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Article Title: BiLSTM Classifier-Driven Framework for Early Detection and Classification of Alzheimer's Disease from MRI Imaging

BiLSTM Classifier-Driven Framework for Early Detection and Classification of Alzheimer's Disease from MRI Imaging

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ABSTRACT

In a medical and technological stage of development, medical images are a big part of everyday lives. Alzheimer's disease (AD) is the most common form of dementia, a neurological condition that primarily affects elderly people and has an uncertain etiologic. The first clinical sign of AD is selective memory impairment, and while some of its symptoms can be reduced with current medications, there is currently no cure. Magnetic resonance imaging (MRI) of the brain is used to assess patients who have AD. This paper proposes an innovative approach for the detection of Alzheimer's disease from MRI images, incorporating advanced techniques. Initially, an Adaptive Median Filter (AMF) is applied to the MRI images to remove noise, ensuring high-quality input data. Next, the images are segmented using K-means clustering, allowing for the separation of relevant regions associated with AD. Features are then extracted from the segmented images using the Scale-Invariant Feature Transform (SIFT), capturing key patterns for further analysis. Finally, a Bidirectional Long Short-Term Memory (BiLSTM) framework is proposed as a hybrid model to enhance the classification of AD images, leveraging both forward and backward temporal information to overcome challenges in MRI analysis. The assessment of proposed work using python software reveals that the proposed framework with BiLSTM classifier ranks with improved accuracy of 97.8 % when compared to the other techniques.

Keywords: Alzheimer's disease, Adaptive Median Filter (AMF), K-means clustering, Scale-Invariant Feature Transform (SIFT), Bidirectional Long Short-Term Memory (BiLSTM)

1 Introduction

As per the reports of World Health Organization (WHO), one of the major diseases throughout the world is Alzheimer's disease. There are different types of dementia and Alzheimer's disease found approximately among 50 million people all around the world. Alzheimer's disease is primarily caused by memory loss [1]. To evaluate the brain changes connected with Alzheimer's diseases (AD) in different brain regions, research has been going in identifying the solution for diagnosis, prognosis and preventing its movement [2].

Neurodegenerative and progressive disorders are common in Alzheimer's diseases (AD) were short-term memory loss is the major symptoms. AD patient faces many problems in their daily life such as they face mental and memorable activities. To enhance the AD patient's quality of

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life and to cure, there is no treatment yet find for AD but in the early stage using the symptoms is slowdown [3]. However these observations and computations are subjective, imprecise, and incomplete, the diagnosis of AD is based on qualitative interviews with evaluation of the individual's behavior and psychiatric history. A number of instruments are available for the quantitative evaluation of mental illnesses like AD [4].

