# Early Diagnosis of Alzheimer's Disease with Transfer Learning Techniques Via ResNet50 and FSBi-LSTM

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*Alzheimer's Disease (AD) is a neurological disorder marked by cognitive deterioration and neurological impairment that affects cognition, memory, and behavioral patterns. Alzheimer's is an incurable disease that predominantly impacts individuals over the age of 40. A patient's MRI (Magnetic Resonance Imaging) scan and cognitive assessment are manually analyzed to diagnose Alzheimer's disease. Recently, Artificial Intelligence (AI), particularly through Deep Learning, has pioneered innovative techniques for automated medical image identification. We devised a deep learning methodology for Alzheimer's disease identification utilizing Magnetic Resonance Imaging (MRI) data. The suggested method, termed Res+FSBILSTM, employs ResNet50 as a pre-trained model for feature extraction from MRIs, thereafter identifying Alzheimer's disease through a Fully-Stack Bidirectional Long-Short Term Memory deep learning model. The experimental results demonstrate that the suggested method surpasses state-of-the-art techniques across all evaluation metrics, rendering it a viable tool for medical professionals in identifying Alzheimer's disease using brain radiological images. Ultimately, we achieved results with an accuracy of 99.6%, an F1-score of 97.7%, an area under the curve of 99%, a recall of 97.3%, and a precision of 99.6%.*

*Povzetek: Predstavljena je izboljšana metodo zgodnjega diagnosticiranja Alzheimerjeve bolezni z uporabo prenosa učenja prek ResNet50 in FSBi-LSTM. Sistem uporablja MRI slike za avtomatizirano identifikacijo bolezni in omogoča hitro prepoznavanje zgodnjih faz bolezni, kar omogoča učinkovitejše klinične diagnoze in obravnavo pacientov.*

## 1 Introduction

The predominant kind of dementia necessitating extensive medical intervention is Alzheimer's disease (AD). For effective patient therapy to begin, an early and accurate assessment of the prognosis for AD is necessary [1]. The research found that there are 10 million new instances of dementia reported per year [2]. According to the World Health Organization (WHO), AD has overtaken cancer as the leading to death, with the quantity of AD By 2050, there will be 152 million patients. AD is a chronic neurological brain illness that progressively damages brain tissue, leading to cognitive
decline and memory loss, and ultimately hastening the loss of ability to carry out daily tasks [3]. A condition known as AD is brain-neurological degeneration [4]. It is classified as dementia, which is brain atrophy that impairs memory and results in loss of cognitive abilities related to behavior, social interaction, and reasoning. Protein fragments build up in the brain, which is the cause of it [5, 6, 7]. The human brain develops plaques and tangles around the neurons, causing aberrant hippocampal and lobe shrinkage as well as enlarged ventricles [8]. It is a deadly illness that is incurable [9, 10], causing the patient to suffer for the rest of their life and their family great emotional, physical, and financial hardship. There are no known causes of AD, and there are no treatments or drugs that can effectively cure dementia. A pre-clinical stage of AD called mild cognitive impairment (MCI) is a transitional condition that occurs between normal aging and AD. Early detection of the risk and severity of AD is crucial [11,12]. Many researchers worldwide have developed a multitude of Machine Learning (ML) [13] and Deep Learning (DL) [14] algorithms throughout the years for the purpose of AD detection and classification. The DL algorithms have been used by numerous academics with impressive results still, there's space for development. In this set of DL models [15,16], and [17] that introduce a hybrid Convolutional Neural Network (CNN), a CNN model with slice selection, and a CNN model with histogram stretching. A CNN model with skull striping was presented by others [18] and in [19]. However, because CNN is a black-box, these deep models are predominantly biased towards categorization. Several researchers have created a variety of techniques and applications for automatic neuro-image segmentation in the literature on AD [20]. While there is little attention on CNN layers to visualize the classification process, these applications are useful tools for segmenting neuro-images. Each convolution layer's feature map shows the different filters that are applied to the image and gives an indication of the kinds of filters the model applies to the image to

extract features [21]. In sequence analysis, the recurrent neural network (RNN) is a potent model. Since RNN uses a "state" vector in its hidden units, all historical information about the sequence is inherently contained in it[22]. Long short-term memory (LSTM), an enhanced version of RNN, can handle gradient explosion or gradient disappearance issues more successfully than RNN by controlling information flow across numerous gates[23]. Moreover, contextual information can be present in both directions for bidirectional LSTM (Bi-LSTM) [24]. In fact, by stacking the LSTM to examine the spatial information of feature maps from CNN layers as well, Bi-LSTM may obtain more information without having to select the scanning direction. Therefore, we propose to use the fully stacked Bi-LSTM (FSBi-LSTM) instead of the traditional Bi-LSTM [25].In this paper, we create an innovative deep learning network that employs fully stacked bidirectional LSTM (FSBi-LSTM) and CNN layers of ReseNet50 [26] to diagnose AD using multimodal input. The goal of the proposed model is to produce a classification result that is accurate enough to identify AD at an earlier stage. The research study's primary contributions are:

- Combining traditional image processing techniques like thresholding and morphological operations with modern deep learning approaches such as U-Net provides a robust method for brain extraction.
- By incorporating FSBiLSTM with ResNet50, you can leverage the power of ResNet50's strong feature extraction capabilities while benefiting from FSBiLSTM's ability to generalize from a few examples.
- Improved generalization: ResNet50 is a powerful deep neural network architecture known for its ability to learn rich representations from images. By combining it with FSBiLSTM, which specializes in few-shot learning, you can potentially improve the generalization performance of ResNet50 on new, unseen classes with limited training data
- Using ResNet50 for Spatial Learning: ResNet50 is an incredibly potent convolutional neural network (CNN) that is highly skilled at extracting detailed spatial characteristics from individual MRI slices. These characteristics are essential for detecting alterations linked to Alzheimer's disease because they capture minute details and patterns.

The rest of the paper is arranged as follows: Section 2 provides a summary of the relevant studies for the suggested model. Next, in Section 3, we provide a thorough explanation of our methodology. The experiment's results are described in Section 4. The dissection is provided in Section 5. Finally, Section 6 contains a summary of our findings.

## 2 Related work

In recent years, various methods have been suggested to enhance the accuracy of image classification. We analyze various machine learning (ML) classification frameworks employed in neuroimaging, along with techniques based on a convolutional neural network. Machine learning techniques have been increasingly utilized in recent years for the early identification of Alzheimer's disease, particularly in multi-class and binary classification tasks. Yiming Ding et al. [27] Suggested doing a retrospective analysis of 2109 18F-FDG PET imaging tests that were gathered prospectively from 1002 patients. The majority of patients had numerous scans, and the dates of the scans ranged from May 2005 to January 2017. The researchers created and verified a deep learning algorithm, especially a convolutional neural network using InceptionV3 architecture. The model underwent training using 90% of the dataset and was subsequently evaluated using the remaining 10%, in addition to an independent test set. The model's performance was compared to that of radiologic readers. The model's performance was assessed by sensitivity, specificity, receiver operating characteristic (ROC), saliency map, and t-distributed stochastic neighbor embedding. The study's authors are C. Suh and colleagues [28]. Developed a deep learning technique employing a dataset of T1-weighted brain MRI scans from consecutive patients diagnosed with Alzheimer's disease and moderate cognitive impairment. The researchers developed a two-step system employing a convolutional neural network for brain parcellation, subsequently applying three classification techniques, including XGBoost, for disease prediction. The categorization experiments were performed with a 5-fold cross-validation method. The diagnostic efficacy of the XGBoost algorithm was evaluated against logistic regression and a linear SVM. The areas under the curve were calculated to differentiate between Alzheimer's disease and moderate cognitive impairment, as well as between mild cognitive impairment and healthy controls. Hina Nawaz et al. [29] proposed a pre-trained AlexNet model for the extraction of deep features in the detection of Alzheimer's disease stages. Transfer learning uses the initial layers of the pre-trained AlexNet model to extract deep features from the CNN. SVM, k-nearest Neighbor (KNN), and Random Forest (RF) are employed to classify the extracted deep features through machine learning techniques. The study is authored by Hadeer A. Helaly and colleagues.[30] . This investigation focuses on the prompt identification and classification of Alzheimer's disease through the application of an advanced machine learning method referred to as CNNs. The E2AD2C framework is designed to identify and categorize various stages of Alzheimer's disease at an early phase. Two primary methodologies are utilized for medical picture categorization and the identification of Alzheimer's disease. The preliminary method utilizes fundamental CNN architectures to analyze 2D and 3D structural brain scans sourced from the ADNI dataset. This technique attains classification accuracies of 93.61% and 95.17% for multi-class Alzheimer's Disease stage classifications. The alternative method involves employing transfer learning with the VGG19 pre-trained model, which has been optimized to achieve 97% accuracy in diagnosing multi-class Alzheimer's disease

