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# Design and Development of a Deep Learning Model for Classification of Alzheimer's disease Using Magnetic Resonance Images

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**ABSTRACT**

**Alzheimer's disease, an incurable neurodegenerative condition predominantly affecting memory functions in the elderly, presents a significant global health challenge, particularly among individuals aged over 65 years. Early and accurate diagnosis is crucial for effective management and intervention. However, manual diagnosis by healthcare professionals is prone to errors and time-consuming due to the increasing number of cases. While various techniques have been employed for diagnosis and classification, there remains a need for improved accuracy in early detection solutions. In this research, we propose a deep learning-based approach utilizing Convolutional Neural Network (CNN) architectures for the diagnosis and classification of Alzheimer's disease. The proposed model distinguishes Alzheimer's disease into four categories: Non-Dementia, Very Mild Dementia, Mild Dementia, and Moderate Dementia. The CNN architecture, with optimized hyper parameters, demonstrated superior performance during both training and testing phases, achieving accuracy values of 0.977 and 0.994, respectively. The proposed model offers a practical solution for real-time analysis and classification of Alzheimer's disease, potentially enhancing early intervention strategies and patient care.**

Keywords - **Alzheimer's disease; deep learning; biomarkers; positron emission tomography; Magnetic Resonance Imaging; mild cognitive impairment.**

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## I. INTRODUCTION

Alzheimer's disease (AD) stands as the most prevalent neurodegenerative condition, typically manifesting with an initial stage termed Mild Cognitive Impairment (MCI), characterized primarily by memory loss, which progressively deteriorates alongside behavioral issues and declining self-care [1]. However, not all individuals diagnosed with MCI progress to AD [2]. A minority develop non-AD dementia, while some remain stable in the MCI phase without advancing to dementia [2]. Given the absence of a cure for AD, accurate identification of those likely to transition from MCI to AD is imperative. Similarly, discerning individuals in the MCI stage unlikely to develop AD is crucial to spare them from potentially ineffective or harmful pharmacological interventions. Consequently, significant efforts have been directed towards developing early detection tools, especially targeting pre-symptomatic phases, aiming to mitigate or impede disease progression. Advanced neuroimaging techniques, including Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET), have been instrumental in uncovering structural and molecular biomarkers associated with AD [3].

Rapid progress in neuroimaging methodologies has underscored the importance of integrating large-scale, high-dimensional multi-modal neuroimaging datasets [4]. Consequently, there has been a surge of interest in computer-assisted machine learning approaches for the integrative analysis of neuroimaging data. Established machine learning algorithms such as Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), and Decision Trees (DT) have shown promise in facilitating early diagnosis and prediction of AD progression. However, prior to employing such techniques, meticulous preprocessing steps are essential. Furthermore, these approaches necessitate feature extraction, feature selection, dimensionality reduction, and feature-based classification for effective classification and prediction. These stages require expertise and involve numerous optimization steps, rendering them time-intensive [5]. To address these challenges, deep learning (DL), an emerging domain within machine learning, which utilizes raw neuroimaging data to derive features through "on-the-fly" learning, has garnered significant attention in the realm of large-scale, high-dimensional neuroimaging analysis.Motivated to unfurl the power of DL techniques in AD diagnosis, we present an extensive review of the current state-of-the-art in the area of DL-based AD diagnosis.

Alzheimer's disease (AD) represents an incurable neurodegenerative condition characterized by global prevalence and marked by the presence of β-amyloid (Aβ)

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plaques and tau-containing neurofibrillary tangles [6]. Cognitive impairment is its primary symptom, predominantly afflicting individuals aged 65 and older, with 10% of cases manifesting before this age threshold. AD affects various cognitive functions including language, attention, comprehension, reasoning, and memory, thereby impacting daily activities. It stands as the most common form of dementia, contributing to about two-thirds of cases attributed to aging. In 2020, it ranked as the seventh leading cause of death in the United States [7]. While treatments aim to ameliorate symptoms, a definitive cure remains elusive.

