Alzheimer's Disease prediction using Convolutional Neural Network (CNN) with Generative Adversarial Network (GAN)

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***Abstract*—Alzheimer's is the most common form of dementia in older individuals, which presents a global health challenge with 10 million new cases annually. This neurological disorder causes neurodegenerative alterations in the brain to unfold gradually, commencing with mild memory impairment and then escalating to loss of social interaction and awareness of the environment. Alzheimer Disease International (ADI) believes that 75% of dementia cases globally go undetected, making the early diagnosis challenging. Currently, stopping the development of Alzheimer's disease is difficult since there are no viable diagnosis and treatment solutions available. To overcome these challenges, there is now great interest in using machine learning (ML) for early diagnosis of metabolic disorders such as Alzheimer's. In this work, we propose utilizing a deep convolutional neural network to detect the different phases of Alzheimer's disease using brain MRI structural data analysis. Magnetic resonance imaging (MRI) aids in the early detection of Alzheimer's disease and achieves greater efficacy for initial-stage detection. Clinicians can use the suggested categorization approach to diagnose these disorders much earlier. With these ML algorithms, it is highly advantageous to reduce yearly death rates of Alzheimer's disease in early diagnosis. The suggested technique achieves improved results, with an approved mean score of 96.1% on Alzheimer's Disease test data. Compared to previous efforts, the current score for accuracy is much greater.**

Keywords: Alzheimer's disease, dementia, early detection, deep convolutional neural network

I. INTRODUCTION

Alzheimer's disease is a neurological disorder that worsens over time, beginning with moderate memory loss and progressing to the inability to converse or respond to the environment. The procedure involves the collapse of brain networks, leading healthy neurons to lose function gradually. The hippocampus, amygdala, and entorhinal cortex all suffer early neuronal loss, which is critical for the development of memories [1]. When neuronal loss spreads to other parts of the brain, volume decreases. Unfortunately, there is no effective treatment for Alzheimer's disease, and progress towards creating one has been slow. Alzheimer Disease International estimates that 75% of dementia patients globally are undiagnosed, with rates as high as 90% in some low- and middle-income countries. However, a diagnosis is merely the first step on a difficult path. Alzheimer's disease, which occurs mainly in its earliest phases, can cause people to forget new information [2]. They may also have difficulties planning, math, and accomplishing everyday duties. Another typical symptom is losing track of time, dates, and seasons. In certain circumstances, vision difficulties may also occur. Changes in judgement and decision-making are possible as well. Early identification is critical because it enables the investigation of treatment alternatives that may alleviate symptoms and allow for the preservation of independence for a longer time. Furthermore, early diagnosis enhances the likelihood of participation in clinical treatment studies and the advancement of research activities [3].

While the specific aetiology of Alzheimer's disease is unknown, it is known that the brain's enzymes cease operating correctly, altering the activity of brain cells or neurons and beginning a chain of events. Neurons are damaged and cease contact with their partner neurons, leading to death [4]. Alzheimer's disease, according to the researchers, is caused by a combination of genetic, behavioural, and environmental variables that impair the central nervous system over time. However, congenital abnormalities produce Alzheimer's in a small percentage of instances, virtually always resulting in disease progression. In these circumstances, the disease generally manifests itself in midlife. To develop an accurate categorization of Alzheimer's disease, doctors must use a combination of diagnostic procedures, medical history, and other information. Neuroscience examinations, intellectual and behavioural assessments, cerebral imaging methods such as MRI, CT, PET scans, and cerebrospinal fluid or blood testing are all included [5]. Using these tools, doctors may reliably identify Alzheimer's disease and establish a treatment plan suited to the patient's specific needs. Even when all other possible reasons have been ruled out, the clinical finding of Alzheimer's disease remains a behavioural diagnosis because there are no tests that can definitively diagnose Alzheimer's disease in vivo. The lack of a

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precise diagnostic test severely limits early intervention and preventative research. Unfortunately, 50% and 90% of dementia patients are believed to go untreated during routine clinical examinations, stressing the need for improved diagnosis tools and increasing awareness of the condition [6].

