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Generative Data Augmentation and ARMD Classification

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Abstract: Age Related Macular Degeneration (ARMD) is a type of eye disease which normally have an effect on the central vision of a person. This Disease might sometimes lead to permanent vision loss for some people. It affects the people over the age of 50. So, basically there are 2 different types of ARMD i.e., Dry and Wet. Dry ARMD will generate a tiny amount of protein deposits called drusen, whereas Wet ARMD occurs whenever any abnormal blood vessel is developed under the retina, so sometimes this blood vessels might leak blood fluid, this type of ARMD is very severe and can even lead to permanent central vision loss. Therefore, it is necessary for early detection of the disease. Generative Data Augmentation for ARMD Classification is deep learning based which uses Convolutional Neural Network (CNN) model for generating images to accurately identify the disease.

Deep Learning Diagnostic models require expertly graded images from extensive data sets obtained in large scale clinical trials which may not exist. Therefore, (Generative Adversarial Networks) GAN-based generative data augmentation method called Style GAN is used for generating the images. Generative deep learning techniques is used to synthesize new large datasets of artificial retinal images from different stages of ARMD using the images from the already existing datasets. The performance of ARMD diagnostic DCNNs will be trained on the combination of both real and synthetic datasets. Images obtained by using GAN appear to be realistic, and increase the accuracy of the model. It then continues with classifying the retinal images into one of the three classes i.e., dry, wet or normal using CNN model. It also compares the accuracy against the model with traditional augmentation techniques, towards improving the performance of real-world ARMD classification tasks.
Keywords: Age-Related Macular Degeneration, Deep Learning, Generative Adversarial Networks.

I. INTRODUCTION

Age-related macular degeneration (ARMD) is the most common cause of severe vision loss in elderly persons in developed countries and accounts for one-third of cases of untreatable vision loss. ARMD is a painless, irreversible, degenerative eye condition associated with the damage and ultimate death of photoreceptors. There are two types of ARMD, dry and wet; dry ARMD is far more common, but wet ARMD is usually a more advanced disease state and is associated with rapid distortion and sudden loss of central vision. Various agents are used for treatment, and lifestyle changes and dietary constituents are important for preventing ARMD and halting its progression. As new therapies become available, early identification of patients with risk factors for ARMD will be increasingly important. On the same note, retinal fundus images are exceptionally valuable source of information for ophthalmologists to be able to recognize retina problems.

As prevention is better than cure, early detection could improve the chances of cure and be able to prevent blindness. Retinal problems like diabetic retinopathy and retinitis pigmentosa can be diagnosed using retinal fundus images by medical experts. In the most recent times, machine learning research is going on for diagnosing diseases like diabetic retinopathy [6], glaucoma by extracting features and then classifying the image. Researchers are trying to come up with the optimal ways of being able to automatically classify retinal problems from those of the healthy ones with the help of feature extraction. But most importantly, to be able to classify retinal fundus images accurately, a decent size of the dataset is necessary. When the dataset size does not match with the user requirements, generation of more images is needed. Hence the usage of Generative Adversarial networks became necessary.

Generative Adversarial Networks (GAN) are powerful classes which consist of generative model and discriminator model. Generative models generate realistic images that are hard to differentiate from real images. Using Generative adversarial networks, the dataset that is currently being used could be increased as it synthesizes fake images that are very hard to separate apart from the actual images.

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II. LITERATURE SURVEY

1) Neural Networks and Deep Learning: A neural network comprises several key elements that work together to process information and make predictions. These include neurons, which act as functions that receive input from the preceding layer and generate an output in the form of a binary value. The input layer and its neurons receive input data, while hidden layers contain numerous neurons that process the input and transmit it to the output layer. Synapses connect the neurons and layers to allow the flow of information within the network. The complexity and depth of the neural network depend on the number of hidden layers, and the amount of input data required to solve a problem increases with network size.
2) Generative Adversarial Networks: A generative adversarial network [1], also known as a GAN. It is an unsupervised deep learning framework that can learn from a set of training data and produce new images [2] that shares same properties as training data.
   Two neural networks comprise a generative adversarial network:
   a) Generator: which learns to generate realistic fictitious data from a random seed The generator's fake examples are used as negative examples to train the discriminator.
   b) Discriminator: which learns to distinguish between fake and real data The discriminator penalizes the generator if it produces implausible results.

