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Optimizing Deep-Transfer Learning Model for Early Disease Diagnosis of Alzheimer's in Clinical Data

Dr. Prithviraj Singh Rathore
Assistant Professor
Department of Computer Sciences and Applications
Mandsaur University
Mandsaur
prathviraj.rathore@meu.edu.in

***Abstract*—Early and precise identification of Alzheimer's disease (AD) must be addressed in order to improve patient outcomes and reduce the socioeconomic impact of this degenerative neurological condition. The subjectivity of tested processes, such as magnetic resonance imaging (MRI) decoding and cognitive evaluation, is limited by factors including cost and time constraints. This work proposes a more effective approach to deep transfer learning with the VGG-19 architecture to accurately and robustly distinguish AD using MRI images. The suggested architecture incorporates essential preprocessing techniques as data augmentation, scaling, normalization, denoising, contrast improvement, and skull stripping. These phases improve the quality of images and broaden the variety of data. The model was trained and evaluated using 10-fold cross-validation with an 80:20 split on an image dataset containing both AD and healthy controls (OASIS). The model indicates excellent accuracy, precision, recall, and F1-score of 99.22%. Compared with ML techniques, the VGG-19 is more effective at identifying AD-specific traits. Based on these findings, the proposed technique is a clinically scalable solution, an efficient and automated tool for facilitating the real-time detection of Alzheimer's disease.**

***Keywords*—Alzheimer's Disease, Deep Transfer Learning, VGG-19, MRI Classification, Early Diagnosis, Clinical Data.**

I. Introduction

Clinical neuroscience is a rapidly evolving field within care management, focusing on the mechanics of the human brain and its response to neurological illnesses that impair cognition, memory, and behaviour [1][2]. The growing number of older people is making Alzheimer's disease (AD) more common. This is a condition that is very important in the world [3][4]. AD is a degenerative neurological disorder that diminishes quality of life by impairing memory, cognition, and daily functioning [4][5]. The increasing incidence of AD highlights the critical need to diagnose it early and correctly early intervention could potentially increase the effectiveness of the treatment process, better care delivery to patients and lower the overall medical expenses [6][7]. Traditional diagnosis is performed by neuroimaging, such as positron emission tomography (PET), magnetic resonance imaging (MRI), biomarker analysis, and cognitive tests [8][9]. These techniques are practical, however, they have some limitations because they are costly, obstructive as well as time consuming [10]. In addition, the neuroimaging data are highly complex and in most cases subjective making it difficult to detect alterations in their early stage. These issues underscore the need to have automated, objective and scalable diagnostic systems. Clinical neuroscience has become the focus of disruptive technologies in the form of Artificial Intelligence (AI) [11][12]. It is possible to use the DL algorithms to automatically derive hierarchical features in neuroimaging data [13]. It becomes more convenient to them to detect early symptoms of AD, e.g. brain shrinkage and vascular issues. Nevertheless, traditional DL can be defined as highly labelled, overfitted, and possessed minimal generalization to other groups of patients, thus restricting the generalizability of its use as a therapy [14]. These errors can be corrected using transfer learning to enhance models that were trained with a large amount of data in medical imaging [15][16]. This minimizes the need to have large labelled datasets, generalizes better and also speeds up the training process. One of the architectures which are top in terms of deep layered architecture, and strength on fine-grained spatial features are VGG-19 [17]. The VGG-19 can transform the sphere of diagnostics as it is scalable, reliable, and clinically relevant, which will solve the limitations of the existing diagnostics and allow early and accurate diagnosis of AD.

A. Motivation and Contribution of Paper

To accurately and quickly diagnose AD, a progressive neurological condition with no treatment, the study was started. Inconsistencies might result from subjective diagnosis answers based on professional MRI image interpretation. Deep transfer learning also provides an effective solution, as it automates the feature extraction and classification of MRI data with greater accuracy and reliability. These strategies can be optimized to provide scalable computer-aided diagnosis systems to facilitate clinical decision-making in time and improve early detection strategies of AD. The work's primary contributions are as follows:

- Cross-sectional OASIS MRI scans were used and the balance selection of subjects based on Clinical Dementia Rating (CDR) scores was made.
- Sanitized fundamental pre-processing methods, such as normalization, denoising, skull stripping, downsizing, and augmentation.
- Handled limitations on datasets to enhance the resilience and the applicability of the system.