stages. Resampling methods, including oversampling and downsampling, are utilized to address the problem of class imbalance in a dataset. Data augmentation techniques are employed to increase dataset size and alleviate overfitting concerns. Fazal Ur Rehman Faisal [31] concentrated on devising a deep learning technique for the extraction of Alzheimer's disease (AD) biomarkers from structural magnetic resonance imaging (sMRI) data. CNNs were complexity and improve efficiency. The proposed approach was evaluated against leading methodologies for AD classification,

exhibiting enhanced performance for accuracy and area under the ROC curve. The convolution operation utilized in the proposed method was considered appropriate for Alzheimer's disease diagnosis, demonstrating its efficacy in appropriately classifying the brain picture. Y. F. Khan et al. [32] utilized a Stacked Deep Dense Neural Network (SDDNN) model, integrating Convolutional Neural Network (CNN) and Bidirectional Long Short-Term Memory (Bidirectional LSTM). The training utilized the DementiaBank clinical transcript dataset under two configurations: randomly initialized parameters and GloVe embedding. Hyperparameter optimization via GridSearch enhanced model performance, attaining 93.31% accuracy with GloVe embedding and fine-tuning.

Ahsan Bin Tufail et al. [33] utilized transfer and non-transfer learning-based CNN architectures in both 2D and 3D domains for binary and multiclass classification tasks. Custom 3D CNN architectures were created for binary classifications of AD/NC, AD/MCI, and NC/MCI, as well as for multiclass classification of AD/NC/MCI. Transfer learning utilizing the Xception architecture was employed for the classification of MCI and AD, as well as for the multiclass categorization of NC, MCI, and AD. A bespoke CNN architecture in the 2D domain was employed for the categorization of NC and MCI, as well as NC and AD classes. Evaluation utilized performance criteria such as CEN, RCI, GM, IBA, and MCC. Data augmentation methods, such as random zooming in and out, were employed to enhance dataset size for better generalization of deep learning algorithms. R. Tandon et al. [34] utilize deep learning methodologies for the segmentation and classification of Alzheimer's Disease through brain imaging data. The suggested approach amalgamates segmentation models with classification frameworks to enhance diagnostic precision. The system attains remarkable performance utilizing datasets such as MRI scans, with classification accuracy reported to exceed 90%.

employed and trained on sMRI brain pictures sourced from ADNI datasets to categorize images into Alzheimer's disease, mild cognitive impairment (MCI), and cognitively normal (CN) groups. Features from several layers were integrated to hierarchically convert MRI pictures into more concise high-level features, facilitating the classification process. The strategy sought to diminish the number of parameters to decrease computational

The study highlights the significance of precise segmentation in improving the diagnostic efficacy of deep learning models for Alzheimer's detection [35]. A proposed retrospective cohort study involving 532 participants, employing Positron Emission Tomography (PET) and Magnetic Resonance Imaging (MRI) images, alongside cognitive evaluations. The authors developed a novel computational phenotyping method that utilizes Partial Volume Correction (PVC) and subsets of neuropsychological assessments in an impartial manner. The pipeline employs a Regional Spread Function (RSF) technique for PVC and a t-distributed Stochastic Neighbor Embedding (t-SNE) manifold. The objective was to develop a new method for analyzing variations in cognitive scores and PET characteristics to identify multiple phenotypes of Alzheimer's disease (AD) using hyperparametric analysis.[36] Ullah et al. (2023) introduced modifications to pre-trained deep learning models, including ResNet and DenseNet, aimed at enhancing brain tumor classification. Their approach enhanced accuracy and robustness through transfer learning and domain-specific fine-tuning, effectively addressing challenges such as overfitting in limited medical datasets. The research indicated that these improved models outperformed conventional methods, highlighting their appropriateness for clinical use.[37] Chegireddy and Srinagesh (2023) proposed a new deep-learning approach for predicting pancreatic cancer by utilizing human MRI data, incorporating variants of Harris Hawks Optimization (HHO) with the VGG16 architecture model. Their approach employed HHO variants to optimize hyperparameters and enhance feature selection, improving the predictive performance of VGG16. The proposed method achieved high accuracy and robustness, outperforming traditional models and standard deep learning techniques. This study emphasizes the potential of integrating metaheuristic algorithms with deep learning frameworks to enhance diagnosis accuracy in medical imaging.

Table 1: Comparison of machine learning methods for alzheimer's disease classification

| No. | Method | Dataset Used | Accuracy (%) | F1 Score | Key Features |
|---|---|---|---|---|---|
| [27] | Deep Learning on 18F-FDG PET (Ding et al.) | Brain PET scans (N = 1,002) | 92 | - | Predicts Alzheimer's diagnosis with PET imaging using deep neural networks. |
| [28] | 3D T1-Weighted Images (Suh et al.) | ADNI dataset | 89.5 | 0.88 | Brain segmentation and classification using 3D CNNs. |
| [29] | Deep Feature Real-Time Detection (Hina et al.) | Proprietary | 87 | - | Stage detection with real-time deep feature-based processing. |
| [30] | Early Detection via CNN (Helaly et al.) | ADNI | 93.2 | 0.91 | Focus on early diagnosis using convolutional networks. |
| [31] | Whole Brain MRI (Faisal & Kwon) | OASIS and ADNI | 94.5 | 0.92 | Automated detection leveraging MRI-based deep learning. |
| [32] | Stacked Dense NN on Audio Data (Khan et al.) | Proprietary | 85.6 | 0.84 | Predicts dementia using audio transcript data with stacked neural networks. |
| [33] | 2D/3D CNN with PET Neuroimaging (Ahsan et al.) | ADNI and OASIS | 92.8 | 0.89 | PET neuroimaging-based early-stage categorization in 2D and 3D domains. |
| [34] | Deep Learning for AD (Buvaneswari et al.) | ANDI | 95 | - | the study demonstrates that combining SegNet for feature extraction with ResNet-101 for classification can effectively identify Alzheimer's disease with high accuracy and sensitivity. |
| [35] | Manifold Learning on PET (Campanioni et al.) | Proprietary | 91.3 | - | Epigenetic phenotyping using PET imaging and manifold learning. |
| [36] | DBNs with IoT Detection (Alqahtani et al.) | Proprietary | 90.5 | 0.87 | Combines deep belief networks with IoT for detection and classification. |
| [37] | Ensemble Learning with Synthetic Data (Mujahid et al.) | Proprietary | 93.8 | 0.90 | Ensemble approach using synthetic data augmentation for robust predictions. |

# 3 Methodology

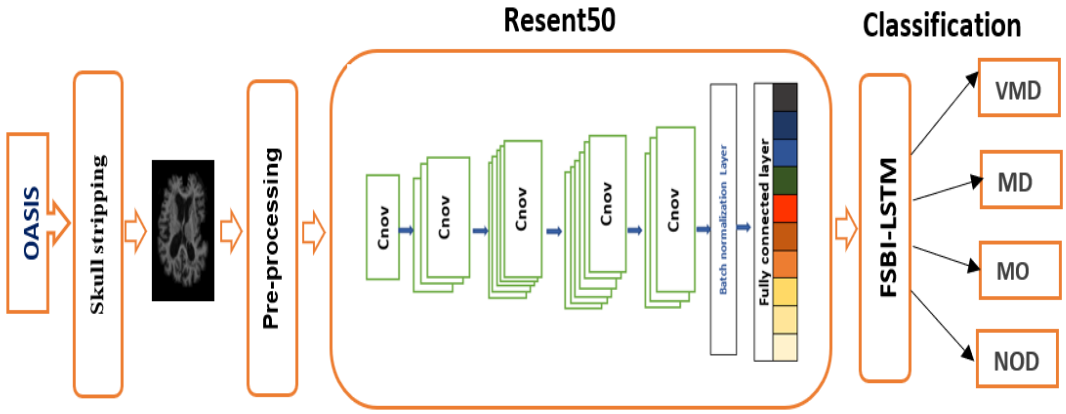


Figure 1: The overall framework of the proposed method.

