Identification of Alzheimer's Disease using Convolutional Neural Networks and Inception V3 Transfer Learning Technique

B. Shakila
Department of Electrical and Electronics Engineering
NIT Nagaland, Nagaland, India
shakila@nitnagaland.ac.in

Abstract*—Recent studies found that Alzheimer's Disease (AD) is one of the six leading causes of death in the US and the sufferers are expected to double across the globe, by the year 2050. The ability of patients to take preventative measures before permanent brain damage depends on an early and correct diagnosis of AD. This is because patients can do so when they are aware of the seriousness of the condition and risks for development. Machine learning methods, particularly predictive modelling and pattern recognition, have advanced significantly in the last ten years. Drug delivery systems and medical imaging have emerged as critical tools in biomedical sciences for assisting researchers in grasping problems holistically and resolving difficult medical challenges. Deep learning is a machine learning technique for categorization that pulls out low- to high-level features. Convolutional Neural Networks (CNNs) are used in this study to discriminate between an Alzheimer's brain and a healthy, normal brain. The benefit of categorizing this type of medical data is that it can be used to develop a predictive model or system that can recognize AD symptoms when compared to those of healthy patients and can also establish the phases of the illness. The most challenging part of using CNN to classify clinical data for medical disorders like AD has always been choosing the most effective discriminative features.

Keywords— Alzheimer's Disease, Machine Learning, Deep Learning, Convolutional Neural Networks, Magnetic Resonance Imaging, Confusion Matrix, Receiver Operating Characteristics Curve

I. Introduction

The World Health Organisation (WHO) reports that Alzheimer's disease is currently one of the most prevalent diseases in the world. Worldwide, there are more than 50 million people who have AD or another kind of dementia. A new case of Alzheimer is identified worldwide every year at a rate of approximately ten million, or one instance every three seconds. By 2050, there will be 152 million cases of dementia, up from 82 million in 2030 [1].

The typical brain condition associated with AD impairs people's capacity for clear thinking. Loss of the capacity to read, write, and think is a symptom of the illness. They could even forget the names of their own family members in difficult situations. People who have beta-amyloid signals in their brain cells are susceptible to AD. According to estimates, the prevalence of AD is 5% among people 65 and older, and in developed countries, this number is startlingly higher (about 30%) for people 85 and older.

The most prominent symptom of Alzheimer's disease is memory loss. Patients eventually lose the ability to recall details about themselves, including names, ages, and addresses. Because it is a gradual process, patients occasionally completely lose all memory of their loved ones. Numerous tests and evaluations must be completed for a precise evaluation of AD. As the average lifespan increases globally, this is predicted that the number of AD sufferers would quickly increase. A little more over 16 million Americans provide unpaid care to six million AD patients, amounting to around 18.5 billion hours and $234 billion. While the death rate from Alzheimer's has climbed by 145% over the 20 years prior, the death rate from heart attacks has decreased by nine percent. Only 16% of these elderly people receive the essential treatment and examinations.

Early detection and effective treatment can stop the patient from suffering from severe AD. One of the most frequent factors that significantly affects the human brain is brain cortex shrinkage. While the hippocampus is primarily affected by normal shrinkage, the affected person's cortex shrinks. One's ability to think and remember daily tasks is impacted by a decrease in the hippocampal area because it causes the cerebral cortex to contract and the ventricles to grow. Functional Assessment Questionnaire (FAQ), Mini-Mental State Examination (MMSE), Global Deterioration Scale (GDS), Clinical Dementia Rating (CDR), and several other clinical evaluation parameters for the diagnosis of AD were created by the National Institute of Ageing (NIA).

AD can be diagnosed in a variety of ways, all of which require comprehensive clinical data [2]. Forgetting previously had encounters or experiences is one of the illness' early symptoms. It ultimately leads to serious memory issues and a decline in one's capacity to carry out daily chores. The symptoms' development may be slowed down or helped by medication. Both those who are ill and the people who care for them can benefit from programmes and services. Significant loss of brain function in its advanced stages may lead to dehydration, starvation, or infection. The fatal AD is currently incurable and has no known treatment.

Research into the causes of Alzheimer's disease currently focuses on two proteins namely plaques and tangles. Plaques: The beta-amyloid protein is a fragment of a larger protein. These fragments appear to damage neurons and hinder communication between brain cells when they accumulate.. These aggregates become larger clumps known as amyloid plaques when they combine with other cellular debris. Tangles: Tau proteins are part of the internal support and transportation network that brain cells use to transport nutrition and other essential components. Tau protein clusters, known as neurofibrillary tangles, change the organisation and shape of brain tissue in AD [3]. The tangles damage cells and interfere with the transport system.