- The use of VGG-19 in the effective extraction and classification of Alzheimer was implemented using transfer learning.
- The performance of the model was measured using the following metrics: recall, accuracy, precision, and F1-score.

B. *Justification and Novelty of the Paper*

This research is justified by the fact that it is a subject of critical importance to find accurate, early and scalable detection of Alzheimer's disease, the progressive neurological disorder that has important clinical and societal implications. The innovation of this work consists of maximization of a VGG-19 deep transfer learning model with the complex of pre-processing, data augmentation, and fine-tuning, which makes it possible to classify MRI scans with robustness and almost perfect results. In contrast to earlier methods which were limited by limited datasets, single-modal inputs, or older ML models, the framework offers high accuracy, precision-recall balance, reduced overfitting, and clinical scalability, and is a realistic, automatic, and dependable solution to facilitate early AD detection in real time.

C. *Structure of the Paper*

The structure of the paper is as follows: Section II is a review of the related research. Section III contains the description of the methodology, model design, and the assessment terminology. In Section IV, the results and a comparative analysis are provided. Section V contains the study conclusion and the future directions.

II. Literature Review

The literature proves that DL and transfer learning on both MRI and multimodal data can be used to identify AD early with high accuracy, but research gaps are observed through limitations in size of datasets, modality, and long-term validation.

Nasra and Gupta (2025) comprehensively test the functionality of the proposed model with an MRI image data of identified and pre-processed healthy controls, MCI and AD individuals. The transfer learning and regularization techniques served to re-train the existing trained DenseNet model to the medical application to use its classification power to identify it accurately. Moreover, the DenseNet model attained a mean test accuracy of 92.5% with skilled data augmentation and model training methods [18].

Praneeth et al. (2024) present a DL-based prediction framework using the improved EfficientNetB6 algorithm on the 20,000 MRI scans from the AD Neuroimaging Initiative (ADNI). To differentiate between AD progression and MRI images of a healthy cognitive state, aim for 97.78% accuracy and 98.21% F1 score [19].

Desai, Kumar and Pandey (2024) studied DL for AD detection. DenseNet, with a 90% score and a 0.17 validation loss, is the best CNN for training to classify AD. Multimodal fusion uses MRI, PET scans, and perhaps other modalities to create AD's complexity and improve diagnosis [20].

Mahmood, Alam and Sultana (2024) examine the efficacy of various DL systems in using MRI brain imaging to diagnose AD. The study thoroughly examined popular DL and ML architectures. Approximately 6,400 brain MRI pictures from the Kaggle dataset were divided into four groups. The accuracy achieved by the CNN model was a record 98.44% [21].

Dinesan et al. (2023) research demonstrates the value of DL algorithms for early AD identification and treatment. The study uses MRI and a CNN to detect AD, achieving a high accuracy rate (train 86.34, validation: 86.45). Indicators of the CNN architecture's clinical relevance include its speed and generalizability to populations utilized in the clinical categorization of AD [22].

Archana and Kalirajan (2023) provided research on the use of DL techniques in medical imaging, specifically in middle-aged and older adults who have been diagnosed with AD, a neurological disorder, gradually lose their mental abilities. They categorize brain neuroimages into categories for those with moderate impairment (MCI), AD and cognitively normal (CN), and healthy people using the MRI dataset ADNI. The findings demonstrate that, with an accuracy of 95.82%, CNN's categorization rate performs better than CNN's [23].

Table I pinpoints the methods, data, results, constraints, and future studies to show a gap in clinical validation of early AD diagnosis.

