



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

# IJIRSET

International Journal of Innovative Research in  
**SCIENCE | ENGINEERING | TECHNOLOGY**



# INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 12, Special Issue 2, April 2023

**ISSN** INTERNATIONAL  
STANDARD  
SERIAL  
NUMBER  
INDIA

 9940 572 462

 6381 907 438

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# Alzheimer's disease Detection Using Deep Learning Algorithms

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**ABSTRACT:** Identifying Alzheimer's disease (AD) and its prodromal form, Mild Cognitive Impairment (MCI), is crucial for patient care and has recently been a research hotspot due to the prevalence and huge societal impact that AD has on health. Existing studies have employed machine learning approaches to detect early Alzheimer's disease by evaluating various biomarkers. As with the existing system with an accuracy of 85%, the early layers of a progressive GAN generate very low-quality images, and successive layers add details. Because of this method, the cGAN can train faster than identical non-progressive GANs while producing higher-resolution, more accurate images. However, in the majority of current studies, the inability to adequately extract high-level brain features reflecting the fundamental abnormalities of physical brain regions linked with Alzheimer's disease becomes a bottleneck of diagnosis performance. To assess AD brain pictures, the proposed model combines a deep convolutional neural network (CNN) with a conditional generative adversarial network (cGAN). The dataset is pre-processed to get a clear representation of the grey matter in the brain, and the cGAN is utilized to generate more training instances for the model to improve accuracy. In the training phase of cGAN-ADD, the generator learns to integrate the disease category feedback from the classifier into the 2D-brain slice picture reconstruction process for image improvement. The retrieved brain properties are sent into the classifier, which outputs the posterior probability of sick states (Normal, AD, Mild and Very Mild). The model was trained with TensorFlow and Keras and has a 94.88% accuracy. The ADNI dataset is used to train and test the model.

**KEYWORDS:** Alzheimer's Disease, Deep Learning, Conditional Generative Adversarial Network (cGAN), Convolution Neural Network (CNN), Alzheimer's Disease Neuroimaging Initiative (ADNI).

## I. INTRODUCTION

Alzheimer's disease is an incurable, cell degenerative neurologic ailment that causes the brain to shrink (atrophy) or the brain cells to die. Alzheimer's Disease is the most prevailing form of Dementia (Loss of Memory), which is defined as a successive decrease in mental, behavioural, and social abilities that affects a person's capacity to function on one's own. In India, Alzheimer's disease has affected around 4 million people with age 65 and older. 80% of those are 75 or older. Provided that, Dementia affects at least 44 million people globally, Hence Alzheimer's Disease is a global health problem that needs attention. Early symptoms of the illness include forgetting previous conversations or encounters. A person with Alzheimer's disease will experience significant memory loss and lose the ability to perform basic tasks as the disease worsens. With medication, symptoms may temporarily improve or deteriorate more gradually. Patients with Alzheimer's disease may benefit from these treatments by performing better and maintaining their independence. Numerous services and programs are available to support people with Alzheimer's disease in their careers. Currently, there is no known treatment that can halt the brain's progression of Alzheimer's disease. Late in the illness, complications brought on by a severe loss of brain function, such as dehydration, malnutrition, or infection, lead to death. A high likelihood of progression is revealed by early Alzheimer's disease detection.

### LIMITATIONS IN THE EXISTING SYSTEM:

- Existing studies have employed machine learning approaches to detect early Alzheimer's disease by evaluating various biomarkers.
- As with the existing system, the accuracy is 85%.
- The early layers of a progressive GAN generate very low-quality images, and successive layers add details.