Ageing is the main known cause of risk of AD. According to a study, there are 4 fresh diagnoses for each thousand persons aged 65 to 74 every year. For every thousand people in the 75 to 84 age bracket, there are 32 new diagnoses overall. Adults 85 and older had 76 new diagnoses per 1,000 patients. The likelihood of developing AD is high, while either the patient's parent or sibling was suffered from the same disease. Given the complexity of the genetic impacts, it is still debated how precisely genes within families affect.

An apolipoprotein E (APOE) gene variation is a more clearly defined genetic component. Alzheimer's disease risk is increased by the APOE e4 gene variation. The APOE e4 allele is present in a staggering 25–30% of people. However, not everyone who carries this specific gene experiences illness. Inheriting any one of three unusually mutated genes will almost certainly result in Alzheimer's disease. Just over one percent of Alzheimer's sufferers are, however, impacted by these changes.

Mild cognitive impairment (MCI) [3]: A person having MCI observes a faster decline in their ability to recall information or other cognitive abilities than is typical for someone of their age. The person's ability to operate in socially or professional environments is unaffected by the deterioration, though. However, dementia is substantially more likely to develop in those with MCI. AD-related dementia is more likely to arise as a result of MCI because the condition primarily affects memory.

Identification of abnormalities in the medical history through artificial intelligence is critical in the early diagnosis of any genetic illness, complementing clinical evaluations [4]. Cheaper RF based neuroimaging techniques to measure the degenerative brain changes connected to AD [5] has been proposed to ease the financial burden of the medical victims. ML algorithms have been developed to create classifiers using imaging data and clinical measurements for the purpose of diagnosing AD. Since almost ten years ago, automated AD detection has attracted interest.

Prior to 2019, reviews were only done on feature selection in machine learning methods. However, further research showed that transfer learning and end-to-end deep learning algorithms deliver good results. Further, the detection also concentrated on artificial neural networks (ANN) [6], support vector machines (SVM), and deep learning [7] techniques and so on. Sophisticated deep learning methods including Deep Convolutional Neural Networks (DCNNs) [8], pre-trained CNNs, Recurrent Neural Networks (RNN), auto encoders, and combinations of CNN and RNN were explored.

II. Methodology And Implementation

In health sector, Artificial Intelligent are frequently used for classification of diseases by utilizing medical images or data. Deep learning is a part of AI, which works similar to biological neural operation. Recent advancement in Deep learning technologies has busted the utilization of deep learning models and their variants. Among the most effective models in this domain are Convolutional Neural Networks (CNNs), which excel in processing and analyzing visual data such as medical images. CNNs are composed of multiple layers, including convolutional layers that capture essential features, optional pooling layers that reduce the dimensionality of data (often through max pooling), and non-linear activation functions like ReLU that enable the model to learn complex patterns. To further enhance the accuracy and robustness of CNNs, advanced techniques such as residual learning and dropout have been introduced. Residual learning helps in addressing the vanishing gradient problem, improving the model's ability to learn deeper features, while dropout prevents overfitting by randomly deactivating neurons during training. Transfer learning is another valuable approach, where a model trained on a large dataset for one task is fine-tuned for a different, yet related, task. This method is particularly advantageous in situations where the available data for training is limited, allowing models to be adapted efficiently without needing vast amounts of new data. These combined strategies are crucial in improving deep learning applications in medical fields, where precise and early diagnosis is vital.

A. Description of Dataset

The dataset used in the study has fragmented in three parts namely training, validation and testing. The model has trained on four different classes named MildDemented, VeryMildDemented , NonDemented, ModerateDemen.

B. Data Pre-processing

The pre-processing stage in MRI data analysis is crucial for improving the accuracy of the data and preparing it for reliable statistical analysis. One of the key steps is the removal of noise, which originates from various sources, such as patient movement, signal inconsistencies, and geographic distortions in the scans. These noises can significantly affect the quality and reliability of the data. The various data-preprocessing techniques used in this study are as follow:

1) *Scaling:* It is critical for ensuring that data from various scans is consistent and comparable. MRI scans are frequently collected under various conditions, such as varied machine settings or patient positions, which can cause variations in signal intensity and image quality. Scaling corrects these anomalies by altering intensity levels across scans, bringing them to a consistent scale. This step guarantees that intensity variations are not mistaken as biological differences. By making the scans uniform, scaling enables for more accurate analysis and comparison of pictures, which is critical in medical imaging studies where exact measurements are required.

