ISSN 2278-3091
Volume 12, No.3, May - June 2023
International Journal of Advanced Trends in Computer Science and Engineering
Available Online at http://www.warse.org/IJATCSE/static/pdf/file/ijatcse021232023.pdf
https://doi.org/10.30534/ijatcse/2023/021232023

Diabetic Retinopathy Classification using Transfer learning

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Received Date April 14, 2023 Accepted Date: May 17, 2023 Published Date: June 06, 2023

ABSTRACT

Diabetic Retinopathy (DR) is an eye illness that impacts individuals who have diabetes and damages their retina over time, eventually causing blindness. Due to lesions in the retina that are formed because of retinal blood vessel rupture, it impairs vision and, in the worst-case scenario, results in severe blindness. To prevent severity and to lessen challenges in identifying tiny lesions throughout the disease's advanced stages, it is now crucial to diagnose the condition early as, it manifests itself without any symptoms. Even ophthalmologists find it challenging and time-consuming to identify this condition. Early DR case identification and classification is essential for delivering the required medical care.

This study proposes applying deep learning techniques to detect DR in retinal fundus images. The data acquired for this process may be incomplete and imbalanced. Data augmentation balances the data and increase the quantity of retinal images. As deep-learning algorithms need more data to process, DCGAN Augmentation technique is employed. The CNN (Convolutional Neural Network) methods, specifically the VGG16 and DenseNet121 architectures, are employed for DR early detection in order to let patients to receive therapy at the appropriate time..

Key words : Deep Learning, Diabetic Retinopathy, Data Augmentation ,DR Detection, DR Classification.

1. INTRODUCTION

The eye's anatomy is intricate. Changes in the eye's primary structure may affect the eyes and nearby structures. Over 93 million people worldwide including 17.6% of Indians, have symptoms, making it difficult to administer a timely and efficient course of treatment. Therefore, early medical intervention is necessary for detection.

To identify DR by the presence of lesions linked with the vascular anomalies brought on by the disease, an ophthalmologist or other trained physician must view and assess digital colour retinal images. This is time-consuming and laborious process. The automated DR screening approach will hasten the detection and decision-making processes, aiding in the management or control of DR advancement. Using CNN models like VGG16 (Visual Geometry Group 16) and DenseNet 121, this method proposes an automatic classification system that evaluates fundus images with different illumination and fields of view and classifies them into normal and abnormal. Figures 1 and 2 below depict a normal retina and a retina damaged by diabetic retinopathy, respectively.

Figure 1: Normal Retinal image

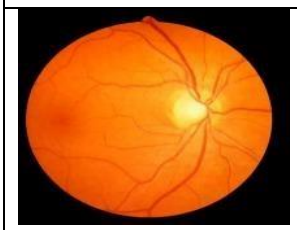
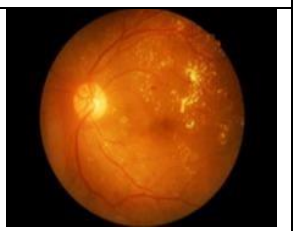


Figure 2: Image of retina affected with Diabetic Retinopathy



There is a dataset size limit in medical imaging due to issues with privacy and annotation costs. To train the models for image segmentation, detection, and classification, enormous amounts of data are required. The process of annotating medical images is quite expensive and time-consuming, and it

produces a very tiny set of clinical image data for tasks involving image classification. Most frequently, data augmentation is used to increase the quantity of the data, which also prevents overfitting in cases where there is a lack of data. In certain cases, the dataset size is increased by using conventional data augmentation approaches. Although there is no assurance that it will be advantageous in the domains with insufficient data, particularly the clinical image data, and it may lead to more overfitting. In the proposed work, the Deep Convolutional Generative Adversial Network (DC-GAN)[1], a contemporary data augmentation method, is demonstrated. This process creates synthetic medical images.

VGG16, Densenet121 are used for classification of retinal images into DR and no DR which are primarily based on CNN Architecture. The architecture of convolution neural networks (CNNs) dictates the network's performance. The convolution layer, the pooling layer, and the fully linked layer are all part of it. Three layers are involved in this process: a feature extractor (the first two) and a classification layer (the third). Convolutional features are reduced in dimension thanks to the pooling layer. The feature extracted by the fully connected layer is then used by softMax to classify the images. The learnable filters in the convolution layer retrieve the information from the input image. The two-dimensional feature map is created by taking the dot product of each filter with the raw picture pixel in a sliding window. The ReLU is one of the most common activation functions. Feature maps can be reduced by using "max pooling," a subsampling layer. It's then possible to connect each feature map to the completely connected layer. Using softMax, each class is assigned a decimal probability [2].