## II. RELATED WORKS

Morteza Amini, Mir Mohsen Pedram, AliReza Moradi, and Mahshad Ouchani have reviewed various ML methods for AD classification and detection. Data time usage and cost should be taken into account when collecting various images. Additionally, the performance of the use of combined data has been promising. Therefore, this trade-off should address the issue. Due to its easy accessibility and variety of data set stages, the ADNI data set has been the subject of the majority of research. They have studied and compared the classifications of AD, NC, and MCI. The use of various data sets will increase the data set's controversy and variety. Consequently, using a variety of data sets will result in better and more thorough results. [1] Samsuddin Ahmed, Byeong C. Kim, Kun Ho Lee, and Ho Yub Jung have used CNN classifiers based on TVP to stage AD using the sMRI modality. The experiment made use of the GARD sMRI data set. We have taken into account all NIA-AA-recommended classifications (aAD, mAD, ADD, and NC). According to the study, the hippocampi, amygdalae, and insulae provided distinguishing characteristics for the diagnosis of ADD and milder forms of AD. The learned models' true positive diagnostic rates for AD/NC, AD/mAD, AD/aAD, mAD/aAD, mAD/NC, and aAD/NC were 95.08%, 88.52%, 93.44%, 73.02%, 88.52%, and 57.38%, respectively, while their false favorable rates were 9.38%, 15.63%, 14.93%, 32.35%, 27.03%, and 53.33%. Our ROI-based models do not provide enough information for the diagnosis of aAD, as evidenced by the highest false positive rate and lowest true positive rate in diagnosing aAD. [2] Tanushree Mukherjee, Sagar Sharma, and K. Suganthi have presented this paper and it uses an adversarial learning-based methodology to synthesize medical images for tissue recognition in medical images. The representativeness and sufficiency of training samples have a significant impact on the performance of medical image recognition models. The need to synthesize image samples results from the high cost of collecting substantial quantities of real-world medical images. The development of a medical image synthesis model in this study uses generative adversarial networks (GANs), which are made up of a generative network and a discriminative network. In order to train a CNN classification model for tissue recognition, synthetic images are generated. The tissue recognition accuracy of 98.83% obtained through experiments with synthetic images demonstrates the usefulness and effectiveness of synthesizing medical images using GAN models. [3] Yan Zhao, Baoqiang Ma, Pengbo Jiang, and Debin Zeng have proposed this paper and they have used the mi-GAN can produce high-quality individual 3D brain MRI images. The Alzheimer's Disease Neuroimaging Initiative (ADNI) is the subject of experiments. With a structural similarity index (SSIM) of 0.943 between the generated and real MRI images in the fourth year, our mi-GAN exhibits state-of-the-art performance. In comparison to conditional GAN and cross-entropy loss, the pMCI vs. sMCI accuracy is improved by 6.04% with mi-GAN and focal loss. [4].

## III. METHODOLOGY

As with the existing system with an accuracy of 85%, the early layers of a progressive GAN generate very low-quality images, and successive layers add details. Because of this method, the cGAN can train faster than identical non-progressive GANs while producing higher-resolution, more accurate images. To begin, the dataset is utilized as input. The dataset is pre-processed in order to generate a clear image of the brain's grey matter. In order to enhance accuracy, cGAN is utilized to create more training cases for the model. During the training phase of cGAN-ADD, the generator learns to incorporate the classifier's disease category feedback into the 2D-brain slice picture reconstruction process for image improvement. During the prediction START cGAN Implementation Image Pre-processing CNN Classification STOP 10 phase, the stacked CNN layers collect high-level brain features from category-enhanced 2D brain slice pictures. The retrieved brain attributes are sent into the classifier, which outputs the probability of unwell states in the future (Normal, AD, Mild, and Very Mild). The model is trained using TensorFlow, and the classification performance

is evaluated using Keras. The model is trained and tested using the ADNI dataset. Two different algorithm model is implemented showing the respective outputs.

- ❖ CNN (CONVOLUTIONAL NEURAL NETWORKS)
- ❖ cGAN (CONDITIONAL GENERATIVE ADVERSARIAL NETWORKS)