AD is stratified into Non-Dementia, Very-Mild Dementia, Mild Dementia, and Moderate Dementia categories, distinct from DSM-5 classifications Symptoms vary depending on disease stage, commonly starting with short-term memory loss and language difficulties. Early symptoms often go unnoticed, posing a challenge for timely intervention. Early diagnosis is pivotal for initiating potential treatments during the incipient stages, yet its complexity arises from subtle symptom presentation and diagnostic ambiguity. Neuropsychological assessments are typically employed for early detection, though manual analysis is labor-intensive and time-consuming given the volume of symptomatic patients [8].

Despite the ideal scenario of early diagnosis by medical experts, the manual analysis of extensive medical imaging data from numerous patients is impractical. Automating this process is imperative to ensure accuracy and efficiency. Various techniques, including the Internet of Medical Things (IoMT), MRI or CT image analysis, machine learning, and deep learning methodologies, are pivotal in addressing this need within the medical domain . Initiatives like the MICCAI BRATS challenges leverage deep learning and machine learning approaches on MRI or CT images to advance diagnostic capabilities [9].

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## II. BACKGROUND

Alzheimer's disease (AD) is a rapidly growing global health concern primarily affecting the elderly population, characterized by incurable neurodegeneration in the brain. The challenge lies in its early diagnosis due to the absence or minimal manifestation of symptoms in its initial stages. [6]introduced a technique integrating machine learning with Laser-Induced Breakdown Spectroscopy (LIBS) for diagnosing AD by analyzing micro drop plasmas in AD patients and healthy controls, achieving an 80% classification accuracy.

[10] proposed nanotechnology-based approaches for accurate early diagnosis and treatment of AD, emphasizing the use of nanocarriers delivering bioactives as a promising strategy compared to conventional therapies. [11] explored neuropathological diagnosis methods for AD, highlighting the role of Artificial Intelligence and machine learning in managing and diagnosing the disease in its early stages.

[12] proposed a deep learning-based solution analyzing brain sub-regions to diagnose AD, achieving high accuracy, sensitivity, and specificity values of 95%, 95%, and 94% respectively, particularly focusing on the hippocampus region. [13] evaluated various deep learning techniques for AD diagnosis, with transfer learning approaches yielding impressive accuracy and precision scores of 98.0% and 98.1% respectively. [14] introduced a real-time model utilizing CNN, k-nearest neighbours (KNN), and support vector machine (SVM) algorithms, achieving outstanding performance with 99.21% accuracy in classifying AD stages.

Suk and Shen [15] introduced a hybrid model combining Sparse Regression Networks with CNNs for AD diagnosis. This approach generated multiple target-level representations through Sparse Regression Networks, which were then integrated by CNNs to optimize output label identification.

Billones et al. [16] adapted the 16-layered VGGNet for classifying subjects into AD, Mild Cognitive Impairment (MCI), and Healthy Controls (HC) solely based on structural MRI scans, achieving robust classification accuracy without the need for image segmentation.

Sarraf and Tofighi [17] and [46] employed LeNet architecture for AD classification using functional MRI and structural MRI scans, respectively, highlighting CNNs' effectiveness in medical imaging due to their shift-invariant and scale-invariant properties.

Gunawardena et al. [18] compared CNNs with Support Vector Machines (SVMs) for early-stage AD diagnosis using structural MRI, demonstrating CNNs' superior performance. Basaia et al. [49] developed a CNN model for AD diagnosis utilizing data augmentation and transfer learning techniques to enhance computational efficiency and overcome dataset limitations.

Wang et al. [19] designed an eight-layered CNN model for AD diagnosis, exploring various activation and pooling functions to optimize model configuration. Karasawa et al. [51] proposed a 3D-CNN based on ResNet architecture, achieving superior performance compared to existing benchmarks.

