toward clinical decision-making, reflecting the need for a valid strategy for early AD detection.

The DEMentia NETwork (DEMNET) model was suggested by Murugan S. et al. [12] and employs a CNN for early detection of dementia and magnetic resonance imaging of Alzheimer's illness. Utilising the Synthetic Minority Over-sampling Technique (SMOTE) method, researchers rectify the dataset's class imbalance and attain enhanced performance. The overall accuracy was 95.23% according to these findings, with a 97% AUC on the test data and an accuracy of 84.83% on the ADNI dataset, hence proving the validity of DEMNET as a decision support system for medical doctors to predict the severity of dementia.

Arafa, D. A. et al. [13] proposed a deep learning framework that classifies the stages of AD using MRI images with two architectures: a CNN trained from scratch and a pre-trained VGG16 model. This was undertaken to enhance early diagnosis using advanced feature extraction and classification methods. As a result, the subsequent findings demonstrated that the accuracy rates for the suggested CNN model and the refined VGG16 model, respectively, reached 99.95% and 97.44%. The approaches presented here, therefore, become feasible and facilitate the analysis of medical images.

To identify the early stages of Alzheimer's disease, Kim et al. [14] suggested a multimodal three-dimensional deep learning approach based on mid-fusion. This approach would combine imaging data from MRI, 18F-FluoroDeoxyGlucose positron emission tomography (FDG-PET), Aβ PET, and Tau PET to extract the most informative features. The model

effectively learned complex relationships across modalities using depthwise separable convolution blocks and mixing skip connections for feature fusion, focusing on regions such as the hippocampus and temporal areas. A strong performance was reached: a balanced accuracy of 1.00 for AD vs. cognitively normal and 0.76 for MCI vs. cognitively normal proved that this model is effective in early detection.

Mehmood A. et al. [15] described a DL model for early AD detection based on transfer learning. The algorithm classifies MRI images into four categories: Alzheimer's disease (AD), LMCI (late mild cognitive impairment), EMCI (early mild cognitive impairment), and NC (normal control). This model followed the VGG model architecture with pre-trained weights since there is an issue with the limited number of available annotated datasets for transfer learning. In the end, the model's performance was pretty good: 98.73% accuracy for AD vs NC classification and 83.72% for EMCI vs LMCI.

Jia H. et al. [16] introduced the development of a data augmentation technique for better Alzheimer's disease detection based on functional connectivity data. This technique uses multimodal empirical mode decomposition to separate EEG signals into inherent mode functions and then recombines these IMFs, creating virtual trials that can expand on small datasets. Three neural networks underwent testing. ResNet, BrainNet CNN, and EEGNet. The results highlighted the following improvements: for ResNet, accuracy was increased by 5.24% for the mild Alzheimer's dataset and 4.50% for the mild cognitive impairment datasets.

Chen, S., et al. [17] introduced a multimodal classification methodology integrating EEG, eye movement, and behavioral data to diagnose AD and Mild Cognitive Impairment (MCI) early. Considering the imperative for noninvasive, inexpensive screening, several paradigms are applied in differential task difficulties, such as resting-state EEG and eye movement tasks for AD and delayed match-to-sample tasks for MCI. It performed exceptionally well in detecting AD, with 100% and 88.81% for MCI; hence, multimodal data fusion improves diagnosis performance.

Matlani, P. [18] presented a hybrid deep learning model, Bi-directional Long Short-Term Memory (BiLSTM) coupled with an Artificial Neural Network (ANN) to improve early AD diagnosis using MRI data. The advanced model is used here for increased diagnostic accuracy and reduced overfitting. Image preprocessing is done by adaptive Wiener filtering. Then, feature extraction is performed by the Principal Component Analysis, which uses a Normalized Global Image Descriptor (PCA-NGIST) approach, and the Improved Wild Horse Optimization (IWHO) algorithm enhances feature selection. The proposed model showed the accuracy on the ADNI dataset as 99.22% and on the OASIS dataset as 98.96%.

