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A novel automated deep learning approach for Alzheimer's disease classification

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ABSTRACT

Alzheimer's disease is a degenerative brain illness, incurable and progressive. Globally for every two seconds, someone is affected by Alzheimer's disease. Alzheimer's disease in the elderly is difficult to diagnose due to the complexity of the brain structure. Its pixel intensity is similar and systematic distinction is necessary. Deep learning has inspired a lot of interest in recent years in tackling challenges in a variety of fields, including medical imaging. One of the drawbacks of deep learning approach is the inability to detect changes in functional connectivity in mild cognitive impairment (MCI) patients' functional brain networks. In this paper, we utilize deep features extracted from two pre-trained deep learning models to tackle this issue. The proposed models DenseNet121 and MobileNetV2 is used to perform the task of Alzheimer's disease multi-class classification. In this method, initially we increased 70 % of dataset and generated images by using cycle generative adversarial networks (CycleGAN). We achieved 98.82% of accuracy with proposed models. It gives best results compared to existing models.

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1. INTRODUCTION

Alzheimer's disease is a neurological disorder in which the brain cells die causing memory loss and mental impairment. The brain is in charge of and supports all the movements and reactions that enable us to think and believe [1]. Our emotions and memories are also enhanced. The most frequent form of dementia is Alzheimer's disease. Due to beta-amyloid found in the brain's plates. As your symptoms develop, so does our ability to remember, think about and recognise current events [2]. Alzheimer's patients eventually require round-the-clock care. A neuropathy is a type of brain illness. A kind of neuropathy is Alzheimer's disease. It is a progressive brain illness that is untreatable. Alzheimer's disease is diagnosed every 4 seconds around the world [3]. It grows slowly and destroys memory cells, robbing people of their ability to think. It is a neurodegenerative disease that causes nerve cell loss or failure [4]. After being diagnosed with Alzheimer's disease then life expectancy is reduced. It affects around one in every ten persons over the age of 65. However, it can sometimes appear at a younger age, and a small number of persons in their twenties have been diagnosed with it [5]. This condition is the most common cause of dementia among the elderly. Dementia impairs the cognitive abilities needed for daily tasks. Alzheimer's disease is responsible for 60–80% of active dementia cases. At first, the symptoms are mild, but they gradually worsen. Non-sympathetic (generalised psychosis), mild (stage 1), severe (stage 2), and moderate dementia (stage 3) are the three stages of Alzheimer's disease. As Alzheimer's disease progresses, as shown in Figure 1.

Figure 1. Image representing healthy brain vs. mild Alzheimer's disease vs. severe Alzheimer's disease

Symptoms are not visible in the early stages and may include difficulty remembering names, loss of critical items and intermediate steps such as scheduling challenges. Alzheimer's disease is the most severe and has symptoms such as mood swings, disorientation, impulsivity, inattention, poor object identification [6]. Alzheimer's disease, however, affects 50 million people globally. Scientists and clinicians today see this condition as a major problem because it is frequently not recognised until the patient presents. They progress to the final stage of the disease due to their cognition [7]. Symptoms are frequently caused by ageing. However, the threat posed by this disease will continue to grow. As a result, elderly adults are more likely to get the condition.