Tang et al. [20] introduced a 3D Fine-tuning Convolutional Neural Network (3D-FCNN) for AD diagnosis, outperforming 2D-CNN models in both binary and multi-class classification tasks. Spasov et al. [21] devised a multi-modal CNN framework for AD diagnosis integrating structural MRI, genetic measures, and clinical assessment data, offering a parameter-efficient and fast solution.

Wang et al. [22] developed a CNN model utilizing fMRI and Diffusion Tensor Imaging (DTI) modalities for AD diagnosis, emphasizing the effectiveness of multi-modal MRI. Islam and Zhang [23] trained a CNN model on an imbalanced OASIS dataset using data augmentation, achieving superior performance over state-of-the-art models.

Yue et al. [24] proposed a CNN-based model for AD diagnosis using structural MRI, achieving high classification accuracy across multiple categories. Jian et al. [57] employed transfer learning with VGGNet16 for AD classification using structural MRI, successfully identifying AD, MCI, and Normal Control (NC) subjects.

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Huang et al. [25] designed a multi-modal CNN model for AD diagnosis utilizing MRI and FDG-PET data, highlighting the importance of the hippocampus as a crucial region of interest. Goceri [26] developed a 3D-CNN approach for AD diagnosis using MR Images, optimizing model performance through a combination of optimizer, activation function, and pooling function.

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## III. PROPOSED METHODOLOGY

The proposed methodology for achieving accurate and early diagnosis of Alzheimer's Disease (AD) is outlined in Figure 1. This methodology addresses the challenges discussed in the Introduction section, particularly focusing on the limitations of existing deep learning techniques in detecting AD at its early stages when symptoms are minimal or absent. The study primarily focuses on, CNN-[27]based hyper parameters deep learning models, for the diagnosis and classification of AD.

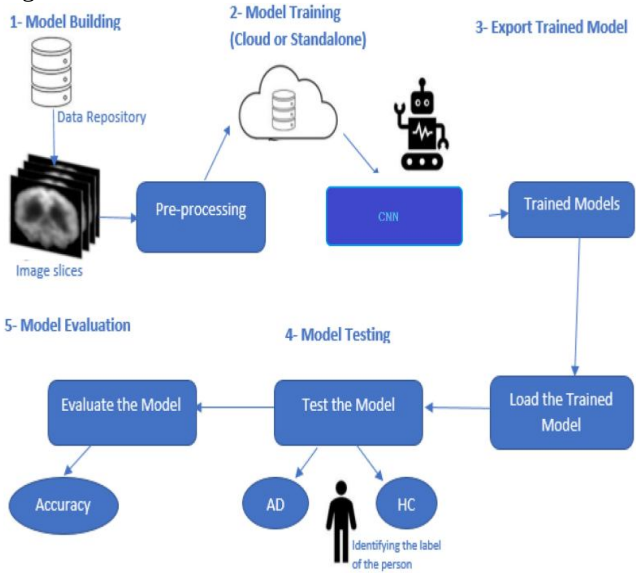

Figure 1: Proposed model methodology.

Convolutional Neural Network (CNN) architecture in above is a diagram of a basic CNN architecture with convolutional layers, pooling layers, and fully connected layers: This output is a summary of a Sequential model in TensorFlow/Keras. Let's break it down:

Model Type: The model is defined as a Sequential model, which means the layers are stacked sequentially.

Layer Details: Each layer in the model is listed along with its type and output shape.

a. Conv2D Layers: These are convolutional layers. They apply a specified number of filters to the input image. For example, the first Conv2D layer has 32 filters, each with a size of 3x3 pixels. The output shape is (148, 148, 32), meaning there are 32 feature maps of size 148x148 pixels.

b. BatchNormalization Layers: Batch normalization layers normalize the activations of the previous layer at each batch. They help in stabilizing and accelerating the training of deep neural networks.

c. MaxPooling2D Layers: Max-pooling layers reduce the spatial dimensions of the input volume. For example, the first MaxPooling2D layer reduces the spatial dimensions by half, resulting in an output shape of (74, 74, 32).