2. RELATED WORK

Many studies have been published recently for the identification and classification of DR, which were helpful in treatment [3]. There are numerous machine intelligence techniques that use mathematical morphology, fuzzy C-means clustering, SVM, image processing algorithms etc. [4].

Attila Budai, and et.al proposed Multi scale Blood Vessel Segmentation in Retinal Fundus Images in 2010[5]. The proposed algorithm starts by extracting the midline pixels of the blood vessels. The final segmentation is obtained by an iterative region growing method that combines the binary images obtained from the midline detection part with the image obtained as a result of the fuzzy segmentation part of the vessel. In this proposed algorithm, the blood vessel is enhanced using modified morphological operations. Noises are removed using Adaptive Fuzzy Switching Median filter from retinal images.

Farrikh Alzami, Abdussalam, Rama Arya Megantara, Ahmad Zainul Fanani proposed Diabetic Retinopathy Grade Classification based on Fractal Analysis and Random Forest in 2019[6]. Fractal dimension is one feature extract that can be used in retinopathy fields because fractal dimension can characterize retinal blood vessels. This paper presented a study based on fractal dimensions, which not only differentiates between healthy and diabetic retinopathy patients, but also severe diabetic retinopathy.

Jingdan Zhang Yingjie Cui, and et.al proposed Blood Vessel Segmentation of Retinal Images Based on Neural Network in 2015[7]. This study proposes a retinal vessel segmentation method based on neural network algorithm. To overcome the problem of low contrast and large variability in retinal images, and construct the feature vector with the intensity from green channel and the vessel enhanced intensity feature. Then, classify the pixels in retinal image with SOM algorithm. Finally, label each neuron in the output layer of SOM as retinal neuron or non-vessel neuron with Otsu's method, and get the final segmentation results.

Morium Akter,Mohammad Shorif Uddin, Mahmudul Hasan Khan proposed Morphology-based exudates detection from color fundus images in diabetic retinopathy in 2019[8]. This paper presents a morphology-based method for the detection of diabetic retinopathy using fundus discharge in color images.

Muhammad Moazam Fraz, and et.al proposed An Ensemble Classification-Based Approach Applied to Retinal Blood Vessel Segmentation in 2010[9]. In this paper, they have presented an effective retinal vessel segmentation technique based on supervised classification using an ensemble classifier of boosted and bagged decision trees.

P. Leela Jancy, B. Latha proposed Deep Learning Techniques for Diabetic Retinopathy Diagnosis using Optical Coherence Tomography in 2022[10]. This article reviews deep learning methods that have been used over the past four years to detect diabetic retinopathy in optical coherence tomography. Segmentation of optical coherence tomography images into retinal layers using deep learning methods is also being investigated. The features used in the classification of diabetic retinopathy are also reviewed.

R. Priya and P. Aruna suggested Diagnosis of diabetic retinopathy using machine learning techniques in 2013[11]. To classify the segmented regions into exudates and non-exudates, an artificial neural network classifier was investigated. The DR has been classified into two categories NPDR and PDR using PNN, Bayes theory and SVM.

M. Seetha, N.Kalyani and Y Sravani devi suggested An Ensemble CNN Model for identification of Diabetic Retinopathy Eye Disease in 2022[12]. This paper is emphasized on the development of a robust and efficient classification model of ensemble CNN to identify the prevalence of diabetic retinopathy from the retinal images and suggest appropriate interventions at an early stage.

Yerrarapu Sravani Devi, Singam Phani Kumar suggested A deep transfer learning approach for identification of diabetic retinopathy using data augmentation in 2022[13]. In this paper

a transfer learning model was proposed with data augmentation techniques and gaussian-blur, circle-crop pre-processing techniques combination to identify every stage of DR using Resnet 50 with top layers.

