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Evaluating the Effectiveness of Alzheimer's Detection Using GANs and Deep Convolutional Neural Networks (DCNNs)

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ABSTRACT

Alzheimer's is a gradually worsening condition that damages the brain, making timely and precise diagnosis essential for better patient care and outcomes. However, existing detection methods using DCNNs are often hampered by the problem of class imbalance in datasets, particularly OASIS and ADNI, where some classes are underrepresented. This study proposes a novel approach integrating GANs with DCNNs to tackle class imbalance by creating synthetic samples for underrepresented categories. The primary focus of this research is demonstrating that using GANs for data augmentation can significantly strengthen DCNNs performance in Alzheimer's detection by balancing the data distribution across all classes. The proposed method involves training DCNNs with both original and GAN-generated data, with data partitioning of 80:10:10 for training/ validation/ testing. GANs are applied to generate new samples for underrepresented classes within the OASIS and ADNI datasets, ensuring balanced datasets for model training. The experimental results show that using GANs improves classification performance significantly. In the case of the OASIS dataset, the mean accuracy and F1 Score rose from 99.64% and 95.07% (without GANs) to 99.98% and 99.96% (with GANs). For the ADNI dataset, the average accuracy and F1 Score improved from 96.21% and 93.01% to 99.51% and 99.03% after applying GANs. Compared to existing methods, the proposed GANs + DCNNs model achieves higher accuracy and robustness in detecting various stages of Alzheimer's disease, particularly for minority classes. These findings confirm the effectiveness of GANs in improving DCNNs' performance for Alzheimer's detection, providing a promising framework for future diagnostic implementations.

1. Introduction

As reported by Alzheimer's Disease International (ADI) in 2020, dementia affects roughly 55 million people worldwide, and this number is anticipated to nearly double every twenty years [1]. Alzheimer's is a chronic brain disorder that gradually impairs neurons, resulting in a marked decline in thinking abilities, memory disturbances, and confusion [2]. Recognizing the condition in its initial phase is vital to slowing down its development and supporting a better quality of life for those affected. Early intervention can help slow cognitive decline, provide an opportunity to implement more

effective treatment strategies, and enable patients and their families to make better long-term plans [3]. However, conventional diagnostic methods currently in common use, such as clinical examinations, cognitive tests, and imaging (MR Images and PET), tend to be expensive, complex, and require specialized expertise from experienced medical personnel [4]. These imaging procedures also require high-tech equipment that is not always available in all health facilities. In addition, the limited amount of available medical image data is a challenge in developing accurate detection models [5].

The use of CNNs in Alzheimer's detection has recently gained widespread use because of its capacity to capture intricate spatial details from brain scans [6]. By using multiple layers of convolution, pooling, and activation, CNNs can identify specific patterns linked to alterations in brain structure caused by Alzheimer's, such as reduced volume of the hippocampus and cortex. In addition, CNNs are also able to recognize the same features even though their positions change [7]. However, previous studies using CNNs still have several shortcomings, especially related to class imbalance in the datasets used [8]. Data imbalance is a common problem in developing CNNs models for Alzheimer's detection, where the amount of data representing a particular class, such as Alzheimer's Disease is much less than the non-demented class or healthy controls [9]. For example, in some public datasets such as ADNI, the number of samples from patients with severe or moderate Alzheimer's is much less than patients without Alzheimer's [10]. Due to this imbalance, CNNs model tend to misclassify new inputs as belonging to the majority class, which in turn lowers the model's precision and responsiveness in identifying Alzheimer's cases [11]. In addition, overfitting is a common problem in CNNs models trained with imbalanced datasets [12]. When the model focuses too much on the majority class, it can result in decreased generalization ability when applied to new data. Several studies have shown that CNNs trained with imbalanced datasets produce low accuracy in detecting minority classes (such as Alzheimer's Disease or Moderate Dementia), even though they perform quite well in classifying the majority class [13]. This is a major challenge because early diagnosis of Alzheimer's depends on the model's ability to detect rare or early-stage cases [14]. To overcome this data imbalance problem, various approaches have been proposed in previous studies, such as data augmentation techniques, cost-sensitive learning, and resampling. However, these methods often have limitations, such as augmentation which only increases the amount of data with simple transformations such as rotation, flipping, or cropping, so it does not produce significant enough variation to improve model performance [15]. These basic transformations fail to capture the subtle, disease-specific changes in brain structure that are characteristic of Alzheimer's, particularly in its early stages. As a result, the model may learn artificial patterns that do not generalize well to real-world data. In addition, resampling methods such as increasing samples from underrepresented classes or decreasing samples from dominant ones may lead to the removal of valuable information or produce a biased model [16].

Cost-sensitive learning approaches, where error weights are calibrated to give a greater penalty to the misclassification of the minority class, have also been implemented by several studies [17]. However, this technique is not entirely effective because it only changes the classification priority without improving the variation of the dataset itself [18]. While it can encourage the model to focus more on the minority class, it does not address the underlying issue of data imbalance by generating more diverse samples. As a result, the model may still struggle with generalization, particularly when faced with rare or complex patterns that are underrepresented in the training data. Furthermore, by merely adjusting misclassification penalties, cost-sensitive learning does not inherently increase the diversity of the training set, which is crucial for improving the robustness of the model in real-world applications. Therefore, a more effective approach is needed to overcome this data imbalance problem. In our study, we will propose an approach that utilizes GANs to overcome the limitations of datasets commonly found in Alzheimer's detection research using CNNs. The integration of GANs with CNNs is expected to enhance Alzheimer's detection performance through the provision of larger and more varied training datasets. Synthetic images generated by GANs can be used to enrich underrepresented datasets, so that CNNs model can learn to recognize patterns that were previously difficult to detect. In addition, the use of synthetic data is also expected to reduce the risk of overfitting and improve the generalization ability of the developed model.