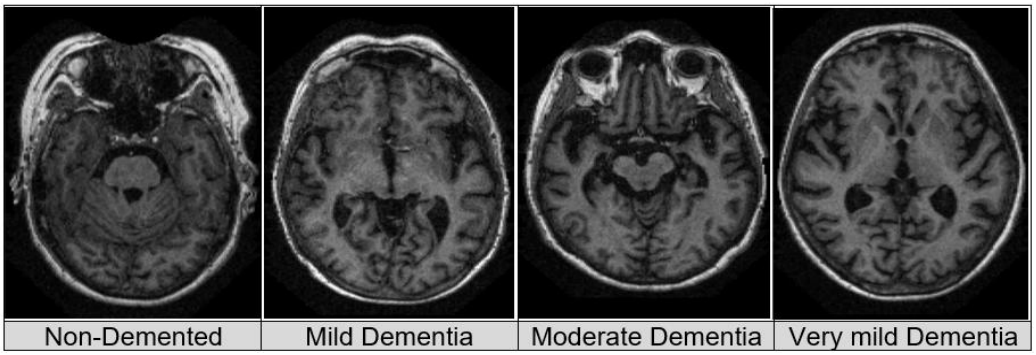


Figure 2: some samples from the OASIS dataset.

The proposed framework is illustrated in Figure. 1, we apply CNN of Resnet50 to extract the basic features datasets that we used from OASIS organization, FSBI-LSTM then is used instead of FC (fully connected layer) to high level semantic, contextual understanding, more.

## 3.1. The datasets

Numerous datasets for Alzheimer's disease classification are accessible online. Numerous AD datasets are unsuitable for this research due to their CSV format. Organizations such as OASIS provide their data sets for educational and research purposes. However, the samples in data sets are presented in a three-dimensional image format. OASIS is a project that grants researchers and the scientific leveraging of semantic information and capturing the contextual dependencies finally, for classifying the disease diagnosis the concatenated learned features are passed to SoftMax in the following description of the proposed techniques for community access to an extensive collection of neuroimaging data. The objective of OASIS is to advocate for open science and enhance the progression of research in neuroimaging and neuroscience. In this dataset, we utilized four classifications: Non-Demented, Mild Dementia, Moderate Dementia, and Very Mild Dementia, as illustrated in Figure 2.

Table 2: Clears the distribution of OASIS datasets.

| Classes | NO. of images | Gender | Age range |
|---|---|---|---|
| Non-Demented *(NOD)* | 100 | F/M | 55-85 years |
| Mild Dementia *(MD)* | 5002 | F/M | 62-85 years |
| Moderate Dementia *(MOD)* | 488 | F/M | 63-85 years |
| Very Mild Dementia *(VMD)* | 102 | F/M | 65-88 years |

## 3.2. Data processing

The initial preprocessing step in our system is skull-stripping, an essential procedure that eliminates non-brain tissues and structures from MRI images to separate the cerebral region. This method is extensively employed in neuroimaging research and clinical applications to improve the emphasis on brain tissues, hence enabling more precise analysis and segmentation. Several methods are available for skull-stripping, ranging from simple thresholding techniques to advanced deep learning models. In our approach, we combine the traditional image processing techniques with a deep learning-based U-Net model to achieve robust and accurate results. Thresholding is initially employed as a straightforward yet efficient technique that transforms a grayscale image into a binary image by juxtaposing pixel intensity values against a specified threshold. Pixels with intensities beyond the threshold are designated as foreground (brain tissue), and those below are categorized as background (non-brain tissue). This approach is most efficacious when a distinct intensity differentiation exists between cerebral and non-cerebral areas. Morphological techniques, like erosion and dilation, are subsequently employed to enhance the binary image, so increasing the segmentation of the brain region by smoothing borders and removing minor aberrations or noise. The extracted brain region is further refined for segmentation through the successive application of erosion, dilation, and opening processes. A pre-trained or custom-trained U-Net model is subsequently utilized to boost segmentation, capitalizing on its capacity to understand complex patterns and features for improved precision in isolating the brain from adjacent structures.

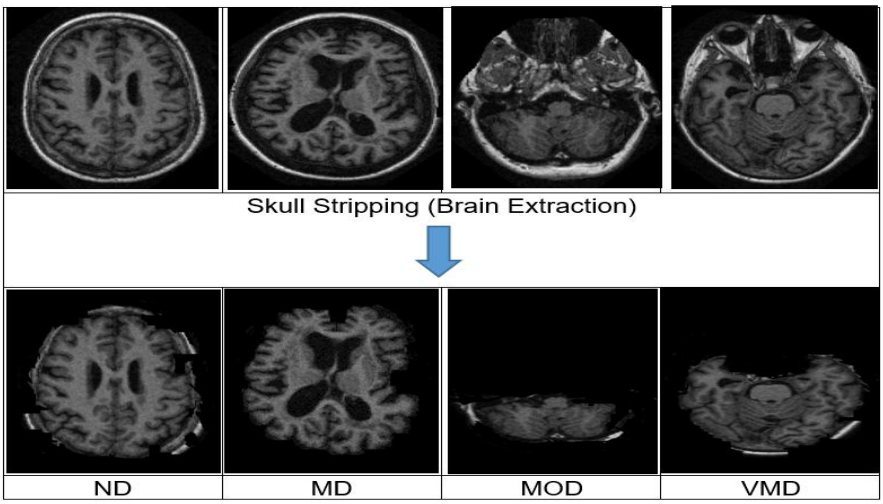


Figure 3: Extracting the brain section for images in the OASIS dataset

Our method for effective skull-stripping commences with noise reduction by Gaussian blur on the grayscale image, subsequently employing Otsu's thresholding technique to dynamically ascertain the appropriate threshold value and transform the blurred image into binary format. Morphological opening is subsequently applied to the binary picture utilizing a preset kernel, followed by dilation to enlarge the region of interest (ROI). Contours are detected in the dilated image utilizing the `cv2.findContours()` function, and the contour with the greatest area is designated as the principal ROI. A mask is generated to correspond with the image dimensions and delineate the chosen contour, therefore isolating the ROI from the original image. The retrieved ROI is further modified with a U-Net model, which improves segmentation and yields effective skull-stripping outcomes. Our method achieves precise and robust skull-stripping by integrating Gaussian blurring, Otsu's thresholding, and morphological operations with the segmentation capabilities of U-Net, thereby combining the simplicity and efficiency of traditional techniques with the sophistication of deep learning for optimal performance across various MRI datasets. Figure 3 illustrates the effectiveness of our skull-stripping approach, showing MRI images before and after processing.

Figure 3 clearly demonstrates that the brain extraction approach we employed is highly effective on the OASIS Foundation dataset since non-brain regions were entirely eliminated from the images, yielding great results in our data analysis. To mitigate the issue of overfitting, we utilized augmentation approaches. Overfitting, a prevalent issue in machine learning and statistical modeling, transpires when a model gets excessively tailored to the training data, leading to inadequate generalization of novel data. Augmented processing entails enhancing the training data by incorporating changes, such the addition of noise, the application of modifications, or the generation of synthetic samples. Augmented processing, through the diversification of the training set, exposes the model to a wider array of patterns and variances, hence mitigating the danger of overfitting.

This strategy enables the model to acquire a greater level of resilience and generalizable representations, improving its performance on unseen data, we applied various augmentation strategies tailored to our specific dataset, such as random rotation in the range [10, -10], both vertical and horizontal shifting in the range (-0.1, 0.1), flips vertical and horizontal randomly, and shear of the original images in the range (-0.1, 0.1). The additional data substantially improved the training process, resulting in a more efficient and dependable model with higher generalization abilities, so increasing its capacity to manage unseen input and ultimately reduce the effects of overfitting. The tables below show the number of images after the augmentation of our OASIS datasets. A pre-processing operation is also applied to improve the ability of the proposed model to elevate the quality of the data and extract relevant features such as image rescaling, image normalization, and skull stripping as mentioned before.