ISBN : 978-81-978522-2-0

2) *Correction:* This process is intended to rectify temporal and spatial distortions induced by patient mobility or the MRI acquisition procedure itself. Slice time correction and motion correction are two typical types of correction procedures. Slice time correction accounts for timing discrepancies between individual image slices, which are not all taken at the same time, resulting in modest temporal delays in the data. In contrast, motion correction accounts for any patient's movement during the scan, which might result in image blurring or misalignment. By performing these corrections, the data becomes more dependable, guaranteeing that subsequent studies are not influenced by distortions or mistakes that happened during the scanning process.
3) *Normalisation*: It entails aligning the scanned images with a standard anatomical template. This process compensates for differences in brain size, shape, and orientation among individuals. Because each person's brain is unique, normalisation guarantees that the MRI data is translated to a shared area, allowing for accurate comparison across participants. This process is crucial for studies involving group analysis since it helps to reduce the confounding effects of anatomical differences, allowing researchers to focus on the regions of interest. Normalisation improves statistical analysis and image interpretation accuracy by converting unique scans to match a universal template.
4) *Filtering:* It is the technique of enhancing or changing MRI images to highlight specific features while removing extraneous or undesirable elements. Filters can be used during MRI pre-processing to reduce noise, sharpen edges, or emphasise certain tissues or structures in the brain. Filters, for example, may increase the contrast between grey and white matter, making it easier to distinguish between these regions of the brain. This procedure increases the clarity and interpretability of the MRI images, allowing researchers and doctors to focus on the most essential features of the scan, such as areas of abnormality or disease.
5) *Skull stripping:* It is a vital early step in MRI data pre-processing that removes non-brain tissues from the image, such as the skull, scalp, and other superfluous structures. This mechanism isolates the brain, allowing for greater attention on neuronal structures without interference from adjacent tissues. Skull stripping is necessary because non-brain tissues can provide noise or irrelevant data, potentially skewing the study. By removing these factors, researchers may focus only on the brain, increasing measurement accuracy and detecting irregularities. Skull stripping is frequently utilised as a foundation for more extensive investigations in studies on brain anatomy and function.

C. *Model Building*

1) *Convolutional Neural Networks (CNNs):* This deep learning model achieved revolutionary advances in a variety of domains, including speech recognition and picture processing, thanks to their ability to find patterns effectively. One important aspect that CNNs address is spatial independence of features, which means that the network does not need to know the actual location of things (for example, faces in photos) to detect them. The network's primary purpose is to find patterns regardless of where they appear in an image. Furthermore, as input propagates through deeper layers of the CNN, the model captures more abstract and sophisticated properties, increasing its capacity to recognise patterns more correctly and generalise across diverse datasets.

2) *Convolution Layers:* The core of the convolution neural network is the convolution layer. It conducts a mathematical procedure called convolution, which involves multiplying an input picture with a series of filters or weights. Each filter isolates certain visual elements, such as edges or textures. The convolution procedure helps to emphasise these characteristics while retaining the spatial connections between pixels. As the input goes through numerous convolutional layers, the CNN can learn more complicated data representations, making it particularly successful at tasks like object identification and picture categorisation.
3) *Stride:* It is an essential parameter in CNNs that controls how the filter traverses across the input picture during the convolution process. A greater stride minimises the size of the output feature map by bypassing certain pixels, lowering computational cost and the number of parameters in the network. Stride also determines the amount of overlap between consecutive filter locations, which can have an impact on feature identification accuracy. By altering the stride, CNNs may balance the quantity of detail acquired with the network's performance, minimising wasteful calculations while still extracting key elements.
4) *Padding:* One limitation of the convolution process is that it tends to lose information around the edges of the input image. This happens because the filter only covers the central part of the image and leaves out boundary pixels. Padding solves this problem by adding extra pixels (usually zeros) around the edges of the image before the convolution is applied. This technique, known as zero-padding, ensures that the output feature map has the same dimensions as the input, preserving the information from the image's borders and allowing the CNN to detect features near the edges more effectively.
5) *Pooling layer:* It is analogous to lowering the resolution in the domain of image processing. The main goal of pooling layer is to reduce the complexity of subsequent layer by down sampling by selecting the maximum value or average value from a set of neighbouring pixels.
6) *Flatten layer:* It is an essential step because it allows the CNN to handle high-dimensional data and prepare it for the final stages of the neural network. After the feature maps have been processed by convolution and pooling layers, they exist as two-dimensional arrays, this 2D arrays converted into a long continious one dimensional vector by the flatten layer. This vector is then passed to the fully connected layer, where the actual classification or prediction tasks are performed.
7) *Fully Connected Layer:* This layer is similar to a sequential neural network output layer connected with all other layer. In this layer, every node is directly connected to every other node in both the previous and subsequent layers. The fully connected layer takes the flattened input from the previous layers and applies weights and biases to make predictions. This layer is where the final classification or decision-making occurs, as it combines the abstract features learned through the convolutional layers to assign labels or probabilities to the input data.