TABLE I. Summary of Related Work in Deep Transfer Learning Approaches for Early AD Diagnosis

Author(s)	Methodology	Dataset	Key Findings	Limitations	Future Work
Nasra & Gupta (2025)	Transfer learning with DenseNet, regularization & data augmentation	Preprocessed MRI scans (Healthy, MCI, AD)	Mean test accuracy: 92.5%; model suitable for clinical diagnosis; DenseNet shows potential as a medical decision support tool	Moderate dataset size; limited multimodal data	Expand dataset diversity; integrate multimodal imaging; validate in larger clinical populations
Praneeth et al. (2024)	Deep learning framework using EfficientNetB6; multi-stage classification including MCI	ADNI (~20,000 MRI scans)	Accuracy 97.78%, F1-score 98.21%; early identification of MCI stages	High computational complexity; resource-intensive	Optimize computational efficiency; improve interpretability; deploy in clinical environment
Desai, Kumar & Pandey (2024)	Comparative CNN models (DenseNet best), multimodal fusion (MRI, PET, other modalities)	ADNI multimodal neuroimaging	DenseNet achieved 90% accuracy, lowest validation loss (0.17); multimodal fusion enhances diagnostic potential	Focused on CNNs only; longitudinal progression not included	Extend to RNN/LSTM models for progression prediction; multimodal fusion refinement
Mahmood, Alam & Sultana (2024)	Comparative analysis of DL & ML architectures; CNN benchmark	Kaggle MRI dataset (~6,400 images, 4 classes)	CNN achieved 98.44% accuracy, outperforming ML models	The dataset limited in size and diversity; 4-class classification may not generalize clinically	Validate on larger clinical datasets; integrate multimodal imaging; real-world deployment
Dinesan et al. (2023)	CNN for MRI-based AD identification	MRI scans	Training 86.34%, validation 86.45%; fast processing and population-level	Lower accuracy than newer models; single modality MRI	Integrate transfer learning; improve preprocessing; multimodal data inclusion

			generalizability; supports clinical use		
Archana & Kalirajan (2023)	CNN classification for AD, MCI, CN, and healthy controls	ADNI MRI dataset	Accuracy 95.82%; early disease diagnosis emphasized; outperforms standard CNNs	Only MRI modality used; limited external validation	Incorporate multimodal data; cross-site and longitudinal validation

III. METHODOLOGY

The approach to Alzheimer's disease detection based on the MRI scan is represented in the presented Fig. 1 in a systematic manner. Quality and consistency MRI data of OASIS are initially pre-processed, including contrast enhancement, denoising and skull-stripping, resizing, normalization, and augmentation. The data is subsequently divided into 80% training and 20% testing sets. VGG-19 model that utilizes transfer learning is trained on the training set to extract features and classify them correctly. Accuracy, precision, recall, F1-score are used to test the performance of the model on the testing set, which is a powerful framework to detect Alzheimer reliably.

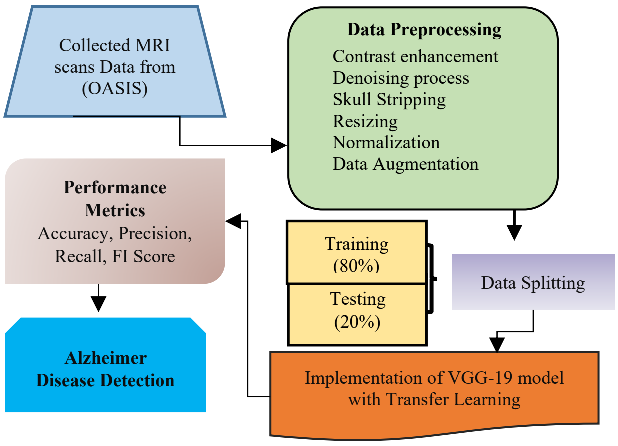

Fig. 1. Proposed Methodology for Alzheimer's Disease Detection

A. Data Collection

The MRI scans of Open Access Series of Imaging Studies (OASIS) are also available in this dataset. It includes cross-sectional and longitudinal images in the present study; the former is used in this research to differentiate AD and healthy controls (HC). These are aged between 18-96. It has 416 preselected participants (200 selected randomly) consisting of 100 with HC and 100 with AD. The subjects categorized based on this variable which is Clinical Dementia Rating (CDR) that has a range of 0 (HC) to 1 (worsening AD).

