Boruta Feature Selection and Deep Learning for Alzheimer's Disease Classification

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Abstract: Alzheimer's Disease (AD) is a progressive neurodegenerative disorder characterized by cognitive decline, memory impairment, and functional deterioration. The early and accurate classification of AD is crucial for timely intervention and management. This study utilizes the Boruta feature selection method to identify the most relevant features for AD classification, selecting the top 15 features based on importance ranking. Three machine learning models—Deep Neural Networks (DNN), Long Short-Term Memory Networks (LSTM), and Support Vector Machines (SVM)—were evaluated using accuracy, precision, recall, and F1-score as performance metrics. The LSTM model demonstrated the highest accuracy (89.30%), outperforming DNN (88.14%) and SVM (84.19%), owing to its capability of capturing temporal dependencies in inpatient data. Results indicate that deep learning models offer superior performance compared to traditional machine learning approaches in AD classification. The study emphasizes the importance of cognitive, lifestyle, and metabolic features in AD diagnosis while acknowledging limitations such as dataset constraints and model interpretability. Future research should improve explainability, incorporate multi-modal data, and leverage real-time monitoring techniques for enhanced AD detection.

Keywords: Deep learning, Feature selection, Boruta Feature Selection.

1. INTRODUCTION

Alzheimer's Disease (AD) is a progressive neurodegenerative disorder that leads to cognitive decline, memory loss, and severe impairment in daily functioning. As one of the most prevalent causes of dementia, AD poses a significant burden on healthcare systems and caregivers [1, 2]. Early diagnosis is crucial for effective intervention and management, as timely therapeutic strategies can help slow disease progression. However, traditional diagnostic methods, such as neuropsychological testing and neuroimaging, are often time-consuming, expensive, and require specialized expertise [3, 4]. Thus, there is a growing need for automated and reliable classification models to assist in the early detection of AD.

Machine learning (ML) and deep learning (DL) techniques have emerged as powerful tools in medical diagnosis, particularly in neurodegenerative diseases [5, 6]. Feature selection plays a critical role in improving classification performance by reducing dimensionality, eliminating irrelevant or redundant features, and enhancing interpretability [7, 8]. In high-dimensional datasets, it is crucial to identify the most significant features, and the Boruta algorithm, an advanced feature selection method, has gained popularity for this task [9, 10]. The proposed research aims to utilize Boruta to obtain the most significant features of AD for classification. Deep Neural Networks (DNNs) have remarkably performed in pattern recognition tasks like disease classification. DNNs are made of multiple layers of neurons, where each layer learns increasingly complex hierarchies of features from the input data, allowing complex patterns related to AD to be modeled. These deep learning methods have succeeded in sequential data analysis and medical diagnosis tasks, particularly with Long-term memory (LSTM), a recurrent neural network (RNN) type [11, 12]. LSTMs maintain long short-term memories so that long dependencies can be mapped in time-series data that is valuable in medical analysis. On top of that, SVMs are popular in biomedical studies because they have a sound theoretical background and can handle high-dimensional data [13, 14]. Irrelevant features can cause overfitting, resulting in lower accuracy and higher computational complexity. The Boruta feature selection technique resolves this challenge by retaining relevant features needed for the relevant classification and discarding those that are unimportant. This research improves classification accuracy and interpretability by incorporating feature selection with ML models. DNNs can capture complex non-linear relationships in the data to produce highly accurate predictions [15, 16]. However, they need a lot of training data and computing power. In order to improve performance, this work utilizes a systematic DNN architecture using several dense layers and dropout methods to avoid overfitting issues. In parallel,

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LSTMs are well-suited for modeling sequential relationships in medical data like EEG signals and speech patterns, effectively remembering relevant properties during long sequences. Since AD progression is a temporal pattern, LSTM networks serve as a good way to learn these changes and result in better classification performance.

The main contribution of this paper is outlined below.

- We have considered the Boruta feature selection algorithm to identify the most important features for AD classification.
- We have considered three classification models: Deep Neural Networks (DNNs), Long Short-Term Memory (LSTM) networks, and Support Vector Machines (SVMs).
- Performance comparison of these models using various evaluation metrics, including accuracy, precision, recall, and F1-score.

he paper is structured as follows: The second section provides a review of the related work on machine and deep learning for AD classification. Section 3 describes the methodology , including feature selection and model development. Section 4 presents the experimental setup, results, and analysis. Finally, Section 5 concludes the study and suggests future work.

