Deep Learning-based Classification of MRI Images for Early Detection and Staging of Alzheimer's Disease

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***Abstract*—Alzheimer's disease (AD) poses a significant challenge to modern healthcare, as effective treatment remains elusive. Drugs may slow down the progress of the disease, but there is currently no cure for it. Early AD identification is crucial for providing the required medications before brain damage occurs. In this course of research, we studied various deep learning techniques to address the challenge of early AD detection by utilizing structural MRI (sMRI) images as biomarkers. Deep learning techniques are pivotal in accurately analyzing vast amounts of MRI data to identify Alzheimer's and anticipate its progression. A balanced MRI image dataset of 12,936 images was used in this study to extract sufficient features for accurately distinguishing Alzheimer's disease stages, due to the similarities in the characteristics of its early stages, necessitating more images than previous studies. The GoogLeNet model was utilized in our investigation to derive features from each MRI scan image. These features were then inputted into a feed-forward neural network (FFNN) for AD stage prediction. The FFNN model, utilizing GoogLeNet features, underwent rigorous training over multiple epochs using a small batch size to ensure robust performance on unseen data and achieved 98.37% accuracy, 98.39% sensitivity, 98.50% precision, and 99.45% specificity. Most remarkably, our results show that the model detected AD with an amazing average accuracy rate of 99.01%**.

Keywords*—*Alzheimer's disease (AD); Convolution Neural Network (CNN); Deep Learning (DL); Transfer Learning (TL); imaging pre-processing

I. Introduction

The biomarkers for Alzheimer's disease are detected through brain MRI scans, by identifying the presence of intracellular neurofibrillary tangles (NFTs) containing hyperphosphorylated tau protein (P-tau) and extracellular plaques comprised of insoluble β-amyloid peptide (Aβ), with genetic factors contributing to 70% of the risk [1]. The stages of Alzheimer's disease (AD) follow a continuum, starting from subtle initial alterations leading to memory impairments and eventual physical decline. Various factors, including age, genetic predisposition, and biological sex, influence the duration of each phase along this continuum [2]. Alzheimer's disease (AD) is the most common and widespread type of dementia, threatens to reach epidemic proportions globally without a definitive cure. Its incidence is rapidly increasing worldwide, as evidenced by approximately 454,000 new cases reported in 2010 and a significant 55% rise in mortality rates from 1999 to 2014. By 2050, there will likely be a rapid increase in AD cases in the US, affecting 5.2 million US citizens aged over 65[3].

A. Significance AD Early Prediction

Alzheimer's disease, primarily impacting individuals aged 65 and above, is influenced by factors such as age, genetics, and familial predisposition. From 2020 to 2060, the number of U.S. citizens aged 65 and above diagnosed with AD is gradually increasing from 6.8 million to 13.8 million. It was the sixth-most common reason for deaths among U.S. citizens in 2019, and subsequently dropped to seventh in 2020 and 2021, primarily due to the COVID-19 pandemic. Among individuals aged 70, 61% of those afflicted with Alzheimer's dementia are anticipated to pass away before reaching 80, a stark contrast to the 30% mortality rate among those unaffected by the condition.

The mortality rate attributed to Alzheimer's rises significantly with age, particularly after 65, with a disproportionate impact on individuals aged 85 and older. Between 2000 and 2019, the mortality rate surged by 33% for the 65-74 age group, 51% for those aged 75-84, and 78% for individuals aged 85 and above. By 2023, the predicted expenditure for medical services and continuous treatment of brain disorders, including AD, is estimated to be 345 billion dollars. Structural biomarkers linked to Alzheimer's disease (AD) can be examined using contemporary imaging techniques like structural magnetic resonance imaging (sMRI)[4].sMRI facilitates the assessment and comprehension of brain structural alterations induced by AD in a non-invasive and efficient manner. These methods are crucial in clinical settings and play a pivotal role in diagnosing AD pathology [5][6][7].

The advancement of deep learning with neural networks has resulted in the introduction of various innovative techniques [8], aiming to enhance the processing and analysis of MRI images. Within MRI brain images, one of the most important tasks is to separate the White Matter, Grey Matter and Cerebrospinal Fluid. Particularly in its early phases, this segmentation is essential for the identification of AD, which holds significant importance in healthcare. Considering the neurodegenerative nature of AD and its extended incubation period, analyzing its symptoms across different stages is imperative. Presently, many researchers strongly support the use of methods for image classification for the diagnosis of AD. Moreover, several advanced deep learning methods have been suggested to accurately categorize the severity of Alzheimer's disease in different patients by analyzing MRI images.