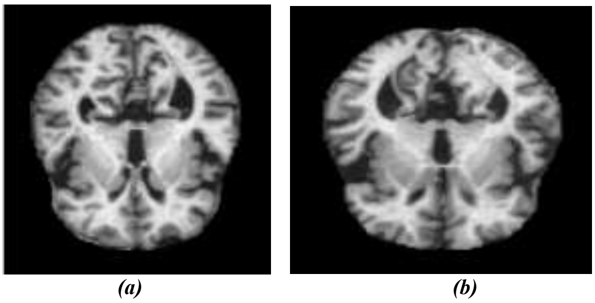

Fig. 2. MRI Scan from OASIS for (a) Healthy Control (HC) and (b) AD Patient

Fig. 2 shows the MRI scans of the OASIS dataset, whereby they depict differences between an AD and an HC patient. Image (a) represents a healthy brain at the level of a healthy person; the brain has clearly defined structural borders, the tissue has a homogeneous intensity and the cortical and sub-cortical regions can be clearly seen. Conversely, image (b) represents a brain of an AD patient, in which structural atrophy is evident, especially in the hippocampus as well as in the cortex.

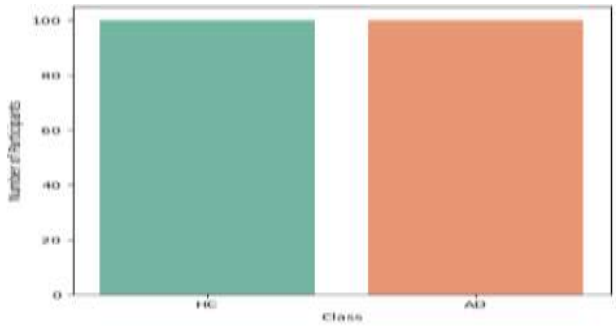

Fig. 3. Class Distribution of the Dataset

The class distribution of participants is shown in Fig. 3, contrasting the HC and AD groups. The two groups and the overall number of participants are shown on the y-axis, and HC and AD are displayed on the x-axis. The two bars are the same height and all the way up to the 100-participant mark. This implies the data is balanced (with the same number of subjects in each of the two groups). In particular, the HC represents 100 participants, and the AD represents 100 participants.

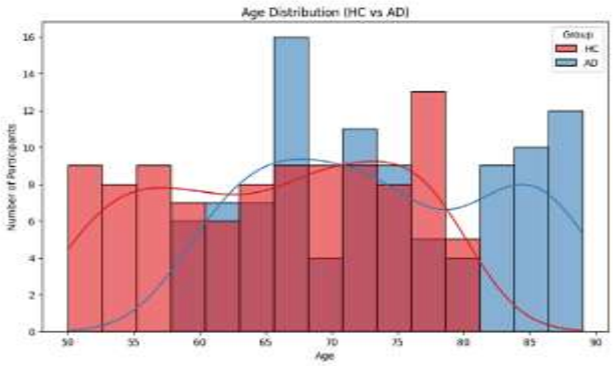

Fig. 4. Histogram of Age Distribution

Fig. 4 demonstrates the age demographics of the participants in two groups: Healthy Controls (HC) and patients with AD. The age is plotted on the x-axis, while the y-axis plots the numeral of participants. According to the red bars, the HC group has a rather bell-shaped distribution, and its highest number is found within the 65 and 75 years. The AD Patients have blue bars, with most of them ranging between 65 and 90 years and a high concentration between 65-70 and 85-90 age bracket.

B. Data Preprocessing

The performance of models is affected by the quality of input images strongly [24]. To improve model performance, the pre-processing process increase the clarity of the image, enhance the structural features, and minimize the noise. The pre-processing steps are as follows:

1) Contrast Enhancement

Enhancement of contrast. Enhance the image's brightness and quality by expanding the pixel value ranges and image border contrast. Equation (1) is utilized to calculate the mathematical contrast enhancement:

$$c(x,y) = \frac{g(x,y) - g_{min}(x,y)}{g_{max}(x,y) - g_{min}(x,y)} \quad (1)$$

Where $g(x,y)$ is the image's pixel value and $g_{max}(x,y)$, $g_{min}(x,y)$Re the highest and lowest pixel intensity values, respectively.