Many researchers have used a variety of methods to identify Alzheimer's disease over the years. The research was done using data from the National Alzheimer's Coordinating Centre. Deng and Wang [8] proposed a model that provides three distinct techniques for determining accuracy and recommended a better strategy. He employed the SVM (support vector machine), random forest, and CNN (convolutional neural networks) algorithms, all of which were trained using shortest path length (SPL) functions. The three models had accuracies of 90%, 95%, and 90%, respectively. Abed *et al.* [9] A transfer learning strategy is used in the proposed methodology to construct multivariate deep neural network (DNN) model for reliable Alzheimer's disease functional-magnetic resonance imaging (fMRI) identification. Visual geometry group (VGG19), Inception V3, and residual network (ResNet50) are three DNN models used to categorise individuals with AD (Alzheimer's disease), MCI (mild cognitive impairment) and CN (cognitively normal). VGG19 obtained 90% accuracy after only 15 epochs, Inceptionv3 reached 85% of accuracy and ResNet50 achieved 70% of accuracy after only 15 epochs. Hussain *et al.* [10] The study develops a 12-level CNN binary classification model that can be used brain MRI data to detect Alzheimer's disease. The open access series of imaging studies (OASIS) dataset was used to train this model. In this the current CNN pre trained models are evaluated four metrics accuracy, recall, receiver operating characteristic (ROC) curve and F1 score. This model is more accurate other than CNN models that use this data set, with a score of 96.75%. Basaia *et al.* [11] developed CNN-based deep learning model to predict MCI using a single structural brain MRI scan (c-MCI). To train the models, the researchers used 3D T1-weighted images from the Alzheimer's disease neuroimaging initiative (ADNI) and non-ADNI datasets. This model achieved 95% of accuracy on the ADNI dataset and 96.35% of accuracy on the non-ADNI dataset. Doshi *et al.* [12] to identify between AD, moderate cognitive impairment (MCI), and cognitively normal people, it proposed a novel ensemble of classification algorithms in a hybrid deep learning architecture (CN). The OASIS dataset was used to train this model, and it outperformed some previous approaches in terms of accuracy. Suresha and Parthasarathy [13] This system uses a variety of feature extraction techniques to categorise data. As per this, the sherlet transform (ST) include extraction approach conveys better outcomes for the discovery of Alzheimer's illness than different strategies for the ST highlight extraction approach, which depended on a comparison study with other component extraction techniques. Using the ST+K-nearest neighbor (KNN) technique, the proposed diagnostic tool had a 94.54% accuracy rate. Jain *et al.* [14] An adjusted Adam optimizer and a profound brain network were utilized to arrange the images as normal, AD, and MCI, separately. Using a directional gradient histogram, the feature extraction accuracy was 96.5%.

2. METHOD

The proposed technique weight-randomizes concatenated deep features from the cycle generative adversarial networks (CycleGAN), MobilenetV2, and DenseNet121 networks to provide a reliable diagnosis of Alzheimer's disease. We constructed the models using the implementation from augmentation. The model architecture is shown in Figure 2. The original dataset was divided into four classes, one for each label and

then matched at random. Each of the CycleGAN models were trained using data from a different MRI slice. Each model was trained for 50 epochs with a batch size of 1, as indicated in the CycleGAN. In order to establish a balanced dataset, the trained model was used to generate enough samples. The actual dataset consists of 6,400 images. We generated 40% of images for every class by using CycleGAN based Data augmentation technique.

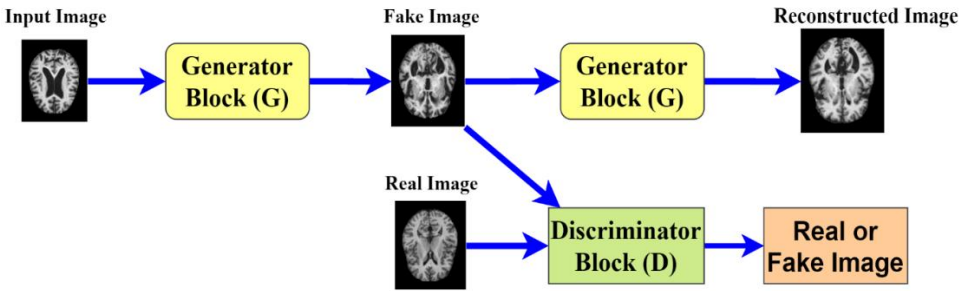

Figure 2. Architecture of CycleGAN

The architecture of CycleGAN has two parts: a discriminator (D) that distinguishes between actual and created images and a generator (G) that generates images to deceive the discriminator. G:X->Y and F:Y->X are two mapping functions in our technique, together with adversarial discriminators Dy and Dx. Calculated the adversarial loss for two mapping functions G and F is given in (1) and (2).