Table3: Number of OASIS images after the augmentation.

| Classes | NO. of images |
|---|---|
| Non-Demented | 990 |
| Mild Dementia | 34216 |
| Moderate Dementia | 4598 |
| Very Mild Dementia | 1002 |

## 3.3 Feature learning (feature extraction)

In this research, we have resorted to building a model based on both CNN and RNN The combination of CNNs and RNNs has been successfully applied to a variety of classification tasks, such as video classification, sentiment analysis, and medical image analysis. By leveraging the strengths of both spatial feature extraction and sequential modeling, the CNN-RNN approach can often outperform models that only use one type of neural network architecture. ResNet-50 has been effectively utilized across multiple domains, notably in medical imaging, namely for the interpretation of MRI (Magnetic Resonance Imaging) pictures. ResNet-50, an abbreviation

for Residual Network-50, is a convolutional neural network (CNN) architecture that has achieved considerable acclaim and efficacy in the domain of computer vision. It was presented by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun in their foundational paper "Deep Residual Learning for Image Recognition" [26] The creation of ResNet-50 was driven by the understanding that deeper convolutional neural networks (CNNs) often encounter the vanishing gradient problem, which hinders their training efficacy.

The vanishing gradient problem arises when gradients transmitted across the network diminish swiftly, obstructing preceding layers from updating their weights and acquiring significant representations. ResNet-50 tackles this difficulty by an innovative architectural design grounded in the principle of residual learning.

The fundamental principle behind residual learning is the incorporation of skip connections or shortcuts, which allow the network to learn residual functions instead of directly fitting the intended underlying mapping. The inclusion of skip connections allows for the direct propagation of gradients throughout the network, hence addressing the issue of vanishing gradients.

ResNet-50 consists of 50 layers, categorizing it as a network of significant depth. The architecture comprises a series of residual blocks, each containing several convolutional layers. The residual blocks are organized in a stratified configuration to form the complete architecture of ResNet-50. The network utilizes a combination of 1x1, 3x3, and occasionally 1x1 convolutional filters, along with batch normalization and rectified linear unit (ReLU) activations, to extract and transform visual input at different levels of abstraction. ResNet-50 is notable for its ability to achieve state-of-the-art accuracy on numerous challenging benchmark datasets, including ImageNet, which contains millions of annotated images. The intricate architecture of ResNet-50 allows it to proficiently capture and represent complicated patterns and hierarchical structures, yielding outstanding performance in applications such as image classification, object detection, and image segmentation. Furthermore, the architecture of ResNet-50 has influenced subsequent developments in CNN design.

## 3.4. Alzheimer's disease detection

In convolutional neural networks (CNNs), the standard approach employs fully connected (FC) layers for high-level analysis. Nonetheless, completely connected (FC) layers are ineffective in acquiring comprehensive spatial information from feature maps, as they connect all neurons indiscriminately, disregarding spatial correlations. In this paper, we have presented an enhanced version of the LSTM (Long Short-Term Memory) framework, termed FSBi-LSTM, to address this issue. LSTM, an acronym for Long Short-Term Memory, is a specialized type of recurrent neural network (RNN) that is proficient in handling sequences and retaining long-term dependencies. In traditional recurrent neural networks (RNNs), the output of a cell at a given time step is determined by the input at that time step and the output of the prior cell. The output is denoted as "ht" and is calculated using the specified formula

$$h_t = \mathrm{f}\,(Ux_t + Wh_{t-1}) \qquad (1)$$

In this context, xt denotes the input at the present time step, U signifies the weight matrix linking the input layer to the hidden layer, and W represents the weight matrix connecting the output of the preceding cell to the current cell.

The function f(·) typically represents the hyperbolic tangent (tanh) function, which constricts input values to a range between -1 and 1. The purpose of employing this activation function is to introduce non-linearity into the network, allowing it to model complex relationships between inputs and outputs. Conventional RNNs have two major issues known as "gradient explosion" and "gradient disappearance." These problems arise due to the gradients either diminishing or escalating during the training phase. The gradient measures the slope of the loss function relative to the network's parameters and is utilized to adjust the network's weights during training. When the gradients decrease to an insignificant level, the network faces difficulties in its learning process and may finally converge to suboptimal solutions. Conversely, if the gradients become very large, the network's weights may experience substantial updates, leading to instability and protracted convergence. The Long Short-Term Memory (LSTM) architecture was developed to tackle these difficulties.

The LSTM model integrates gates as shown in figure 4 and a cell state to control the flow of information inside the network. The present cell state in an LSTM is denoted as "ct". Its principal job is to retain and convey information over different temporal intervals.

The Long Short-Term Memory (LSTM) model employs three fundamental gates: the input gate, the forget gate, and the output gate. Each gate is depicted as a fully connected (FC) layer, consisting of a set of trainable weights. These gates control information transmission by selectively allowing or blocking particular components of the cell state and output.

$$i_t = \sigma\,(W_{xi}x_t + W_{\mathrm{hi}}h_{\mathrm{t-1}} + b_{\mathrm{i}}) \qquad (2)$$

The input gate controls the degree of integration of new input information into the cell state. The calculation of the input gate activation relies on the present input xt and the preceding output $h_{t-1}$. The weights $W_{xi}$ and $W_{hi}$, along with the bias bi, are utilized to compute the activation of the input gate. The sigmoid function σ is employed in this computation. This activation is then applied to the new candidate values, which signify potential alterations to the cell state.

$$f_t = \sigma\,(W_{\mathrm{xf}}\,x_{\mathrm{t}} + W_{\mathrm{hf}}\,h_{\mathrm{t-1}} + b_{\mathrm{f}}) \qquad (3)$$

.

The forget gate determines the fraction of the previous cell state to retain and transmit to the current time step. The activation of the forget gate is determined by the current input xt and the previous output ht−1, utilizing weights

Wxf and Whf. The activation is employed to modify the previous cell state, allowing the LSTM to discard or dismiss superfluous input.

$$o_t = \sigma\,(W_{xo}x_t + W_{ho}h_{t-1} + b_o) \qquad (4)$$

The output gate controls the degree to which the present cell state is disclosed as the output ht. The present input $x_t$ and the preceding output $h_{t-1}$ are taken into account, and their weights are employed to compute the activation of the output gate. The activation is multiplied by the modified cell state to yield the final output $o_t$.

By employing these gates, LSTM effectively alleviates the problems of gradient explosion and gradient vanishing typically faced by traditional RNNs. The gates facilitate the network's regulation of information flow, selectively retain or eliminate data from the cell state, and control the output of information. LSTMs can capture long-range dependencies in sequential data, enhancing their robustness and efficiency for various applications, such as language modeling, speech recognition, and machine translation.

Candidate Memory Cell (g): $g_t$=tanh ($w_g \cdot [h_{t-1}, x_t] + b_g$)

Cell State Update: $c_t = f_t \cdot c_{t-1} + i_t \cdot g_t$

Hidden State Output: $h_t = o_t \cdot \tanh(c_t)$

$C_t$ Is the cell state memory at the specified timestamp, (t), $g_t$ represents the candidate for cell state at timestamp(t).

The Bi-LSTM idea necessitates that each training sequence be processed in both forward and backward orientations utilizing two distinct LSTMs, which are interconnected at the output layer. The configuration provides the essential details to incorporate both forthcoming and historical contextual data within the output layer.