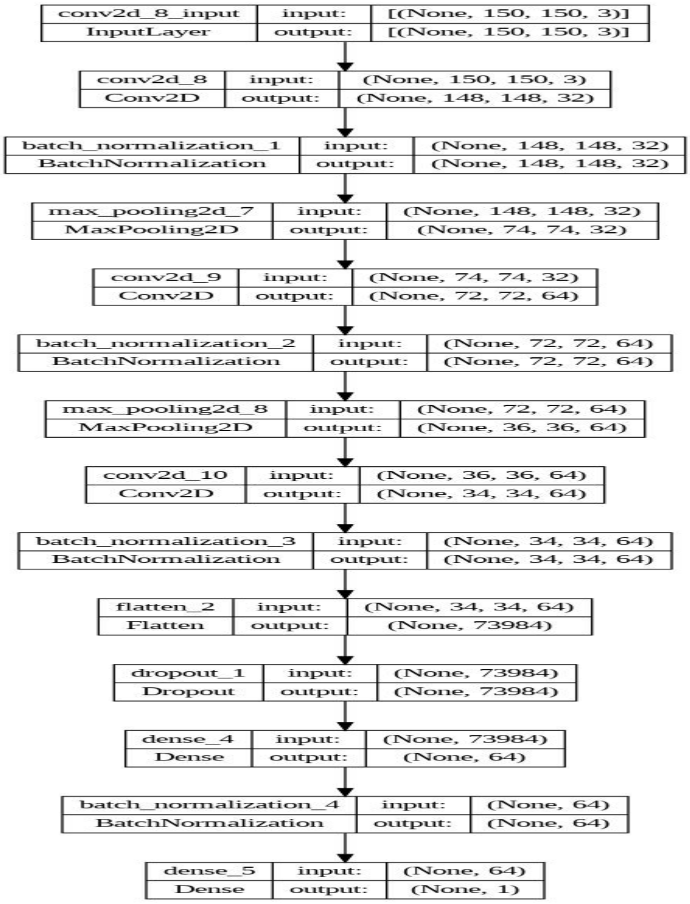

Figure 2: Model Architecture

d. Flatten Layer: This layer flattens the input into a 1D array. It transforms the tensor output from the previous layer (a 3D volume) into a 1D vector.

e. Dropout Layer: Dropout layers are used for regularization. They randomly deactivate a fraction of neurons during training, which helps prevent overfitting by reducing inter-dependencies between neurons.

f. Dense Layers: These are fully connected layers. The first Dense layer has 64 units, and the second Dense layer has 1 unit (for binary classification). The last Dense layer [28] uses a sigmoid activation function for binary classification.

Total Parameters: This section provides information about the total number of parameters in the model. It includes both trainable and non-trainable parameters.

a. Trainable Parameters: These are the parameters that will be updated during training, such as weights and biases in the layers.

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b. Non-trainable Parameters: These parameters are not updated during training. They are typically used by the Batch Normalization layers for normalization.

A deep CNN version is created and used to do program plant species characterization with almost no customer connection. A CNN version may be created from a extensive variety of types of layers, for example, convolutional layers, pooling layers, absolutely related layers, and so on. These layers upload to creating herbal thoughts a reality. Convolutional layers are the facilities of a CNN version and incorporate of a gaggle of learnable channels. Albeit every channel isn't always spatially huge, they count on the a part of stretching out thru the overall profundity of the information records. In this manner, it's far feasible to perform the goal of getting a extent of neurons. The model architecture is depicted in Figure 2 above.