2. Prior Works and Method

2.1. Prior Works

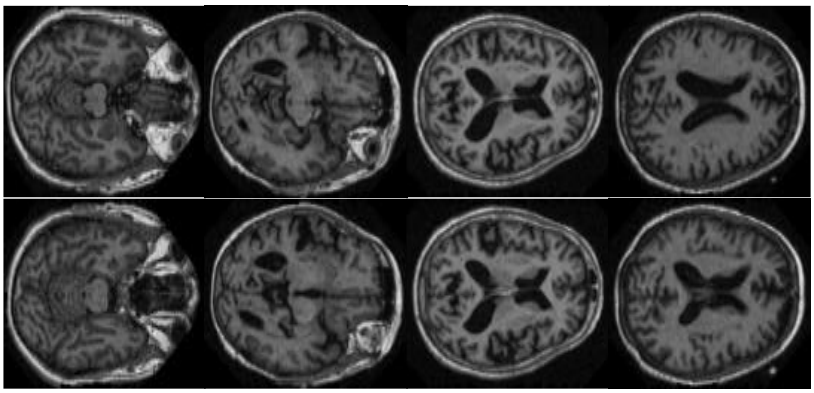
Recent research in Alzheimer's detection has increasingly adopted the CNNs approach and related techniques, due to the ability of these models to extract complex spatial features from MRI. In a study conducted by Ebrahimi et al. (2021), a Deep Sequence Modeling method was developed by combining ResNet-18, TCN, and RNN [19]. This study showed that the TCN model provided the best accuracy of 91.78%, sensitivity of 91.56%, and specificity of 92%, outperforming the RNN-based model in efficiently processing feature sequences from MRI. This model showed an increase in Alzheimer's detection accuracy of up to 10% compared to the conventional CNNs method. Another approach that also showed promising results was the Fuzzy-VGG method proposed by Yao et al. (2023) [20]. By combining fuzzy theory with a VGG-based CNNs architecture, this study aims to address data imbalance and speed up the training process. A two-stage data augmentation strategy was applied using the Cutout technique to improve classification accuracy and accelerate model convergence. This model proved to be superior to other methods in terms of accuracy and training speed, and allows integration with blockchain technology for continuous improvement.

In addition, a study by Shehri, et al. (2022) implemented the DenseNet-169 and ResNet-50 architectures to classify Alzheimer's into four dementia classes [21]. The DenseNet-169 model performed better than ResNet-50 with a test accuracy of 83.82%. This approach is proposed to be applied in real-time Alzheimer's diagnosis using MRI. Furthermore, a study by Sampath, et al. (2024) proposed a Fly-Optimized Densely Connected CNNs-based method to detect Alzheimer's using MRI [22]. This technique uses a metaheuristic algorithm to optimize the implemented CNNs architecture. The results show that this method provides significant improvements in terms of sensitivity, specificity, and accuracy compared to previous methods. In addition, a study by Deepa, et al. (2022) developed a VGG-16 model optimized using the Arithmetic Optimization Algorithm (AOA) to classify different stages of Alzheimer's from MRI [23]. This approach combines ROI adaptive segmentation techniques and parameter optimization to address data imbalance issues and reduce computational time. The results show that this method is able to reduce computational costs, improve accuracy, and overcome the problem of data imbalance that is often encountered in Alzheimer's detection research.

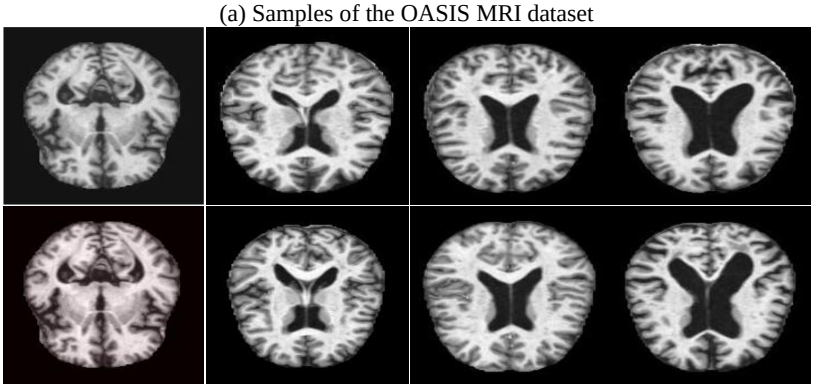
Research by Khagi, et al. (2021) developed an Alzheimer's classification method using 3D CNNs with Segmented Gray Matter extracted from whole-brain MRI [24]. The processed images were used to train a CNNs model that could classify patients into three data classes. This method shows that the 3D CNNs-based approach provides better accuracy than the 2D CNNs-based method, although the limitations of the dataset used are still a major challenge. Research conducted by Haq et al. (2025) developed a Multimodal Fusion model that combines CNNs and LSTM to detect Alzheimer's using the ADNI-1 dataset [25]. This model managed to achieve 92.3% accuracy using fewer parameters and lower processing complexity compared to conventional methods. This study highlights that this approach can reduce processing complexity and improve diagnostic accuracy. Finally, research by Venkat et al. (2025) developed an Alzh-Net architecture that combines two CNNs models optimized to extract features from MRI with various scales and levels of abstraction [26]. This method adopts the U-Net approach to produce more accurate image segmentation. The results show that the Alzh-Net architecture provides better results than other existing methods, with improvements in accuracy and processing speed. Overall, these studies suggest that the CNNs approach and other optimization techniques can improve the accuracy, sensitivity, and specificity of detecting Alzheimer's through MRI. However, the problem of data imbalance and potential overfitting is still not the main focus of some of the previous studies [19]-[26]. Most studies focus more on improving model accuracy through network architecture optimization or combining other deep learning methods, without specifically addressing data imbalance that can affect model performance. Therefore, in this study we propose an approach based on GANs and DCNNs to address the problem of data imbalance and overfitting. This approach is expected to generate realistic synthetic data to enrich minority classes, thereby improving the model's ability to detect Alzheimer's more accurately and reliably.

2.2. Dataset

In Alzheimer's detection research using DCNNs, the datasets that are often used are the OASIS [27] and the ADNI [28]. These two datasets were chosen because they provide a variety of MR images that cover several categories from normal conditions to various stages of Alzheimer's. However, the main challenge in using this dataset is the existence of data imbalance between classes that can affect the accuracy of the DCNNs model. The OASIS dataset is a collection of MR images that are generally divided into four categories, namely non-Dementia (67,222 images), Very Mild Dementia (13,725 images), Mild Dementia (5,002 images), and Moderate Dementia (488 images) [27]. From the data, it can be seen that the non-Dementia category dominates the dataset with a much larger number of images compared to other categories, especially the Moderate Dementia category which is very rarely found. This data imbalance can cause the DCNNs model to be more likely to recognize images from the dominant class (non-Demented) and ignore minority classes such as Mild and Moderate Dementia. OASIS dataset and ADNI dataset for Alzheimer's disease detection shown in Fig. 1.