To facilitate the early detection of Alzheimer's disease (AD), Zhang, Y. et al. [19] developed a multi-modal Graph Neural Network (GNN) framework that integrates structural MRI (sMRI) and PET imaging data with phenotypic data like Mini-Mental State Examination (MMSE) scores. This work overcame the limitations of single-modality analysis and improved diagnostic accuracy. This framework performed node-level and adjacency matrix fusion, followed by a late fusion strategy to obtain the final predictions. The classification results are 96.68% for AD versus normal and 78% for differentiating stable MCI from progressive MCI, outperforming traditional methods.

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3. Proposed Work

a) Dataset Explanation

In the DEAP dataset [20], online self-assessment scored 120 one-minute music video snippets by 14–16 participants based on their dominance, valence, and arousal. participant assessments, physiological information, and face video from an experiment where 32 participants watched a variety of the 40 music videos previously described. Each participant scored the videos, and EEG and physiological data were captured. This task requires the extraction of data and labels from each channel into its own dedicated file. Data from all channels is stored for each participant trial in a row-wise column versus time.

b) Overall Working Process of the proposed NSNLB-CNN-AD method

Figure 1 presents the overall performance of the NSNLB-CNN-AD framework, showing its overall architecture from the acquisition of EEG data to the classification activity in the early detection of AD. Non-invasive EEG biosensors record continuous streams of electrical activity in the brain that could quickly detect subtle neurophysiological changes because of cognitive decline. The framework relies on CNNs to extract spatial and temporal patterns from multichannel EEG signals. This NSO performs hyperparameter optimization to increase the model's accuracy and robustness. Further streamlining is achieved, as it enables fast feature extraction and classifies early-stage AD from healthy subjects with an accuracy of as high as 98%. Thus, it proves to be a reliable tool for the speedy evaluation and management of this disease. The steps that follow provide a thorough explanation.

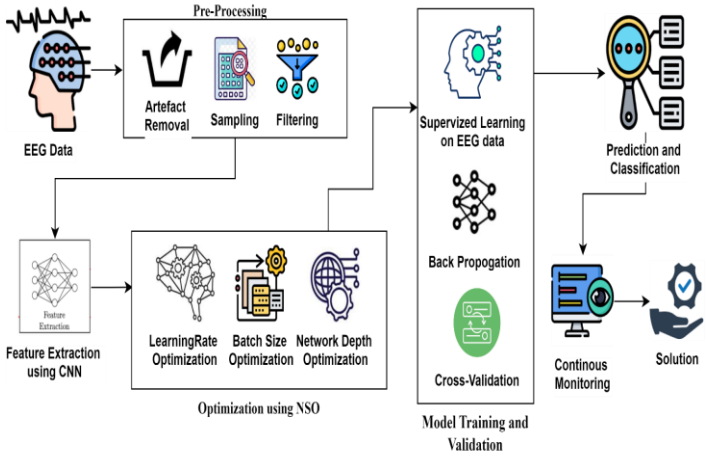

Fig.1 Overall performance of the proposed NSNLB-CNN-AD method

Data acquisition involves acquiring multichannel EEG data using EEG biosensors from early-stage AD patients and healthy controls. It is non-invasive and provides continuous recordings of the brain's electrical activity, allowing subtle monitoring of neurophysiological changes for a long time. The approach provides a rich dataset that forms the backbone for the analysis and early AD detection capabilities of the NSNLB-CNN-AD framework. The representation of EEG data is given in eqn 1.

$$Z(t) = [z_1(t), z_2(t), .., z_n(t)] \quad \text{(Eq.1)}$$

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where $Z(t)$ is the multichannel EEG signal at time t, z_i represents the signal from the i-th electrode (channel), and n is the entire array of electrodes.

Preprocessing of EEG Signals: During the pre-processing data stage, the raw EEG signals are refined to improve signal quality and remove irrelevant components. This is an essential step in which various techniques have been applied to cleanse and enhance the data. Many filtering methods remove the frequency bands linked with noise, whereas other artefact rejection algorithms identify and remove non-neural signals related to eye blinks or muscular movements. Then, the signal is normalized to standardize data from different recordings and subjects. All these preprocessing techniques will ensure that subsequent analyses are done at high quality and relevant neural signals to realise the framework's capability in detecting even minute AD changes. The cleaned EEG data $Z'(t)$ can be expressed as in eqn 2.