The proposed community accommodates of specific types of layers that are convolutional and absolutely related layers. The types of layers for CNNs. The type of the preliminary 5 layers is a convolutional layer, at the same time as the layer type of remaining 3 layers is a very related layer. A absolutely related layer has been used to interface present day neurons to each one of the neurons of the beyond layer. Generally, the engineering of the proposed profound gaining knowledge of business enterprise and the layers of the done community aremade experience of withinside the subtleties that follow. Taking under consideration the end result of the convolutional layer demonstrates that preferred factors are surely the end result of this type of layers and a few manner or some other it thoroughly can be deciphered because the issue extraction process. The convolutional layer must be organized for extricating substantial examples from the information everyday snap shots in which the effects of the decrease layers, first and 2d convolutional layers, are just like the eliminated edges of the normal image and such closeness may be visible withinside the notion a part of the framework that's given in subsequent segment. By searching on the process of the absolutely related layer to the convolutional layer, the absolutely related layer behaves like a classifier withinside the traditional AI calculation. Regardless of the substantial process of the absolutely related layer, this sediment builds the intricacy of the version and it's far computationally steeply-priced undoubtedly.

## IV. EXPERIMENTAL RESULTS AND DISCUSSION:

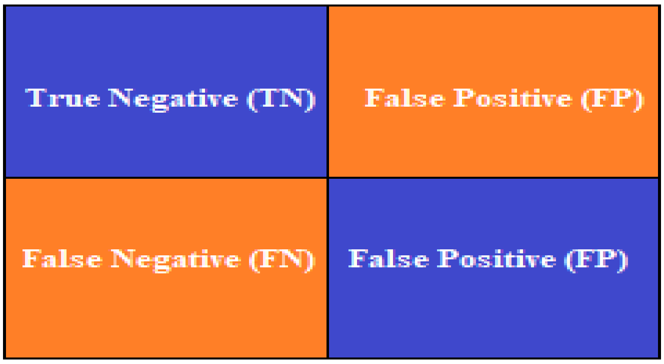
This section provides a detailed explanation of the dataset utilized for both training and testing the model, the experimental analysis conducted for evaluating the proposed model, and the resulting outcomes.

***a) Dataset Description:***

One hundred and thirty-three people with an average age of 73.3 years, including 38 females, were included in the Alzheimer's disease Neuroimaging Initiative (ADNI) picture collection at rsfMRI. The participants were chosen based on the ADNI dataset's availability of rsfMRI pictures. Most of the ADNI individuals were included in the current study. Patients with Alzheimer's disease scored between 0.5 and 1.0 on the Clinical Dementia Rating Scale and between 20 and 30 on the MMSE (CDR). To putit another way, they had scores of 25-32 on the MMSE, a loss of objective memory deficit determined by education-adjusted scores of 23-29 Logical Memory II and 0.5 on the CDR, and no dementia. MMSE scores ranged from 23 to 32, while CDR values were found to be close to zero in the healthy patients

***b) Performance Metrics:***

The performance of the model is analyzed by using the confusion matrix. This will specify the performance of classification models for given test data. This will specify the values for test data that are known. This matrix is divided into two attributes such as predicted values and original values along with an overall number of predictions.




True Negative (TN): The prediction value is false and actual value is also false.
True Positive (TP): The prediction value is true and actual value false.
False Positive (FP): The predicted value is true and actual value is false.
False Negative (FN): The predicted value is false and actual value is true.

**Accuracy:**

Accuracy is a metric used to evaluate the performance of a model, algorithm, or system in correctly identifying or classifying instances within a dataset. It measures the proportion of correct predictions made by the model out of the total predictions made.

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In classification tasks, where the goal is to assign a label or category to each instance, accuracy is typically calculated as the ratio of the number of correct predictions to the total number of predictions:

Accuracy=Number of Correct Predictions/
Total Number of Predictions×100%

A high accuracy value indicates that the model is making a high proportion of correct predictions, while a lower accuracy suggests that the model is making more errors in its predictions. However, accuracy alone may not provide a complete picture of a model's performance, especially in cases where the dataset is imbalanced or when different types of errors have varying levels of importance. Therefore, it's often useful to complement accuracy with other metrics such as precision, recall, F1 score, or area under the receiver operating characteristic curve (ROC AUC) depending on the specific characteristics of the problem being addressed.

