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Article

Alzheimer Disease Classification using Deep CNN Methods Based on Transfer Learning and Data Augmentation

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Abstract: Alzheimer's disease (AD) primarily impacts a distinct demographic, specifically individuals who are 60 years old and older, predominantly affecting the elderly. AD is an emerging neurological disorder characterized by profound disruption of memory and the onset of behavioral abnormalities, significantly complicating an individual's life. Recent progress in research has allowed precise diagnosis by leveraging intelligent technologies, including the use of deep learning and convolutional neural algorithms for tasks such as image quality improvement and magnetic resonance imaging. This research utilized convolutional neural network (CNN) models to automatically extract pertinent features associated with Alzheimer's disease and classify brain MRI images. In contrast to conventional approaches, CNN models exhibit enhanced proficiency in discerning among the four phases of Alzheimer's disease, which encompass mild dementia, very mild dementia, non-dementia, and moderate dementia. This entails utilizing a pre-trained model that has already captured valuable features from one dataset and adjusting it to perform efficiently on a related yet different task. This study delves into the potential of transfer learning to enhance AD classification. Specifically, we employed three state-of-the-art architectures, ResNet-152, VGG16, and Inception-V3, to discern intricate patterns from brain images, after that we applied data augmentation technique that enlarges the size of a training dataset by implementing various modeling and analytical methods. Transfer learning allows us to adapt and refine these pre-trained networks for our Alzheimer's disease classification objective, even in situations where there is a scarcity of labeled data.

Keywords: Alzheimer's disease; transfer learning; deep learning; data augmentation; inception-v3; VGG16; resnet-15; medical image analysis

1. Introduction

Alzheimer's disease (AD) stands as one of the most common neurodegenerative conditions, impacting millions of people globally. Marked by a progressive decline in cognitive function, AD not only places a substantial burden on both patients and their families but also poses an increasing public health concern as the world's population ages. Early and accurate diagnosis of AD is critical for effective intervention and treatment planning; however, it remains a complex and intricate task for clinicians.

Alzheimer’s is conceived as the most neurodegenerative disease, which presents the greatest risk of developing the disease in people with mild cognitive impairment MCI. However, it remains initially to predict which MCI subjects and when progress to Alzheimer’s disease (AD) dementia [1].

In Alzheimer’s disease, there are 6,400 medical MRI images, divided into four categories based on Alzheimer’s disease labels: non-dementia, mild dementia, moderate dementia, and severe dementia.

For the training section, 5,121 images were used to study Alzheimer’s disease, while 1,279 images were used for testing [2].

The accuracy measure is inappropriate due to imbalances in the dataset. Accuracy is a criterion that provides an interpretable score regarding exactitude. Consequently, the model distinguishes between different categories when the score is closer to 1 and higher. Otherwise, the model fails to distinguish between different categories if the scores are lower.

In recent years, the intersection of medical science and artificial intelligence (AI) has ushered in a new era of potential solutions for AD diagnosis. Deep learning, a subfield of AI, has shown remarkable promise in image analysis tasks, including medical image analysis. Leveraging the power of neural networks, deep learning models have demonstrated the capability to detect subtle patterns and anomalies in medical images, thereby aiding in the diagnosis of various diseases, including AD.

Transfer Learning, a technique in deep learning, has emerged as a pivotal approach for harnessing pre-trained neural networks and adapting them to new tasks with limited labeled data. This technique can overcome one of the major challenges in AD classification—insufficient and highly specialized datasets—by using knowledge learned from diverse sources.

In particular, this paper presents a comprehensive exploration of the application of transfer learning in the classification of Alzheimer’s disease using deep learning models. We investigated how pre-trained models can be fine-tuned and adapted to effectively discern AD-related patterns in brain images, there by achieving accurate and reliable diagnoses. Our study not only contributes to the ongoing efforts to improve AD diagnosis but also sheds light on the broader potential of transfer learning in medical image analysis.

The remainder of this paper is organized as follows: Section 2 provides an overview of related work in AD classification and transfer learning, gaps in previous research, and proposed solutions to this problem. Section 3 details the methodology, including the dataset used, model architectures, applying data augmentation technique and training procedures. In Section 4, we present the experimental results and discuss the implications of our findings. Finally, in Section 5, we offer conclusions and avenues for future research.

2. Related Work

The quest for effective Alzheimer’s disease (AD) detection methodologies has spurred significant research efforts in recent years. Various approaches have been explored to tackle this pressing healthcare challenge. Traditional methods, such as cognitive assessments and clinical evaluations, have long been the cornerstones AD diagnosis. However, their limitations in terms of sensitivity and early detection have led researchers to explore novel techniques. One prominent avenue of investigation is the application of machine learning and deep learning to neuroimaging data. Studies using convolutional neural networks (CNNs) and transfer learning have exhibited promising results in automating the diagnostic process. In Addition, a growing body of research has investigated the role of biomarkers, both in cerebrospinal fluid and blood, as potential indicators of AD progression. This paper builds upon these foundations by harnessing the power of transfer learning along with deep learning models, namely ResNet-152, VGG16, and Inception-V3, to advance the state-of-the-art in AD classification. The second part of the study involves creating a simple yet effective framework to achieve high accuracy. We have chosen the data augmentation technique applied to the various architectures noted previously to achieve improved performance.

Recently, Jia Wenjuan et al. [3] used a deep autoencoder for the well classification of MRI images, elaborating five different sets characterizing healthy subjects and subjects with brain disease, neoplasia, inflammation, and brain function disorders. The goal was to convert the initial unbalanced dataset to a more balanced one. The technique used in [4], was the extreme learning machine (ELM) to diagnose attention deficit hyperactivity disorder (ADHD). ELM is designed as a neural network that is characterized by triggering matrix multiplication processes rather than using recurrent improvement of the classifier’s error margin. We proceed by extracting features before proceeding with classification, using the FreeSurfer package [5].

The deep learning technique has proven itself over other classical methods in terms of performance, and the use of a large dataset has reassured good image recognition. Machine learning is performed by the technique of labeling the data provided in the data to extract the hidden discriminating features and transform them nonlinearly in each layer [6].

In many recent articles, to classify diseases that affect the brain, it is useful to use a CNN applied to MRI images [7,8].

To properly assess the quality of a 3D MRI image, it is necessary to use an end-to-end 3D CNN method; this paper presents a large sample of images from various sources. The 3D CNN is also applied to functional magnetic resonance imaging (MRI) [9].