   Both the Generator and Discriminator work opposite to each other to make themselves learn about the image accurately and try to predict it real or fake [3].
3) Style GAN: Style GAN is a type of adversarial generative network. It borrows from the style transfer literature and employs an alternative generator architecture for generative adversarial networks, specifically adaptive instance normalization. Otherwise, it is like Progressive GAN in that it employs a progressively increasing training regimen.
4) Convolutional Neural Networks: They have three layers, they are: Convolutional layer, Pooling layer Fully connected layer. Convolutional layer, which serves as the primary building block and performs the bulk of the computation. The feature detector, also known as a kernel or filter, plays a crucial role in this layer, as it scans the receptive fields of an image to identify specific features. By applying the filter to different areas of the image, a dot product is computed between the input pixels and the filter. This process generates a feature map, activation map, or convolved feature matrix multiplication, which is the output obtained by convolving the input with the filter in a convolutional neural network."

III. METHODOLOGY

The set of principles, practices, and procedures that guide the way research, investigations, or analyses are carried out. It includes concepts relevant to a branch of science and the conceptual study of the body of methods.

A. Architectural Design

Architecture is defined as the art of constructing the basic design of a software system. Architectural design is the process of creating a plan or blueprint for the construction or renovation of a structure.

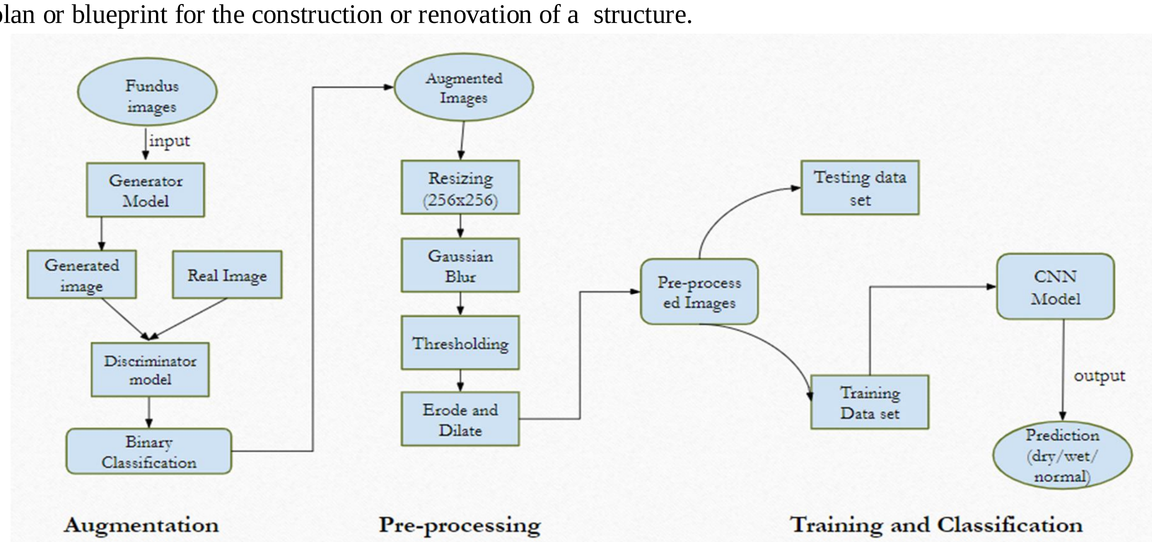

Fig: 3.1 Architectural Design

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B. Modules

1) Dataset

The dataset in the project was collected from a private repository and consist of two classes of images each class consists of 50 images each, Dry and Wet. Along with these two classes, we have also used No ARMD/Normal people eye dataset combined with other two classes. Below are some sample images of 3 classes.

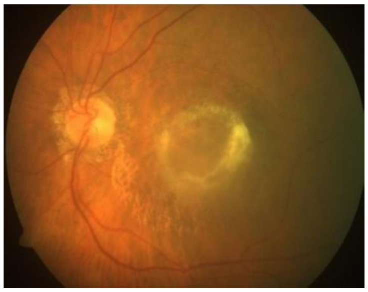
Figure 4: Dry ARMD


Figure 5: Wet ARMD


Figure 6: Normal Retina

2) Algorithm-1 (AUGMETATION)

Generator and Discriminator Models:

Generative Adversarial Networks (GAN) [4] constitutes two models- generator and discriminator. Both generator and discriminator models should be trained using training data. Discriminators are trained using 100% real and 100% fake images. Generator is trained using discriminator loss. Error of the discriminator is back propagated, and the generator model is updated. Initially, the dataset is divided into various batches. The generative adversarial network model is trained using these batches one after the other.