(a) Samples of the OASIS MRI dataset



(b) Samples of the ADNI MRI dataset

Fig. 1. (a) OASIS dataset and (b) ADNI dataset for Alzheimer's disease detection

Meanwhile, the ADNI dataset consists of four main categories, including Alzheimer's Disease (8,960 images), Cognitively Normal (6,464 images), Early Mild Cognitive Impairment (9,600 images), and Late Mild Cognitive Impairment (8,960 images) [28]. Although the data distribution in the ADNI dataset is more balanced compared to OASIS, the number of images from the Cognitively Normal class is relatively less than other classes, which can still cause imbalance in the DCNNs model training process. The use of these two datasets in Alzheimer's detection research using DCNNs presents challenges in terms of model generality and classification accuracy, especially in recognizing images from underrepresented categories.

2.3. Generative Adversarial Networks (GANs)

GANs are part of a broader category of deep learning models that specialize in generating highly realistic synthetic data. This architecture is composed of two primary components, one network responsible for producing data (the generator) and another tasked with evaluating it (the discriminator) [29]. The generator's function is to construct artificial samples that closely resemble actual data by processing random noise, typically drawn from probability distributions like the Gaussian distribution [30]. Meanwhile, the discriminator's role is to assess whether the input it receives is genuine or artificially created by the generator [31]. These two networks are trained simultaneously in a process referred to as adversarial training [32]. During this process, the generator continually tries to mislead the discriminator by generating data that appears increasingly realistic, while the discriminator works to improve its ability to correctly differentiate between authentic and generated inputs. The ultimate goal is to refine the discriminator's precision in making this judgment. The following is the architecture of GANs.

In the described architecture (Fig. 2), the process starts with a noise vector (z) originating from a latent space, which is a low-dimensional input that the Generator transforms into complex data. This noise is typically sampled from a random distribution [33]. The Generator uses this input to produce synthetic data (referred to as fake samples) that closely resemble actual data [34]. These Generators are often designed using deep neural networks, such as fully connected layers or transposed convolution layers (commonly for image generation) [35], and are responsible for creating realistic artificial data structures. Once the Generator produces a synthetic sample, this data is passed to the Discriminator. The Discriminator is another neural network that acts as a binary classifier, determining whether the provided input corresponds to authentic samples or fabricated ones [36]. During training, the Discriminator is exposed to two categories of data: genuine samples from the dataset and artificial ones from the Generator. Its role is to assign a high probability score (near 1) if the data appears real, and a low score (close to 0) if it is identified as fake [37]. The training objectives for both the Generator and the Discriminator in GAN models are expressed using specific loss functions.

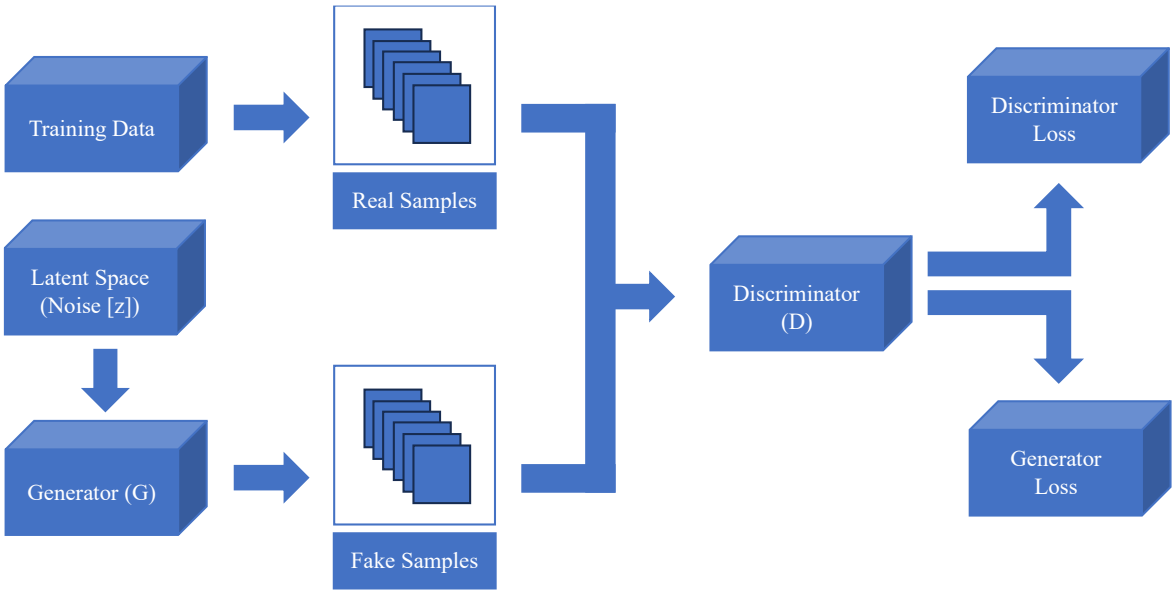


Fig. 2. Architecture of GANs

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

The training phase of GANs consists of two key steps, training the Discriminator and training the Generator. During the Discriminator's training phase, it is provided with actual samples from the original dataset along with artificially generated samples from the Generator [38]. The Discriminator then computes a loss value that reflects how effectively it can distinguish between authentic and

generated data [39]. Its parameters are then optimized using the Gradient Descent method, following this formula:

$$\theta_D \leftarrow \theta_D + \nabla_{\theta_D}[\log D(x) + \log(1 - D(G(z)))] \quad (2)$$

During the training phase of the Generator, the model creates artificial data using random input noise and evaluates its performance based on how effectively the Discriminator can detect the generated data as fake. After that, the Generator updates its internal parameters using a specific optimization formula.

$$\theta_G \leftarrow \theta_G - \nabla_{\theta_G}[\log(1 - D(G(z)))] \quad (3)$$

Alternatively, the Generator can also be trained by maximizing $\log D(G(z))$ to improve model performance, with the formula:

$$\theta_G \leftarrow \theta_G + \nabla_{\theta_G}[\log D(G(z))] \quad (4)$$

GANs offer numerous benefits, such as the ability to produce lifelike synthetic data, enhance low-quality or incomplete images, and tackle class imbalance issues through efficient data augmentation methods [40]. Specifically, in the case of Alzheimer's disease diagnosis, GANs are effective for supplementing datasets with underrepresented classes that are relatively small in quantity [41]. By supplying diverse and high-fidelity synthetic samples, GANs help boost the effectiveness of DCNNs models and decrease the likelihood of overfitting, a common issue in training with uneven data distributions.