Deep Learning models often exhibit increased accuracy when trained on larger datasets. Appropriate data augmentation techniques were employed to create an augmented dataset, incorporating a greater number of images. This expansion of the dataset played a crucial role in enhancing the precision performance of most evaluated transfer learning models [10].

In the literature, there are several methods for detecting AD, either based on classification, or based on deep learning. In this study, we examine in detail some recent and more effective methods that have been published (See Table 1).

Table 1. Research work addressing Alzheimer detection.

Authors	**Techniques**	**Dataset**	**Accuracy**
Morabito and J.M. Ebadi [11]	CNN(MLP)	IRCCS Centro	85.75%
J. Islam and Y. Zhang [12]	Resnet-50	ADNI	93.17%
R.Jain, A. Aggarwal and D.J. Hemanth [13]	VGG16	ADNI	95.07%
Sarraf and G. Tofighi [14]	LeNet-5	ADNI	96.85%
F. Previtali, P. Bertolazzi, G. Felici, and E. Weitschek [15]	Resnet-101	ADNI	97.45%
F. Ftoutou, N. Majdoub and T. Ladhari [16]	Resnet-50 Resnet-50 with data augmentation	ADNI	92.52% 95.62%
N. M. Khan, N. Abraham, and M. Hon [17]	SVM	ADNI	93.05%
R. S.Kamathe and K. R. Joshi [18]	KNN KNN with data augmentation	OASIS	79.80% 90.30%
D. Anand, P.S.Gowr, S.Logesh and S.M.Anand [19]	InceptionV3 Inception with data augmentation	Kaggle Alzheimer's dataset	87.02% 90.30%
Yuan, Y., Meng, F., Zhang, C., Zhou, J., Gao, J., & Han, S [20]	VGG16 Resnet50 InceptionV3	ADNI	95.89% 92.04% 93.80%

Current diagnostic methods exhibit limitations in early detection. By addressing the various shortcomings identified in these research works, we can significantly contribute to the advancement of research in the field of Alzheimer's disease classification through transfer learning and deep learning models, and our work aims to bridge these gaps. In response, this study leverages transfer learning in conjunction with deep learning models, namely ResNet-152, VGG16, and Inception-V3, to advance AD classification. Our research demonstrated remarkable success, outperforming previous methods. By automating and enhancing the diagnostic process, this study offers significant promise in improving the early detection of AD, thereby enhancing patient care and quality of life. Our findings not only advance the state-of-the-art in AD diagnosis but also underscore the effectiveness of transfer learning in medical image analysis.

Nevertheless, these methods are not always dependable or easily available, and they have certain disadvantages. Lately, there has been encouraging progress in the identification of Alzheimer's disease using deep learning models, particularly those that incorporate transfer learning [21].

3. Proposed Methods

A powerful deep learning technique called transfer learning uses a previously trained model's weights to train a new model on a different or related problem. Transfer learning can be used to take advantage of the sizable pre-trained deep convolutional neural networks (CNNs) that have been trained on a sizable amount of visual data in the context of AD classification.

It uses a convolutional neural network. The extremely potent CNN neural network has been extensively employed to address challenging machine learning issues.

The CNN design typically consists of multiple layers that extract features from the input data, such as convolutional, pooling, and fully connected layers. A pre-trained CNN model can be improved on a smaller labeled dataset of brain MRI images to categorize the imagesas normal or abnormal for the classification of Alzheimer's disease.

Numerous studies employ CNNs primarily on raw pixel pictures, necessitating no prior feature determination. By computing convolution over tiny portions of the input space image and sharing the parameters between regions, CNNs use fewer parameters than a fully connected network. Many CNN-based architectures, including AlexNet [22], VGGNet [23], ResNet [24], and GoogLeNet [25], have been created and are intended for 1000-class picture categorization. Figure 1 illustrates the typology of the different methods of detecting AD.

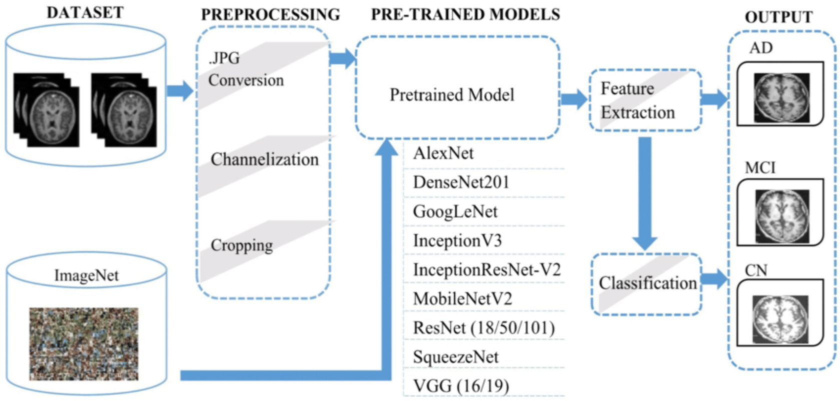


Figure 1. Typology of different methods for detecting Alzheimer's disease.

Figure 1 illustrates the data processing flow from the initial collection to the final classification of patients into a category of Alzheimer's disease. This study highlights the importance of feature extraction from a pre-trained model to enhance the accuracy of classification.

In addition, this work uses three convolution models to build an image classification system containing 4 stages of Alzheimer's evolution, noting that the first one is Inception-v3, the second one was VGG16, and the third one is Resnet-152.

Figure 2 illustrates the architecture of our proposed method, a first "Preprocessing" stage, which includes operations such as data normalization, artifact cleaning, and data preparation for subsequent analysis, was carried out. Then, a splitting of the dataset is necessary to understand the model structure used. One, part of the data is to learn the model, and another part is to test it. A second level of validation is then used to select a suitable model structure. The third step selects the test dataset for model performance validation.

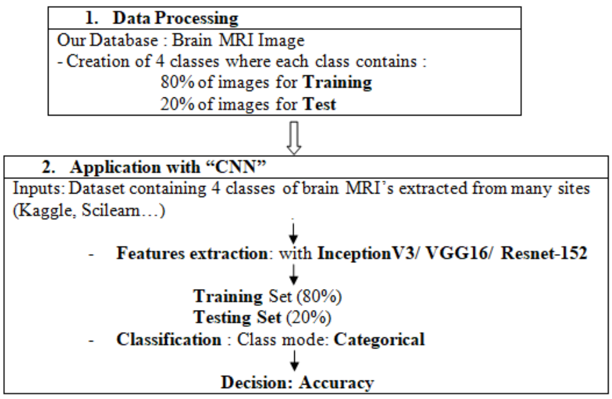


Figure 2. Overview of the proposed Framework.