First, the discriminator model is trained with 100% real examples. Then 100% fake samples are generated using the generator model and discriminator is trained using these 100% fake samples. After the completion of this step, discriminator model is completely trained with both real and fake samples. Next, calculate discriminator loss and update the weights of generator model by back propagating the error. The backpropagation steps will see a large error and will update the model weights accordingly. This makes the generator model better at generating good samples. Weights of the discriminator model are marked as not trainable while updating the generator model. After every 7 epochs, a summary of the model is displayed.

Summary of the model contains the Fréchet Inception Distance (FID) metric and this value is analyzed. A point should be reached where FID metric value is as minimum as possible. This is the point where error rates of both generator and discriminator are equal. An equilibrium is established when the discriminator model cannot distinguish a real sample and the sample generated by the generator.

3) Data Pre-Processing

The process of cleaning data that are taken from different sources and converting it to a meaningful and understandable format. Hence, there are several steps that dataset into meaningful way, where our model can understand like resizing, gaussian blur[8], thresholding, dilating, and eroding.

4) Algorithm-2(CNN)

Convolutional neural network

CNN model [5] is created using 23 layers they are ---3-convolution layers, 4-batch_normalisation layers, 5-activation layer,3-max_pooling layers, 4-dropout layer ,3-dense layers, 1-flatten layer.

C. Comparison of Traditional Augmentation and GAN Based Augmentation

Deep learning models [8] perform better when they are trained with a considerably large dataset. Hence it is advisable to generate new images when the size of the dataset is small. Generative Adversarial Networks (GAN) is an algorithm that generates new images altogether. Data augmentation techniques or Traditional augmentation techniques [9-11] just modify the existing dataset, they do not contribute more to the betterment of the model. Even though Generative Adversarial Networks (GAN) takes more time, it is a powerful model. It is gaining popularity due to its ability to create new images.

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IV. RESULTS AND DISCUSSIONS

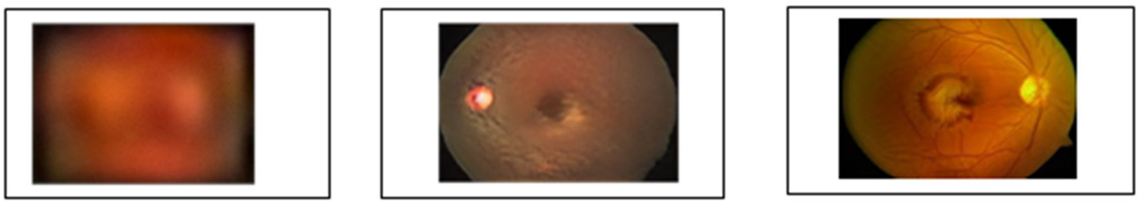
A. GAN

GAN model is evaluated based on FID value. This value between real and fake images should be close to zero.

We have trained the generator model for about 7-8 times with a learning-rate of 0.0025 and a batch-size of 16 for each class of dataset i.e., dry, wet, and normal and achieved the following FID metric values for each class

Wet -> 70.2618
Dry -> 70.5584
Normal -> 77.9778

Below are the sample of generated images at different FID values



fid: 336.3059 fid: 164.976 fid: 70.261

Figure 18 : Sample image generated from network snapshot 000196

B. Experiment Results

```
Epoch 1/15
301/301 [==============================] - ETA: 0s - loss: 0.0184 - accuracy: 0.9952
Epoch 1: val_accuracy improved from -inf to 0.89970, saving model to C:\ARMD-major/model\weights-best-01-0.90.hdf5
301/301 [==============================] - 365s 1s/step - loss: 0.0184 - accuracy: 0.9952 - val_loss: 0.2996 - val_accuracy: 0.8997
Epoch 2/15
301/301 [==============================] - ETA: 0s - loss: 0.0229 - accuracy: 0.9937
Epoch 2: val_accuracy improved from 0.89970 to 0.96108, saving model to C:\ARMD-major/model\weights-best-02-0.96.hdf5
301/301 [==============================] - 367s 1s/step - loss: 0.0229 - accuracy: 0.9937 - val_loss: 0.1233 - val_accuracy: 0.9611
Epoch 3/15
301/301 [==============================] - ETA: 0s - loss: 0.0126 - accuracy: 0.9957
Epoch 3: val_accuracy did not improve from 0.96108
301/301 [==============================] - 366s 1s/step - loss: 0.0126 - accuracy: 0.9957 - val_loss: 0.9213 - val_accuracy: 0.7769
Epoch 4/15
301/301 [==============================] - ETA: 0s - loss: 0.0227 - accuracy: 0.9923
Epoch 4: val_accuracy did not improve from 0.96108
301/301 [==============================] - 365s 1s/step - loss: 0.0227 - accuracy: 0.9923 - val_loss: 0.4171 - val_accuracy: 0.8698
```