*Forward LSTM equations*:

Input Gate ($i_t^f$):

$$i_t^f = \sigma(w_i^f [h_{t-1}{}^f, x_t] + b_i^f) \qquad (5)$$

Forget Gate ($f_t^f$):

$$f_t^f = \sigma(w_f^f [h_{t-1}{}^f, x_t] + b_i^f) \qquad (6)$$

Output Gate ($o_t^f$):

$$o_t^f = \sigma(w_o^f [h_{t-1}{}^f, x_t] + b_o^f) \qquad (7)$$

Candidate Memory Cell ($g_t^f$):

$$g_t^f = \tanh(w_g^f [h_{t-1}{}^f, x_t] + b_g^f) \qquad (8)$$

Cell State Update ($c_t^f$):

$$c_t^f = f_t^f . c_{t-1}^f + i_t^f . g_t^f \qquad (9)$$

Hidden State Output ($h_t^f$):

$$h_t^f = o_t^f . \tanh(c_t^f) \qquad (10)$$

*Backward LSTM equations:*

Input Gate ($i_t^b$):

$$i_t^b = \sigma(w_i^b [h_{t-1}{}^b, x_t] + b_i^b) \qquad (11)$$

Forget Gate ($f_t^f$):

$$f_t^b = \sigma(w_f^b [h_{t+1}{}^b, x_t] + b_f^b) \qquad (12)$$

Output Gate ($o_t^{(b)}$):

$$o_t^b = \sigma(w_o^b [h_{t+1}{}^b, x_t] + b_o^b) \qquad (13)$$

Candidate Memory Cell ($g_t^b$):

$$g_t^b = \tanh(w_g^b [h_{t+1}{}^b, x_t] + b_g^b) \qquad (14)$$

Cell State Update ($c_t^b$):

$$c_t^b = f_t^b . c_{t+1}^b + i_t^b . g_t^b \qquad (15)$$

Hidden State Output ($h_t^b$):

$$h_t^b = o_t^b . \tanh(c_t^b) \qquad (16$$

In these equations, $x_t$ is the input at time step t, $h_{t-1}^f$ and$h_{t+1}^b$ are the hidden states from the previous and next time steps for the forward and backward LSTMs

respectively.$w_i^f$ , $w_f^f$, $w_o^f$, and $w_g^f$ are weights matrices for the input, forget, output, and candidate memory cells for the forward LSTM, respectively. $w_i^b$,$w_f^b$ , $w_o^b$, and $w_g^b$ are weights matrices for the input, forget, output, and candidate memory cells for the backward LSTM, respectively. $b_i^b$,$b_f^b$, $b_o^b$, and $b_g^b$ are bias vectors for the forward LSTM. $b_i^b$,$b_f^b$, $b_o^b$, and $b_g^b$are bias vectors for the backward LSTM. σ represents the sigmoid activation function. tanh is the hyperbolic tangent activation function. These equations delineate the flow of information in both the forward and backward directions of the BiLSTM, enabling the network to capture relationships from both historical and prospective contexts.

FSBi-LSTM denotes Fully Connected Stacked Bi-directional Long Short-Term Memory. The architecture is an advanced iteration of the Bi-directional LSTM (Bi-LSTM) that integrates novel features to boost its ability to capture long-term dependencies and derive significant representations from sequential input.

Essential elements of FSBi-LSTM: Stacked LSTM. The architecture utilizes a succession of vertically stacked LSTM layers. This allows the network to enhance its comprehension of data interconnections by employing the output of the prior layer as input for the following layer.

Bi-directional LSTM: Each LSTM layer is constructed to be bi-directional, indicating that it processes the input sequence in both forward and backward directions. This enables the model to understand context from both ends of the sequence, leading to a more thorough understanding of temporal connections.

A fully connected layer is added subsequent to the Bi-LSTM layers. This layer's objective is to consolidate the outputs of all LSTM cells and generate a cohesive representation. This allows the model to identify common

attributes over the entire sequence, thus encapsulating the complete "trait" information of the subject.

FSBi-LSTM computes the forward hidden sequence $\vec{h}^s$ and backward hidden sequence $\overleftarrow{h}^s$, which is expressed as:

$$\overrightarrow{h_t^s} = \mathrm{H}\left(w_{x\overrightarrow{hs}} x_t \overrightarrow{h_t} + w_{h\overrightarrow{hs}} \overrightarrow{h_{t-1}^s} + \overrightarrow{b_{hs}}\right) \quad (17)$$

$$\overleftarrow{h_t^s} = \mathrm{H}\left(w_{x\overleftarrow{hs}} \overleftarrow{h_t} + w_{h\overleftarrow{hs}} \overleftarrow{h_{t-1}^s} + \overleftarrow{b_{hs}}\right) \quad (18)$$

where $w_{x\overrightarrow{hs}}$ is the forward calculation of $w_x$, $w_{h\overrightarrow{hs}}$h is forward calculation of $w_h$, $\overrightarrow{b_{hs}}$ is a parameter of forward calculation in function H (·), and $w_{x\overleftarrow{hs}}$ , $w_{h\overleftarrow{hs}}$ and $\overleftarrow{b_{hs}}$ are parameters of backward calculations in H (·), and finally [25] the output denoted as

$$y_{st} = \mathrm{h}\left(w_{\vec{h}y}\vec{h}_t + w_{\overleftarrow{h}}y\overleftarrow{h}_t + b_y\right) \quad (19)$$

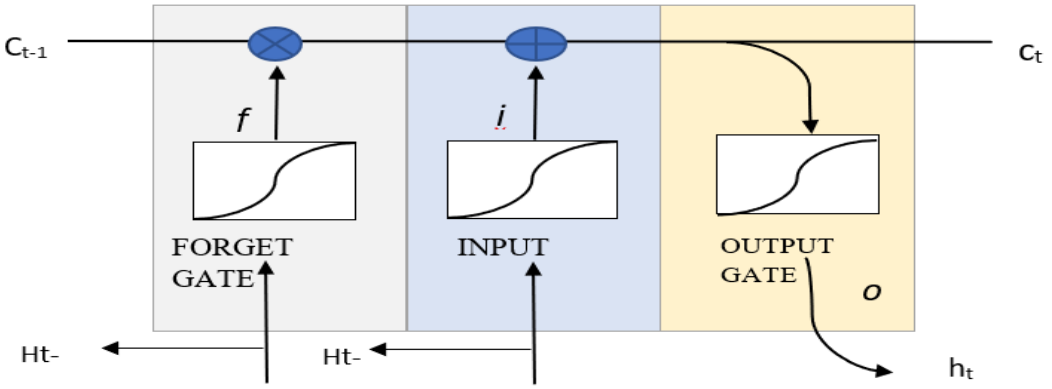


Figure 4: LSTM unit with three gates.

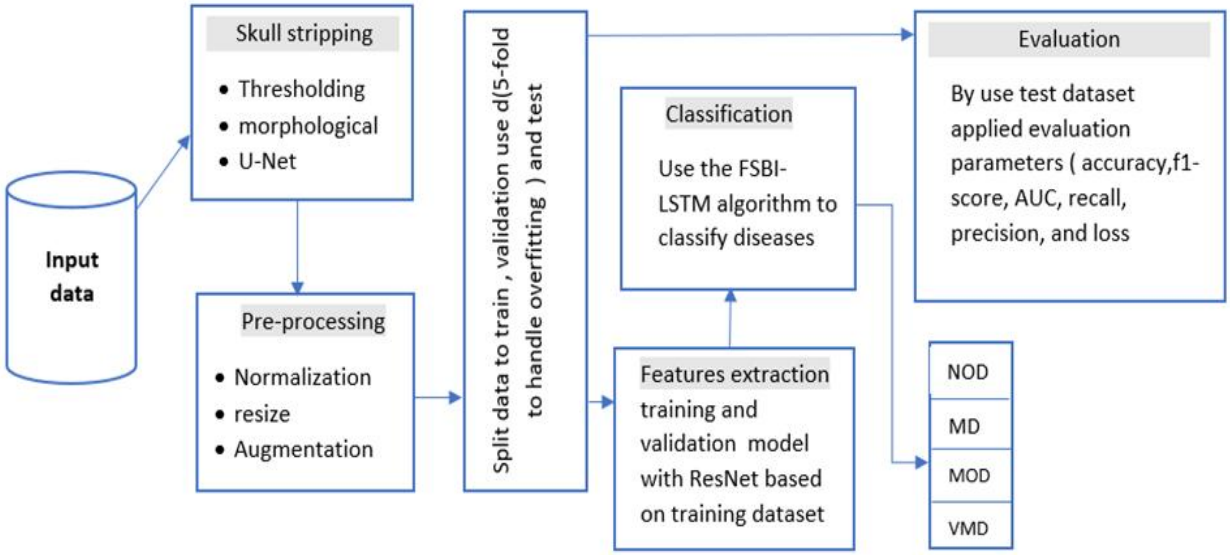


Figure 5: Step-by-step flowchart provide a clearer visualization of the framework

# 4 Experiments and results

## 4.1 Evaluation measures

The experiments were on a Google Colab hosted Jupiter Notebook service in subscription mode with runtime type Python 3 and hardware accelerator T4GPU Tesla T4 is a GPU card based on the Turing architecture and targeted at deep learning model inference acceleration with system RAM 52 GB, the model training was conducted over 20 epochs with a batch size of 32, ensuring an efficient balance between computational efficiency and convergence stability. The Adam optimizer was utilized for optimization, chosen for its adaptive learning rate and capability to handle sparse gradients, which facilitated faster convergence and improved performance during training. the evolution of model was conducted utilizing the validation which is part of the dataset, using several measures ensures a model is resilient from all angles

Successful model training depends on an extensive understanding of these results, for example, high accuracy (over 90%) does not necessarily indicate an excellent model other factors include loss and f1-score, etc. We used many measures to evaluate the performance of our model.