The rest of the paper is organized as follows: Related work is covered in Section II, preprocessing in Section III, the proposed approach in Section IV, the results in Section V, discussion of the results in Section VI, and finally, the conclusion is provided in Section VII.

II. Related Work

In [9] presented the EAD-DNN method, which uses deep neural networks to forecast AD at an early stage. The authors utilize the MRI images and extract key features for classification by using a dataset in CSV format to train a deep Residual Network (ResNet) and Convolutional Neural Network (CNN). Through extensive experiments, the method achieves 98% accuracy in multi-class classification AD prediction. In their study, [10] devised three approaches that exhibit exceptional precision in diagnosing and forecasting the phases of AD. The approaches utilized a combination of features from the GoogLeNet and DenseNet-121 models, as well as handmade features from the DWT, LBP, and GLCM methods, together with CNN models.

In [11] conducted research on the use of the MIRIAD dataset in convolutional neural networks (CNNs) to predict Alzheimer's disease by using MR Image dataset. After less than 30 seconds of calculation, the model produced strong performance metrics: an accuracy of 0.89, a Matthew's Correlation Coefficient of 0.77, an F1-score of 0.89, and an AUC of 0.92.In [12] the paper discusses the difficulty in accurately predicting Alzheimer's disease stages, highlighting the need for explainable artificial intelligence (XAI) models. It compares four XAI models, including Gradient-weighted Class Activation Mapping, Grad-CAM, Score-CAM, and Faster Score-CAM, and evaluates their effectiveness in improving prediction accuracy and interpretability.

The research [13] introduces a 3D convolutional neural network (CNN) model for detecting brain abnormalities related to Alzheimer's disease (AD) by analyzing whole-brain MRI data. The model employs both channel and spatial attention methods to extract pertinent data, hence enhancing accuracy. The study obtained a total accuracy of 79% in classifying three categories (MCI, CN, and AD), and an average accuracy of 87% in distinguishing AD from the other two categories. The 3D CNN model, incorporating attention processes, has superior classification performance in comparison to alternative models. This underscores the promise of deep learning algorithms for the timely identification and forecasting of Alzheimer's disease. The study use the publicly accessible Alzheimer's disease Neuroimaging Initiative (ADNI) dataset, which comprises magnetic resonance imaging (MRI) scans of individuals diagnosed with mild cognitive impairment (MCI), cognitively normal (CN) persons, and those with Alzheimer's disease (AD).

The author in [14] introduces a deep learning approach that utilizes MRI scans to detect Alzheimer's disease at an early stage. The authors employ ResNet-50v2 as the optimal model, attaining an accuracy of 91.84%. The approach also uses visualization techniques like Grad-CAM and Saliency Map to understand focus regions. The authors of [15] introduced a deep learning model that utilizes the VGG16 model for extracting features to diagnose early stages of Alzheimer's disease using MRI scans. The model outperforms previous studies in accuracy and can be used for early identification of AD stages. The methodology includes data selection, feature extraction, and outcome prediction, useful for future research in AD detection.

The study conducted by [16] presents a novel approach for detecting Alzheimer's disease through making use of deep learning techniques. This study aims to classify Alzheimer's disease into several categories, namely no-dementia, very mild, mild, and moderate, with the objective of facilitating the development of personalized treatment strategies for affected individuals. The study achieves high classification accuracy with the VGG-16, Inception-V3, and Xception models, with accuracies of 75%, 70%, and 70% respectively. The paper highlights the importance of early detection of Alzheimer's disease, particularly at stages like very mild, mild, and moderate, to slow or prevent disease progression. In The author of [17] created a deep learning model that uses MRI images to accurately detect AD. The National Institute of Neurological and Communicative Disorders and Stroke devised the criteria and neuropsychological testing used in the model, which may improve patient treatment and early diagnosis.

The author of [18] looked into a group of convolutional neural network models for determining the various phases of Alzheimer's disease. The dataset consisted of 6400 images of MRI brain scans. The adoption of the Synthetic Minority Over-sampling Technique enhanced the efficacy of medical picture analysis. The ensemble model has better results in terms of accuracy when compared to the individual CNN models. The author of [19] studied two datasets: the OASIS dataset with MRI images and the longitudinal dataset with text values. The OASIS MRI dataset utilizes fourteen machine learning techniques. Among these, the InceptionV3 model using ADAM as the Optimizer achieves the highest accuracy.