2.4. Deep Convolutional Neural Networks (DCNNs)

DCNNs are a specialized form of ANNs particularly suited for analyzing visual data. These models incorporate layers such as convolutional, subsampling (pooling), and dense (fully connected) units to automatically get essential characteristics from images and support tasks like classification or regression [42]. DCNNs represent an advanced form of traditional CNNs, enabling the extraction of deeper, more conceptual features from varied and large-scale datasets [43]. The initial convolutional layers in these networks focus on detecting fundamental image elements such as outlines and textures. By applying kernels that slide across the input, these layers produce activation maps that highlight significant visual information. Each kernel contains trainable parameters optimized during the learning phase to capture specific visual cues [44]. Downsampling, often done through max pooling, is applied following convolution to compress the feature dimensions and help prevent overfitting by retaining only the most prominent values within small regions of the image. This process also decreases the overall number of learnable variables in the model [45]. Toward the final stages of the network, dense layers take over to interpret and classify the extracted features [46]. These layers are fully interconnected, meaning each unit in one layer is linked to every unit in the next. The final prediction can be either a class probability (in classification problems) or a continuous numeric output (for regression) [47]. Nonlinear activation functions, like ReLU, are used after both convolutional and dense layers to introduce complexity, enabling the model to interpret more intricate patterns in the input data [48]. Mathematically, each convolution layer in a DCNNs can be expressed as the following convolution operation:

$$y_i = (x * w)_i + b_i \quad (5)$$

Following the convolution process, the output is typically processed using a non-linear activation function like ReLU.

$$ReLU(x) = \max(0, x) \quad (6)$$

After the convolution and activation layers, pooling is performed to reduce the dimensionality of the data. Max pooling can be formulated as:

$$y_i = \max(x_j \; for \; j \; \epsilon \; R) \tag{7}$$

Where R is the local area in the selected image, and x_j are the elements in the area. This function selects the maximum value of the local area to reduce the data dimension and retain important features. After the convolution and pooling layers, the results will be processed by the fully connected layer, which can be formulated as:

$$y = W \cdot x + b \tag{8}$$

Where W is the weight matrix connecting the neurons in the input layer with the output layer; x is the input vector from the previous layer; and b is the bias.

The output of this layer is the probability for each class in the classification (e.g., using softmax on the output layer for multi-class classification):

$$Softmax(x_i) = \frac{e^{x_i}}{\sum_j e^{x_j}} \tag{9}$$

Where x_i is the score for the i-th class, and j covers all classes. Softmax converts these scores into probabilities indicating membership in different classes.

A key benefit of DCNNs lies in their capability to automatically learn and extract features from image data, eliminating the need for extensive manual feature engineering. With multiple convolution and pooling layers, DCNNs can learn from data patterns with increasing levels of abstraction at each layer, from basic features (such as edges) to complex features (such as specific objects or textures) [49]. DCNNs also reduces the number of parameters to be learned, because convolution layers share weights across images. This allows DCNNs to be more efficient in processing large image data and improves model accuracy in tasks such as classification, object detection, and image segmentation [50]. The following is the proposed DCNNs for detecting Alzheimer's disease in this study.

Table 1 shows the proposed DCNNs architecture for Alzheimer's detection with 4-class classification. The model consists of 16 layers divided into convolution, pooling, dense (fully connected) layers, and output layers. The model begins with an input layer that receives MR images sized at 224×224 pixels with 3 color channels. It proceeds through six convolutional layers, structured into three major blocks. Each block contains two convolutional layers followed by a Max-Pooling operation. The first to sixth convolution layers use a 3×3 kernel size with the number of filters increasing gradually from 32, 64, to 128 filters. Each convolution layer uses a ReLU activation function which is known to be effective in dealing with the vanishing gradient problem and speeding up the training process. The Max-Pooling layer used after each convolution block has a pool size of 2×2, which aims to reduce the dimensionality of the resulting image without losing important features. This pooling process helps reduce the number of parameters that need to be learned by the model and prevents overfitting. After going through all the convolution and pooling processes, the data is converted into a 1D vector (Flattening) which is then forwarded to the dense layer. After the Flattening process, this architecture has two dense layers consisting of 224 neurons and 64 neurons with the ReLU activation function. The final stage of this model is the Output layer which uses the Softmax activation function to perform a 4-class classification, which is in accordance with the Alzheimer's detection task. The Softmax function converts the scores generated by the neural network into probabilities for each predicted class. In addition, Table 2. shows the proposed DCNNs with input and output vector shapes.

Table 2 presents the structure of the proposed DCNNs model used for identifying Alzheimer's disease, detailing the input and output dimensions across all layers. The process starts from Convolutional layer 1, which receives an input image of size (224, 224, 3), indicating an image with a resolution of 224×224 pixels and three-color channels. This layer produces an output of size (222, 222, 32), indicating that the convolution process uses 32 filters and reduces the spatial dimension due to the absence of padding. This layer is followed by Max-Pooling which reduces the image size to

(111, 111, 32) through a pooling operation with a filter size of 2×2 and a stride of 2. The architecture then continues with a sequence of alternating convolutional and pooling layers for further feature extraction. Convolutional layers 2 to Convolutional layers 6 gradually change the size and depth of the features of the given image. Each convolution layer is followed by Max-Pooling to reduce the spatial dimension while retaining the most important information. After the sixth convolution layer, the image size is reduced to (3, 3, 128), indicating that the image features have been filtered and condensed into a smaller but richer representation of information. After the convolution and pooling process is complete, the Flatten layer is used to transform the (3, 3, 128) features into (128), converting the data from a multi-dimensional format into a one-dimensional format. This vector is then fed to the Dense 1 layer which has an output size of (224), followed by Dense 2 with an output size of (64). This process allows the network to integrate and combine the features that have been extracted from the image through the previous layers. Finally, the Classification layer produces an output with a size of (4). This indicates that this DCNNs model aims to classify into four different categories, which are related to the stages or types of Alzheimer's disease. This entire process is designed to effectively transform the input image into a more compact feature representation that can be used to make accurate classification predictions.