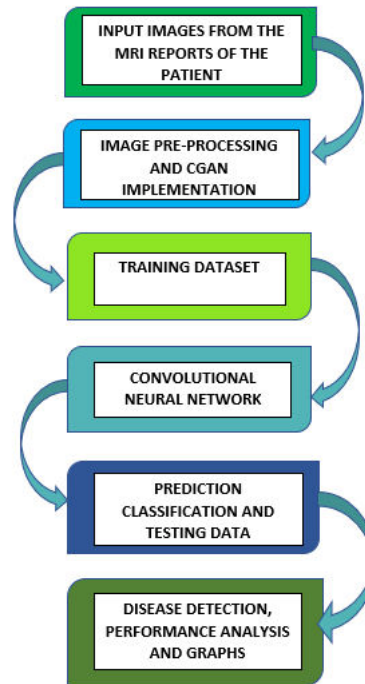


Fig. 2.1 DATAFLOW DIAGRAM

### CONVOLUTIONAL NEURAL NETWORKS (CNN):

Convolutional Neural Network (CNN) is a type of deep neural network that is commonly used in the field of image recognition and analysis. When we feed an image into a CNN, each inner layer outputs a different set of activation maps. Activation maps highlight the important aspects of the supplied input image. In principle, each CNN neuro accepts input in the form of a group/patch of pixels, multiplies their values (colours) by the value of their weights, adds them together, and passes them through the appropriate activation function. The first layer of the CNN often detects numerous aspects of the input image such as horizontal, vertical, and diagonal edges. The output of the first layer is sent into the second layer, which extracts more complicated aspects of the input image such as corners and edge combinations. As one proceeds deeper into the convolutional neural network, the layers begin to recognize numerous higher-level properties. Feature extraction is a technique for extracting and identifying the distinguishing features in an image. a fully connected layer that predicts the image's class using previously collected information and the result of the convolution process.

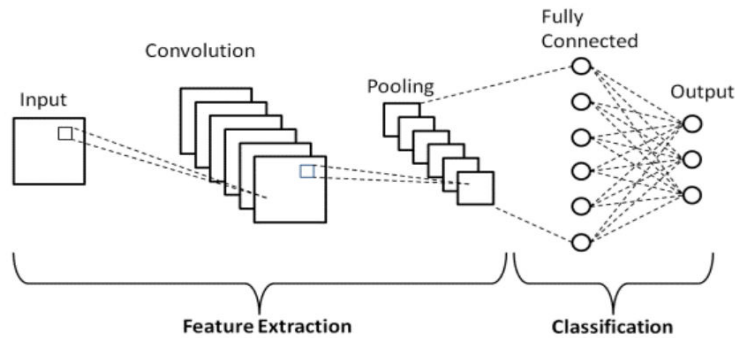


Fig.2.2 CONVOLUTION NEURAL NETWORKS

### CONDITIONAL GENERATIVE ADVERSARIAL NETWORKS (cGAN):

The Basic version of the Generative Adversarial network has two main components, a generator, and a discriminator. A Generator understands and helps to create new images and a Discriminator learns to distinguish between artificial and authentic images. A conditional setup is added as a unique feature in conditional GANs, which makes both the generator and discriminator work dependently on supplementary data (like class labels or data from other models). The Ideal Model of cGAN is hence capable of acquiring knowledge about the multi-modal mapping from feed-ins to outcomes when various contextual data are fed to it.

$$\min_G \max_D V(D, G) = \mathbb{E}_{x \sim p_{data}(x)} [\log D(x, y)] + \mathbb{E}_{z \sim p_z(z)} [\log(1 - D(G(z, y), y))]$$

## IV. EXPERIMENTAL RESULTS

### DATASET DESCRIPTION:

Conditional Generative Adversarial Network require a large training set of MRI images to perform well, thus we collected and created a dataset of MRI images. There are 6,000 images in the collection, all of which are different in size and shape. The dataset is divided into two sets: a training set and a test set. In the both train and test data's there are some categories by their grey matter in the data of images like Mild-Demented, Moderate-Demented, Non-Demented, and Very Mild-Demented with these different types of data. The proposed database's creation is more tedious to figure out because we need to take into consideration about so many factors, including calligraphic style, opaqueness, dots number, and locus arrangement. Even if they are in the same locus, certain characters have different patterns. Examining and evaluation of dataset is created by collecting handwritten styles from many people.

