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Classification of Alzheimer's Disease using Transfer Learning and Support Vector Machine

Shobha S.*[1], Karthikeyan B. R.[2]

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Abstract: Alzheimer's disease, characterized by cognitive decline due to impaired brain cells, remains without a definitive cure. However, early diagnosis can substantially mitigate its impact and improve patient management. Recognizing this, we developed an automated system for interpreting brain Magnetic Resonance Imaging (MRI) scans, aiming not just to detect dementia but also to classify its various stages. Using a transfer learning method, we adapted the AlexNet convolutional network to this specific challenge, training it primarily on un-segmented MRI images. Our model, when tested on the publicly accessible KAGGLE dataset, demonstrated a significant accuracy of 94.49% for multi-class classification. Additionally, our model's prowess wasn't limited to accuracy alone. In multi-class scenarios, it reported a specificity of 97.78%, precision of 77.42%, recall of 94.49%, and an F1-score of 81.08%. Impressively, it surpassed contemporaneous studies, outdoing the 79.8% accuracy of Tooba et al. and the 62.7% by S0rensen et al. The ROC curve further highlighted the model's proficiency in distinguishing between dementia stages, with 'Moderate Dementia' reaching an AUC of 0.97964. Such results underline not only the efficacy of our approach but also its promise as a groundbreaking asset in Alzheimer's diagnostics.

Keywords: *Alzheimer's Disease, Dementia, Brain Deterioration, Early Diagnosis, Magnetic Resonance Imaging (MRI), Automated Detection, Classification System, Transfer Learning, Convolutional Network, Alexnet, KAGGLE Dataset.*

1. Introduction

Alzheimer's disease (AD) is the predominant form of dementia, constituting 60-80% of all cases. It is marked by a profound cognitive decline and diminished daily functionality [1]. While commonly diagnosed in those over 60, there are instances of early-onset AD in individuals as young as their 40s [2]. The number of AD cases in the U.S., currently at 5 million, is projected to triple by 2050. In its early phase, known as mild cognitive impairment (MCI), the disease manifests as subtle memory loss. As it progresses, patients may become entirely non-communicative. Despite ongoing research, effective AD treatment remains elusive [3]. Given the absence of a definitive cure, the emphasis on timely and accurate AD diagnosis has grown, especially with the generation of vast data from diagnostic tests [4].

MRI has been instrumental in AD diagnostics due to its superior contrast and clarity in brain imaging [5]. Leveraging computational methods, features from essential brain regions such as Grey Matter voxels [6] and the hippocampus [7] are extracted to aid the diagnosis. While these techniques enhance early detection, many classify into binary categories without distinguishing dementia stages.

In medical imaging, machine and deep learning concepts, though contemporary, have roots, especially within computer-aided diagnosis (CAD). Their applications range from breast tissue classification [8] to cerebral microbleed detection [9] and brain image categorization [10]. Deep CNNs, in particular, are becoming pivotal in computer vision for their adeptness in tasks like object recognition. Unlike traditional ANNs, CNNs can process multi-layered images, such as RGB. They benefit from parameter sharing, where neurons in a feature map share weight.

The intricacies of CNNs will be explored in Section 3.1. Training these networks presents challenges, like data limitations and computational demands [11]. Researchers are pivoting to transfer learning [12] to overcome these, modifying pre-trained models for different tasks. Propelled by expansive datasets like ImageNet [13], CNNs are increasingly employed in medical image categorization [14]. Adapting these networks for specific medical tasks through transfer learning, particularly fine-tuning their final layers, has been incredibly effective.

Our research uses the AlexNet model [15] to evaluate brain MRIs for AD prediction autonomously. By training AlexNet on ImageNet and applying transfer learning, we can differentiate among various AD stages. This approach showcases the potential of general image features in medical imaging. Tests on 3D MRI scans from the KAGGLE database underline the efficacy of our methodology in AD detection. Key contributions of our study include:

- A transfer learning-based method for AD classification.
- A multiclass algorithm to discern AD progression stages.

[1] *Dept. of ECE, Sapthagiri College of Engineering, Bangalore, India.*
[2] *Dept. of ECE, M S Ramaiah University of Applied Sciences, Bangalore, India.*
** Corresponding Author Email: shobhas.publications@gmail.com*

The structure of this paper: Section 2 delves into related literature, Section 3 outlines our methods, Section 4 presents the results, and Section 5 concludes our findings.