### 4.1.1 Accuracy

Accuracy is the measure of the total of correct predictions out of all accurate ones, and it is calculated using the following formulas:

$$Accuracy = (TP + TN) / (TP + FN + FP + TN) \quad (20)$$

TP, TN, FN, and FP represent True Positive, True Negative, and False Positive values, respectively.

#### 4.1.2 Precision

Precision is the measure of the proportion of correct positive forecasts to the sum of all positive predictions, as determined by the following equation:

$$Precision = TP / (TP + FP) \quad (21)$$

#### 4.1.3 Recall

The recall is commonly known as the sensitivity score or the true positive rate. This is the proportion of correct positive predictions to the total number of correct positive outcomes. The recall is determined using the following equation:

$$Recall = TP/(TP + FN) \quad (22)$$

#### 4.1.4 F1-score

An ideal classification model has precision and recall values of 1.0. The F1 score represents the harmonic mean of precision and recall. The F1 score graph is distinctive in that it displays an individual line for each class designation. The F1 score is computed using the following formula:

$$F1 = 2 * (Precision * Recall)/(Precision + Recall) \quad (23)$$

#### 4.1.5 Loss of function

Loss functions measure the mathematical difference between predicted and actual values. In this study, we employed a categorical cross-entropy algorithm for loss.

$$Loss = y - \bar{y} \quad (24)$$

$$LCE = -\sum_{n=0}^{k} (Li \log pi) \quad (25)$$

#### 4.1.6. Area under curve

AUC, also known as Area Under the ROC Curve, is a quantitative measure utilized to assess the effectiveness of classification models. A single numerical value quantifies the model's capacity to differentiate between positive and negative classes.

#### 4.1.7. Confusion matrix

A confusion matrix is a technique for evaluating the performance of classification models. It displays the actual and expected categories in a tabular style. The four primary metrics obtained from it are False Positives (FP), True Positives (TP), True Negatives (TN), and False Negatives (FN). From these numbers, one can compute metrics like as accuracy, precision, recall, and F1-score. It aids in comprehending the varieties of faults committed by the model and their distribution among various groups.

## 4.2 Comparison with base models

In this section, we compared the proposed model with some base models such as VGG16, Inception, and DanseNet169. The related results using the OASIS dataset are shown in Table 3 and corresponding Figure 5. The Loss values for the proposed, DenseNet169, VGG16, and Inception methods obtained 0.05, 0.093, 0.0525, and 0.098, respectively. Indicating that the model is exhibiting strong performance on the training data by effectively reducing the disparity between predicted and actual values. Based on the accuracy measure ACC, the values 99.6%, 98%, 99.6%, and 97.9% are obtained for the proposed, DenseNet169, VGG16, and Inception methods, respectively.

The F1 score in a multi-class classification model is a crucial indicator for precisely evaluating the model's performance and its efficacy in classifying cases across all classes. Although accuracy is a significant metric, it does not provide a comprehensive overview. The F1 score provides a more thorough assessment of the model's performance. A high F1 score often indicates that the model is producing precise predictions across several classes. A high F1 score may signify varying implications depending on the particular challenge and circumstance. The results indicate that the proposed model achieves the highest F1 score relative to other techniques.

The Area Under the Curve (AUC) statistic is extensively utilized in the assessment of binary classification model performance. In multi-class classification, the AUC metric is generally calculated using a pairwise comparison method (one-vs-all), indicating that the AUC value reflects the model's efficacy in differentiating between two distinct classes. It offers a singular metric that encapsulates the model's overall discriminative capability across all classes; a high AUC signifies an exceptional ability to predict the probabilities of the correct class relative to other classes. The results in Table 3 indicate that the suggested model achieves the second highest AUC score relative to other techniques.

The Recall measure refers typically to a performance metric used in machine learning tasks. In medical research or diagnostic systems recall plays a vital role in identifying potential diseases. It helps in minimizing false negatives of the model. A high recall assists in ensuring that no important medical information is overlooked during the diagnosis. Also, in a situation where the dataset is imbalanced, which can lead to a biased model performing poorly on the minority class, high recall ensures that the

model doesn't miss relevant instances from the minority class. The results in Table 3 indicate that the suggested model achieves the second highest Recall score among the evaluated techniques.

The precision measure realizes the model's ability to make a reliable prediction, especially when dealing with imbalanced datasets. The results in Table 3 indicate that the suggested model exhibits superior Precision values relative to alternative techniques.

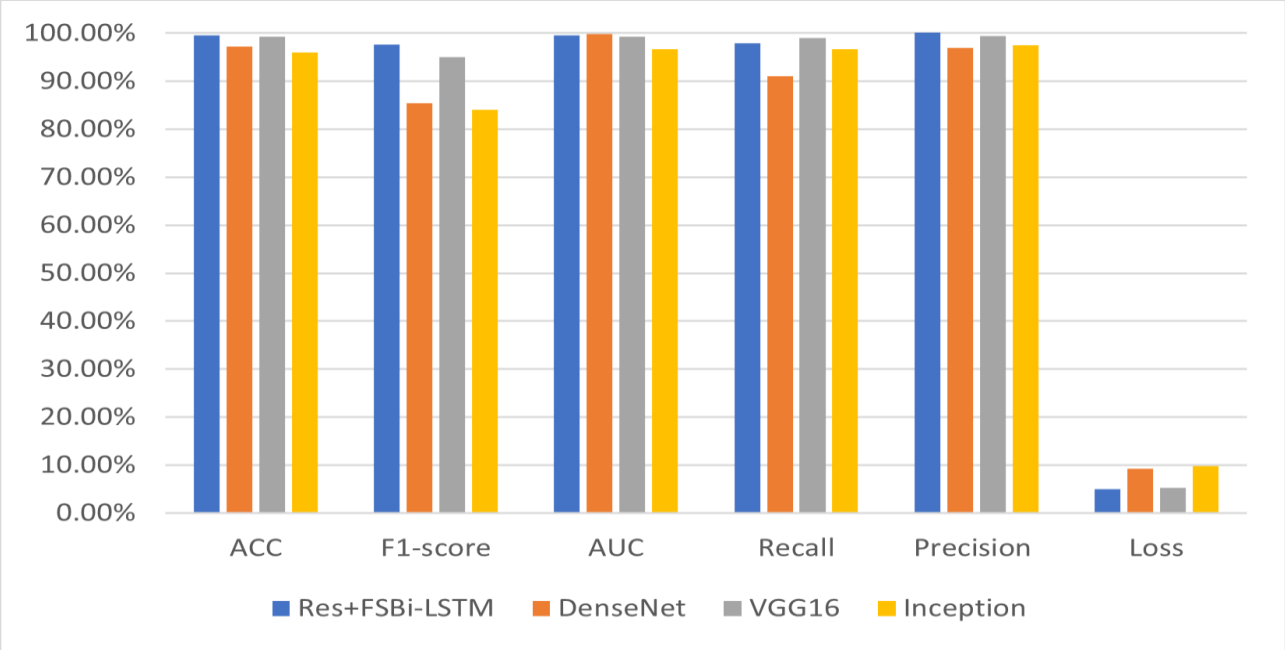


Figure 5: Comparison of the proposed ReS+FSBILSTM model with some base models using OASIS dataset.