Two supervised deep neural network models were proposed by the author in [20] a residual network (ResNet3D) and a 3D-VGG-16 standard convolutional network. ResNet3D outperformed the 3D-VGG-16 network in class prediction, achieving 85% validation set accuracy while using less processing power. ResNet3D may perform better in categorizing photos with a high degree of complexity, according to the research.

Prior research has mostly concentrated on attaining high accuracy in differentiating between Alzheimer's disease (AD) stages. However, concerns regarding the credibility of these results have arisen due to the utilization of unbalanced datasets and a lack of an adequate number of MRI scans. Moreover, the preprocessing methods applied to the data may have inadvertently eliminated vital information, potentially compromising model performance. Furthermore, the models deployed in these studies have been distinguished by their complexity and computationally challenging nature. In contrast, this study addresses these limitations by utilizing a well-balanced dataset with a sufficient number of MRI images. It trains and predicts AD phases using a Feed Forward Neural

Network (FFNN) and extracts features using deep learning techniques. The main highlights of this paper include:

- Image processing techniques were used to resize and eliminate noise in the provided image in order to ensure coherence.
- To balance the dataset, data augmentation techniques were employed, resulting in an expanded dataset size of 12,936 images.
- For Alzheimer's disease stage-wise prediction, a Feedforward neural network (FFNN) model was fine-tuned by utilizing features extracted via GoogLeNet.
- This approach exhibited notable performance improvements when compared to current techniques as shown in Table I.

TABLE I. COMPARISON OF STATE-OF-THE-ART METHODS WITH THE PROPOSED APPROACH

S.NO	Author	Dataset	Feature Extraction Method	Classification Model	Accuracy
1	Thangavel et al., 2023	MRI Images	CNN and ResNet	CNN and ResNet	98
2	Khalid et al. 2023	6400 MRI Images	GoogLeNet	Feed Forward Neural Network (FFNN)	94.80
3	De Silva and Kunz.2023	MIRIAD dataset (708 MRI Images)	CNN	CNN	92
4	Jahan et al., 2023	MRI Images	EfficientNetB7	EfficientNetB7	91.76%
5	George et al., 2023	ADNI dataset (1876 MRI images)	3D-CNN	3D-CNN	79%
6	L et al., 2023	ADNI 2 dataset	ResNet-50v2	ResNet-50v2	91.84
7	Sharma et al., 2022	6400 or 6300 MRI Images	VGG16	CNN	90.4%
8	Rama Ganesh et al., 2022	OASIS dataset	VGG-16	CNN	75%
9	Ahmad et al., 2023	MRI Images	CNN	CNN	97.44%
10	Li et al., 2023	6400 MRI images	CNN	CNN	--
11	Amrutesh et al., 2022	OASIS dataset	InceptionV3	InceptionV3	92.13%
12	Armonaite et al., 2023	ADNI Dataset	3D VGG 16,ResNet 3D	3D VGG 16,ResNet 3D	85%
13	Proposed Method	Kaggle Dataset (12936 MRI Images)	GoogLeNet	FFNN	98.38

III. DATASET DESCRIPTION AND PREPROCESSING

A. *MRI Image Dataset*

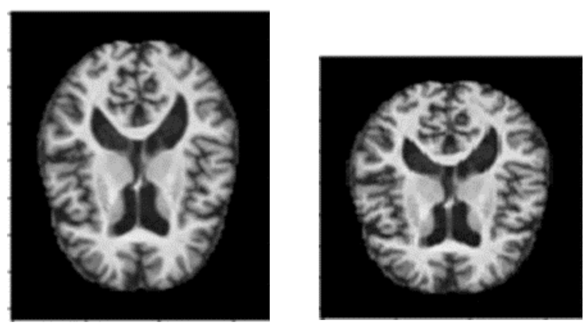
The study utilizes a MRI dataset from Kaggle which focused on Alzheimer's disease classification. This dataset comprises 6400 structural MRI (sMRI) images are grouped into four distinct categories. Specifically, there are 896 images representing mild demented cases, 3200 for non-demented cases, 64 for moderately demented cases, and 2240 for very mild demented cases. Each MRI image in the dataset has dimensions of 176 × 208 and is in.jpg format. The MRI imaging data mentioned above is accessible on the Kaggle website [21].