2. Related Work

Over the past decade, the medical research community has seen a proliferation of techniques aimed at classifying Alzheimer's disease (AD). Such advancements in classification methodologies assist in early detection and monitoring of disease progression and treatment efficacy. Our systematic review of these methodologies offers a comprehensive understanding, breaking them down based on classification levels, including binary (e.g., AD vs. normal) and multiclass classifications (e.g., AD vs. Mild Cognitive Impairment vs. normal).

Wang et al. [16] approached this challenge differently. They focused on calculating a 3D displacement field to group test subjects. The features extracted from this process were then streamlined using mathematical techniques: Bhattacharya distance, student t-test, and Welch's t-test. The refined features formed the basis for training an advanced algorithm - the Support Vector Machine (SVM) classifier. The accuracy they achieved was an impressive 93.05%.

In a subsequent study, Beheshti et al. [1] delved deeper into the importance of GM volume reduction. They employed voxel-based morphometry (VBM) to detect local and broad-based GM shrinkage. This analysis resulted in demarcating Volumes of Interest (VOIs). The features mined from these VOIs underwent optimization using genetic algorithms and, when passed through SVM classification, returned an accuracy of 84.17%.

Other research, such as the one documented in [5], also found merit in focusing on regions that witnessed significant GM volume reduction. The values from these VOIs were treated as raw features. These underwent simplification using feature ranking techniques, and when subjected to SVM classification, an accuracy of 92.48% was achieved.

Taking a different anatomical route, Ramaniharan examined the corpus callosum's shape variations by segmenting Tl-weighted MRI scans [17]. They then derived morphological features using the intricate Laplace Beltrami eigenvalue shape descriptor. When ranked based on information gain, the ensuing reduced features were classified using SVM and the K-Nearest Neighbor (KNN) algorithms. The latter was particularly successful, recording a 93.7% accuracy.

Guerrero's study [18] proposed a feature extraction framework based on significant inter-subject variability. By deriving Regions of Interest (ROIs) through a sparse regression model tailored for variable selection, they achieved an accuracy rate of 71%.

The study presented in [19] was also noteworthy. This research integrated wavelet entropy and predator-prey Particle swarm techniques specifically for AD classification. Leveraging a Single-hidden-layer Neural Network for classification, they achieved a commendable accuracy rate of 92.73% for binary classification.

In [20], the focus was on segmenting images into the primary brain constituents: Gray Matter (GM), White Matter (WM), and CSF. The GM-segmented Regions of Interest (ROI) was the foundation for creating similarity matrices. The uniqueness of this study was the incorporation of the Functional Activities Questionnaire (FAQ) alongside SVM to bolster AD classification accuracy. Their binary classification efforts resulted in an 84.07% accuracy rate.

Incorporating multiple diagnostic tools, the study in [21] combined Fuzzy C-means and the Weighted Probabilistic Neural Network for classification. Their process started by extracting ROIs linked to crucial brain areas - the Hippocampus and Posterior Cingulate Cortex. An interesting approach they employed was the removal of questionable samples from their training data, aimed at bolstering classification performance. Their method succeeded, with accuracy reaching 98.63%, 95.4%, and 96.4% for various binary classifications.

Recent advancements in machine learning and deep learning have also found applications in Alzheimer's classification. Ahmed et al.'s work [22] used circular harmonic functions (CHF) to glean local features from critical brain regions, achieving a 62.7% accuracy for multi-class classification tasks on the renowned ADNI database. On the other hand, Sarraf's research [23] integrated deep learning methodologies like CNN and auto-encoders. The results were promising, with an accuracy peak of 98.4%.

H.I Suk et al. [24] further advanced the role of deep learning in this domain. They focused on classifying three pivotal stages of the disease and achieved high accuracy rates using auto-encoder networks and SVM-based classifications.

Siqi Liu et al.'s work [25] presented a sophisticated method of extracting neuro-imaging features for AD diagnosis. Their method was dual-layered: a zero-masking method for low-level features and a stacked autoencoder network for high-level ones. Their SVM classifier then achieved 86.86% accuracy.

The future of Alzheimer's classification looks bright, with new methodologies integrating multiple features, cutting-edge machine learning techniques, and deep learning architectures. As research continues to evolve, the hope is that these advancements will play a pivotal role in early detection, effective treatment, and a potential cure for Alzheimer's disease.

3. Suggested Approach

The approach introduced harnesses the power of transfer learning to detect Alzheimer's disease. The ensuing section delves into the crucial components required to craft a potent CNN-driven Computer-Aided Diagnosis (CAD) framework. An outline of the envisaged CNN architecture for Alzheimer's disease identification is depicted in Figure 1.