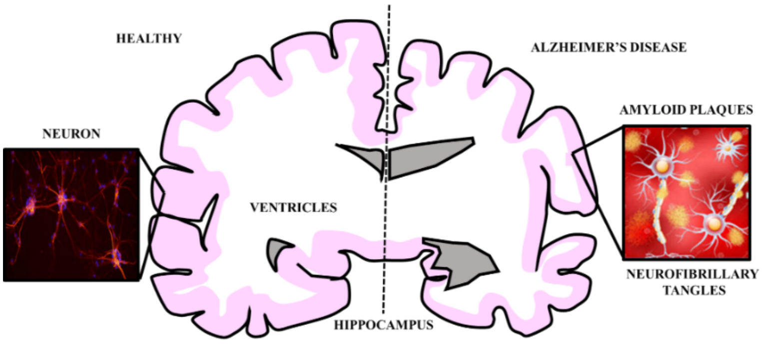

Figure 1: Healthy brain vs Alzheimer's disease

Magnetic Resonance Imaging (MRI) scans for brain syndrome in human is easy. For detecting brain structure and brain function an MRI is a powerful tool and early indication of AD it is a valuable and important one. MRI image is given to a preprocessing pipeline for reducing the unwanted noise using filtering technique, including image resizing, labeling, normalization, and color modification. At next, training and testing images are from the pre-processed data a median filter is used and fuzzy c-means clustering for segmenting the AD image and then using feature selection technique the AD image is featured. [5-7].
In comparison with deep learning and conventional machine learning to detect AD, Deep learning detect the AD disease more clearly and exactly. On this paper through different image modalities a classification is used to detect the AD disease a technique called machine learning –based technique. [8, 9] To capture the temporal features RNN is applied for longitudinal time series images. When compared to old RNN, the LSTM structure is more difficult [10-12] .The volumetric feature is developed from CNN using the trained Deep Neural Network (DNN) model to find the AD disease [13]. From the benchmark dataset to generate more data in the training a Generative adversarial network (GAN) technique is applied [14]. On MRI scan an unsupervised convolutional Spiking Neural Networks (SNN) is pre-trained and then for training purpose it is given to the supervised deep Convolution Neural Network (CNN) for the classification in AD [15].

2 Related Work

S. M. Mahim et al (2024) [16] have presented a novel framework combining a Gated Recurrent Unit (GRU) and Vision Transformer (ViT) for automated AD detection from MRI dataset. ViT extracts critical spatial features, while GRU establishes correlations, achieving exceptional

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of 99.69% accuracy in binary classification and 99.53% accuracy in 4-class. It addresses class imbalance issues and incorporates Explainable AI (XAI) to enhance interpretability for clinical use. Strengths include high accuracy, robustness, and transparency, but reliance on preprocessed datasets and computational demands limit real-world applicability.

Tanveer et al (2024) [17] have developed fuzzy logic with Deep Learning (DL) for AD diagnosis focus on addressing data imprecision issues. This approach enhances interpretability and handles uncertainties in neuroimaging data, offering improved diagnostic accuracy and robust decision support systems. However, challenges remain in harmonizing multimodal data, managing computational complexity, and achieving widespread clinical adoption.

Baiying Lei et al (2024**)** [18] have presented Hybrid Federated Learning (HFL) framework for AD detection using unlabeled data with a novel Brain-region Attention Network (BANet) to enhance interpretability by focusing on regions of interest (ROIs) in brain imaging. This proposed method effectively utilizes multi-center datasets, and improves robustness through self-supervised learning. However, challenges include the computational complexity of federated learning and potential limitations in generalizability across diverse datasets.

Francesco Conti *et al* (2024) [19] developed a Raman spectroscopy (RS) combined with topological data analysis to distinguish AD patients, achieving a high classification accuracy of 86%. The approach shows improved reliability and potential to uncover biologically relevant spectral features, enhancing AD subtypes and molecular mechanisms. However, limitations include the need for further validation on larger, diverse datasets and refinement to increase interpretability of specific spectral bands.

Abdullah Lakhan et al (2023) [20] have developed an Evolutionary Deep Convolutional Neural Network Scheme (EDCNNS) in digital healthcare systems for AD detection. EDCNNS optimizes feature extraction, selection, and execution using fog and cloud computing, achieving significant improvements with computational efficiency and prediction accuracy, making it suitable for resource-constrained environments. Despite, drawbacks include complexity of implementation and potential scalability issues in real-world scenarios.

The main contributions of this study include

- An adaptive median filter is utilized to effectively eliminate noise from the input AD MRI images, enhancing image quality for analysis.
- K-means clustering is employed to segment MRI images, isolating ROI for better feature extraction and analysis.
- SIFT to extract distinctive features from the segmented AD images, facilitating robust data representation.
- A BiLSTM-based framework is proposed, specifically addressing challenges in MRI analysis for AD prediction.

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3 Proposed Work

For predicting the AD in early stage following methods are proposed. Firstly the input data is given to the preprocessing step were an adaptive median filtering technique is applied to remove unwanted noise from AD image from MRI and given to segmentation process.