$$Z'(t) = Preprocessing\ (Z(t)) \quad \text{(Eq.2)}$$

Feature Extraction using CNNs: The NSNLB-CNN-AD framework has a CNN architecture specialising in multichannel EEG data analysis for recognising early warning indicators of Alzheimer's disease. This network architecture is specially designed to record the complex temporal and spatial patterns of the brain's electrical activity. The network's input layer consists of a 3D tensor, representing multichannel EEG data over time steps and features. Consecutively, the data gets hierarchically extracted by several convolutional layers. These layers employ 2D convolution on the temporal and spatial dimensions of the EEG signals together. Spatial filtering over the EEG channels detects region-specific patterns related to AD, whereas temporal conveys detect sequences and patterns along the time axis. Figure 1 shows the feature extraction procedure using CNNs.

Figure 2 illustrates how the CNN in the NSNLB-CNN-AD framework extracts spatial and temporal patterns from multichannel EEG data. Convolutional layers identify region-specific and sequential patterns, while pooling layers reduce dimensionality. Non-linear activations (e.g., ReLU) enhance learning, and the final sigmoid layer classifies subjects as healthy or AD-positive.

However, it also includes pooling layers that minimise the feature map sizes and add some translation invariance. There is non-linear activation after every convolutional layer, often ReLU since this nonlinearly allows the network to learn increasingly complex patterns. An architecture may include batch normalization to stabilize the learning process and generalize better, together with dropout to avoid overfitting. Toward the end of the network, there may be a global pooling layer to cut down on the number of parameters. The last few layers of the network comprise one or more fully connected layers that integrate features from all parts of the input, culminating in an output layer with activation of the sigmoid operation on binary classification of AD versus non-AD cases.

This convolutional operation is expressed as in eqn 3.

$$C_{ij} = \sigma\left(\sum_{a=0}^{A-1}\sum_{b=0}^{B-1} Z'_{(i+a)(j+b)} \cdot K_{mn} + b\right) \quad \text{(Eq.3)}$$

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where C_{ij} is the feature map value at the position (i,j), Z' is the input EEG matrix, K is the convolution kernel of size $A \times B$, b is the bias term, and σ is the activation function (e.g., ReLU).

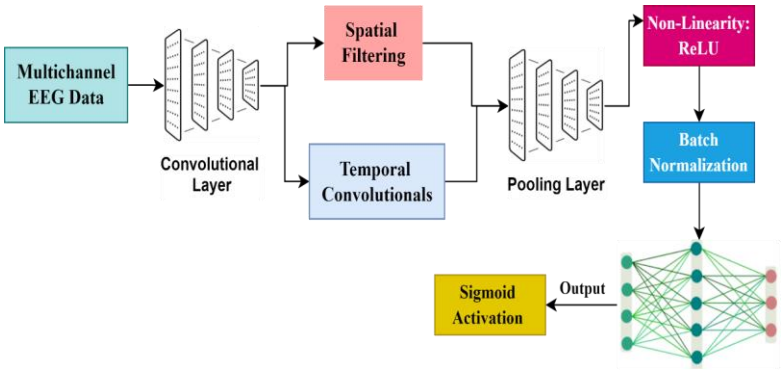

Fig.2 Feature Extraction Using CNNs

Hyperparameter Optimization using NeuroSense Optimization (NSO): The NSO algorithm ensures that key critical performance hyperparameters get optimized so that the CNN model can be fine-tuned in early AD detection. The learning rate modification is used to facilitate smooth and stable convergence during the training of this model. Thus, it keeps it from overshooting or converging very slowly. Further, the batch size is optimally chosen to balance training efficiency with generalization so that meaningful EEG patterns can be learned without leading to any overfitting. NSO determines the most optimal network depth, such that the architecture should be deep enough to represent the complex spatiotemporal features present in EEG signals but shallow enough to avoid any redundant complexity. Besides, it determines the dropout rate to avoid overfitting, enhancing its robustness and reliability over unseen data.