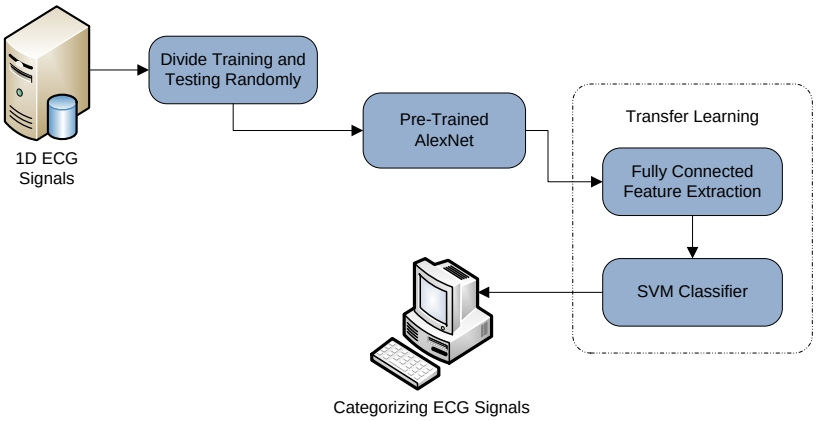

Fig 1. Block Diagram of the Proposed Approach

3.1. Leveraging AlexNet: A Pre-trained CNN Architecture

A Convolutional Neural Network (CNN) is a specialized multi-layered neural network crafted to identify patterns directly from image pixels, diminishing the need for extensive preprocessing [26]. At its core, a CNN comprises three primary layers: convolution, pooling, and fully connected layers. The convolution layer is the backbone, handling most of the computational workload. It processes input data using convolution operations, passing the results to the next layer. The filters within this layer act as feature identifiers, navigating through the input to create feature maps.

Sandwiched between successive convolution layers, the pooling layer is instrumental in downsizing spatial dimensions and curtailing computational intensity. Executing pooling on segmented portions of the input lightens the computational burden for ensuing convolution layers. The fusion of convolution and pooling layers aids in distilling and capturing features from input visuals. Culminating this process, the fully connected layer delivers the final verdict, correlating with the class numbers. While all CNNs adhere to a foundational blueprint, specific architectures may differ. Our research used the renowned AlexNet architecture as the bedrock for detecting Alzheimer's [27].

3.2. Parameters for Transfer Learning

Transfer learning is a pivotal technique in many deep learning applications, especially when training data for parameter calibration is scarce. At its core, transfer learning capitalizes on a pre-established network, such as AlexNet, using it as a foundational springboard for addressing a new challenge. AlexNet, as an illustration, has its roots in training on ImageNet, a comprehensive dataset teeming with labeled imagery. With transfer learning, the ingrained parameters from the deeper layers of AlexNet (barring the final three layers) are co-opted and harnessed. These concluding three layers, encompassing the softmax, fully connected, and output classification layers, are reconfigured or replaced to tailor the network to the distinct classification task in focus. These fully Connected Features train the SVM Classier using RBF Kernal.

AlexNet is a CNN model that's been pre-trained on the extensive ImageNet dataset, which serves as the foundational Domain (D_s). The architecture of AlexNet boasts over 60 million parameters. Directly harnessing such a vast parameter set from a mere thousand training images can be risky. The central premise of this study is that the internal layers of the CNN are adept at extracting universal image features. Initially trained in one domain (D_s) (in this context, ImageNet), these parameters can then be repurposed and applied to a distinct task (O_1) (in this case, Alzheimer's classification).

Support Vector Machines (SVM) is a conventional supervised classification and regression task method. It operates by distinguishing target classes in n-dimensional or multi-dimensional spaces. The core objective of SVM is to identify the ideal decision boundary, characterized by the largest margin, for classifying new data entries. Even though multiple decision boundaries can be present in an n-dimensional space, the desired boundary is always the one that classifies data most simply. This optimal boundary in SVM is referred to as a hyperplane, the dimensions of which are dictated by the dataset's attributes. The goal is to establish hyperplanes that maximize margins, where these margins act as a buffer determining the proximity between data points. A key aspect of SVM is its kernel, which computes the distances between data points x-n and x-m. When data points are in closer proximity, the kernel

produces higher values. Figure 2 offers a visual representation of the SVM kernel [28].