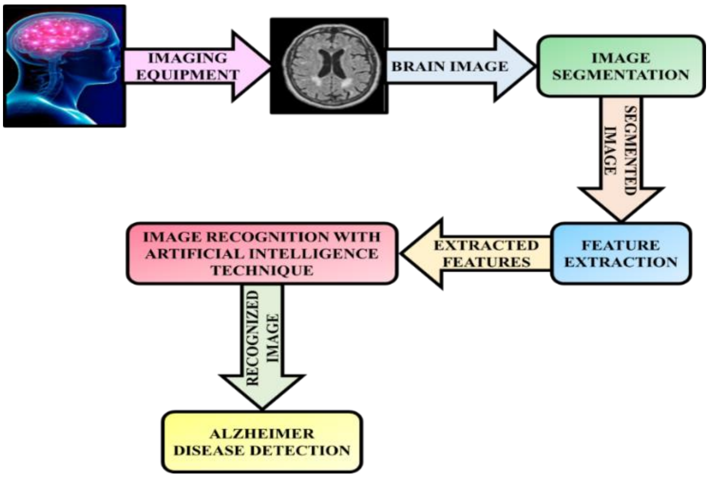

Figure 2: Proposed Block Diagram

Secondly the segmentation process uses the k-means clustering for segmenting or clustering the filtered AD image. And by using SIFT algorithm a segmented AD image features are extracted, that detects AD images. Finally, featured image is given to the classification process were a BiLSTM is used for classifying the AD image. The BiLSTM has two LSTM one is on forward direction and other is on backward direction which is used to classify the AD image clearly for getting better accuracy when compared to the other techniques.

3.1 Preprocessing by Adaptive median filter

Adaptive median filter is a pre-processing technique that reduces unwanted noise in AD images. In order to eliminate the drawbacks, the median matches each pixel in the adjacent pixel. For better output result an adaptive median filter is used and the size of the degraded AD image is adjustable. In adaptive median filter a two-step process is done one is to find the median value for the kernel and the other is to find the pixel value is impulse or not.
Implementation of adaptive median filter $Zmed$ is the median of gray levels in y ,$Zmin$ is the minimum gray level value in $Zmax$ is the maximum gray level value in Sxy,Zxy is the gray level at synchronizes (x, y) and $smax$ is themaximum permitted size of Sxy. Stated as
Level P:

$$P1 = Zmed - Zmin \tag{1}$$

$$P2 = Zmed - Zmax \tag{2}$$

Level Q if $P1 > 0$ and $P2 < 0$. Otherwise, enlarge the window.

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If window size <= $S_{max\ repeat}$ level P

Else output Z_{xy}.

Level Q:

$$Q1 = Zxy - Zmin \tag{3}$$

$$Q2 = Zxy - Zmin \tag{4}$$

3.2 Segmentation by k-means clustering

K-Means Clustering is coming under unsupervised learning algorithm it is used to segment the clustering center. First, randomly initialize k points in the AD image called cluster centroids. The main objective of k-means clustering has three points one is grouping similar data points in AD image; other is minimizing within cluster distance in AD and maximizing between cluster distances in AD. Evaluating a distance metric involves minimizing within-cluster distance. Furthermore, maximizing the distance between clusters is utilized to maximize the distance between them.

$$Euclidean\ Distance = \sqrt{(x1 - x2)2 + (y1 - y2)2} \tag{5}$$

$$Centroid = \frac{(x1+x2+x3)}{3}, \frac{(y1+y2+y3)}{3} \tag{6}$$

This formula can be extended to encompass n points as follows:

$$Centroid = \frac{(x1+x2+\cdots+xn)}{n}, \frac{(y1+y2+\cdots+yn)}{n} \tag{7}$$

K-means clustering operates on the basis of initialization, centroids, assignment, and outcome. In addition to serving as the initial cluster centroids in AD image, initialization involves choosing K points from the MRI dataset. AD Image is assigned on the cluster centroids. Continue till convergence. When the centroids stop changing sharply, convergence takes place in the AD image.