The principal aim of NSO is to reduce the loss function, such as cross-entropy loss, while maximizing performance metrics like accuracy and sensitivity. By optimizing these objectives, NSO ensures that the CNN model accurately captures subtle patterns in EEG data, which is crucial for early AD detection. The objective function for NSO is expressed as in eqn 4.

$$\theta^* = \arg min_\theta J(\theta) \quad \text{(Eq.4)}$$

where θ represents the hyperparameters and $J(\theta)$ is the cross-entropy loss function expressed in eqn 5.

$$J(\theta) = -\left(\frac{1}{m}\right)\sum_{i=1}^{m}(y_i \log(y_i') + (1-y_i)\log(1-y_i')) \quad \text{(Eq.5)}$$

where m is the quantity of training examples, y_i is the actual label and y_i' is the expected likelihood.

Model Validation and Training: The optimized CNN model is trained by supervised learning on labelled EEG data in the proposed framework of early AD detection. The dataset consists of healthy subjects and subjects with AD, allowing it to train on cognitive decline patterns. During supervised learning, CNN is fed with labelled EEG samples

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associated with the a priori labels, namely “healthy” and “AD.” The CNN learns from the relevant spatiotemporal features extracted from the EEG signals and maps these features to the corresponding labels. Iteratively, the weights of the CNN get adjusted to minimize the classification error; thus, it could classify AD at an early stage from unseen data with high accuracy. It finds the discrepancy between its forecasts and the real labels in the training data. It backpropagates through the network, updating weights with this error in such a way that it minimizes further errors.

The weight updates are made by applying the gradient descent algorithm. The formula for the weight update is given in eqn 6.

$$Weight_{t+1} = Weight_t - \omega \left(\frac{\partial J(\theta)}{\partial Weight_t} \right) \quad \text{(Eq.6)}$$

where $Weight_t$ is the weight matrix at iteration t, $Weight_{t+1}$ is the updated weight matrix at iteration $t+1$, ω sets the training rate, which finds out the increment size of on a regular basis, $\frac{\partial J(\theta)}{\partial Weight_t}$ is equal to the loss function's gradient $J(\theta)$ concerning the weights.

Cross-validation will ensure that the CNN model generalizes well to unseen data by splitting the dataset into several folds; this will reduce overfitting. In each iteration, a subset is held out for validation, while the rest are used for training, giving a reliable estimate of the model performance. This way, the model can find important patterns in the data rather than merely regurgitate it. While dropout regularization randomly turns off some neurons in each training step, allowing the network to learn multiple and diverse representations, cross-validation coupled with dropout makes the model more robust and accurate. A more realistic possibility of early Alzheimer's disease diagnosis emerges as a result.

Prediction and Classification Using the Trained CNN Model: Once the CNN model is trained and validated, it is deployed for binary classification of new, unseen EEG data to detect Alzheimer’s Disease (AD). The binary classification task aims to predict whether a given EEG sample belongs to either a healthy person or one in the early stages of AD. The prediction is expressed mathematically as in eqn 7.

$$P' = f(Z') \quad \text{(Eq.7)}$$

where P' is the predicted class label (0,1), 0 represents healthy, and 1 represents AD-Positive. Z' is the new EEG data fed into the model. $f(.)$ Refers to the trained CNN model function, processes the input data, and returns a prediction.

4. Result and Discussion

a) Performance Metrics

This section compares the proposed method with traditional methods, such as DEMNET [12], BiLSTM-ANN [18], and GNN [19], mentioned in the literature review, for metrics like accuracy, F1-Score, Specificity, and Sensitivity (Recall). The NSNLB-CNN-AD framework detected AD in the early stage with an accuracy of 98%. It is highly sensitive for the identification of actual positive AD cases and exhibits a high degree of specificity, evidenced by very few false positives for healthy subjects. Therefore, its balanced F1 score has guaranteed reliable detection- a robust tool for early AD diagnosis and intervention.

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Accuracy: The percentage of correct predictions (positive and negative) out of all predictions made by the model is called accuracy. It shows the way the model generally does at distinguishing between healthy people and people that test positive for AD. The more precise the model's classifications, the greater the accuracy value. Eqn 8 allows for its realisation.

$$A = \frac{(TP+TN)}{TP+TN+FP+FN} \quad \text{(Eq.8)}$$

where TP is the True Positives (correct AD predictions), TN refers to the True Negatives (correct healthy predictions), FP is the False Positives (healthy predicted as AD), and FN refers to the False Negatives (AD predicted as healthy).