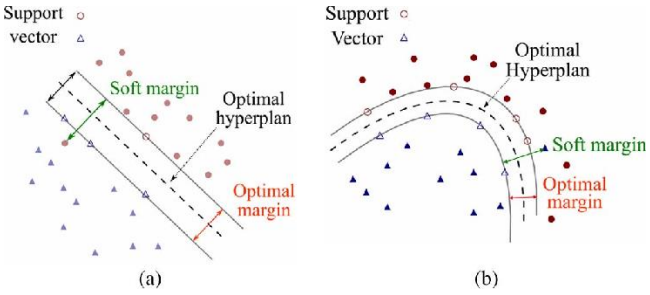

Fig 2. Linear and Non-Linear SVM.

The Radial Basis Function (RBF) Kernel is implemented, akin to the K-Nearest Neighbor (K-NN) Algorithm. Retaining only support vectors during the training phase harnesses the advantages of K-NN while circumventing space complexity issues. RBF kernels use various kernelized machine-learning techniques, including SVM classification. The mathematical representation of the RBF kernel is illustrated in Equation 1.

$$k(\vec{x}_i, \vec{x}_j) = exp(-\gamma \|\vec{x}_i - \vec{x}_j\|^2) \; for \; \gamma > 0 \qquad (1)$$

where,

$\vec{x}_i, \vec{x}_j$ = feature vectors

$\gamma = \frac{1}{2\sigma^2}$

σ = free parameter

3.3. Adapted Network Structure

The selected structure is built upon the pre-existing AlexNet model. The system inputs an RGB image of 227 x 227 pixels. As this image traverses the network, it gets classified into various categories in the ImageNet dataset. The design encompasses five consecutive Convolutional (C) layers, named C1 through C5, succeeded by three Fully Connected (FC) layers: FC6, FC7, and FC8. The comprehensive layout of this framework can be seen in Figure 3.

Figure 3 depicts the architecture of AlexNet. AlexNet is a groundbreaking deep-learning model pivotal in advancing the field of computer vision. Designed with a deep arrangement of layers, the architecture embodies convolutional layers responsible for filtering and feature extraction, pooling layers that reduce spatial dimensions, and dense, fully connected layers for final classification. This strategic orchestration of layers allows the model to recognize intricate image patterns, positioning AlexNet as a cornerstone in image-based machine learning.

To classify Alzheimer's, we aim to craft a system that can allocate scores to the target classes. Notably, the classes learned by the pre-trained network might not align with those of the current task. The primary layers of the network discern basic features like edge outlines from the training visuals, while the concluding fully connected layers home in on class-specific attributes pivotal for image classification. To harness the power of transfer learning, we inherit all layers of AlexNet, barring the last trio, designating them as transfer layers. These concluding three layers of AlexNet are supplanted with tailored SoftMax layers, dense layers, and an end classification layer, empowering them to assimilate the unique features of the Alzheimer's dataset.

The foundational five layers, sourced from AlexNet (nurtured on ImageNet), remain intact and static. The subsequent adaptive layers undergo training utilizing Alzheimer's datasets. Parameters tied to the dense FC layer encompass the bias learn rate factor, weight adaptation factor, and the concluding output dimension. The FC layers' output dimension corresponds to the class label count. The bias dictates the bias adaptation speed learn rate factor, and the weight adaptation rate orchestrates the holistic learning rate, both pegged at 50. The Softmax layer channels Softmax operations onto the incoming data. Specifications like the output dimension and function designation for multi-label classification are finalized for the classification process. The Cross-Entropy Function for k distinct classes is the chosen loss function, with the class count deciding the output dimension.

3.4. Network Training and Precision Adjustment

AlexNet's architecture is trained using the ImageNet dataset, which contains images across 1000 unique classes. For

image classification within the desired domain, the inherited CNN layers are precisely adapted using the target dataset, ensuring that the foundational features from ImageNet are retained. This method allows the CNN structure to undergo training on the target dataset with an increased learning rate, incorporating specific features from the domain into the layers intended for adaptation. The last three fully connected layers are refashioned to the desired domain, positioning them to classify target images aptly. This strategy transfers the preliminary model's low-level features to the target problem, speeding up the learning curve for new challenges.

The training procedure uses 70% of the dataset in our proposed framework. Several vital parameters impact the training, such as Batch Size, Epoch Count, Learning Rate, and Frequency of Validation. A batch size of 8 and a learning rate 1e-4 are implemented throughout the training phase. Training continues for up to 30 epochs, with the bias and weight learning factors set at 50. The optimization technique chosen is Stochastic Gradient Descent with Momentum (SGDM), which lowers the loss function and adjusts the bias and weight values. This repeated action equips the modified layers to recognize the distinct features essential for the Alzheimer's dataset, guided by the selected training parameters.