2) Denoising Process

The image denoising method uses a variety of filters to remove noise. The median filter reduces noise while preserving edges by substituting the median of each pixel with the median of its neighbors. The Gaussian filter uses Equation (2) to calculate the mask size and remove noise:

$$G(x) = \frac{1}{o\sqrt{2\pi}} * e^{\left(\frac{-1}{2}\right)\cdot\left(\frac{x-u}{o}\right)^2} \quad (2)$$

Where the input value is denoted by x, the mean of u, and the standard deviation by o. The data before and after using the pre-processing approaches are displayed in the Fig. 5.

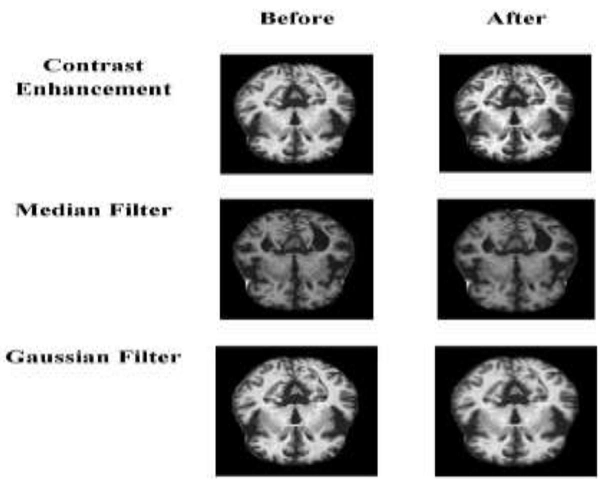

Fig. 5. Dataset Before and After Applying Preprocessing Techniques.

- **Skull Stripping:** This step reduces irrelevant variability and improves classification performance.
- **Resizing:** All MRI images are reduced to 224 by 224 pixels to ensure that they fit the VGG-19 input, maintain the same size and retain brain structures to suit the model training process.

C. Normalization

The process of normalization involves scaling pixel intensities of an image to a normalized value that provides the image with a consistent numerical representation in all images. This study uses Min-Max normalization of all the MRI scans, in which the pixel values are rescaled to the range [0,1] [25]. Mathematically, Min-Max normalization is expressed as shown in Equation (3):

$$I_{norm} = \frac{I - I_{min}}{I_{max} - I_{min}} \quad (3)$$

Where I is the pixel intensity of the skull-stripped brain image, and I_{min} and I_{max} He pixel intensity values at the minimum and maximum, respectively.

D. Data Augmentation

Data augmentation technique used for deep learning suggests altering the source photos to increase the dataset's size and diversity. In medical imaging, datasets can be small, which helps avoid overfitting and saves on generalizations. Augmented samples introduce the model to varying variations, while maintaining important clinical characteristics. Rotation, flipping, scaling, shifting, shearing, zooming, cropping, and brightness adjustment are such techniques that enhance the strength of the technique and substantially boost classification accuracy.

E. Data splitting

The training and test subgroups of the dataset are divided 80:20. To train the model, one uses the training set, while to test it, one uses the testing set for evaluation.

F. Proposed VGG-19 model with Transfer Learning

The DL model used for early AD is based on VGG-19. The convolutional and pooling layers of the pre-trained network remain frozen feature extractors for classification, while the fully connected layers are rearranged. A final Softmax layer for prediction and a 128-neuron dimensionality reduction layer are features of the updated architecture, known as VGG-19-TransL. Dropout and L2 regularization are applied to reduce overfitting [26]. For an input image I, convolution and activation are expressed as in Equation (4):

$$f_i = I * w_i + b_i, \quad (4)$$

where w_i and b_iNote the weight and bias of the ith filter. Dimensionality reduction is performed using max-pooling, as mentioned in Equation (5):

$$f_i^{max} = \max_{j \in P \times P} \hat{f}_j \quad (5)$$

The training process uses a two-stage transfer learning strategy. During the feature extraction stage, only the recently connected layers are trained; the convolutional and pooling layers remain frozen. The pre-trained features are adjusted to fit AD-specific patterns during the fine-tuning stage by unfreezing a few higher-level convolutional layers and retraining them at a slower learning rate [27]. Final classification is carried out using the SoftMax layer, as expressed in Equation (6):

$$Y_{out}(O_i) = \frac{e^{O_i}}{\sum_{c=1}^{C} e^{O_c}} \quad (6)$$

This framework leverages pre-trained knowledge for effective feature representation while refining the paradigm for accurate classification of AD phases.