2. Related Work

Authors [17] proposed integrates electroencephalography (EEG) signals, genetic data, and polygenic risk scores (PRSs) into machine learning models, comparing XGB, RF, and SVM for optimal classification. By combining EEG and genetic information, the SVM model achieved a high accuracy of 0.920, demonstrating the potential of a multimodal approach for enhancing AD diagnosis beyond traditional imaging constraints.

Authors [18] study reviews research from 2016 to 2024, analyzing various classification algorithms and confirming the superior performance of deep learning frameworks in AD classification. The findings highlight the effectiveness of advanced computational techniques in accurately categorizing different stages of the disease, aiding in improved diagnosis and treatment planning.

Authors [19] proposes an ensemble deep learning model incorporating Soft-NMS for improved candidate merging, an enhanced ResNet50 for feature extraction, and a Bi-GRU for processing sequential data, achieving a high classification accuracy of 98.91%. While the model demonstrates superior performance, future research should address data limitations, integrate multimodal imaging, and explore explainable AI for enhanced clinical applicability.

Authors [20] study proposes a reinforcement learning-based data augmentation method that adapts dynamically by using feedback during augmentation, improving classification accuracy. Experimental results on the ADNI dataset demonstrate superior performance over existing techniques across various evaluation metrics, highlighting the effectiveness of the proposed approach.

Authors [21] presents reviews on various machine learning approaches, particularly transfer learning models, for AD classification using neuroimaging data such as MRI, PET, and fMRI. By analyzing different phases of development, including image preprocessing and feature extraction, the study highlights challenges and research directions for improving automated AD detection systems.

Authors [22] proposes the EGELU-SZN technique, which processes MRI images using advanced segmentation and feature extraction methods to classify AD, CN, and MCI effectively. The experimental results demonstrate superior performance, achieving high accuracy (95.99%) and outperforming benchmark methodologies in classification metrics.

Authors [23] introduces ADNet, a deep learning model that enhances classification accuracy by integrating an inverted bottleneck, independent downsampling layers, and depth-wise convolutions. Experimental results demonstrate that ADNet outperforms existing models, achieving an impressive 99.81% accuracy with strong precision and recall across binary classifications.

Authors [24] study enhances the 3D-VGG-16 deep neural network by incorporating dropout, modifying fully connected layers, and integrating machine learning classifiers (GPC, SVM, RF) for improved classification accuracy.

Authors [25] presents recent advancements in deep learning-based AD detection, focusing on neuroimaging modalities, data preprocessing, and classification techniques. Additionally, it provides a comparative analysis of various deep learning models

and discusses challenges in AD detection and classification.

Authors [26] explores Alzheimer's disease (AD) classification using fractal and renormalization group approaches applied to multiscale brain networks. By integrating fractal metrics across different network scales, a fused feature vector was created, enhancing classification accuracy.

Table 1: Feature Importance Ranking for AD Classification

Feature	Rank
Memory Complaints	1
ADL	1
MMSE	1
Functional Assessment	1
Behavioral Problems	1
Sleep Quality	2
Cholesterol HDL	3
Cholesterol Triglycerides	4
Cholesterol LDL	5
Diet Quality	6
BMI	6
Physical Activity	8
Cholesterol Total	9
Alcohol Consumption	10
Diastolic BP	11
Systolic BP	12
Age	13
Education Level	14
Ethnicity	15
Cardiovascular Disease	16
Diabetes	17
Hypertension	18
Family History of Alzheimer's	18
Smoking	20
Difficulty Completing Tasks	20
Gender	22
Personality Changes	23
Forgetfulness	24
Confusion	25
Disorientation	26
Head Injury	27
Depression	27

3. PROPOSED WORK

Alzheimer's Disease (AD) is a neurodegenerative disorder characterized by cognitive decline and memory impairment. Early and accurate diagnosis of AD is essential for effective treatment and management. Machine learning (ML) techniques, especially deep learning models, have shown significant promise in classifying Alzheimer's Disease from clinical and imaging data.

In this study, we employ Boruta feature selection to identify the most relevant features for classification. The selected features are then used as input for three different classifiers: Deep Neural Network (DNN), Long Short-Term Memory (LSTM), and Support Vector Machine (SVM).