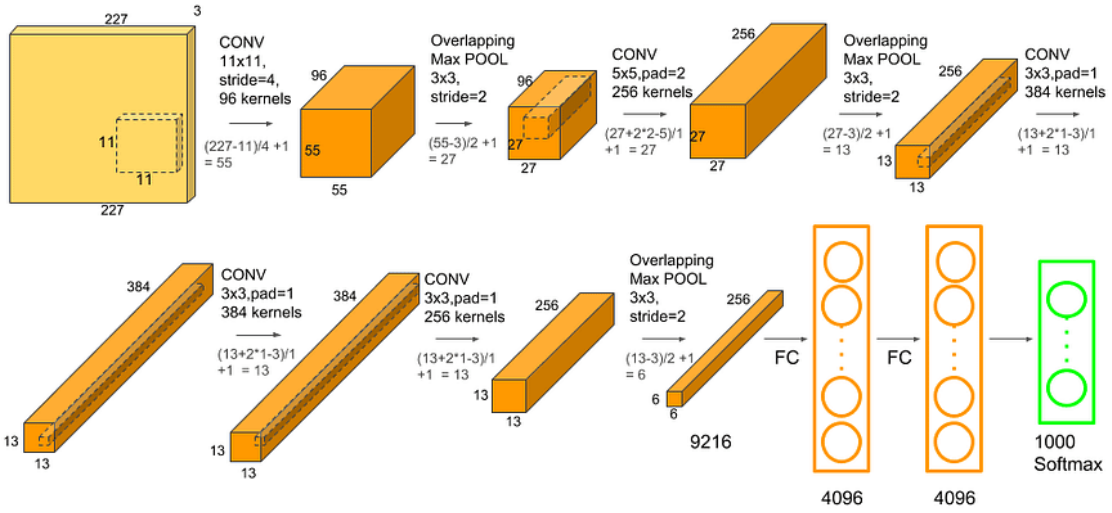

Fig 3. AlexNet Architecture [29]

3.5. Proposed Network Details

The proposed method uses images from all the records to train an AlexaNet 2D Network. The AlexaNet 2D Network consists of convolution layers, a fully connected layer, and a SoftMax output layer, which enables the classification of the images into four classes: Non-Dementia, Very Mild Dementia, Mild Dementia, and Moderate Dementia.

Table 1. AlexaNet layers detail

Layer_Name	C1	C2	C3	C4	C5
Input_Size	227x227x3	27x27x96	13x13x256	13x13x384	13x13x384
Num_Filters	96	256	384	384	256
Filter_Size	11x11x3	5x5x48	3x3x256	3x3x192	3x3x192
Stride	4	1	1	1	1
Padding	0	2	1	1	1
Activation_Fn	ReLU	ReLU	ReLU	ReLU	ReLU
Output_Size	55x55x96	27x27x256	13x13x384	13x13x384	13x13x256
Additional_Ops	Max-Pooling 3x3, stride 2	Max-Pooling 3x3, stride 2	None	None	Max-Pooling 3x3, stride 2

Table 1 provides detailed information on the layers of the AlexaNet model. The input size is 227x227x3, representing

a 3-channel color image with dimensions of 227x227 pixels. The layers in the AlexaNet model are as follows: Conv1, Conv2, Conv3, Conv4, Conv5, and the 3 fully connected layers. This table provides valuable insights into the architecture of the AlexaNet model, helping to understand the transformations and operations applied to the input data through the various layers to achieve accurate classification results.

During training, the network learns to extract meaningful features from the images and classify them accurately into the respective classes. The SoftMax output layer assigns probabilities to each class, and the spectrum is classified into the class with the highest probability.

4. Experimental Setup and Results

This section is foundational to any research as it sheds light on the methods and tools used to conduct experiments and the subsequent findings. In this chapter, the researchers meticulously outline the equipment, software, and datasets they chose for their investigations. They dive deep into the processes of image pre-processing and the metrics used to evaluate results. Key to this section is the detailed exposition of results obtained from the experiments. These findings are presented in various formats, such as tables and figures, for a comprehensive understanding. Discussions around the results offer insights into their implications and significance. This chapter is vital as it substantiates the research's claims and conclusions by providing empirical evidence.

4.1. Tools and Software Configuration

We utilized a convolutional neural network approach to detect Alzheimer's disease. Our computational framework was built and tested on a system featuring the Intel Core i7 10th generation processor, known for its powerful multi-core processing, which is ideal for deep learning tasks. The system operated on Windows 10, a 64-bit version, lauded for its user-friendly interface and broad software and hardware compatibility. Graphics computations were handled by an NVIDIA GTX card equipped with 2GB dedicated memory. Optimized for parallel processing, this card is invaluable for deep learning algorithms demanding extensive matrix operations. Our system was equipped with 8GB RAM, providing ample data storage and processing memory during the model development stages. All simulations and computations were executed using MATLAB 2019B.