In addition, selecting the appropriate hyperparameters for DCNNs is crucial for building an effective Alzheimer's detection model. The following are the proposed hyperparameter tuning strategies for DCNNs. Hyperparameter tuning on the proposed DCNNs shown in Table 3.

Table 1. Architecture of the proposed DCNNs for Alzheimer's disease detection

Layers	Layer (Type)	Properties
1st	Input	input shape = 224 × 224 × 3
	Convolutional 1	kernel size = 3 × 3, 32 filters
2nd	Max-Pooling	pool size = 2 × 2
3rd	Convolutional 2	kernel size = 3 × 3, 32 filters
4th	Max-Pooling	pool size = 2 × 2
5th	Convolutional 3	kernel size = 3 × 3, 64 filters
6th	Max-Pooling	pool size = 2 × 2
7th	Convolutional 4	kernel size = 3 × 3, 64 filters
8th	Max-Pooling	pool size = 2 × 2
9th	Convolutional 5	kernel size = 3 × 3, 128 filters
10th	Max-Pooling	pool size = 2 × 2
11th	Convolutional 6	kernel size = 3 × 3, 128 filters
12th	Max-Pooling	pool size = 2 × 2
13th	Flatten	convert to 1D vector for Dense
14th	Dense 1	224 neurons, ReLU
15th	Dense 2	64 neurons, ReLU
16th	Output	4-class classification, Softmax

Table 2. Proposed DCNNs structure with input and output vector forms

Layer (Type)	Input	Output
Convolutional 1	Input: (None, 224, 224, 3)	Output: (None, 222, 222, 32)
Max-Pooling	Input: (None, 222, 222, 32)	Output: (None, 111, 111, 32)
Convolutional 2	Input: (None, 111, 111, 32)	Output: (None, 109, 109, 32)
Max-Pooling	Input: (None, 109, 109, 32)	Output: (None, 54, 54, 32)
Convolutional 3	Input: (None, 54, 54, 32)	Output: (None, 52, 52, 64)
Max-Pooling	Input: (None, 52, 52, 64)	Output: (None, 26, 26, 64)
Convolutional 4	Input: (None, 26, 26, 64)	Output: (None, 24, 24, 64)
Max-Pooling	Input: (None, 24, 24, 64)	Output: (None, 12, 12, 64)
Convolutional 5	Input: (None, 12, 12, 64)	Output: (None, 10, 10, 128)
Max-Pooling	Input: (None, 10, 10, 128)	Output: (None, 5, 5, 128)
Convolutional 6	Input: (None, 5, 5, 128)	Output: (None, 3, 3, 128)
Max-Pooling	Input: (None, 3, 3, 128)	Output: (None, 1, 1, 128)
Flatten	Input: (None, 1, 1, 128)	Output: (None, 128)
Dense 1	Input: (None, 128)	Output: (None, 224)
Dense 2	Input: (None, 224)	Output: (None, 64)
Classification	Input: (None, 64)	Output: (None, 4)

Table 3. Hyperparameter tuning on the proposed DCNNs

Hyperparameter	Value	Justification
Learning Rate	0.001	A learning rate of 0.001 is widely used in deep learning and provides a balance between convergence speed and stability.
Batch Size	64	A batch size of 64 was selected for optimal computational efficiency while avoiding overfitting.
Optimizer	Adam	Adam is effective for handling sparse gradients and non-stationary objectives, which is suitable for deep architectures.
Epochs	100	100 epochs were chosen after preliminary tests, but training was stopped early if no improvement was observed.
Dropout Rate	0.5	A dropout rate of 0.5 was chosen to prevent overfitting while maintaining the model's ability to generalize.
Loss Function	Cross-Entropy	Cross-entropy is well-suited for classification tasks and adversarial training.

3. Results and Discussion

3.1. The Use of GANs on the OASIS and ADNI Datasets

This study focuses on the development of an Alzheimer's detection method using the GANs approach integrated with the DCNNs architecture. The main objective of this study is to improve the accuracy of classifying brain images obtained through MR images, by utilizing the power of DCNNs in extracting features and GANs in correcting the imbalanced data contained in the dataset. DCNNs are used as the main model to identify relevant patterns and features from input images [51], while GANs play a role in generating new synthetic data that is similar to the underrepresented data, thus helping to overcome the problem of imbalanced data distribution [52].

In this study, the two main datasets used are OASIS and ADNI. Both of these datasets are extensively applied in research related to the diagnosis of Alzheimer's because they provide various MRI images from subjects with different levels of severity. However, the challenge faced in using these datasets is the imbalanced class distribution. According to the OASIS dataset, samples are divided into four main categories, namely non-Demented (ND) which represents individuals without signs of dementia, Very Mild Dementia (VMD) which indicates an early stage of mild dementia, Mild Dementia (MD) which indicates a more pronounced mild dementia stage, and Moderate Dementia (MoD) which indicates a stage of dementia with more severe symptoms. Data imbalance in the OASIS dataset commonly arises due to the disproportionately higher number of samples in the non-demented (ND) category compared to the other groups.

The ADNI dataset was also incorporated into this research and is categorized into four unique groups, including Normal Cognitive Status (CN), which refers to individuals with standard mental functioning. The remaining categories are Early Mild Cognitive Impairment (EMCI), which represents an initial level of minor cognitive decline, Late Mild Cognitive Impairment (LMCI) for those experiencing progressing moderate cognitive challenges, and Alzheimer’s Condition (AD), describing people officially diagnosed with Alzheimer’s disease. Similar to the OASIS dataset, ADNI also exhibits unequal class proportions. The GAN-based method applied in the context of this study aims to address the issue of this imbalance by producing synthetic information that mimics data from the underrepresented class. The following is the data distribution on the OASIS & ADNI dataset before and after the use of GANs.