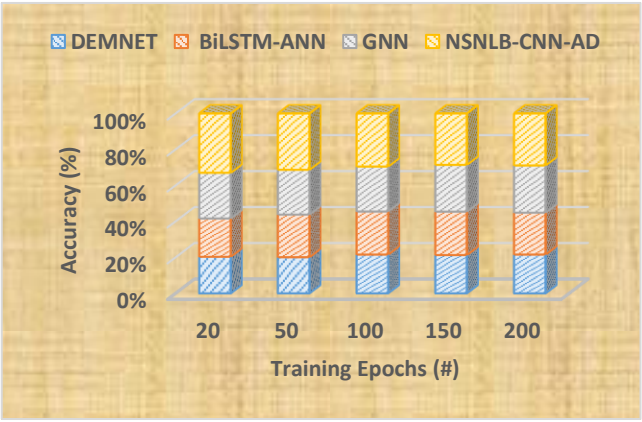

Fig.3 Accuracy Analysis

Figure 3 displays a comparison of the suggested NSNLB-CNN-AD framework's performance with those of other models, including GNN, DEMNET, and BiLSTM-ANN. CNN-based feature extraction combined with optimization of hyperparameters driven by NSO may support such high accuracy. This combination enables the detection of subtle EEG patterns associated with early AD. The results prove that the proposed framework possesses very strong performance and generalization, which can be employed to diagnose early AD with high reliability.

F1-Score: This performance statistic aims to find a happy medium between accuracy (the proportion of positive predictions that pan out) and recall (the model's ability to identify actual positives). Since it considers both FP and FN, it is especially helpful in cases where the dataset is unbalanced. This can be foreseen using equation 9.

$$F1 - Score = 2\left(\frac{Precision \times Recall}{Precision + Recall}\right) \quad \text{(Eq.9)}$$

where $Precision$ is obtained by the eqn 10, and $Recall$ is obtained by the eqn 11.

$$Precision = \frac{TP}{TP+FP} \quad \text{(Eq.10)}$$

Figure 4 presents the F1-score evaluates the suggested model against the existing alternatives. Keeping a healthy balance between recall and precision during early AD

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detection, the NSNLB-CNN-AD model outperformed all the categories investigated for the experiment, as seen in the figure. This is because the model enhances the ability to identify patients with AD positively, with reduced false negatives and positives. This turns into the fact that NeuroSense Optimization significantly contributes to the development of CNN model performance for more reliable early-stage AD diagnosis based on EEG records.

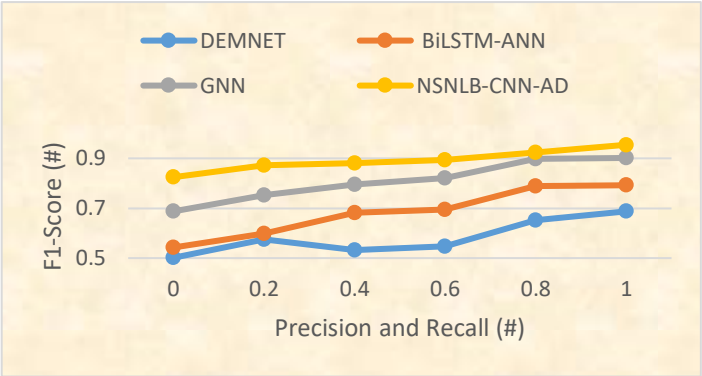

Fig.4 F1-Score Analysis

Sensitivity: or A measure of the accuracy of identifying true positive cases, is recall, often known as the True Positive Rate. This demonstrates the model's accuracy in identifying AD-positive individuals when applied to the detection context. Since missing AD-positive cases, such as false negatives, can delay early intervention, high sensitivity is critical. This can be achieved through equation 11.

$$Sensitivity\ or\ Recall = \frac{TP}{TP+FN} \qquad \text{(Eq.11)}$$

Figure 5 displays the results of the NSNLB-CNN-AD model's sensitivity analysis. It stands for the model's accuracy in detecting AD instances. The sensitivity obtained for the proposed model is high, which shows its strength in detecting true positive cases of early-stage AD. As can be perceived from the figure below, the NSNLB-CNN-AD model outperformed other methods with a higher sensitivity since CNNs can extract meaningful spatiotemporal patterns from EEG signals, and NeuroSense optimizes the hyperparameters for better detection of cognitive impairments at an early stage.