4.2. Data Collection

The parameters of the CNN were primed via pre-training on the ImageNet database. In particular, the AlexNet structure was primed using the expansive ImageNet dataset, which contains over 1.2 million high-definition images spanning nearly 1000 unique classes. These images, sourced from the internet, were labeled manually by human evaluators.

Fine-tuning describes tailoring a pre-trained CNN to suit a specific dataset. In the context of this research, the target dataset originated from the publicly accessible KAGGLE repository. This collection comprises brain MRI scans from individuals, ranging from those deemed normal to those diagnosed as very mildly demented, mildly demented, and patients with Alzheimer's.

The collected data featured 6400 image samples procured from participants aged between 18 and 96, thus capturing the gamut of Alzheimer's evolution across varying age demographics. The training was executed using the entirety of the dataset's images.

Every dataset image was matched with a Clinical Dementia Rating (CDR) metric as the reference standard. The dispersion of the CDR ratings amongst the training and evaluation samples was meticulously curated to reflect every phase of Alzheimer's progression, as detailed in Table 2.

Table 2: Corresponding Mental States Based on Clinical Dementia Rating (CDR) Values in the KAGGLE Dataset.

Clinical Dementia Rate	Corresponding Mental State	No. of Image Samples
0	Non-Demented	3200
0.5	Very Mild Demented	2240
1	Mild Demented	896
2	Moderate Demented	64

4.3. Performance Assessment Criteria

The performance assessment of classification results derived from the AlexNet architecture uses several evaluation metrics [30]. A brief description of each of these metrics follows. Equations for the performance evaluation metrics are as follows:

$$Accuracy = TP + TN/TP + TN + FP + FN$$

$$Specificity = TN/TN + FP$$

$$Sensitivity\ (Recall) = TP/TP + FN$$

$$Precision = TP/TP + FP$$

$$F1\text{ - }score = 2\ (Precision * Sensitivity/Precision + Sensitivity)$$

In the equations provided, FP represents false positives, FN denotes false negatives, TP stands for true positives, and TN signifies true negatives.

4.4. Outcomes and Analysis

In this section, the findings from the study are collated, analyzed, and interpreted. It provides insights into the efficacy of the adopted methodology and its implications.

4.4.1. Training Performance

Originally trained in thousands of classes, AlexNet's feature representations might appear generalized due to its vast source domain diversity. In contrast, our specific dataset is narrower in the class scope. Therefore, we fine-tuned the fully connected layers of AlexNet to emphasize features specific to our target classes rather than those from the broader domain.

The database used for the proposed method consists of MRI images for each of the four cases: Non-Demented, Very Mild-Demented, Mild-Demented, and Demented. The dataset is split into three sets: training, validation, and testing, following a 70-10-20 ratio, respectively.

Data augmentation is a technique used to increase the diversity of the dataset by applying various transformations to the existing data, thereby improving the model's generalization. Table 3 outlines the dataset distribution across various dementia stages for training, validation, and testing sets pre- and post-augmentation. The 'Non-Demented' category remained stable after augmentation, while the 'Very Mild Demented' and 'Mild Demented' categories saw an uptick in images. The 'Moderate Demented' group, initially with fewer images, notably expanded post-augmentation. This table highlights the balancing effect of image augmentation across categories.

Table 3. Dataset details with the number of the training set, validation set, and testing set

Categories	Augmentation		Training set	Validation Set	Testing Set
	Before	After			
Non-Demented	3200	3200	2240	320	640
Very Mild Demented	2240	3200	2240	320	640
Mild Demented	896	3200	2240	320	640
Moderate Demented	64	640	448	64	128

Additionally, the model achieves a validation accuracy of 93.54%. Validation accuracy is important as it estimates how well the model will perform on unseen data. The validation accuracy suggests that the model generalizes well to new and unseen data. And it is a positive indicator that the model is not overfitting.

Training the model involves several parameters that contribute to its performance. Table 4 provides a comprehensive overview of the training parameters utilized.

Table 4: Training Parameters

Parameters	Corresponding Values
Validation Accuracy	94.28
Time is taken to Train	671 min 48 sec
No Epoch	20
Max No of Iterations	48
Learning Rate	0.01
Hardware Resource	Single CPU
Validation Frequency	10

The validation accuracy, a key indicator of the model's precision, is 94.49%, showcasing the model's ability to

perform well on unseen data. The total time for the training process was approximately 671 minutes and 48 seconds, indicating the computational resources required for the training phase. With 8 epochs and a maximum of 48 iterations, the model underwent substantial learning iterations to optimize its performance.