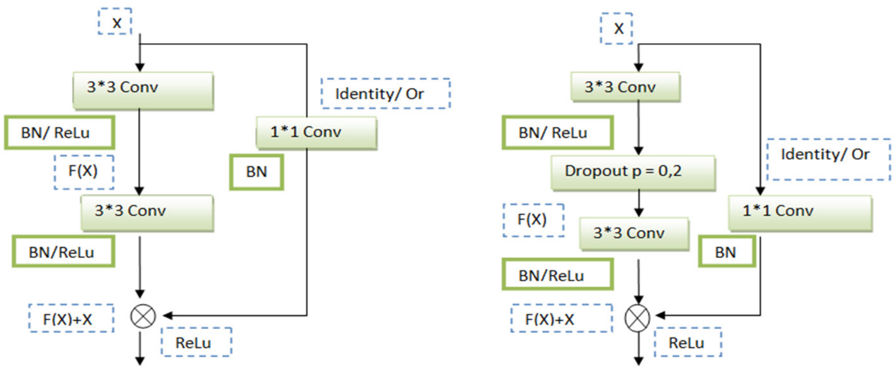
Model development is underway for later implementation within our dataset. During the training phase, our CNN model extracts patterns and features from images to characterize them, aiding in the identification of different stages of Alzheimer's disease. The learning step involves initializing weights in the hidden layer and comprises feedback and back-propagation processes. In contrast, the testing stage involves classification using weights obtained during the learning phase. While the testing process closely resembles the learning process, it excludes backpropagation. The accuracy of the classification process is determined by the feedback outcome.

3.1. Resnet-152 Architecture

If the depth is greater than a certain level, degradation is produced so that the accuracy is saturated and then degrades rapidly. Excessive adjustment does not cause such degradation. He et al. [26] reformulated layers as learning residual functions with reference to layer inputs, instead of learning unreferenced functions and presented the deep residual learning framework. As shown in Figure 3a, a simple CNN block directly learns the target function H(X). In particular, the ResNet block in Figure 3b has a different learning objective defined:

$$F(X) = H(X)X$$

This naming is in the sense that the residue of X in H(X) is learned. This implies that it is easier to learn the residue than to learn all H(X). ResNet learns a complicated goal by taking a detour. This concept can also be represented by a "shortcut connection", which performs identity mapping, and X is added to the output of the stacked layer.



(**a**) Plain CNN Block (**b**) Resnet Block

Figure 3. CNN Architecture vs. ResNet Architecture.

The difference between the various Resnet variants (Resnet-18, Resnet-34, Resnet-50, Resnet-101, and Resnet-152) lies in the number of layers and the complexity of the architecture. Research shows that a deeper variant is the most efficient alternative in terms of accuracy rate. An example of Resnet-152, the architecture adopted in our study.

Resnet-152 is a specific variant of ResNet architecture. The number "152" refers to the depth of the network, indicating that it has 152 layers [27]. This variant is significantly deeper than the original ResNet-50, which has 50 layers. It is used for various tasks in computer vision, including image classification, object detection, and segmentation. It is known for its ability to capture complex features and patterns in images because of its deep structure. However, deeper networks can be more challenging to train and may require more computational resources.

3.2. VGG16 Architecture

VGGNet was developed by Simonyan and Zisserman. This network has a very uniform architecture, which makes it very interesting. The VGGNet includes several filters, and a 3 × 3 convolution. Notably, to properly extract the features of such an image, VGGNet was the most powerful and robust model.

In our research work, we adopted the VGG16 architecture, which allowed us to create a very powerful precision system compared with other previously used architectures [28]. Figure 4 illustrates the VGG16 architecture.

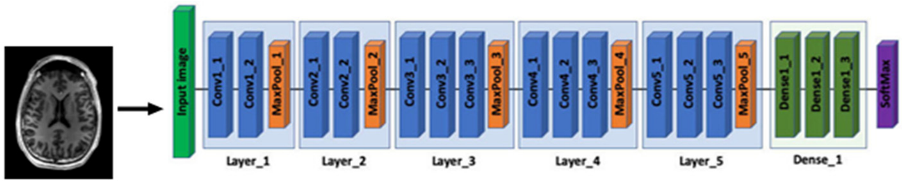


Figure 4. VGG16 Architecture.

The VGG16 classification system is one of the best intelligent methods in terms of accuracy in the classification of images. It serves to expand the amount of data by classifying the input images into various categories. The model is qualified deep; there are 16 layers of weights, where some represent convolutions of layers or so-called convolutional layers and are fully connected carrying the parameters that can be learned. Of course, the major problem with deep neural networks is that the computation will be very energy intensive and powerful.

Table 2 gives an overview of how the model is structured and how data flows through it during the forward pass. We then found 16 layers, the output shape of each layer, and the number of parameters. This means that there are over 7 million weight parameters.

Table 2. VGG16 Model.

Layer (Type)	**Output Shape**	**Param #**
Input_1 (Input Layer)	(None, 224,224,3)	0
Block1_conv1 (Conv2D)	(None, 224,224,64)	1792
Block1_conv2 (Conv2D)	(None, 224,224,64)	36928
Block1_pool(MaxPooling2D)	(None, 112,112,64)	0
Block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
Block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
Block2_pool(MaxPooling2D)	(None, 56, 56, 128)	0
Block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
Block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
Block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
Block3_pool(MaxPooling2D)	(None, 28, 28, 256)	0
Block4_conv1(Conv2D)	(None, 28, 28, 512)	1180160
Block4_conv2(Conv2D)	(None, 28, 28, 512)	2359808
Block4_conv3(Conv2D)	(None, 28, 28, 512)	2359808
Block4_pool (MaxPooling2D)	(None, 14,14,512)	0

This model is so simplified that it is easy to use, but it does raise some difficulties in terms of the total number of parameters in this model, which exceeds 7M and is over 500 MB in size. This giant size poses some limitations in the field of advanced computing, since the inference time required is longer.

3.3. Inception V3 Architecture

Inception version 3 is a CNN architecture of the Inception v1, v2, v3, and v4 lineage, its representation being 22 layers, with the interest of improving the usability of a labeled smoothing. Then, a 7 × 7 factorization of the convolutions is performed, and finally, an additional classification system is implemented to synthesize the labels further down the network. The network consists of parallel links (see Figure 5).