Recall (Sensitivity): Recall, also known as sensitivity or true positive rate, measures the proportion of actual positive cases that were correctly identified by the model. It is calculated as the ratio of true positives to the sum of true positives and false negatives.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

A high recall value indicates that the model is effectively capturing the positive instances, minimizing false negatives.

Precision: Precision measures the proportion of predicted positive cases that were actually positive. It assesses the model's ability to avoid false positives. Precision is calculated as the ratio of true positives to the sum of true positives and false positives.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

A high precision value indicates that the model's positive predictions are accurate and reliable, with fewer false positives.

Table 4.1: Comparative performances for detection and classification of Alzheimer’s

| Algorithms | Precision | F1-measure | Accuracy | Recall |
|---|---|---|---|---|
| **ANN** | **85.67** | **86.89** | **87.12** | **84.91** |
| **Normal CNN** | **89.34** | **89.56** | **90.23** | **91.12** |
| **Proposed Model** | **96.67** | **97.54** | **99.47** | **98.45** |

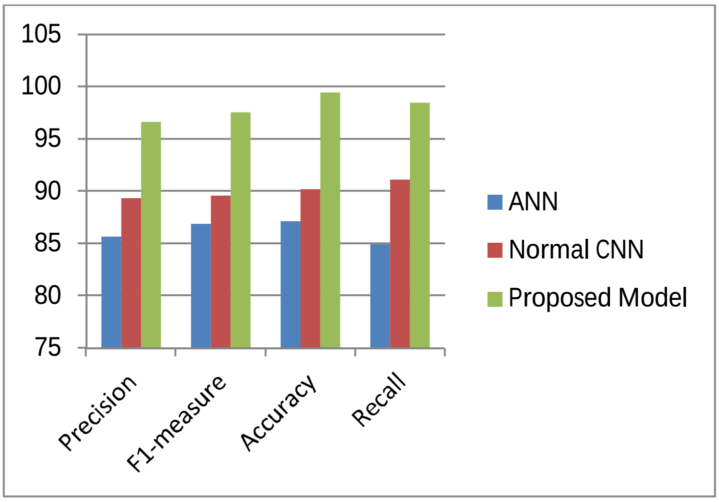


Figure 3 : Comparative performances of various DL Algorithms

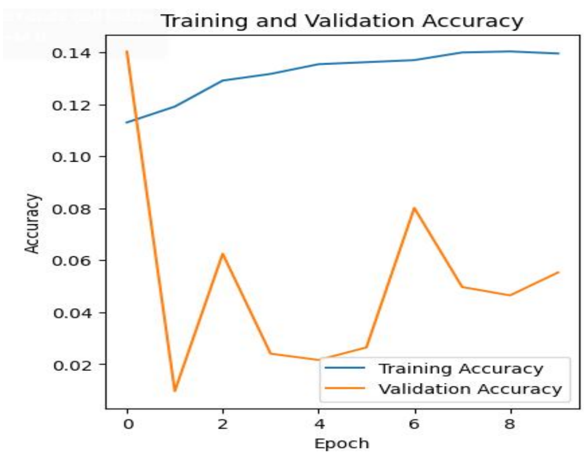


Figure 4 : Training and validation Accurac

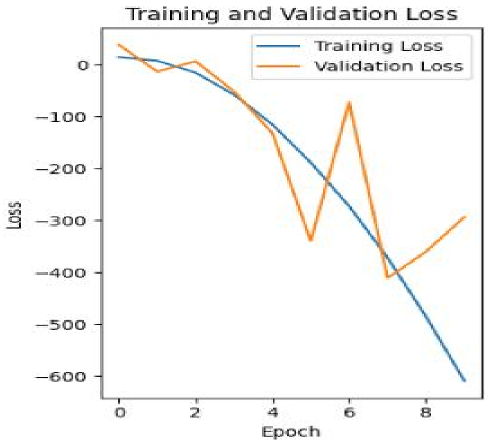


Figure 5 : Training and validation Loss

After successfully training the proposed model using the training dataset, the model was evaluated in the test phase, where four test cases were performed sequentially.