D Transfer Learning Technique

This study incorporates transfer learning technique named inception V3 for detecting Alzheimer from MRI images. The study shows that 42-layer inception V3 have application level of accuracy in picture recognition. This model consists of fully connected layer, dropout layer, maximum pooling layer, average pooling layer, concatenation and a softmax function given in Fig. 1. The fundamental features of this model are

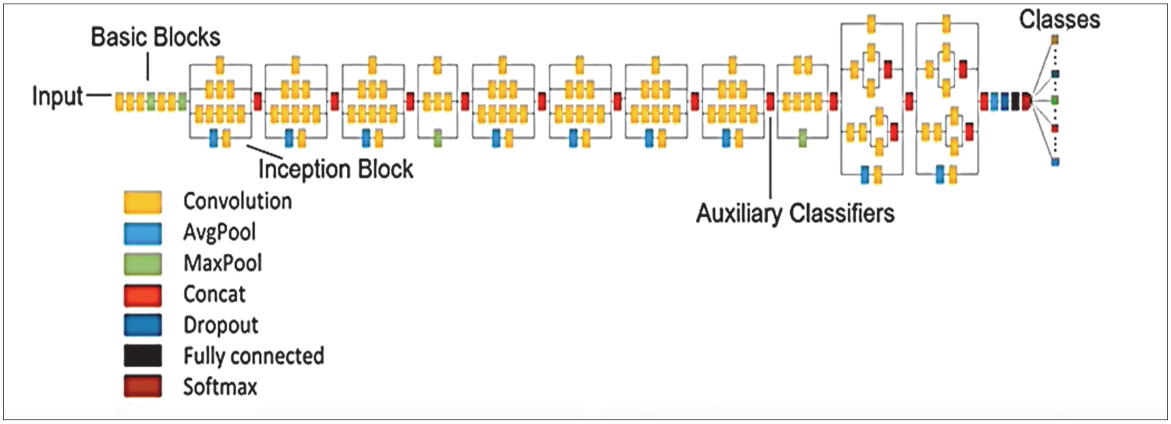


Fig 1 Architecture of proposed model

1) *Factorizing Convolutions:* Factorisation in convolutions is a technique for reducing the number of parameters and computational complexity in deep neural networks while retaining or enhancing performance. This may be accomplished using two techniques: factorisation into smaller convolutions and factorisation into asymmetric convolutions. The first technique replaces a single big convolutional filter with many smaller filters, reducing the number of parameters while simultaneously allowing for more complicated feature extraction at a reduced computational cost. The second method, asymmetric convolution factorisation, divides a square filter into numerous rectangle filters to reduces the amount of connections and parameters without losing speed. This approach reduces the amount of connections and parameters while maintaining performance, capturing the input's fundamental spatial properties.
2) *Auxiliary Classifier:* Auxiliary classifiers are used to accelerate the convergence of very deep neurons of the network. To adjust and minimize the loss function and avoide overfitting and under fitting, a regularizer is provided by auxiliary classifiers in the inception V3 model architecture.
3) *Efficient Grid Size Reduction:* Several techniques were used by the Inception V3 model to optimize the network for better model adaptation. It is more efficient. It has a larger network than the Inception VI and V2 models, but its speed is unaffected. It is less computationally expensive.