Figure 22: CNN Model Output

```
1/1 [==============================] - 0s 64ms/step
```

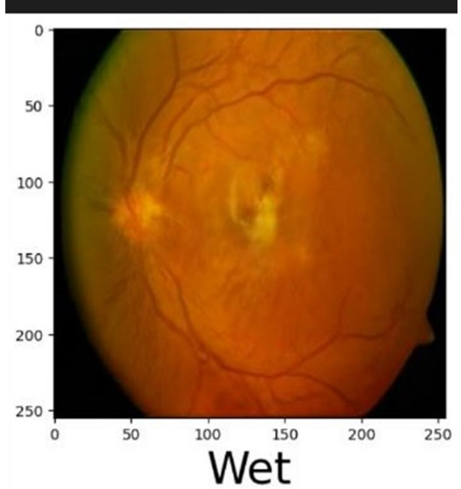


Figure 23: Classifying New Image

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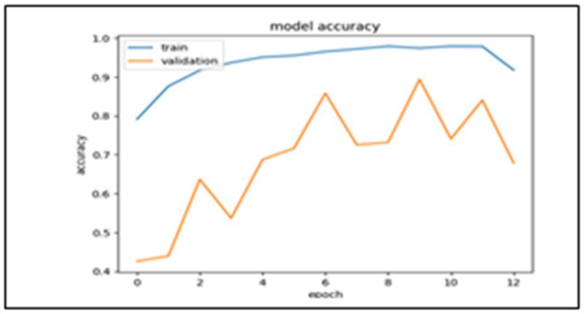

Figure 24: Model Accuracy Figure

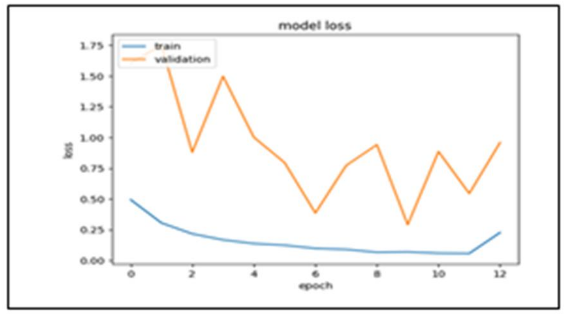

Figure 25: Model Loss

C. Comparison between classification of images GAN Technique and Traditional Augmentation

Table 1: Comparison between classification of images generated using GAN and Traditional Augmentation

	Dataset set size	No: of epochs	Validation Accuracy	Validation loss
Traditional technique	2000	40	0.92	0.215
GAN technique	2000	40	0.96	0.123

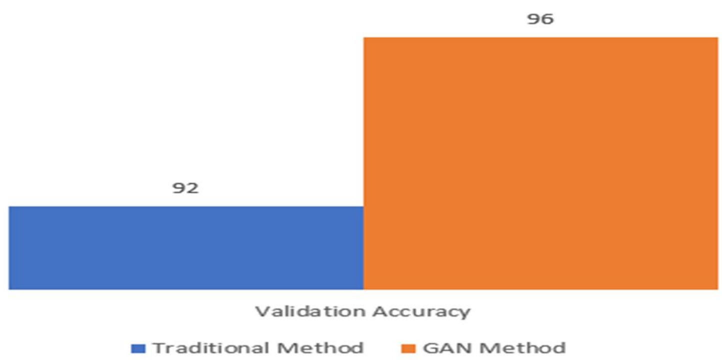

Figure 26: Validation Accuracy Comparison

V. CONCLUSION

This research focused designing Age related Macular Degeneration prediction which require descent amount of data is acquired using Style GAN on given dataset. Synthesized images dataset is then prepared by selecting the images at some random snap seed value and save into a folder. This step is followed for every class (Dry, Wet, Normal).

Later these images were combined and used for classification using CNN model and acquired 96 percentage of validation accuracy.

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