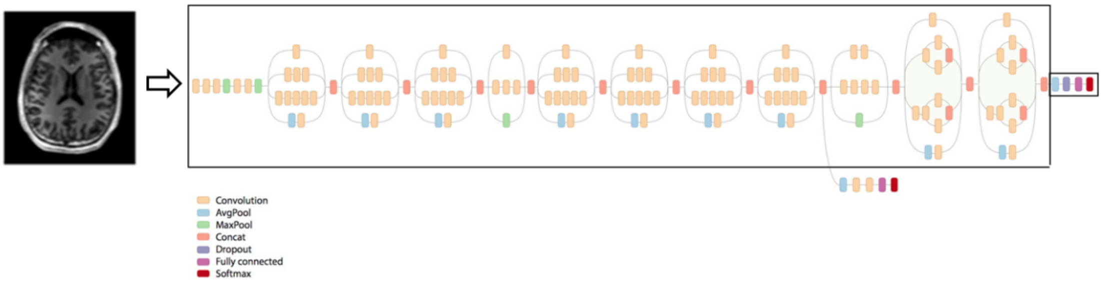


Figure 5. Inception V3 Architecture.

Previously, we described in Figure 5 the architecture of Inception-v3, which has three Inception modules weighted by trying to reduce the grid size, which is a crucial step. When the learning operation is about to end, the accuracy is almost saturated, and any auxiliary classifier will behave as a regularizer. Figure 6 shows the Inception-v3 architecture with Tensorflow.

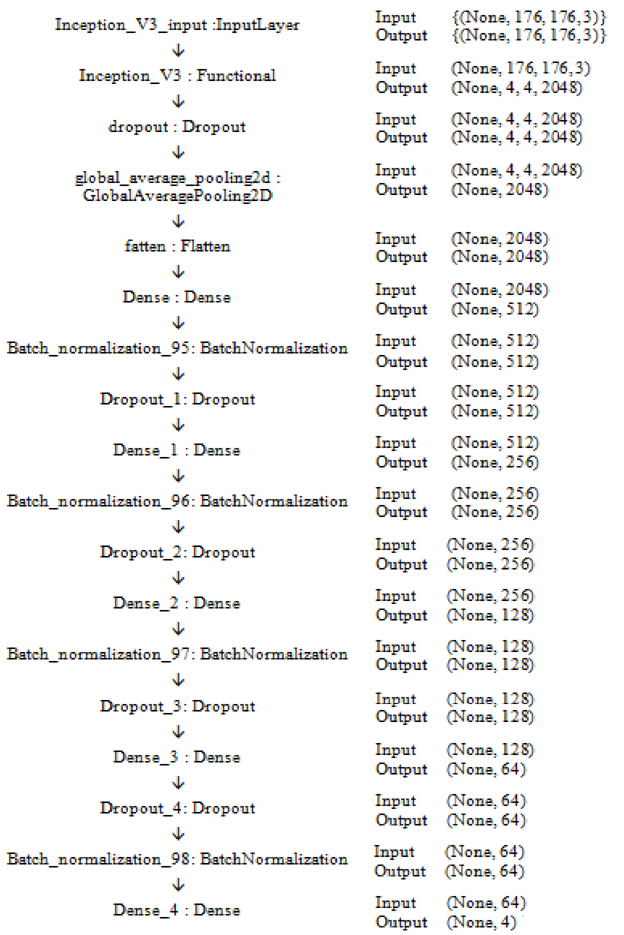


Figure 6*.* Inception-v3 Architecture with Tensorflow.

The inception–v3 architecture is a convolutional neural network designed for image classification tasks. It is known for its efficient use of computation resources by using inception modules that employ various filter sizes. Figure 6 illustrates a simplified explanation of the Input and input layers, convolutional layers, inception modules, reduction blocks, fully connected layers, and auxiliary classifiers.

Table 3 gives an overview of how the model is structured and how data flows through it during the forward pass. We then found 22 layers, the output shape of each layer, and the number of parameters. This means that there are over 40 million weight parameters.

Table 3. Inception-v3 Model.

Layer (Type)	Output shape	Param #
Inception_V3 (Functional)	(None, 4,4, 2048)	21802784
Dropout (Dropout)	(None, 4,4, 2048)	0
Global_average_pooling2d (AveragePooling)	(None, 2048)	0
Flatten (Flatten)	(None, 2048)	0
Batch_normalization_94 (BatchNormalization)	(None, 2048)	8192
Dense (Dense)	(None, 512)	1049088
Batch_normalization_95 (BatchNormalization)	(None, 512)	2048
Dropout_1 (Dropout)	(None, 512)	0
Dense_1 (Dense)	(None, 256)	131328
Batch_normalization_96 (BatchNormalization)	(None, 256)	1024
Dropout_2 (Dropout)	(None, 256)	0
Dense_2 (Dense)	(None, 128)	32896
Batch_normalization_97 (BatchNormalization)	(None, 128)	512
Dropout_3 (Dropout)	(None, 128)	0
Dense_3 (Dense)	(None, 64)	8256
Dropout_4 (Dropout)	(None, 64)	0
Batch_normalization_98 (BatchNormalization)	(None, 64)	256

4. Experiments and Results

In this section, we present the Alzheimer disease datasets used for the experiments. Thereafter, we detail and discuss the experimental settings. The obtained results are then presented and compared with the proposed systems.

This section illustrates the collection of data; the database adopted in this work is about the images of Alzheimer's disease. The classification results will be good in terms of performance, when the adopted database is varied and large. Moreover, a stage of analysis and discussion of the parameters of the experiment is necessary for the realization of the study (See Table 4). Finally, a comparative study with the applied systems is elaborated.

Table 4. Parameters of Model Resnet-152.

Total paras	14 815 044
Trainable paras	100 356
Non-trainable params	14 714 688

Non-trainable parameters refer to the number of parameters in a neural network model that are not updated or learned during the training process. In this study, you mentioned that there are 14714688 non-trainable parameters in our model (Resnet-152). This number represents the total number of non-trainable parameters across all layers that fall into this category.

4.1. Dataset

In the different works elaborated, we note that most authors use the images of magnetic resonance MRI, to classify the diseases well.

In the field of clinical imaging, the MRI Magnetic Resonance Imaging is designed as the type of image that stands out for its power in terms of accuracy and clarity. In the MRI images, the nervous tissues where the anomalies reside are very clear to detect tumors of any disease [29].