B. *Preprocessing*

The resizing process in MRI images removes unnecessary black regions, improving focus and efficiency. This reduces computational complexity, memory, and processing time, and expedites training and evaluation processes. The grayscale images are resized to 108x128 pixels as depicted in Fig. 1.

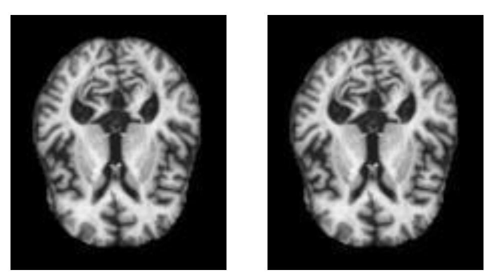
C. *Enhancement of MRI Images using Adaptive Median Filter*

Reducing machinery impulse noise often involves using specific denoising techniques that are effective for the characteristics of such noise. Here are some techniques commonly employed for reducing impulse noise in images. Machine impulse noise reduction involves using denoising techniques like median filtering and adaptive median filtering. Median filtering replaces pixels with median values, while adaptive filtering adjusts filter size based on local image characteristics, effectively handling different noise levels. Fig. 2 Illustrates MRI image before and after noise removal.



Original Image (176 x 208)   Resized Image (108 x128)

Fig. 1. Resizing MRI image.



Before noise removal   After noise removal

Fig. 2. Illustrating noise removal using adaptive median filter.

The adaptive filter [22] operates through a two-step process: determining the kernel's median value and checking the current pixel value for impulse noise. If a pixel's value is distorted, it transforms it to the median or keeps it grayscale. The adaptive median filter operates on two distinct levels, referred to as Level 1 and Level 2, which function in the following manner:

D. Algorithm

V_{min}, Vmax and V_{mid} are the minimum, maximum and median gray scale values found within the window W_{xy} respectively. V_{xy} represents the grayscale value at the coordinates (x, y), W_{xy} represents the window size relative to the coordinates (x, y), W_{max} indicates the maximum permissible size for W_{xy}.

Level-1:

W_{xy} = Dimensions of the window relative to coordinates (x, y)

Calculate $P_1 = V_{med} - V_{min}$

Calculate $P_2 = V_{med} - V_{max}$

if $P_1 > 0$ AND $P_2 < 0$

*go to **Level-2***

else

Increase size of the window (W_{xy})

if $W_{xy} <= W_{max}$

*Repeat **Level-1***

else

Output V_{xy}

Level -2: *$Q_1 = V_{xy} – V_{min}$*

$Q_2 = V_{xy} – V_{max}$

if $Q_1 > 0$ and $Q_2 < 0$

Output V_{xy}

else

Output V_{med}

E. Data Augmentation

Medical research, especially in neuroimaging, faces challenges in acquiring a large number of scans due to privacy concerns. Limited and imbalanced datasets can result in overfitting, reducing model effectiveness. To address this, data augmentation techniques [23], [24] are utilized. Horizontal flipping augmentation is applied to the original dataset to generate more images as shown in Fig. 3. While other augmentation methods like brightness adjustment, zoom, and rotation were tried, they did not improve the proposed model's performance. Table II indicates that the non-dementia category remained the same, with five scan images generated from each mild dementia image. The moderate dementia category has fewer images, resulting in fifty scan images being generated from each image. In the mild dementia category, three images are generated from each image.

TABLE II. CLASS-WISE COMPARISON OF THE MRI DATASET PRE- AND POST-AUGMENTATION

Class label	Before Augmentation	After Augmentation
Mild_Demanted	896	3296
Moderate_Demented	64	3200
Non_Demented	3200	3200
Very_Mild_Demented	2240	3240
Total	6400	12936

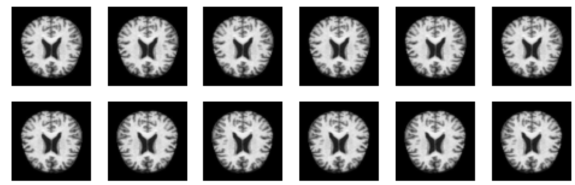


Fig. 3. Sample images generated using data augmentation.

IV. PROPOSED METHODOLOGY

In the previous study, the authors employed intricate deep learning methods to extract and merge features from various techniques, necessitating substantial computational resources for feature extraction. In our research, we aim to devise a straightforward framework that achieves superior accuracy compared to current state-of-the-art approaches. The proposed framework consists of two main tasks: the first involves retrieving features from MRI images using the CNN model, while the second involves diagnosing the extracted features using the FFNN method.