3.1. Feature Selection using Boruta Algorithm

Feature selection is a key process in machine learning that improves the performance of the models and reduces computational costs. The Boruta algorithm of random forest classifier variants, in many ways, acts as a wrapper of it and a recursive feature elimination process that creates shadow attributes to not just identify important features but significantly emphasize them with respect to randomized features.

3.2. Boruta Algorithm

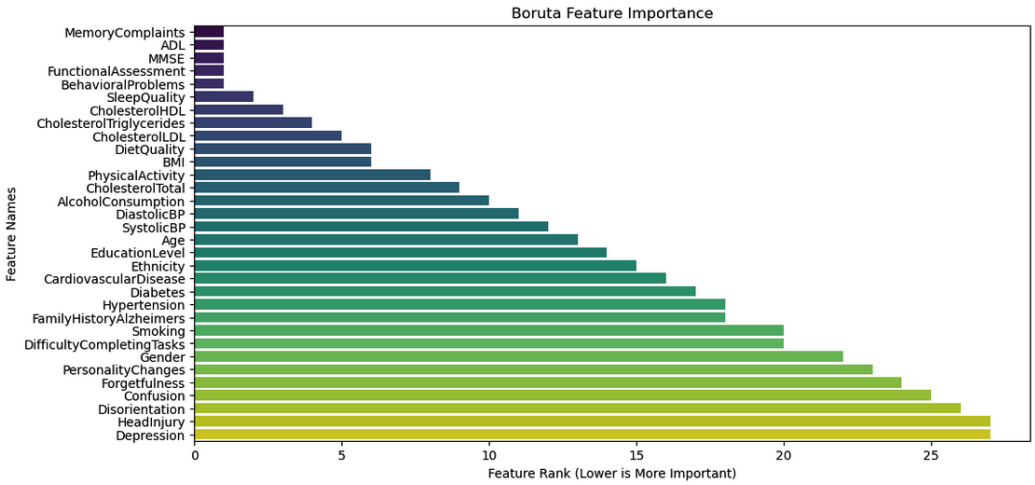
The Boruta Algorithm is a wrapper method in which features (X) are used as input for predicting (y) the target variable for a given dataset (D = X, y). Next, a classifier, in this case a Random Forest, is trained on the resulting combined data, where the original features are included with their shadow features. Using the Gini impurity measure (which is defined as

$$I(f_i) = T\sum_{t=1}^{T} I_t(f_i) \tag{1}$$

For a given feature $f_i), I(f_i)$ is the importance of that feature, $I_t(f_i)$ is the importance computed at tree (t). The subsequent step compares each feature's importance with the most important among shadow features, i.e., a feature (f_i) is selected.

$$fI(f_i) > \max(I_{shadow}) f_i^{selected} \tag{2}$$

Any features that perform worse than shadow features are discarded, and this process continues iteratively until convergence occurs. Using the Boruta



Figue 1: Boruta Faeture Rank.

algorithm, the 15 most important features were selected to train a classifier and it is described in the Table **1**.

3.3. Classification Models

Three classifiers were trained using the selected features: DNN, LSTM, and SVM.

3.4. Deep Neural Network (DNN)

A DNN is made of deep layers of neurons in which each layer learns fairly complex functions by applying non-linear activation functions. Our model has an input layer of 15 neurons representing each selected feature. It consists of multiple hidden layers for representational hierarchy. The initial one-hidden layer consists of 128 neurons in a dense layer with a ReLU activation function, mathematically expressed as

$$h_1 = \sigma(W_1 X + b_1). \tag{3}$$

To avoid the model overfitting, a dropout layer with a 30% dropout ratio is applied. The second hidden layer with 64 ReLU neurons expressed as

$$h_2 = \sigma(W_2 h_1 + b_2), \tag{4}$$

Then, there is another dropout layer with a 30% rate. For binary classification, the output layer uses a sigmoid activation shown as

$$\hat{y} = \sigma(W_3 h_2 + b_3). \tag{5}$$

3.5. Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) that is particularly effective for sequence learning. Although it is typically used for time-series data, we reshape our features into a sequence format to take advantage of LSTM's memory capabilities. The input layer consists of 15 features, which are reshaped into a sequence of shape (15,1). The network includes two LSTM layers to capture temporal dependencies. The first LSTM layer consists of 50 units with return sequences enabled, allowing the full sequence of hidden states to be passed to the next layer. This is mathematically expressed as