$$loss_{adv}(G, D_y, x) = \frac{1}{m}\sum_{i=1}^{m}\left(1 - D_y(G(x_i))\right)^2 \quad (1)$$

$$loss_{adv}(F, D_x, y) = \frac{1}{m}\sum_{i=1}^{m}\left(1 - D_x(F(y_i))\right)^2 \quad (2)$$

applied cycle consistency loss for two mapping functions G and F is given in (3).

$$loss_{cycle}(G, F, X, Y) = \frac{1}{m}\sum_{i=1}^{m}\left[[F(G(x_i)) - x_i] + [G(F(y_i)) - y_i]\right] \quad (3)$$

By combining these loss terms and weighting the cycle-consistency loss by a hyperparameter λ, we can now generate the entire objective function.

$$Loss_{full} = Loss_{adv} + \lambda\, Loss_{cycle} \quad (4)$$

The Final optimization of a CycleGAN is done using a joint loss function for D and G is given in (5).

$$Min_G Max_D Y(D, G) = E_{p\sim s_{data}}(P)\,[\log D(p)] + E_{r\sim s_r}(R)\left[\log\left(1 - D\left(G(r)\right)\right)\right] \quad (5)$$

Where F, G are generators and D is a discriminator, $E_{p\sim s_{data}}(P)\,[\log D(p)]$ is logarithmic probability of D to predict the real-world data. $E_{r\sim s_r}(R)\left[\log\left(1 - D\left(G(r)\right)\right)\right]$ is the logarithmic probability that G generated data is fake data, r represents random noise as input, p is a real example and s denotes probability distribution.

2.1. Dataset description

Alzheimer's MRI images dataset is available in Kaggle.com. This dataset contains 6,400 images, which are divided into four classes named mild-demented, very mild-demented, non-demented and moderate-demented [15]–[18]. CycleGAN data augmentation increased dataset to 20,926 images. The functionality is then distributed across the 70% train dataset and the 30% test dataset. Balanced multi-class data is prepared for classification using CycleGAN data augmentation for classes with fewer images to balance with other classes. It shows in Table 1. The dataset after pre-processing shows in Figure 3.

Table 1. Splited four classes MRI image dataset for training and testing

Train/test	Classification	No of images	Total	Percentage
For training	Non-demanted	3,788	14,648	70%
	Very mild-demeted	3,700		
	Mild-demented	3,600		
	Moderate-demented	3,560		
For testing	Non-demanted	1,629	6,278	30%
	Very mild-demeted	1,600		
	Mild-demented	1,569		
	Moderate-demented	1,480		
Total			20,926	

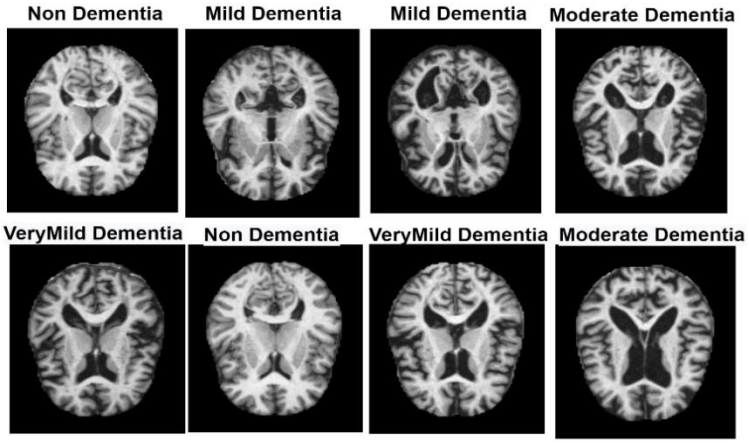

Figure 3. After pre-processing four classes dataset

Figure 4 depicts the flow of proposed methodology. The data comes from the training data set and is then used to feed the models. The data is then trained and tested to ensure that the testing accuracy is achieved. The sick image is extracted from the data set after the accuracy is compared. i.e., 4 classes: mild-demented, moderate-demented, non-demented and very mild-demented.