| *Methods* | *ACC* | *F1-score* | *AUC* | *Recall* | *Precision* | *Loss* |
|---|---|---|---|---|---|---|
| ReS+FSBILSTM | **99.60%** | **97.7%** | 99% | 97.3% | **99.60%** | **0.05** |
| DenseNet | 98% | 85.40% | 95.00% | 91% | 98% | 0.093 |
| VGG16 | 99.30% | 95.80% | **99.30%** | **99%** | 99.60% | 0.052 |
| Inception | 97.90% | 84% | 99% | 96.9% | 97.90% | 0.098 |

Table 4: Evaluation of the proposed Res+FSBi-LSTM model against several baseline models utilizing the OASIS dataset

We have conducted statistical significance tests to compare our model's performance against other methods. To compare our model's performance metrics accuracy,

F1 score, and AUC with those of other models on the same test sets table 5 presents the results of pairwise t-tests comparing FSBi-LSTM with DenseNet196, Inception, and VGG16 with the area under the curve for 20 epochs

In terms of AUC, ReS+FSBILSTM vs DenseNet t—t-statistic is obtained at 15.19 (large positive value) and p-value $\mathbf{4.41\times10^{-12}}$ **(**extremely small), which means ReS+FSBILSTM significantly outperforms DenseNet, ReS+FSBILSTM vs Inception t-statistic achieved 11.76 (large positive value) and p-value 3.66×10−10 (extremely small) ReS+FSBILSTM significantly outperforms Inception in terms of AUC, and finally ReS+FSBILSTM vs VGG16 is obtained t-statistic 0.073 (near zero), p-value 0.94 (much greater than 0.05) There is no significant difference in AUC between ReS+FSBILSTM and VGG16. ReS+FSBILSTM significantly outperforms DenseNet and Inception. However, there is no significant difference between ReS+FSBILSTM and VGG16. This implies that both methods are equally good in terms of AUC, based on this analysis.

Table 5: presents the results of pairwise t-tests comparing FSBi-LSTM with DenseNet196, Inception, and VGG16 with the area under the curve for 20 epochs

| Method 1 | Method 2 | t-statistic | p-value |
|---|---|---|---|
| ReS+FSBILSTM | DensNet196 | 15.19050438 | 4.41E-12 |
| ReS+FSBILSTM | Inception | 11.7573442 | 3.66E-10 |
| ReS+FSBILSTM | Vgg16 | 0.073432834 | 0.942229262 |

Table 6: presents the results of pairwise t-tests comparing FSBi-LSTM with DenseNet196, Inception, and VGG16 with the accuracy for 20 epochs

| Method 1 | Method 2 | t-statistic | p-value |
|---|---|---|---|
| ReS+FSBILSTM | DensNet196 | 23.54977478 | 1.60E-15 |
| ReS+FSBILSTM | Inception | 13.98856186 | 1.87E-11 |
| ReS+FSBILSTM | vgg16 | 13.74847329 | 2.52E-11 |

Table 7: presents the results of pairwise t-tests comparing FSBi-LSTM with DenseNet196, Inception, and VGG16 with the f1-score for 20 epochs

| Method 1 | Method 2 | t-statistic | p-value |
|---|---|---|---|
| ReS+FSBILSTM | DensNet196 | 10.7768 | 2.79E-09 |
| ReS+FSBILSTM | Inception | 10.54124 | 3.94E-09 |
| ReS+FSBILSTM | Vgg16 | 41.35215 | 2.69E-19 |

In terms of accuracy, ReS+FSBILSTM demonstrates significantly superior performance compared to DenseNet196, Inception, and VGG16. The comparison with DenseNet196 yields a t-statistic of 10.78 and a p-value of $2.79\times10^{-9}$, indicating a highly significant difference in favor of ReS+FSBILSTM. Likewise, ReS+FSBILSTM surpasses Inception with a t-statistic of 10.54 and a p-value of 3.94×10−9, indicating a significant performance superiority. The comparison with VGG16 demonstrates a substantial disparity, evidenced by a t-statistic of 41.35 and a p-value of 2.69×10−19, highlighting pronounced statistical significance. The results demonstrate that ReS+FSBILSTM markedly outperforms all three techniques in accuracy, as indicated by the notably high t-statistics and minimal p-values.

The findings indicate that the f1-score of ReS+FSBILSTM is markedly superior to that of DenseNet196, Inception, and VGG16. The comparison with DenseNet196 results in a t-statistic of 23.55 and a p-value of 1.60×10−15, signifying a substantial performance disparity. The t-statistic for Inception is 13.99, accompanied by a p-value of 1.87×10−11, indicating a significant disparity. Likewise, ReS+FSBILSTM surpasses vgg16, exhibiting a t-statistic of 13.75 and a p-value of 2.52×10−11. The results indicate that ReS+FSBILSTM substantially outperforms all other approaches in f1-score, evidenced by highly significant p-values and notable performance benefits as represented in the huge t-statistics.

The confusion matrix offers a comprehensive evaluation of the model's efficacy on the test dataset. The model has high precision and recall for the Non-Demented and Moderate Dementia categories, with no misclassification among unrelated classes. The Non-Demented class attained 192 genuine positives, with merely five occurrences incorrectly classified as Mild Dementia, whereas the Moderate Dementia category scored 895 true positives with minimal misclassification. The matrix indicates a degree of overlap between Mild Dementia and Moderate Dementia, possibly attributable to the similarity of characteristics between these illnesses, resulting in 129 cases of Mild Dementia being erroneously categorized as Moderate Dementia.

Additionally, a slight bias toward the dominant Mild Dementia class is observed, as it constitutes the majority of the dataset, with 6,658 correctly classified instances and limited misclassifications across other classes. These findings highlight the need for addressing class imbalance and enhancing feature extraction to improve the distinction between closely related dementia categories, particularly between Mild and Moderate Dementia.

Table 8: Comparison of the proposed Res+FSBILSTM model with state-of-the-art methods using MRI dataset.

| **Methods** | **ACC** | **F1-score** | **Recall** | **Precision** | **AUC** |
|---|---|---|---|---|---|
| DBN-MOA [36] | 97.46 | 93.187 | 95.789 | 94.621 | - |
| VGG16-EfficientNet-B2[37] | 97.07 | 97.16 | 97.27 | 96.91 | 99.59 |
| VGG16-SVM-with-Aug [38] | 98.67 | 95.39 | 91.2 | 100.00 | - |
| CNN+LSTM [39] | 98.50 | - | 98.00 | 94.80 | - |
| **Res+FSBILSTM (proposed)** | **99.66** | **97.7** | **97.4** | **97.45** | **99.6** |

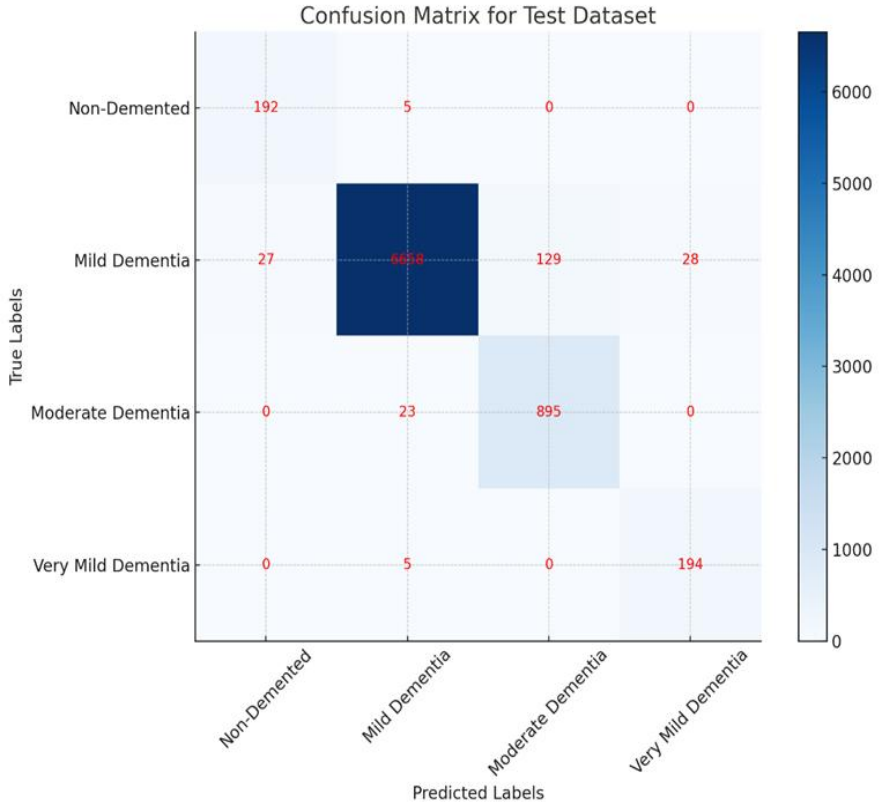


Figure 6: Performance evaluation using confusion matrix for dementia classification