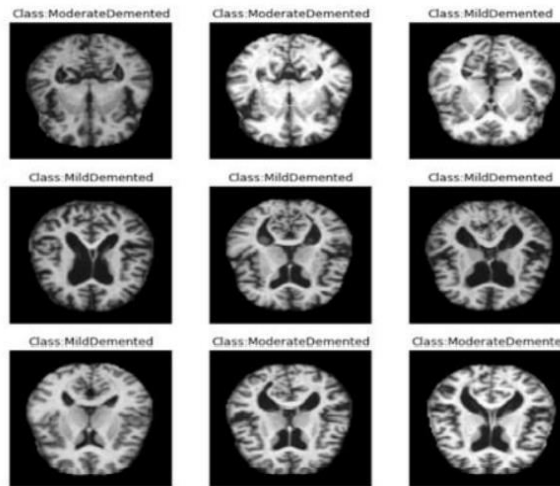


Fig 3.1 SAMPLE DATASET

**PARAMETERS FOR EVALUATION:**

The parameters that are used for evaluating the dataset are Precision, F1 score, recall, and Balanced Accuracy score.

**Precision:**The ratio of accurately classified positive samples (True Positive) to all samples that were correctly or incorrectly classified as positive is known as precision.

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

**F1Score:**It is employed to evaluate categorization methods that label examples as "positive" or "negative." A technique for combining precision and recall is the F-score, which is described as the harmonic mean of the model's precision and recall.

$$\text{F1 Score} = 2 * ((\text{precision} * \text{recall}) / (\text{precision} + \text{recall})).$$

**Recall:** By dividing the percentage of Positive samples that were correctly identified as Positive by the total number of Positive samples, the recall is calculated. A recall is a metric that gauges how well a model can identify positive samples. The recall increases as the number of positive samples found rises.

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN}).$$

**Balanced Accuracy score:**Balanced accuracy is necessary for both binary and multi-class classification. When working with unbalanced data or when one of the target groups appears much more frequently than the other, it can be applied. It is the sensitivity and specificity's arithmetic mean.

$$\text{Balanced Accuracy Score} = (\text{Sensitivity} + \text{Specificity}) / 2$$

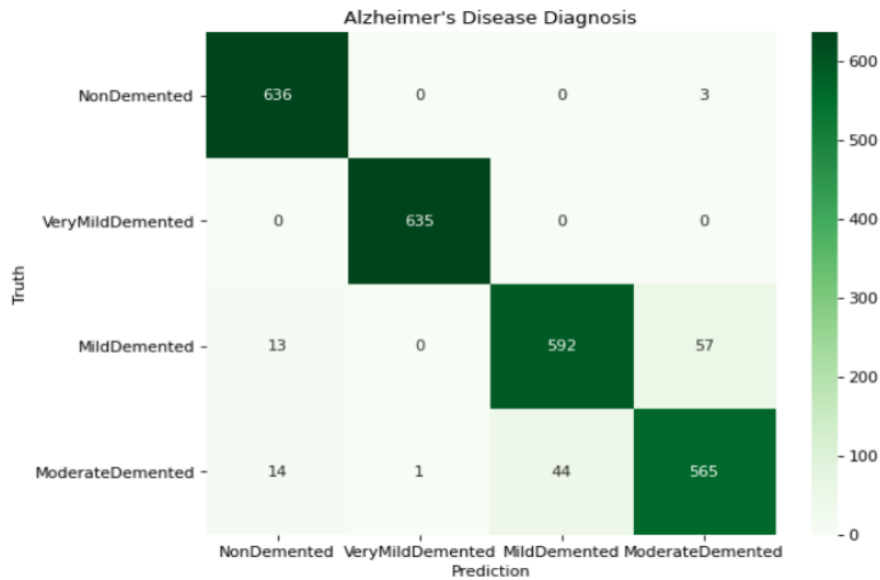


Fig.3.2 SAMPLE OUTPUT

### V. CONCLUSION

The previously viewed related documents on the Diagnosis and Detection of Alzheimer’s Disease have data related to how they distinguish between AD patients and healthy controls. Most of the previous research focuses on AD Diagnosis and MCI based on deep learning using CNN with the binary and multi-class classification that reached better precision up to 85%. Here we have used CNN deep learning architecture with LeNet5 and fMRI which has enabled us to distinguish between AD patients to that of normal and healthy ones with a better precision of up to 94.88% using the Alzheimer’s Disease Neural Initiative (ADNI) dataset.

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