Deep convolutional neural networks (CNNs) have proven particularly successful for computer vision applications due to their ability to handle massive datasets. CNNs have effectively handled computer vision problems such as object categorization, identification, and segmentation. Furthermore, deep learning with CNNs may mimic human brain activity, making it a feasible solution for real-world problems [7]. CNNs have made significant progress in picture classification tasks, and the findings of image analysis are promising for use in medicine. CNN deep learning models have also been used to detect Alzheimer's illness. Another type of neural network under development is the Generative Adversarial Network (GAN). GANs are artificial neural networks consisting of a pair of networks: the generator and a tool for discrimination. The machine that generates information produces synthetic data that seems to be actual data, whilst the device that discriminates oversees discriminating between real and phoney data [8]. The generator generates synthetic data by converting samples from a random noise distribution into a format that is like accurate data. The discriminator then compares the produced data to the initial information to determine if it is genuine or a forgery. The two networks are trained in a feedback loop whereby the creator seeks to trick the system of discrimination by generating more convincing information. At the same time, the discriminator aims to increase its capacity to distinguish between real and fake input. The purpose of training a GAN is to generate data equivalent to real-world data and may be used for various tasks such as image, video, and text production [9-11].

Despite delivering high-quality data, GANs may be challenging to train and need careful network architecture and hyperparameters tuning. This is because the efficacy of GANs is defined as the generator's ability to generate fake information that is indistinguishable from genuine data. In this study, the authors offer an innovative method for identifying Alzheimer's disease that uses generative adversarial networks (GANs). This approach uses GANs to produce medical pictures like real-world images, which may be utilized to aid in diagnosis. Overall, the sample demonstrates the capabilities of deep learning via CNNs and GANs in tackling real-world challenges, particularly in medical image processing. The proposed method for forecasting the development of Alzheimer's disease using brain MRI images employs a Convolutional Neural Network (CNN) model supplemented by Generative Adversarial Networks (GANs). GANs are used to create new image samples, which improves CNN's ability to make accurate projections [12].

II. LITERATURE REVIEW

TABLE 1 – COMPARISON OF THE DIFFERENT DEEP LEARNING METHODS USED FOR ALZHEIMER'S PREDICTION AND CLASSIFICATION WITH RESPECT TO ACCURACY, PRECISION, RECALL, F1 AND OTHER SCORES

S.No.	Publication Title and Year	Dataset	Model	Accuracy	Other Scores
1	An MRI-based deep learning approach for accurate detection of Alzheimer's disease **[2022]**	Open Access Series of Imaging Studies (OASIS) provided the data for this study database	VGG16	96.39	-
			DenseNet121	96.29	-
2	Multimodal ensemble model for Alzheimer's disease conversion prediction from Early Mild Cognitive Impairment subjects **[2011]**	Alzheimer's Disease Neuroimaging Initiative Database (ADNI)	The model combines Random Forest clinical feature prediction alongside a Convolutional Neural Network (CNN) that performs predictions based on diffusion tensor imaging (DTI)	89.2	Precision: 90.7% Recall: 98% F1-Score: 94.2
3	A deep ensemble hippocampal CNN model for brain age estimation applied to Alzheimer's diagnosis **[2022]**	Neuroimage Analysis Center (NAC), the Alzheimer's Disease Neuroimaging Initiative (ADNI)	Convolutional neural network (CNN) consisting of 16 blocks adapted for 3D images	-	MAE: 3.64 RMSE: 5.32