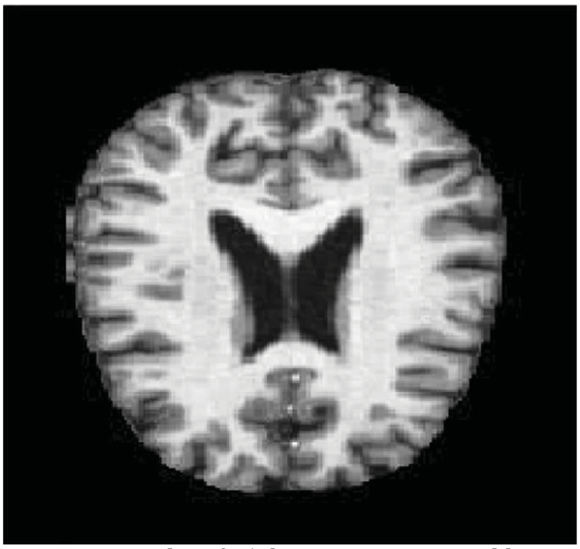

Figure 6: Test classified the image as very mild AD.

Figure 7: Test classified the image as  mild AD.

Figure 8:Test classified the image as Non-Dementia.

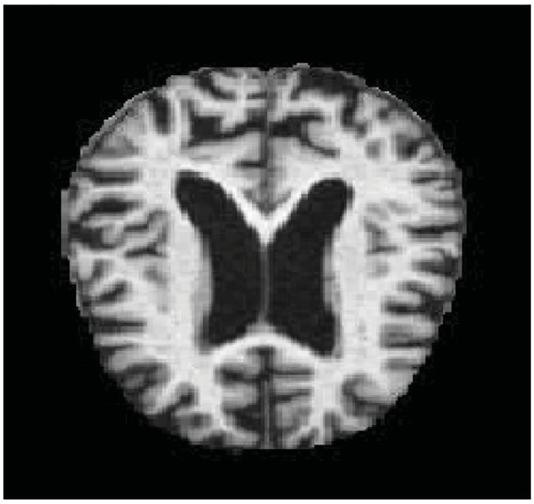

Figure 9: Test classified the image as Moderate Dementia

Following successful training of the proposed model utilizing CNN architectures, the testing phase demonstrated superior performance in diagnosing and classifying AD. This application holds potential for future utilization in aiding real-time diagnosis and classification of medical images.

Both statistical analysis and visual representations demonstrate that the proposed model surpasses other techniques discussed in the literature review. Offering accurate early diagnosis and precise classification, this model holds promise for real-time implementation. Its efficacy suggests it will significantly aid in the successful classification of Alzheimer's disease.

## V. CONCLUSION

Achieving an accuracy of 0.9947in Alzheimer's disease classification underscores the promising efficacy of the proposed Convolutional Neural Network (CNN) method. Such a high level of accuracy signifies the model's ability to accurately discern AD-related biomarkers from neuroimaging data, highlighting its potential as a valuable tool in early detection and diagnosis.

With such remarkable accuracy, the CNN method holds promise in clinical settings, where timely interventions based on accurate diagnoses are crucial for improving patient outcomes. Furthermore, this level of accuracy suggests that the CNN approach may outperform traditional methods, such as Structural Magnetic Resonance Imaging (sMRI), in terms of both sensitivity and specificity.

Continued refinement and validation of the CNN method, along with further investigation into its robustness across diverse datasets and patient populations, are essential next steps. Additionally, efforts to integrate this CNN approach into existing diagnostic workflows and clinical practice guidelines can facilitate its adoption and maximize its impact on patient care. Overall, the achieved accuracy underscores the potential of deep learning techniques in advancing the field of Alzheimer's disease research and clinical management, offering hope for improved early detection and intervention strategies in the fight against this devastating neurological disorder. In the future, we plan to extend the disease detection with more data sets and use the different measures to detect the system's accuracy.

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