E Performance Matrices

After the model has been trained, it is essential to evaluate how well it performed on the data set. The testing dataset enables us to figure out the extent to which the model will be able to apply to data that was not utilised in its training phase because the model has never encountered the data before. We'll use a few of Scikit- Learn's metrics for this. Important measures include accuracy, F1 score, ROC AUC, precision, recall, and log loss. Several learning algorithms have been proposed. Evaluating the effectiveness of an algorithm is frequently beneficial. These assessments are frequently relative, deciding which competing technique is most appropriate for a certain scenario. Worse, they create metrics solely for the programme. In this article, we'll look at some of the most commonly used metrics for problem classification. The following are the most commonly used performance metrics for classification problems:

Matrix of Confusion: The confusion matrix serves as a summary of anticipated results in a particular table format that makes it possible to see how well a machine learning model is performing. For a binary classification problem with two classes classification problem confusion matrix shown in Fig. 2.

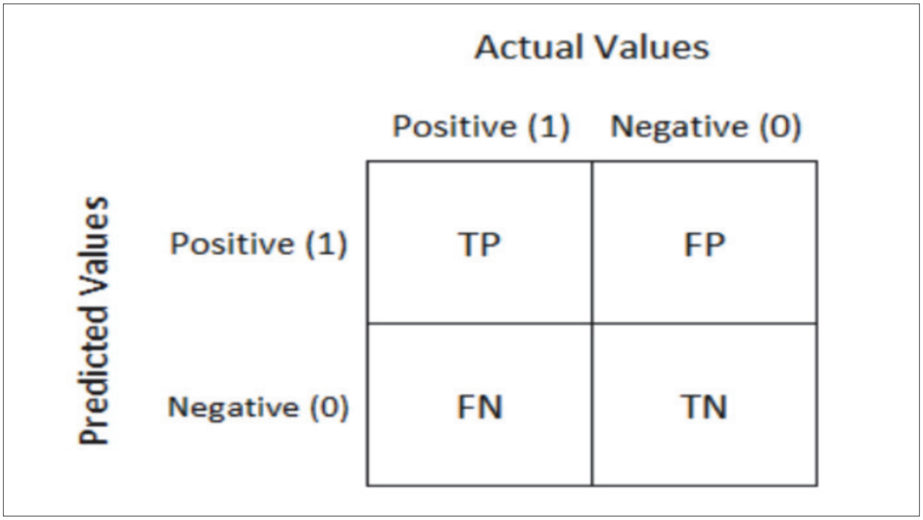


Fig 2 Confusion matrix for binary class.

Confusion matrix components include True Negatives (TN), False Positives (FP), True Positives (TP), and False Negatives (FN). True Negatives (TN) are the number of cases in which the model properly predicted the negative class. False Positives (FP) arise when the model predicts a positive class when the label is really negative." True Positives (TP) are cases in which the model accurately predicts the positive class. Finally, False Negatives (FN) occur when the model predicts a negative class but the actual label is positive. These components give insights into the model's accuracy.

1) *Precision:* This statistic assesses how accurate the positive predictions made by a model are. It's quantified as the proportion of TP to the sum of TP and FP. Precision is particularly useful when there is a high cost associated with false positives since it concentrates on the precision of positive predictions, preventing the model from overpredicting the positive class. Equation (1) measures how precise the confusion matrix component is.

$$\frac{TP}{(TN+FP)} \tag{1}$$

2) *F1 Score:* The F1 score provides a fair evaluation of accuracy and recall by taking the harmonic mean of the two. When accuracy and recall are needed simultaneously, or when there is an uneven class distribution, it is quite helpful. Equation (2) provides the F1 score, which integrates recall and accuracy into a single statistic. This enhances the overall assessment of the model's performance when these two measures are compromised.

$$F1\ Score = \frac{2 \times Recal \times Precision}{Recall + Precision} \tag{2}$$

3) *Recall*: It can be expressed as sensitivity or true positive rate. Recall measures the model's ability to identify all relevant positive cases. It is calculated as the ratio of TP to TP + FN. A high recall means that the model successfully identifies the majority of true positive cases. This is crucial in situations when missing a positive instance (FN) may have serious consequences, such as medical diagnosis.

$$\frac{TP}{(TP+FN)} \tag{3}$$

ISBN : 978-81-978522-2-0

III. Result And Evaluation

The proposed model is trained over 50 iterations with an initial learning rate of 0.001. The algorithm is trained with an optimiser known as the RMS prop. Each epoch's Area under Curve (AUC) is calculated to evaluate if the model properly distinguishes between the positive and negative classes.