4	Alzheimer Detection Using Deep Convolutional GAN **[2021]**	Kaggle-based Brain MRI labeled-dataset	GAN (to generate synthetic images) CNN & ResNet50 (to classify various stages of AD)	CNN - 69 ResNet50 - 82	-
5	Visualizing Convolutional Networks for MRI-based **[2018]**	Alzheimer's Disease Neuroimaging Initiative (ADNI)	CNN with 4 Conv2D layers and two fully connected layers	0.77 ± 0.06	-
6	Enriching Neural Models with Targeted Features for Dementia Detection **[2019]**	Subset of Dementia Bank (Becker et al.,1994)	CNN-LSTM (CNN Long Short-Term Memory Network)	83.84	Precision: 86.83 Recall: 94.97 F1-Score: 90.58
7	Convolutional neural networks for Alzheimer's disease detection on MRI images **[2021]**	-	CNN for both 2d and 3d images RNN (Recurrent Neural Network)	96.88	-
8	Deep Multi-Branch CNN architecture for early Alzheimer's detection from Brain MRIs **[2022]**	(ADNI) Alzheimer's Disease Neuroimaging Initiative (6338 MRI images)	CNN with 5 Conv2D layers	99.05	-
9	Multimodal Attention-based Deep Learning for Alzheimer's Disease Diagnosis **[2022]**	ADNI database	FCNet, CNN	77.78	Precision: 90% Recall: 70% F1-Score: 76.66%
10	Transfer Learning with intelligent training data selection for prediction of Alzheimer's Disease **[2019]**	ADNI - Alzheimer's Disease Neuroimaging Initiative	Convolutional neural network (CNN) and Transfer Learning	99.04	-

III. MATERIALS AND METHODOLOGY

A. DATASET DESCRIPTION

Although modern Alzheimer's drugs are unable to prevent the illness from happening, they can temporarily reduce the progression of signs while increasing the quality of life for those with Alzheimer's and those who work. Image processing is crucial in diagnosing Alzheimer's disease early on so that patients can be treated before irreparable brain damage occurs.

The dataset contains four phases of Alzheimer's disease that have previously been divided into two directories for testing and training purposes.

1. Non-Demented
2. Very Mild Demented
3. Mild Demented
4. Moderate Demented

No. of files in the directory

1. Mild Demented: 896
2. Moderate Demented: 64
3. Non-Demented: 3200
4. Very Mild Demented: 2240

B. DATA PREPARATION – PRE-PROCESSING METHODS

1) Median Filter: It is employed for noise reduction. It effectively removes impulsive noise, that is, salt and pepper noise.

2) Gaussian Filter: It is used to remove noise in high-frequency components and to blur picture regions. It replaces the pixel values with the weighted average of pixels based on gaussian distribution.

3) Sharpening Filter: These filters enhance the edges of the object in the image. They can be used as edge detectors. The contrast along the edges is increased to leave a sharper final image.

4) Emboss: It enhances the edges in the images. It forms a 3D design that pops out of the surface. It replaces the pixel with a shadow or highlight.

Furthermore, the mean square error and root mean square error are applied for median, gaussian, sharpen and emboss filters. The MSE and RMSE values are used to calculate how much the picture quality has deviated from the original. The lesser the variance, the greater the quality and the less favourable the score. The PSNR score is used to compare the quality of the original picture to that of the compressed or reconstructed image. The higher the PSNR quantity, the greater the reconstructed image quality [13].

C. FEATURE SELECTION

The selection of suitable characteristics can have an important effect on the deep learning model's effectiveness. By capturing the most essential characteristics, the model's complexity may be reduced, leading to shorter training times, improved generalization, and less overfitting. The goal of feature selection is to minimize the dimensionality of the input variables while maintaining or improving the model's performance. The goal of feature selection is to identify the essential traits that distinguish persons with Alzheimer's disease from healthy ones. It is critical to do feature selection to determine the most relevant traits for Alzheimer's detection [14, 15].

D. MODELS USED

The most prevalent kind of deep learning framework is a convolutional neural framework (CNN or ConvNet). Analyzing visual images. They are frequently referred to as shift-invariant or space-invariant ANNs due to the regular stresses imposed by design and translation consistency (false neural organizations) [16]. Some of the employs comprise image and video confirmation, recommender systems, image representation, clinical image evaluation, normal language planning, and cash-related chronological courses of action.