Fig. 3 and Fig. 4 show the data distribution in two neuroimaging datasets commonly used in Alzheimer's and cognitive impairment research, the OASIS Dataset and the ADNI Dataset, both before and after augmentation using GANs. The purpose of this augmentation is to address the problem of class imbalance, which is a common problem in medical data and can affect the performance of classification models. In Fig. 3, the initial data distribution in the OASIS Dataset shows a very large imbalance. The ND class dominates at 77.77% (67,222 data), while the VMD class is only 0.56% (488 data), MD is 15.88% (13,725 data), and MoD is 5.79% (5,002 data). This

imbalance has the potential to cause bias in machine learning models because the model tends to learn more from the majority data and fails to recognize data from the minority class [53]. After augmentation with GANs, the distribution becomes balanced, with each class having 70,000 data (25%). This shows the success of GANs in generating synthetic data that resembles the original data for the minority class, thus improving the data representation in model training [54].

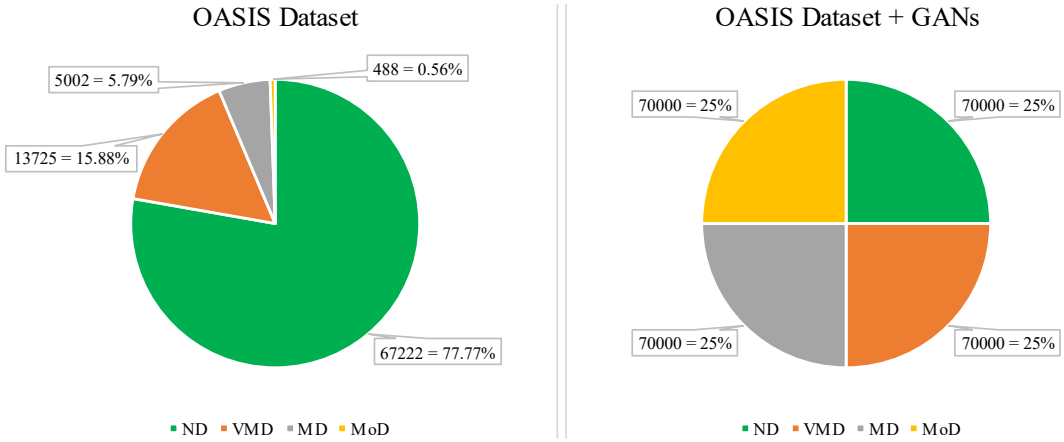


Fig. 3. Data distribution on the OASIS dataset before and after using GANs

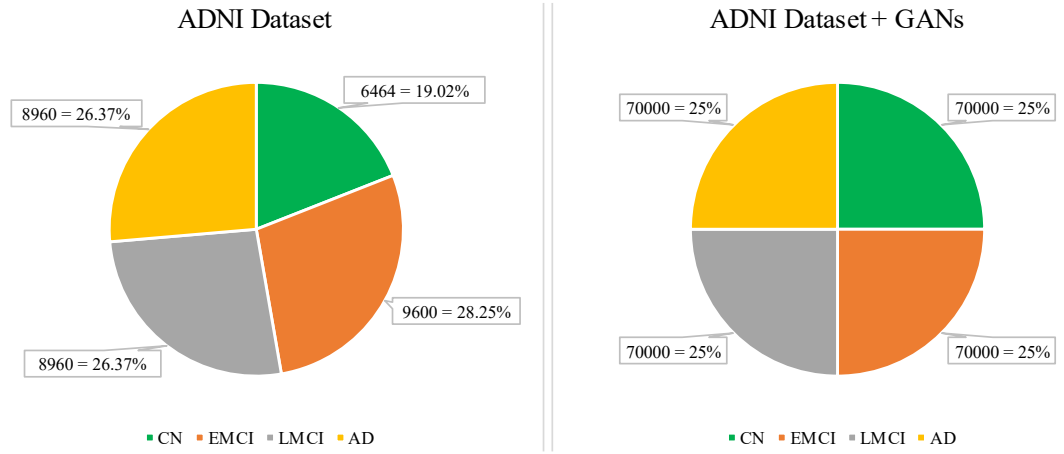


Fig. 4. Data distribution on the ADNI dataset before and after using GANs

Meanwhile, Fig. 4 shows the data distribution in the ADNI Dataset. The initial distribution shows that the AD class has the largest proportion, which is 28.25% (9,600 data). The LMCI and CN classes each contribute 26.37% (8,960 data), while EMCI is only 19.02% (6,464 data). Although the imbalance is not as bad as OASIS, this distribution can still cause imbalance in the learning process. After the augmentation process with GANs, each class is balanced, which is 70,000 data (25%). As in the OASIS Dataset, this shows that GANs can be used to augment synthetic data that resembles the original data in the minority class without losing the representation of valid distributions [55]. Overall, these two figures (Fig. 3 and Fig. 4) show that the use of GANs as a data augmentation technique is very effective in solving the problem of class imbalance in medical datasets. By creating a balanced distribution between classes, the model built on the data is expected to have better and fairer classification performance, especially in recognizing rare conditions that are very important to detect early such as mild dementia or early Alzheimer's [56].

3.2. Alzheimer's Disease Detection Using the OASIS Dataset

This study conducted an evaluation of DCNNs for Alzheimer's disease detection on the OASIS dataset through two separate scenarios, one excluding GANs and the other involving the use of GANs. The purpose of this comparison is to evaluate how much performance improvement is produced by

applying the GANs methods in addressing class imbalance issues present in the OASIS dataset. The dataset was divided into specific portions for training and testing, where 80% of the samples were allocated for training purposes, 10% served as validation, and the remaining 10% were designated for testing. The OASIS dataset is divided into four classes, namely ND, VMD, MD, and MoD. The following are the results of testing the DCNNs model in Alzheimer's detection using this dataset.

In Table 4, the DCNNs model trained using the original OASIS Dataset shows good performance in the majority class, namely ND, with Sensitivity (99.39%), Specificity (99.58%), Precision (99.88%), Accuracy (99.43%), and F1 Score (99.63%). However, this good performance is largely due to the much larger amount of ND class data than other classes. The model learns more from the majority class, so it can recognize data from that class very well. This results in a classification bias towards minority classes such as VMD and MoD. Especially in the MoD class, the model performance is very low with a Sensitivity of 87.72%, Precision of 79.37%, and F1 Score of 83.33%. The low Sensitivity value indicates that the model is unable to detect most MoD cases well. The low Precision also indicates that the model often misclassifies data from other classes as MoD. This indicates that significant data imbalance is the main cause of the model's low performance on minority classes [57].