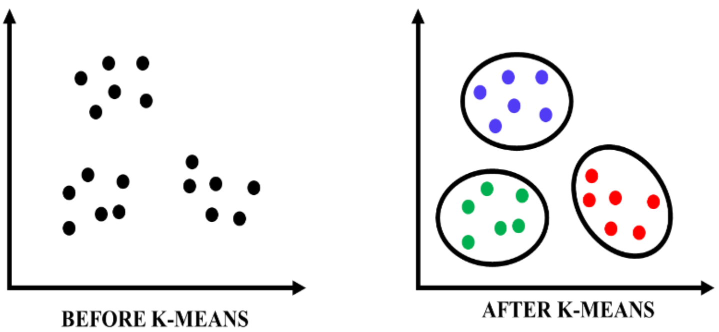

Figure 3: K-means Clustering

3.3 Feature Extraction

SIFT (Scale-Invariant Feature Transform)

For feature detection and description a computer vision technique called SIFT is used. SIFT is used to identify AD images that are tough to rotation, scale, and affine transformation changes. After identifying crucial points based on their local intensity extrema, descriptors are added to capture the local picture information surrounding key points. To detect distinctive feature called keypoints in AD images a SIFT algorithm is used. The main steps in SIFT algorithm are

i) Scale-Space Extrema Detection

The AD images are detected using a keypoints across different scales. In order to smooth the AD image to changing degrees, the method uses a gaussian blur at different measurements. See the AD image change from clear to blurry as a result. Its equation by

$$L(\mathrm{x},\mathrm{y},\sigma) = \mathrm{G}(\mathrm{x},\mathrm{y},\sigma) * \mathrm{I}(\mathrm{x},\mathrm{y},) \tag{8}$$

Wherever,

$L(x, y, \sigma)$ denoted as blurry image at scale σ

$G(x, y, \sigma)$ denoted as Gaussian kernel

$I(x, y)$denoted as the original image

ii) Keypoint Localization

To estimate a location near a given point a Taylor series expansion is used in AD image. Then to improve the location and scale a Difference of Gaussians (DoG) function is used. To remove the edges in AD image DoG function has higher response. A Harris cornor is also functioning as a detector. The primary curvature is calculated using a 2x2 Hessian matrix (H).

iii) Orientation Assignment

For each keypoint an orientation is assigned and to make the image rotation invariant. A region is drawn around the keypoint position based on the scale, gradient magnitude, and direction that are designed in the AD image.

iv) Keypoint Descriptor

Using AD image a keypoint is taken as a 16x16 neighbourhood around it. A total of 128 bin values are obtained by splitting the AD image into 16 4x4 sub-blocks and assigning an 8-bin orientation histogram to each sub-block. A vector is represented by a keypoint descriptor.

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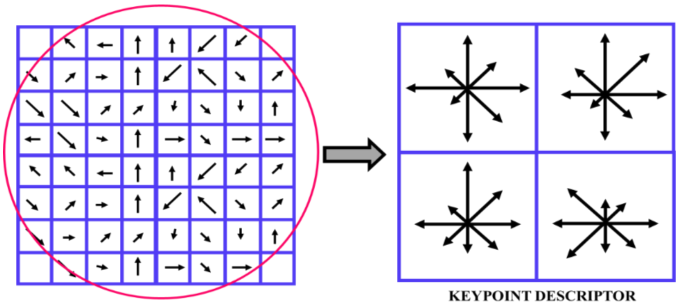

Figure 4: Keypoint Descriptor

3.4 Classification

Bidirectional LSTM

BiLSTM is a classification technique. When two hidden states are used in a bidirectional LSTM, the information travels both forward and backward. Information passes from the backward to the forward unidirectional LSTM. In principle, BRNN works by breaking down a typical RNN's neurons into bidirectional pathways.

To comprehend Bi-LSTM by utilizing its elements and features: Long Short-Term Memory, or LSTM: An RNN type called LSTM was generated to get over the disadvantages of conventional RNNs in terms of identifying long-term dependencies in sequential data for AD images. Because of its internal memory state, which can hold data over extended periods of time, LSTMs are able to capture AD image needs that distance multiple time steps. Bidirectional Processing: Unlike traditional RNNs, which only analyze input sequences in one direction, Bi-LSTM methods the sequence in both directions instantaneously. The sequence is processed forward by one of its two LSTM layers and backward by the other. Each layer monitors its own hidden statuses and memory cells.

Forward Pass: In the forward pass, the forward LSTM layer receives the input sequence (AD image) from the first to the last time step. Backward Pass: The backward LSTM layer receives the input sequence in reverse order, from the last time step to the first, all at once. Combining forward and Backward States: Following the completion of the forward and backward passes, at each time step both LSTM layers are combined.