A. Convolution Neural Network

Multiple layers are used in CNN models for deep feature map extraction [25]. These layers are used to detect local characteristics and combine related ones. To comprehend raw data representations, they go through a rigorous dataset training process [26]. The input image undergoes convolution by the convolutional layer, resulting in the creation of feature maps. The pooling layer decreases the dimensions of the feature maps [27].

B. Convolutional Layers

CNNs utilize convolutional layers to extract features from images. The output dimensions of these features are determined by several parameters, including the size of the input, the size of the kernel, the stride, and the padding. Equation (1) provides the formula to determine the output size Y (t) for a given input image size X(t):

$$Y(t) = \frac{X(t)-K+2P}{S} + \quad (1)$$

Where X (t): Input size at time t, K: Kernel size, S: Stride, P: Padding

C. Pooling Layer

CNN designs employ average and max pooling in their pooling layers to reduce feature dimensionality. While average pooling calculates and replaces the selected pixels, Max pooling selects the highest pixel value from a grid of pixels. For each location (i, j) the output feature map, computed by using (2).

$$O(i,j) = \max_{(u,v)\in poolingwindow} Input(i \times S + u, j \times S + v) \quad (2)$$

Where (u, v) iterates over the pooling window size p × p, and S is the stride of the max pooling operation.

D. *Deep Feature Extraction*

In image processing techniques, feature extraction involves applying algorithms to images to identify and isolate characteristics essential for image classification. Feature extraction serves as a means of reducing the dimensionality of the data. Transfer learning [28] improves performance of image classification by employing pre-trained neural network models such as autoencoders, wavelet scattering, and deep neural networks. In this study, we utilized the GoogLeNet model [29] as shown in Fig. 4 model to extract features through multiple convolutional layers. Each image yielded 768 distinctive features, with each feature map sized at 5x6. Consequently, this produces an array with dimensions of (12936, 5, 6, 768).

E. *Feed-Forward Neural Networks (FNN)*

The FFNN [30], [31] facilitate precise categorization of input images into various classes by utilizing extracted features. Widely employed for image classification [31], FFNNs consist of three layers: an input layer with units sized according to features, hidden layers performing intricate operations with specific weights, and an output layer featuring neurons corresponding to dataset classes. In this feed-forward neural network model comprises following layers:

1) Flatten layer: This layer transforms the input data into a one-dimensional array, suitable for input into subsequent dense layers.

2) Dense layer: This densely connected layer consists of 512 neurons, with each neuron being interconnected with every other neuron in the layer above. The model is capable of detecting complex patterns and correlations in the data because to the non-linear properties generated by the ReLU activation function.

3) Dropout layer: Dropout is a method of regularization that mitigates overfitting by randomly disabling a fraction of neurons throughout the training process (in this case, 50%).

4) Dense output layer: The final output of the model is produced by this layer, which consists of 4 neurons .The Softmax activation function standardizes the output probabilities, making them understandable as class probabilities. The model depicted in Fig. 5 was trained using categorical cross-entropy loss, optimized with Adamax, and evaluated based on accuracy.

The proposed system comprises the steps illustrated in Fig. 6. Initially, MRI images from the AD dataset undergo resizing, enhancement, and balancing. Subsequently, these processed images are fed into the GoogLeNet deep learning model. The convolutional layers of the GoogLeNet model extract MRI image features, which are then stored in a feature matrix of dimensions (12936, 5, 6, 768). In the third step, this feature matrix is forwarded to the FFNN network for training and assessing the FFNN's performance and efficiency.

Fig. 4. GoogLeNet architecture.