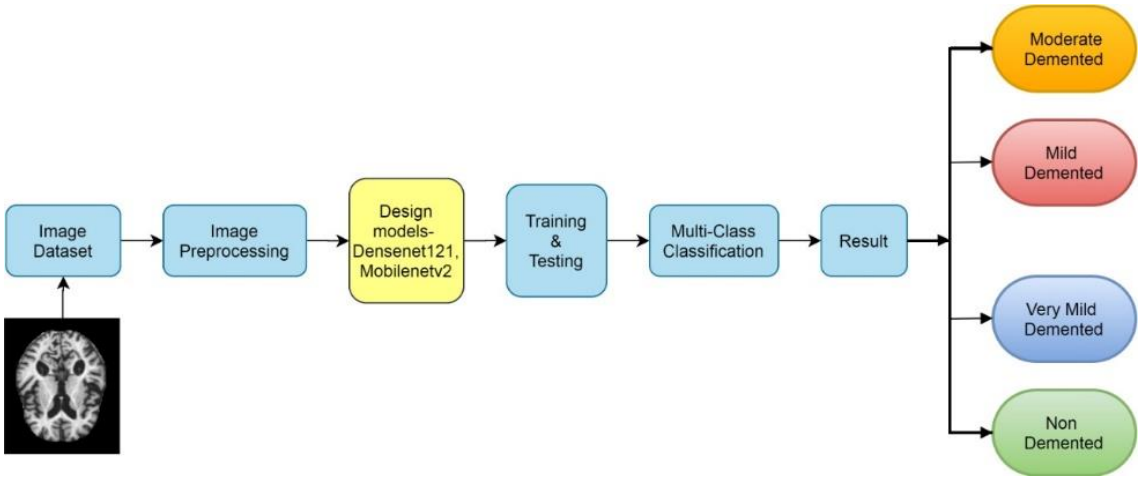

Figure 4. Flowchart for proposed methodology

2.2. DenseNet121

DenseNet121 is a feed-forward network architecture in which each layer is connected to every other layer directly. It has four dense blocks, three transition layers, and 121 layers in total, as shown in Figure 5. (1-classification, 3-transition, and 117-conversion).

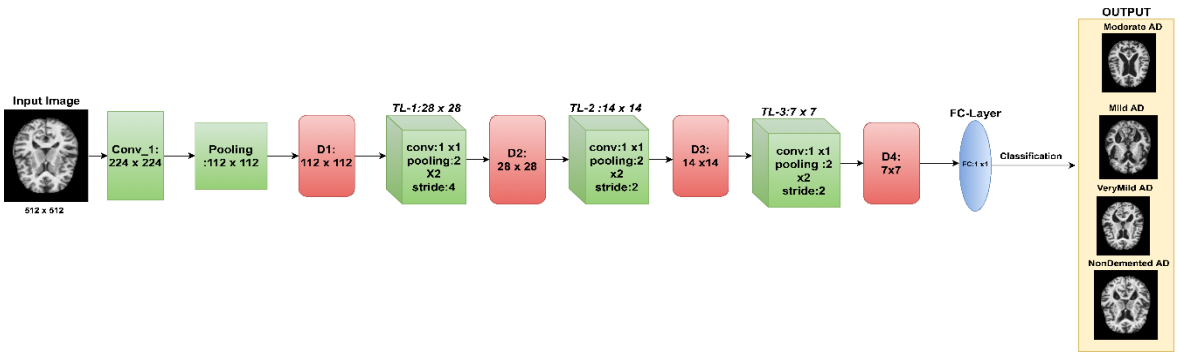

Figure 5. Proposed DenseNet121 model basic architecture

2.2.1. Dense block

Dense block is crucial block in the DenseNet121 system. It improves information flow between layers. Batch normalization, ReLu (rectified linear unit) and convolution are the components. The precise equation is given in (6).