$$h_t = \sigma(W_h h_{t-1} + W_x X_t + b_h), \tag{6}$$

where h_t represents the hidden state at time step t, X_t is the input at t, and W_h, W_x, and b_h are the respective weight matrices and bias term. To mitigate overfitting, a dropout layer with a 30% dropout rate is applied after this LSTM layer. The second LSTM layer consists of 25 units and does not return sequences, ensuring that only the final hidden state is passed to the subsequent layer. Another dropout layer with a 30% rate is included to further regularize the network. Finally, a dense output layer with a sigmoid activation function is used for binary classification. The model is trained using the Binary Cross-Entropy loss function and optimized using the Adam optimizer to achieve efficient learning.

3.6. Support Vector Machine (SVM)

SVM is a powerful classifier that finds the optimal hyperplane to separate classes using the decision function:

$$f(X) = w^T X + b \tag{7}$$

where w and b are learned parameters. We used a linear kernel for binary classification.

4. RESULTS AND DISCUSSION

Feature selection is a crucial step in Alzheimer's Disease (AD) classification, helping to reduce dimensionality, improve model performance, and enhance interpretability. In this study, the Boruta feature selection method was employed, identifying the most relevant features by iteratively comparing them with randomly permuted shadow features. The ranking of various features based on their importance in AD classification revealed that Memory Complaints, Activities of Daily Living (ADL), Mini-Mental State Examination (MMSE), Functional Assessment, and Behavioral Problems were the most critical. These features are strongly associated with cognitive decline and serve as key indicators in the clinical diagnosis of AD.

Furthermore, Sleep Quality, Cholesterol Levels (HDL, LDL, Triglycerides, and Total), Diet Quality, Body Mass Index (BMI), and Physical Activity were identified as important predictors, thereby indicating the role of both lifestyle and metabolic factors in the progression of AD. Indicators of cardiovascular health (Diastolic and Systolic Blood Pressure), along with metabolic conditions (Diabetes, Hypertension, and Family History of Alzheimer's), contributed to AD classification, although with lower importance rankings. In order to tune the performance of the model while keeping it as simple as possible, the best 15 features were brought forward to be used in classification. Deep Neural Networks (DNN), Long Short-Term Memory Networks, and Support Vector Machines were used to assess the classification models. The models were evaluated based on accuracy, precision, recall, and F1 score. Accuracy is defined as the proportion of correctly classified instances:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{8}$$

Precision measures the fraction of true positive instances among all positive predictions:

$$Precision = \frac{TP}{TP + FP} \tag{9}$$

Recall, also known as sensitivity, quantifies the ability of the model to correctly identify positive instances:

$$Recall = \frac{TP}{TP + FN} \tag{10}$$

F1-Score provides a harmonic mean between precision and recall:

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{11}$$

Where TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) represent the four types of classification results. The accuracy of the DNN model was equal to 88.14%, the precision was 86.96%, the recall was 78.43%, and the F1-score was 82.47%, respectively. The model showed an excellent classification performance thanks to its ability to learn complex data relations. Nevertheless, the recall score indicates that there may be some false negatives here, which indicates the need for greater sensitivity. The results are described in the Table **2**. The LSTM model achieved the best scores, with an accuracy of 89.30% and a precision of 85.43%, recall of 84.31%, and F1-score of 84.87%. The significantly better performance of LSTM is likely due to its strength in capturing temporal dependencies in the data, which is crucial for recognizing the sequential pattern of cognitive decline in AD patients. Support Vector Machine (SVM): accuracy is 84.19%, precision is 80.58%, recall is 73.20% , and F1-score is 76.71%. Though SVM is a more sophisticated classifier, its lower recall score suggests it struggles to detect all positive cases correctly. This indicates that deep learning models like DNN and LSTM can better capture the non-linear and high-dimensional relationships among AD-related features. The performance results show that deep learning models, especially LSTM, have performed far better than traditional machine learning approaches such as SVM. This LSTM feature of sequential modeling resulted in superior classification accuracy. Although DNN has the highest overall accuracy among these methods, it possesses lower recall than LSTM

Table 2: Results

Model	Accuracy	Precision	Recall	F1-Score
DNN	0.881395	0.869565	0.784314	0.824742
LSTM	0.893023	0.854305	0.843137	0.848684
SVM	0.841860	0.805755	0.732026	0.767123