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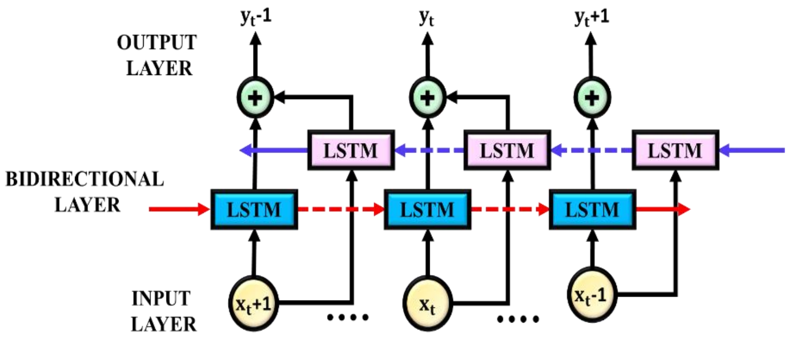

Figure 5: BiLSTM

Above Figure 5 shows the BiLSTM in both direction as forward and backward.

Evaluation metrics

Using various performance metrics the future framework to training data is evaluated. And these metrics are accuracy, precision, recall, F1 score and AUC. Using the following equation each metrics are defined as

i) Accuracy: From the predicted data accuracy measures the amount of suitably recognized samples. The formula for calculating accuracy is to divide the total quantity of samples (TS) by the sum of true positives (TP) and true negatives (TN).

$$Accuracy = \frac{(TN+TP)}{TS} \tag{9}$$

ii) Precision: By dividing True Positives by the sum of True Positives and false positives (FP) computation is achieved. The ratio of accurately (TP) to the sum of projected positive samples (AD) is called precision.

$$Precision = \frac{(TP+TP)}{FP} \tag{10}$$

iii) Recall: TP is divided by the sum of TP and FN to find the ratio of TP to the total number of AD patients in the dataset.

$$Recall = \frac{(TP)}{(TP+FN)} \tag{11}$$

iv) F1 -score: A collective measure of precision and recall is called as F1 score.

$$F1 - score = \frac{(2*\text{Precision}*\text{Recall})}{(Precision + Recall)} \tag{12}$$

At last, the simulation performance across different classifications is evaluated using the AUC, which describes the connection between the true positive and false positive rates.

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4 Result and Discussion

Dataset Collection

The publicly available Kaggle online source provided the Alzheimer's Dataset (Brain MRI Images) used in this work. The proposed model is analysed on MRI data consisting of four classes of impairments mild impairment, moderate impairment, no impairment and very mild impairment. This contains totally of 10240 train counts and 1279 of test counts. The dataset is distributed as 80% for training and 20% for testing. Deep learning models are then applied to train on this data.

Image Count Summary

Combined Image Counts by Class

Class	Train Count	Test Count
Mild Impairment	2560	179
Moderate Impairment	2560	12
No Impairment	2560	640
Very Mild Impairment	2560	448
Total	10240	1279

Figure 6: Image count summary

The Figure 6 shows the image's summary count. Mild impairment is represented by 2560 trains and 179 tests; moderate impairment is represented by 2560 trains and 12 tests; no impairment is represented by 2560 trains and 640 tests; and very mild impairment is represented by 2560 trains and 448 tests. These four types of impairment are used in the proposed work. Additionally, there are 1279 trains out of a total of 10240.

Dataset pre-processing

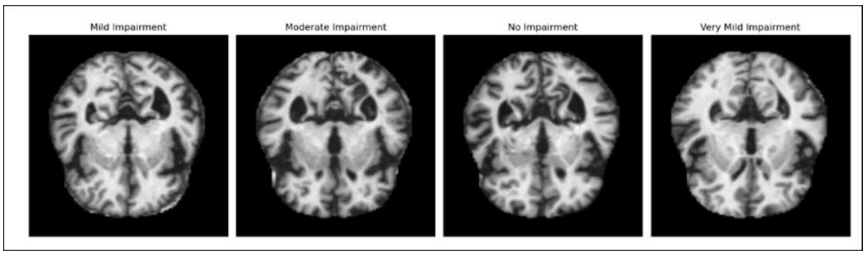

Figure 7: Mild, moderate, no and very mild impairment of MRI image dataset

The image illustrates brain scans representing different levels of cognitive impairment, progressing from healthy to varying degrees of decline. These scans highlight the progression of impairment, emphasizing the importance of early detection for effective intervention.