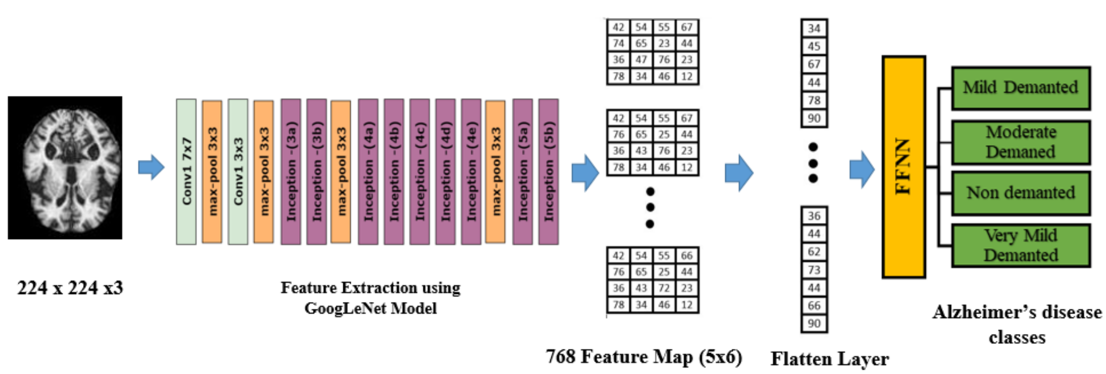


Fig. 5. Methodology diagnosing MRI images using a feedforward neural network.

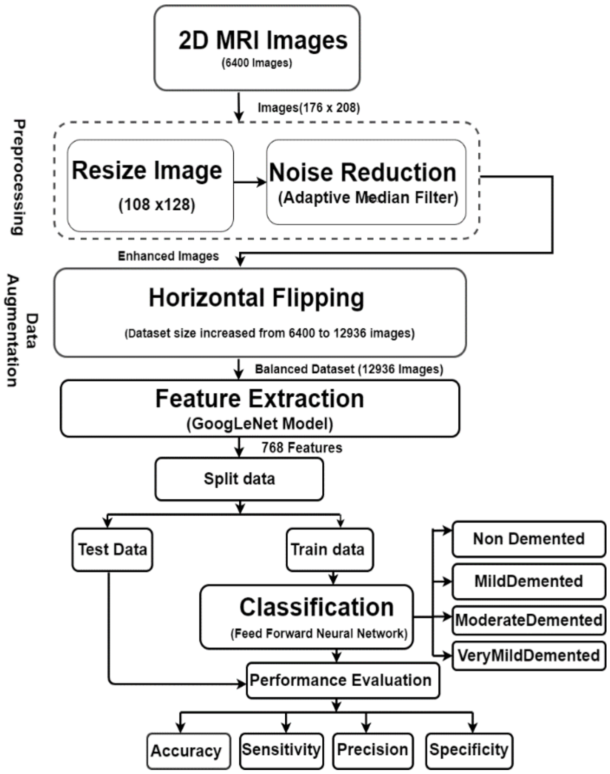


Fig. 6. Proposed methodology architecture.

V. RESULTS

The results section provides the findings of proposed model in terms of various metrics. The model was executed and evaluated using Google Colab, a cloud-based platform, with local machine training discarded due to long run times and the need for hardware optimizations. The GoogLeNet model was utilized for feature extraction, yielding 768 features, each feature map with dimensions of (5, 6). Subsequently, the extracted feature matrices were partitioned into training (80%) and evaluation (20%) sets to evaluate the performance of the model. The FFNN model underwent rigorous training for 50 epochs with a batch size of 16, and multiple runs were conducted to enhance performance and ensure robustness as shown Table III. Table IV shows that the FFNN model with GoogLeNet features obtained 98.37% accuracy, 98.39% sensitivity, 98.50% precision, and 99.45% specificity. Table V shows the findings of a multistage classification of Alzheimer's disease (AD) as a confusion matrix.

TABLE III. DISPLAYS THE LOSS AND ACCURACY THROUGHOUT THE TRAINING AND TESTING PHASES

# Run	No.of epochs	Batch size	Training Phase		Validation Phase	
			Loss	Accuracy	Loss	Accuracy
1	50	16	0.0167	0.9938	0.0784	0.9706
2	50	16	0.0065	0.9979	0.0985	0.9749
3	50	16	0.0072	0.9973	0.1070	0.9760
4	50	16	0.0065	0.9973	0.0996	0.9776
5	50	16	0.0034	0.9989	0.1141	0.9784
6	50	16	0.0017	0.9994	0.1172	0.9838

Fig. 7 and Fig. 8 present a comparison between the training and validation phases over 50 epochs. Fig. 7 reveals a minor discrepancy between validation and training accuracies, indicating consistent performance. Notably, the validation accuracy maintains a consistently high level with minimal fluctuations, reflecting the model's robustness. Meanwhile, Fig. 8 illustrates the evolution of training and validation loss over epochs. Initially, both training and validation losses decrease gradually, indicating effective these observations imply that the model demonstrates effective learning.