$$x_1 = H_1([x_0, x_1, \ldots\ldots, x_{l-1}]) \quad (6)$$

The concatenation of the feature maps produced in layers is denoted by $[x_0, x_1, \ldots\ldots, x_{l-1}]$. 0, 1,..n, l-1, H1(.) is defined as a composite function of three operations on the l^{th} layer input [19].

2.2.2. Transition layer

Transition layer is to adjust the size of feature maps by being put between two dense blocks. There is a batch normalization, ReLU convolution 1×1 and average pooling layer 2×2 included. Convolution is the process of obtaining features from the output of the preceding layer and analysing them. All of the returned features shared to convolution kernel, commonly known as a filter, with a set of weights [20]–[23]. The weight values must be passed through an activation function to increase their nonlinearity (such as ReLU or sigmoid). The process of convolution can be described in (7).

$$Z^l = W^l . f_1\left(z^{(l-1)}\right) + b^l \quad (7)$$

The activation function is $f_1(.)$ and Z^l is the state of the lth layer neuron. The weight matrix and bias from (l-1) th to l^{th} are represented by W^l, b^l.

2.3. MobileNetV2

MobileNetV2 is a CNN architecture that should work well on mobile devices. It is based on an inverse residual structure with residual links between the bottleneck layers. The extended middle layer uses lightweight depth convolution to filter features with non-linear sources. The MobileNetV2 design contains a full convolutional layer with 32 filters and 19 bottleneck layers [24]-[27]. In Figure 6 shows the proposed architecture.

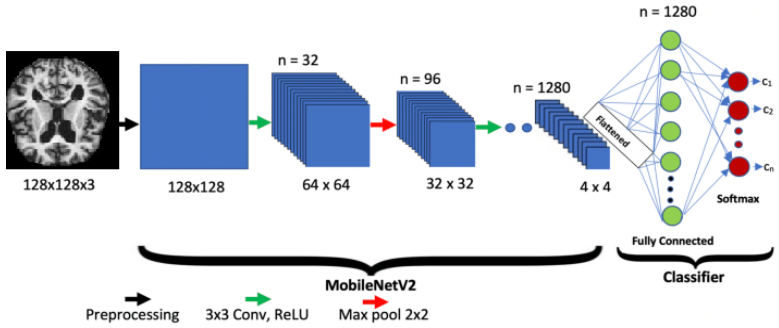

Figure 6. Proposed MobileNetV2 model basic architecture

MobileNetV2 has two distinct sorts of blocks. The first is a 1 stride length residual block, while the second is a 2-stride length block to lower the size. Both block types have 3 layers each. The first layer this time is a 1×1 ReLU6 convolution. The depth convolution layer comes next. Another 1×1 convolution, but this time with no non-linearities, makes up the third layer. According to the argument, if ReLU is applied again, the deep network will only have the power of a linear classifier in the non-zero volume portion of the output domain.