In Table 5, the DCNNs model was trained using data that had been augmented with GANs. This augmentation technique generates the same amount of data for each class (70,000 samples per class), thus addressing the data imbalance problem present in the original dataset. The results show significant performance improvements with all metrics approaching or reaching perfect values (99.96% to 100%) for each class. The most prominent improvement is seen in the MoD class, which previously had low performance. After augmentation, the MoD class achieved Sensitivity, Specificity, Precision, Accuracy, and F1 Score values of 100%, indicating that the model can recognize data from this class very well without any misclassification. Comparison between Table 4 and Table 5 confirms that the use of GANs as a data augmentation method successfully overcomes the problem of class imbalance. By increasing the number of samples from the minority class, GANs allow the model to learn the patterns of each class evenly and fairly [58].

Table 4. Performance of the proposed DCNNs in Alzheimer's detection (OASIS without GANs)

Condition	Performance Evaluation				
	Sensitivity	**Specificity**	**Precision**	**Accuracy**	**F1 Score**
ND	99.39	99.58	99.88	99.43	99.63
VMD	99.56	99.48	97.25	99.49	98.39
MD	99.03	99.93	98.84	99.87	98.94
MoD	87.72	99.85	79.37	99.77	83.33
Average	**96.42**	**99.71**	**93.83**	**99.64**	**95.07**

Table 5. Performance of the proposed DCNNs in Alzheimer's detection (OASIS + GANs)

Condition	Performance Evaluation				
	Sensitivity	**Specificity**	**Precision**	**Accuracy**	**F1 Score**
ND	99.87	100.00	99.99	99.96	99.93
VMD	99.99	99.96	99.87	99.96	99.93
MD	100.00	100.00	99.99	100.00	99.99
MoD	99.99	100.00	100.00	100.00	99.99
Average	**99.96**	**99.99**	**99.96**	**99.98**	**99.96**

3.3. Alzheimer's Disease Detection Using the ADNI Dataset

Similar to the Alzheimer's detection scenario in the OASIS dataset, this study also implements DCNNs with two different scenarios on the ADNI dataset, namely without using GANs and with GANs. The purpose of implementing these two scenarios is to evaluate the effectiveness of using GANs in overcoming class imbalance in the ADNI dataset, as well as to compare the performance of DCNNs before and after the implementation of the GANs technique. The process of training and evaluating the DCNN model on the ADNI dataset follows the same data split approach used in the OASIS dataset. Specifically, 80% of the total dataset is allocated for training purposes, 10% is

designated for validation, and the remaining 10% is reserved for testing. This method ensures the model has access to a substantial amount of data during training while also allowing it to be reliably tested on unseen data. The ADNI dataset is categorized into four groups that reflect various stages of cognitive decline and Alzheimer's disease, which include CN, EMCI, LMCI, and AD. The next section presents the DCNN performance results for Alzheimer's prediction using this dataset.

Table 6 and Table 7 present the performance of DCNNs models in detecting various stages of Alzheimer's using the ADNI Dataset, before and after augmentation with GANs. In Table 6, which reflects the performance of the model without augmentation, it is apparent that the performance for the LMCI class is lower than the other classes, especially in terms of Specificity (94.17%), Precision (85.51%), and F1 Score (88.73%). However, it is important to note that the amount of data in the LMCI class is equivalent to the AD class, so the low performance is not due to data imbalance, but is likely due to the overlapping clinical and imaging characteristics between LMCI and other classes, especially EMCI and AD. Clinically, LMCI is on the transition spectrum from mild cognitive impairment to Alzheimer's, so its imaging features can be very similar to those two classes [59]. As a result, the model tends to have difficulty distinguishing LMCI from EMCI or AD, resulting in many misclassifications (FP and FN).

Table 6. Performance of the proposed DCNNs in Alzheimer's detection (ADNI without GANs)

Condition	Performance Evaluation				
	Sensitivity	Specificity	Precision	Accuracy	F1 Score
CN	99.53	99.85	99.37	99.79	99.45
EMCI	86.91	97.99	94.43	94.87	90.51
LMCI	92.19	94.17	85.51	93.63	88.73
AD	93.51	97.61	93.19	96.55	93.35
Average	**93.03**	**97.41**	**93.13**	**96.21**	**93.01**

Table 7. Performance of the proposed DCNNs in Alzheimer's detection (ADNI + GANs)

Condition	Performance Evaluation				
	Sensitivity	Specificity	Precision	Accuracy	F1 Score
CN	99.22	99.99	99.97	99.80	99.59
EMCI	99.91	99.36	98.12	99.50	99.01
LMCI	98.31	99.58	98.73	99.26	98.52
AD	98.67	99.77	99.31	99.50	98.99
Average	**99.03**	**99.68**	**99.03**	**99.51**	**99.03**

In contrast, in Table 7 after augmentation with GANs, the performance on all classes, including LMCI, improved significantly and became more uniform. In the LMCI class, the F1 Score increased to 98.52%, with an increase in Precision and Sensitivity to 98.73% and 98.31%, respectively. This shows that augmentation with GANs not only plays a role in increasing the data, but also helps to elaborate more distinctive and distinguishable feature representations between classes, even for previously ambiguous conditions such as LMCI. In addition, consistent improvements across metrics and classes indicate that the model trained with augmented data is better able to generalize to the complex classification patterns present in the ADNI dataset. The overall average model performance also experienced a significant increase from 93.03% (Sensitivity), 93.13% (Precision), and 93.01% (F1 Score) to 99.03% respectively. Meanwhile, Specificity increased from 97.41% to 99.68% and Accuracy from 96.21% to 99.51%. This indicates that augmentation using GANs effectively improves the stability and classification accuracy of the model as a whole, not only because of the improvement in data distribution, but also because it enriches the diversity and depth of representative features in training [60].