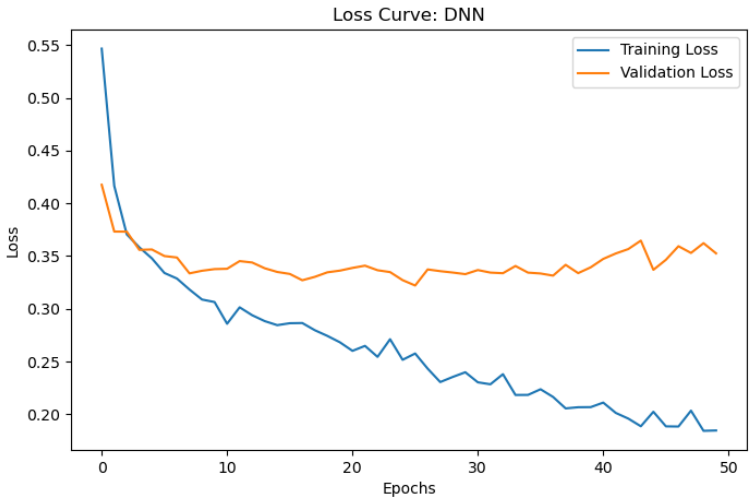


Figure 2: Loss Curve DNN.

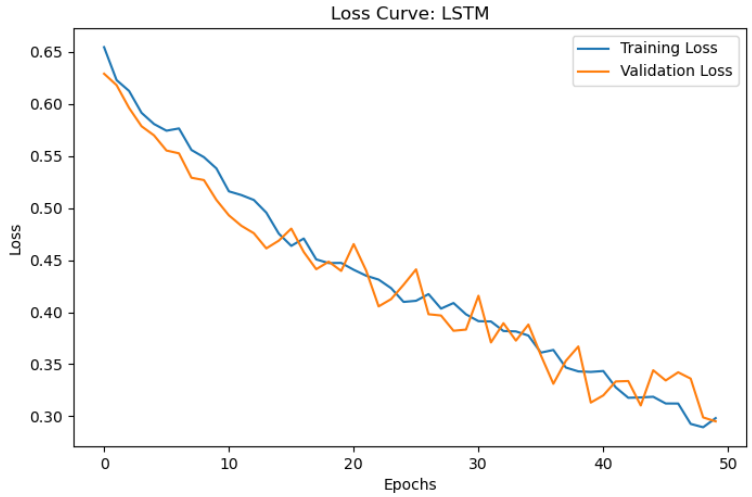


Figure 3: Loss Curve LSTM.

and thus suffers from an inability to accurately classify some AD-positive cases. This underscores the need for better sensitivity to further our ability for early diagnosis. The findings strongly support the clinical relevance of key features. The fact that Memory Complaints, ADL, MMSE, and Functional Assessment are ranked so high reestablishes their significance in clinical diagnosis by established AD diagnostic criteria. Furthermore, lifestyle and metabolic factors, including Sleep Quality, Cholesterol Levels, and Physical Activity, underscore more modifiable risk factors in AD progression and prevention. Unfortunately, despite the promising results, there are some limitations. Data size and diversity may limit generalizability, and larger, more diversified datasets should be explored for future validation. Although deep learning models showed high performance, they demand more computational resources and generally work in a "black box" manner. Future work should consider explainability methods to improve the interpretability of the models. Moreover, incorporating multimodal data, including genetic markers, imaging, and longitudinal cognitive assessments, could provide more accurate classifications. Wearable sensors and artificial intelligence still have the opportunity to perform real-time monitoring and diagnostics that could lead to early diagnosis and treatment. Feature selection matters in AD classification; cognitive, lifestyle, and metabolic factors were heavily weighted. Among all classification models, LSTM showed the best accuracy, showing the ability to learn sequential dependencies in ADGI. Deep learning methods have considerable promise in supporting early diagnosis, but more work is needed to improve interpretability and practice applicability. Developing machine learning methods for AD diagnosis can improve accuracy and assist in patient