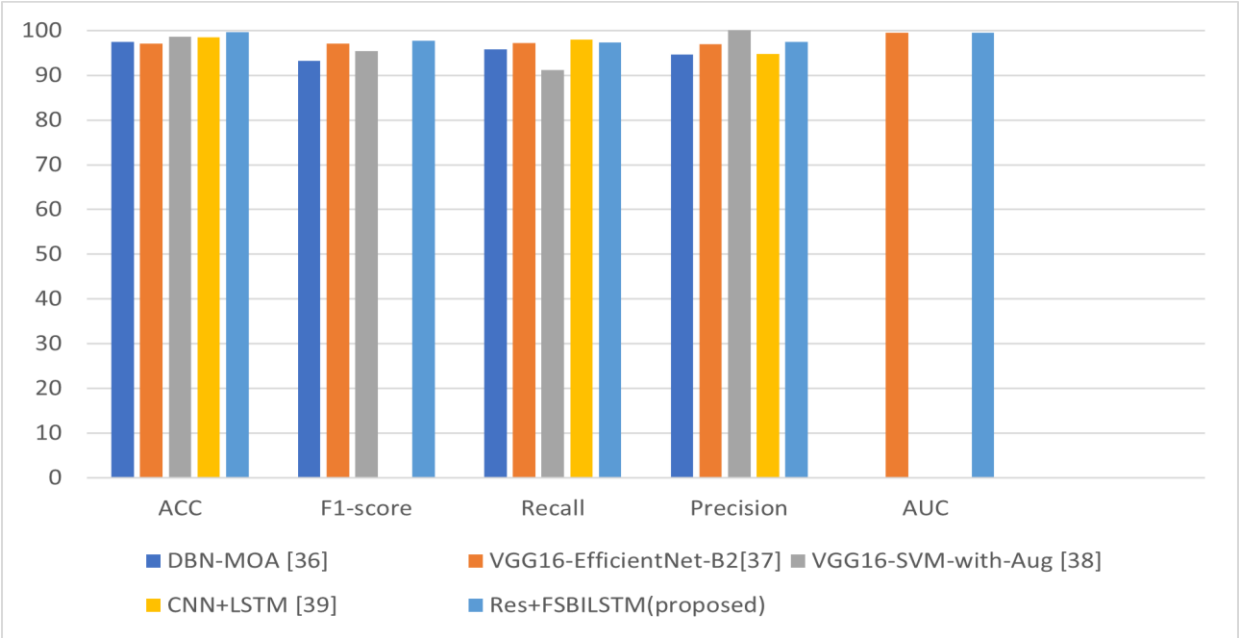


Figure 7: Comparison of the proposed ReS+FSBILSTM model with other methods using the OASIS dataset.

## 5 Discussion

We chose those studies from the literature that considered multiclass datasets for comparison with the proposed method. DBN-MOA [38] is a Deep Belief Network (DBN) trained with the Mayfly Optimization Algorithm (MOA). The VGG16+EfficientNet-B2 model [39] is a combination of VGG16 and EfficientNet-B2 pre-trained model. VGG16-SVM-with-Aug [40] uses transfer learning and augmentation techniques to detect Alzheimer's disease. The CNN+LSTM [41] method is a combination of CNN with LSTMN. Considering the results on Table 4 and corresponding Fig. 6 show that the proposed method can outperform other methods in all

criteria such that we can suggest it as a reliable tool for Alzheimer's disease diagnosis.

Our method employs ResNet50 combined with FSBiLSTM for MRI classification, leveraging advanced preprocessing via skull stripping using thresholding, morphological operations, and U-Net models. Compared to other SOTA methods, such as DBNs used in IoT-based detection (Alqahtani et al., 2023), ensemble learning with synthetic techniques (Mujahid et al., 2023), and deep learning-based classification (Sorour et al., 2024; Balaji et al., 2023), our approach demonstrates superior accuracy in MRI image classification due to robust feature extraction and temporal modeling of FSBiLSTM. However, slight trade-offs in sensitivity were observed when evaluated against ensemble methods (Mujahid et al., 2023), which excel at reducing overfitting with adaptive sampling techniques.

Architectural improvements, such as FSBiLSTM's ability to capture spatial and temporal dependencies, significantly improved generalization in MRI-based Alzheimer's detection. Preprocessing techniques like skull stripping ensured cleaner input data, reducing noise and enhancing classifier performance. Conversely, the ensemble approaches developed by Mujahid et al. employed oversampling techniques that marginally surpassed our method in detecting the minority class. DBNs by Alqahtani et al. achieved commendable efficiency in IoT integration but lacked MRI-specific enhancements, limiting their effectiveness in image-based classification tasks. For clinical use, the higher accuracy of our method ensures more reliable Alzheimer's diagnosis, particularly in early-stage detection where subtle changes in MRI images are critical. The sensitivity trade-off highlights a need for future enhancements in minority class detection, ensuring that cases with subtle features are not overlooked. Practical application also benefits from the efficient preprocessing pipeline, making the approach scalable for large-scale diagnostic workflows in hospitals.

The proposed method's architectural and data processing enhancements translate into significant practical benefits for Alzheimer's diagnosis. It not only improves accuracy and generalizability but also addresses operational and ethical challenges, making it a highly viable tool for real-world clinical applications.

In summary, the proposed method's superior performance can be attributed to a synergy of architectural improvements, optimized training, and effective data handling techniques, making it a promising tool for Alzheimer's disease diagnosis.

Table 9: Comparison of methods for alzheimer's disease diagnosis using MRI images

| Model | Architectural Improvements or Data Processing Techniques | Strengths | Limitations |
|---|---|---|---|
| DBN-MOA | Deep Belief Network with Mayfly Optimization Algorithm for improved convergence. | Effective optimization with MOA; robust for certain datasets. | Limited feature extraction capability compared to modern CNN-based models. |
| VGG16+EfficientNet-B2 | Combination of VGG16 and EfficientNet-B2 pre-trained models for robust feature extraction. | Combines strengths of two pre-trained models, robust for general imaging tasks. | Generic architecture may miss domain-specific nuances in Alzheimer's diagnosis. |
| VGG16-SVM-with-Aug | Transfer learning with augmentation techniques; simple architecture for binary classification. | Utilizes transfer learning and augmentation; good for binary classification. | Struggles with multiclass datasets and lacks adaptability for complex progressions. |
| CNN+LSTM | Combines CNN for spatial features and LSTM for temporal patterns in sequential data. | Captures both spatial and temporal features; suited for sequential data. | Computationally intensive; may not outperform specialized Alzheimer focused methods. |
| Proposed Method | Combines ResNet50 for feature extraction with FSBILSTM for classification. Skull stripping preprocessing via threshold and morphological operations, implemented with U-Net. | Excels in feature extraction, multiclass handling, and optimization; designed for Alzheimer's MRI. | Requires high computational resources to fine-tune effectively. |

# 6 Conclusion

In this paper, we proposed a method for skull stripping gathering both of thresholding and morphological Operations with U-net Our method effectively handles diverse medical imaging modalities, including MRI, and PET scans, this distinguishes it from other methods that treat only a specific type accurately and as for anther types may be treated with moderate accuracy or not dealt with at all, it achieved high accurate comparing with others method extracting the brain from human skull we also proposed model combined between the CNN layers of Resnet50 to features extraction after skull stripping and pre-processing operation then used FSBILSTM for do the classification the input MRI images from two reliable datasets OASIS to the four classes, the various The matrices utilized to assess the efficacy of the proposed model indicate a high accuracy of 99.6%, an F1-score of 97.7%, and an AUC of 99.6%. We will incorporate additional pre-trained architectural models and refine various transfer learning models to get more reliable and favorable outcomes in the future.

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