3. RESULTS AND DISCUSSION

We examined 7 models in this study, each on the same dataset. Alzheimer's disease detection model detects the accuracy of MRI image. In data augmentation techniques we used the CycleGAN. Actually, the original dataset consists of 6,400 images for four classes. By using CycleGAN, we increased the images to 20,926 and each class contains 5,231 images and get a balanced dataset for all classes. The network is trained from scratch on 50 data epochs of 314 batches each. All experiments are performed by splitting the data 30% as test data and 70% as training data. 15% data from train set is used in validation set. We achieved the following results for the DenseNet121 model and MobilNetV2: training and testing accuracy was 97.16%, 98.03% and overall accuracy was 98.88% for DenseNet121. Similarly, the MobileNetv2 model have training and testing accuracy was 97.03%,97.12% and overall accuracy was 98.23%. We compare the performance of multi-class classification with a variety of common transfer learning architectures. Among the several models experimented in our research, DenseNet121and MobileNetV2 has got best accuracy. When compared to the existing models in Table 2, our proposed work models, DenseNet121 and MobileNetV2, have a higher accuracy of 98.88% and 98.02%, respectively. In Figure 7 it depicts the graphical representation of comparative results.

Table 2. Comparative results of Alzheimer's disease MRI images multi-class classification

S.NO	No. of Epochs	Models	Training accuracy	Validation accuracy	Testing accuracy
1	50	CycleGAN+DenseNet121	97.16	98.03	98.88
2	50	CycleGAN+mobileNetV2	97.03	97.12	98.23
3	50	Resnet152	91.64	93.87	96.28
4	50	Resnet50	91.5	93.13	96.06
5	50	GoogleNet	91.3	92.18	95.21
6	50	VGG19	90.05	91.45	94.32
7	50	VGG16	89.56	91.06	93.32

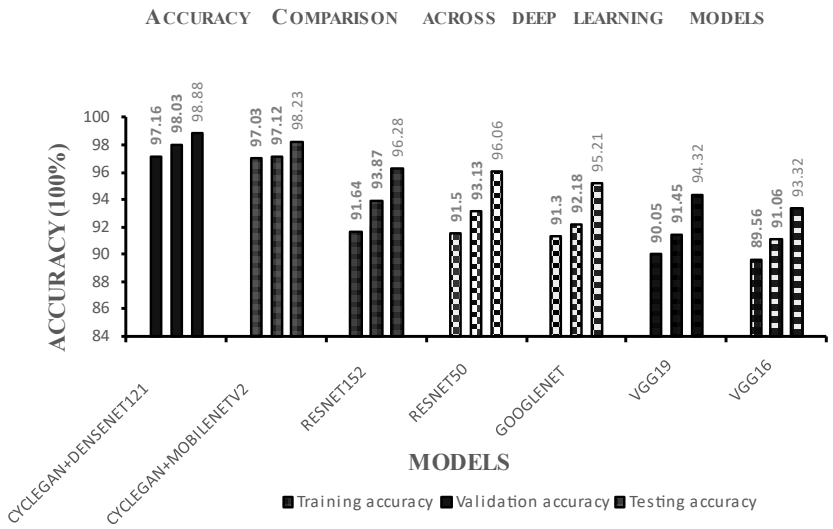

Figure 7. Graphical representation for comparative results of Alzheimer's disease MRI images

4. CONCLUSION

We presented a convolutional network-based framework for the classification of structural MRI images for the diagnosis of Alzheimer's disease. In this paper define promising solutions for detection of

disease in the early stages. Here we used DenseNet121 and mobileNetV2 models for disease classification. We used CycleGAN for image augmentation. The network was trained and tested using DenseNet121 and MobileNetV2 deep models. The results of both models outperformed all other methods in the literature regarding multiclass classification. By using the model DenseNet121 we achieved 98.88% accuracy and for MobileNetV2 we achieved 98.02% accuracy. Our proposed models achieved highest accuracy compare to the existing Models. The network was trained and tested using deep models DenseNet121 and MobileNetV2 models. The results of both models outperformed all other methods in the literature regarding multiclass classification. The proposed approach improves the classification accuracy by about 2%. Compared to most existing tasks. A performance improvement in a particular class is achieved by improving the performance of all classes as well. It shows the potential to integrate deep models directly from scratch to learn features distinct from neuroimaging data, and is of great importance for medical and neuroimaging processing. Future work may include integrating patient clinical data with imaging data and creating more robust systems using multimodal data.

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