To classify brain MRIs into normal, very-mild, mild, and moderate Alzheimer classes using a convolutional neural network (CNN), it is essential to have a dataset that reflects the characteristics of the problem at hand. Our dataset is accumulated from many sources such as Google, Kaggle and medical institutions. It follows all ethical guidelines and privacy regulations related to medical data. The dataset is divided into four classes, each corresponding to a different level of Alzheimer's disease progression:

- **Normal:** Brain MRIs from individuals with no signs of Alzheimer's disease.
- **Very-mild Alzheimer's:** MRIs from individuals with very early-stage Alzheimer's disease, often referred to as mild cognitive impairment (MCI) or early-stage Alzheimer's.
- **Mild Alzheimer's:** MRIs from individuals with mild Alzheimer's disease.
- **Moderate Alzheimer's:** MRIs from individuals with moderate-stage Alzheimer's disease.

The distribution of samples in these classes is balanced, similar, and representative of the actual prevalence of Alzheimer's disease stages. Then, the valuation of the proposed system is manifested by the accumulation of 6,400 MRI-like images of AD to evaluate the proposed system; we create an AD dataset consisting of 6,400 MRI images. The collected dataset is divided into two sub-datasets: the first corresponds to the training part 80%, and the second corresponds the test part 20%. For both parts of the images, there are four classes of images where each class represents a specific stage of Alzheimer's disease (See Figure 7).

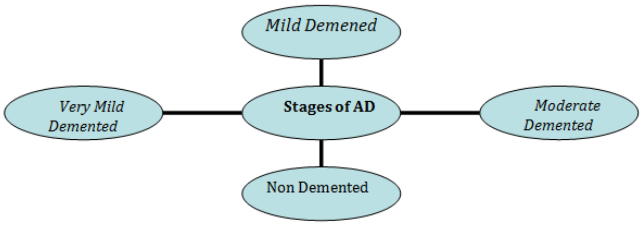


***Figure** 7.* Stages of Alzheimer's Disease.

The images used are all 224 × 224 pixels in size. Validation of the model was performed on a training subset containing 5,121 images and other data set containing 1,279 images to test the model. For all data sets, either for learning or testing, a classification according to the severity of the Alzheimer's disease (Stages of Alzheimer) is used. Figure 8 shows samples of brain tumor images that are selected from the global database.

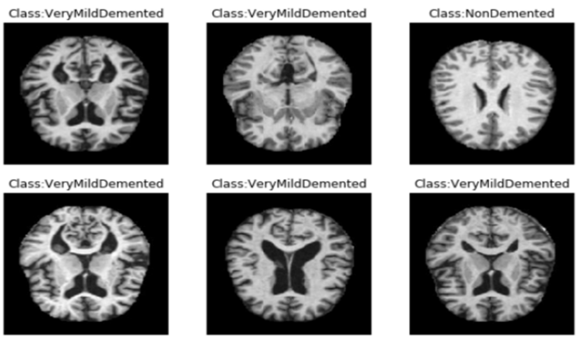


Figure 8. Samples of Brain MRI's images with stages of Alzheimer.

Each image encapsulates unique pathological features indicative of different degrees of cognitive impairment, offering valuable insights into the morphological changes occurring within the brain throughout the course of the disease. The diversity depicted in these images underscores the complexity of Alzheimer's disease and highlights the importance of accurate diagnostic tools in clinical practice.

4.2. Data Augmentation

Research into disease detection using deep learning necessitates a vast quantity of data, which is often challenging to procure. To address this issue, we opted for a more efficient data augmentation technique. Augmenting the entire training dataset also aids in mitigating the risk of overfitting.

To ensure the model's robustness and generalization capability, literature resorts to techniques that can increase data volume, in other words, to augment the size of data samples. Data Augmentation is a common technique in the field of machine learning that enlarges the size of a training dataset by implementing various modeling and analytical methods [30–32]. The "Keras ImageDataGenerator" class is used to extract data from the learning database. The augmentation process is controlled by specifying parameters like zoom, brightness, range, and horizontal flipping. This allows for the variation of the zoom factor, adjustment of brightness, and horizontal flipping of images, resulting in enhanced diversity and additional variations within the augmented dataset. Consequently, image augmentation proves to be a powerful strategy for augmenting the size of the training dataset and improving the resilience of machine learning models, achieving optimal results by configuring the parameters as follows:

- Rotation range: 40

- Width and height shift ranges: 0.1
- Horizontal flip: True
- Fill mode: Nearest

The subsequent Figure 9 depicts an example of original images alongside their preprocessed and augmented versions.

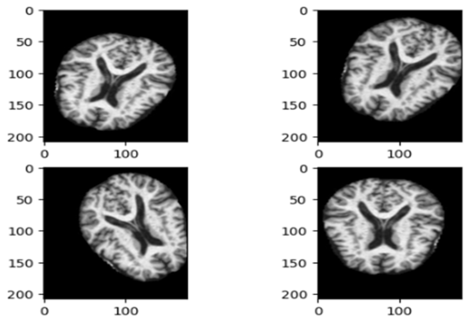


Figure 9. Samples of Brain MRI's images after using Data Augmentation.

Based on the output provided, it seems that the data generators have effectively located the images and autonomously organized them into the appropriate directories corresponding to the four distinct labels assigned to each MRI image.

4.3. Experimental Settings

The challenge of this work is to highlight a powerful model to predict to which class of disease an image belongs, precisely, to predict Alzheimer's disease at an early stage of life. Let's talk about the experimental part; on the one hand, we develop a database collection for brain MRI images containing 4 different stages of severity of Alzheimer's disease. We explain in detail and discuss the frameworks of the experiments. In particular, 2 intelligent convolutional neural network systems CNN were adopted for each part of the experiment: the first system was VGG16, the second was Resnet-152 and the third was is Inception-v3.

To properly evaluate the classification through the two proposed systems, it was necessary to have the learning and testing parts of the brain MRI images. We used Python 3.7 through the interactive interface Anaconda. Our framework was validated by VGG16, Resnet-152 and Inception-v3 applied to MRI images of 224 × 224 × 3 extensions.