The learning rate 0.01 was crucial in controlling the step size during gradient descent, impacting the convergence speed and optimization quality. The training was executed on a single CPU, demonstrating the hardware resource utilized for this phase. Moreover, validation frequency, set at 10, signifies that the model's performance on the validation dataset was assessed every 10 iterations, ensuring a balance between frequent assessment and efficient computation.

4.4.2. Outcomes of Alzheimer's Classification

Using a transfer learning approach with the CNN architecture, we classified images from the KAGGLE repository. This classification addressed both the nuanced stages of Alzheimer's detection. Given the significant emphasis on Alzheimer's in medical studies, recognizing its varying stages plays a pivotal role in timely interventions, highlighting the relevance of multi-stage classification. By harnessing the foundational layers of the AlexNet model, trained on the expansive ImageNet dataset, we could capitalize on the rich, low-level features derived from over a million images. These foundational layers were adapted and then meticulously tailored on the full and segmented brain scans.

Modifications were made to the final three layers of the model to accommodate the specific classification objective. We trained the CNN model with raw images to capture task-centric features. This strategy retained the foundational features from the original domain while optimizing the learning speed. We diligently documented the training and evaluation phases, conducted over ten epochs for each data category, and subsequently assessed the outcomes represented by confusion matrices.

Our devised approach was exhaustively trained and evaluated for multi-faceted Alzheimer's classification tasks. Figure 4 visually presents the results of classifications.

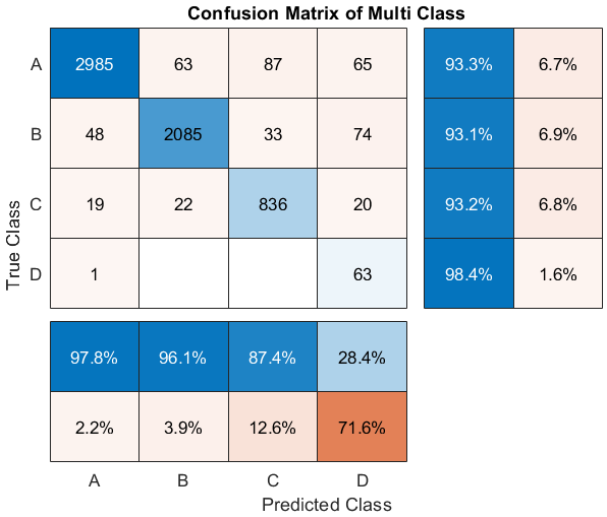

Fig 4: Confusion Matrix for Multi-class Classification.

Derived from the confusion matrices, the evaluation metrics provide a thorough understanding of the CNN model's efficacy in classifying MRI scans using transfer learning. This is applicable for multi-class tasks. The specific evaluation metrics, as described earlier, are presented in Table 5.

Table 5. Performance Parameter Measures

Metrics	***Measurements***
Specificity	*97.78%*
Accuracy	*94.49%*
Precision	*77.42%*
Recall	*94.49%*
F1-score	*81.08%*

From a statistical standpoint, the system demonstrated pronounced proficiency in the multi-class classification of

images when analyzing classification accuracies and prediction errors. Leveraging unsegmented images streamlined the process, trimming computational demands by two-thirds and yielding an impressive accuracy rate of 94.49%.

Recognizing and classifying Alzheimer's is significant in multi-class contexts, drawing considerable research interest. As discussed in the related work section, prior studies have focused on layered Alzheimer's classification. Furthermore, a comparative review juxtaposed our introduced methodology with other prevalent multi-class classification techniques.

While previous methods have demonstrated commendable accuracy in differentiating individuals with Alzheimer's from healthy subjects, using transfer learning as a benchmark for accuracy is a pioneering approach in Alzheimer's classification. Diagnosing Alzheimer's with precision in a test subject is crucial, but identifying the stage of the disease is equally vital. This information guides the appropriate care and intervention tailored to the patient's needs. Though some efforts mirror aspects of our approach, they haven't leveraged the techniques we've proposed.