The AUC, loss, and accuracy training and validation curves. The model's accuracy during training is 96%, validation is 98%, and testing is 86.71%. The confusion matrix used to categories the phases of dementia and predict AD. The projected class and labelled classes from the four separate categories are plotted on the confusion matrix. The model performance over the training dataset is provided by the confusion matrix. The computation is done for a total of 604 images that are classified as NonDemented, 635 images that are classified as VeryMildDemented, 468 images that are classified as MildDemented, and 518 images that are classified as Moderate Demented. The confusion matrix is used to generate the individual class metrics.

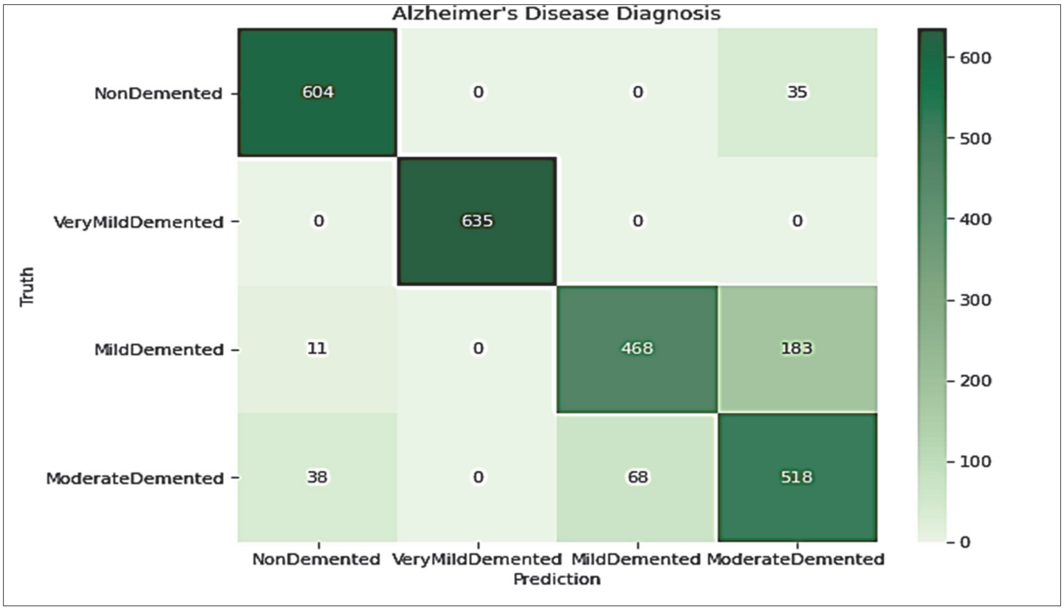
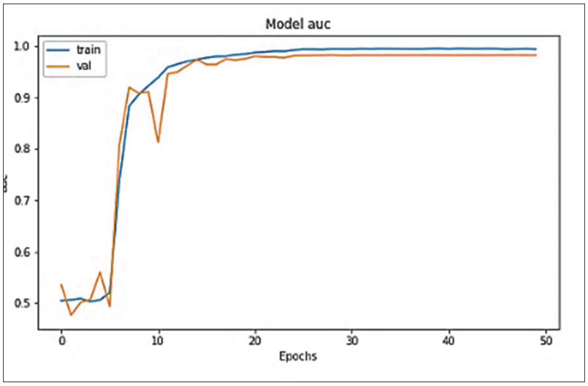


Fig 3 Confusion matrix

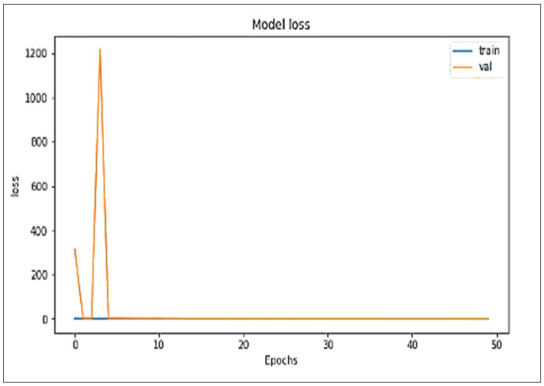
TABLE 1 Performance Indices of Individual Class

Types	Precision	Recall	F1score
Non-Demented	92%	0.950	0.930
Very-MildDemented	100%	1.000	1.000
Mild-Demented	87%	0.710	0.780
Moderate-Demented	70%	0.830	0.760