4.4. Results and Discussion

4.4.1. CNN's Architectures

To classify brain MRIs into normal, very-mild, mild, and moderate Alzheimer classes, one of the most performed system "A Convolutional Neural Network (CNN) "model is used. The data comprise 6,400 images. This experimental study focuses on the performance of the CNN convolutional neural system, as well as the VGG16, Inception-v3, and Resnet-152 architectures that are integral parts of it [33]. The performance of our proposed system is summarized in the following figure. As expected, the Inception-v3 method gives robust and better results than VGG16, and Resnet-152 gives robust and better results than Inception v3.

The performance of a diagnostic model for Alzheimer's disease across different stages (non-demented, very mild demented, Mild demented, Moderate demented) involves evaluating the model's ability to accurately classify individuals into these categories. Here is a description of what each category entails in terms of diagnosis and corresponding performance metrics to evaluate the model's effectiveness for Alzheimer's disease diagnostics.

Figure 10 illustrates a confusion matrix of the classification model Inception-v3: here the table shows the counts of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) cases for each category. Each row of the matrix corresponds to the true categories, and each column corresponds to the predicted categories.

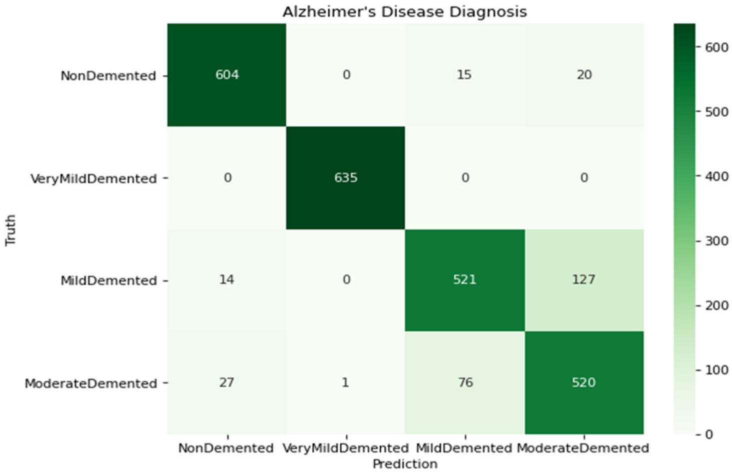


Figure 10. Performance of the proposed methods (Inception–v3).

Here is how we might explain the elements of a confusion matrix for this scenario:

True Positives (TP): These are cases in which the model correctly predicted a specific stage of Alzheimer's disease. For example, if an individual is truly in the "mild demented" category and the model predicts "mild demented", it's a true positive.

True Negatives (TN): These are cases in which the model correctly predicted a category other than the specific stage being evaluated. For instance, if an individual is truly "non-demented" and the model correctly predicts "non-demented", it's a true negative for that category.

False Positives (FP): These are cases where the model predicted a certain stage, but the individual is actually in a different stage. For instance, if an individual is "very mild demented", but the model predicted "mild demented ", it's a false positive for "mild demented".

False Negatives (FN): These are cases where the model failed to predict a certain stage correctly.If an individual is "mild demented", but the model predicted "non- demented ", it's a false negative for "mild demented".

- Accuracy can be calculated as (TP+TN)/ Total.
- Precision for a category is TP/(TP+FP)
- Recall that for a category is TP/(TP+FN)
- Specificity is calculated as TN/(TN+FP), revealing how well the model identifies true negative cases.

Certainly, the plot of metrics for the VGG16 architecture with an accuracy of 80% would provide insights into how the model performs during training and evaluation. Metrics commonly plotted alongside accuracy include loss and possibly other metrics such as validation accuracy, validation loss, and confusion matrix (see Figure 11).

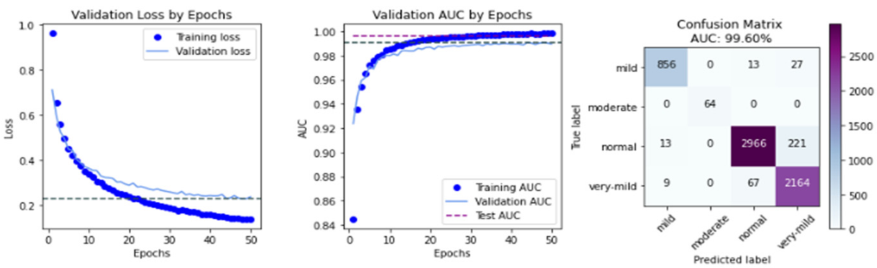


Figure 11. Performance of our proposed methods: (VGG16).

In the context of Resnet architecture with an accuracy of 98%, a loss plot typically refers to a graphical representation of how the loss function changes over the course of training (see Figure 12).

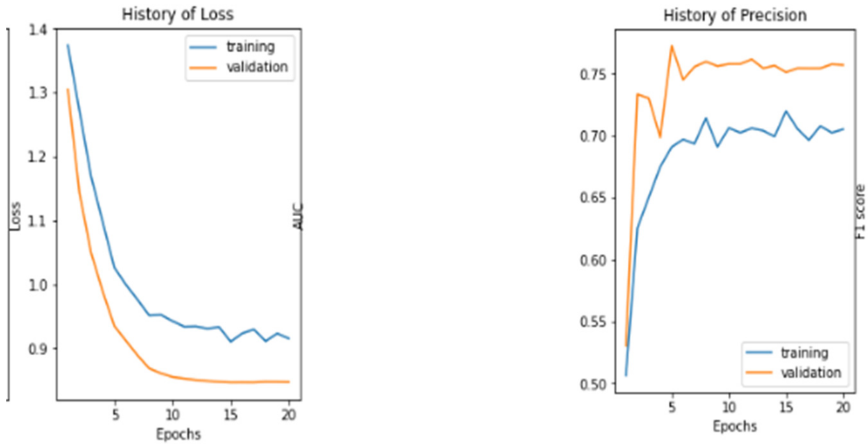


Figure 12. Performance of our proposed methods: (Resnet-152).

Table 5 illustrates the results obtained by applying Resnet-152, VGG16, and inception-v3. As noted, the recording of a very high accuracy rate, with respective values of 98%, 96%, and 80%, ensured that the characteristics of the neural approach to Alzheimer's disease are very effective. We compared the performance of different models (ResNet-152, Inception-v3, and VGG16) in terms of accuracy for the Alzheimer classification task. We focus on two main points:

- **Relative performance:** ResNet-152 achieves the best result with an accuracy of 98%, followed by Inception-v3 with 96%, while VGG16 achieves an accuracy of 80%. This indicates that ResNet-152 is the best-performing of the three models evaluated.
- **Acceptable accuracy:** An accuracy of 80% for VGG16 can still be considered an acceptable performance in the context of our classification task. However, it is generally desirable to obtain the highest performance possible.