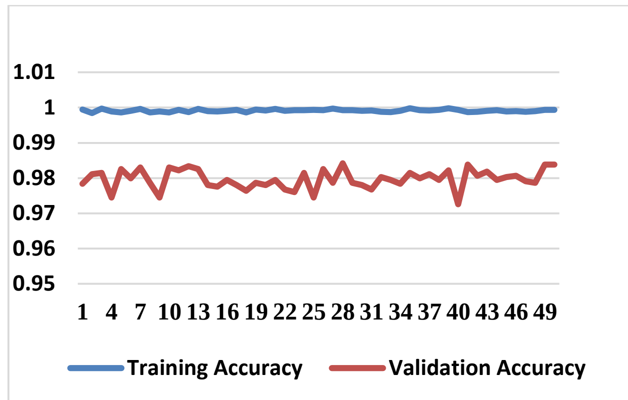


Fig. 7. Training accuracy vs validation accuracy.

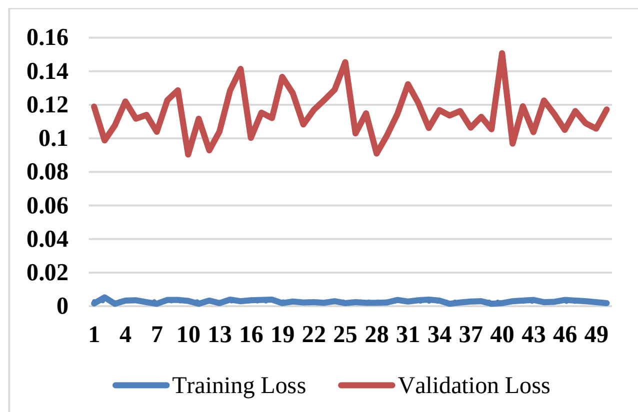


Fig. 8. Training loss vs validation loss.

Remarkably, the validation loss exhibits little variation in later epochs, underscoring the model's resilience. These observations imply that the model demonstrates effective learning and generalization.

Table VI provides a detailed exploration known as the AD class-wise confusion matrix, which serves the purpose of analyzing the efficiency of the model on a class-by-class basis. By examining this matrix, we can discern how accurately the model performs for each individual class within the AD dataset. False negatives have a higher significance in medical diagnosis and prediction than false positives, especially in the case of AD prognosis. The model had zero false negatives, indicating its accuracy in predicting cases of mild dementia. Furthermore, the model shows extremely few erroneous negative predictions when separating non-demented individuals from moderate and very mild dementia cases. Overall, the model performs commendably in predicting AD stages compared to the state-of-the-art method outlined in the literature survey.

TABLE IV. DISPLAYS THE FFN RESULTS BASED ON THE GOOGLE NET'S FEATURES (CLASS-WISE ACCURACY, SENSIVITY, PRECISION AND SPECIFICITY

MODEL	CLASS OF AD	ACC (%)	SEN (%)	PREC (%)	SPC (%)
AD CLASSIFICATION USING FFNN MODEL BASED ON FEATURES FROM GOOGLENET	**Normal**	98.53	97.59	97	98.85
	Mild	99.76	99	100	100
	Moderate	99.15	100	100	100
	Vmd	98.60	97	97	98.97
	Average ratio	99.01	98.39	98.50	99.45

NORMAL: **NON_DEMENTED,** MILD**: MILD_DEMENTED,** MODERATE: **MODERATE_DEMENTED**, VMD: **VERY_MILD DEMENTED,** ACC**: ACCURACY,** SEN: **SENSITIVITY**, PREC: **PRECISION**, SPC: **SPECIFICITY.**

TABLE V. CONFUSION MATRIX FOR MULTISTAGE AD CLASSIFICATION

		Actual			
Predicted	Non Demanted	649	0	0	16
	Mild Dementia	2	636	0	4
	Moderate Dementia	0	0	639	0
	Very Mild Dementia	20	0	0	622
		Non Demanted	Mild Dementia	Moderate Dementia	Very Mild Dementia