The overall precision, recall, and F1-score value of the NonDemented, VeryMildDemented, MildDemented, and Moderate Demented show in table 1. with the testing dataset. The graph between the model acurracy and the number of epochs and model losses with number of epochs is shown in Fig. 4 and 5 respectively



[5] Accuracy vs epoch



[6] Loss vs epoch

IV. Conclusion

Alzheimer's DISEASE (AD) is a common neurological condition that mostly affects elderly people. Early detection is therefore essential for proper care and averting accidents. This project uses deep learning to help with automated Alzheimer's disease (AD) detection. The main objective of this study is to create a useful procedure for people to use in order to take the essential and suitable precautions against developing AD. We might be able to use this initiative to make a brain MRI scan's diagnostic available to everyone if one is available. Deep learning is a rapidly expanding field, and patients stand to gain greatly from its use in the healthcare sector. Particularly CNNs can offer helpful information for Alzheimer's disease diagnosis.

References

[1] Scheltens, P., Blennow, K., Breteler, M. M., De Strooper, B., Frisoni, G. B., Salloway, S., & Van der Flier, W. M. (2016). Alzheimer's disease. The Lancet, 388(10043), 505-517.

[2] DeTure, Michael A., and Dennis W. Dickson. "The neuropathological diagnosis of Alzheimer’s disease." Molecular neurodegeneration 14.1 (2019): 32.

[3] I. S. Jacobs and C. P. Bean, “Fine particles, thin films and exchange anisotropy,” in Magnetism, vol. III, G. T. Rado and H. Suhl, Eds. New York: Academic, 1963, pp. 271–350.

[4] *Liu, S., Liu, S., Cai, W., Pujol, S., Kikinis, R., & Feng, D. (2018, April). Early diagnosis of Alzheimer's disease with deep learning. In 2018 IEEE 11th international symposium on biomedical imaging (ISBI) (pp. 1015-1018). IEEE.*

[5] *V. M. C. Naik, M. Prakash and B. Shakila, "Diabetes Prediction Using Supervised Machine Learning Models," 2023 IEEE 4th Annual Flagship India Council International Subsections Conference (INDISCON), Mysore, India, 2023, pp. 01-07, doi: 10.1109/INDISCON58499.2023.10270102.*

[6] Saied, I. M., Arslan, T., & Chandran, S. (2021). Classification of Alzheimer's Disease Using RF Signals and Machine Learning. IEEE Journal of Electromagnetics, RF and Microwaves in Medicine and Biology, 6(1), 77-85.

[7] Fouladi, S., Safaei, A. A., Arshad, N. I., Ebadi, M. J., & Ahmadian, A. (2022). The use of artificial neural networks to diagnose Alzheimer’s disease from brain images. Multimedia Tools and Applications, 81(26), 37681-37721.

[8] Marwa, E. G., Moustafa, H. E. D., Khalifa, F., Khater, H., & AbdElhalim, E. (2023). An MRI-based deep learning approach for accurate detection of Alzheimer’s disease. Alexandria Engineering Journal, 63, 211-221.

[9] Nawaz, A., Anwar, S. M., Liaqat, R., Iqbal, J., Bagci, U., & Majid, M. (2020, November). Deep Convolutional Neural Network based Classification of Alzheimer's Disease using MRI Data. In 2020 IEEE 23rd International Multitopic Conference (INMIC) (pp. 1-6). IEEE.

[10] *Ebrahimi-Ghahnavieh, A., Luo, S., & Chiong, R. (2019, July). Transfer learning for Alzheimer's disease detection on MRI images. In 2019 IEEE International Conference on Industry 4.0, Artificial Intelligence, and Communications Technology (IAICT) (pp. 133-138). IEEE.*

[11] Alvi, A. M., Siuly, S., De Cola, M. C., & Wang, H. (2022). DRAM-Net: A Deep Residual Alzheimer’s Diseases and Mild Cognitive Impairment Detection Network Using EEG Data. In International Conference on Health Information Science (pp. 42-53). Springer, ChamR. Nicole, “Title of paper with only first word capitalized,” J. Name Stand. Abbrev., in press.

[12] Y. Yorozu, M. Hirano, K. Oka, and Y. Tagawa, “Electron spectroscopy studies on magneto-optical media and plastic substrate interface,” IEEE Transl. J. Magn. Japan, vol. 2, pp. 740–741, August 1987 [Digests 9th Annual Conf. Magnetics Japan, p. 301, 1982.