However, GAN-based augmentation techniques also have notable limitations that must be considered. Firstly, GAN-generated synthetic samples might inadvertently include unrealistic artifacts or noise patterns that differ significantly from real-world data, potentially impairing model generalization [61]. Secondly, the quality of synthetic data produced by GANs largely depends on the

initial training dataset, meaning any inherent bias or inaccuracies in the original data may be amplified in the synthetic samples [62]. Thirdly, GANs require substantial computational resources and careful tuning of their architectures and hyperparameters to produce consistently reliable outputs [63]. Fourthly, it remains challenging to evaluate the biological validity and clinical reliability of GAN-generated data, raising questions about their practical application in medical diagnostics [64]. Lastly, ethical issues concerning transparency, interpretability, and patient safety can arise from relying on synthetic data for clinical decision-making, necessitating careful consideration and validation before deploying such augmented datasets in clinical practice [65].

3.4. The Proposed GANs + DCNNs Approach Compared with Existing Methods

The findings from the DCNNs testing results on the OASIS and ADNI datasets show that the use of GANs as a data augmentation method successfully improves the classification performance on both datasets, but with different levels of improvement. The application of DCNNs combined with GANs can significantly improve the classification performance for detecting various stages of Alzheimer's disease, especially in identifying minority classes that were previously difficult to detect. The use of GANs has been shown to provide a major contribution to the data augmentation process to improve the accuracy of DCNNs-based classification models. In addition, the following is a comparison of the proposed approach with existing methods.

Table 8 shows a comparison of the performance of various methods that have been used in previous studies to detect Alzheimer's disease using the OASIS and ADNI datasets, and compares them with the method proposed in this study, namely GANs + DCNNs. For example, a study conducted by Ebrahimi et al. (2021) using a combination of ResNet18 + TCN (Temporal Convolutional Network) produced an accuracy of 91.78% [19], while AlSaeed et al. (2022) using a combination of ResNet50 + Softmax, SVM, and RF showed an accuracy range of 85.70% to 99% [67]. Other studies such as those conducted by El-Assy et al. (2024) using CNN obtained the highest accuracy on the ADNI dataset, namely 99.13% - 99.57% [74]. On the OASIS dataset, a study by Venkat et al. (2025) using a combination of CNN + AlexNet achieved an accuracy of 99.49% [26], while another study by Salami et al. (2022) used a combination of ResNet, DenseNet, and Inception-V3 with an accuracy range of 80.98% - 87.75% [69]. Several studies that combine CNN models with more complex networks, such as CNN + LSTM by Noh et al. (2023) and Haq et al. (2025), also showed quite high accuracy of 96.43% [72] and 92.3% [25].

Table 8. Comparison of the performance of the proposed GANs + DCNNs with existing methods

Research	Dataset	Models	Accuracy
Ebrahimi et al. (2021) [19]	ADNI	ResNet18 + TCN	91.78%
Fu'adah et al. (2021) [66]	OASIS	AlexNet	95%
AlSaeed et al. (2022) [67]	ADNI	ResNet50 + Softmax, SVM, and RF	85.70% - 99%
Odusami et al. (2022) [68]	ADNI	ResNet18 and DenseNet121	93.06% - 98.86%
Shehri et al. (2022) [21]	OASIS	ResNet50 and DenseNet169	81.92% - 83.82%
Salami et al. (2022) [69]	OASIS	ResNet, DenseNet, and Inception-v3	80.98% - 87.75%
Bamber et al. (2023) [70]	OASIS	CNN	98%
Celebi et al. (2023) [71]	ADNI	Xception	95.81%
Noh et al. (2023) [72]	ADNI	CNN + LSTM	96.43%
Shamrat et al. (2023) [73]	ADNI	Inception V3	98.68%
El-Assy et al. (2024) [74]	ADNI	CNN	99.13% - 99.57%
Venkat et al. (2025) [26]	OASIS	CNN Alzh-Net	99.49%
Haq et al. (2025) [25]	ADNI	CNN + LSTM	92.3%
Proposed models	**OASIS & ADNI**	**GANs + DCNNs**	**99.51% - 99.98%**

The model proposed in this study, namely a combination of GANs + DCNNs applied to the OASIS and ADNI datasets, showed a very significant increase in performance. With an accuracy ranging from 99.51% to 99.98%, this method outperforms most of the methods in previous studies. This advantage is mainly due to the ability of GANs to overcome the problem of class imbalance which is a major challenge in medical datasets such as OASIS and ADNI [75]. These results indicate

that the integration of GANs with DCNNs can provide a more effective and accurate solution in detecting various stages of Alzheimer's disease. The increase in accuracy obtained from this method indicates that the use of GANs as a data augmentation technique is able to improve the generalization capability of the DCNNs model, resulting in better classification performance compared to conventional approaches.

4. Conclusion

This research clearly shows the effectiveness of applying GANs in combination with DCNNs for identifying Alzheimer's disease. The proposed method seeks to boost classification performance by solving the class imbalance issue seen in the OASIS and ADNI datasets. Through the creation of synthetic data for underrepresented groups, GANs help equalize the dataset distribution, enabling DCNNs to learn more effectively across a broader range of samples. Experimental findings indicate that the incorporation of GANs greatly enhances DCNN model performance, particularly on the OASIS dataset, which originally suffered from a significant class imbalance. The model attained an impressive average accuracy of 99.98% and an F1 Score of 99.96% on the OASIS dataset following the implementation of GANs. Similarly, significant enhancements were observed on the ADNI dataset, especially in identifying EMCI and LMCI cases, with the average accuracy rising to 99.51% and the F1 Score reaching 99.03%. The proposed GANs + DCNNs model outperforms most existing methods reported in the literature, making it a highly effective approach for Alzheimer's detection. The comparison with previous studies confirms that the integration of GANs into DCNNs provides a robust solution to the class imbalance problem, which is a critical challenge in medical image analysis. By improving the classification performance across all classes, especially the minority classes, this approach demonstrates its potential as a reliable diagnostic tool for Alzheimer's. Although the GANs + DCNNs approach has shown notable success, several aspects still warrant deeper investigation (one of which is the realism of the synthetic data produced by GANs). Upcoming research will aim to enhance the quality of this generated data to ensure it closely mirrors the attributes of actual images, especially those belonging to underrepresented classes. Developing more advanced GAN architectures or combining GANs with other generative models such as Variational Autoencoders (VAEs) may provide better results. Additionally, systematic validation frameworks should be established to rigorously assess the biological plausibility and clinical utility of synthetic data. Moreover, addressing computational efficiency and scalability will be essential to facilitate practical deployment of these advanced generative methods in clinical environments.

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