TABLE VI. DESCRIBES AD CLASS-WISE CONFUSION MATRIX

		Actual	
Predicted		T	F
	T	649	16
	F	22	1901

Non Demanted

		Actual	
Predicted		**T**	**F**
	T	**639**	**0**
	F	**22**	**1949**

Moderate Demanted

		Actual	
Predicted		**T**	**F**
	T	**639**	**6**
	F	**0**	**1946**

Mild Demanted

		Actual	
Predicted		**T**	**F**
	T	**622**	**16**
	F	**20**	**1926**

Very Mild Demanted

VI. DISCUSSION

This work presented a deep learning model for the early detection of Alzheimer's disease (AD). The model utilizes the GoogLeNet deep learning neural network for feature extraction, with the extracted features then being fed into a Feedforward Neural Network (FFNN) for stage-wise classification of MRI images. Due to the similarity of features in the early stages of Alzheimer's, the system focuses on extracting more features from MRI images by increasing the dataset size to 12,936 images to accurately distinguish between different AD stages. Earlier studies used only 6,400 images.

The model demonstrates excellent results with an average stage-wise accuracy of 99.01%. The performance of the model was compared with previous relevant studies, as shown in the Table VII. It was noted that the proposed system's results surpassed those of earlier studies in stage-wise AD classification. In previous studies, there were no consistent results in AD stage-wise classification, particularly in distinguishing mild dementia cases, which achieved an accuracy of only 69%. The proposed model achieves over 98% accuracy in each stage-wise classification of AD.

TABLE VII. COMPARISION OF CLASS-WISE ACCURACY OF PROPOSED METHOD WITH STATE OF ART METHODS

Techniques	Features	Mild Dementia	Moderate Dementia	Non Dementia	Very-Mild Dementia	Accuracy %
FFNN	GoogLeNet	88.8	69.2	97.7	94	94.80
FFNN	DenseNet-121	83.2	69.2	97	93.5	93.60
FFNN	GoogLeNet + DenseNet-121	94.4	69.2	98.6	97.1	97.2
Proposed Model Fine-tuned FFNN	GoogLeNet	99.76	99.15	98.53	98.60	99.01

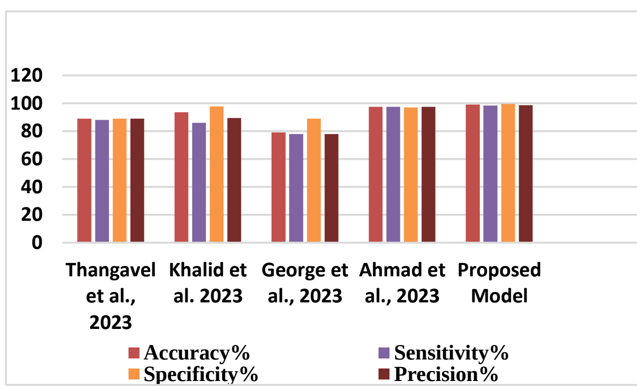


Fig. 9. Performance comparison of proposed model with state of art methods.

Sensitivity and specificity are critical in medical diagnosis. Fig. 9 shows a comparison of performance metrics such as sensitivity, specificity, precision, and accuracy. The proposed methodology achieves very good performance with a low number of errors and demonstrates higher sensitivity and specificity compared to previous studies. The model performs impressively in distinguishing mild and moderate dementia cases with almost zero errors. Thus, the results achieved by the proposed system significantly surpass those of previous relevant studies in stage-wise AD classification.

VII. Conclusion

The substantial impact of Alzheimer's disease (AD) on brain health and its incurable nature provide considerable hurdles for the medical industry. Early prediction of AD is critical to impede its advancement to late stages, which entail severe brain cell deterioration and eventual fatality. This research has notably advanced effective methodologies for AD detection and progression prediction. The study primarily focused on tackling key obstacles in AD prediction, emphasizing the construction of a meticulously curated and balanced dataset for robust analysis. Furthermore, sophisticated image preprocessing techniques were applied to ensure data quality while retaining crucial information, thus ensuring reliable analysis.

The methodology relied on a FFNN improved with features from the GoogLeNet model, resulting in a powerful predictive model for AD progression. Impressively, this model surpassed existing methods, demonstrating its efficacy in addressing the complexities of AD prediction. Results from the FFNN model were highly promising, boasting exceptional accuracy, sensitivity, precision, and specificity. Specifically, the FFNN achieved remarkable metrics such as 99.01% accuracy, 98.39% sensitivity, 98.50% precision and 99.45% specificity highlighting the methodology's effectiveness in accurately predicting AD progression and offering avenues for early intervention and improved patient outcomes. By looking at false negative cases to find trends or features that the model might be lacking, this work can be improved even more. Investigating the most recent approaches can help to decrease these errors.

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