CNN is divided into two sections: classification and hidden layers/feature extraction. Convergence is a critical component of a CNN when retrieving highlights. The mathematical technique of merging two talents to produce a third is known as convolution. It combines two types of data. To create an element map, a CNN employs a channel or component (both words are interchangeable). Convolution is accomplished by simply shifting the channel that traverses the data. A structure for expansion is done at each site, and the results are summarized and exhibited on the highlighted map. The information we provide is subjected to many convolutions, each of which uses a separate data channel. As a result, many component maps have been built. The output of the convolution layer was eventually used to create these element maps. Like other neural networks, we make use of an initiating capacity to make our yield indirect [17]. A convolutional neural network will transfer the convolution's yield through the actuation process. The ReLU might get off to a strong start with this endeavour. The convolution channel decides how big each step should be. The channel moves across each pixel with a step size of 1. The amount of space between the cells will decrease because of raising the step size, which will cause your channel to glide across the contribution at a longer interval [18]. Because the dimension of the element mapping is always smaller than the amount of data contained therein, we must devise strategies to prevent our element map from shrinking. Use this area for padding. To prevent our element map from decreasing, an additional layer of negative-esteem pixels is utilized to disguise the zero contributions.

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Cushioning improves productivity while preserving the amount of space after convolution and guaranteeing that the component's dimension and step dimensions match the data being transmitted. The pooling layer is typically included in CNN layers after a convolution layer. The number of characteristics and computations in the system may be gradually reduced via pooling. Preparation time is minimized due to the removal of overfitting [19].

The DCGAN is built on top of the GAN paradigm, which comprises a discriminator D and a generator G that operate counter to one another. Both have been employing the CNN model. Using the training data, the generator creates synthetic pictures, which are subsequently reviewed by D, which determines whether the representation is accurate [20]. DCGAN training is described by the following formula:

minimax(D,G)=Ex~pdata(x)[logD(x)]+ Ez~pz(z)[log(1-D(G(z)))]

In this scenario, x represents one, z represents an aspect ratio d vector with arbitrary values, and the probability distributions of x and z are pdata(x) and pz(z), respectively. The D(x) distribution of probabilities is produced by the pdata(x) picture, whereas the (1- D(G(z)) probability distribution is produced by the pz(z) picture. D is trained to raise an adequate answer rate, whereas G lowers log(1-D(G(z)) to mislead D.

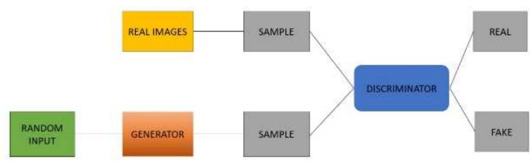

Fig. 1. Schematic diagram showing the working of GAN

IV. RESULTS AND DISCUSSION

The phases are classified as Very Mild Demented, Moderate Demented, Mild Demented, and Non-Demented, and the method of diagnosis is Magnetic Resonance Imaging (MRI). Therefore, our project aids in identifying and correcting brain disorders. We utilized GAN to enhance the dataset size by producing fake photos, and the visualizations of the GAN-generated images for each stage are shown below.

MRI has additionally used Neural Networks to gather characteristics and categorize them based on the amount of damage/abnormality. The image below illustrates a CNN model's confusion matrix and the model's accuracy and loss curve.