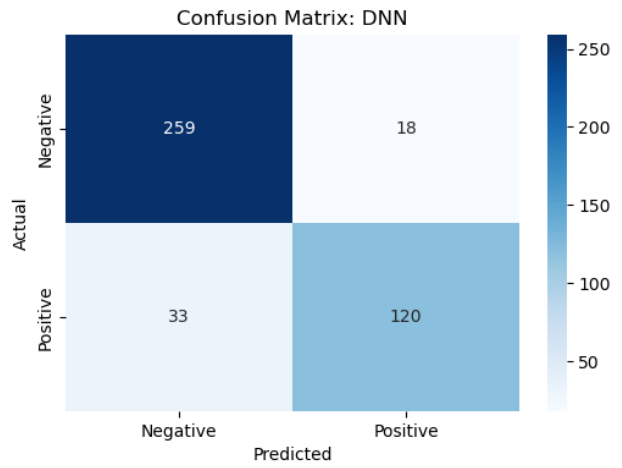


Figure 4: Confusion Matrix DNN.

management strategies. The loss curve of DNN and LSTM are described in Figures **3** and **4**. The confussion matrix of DNN, LSTM and SVM are depicted in Figures **4**, **5** and **6**.

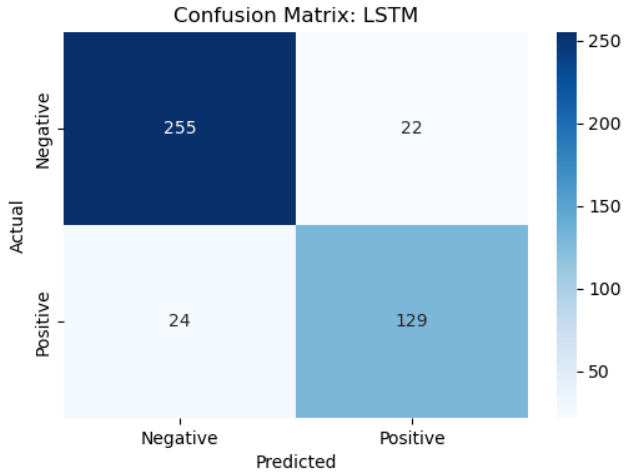


Figure 5: Confusion Matrix LSTM.

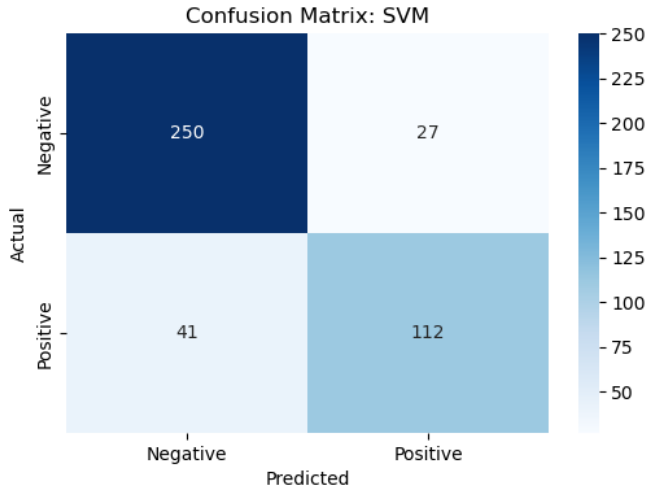


Figure 6: Confusion Matrix SVM.

5. CONCLUSION

The proposed study highlighted that feature selection and deep learning models play a pivotal role in the classification of the disease and are promising findings in the field of Alzheimer's Disease. The study, therefore, underscores the importance of cognitive, lifestyle, and metabolic risk factors in AD diagnosis by employing the Boruta method for identifying the most relevant predictors. The LSTM model showed an accuracy superior to classification, highlighting how well the LSTM captured sequential patient data dependencies. Deep learning models perform better than traditional generalization approaches, but challenges persist with model interpretability and dataset limitations. Further investigations are necessary to enhance the explainability of the models towards better clinical uptake. Attention mechanisms and interpretable AI could be used to see what features the model more closely followed, making it easier for healthcare professionals to trust and validate the model's decision. Moreover, integrating multi-modal information, including neuroimaging, genetic, and longitudinal data, could enhance the models' predictive performance and classification accuracy. The use of wearable devices and an IoT-based solution for real-time monitoring may allow an ongoing tracking of cognitive decline, a key aspect of AD management. In addition, more and different datasets should be studied to improve generalizability and robustness. The inclusion of underrepresented populations will be essential for accuracy, particularly in reducing biases in AD classification models. Clinicians, data scientists, and neurologists will be an important bridge to close the gap between machine learning and the clinical application of these advances.

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CONFLICT OF INTEREST

The authors declare no conflicts of interest

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