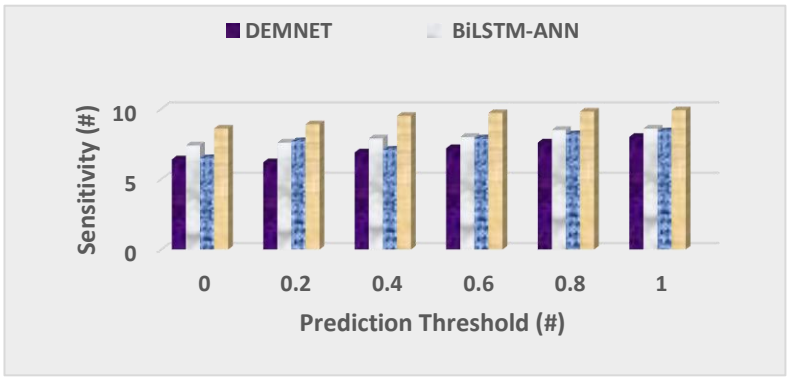

Fig.5 Sensitivity Analysis

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Specificity: This means that the specificity or so-called True Negative Rate means that the model can identify healthy subjects, that is, negative cases. For instance, considering the detection of AD, high specificity is not a coincidence when it guarantees that few healthy subjects are classified as AD-positive and when the misclassification of healthy subjects will have an extremely low rate of FP. This is to avoid putting them under stress and other unnecessary testing for healthy people. This can be calculated by the eqn 12.

$$Specificity = \frac{TN}{TN+FP} \quad \text{(Eq.12)}$$

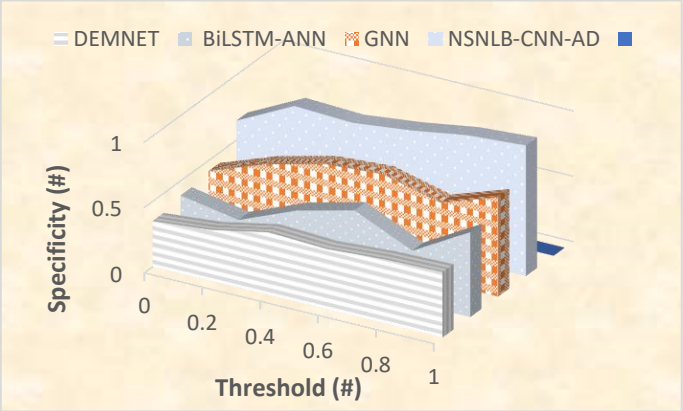

Fig. 6 Specificity Analysis

Figure 6 shows the specificity analysis of the NSNLB-CNN-AD model; this is generally the ability of the model to identify healthy ones correctly with a minimum number of misclassifications for AD cases. The high value for the specificity among the models provides adequate identification of the healthy subject without false alarms or positives. Such a performance result will serve to prevent stress and unnecessary medication conditions among people wrongly diagnosed with AD. Such feature extraction with CNN allows, together with NeuroSense optimization, a more précised differentiation between healthy and AD-positive cases.

5. Conclusion

The NSNLB-CNN-AD framework has presented a powerful, non-invasive approach to the early diagnosis of AD using EEG biosensing. By integrating CNNs with NeuroSense optimization, the proposed model developments have been made in feature extraction and hyperparameter optimization, enabling it to learn subtle neurophysiological patterns linked to early cognitive impairments. That would give an overall improved detection accuracy of 98%, outperforming the conventional diagnostic methods in sensitivity and specificity. This framework provides real-time brain monitoring, which is cost-effective compared to conventional imaging techniques, thus making it accessible for clinicians and researchers. The idea is dependent on EEG data, and this is one limitation that could defeat the model since signal noise and individual variability can create changeability in results. Increasing the size and diversity of the dataset may yield further improvements in generalizability at a larger population level and across different stages of AD.

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