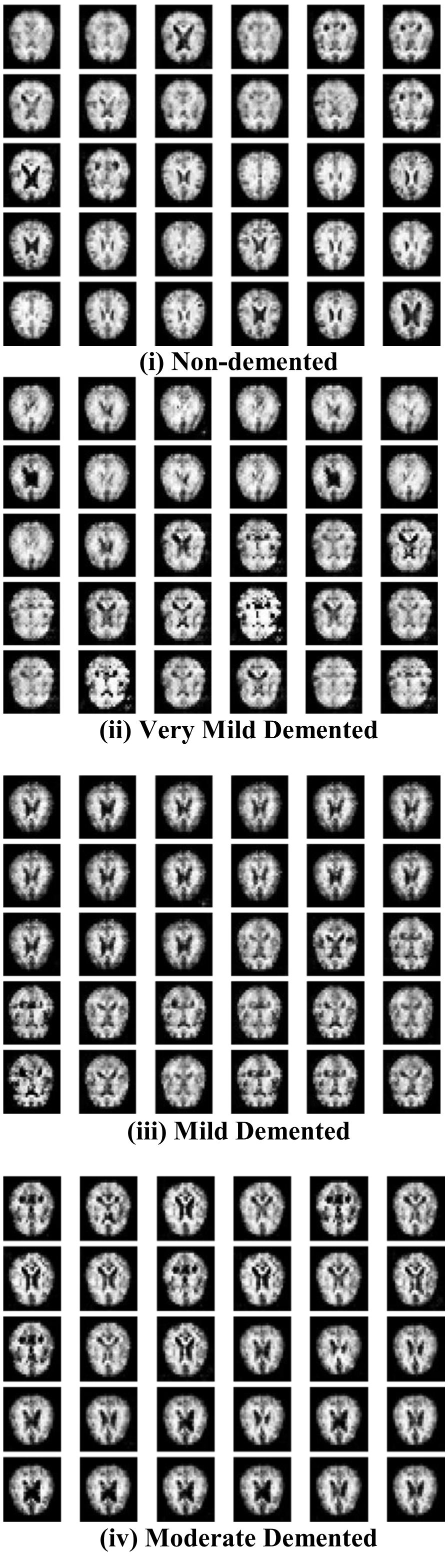

Fig. 2. Visualization of GAN-generated images of brain MRI of various stages of Alzheimer's which includes (i) non-demented, (ii) Very Mild Demented, (iii) Mild Demented, (iv) Moderate Demented

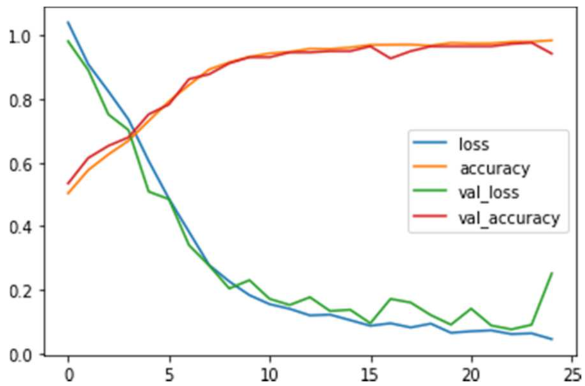

Fig. 3. Accuracy and Loss curve of the model

To summarize, CNN architecture classification accurately predicts the stages of Alzheimer's disease. Furthermore, the more synthetic photos generated, the more accurate the model.

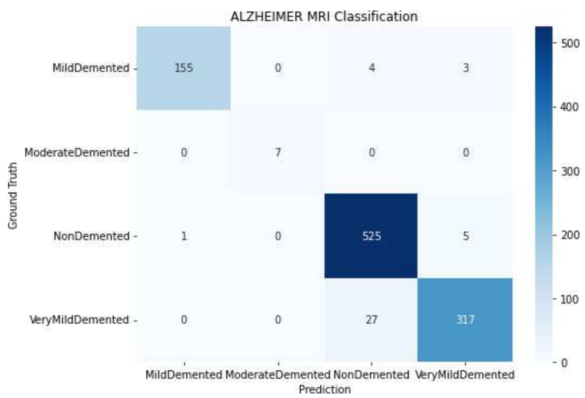

Fig. 4. Confusion Matrix of CNN Model

Deep Convolutional Generative Adversarial Networks (DCGANs) are an unsupervised generative modelling approach that generates synthetic pictures. A technique has been presented that uses annotated Magnetic Resonance Imaging (MRI) datasets and then executes DCGAN on the limited amount of data, consequently broadening dataset size and diversity using GAN. CNN, the accuracy of classification was 69%. With GAN encompassed into the CNN model, we accomplished an accuracy of 96%.

V. CONCLUSION

This research demonstrates the use of deep learning to categorize computerized brain MRI images into different stages of Alzheimer's disease. The CNN model was used as the foundation for the implementation, which was carried out using the programming language Python and scientific tools. Although preliminary investigations have resulted in encouraging outcomes, further investigation needs to be done. Even if the model is nearly 96 percent correct, there is a risk of overfitting due to the magnitude of the dataset, even after creating fake images with GAN. Furthermore, the 96% accuracy of the prediction model shows that it might be used. Even though more work remains to be done as a decision-support tool. Medical doctors' input and presence are still essential for an accurate diagnosis of this disease. To build a reliable and trustworthy illness categorization model, collecting as much data as possible is necessary.

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