Table 5. Accuracy rate of the proposed methods.

DataSets	Methods	Accuracy
Our Dataset	Resnet-152	98%
	Inception-v3	96%
	VGG16	80%

4.4.2. CNN's Architectures with Data Augmentation Technique

A comparative study was conducted to assess the performance of VGG16, Resnet-152, and Inceptionv3 models, including an analysis of results with and without the application of data augmentation technique. The findings demonstrate a significant improvement in the accuracy and robustness of the models when data augmentation is utilized. This enhancement is particularly notable in the classification of brain MRI images across various stages of Alzheimer's disease. The addition of augmented data has enriched and diversified the training dataset, resulting in more generalizable and effective models. These observations underscore the importance of data augmentation in the training process of convolutional neural networks for medical image classification tasks such as Alzheimer's disease detection.

Figure 13 depicts a confusion matrix for the VGG16 classification model. In this visual representation, the table displays the counts of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) cases for each category. Each row in the matrix corresponds to the true categories, while each column corresponds to the predicted categories.

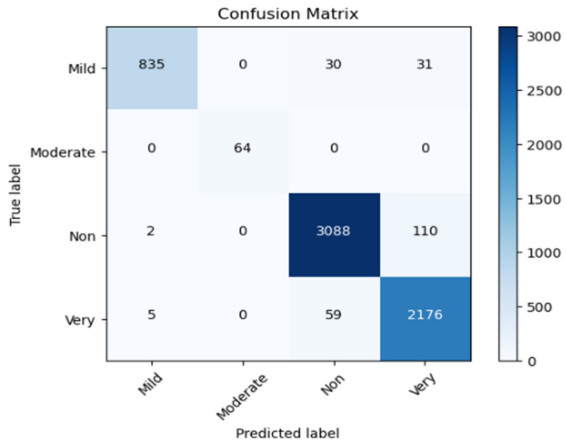


Figure 13. Confusion matrix of the proposed methods (VGG16) with data augmentation method.

These graphs displays the VGG16 model's loss and accuracy on both training (train) and validation (val) data at each epoch. The first legend indicates 'train' for training data and 'val' for validation data, the second legend indicates 'train' for training data and 'val' for validation data (see Figure 14).

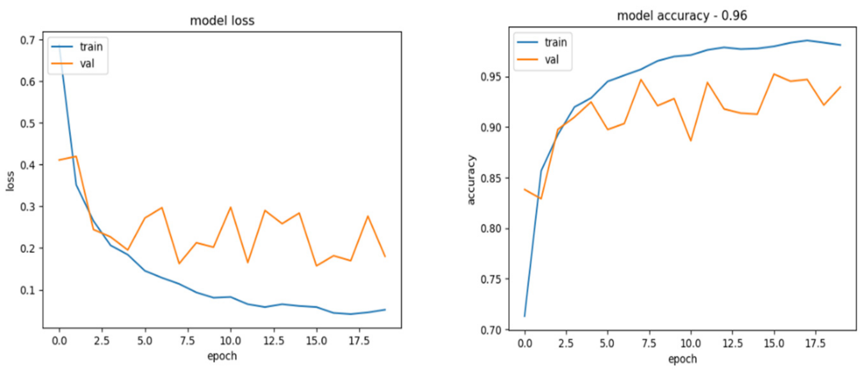


Figure 14. Performance of the proposed methods (VGG16) with data augmentation method.

The accuracy value achieved with the application of data augmentation techniques stands at an impressive 96%, demonstrating the substantial impact of this method on model performance. In contrast, without data augmentation, the accuracy rate remains at 80%. This stark contrast emphasizes the pivotal role that data augmentation plays in enhancing the effectiveness of the classification model. The significant increase in accuracy underscores the importance of leveraging advanced techniques like data augmentation in optimizing model outcomes, particularly in complex classification tasks like medical imaging analysis.

These graphs illustrate the performance of our proposed method, Inception-v3, with data augmentation. The first graph displays the training and validation loss evolution per epoch for the Inception-v3 model (see Figure 15). It reveals a decreasing trend in loss over epochs for training and validation data, suggesting model convergence. The second graph illustrates the progression of training and validation accuracy per epoch for the same model. A consistent increase in accuracy is observed throughout the training process, reaching a value of 98% at the end of epochs. These results attest to the effectiveness of data augmentation method in enhancing the performance of the Inception-v3 model in image classification, highlighting its utility in computer vision tasks.

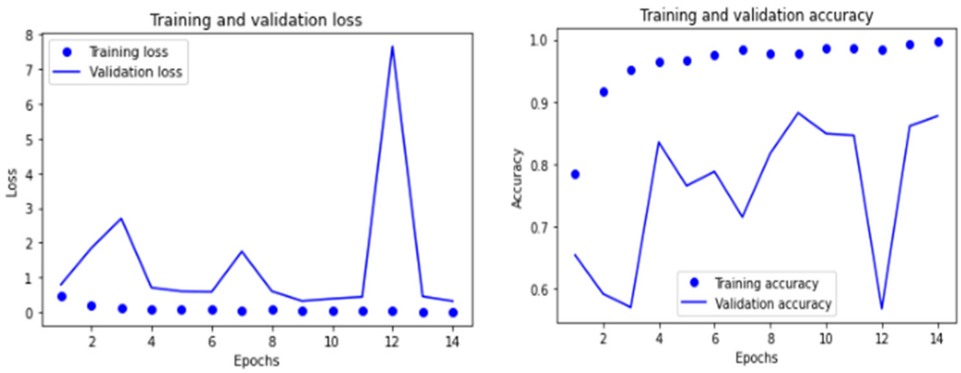


Figure 15. Performance of the proposed methods (Inception-v3) with data augmentation method.

The model loss and model accuracy of our Resnet-152 model were evaluated to demonstrate its performance. With the application of data augmentation techniques, the model achieved an outstanding accuracy of 99%. The model loss consistently decreased over epochs, indicating effective learning and convergence. Similarly, the model accuracy exhibited a steady increase, reflecting the model's ability to accurately classify data instances (see Figure 16). These results underscore the efficacy of data augmentation in enhancing the performance of the Resnet-152 model.