G. Performance Metrics

To evaluate the efficacy of ML models, performance assessment measures are frequently used. Several factors are considered for model evaluation, False Negative, True Negative, and FP, respectively [28]. Using these elements, several performance measures can be computed, which are listed below:

Accuracy: To determine accuracy, divide the sum of the number of datasets by TP+TN, the number of accurate forecasts [29]. Equation (7) presents the accuracy.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (7)$$

Precision: The accuracy is obtained by dividing the total number of True positive predictions (TP), as shown in Equation (8).

$$Precision = \frac{TP}{TP+FP} \quad (8)$$

Recall: The percentage of correct positive predictions relative to the total number of class observations is known as its ratio, which may be quantitatively described using Equation (9):

$$Recall = \frac{TP}{TP+FN} \quad (9)$$

F1-Score: It is a single indicator that blends sensitivity and accuracy. Measures 1 and 0 are the highest and lowest. Equation (10) provides an illustration of the f1-score:

$$F1\ score = \frac{2.(Precision \cdot Recall)}{Precision+Recall} \quad (10)$$

Loss function: The observed and projected values' mathematical differences are calculated [30]. In this research, its AD loss function is the binary cross-entropy loss.

These assessment indicators allow a detailed analysis of the models functioning and provide accurate, reliable, and robust predictions.

IV. Result Analysis and Discussion

The Python version of the suggested model to diagnose early AD cases was based on the Keras framework. It was also trained using Tesla T4 chip with 14GB of DDR4 RAM which really enhanced its processing speed. Analyzed some of the major indicators to determine its efficiency. The model has an accuracy, precision, and recall of 99.22% and an F1-score of 99.21%, as indicated by Table II. These outcomes indicate that the classification is not biased and highly accurate. This shows that VGG-19 deep transfer learning model is an effective technique of diagnosing AD accurately and promptly.

TABLE II. Performance Metrics of the Proposed Model for Early Alzheimer's Disease Diagnosis

Metrics	VGG-19
Accuracy	99.22
Precision	99.22
Recall	99.22
F1-score	99.21

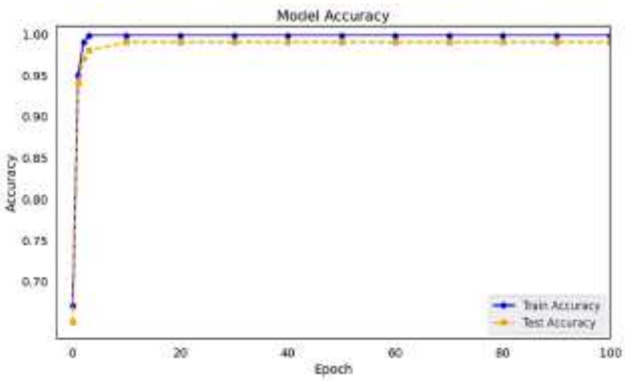

Fig. 6. Accuracy Curve for Training and Testing Data for the VGG-19 Model

Fig. 6 shows the performance of a VGG-19 model in 100 epochs. The accuracy of the training rapidly attains and remains near the value of 1.0 (or 100%), whereas the accuracy of the tests is rapidly stabilized only slightly less than 1.0, approximately 0.99. The graph shows the model learns very fast, and once the epochs have reached 10, the model can be very effective in both the test and the training datasets.

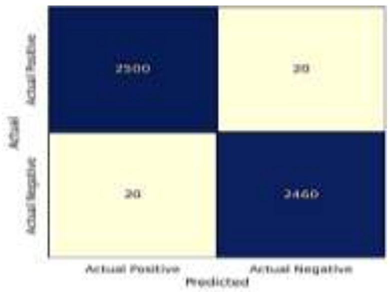

Fig. 7. Confusion Matrix for the VGG-19 Model

The confusion matrix of actual and predicted results is presented in Fig. 7. The model accurately typed 2500 patients with Alzheimer and 2460 healthy people, and there were only 20 false negatives and 20 false positives, which means that the model was very accurate in general.