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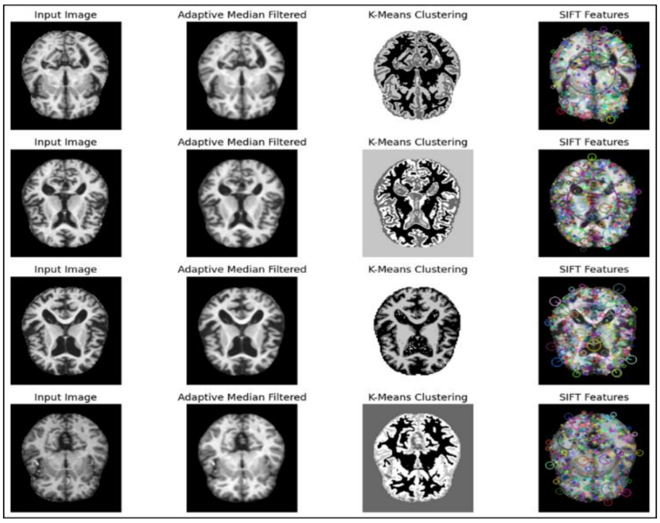

Figure 8: Four stages of AD images

Above Figure 8 shows the input MRI image, adaptive median filtered image, k-means clustering image and SIFT features for AD detection. From the input image the image is resized, and then using adaptive median filter the unwanted noises are removed, then given to the segmentation their k-means clustering clusters the disease and then given to feature extraction their the feature is extracted using SIFT features.

Model loss and model accuracy

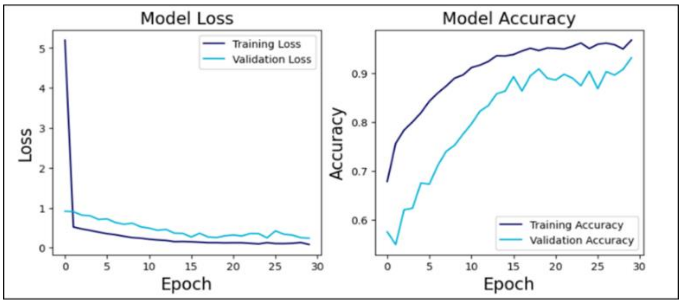

Figure 9: Model loss and model accuracy

The graph in Figure 9 depict 30 epochs. The Model Loss graph displays a reliable decline in both training and validation loss, representing improved learning and reduced error. The Model Accuracy graph illustrates increasing accuracy of 97.8%, with the model achieving high performance and minimal overfitting.

Confusion matrix

Alzheimer Disease detection stages are predicted using confusion matrix. Mild impairment, moderate impairment, no impairment and very mild impairment true label and predicted label are predicted from the four stages.

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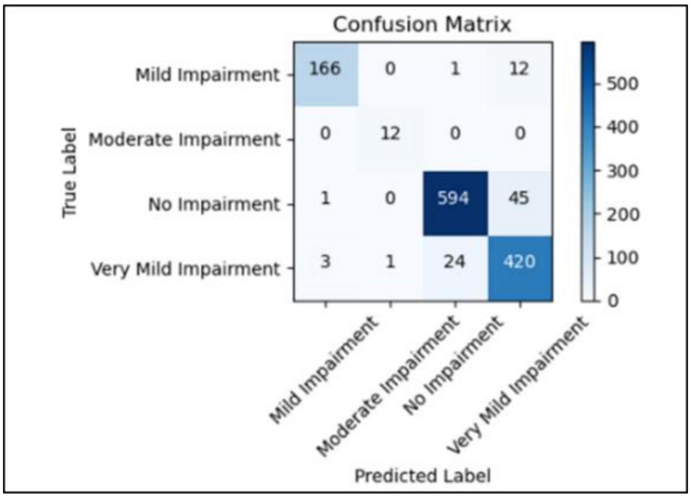