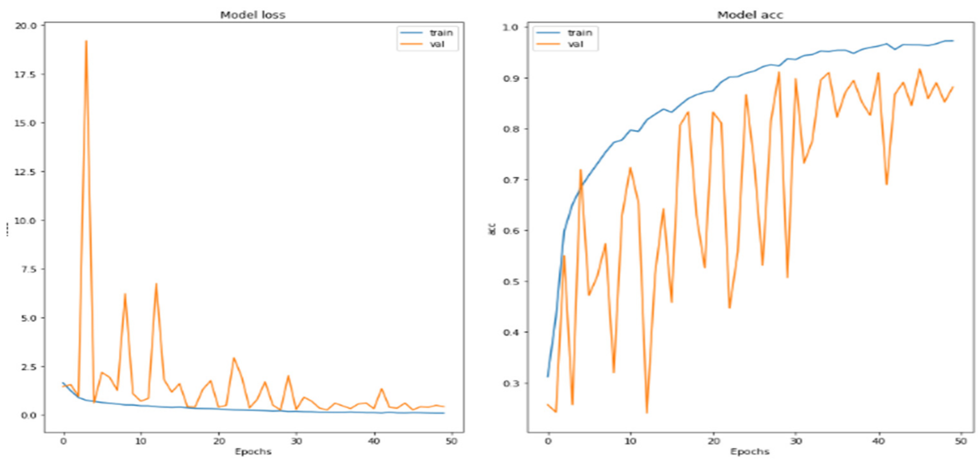


Figure 16. Performance of the proposed methods (Resnet-152) with data augmentation method.

The results of the area under the ROC curve (AUC-ROC) for the ResNet-152 model with data augmentation are exceptional (see Figure 17): 0.9922 for MildDemented, 1.0000 for ModerateDemented, 0.9976 for NonDemented, and 0.9946 for VeryMildDemented. The overall (micro-average) AUC-ROC is 0.9972, indicating the model's excellent ability to discriminate between different dementia classes. With the application of data augmentation, the ResNet-152 model achieved remarkable performance, reaching an accuracy of 99% (see Table 6).

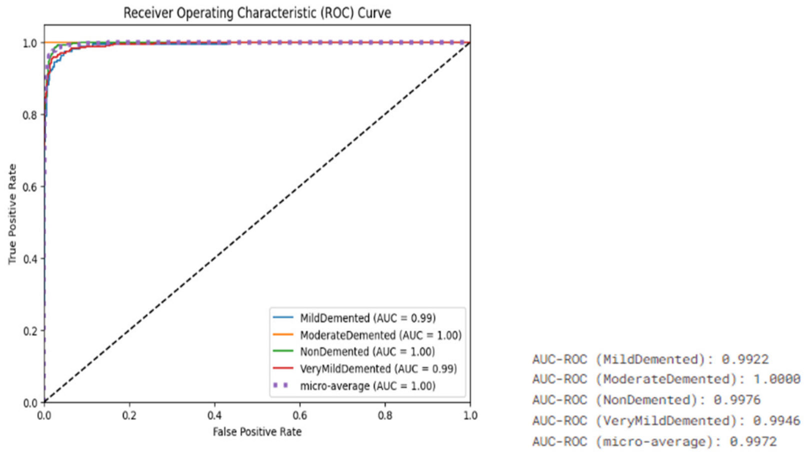


Figure 17. Receiver Operating Characteristic (ROC) Curve of Resnet152 model with data augmentation.

Table 6. Accuracy rate of the proposed methods with/ without Data Augmentation.

DataSets	**Methods**	**Accuracy**
Our Dataset	Resnet-152	98%
	Inception-v3	96%
	VGG16	80%
Our Dataset with data Augmentation	Resnet-152	99%
	Inception-v3	98%
	VGG16	96%

In summary, Table 7 provides a comparative overview of the different methods and their accuracies for the detection of AD. Our proposed models (ResNet-152, VGG16 and Inception-v3) show competitive performance, with ResNet-152 achieving the highest accuracy of 98%. Comparison with other architectures, such as VGG19, ResNet-50, and ResNet-101, provides valuable insights into the effectiveness of different neural network models for this task. We concluded the robustness of the detection system and the classification of Alzheimer's disease marked a promising result compared with other methods that gave fewer interesting results. Considering the noted results, we can conclude that the CNN model can provide classification values for the precision metric.

Table 7. Performance Comparison using Brain MRI's Dataset.

Authors	**Architecture**	**Accuracy**
Our Proposed	Resnet-152	98%
	Resnet-152 with Data augmentation	**99%**
	Inception-v3	96%
	Inception-v3 with Data augmentation	98%
	VGG16	80%
	VGG16 with Data augmentation	96%
[10]	CNN(MLP)	85%
[2]	VGG19	82%
[11]	Resnet-50	93.18%
[14]	Resnet-101	97%

The Resnet-152 architecture has been very successful in the diagnosis of Alzheimer's disease. In fact, the four-stage classification of this disease gives an accuracy of 98%. This proves that our system outperformed many existing techniques and methods in terms of accuracy.

5. Conclusions

In conclusion, by leveraging deep CNNs and transfer learning, it is becoming feasible to accurately identify Alzheimer's disease from brain MRI scans. This can significantly enhance early disease detection and diagnostic accuracy. Overall, AD can be effectively classified using the deep CNN classification approach. However, this study also demonstrates the efficiency of neural network techniques in classifying brain tumor cells into different age categories to detect Alzheimer's disease in its early stages. Our investigation reveals that combining various systems can lead to improved accuracy and performance. Furthermore, we can explore additional settings to enhance performance beyond the existing techniques. Models such as VGG16, ResNet, and Inception V3 have proven their utility in disease detection. However, the field of medical deep learning continues to evolve, with exciting trends that promise continued enhancements in early disease detection and management. The integration of more advanced models, increased explainability, and deeper integration into healthcare holds substantial promise for both patients and healthcare professionals. Staying informed about these developments is imperative as we strive for further progress in this ever-evolving field. One of the most noteworthy trends in disease detection using deep learning is the vision Transformer (ViT), which will be a focal point for our future work.

Author Contributions

S.J. carried out the bibliographic studies on Alzheimer Disease Classification, participated in the implementation of the system and drafted the manuscript. H.L. and M.E. participated in the design and coordination of the study. M.K., H.L. and M.E. helped to draft the manuscript. All authors have read and agreed to the published version of the manuscript.

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Conflict of Interest Statement

The authors declare no conflicts of interest.

Data Availability Statement

Data supporting reported results are publicly available at https://www.kaggle.com/datasets/sachinkumar413/alzheimer-mri-dataset.

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