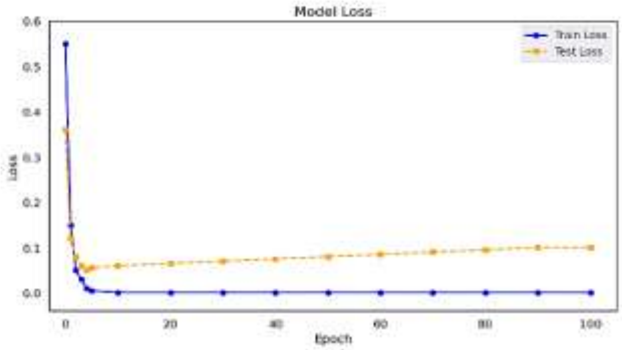

Fig. 8. Loss Curve for Training and Testing Data for the VGG-19 Model

In Fig. 8, the performance of VGG-19 model is depicted in 100 epochs. Loss is minimized within a short time to almost 0, which implies that the training data is learned well. Test loss also decreases but it starts increasing after approximately 20 epochs in training loss being low, which is overfitting.

```
              precision    recall  f1-score

           0      98.81     99.63     99.21
           1      99.63     98.81     99.21

    accuracy                          99.22
   macro avg      99.22     99.22     99.21
weighted avg      99.22     99.22     99.21
```

Fig. 9. Classification report of VGG-19 model

The VGG-19 model's classification report, which shows the model's performance in two classes, is shown in Fig. 9. Class "0" has a precision of 98.81% and a recall of 99.63%, whereas class "1" has a precision of 99.63% and a recall of 98.81%. The model works well with outstanding and balanced outcomes in both classes, as seen by the overall accuracy of 99.22% and the weighted and macro averages being close to 99.22% and 99.21%, respectively.

A. Comparative Analysis and Discussion

In this section, ML models to early detect Alzheimer are compared. VGG-19 has the highest accuracy of 99.22 and beats Gradient Boosting (93.64%), XGBoost (91) and Decision Tree (80.46) as shown by Table III and thus VGG-19 has the potential to be a reliable early detection.

TABLE III. PERFORMANCE COMPARISON OF MODELS FOR ALZHEIMER'S DISEASE DETECTION

Models	Accuracy	Precision	Recall	F1-score
GB [31]	93.64	93.71	93.64	93.66
XGBoost [32]	91	93	90	92
DT [33]	80.46	80	79	78
VGG-19	99.22	99.22	99.22	99.21

As the results of the experiment clearly show, the suggested VGG-19 transfer learning model offers a significant improvement in the detection of Alzheimer's disease as opposed to the standard machine learning methodology. The fact that 99.22% of all the performance metrics are achieved implies that not only high accuracy is achieved but also balanced precision and recall which are important to clinical reliability. This is a greater standard by which this work is set. Bias was minimized by the balanced dataset, as well as a powerful pre-processing pipeline, which guaranteed generalizability. These results point to the possibility of transfer learning to close the chasm between research models and actual clinical application.

V. CONCLUSION AND FUTURE WORK

The increasing prevalence of AD requires the elaboration of accurate, expandable, and therapeutically advantageous diagnostic models. The proposed VGG-19 transfer learning model is more accurate, precise, and has higher recall and F1-score than, Gradient Boosting (93.64%), XGBoost (91%), and Decision Trees (80.46%), with an accuracy and precision of 99.22%. These results argue in favor of the soundness of the framework in making complex structural inferences of MRI scans and also do not overfits or does not destabilize with validation folds. It is one of the strong points of this work, that advanced pre-processing and augmentation are also utilized with deep transfer learning to demonstrate that even unimodal MRI data may be used to provide near-perfect classification under the assumption of successful optimization. This method is also an excellent candidate to be implemented in a real-world healthcare environment over the previous methods that were restricted by smaller datasets or necessitated multimodal input to conduct their analysis. Its applicability is however limited due to the use of single dataset (OASIS). The future research can be expanded with the validation on wider and more diverse cohorts, multimodal data, such as PET images, genetic variables, and cognitive scores, in addition to explainable AI (XAI) techniques to increase the extent of interpretability among clinicians. Its ability to explore real-time implementation in edge or cloud settings, adaptive learning based on the alteration of incoming data, and multi-class staging of Mild Cognitive Impairment (MCI) progression will also make it useful to precision-based AD.

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