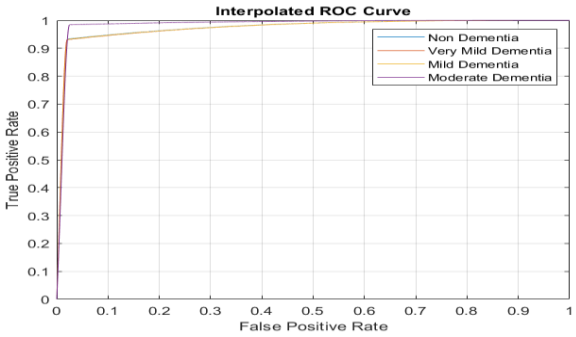

Fig 5. Multi-Class ROC for Alzheimer's Classification

Figure 5 presents the Receiver Operating Characteristic (ROC) curve for the multi-class classification system that differentiates between the 'Non-Dementia,' 'Very Mild Dementia,' 'Mild Dementia,' and 'Moderate Dementia' categories. The Area Under the Curve (AUC) values offer insights into the model's ability to distinguish between the classes effectively. Specifically, the 'non-dementia' class achieved an AUC of 0.95578, 'Very Mild Dementia' registered an AUC of 0.95519, and 'Mild Dementia' recorded an AUC of 0.9551. In contrast, the 'Moderate Dementia' class marked the highest with an AUC of 0.97964. These AUC scores underscore the model's strong performance in classifying the distinct dementia stages.

In this regard, Tooba et al. introduced a combined feature vector, integrating textural and clinical data, to classify various stages of Alzheimer's using MRI scans. Their method reported an overall accuracy of 79.8% for the multi-classification task. A blended feature vector combining structural and morphological attributes was introduced in a parallel endeavor. Employing this combined vector, S0rensen et al. achieved a multi-class classification accuracy of 62.7%. When juxtaposed with these methodologies, our strategy, which harnessed the AlexNet architecture through transfer learning, emerged superior, recording a peak accuracy of 94.49%, as delineated in Table 6.

Table 6. State-of-Art Comparison for Multi-class Classification Approaches.

Methods	Accuracy (%)
Beheshti et al. [1]	84.17
Altaf, T	92.48
Wang et al. [16]	93.05
Proposed Approach	**94.49**

5. Conclusions

Detecting the various stages of Alzheimer's disease presents unique challenges, particularly when delving into multiclass classification. To address these intricacies, our team devised a tailored solution using a transfer learning approach, specifically leveraging the robust architecture of AlexNet. This adaptation entailed utilizing both segmented and un-segmented MRI brain images. Remarkably, our fine-tuned convolutional neural network (CNN) achieved an impressive 94.49% for multiclass challenges.

Furthermore, our model's efficacy extends beyond just accuracy. With a specificity of 97.78%, a precision of

77.42%, a recall of 94.49%, and an F1-score of 81.08% in multi-class scenarios, our system consistently outperformed other research efforts, such as Tooba et al.'s 79.8% and S0rensen et al.'s 62.7% accuracy rates. The distinctions in dementia stages were vividly illustrated by the ROC curve, particularly with 'Moderate Dementia' achieving an AUC of 0.97964. These results validate our approach's superiority and emphasize its potential as a valuable tool in Alzheimer's diagnostics and care.

Conflicts of interest

The authors of this manuscript at this moment state that they have no financial, personal, or professional conflicts of interest that could have influenced the work reported in this paper. This declaration encompasses all forms of potential conflicts, ensuring the integrity and impartiality of the research and its findings.

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Authors

Shobha S is an Associate Professor in the ECE Department at Sapthagiri College of Engineering, Bangalore. She has more than 19 years of academic experience. She holds a bachelor's degree in Electronics and Communications and a master's in digital Electronics and Communication from M S Ramaiah Institute of Technology, Bengaluru, India. Her research interests are Digital Image Processing, Machine Learning, and Deep learning techniques. She has more than 5 publications.

B. R. Karthikeyan is an Associate Professor in the ECE Department and Head of the Centre for Signal Processing and Communication Systems Research at Ramaiah University of Applied Sciences (RUAS), Bangalore. He has more than 15 years of academic and research experience. He is also experienced in coordinating funded research projects from government organizations and public and private sectors. He holds B.E. degree in Electronics and Communications from the Anna University, Chennai, India, and M.Sc. [Engg] and Ph. D from Coventry University, U.K in 2015. His current research interests are Antenna Arrays, DOA Estimation, Digital Beamforming Techniques, Baseband Signal processing for wireless communication, Adaptive algorithms, Machine Learning and Deep learning techniques. He has completed several sponsored research projects for various commercial and defense applications. He has 10 journal publications, 3 conference publications and 2 patents to his credit. He is also a reviewer for IEEE Antennas and Wireless Propagation Letters.