Figure 10: Confusion matrix for AD image

The confusion matrix in Figure 10 evaluates the model's performance in predicting different levels of cognitive impairment. It shows high accuracy for all classes, with 166 cases of Mild Impairment, 12 cases of Moderate Impairment, 594 cases of No Impairment, and 420 cases of Very Mild Impairment correctly classified. Misclassifications are minimal, with most errors occurring between similar classes, such as No Impairment and Very Mild Impairment. Overall, the model demonstrates robust performance with strong classification accuracy across all categories.

	precision	recall	f1-score	support
Mild Impairment	0.94	0.91	0.93	179
Moderate Impairment	0.86	1.00	0.92	12
No Impairment	0.94	0.95	0.94	640
Very Mild Impairment	0.91	0.91	0.91	448
accuracy			0.93	1279
macro avg	0.91	0.94	0.93	1279
weighted avg	0.93	0.93	0.93	1279

Figure 11: Four stages of precision, recall, f1-score, and accuracy

The precision, recall, f1-score, and accuracy value for AD detection of the four stages are mild impairment with precision of 0.94, recall of 0.91 and f1-score of 0.93, moderate impairment of precision of 0.86, recall of 1.00 and f1-score of 0.92, no impairment of precision of 0.94, recall of 0.95 and f1-score of 0.94, and very mild impairment of precision of 0.91, recall of 0.91 and f1-score of 0.91 are required.

Comparison for the proposed method

In contrast, several other studies [21, 22] unnoticed the time series component of the training data and just used baseline data. These studies did not sufficiently explain their findings and lacked training data for illness analysis.

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Table 1: Comparison for proposed method

Study	Dataset	Accuracy
Kang *et al.*[21]	MRI	90.36 %
Helaly *et al.* [22]	MRI	94.34 %
Zhang *et al* [23]	MRI	96.61 %
Proposed Approach	MRI	97.8 %

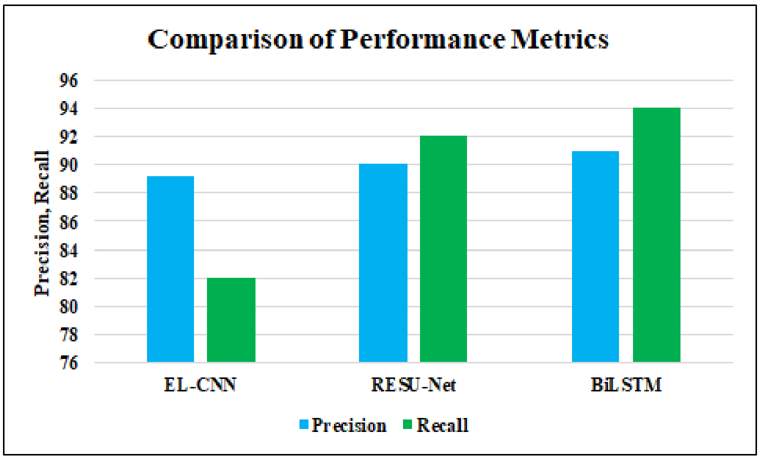

Figure 12: Comparison of performance metrics

For Precision and recall it gives better predicted value when compared to the EL-CNN [21] and RESU-Net [22]. Precision value of 91% and recall of 94% for the proposed BiLSTM method.

5 Conclusions

The proposed work demonstrates a robust framework for AD diagnosis using MRI data, leveraging advanced techniques like BiLSTM to significantly enhance accuracy and reliability. Through systematic preprocessing, segmentation, and feature selection, the framework effectively addresses key challenges in MRI analysis. Using the proposed technique prediction accuracy of 97.8% is achieved which is high when compared to the previous technique. This robust framework not only facilitates early and precise AD detection but also provides an accessible and efficient solution for clinical applications, aiding in timely treatment and better patient outcomes.

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