3. METHODOLOGY

Diabetes is a global disease that can cause microvascular composition in the human eye, such as diabetic retinopathy (DR), and can be a major cause of vision loss. The proposed method is promising and efficient compared to previous state-of-the-art approaches, thus reducing the number of misclassifications. The architecture of the proposed system is shown in Figure 3.

To identify DR in the retinal images, this study utilizes VGG16 and DenseNet 121 as classification techniques. The architecture of the proposed system is shown in the figure.

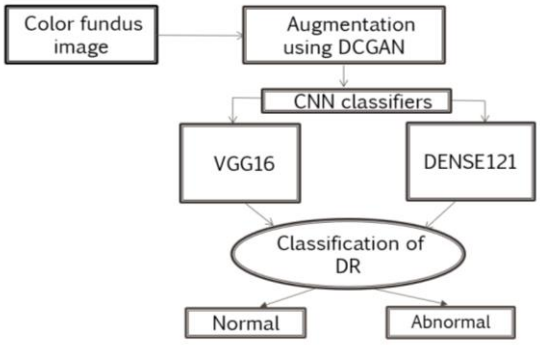


Figure 3: Architecture of the system

DCGAN-based generative data augmentation methods with dynamic input sampling are used to improve real-world diabetic retinopathy classification tasks, and their performance is compared with the image feature transfer technique. The results show that the addition of generative information can significantly improve the classification performance compared to the baseline. After adding the image, two CNN models - VGG16 and DenseNet121 - are used to detect DR. Each model facilitates disease detection by indicating whether the image is normal or abnormal. We then check the accuracy of both models.

4. IMPLEMENTATION

The modules are:

- Dataset Collection
- Pre-processing of Data
- Augmentation of Data
- Classification

4.1 Dataset Collection:

A real-time dataset was collected for this classification to overcome all the shortcomings of existing systems (Table 1). The source of the information is retinal images taken by LVPEI Hospital. The data consists of 415 fundus images of diabetic retinopathy. Fundus images are captured by different cameras on the market, such as Canon, Zeiss, and Kowa, resulting in different image resolutions. Annotations were evaluated by trained readers with quality control.

Table 1: Total number of images: - 415

Types of DR	No. of Images
Normal	208
Abnormal	207

4.2 Pre-processing of Data:

Image preprocessing, such as image resizing, is used to improve accuracy and reliability. Image resizing - Image interpolation occurs when you resize or warp an image from one grid of pixels to another. Image resizing is necessary when you need to increase or decrease the total number of pixels, while resizing can be done when correcting lens distortions or rotating an image. zoom means to increase the number of pixels, so when you zoom in on an image.

Conversion - rgb to gray: For this process, color image is converted to gray scale image by the calculation of average value. that means 3 channels can be converted into single channel.

gray scale to black&white(b/w): in this process, threshold value is calculated using (max+min)/2. then take two conditions for the conversions then convert into array format.

4.3 Augmentation of Data: Deep Convolutional Generative Adversarial Network (DC-GAN):

The detection and identification of eye illnesses like glaucoma, cataracts, and ARMD are just a few examples where deep learning has done well. As deep learning models require enormous amounts of data to analyse, balanced retinal fundus images are produced using the DCGAN architecture. Pre-processing of the data and Data Augmentation Using DCGAN are both included in the suggested application. There are two steps in DCGAN training: (1) Training for discriminator networks; (2) Training for generator networks. The discriminator's primary goal is to accurately identify whether the input image is false or real, and it works to improve the function generator's ability to produce fake images. First, the discriminator is trained to compute log D(x) on a set of original images. Second, a batch of fake images is

created by the generator, and this batch is used to train the discriminator function and determine accuracy. This process is repeated till discriminator network cannot distinguish between real and fake images [2].

4.4 Classification of Diabetic Retinopathy using VGG16:

VGG16 is a 16-layer deep neural network (Figure 4), as suggested by its name. With 138 million parameters in total, VGG16 is therefore a huge network even by today's standards. The convolution layers in VGG16 have the same padding, a 3x3 filter, a stride 1, and a maxPool layer of a 2x2 filter of a stride 2 filter. Throughout the entire architecture, convolution and max pool layers are arranged in the same manner. It has two fully interconnected layers at the very end, followed by a SoftMax for output. Pre-trained weights from the ImageNet database are used to train VGG-16.

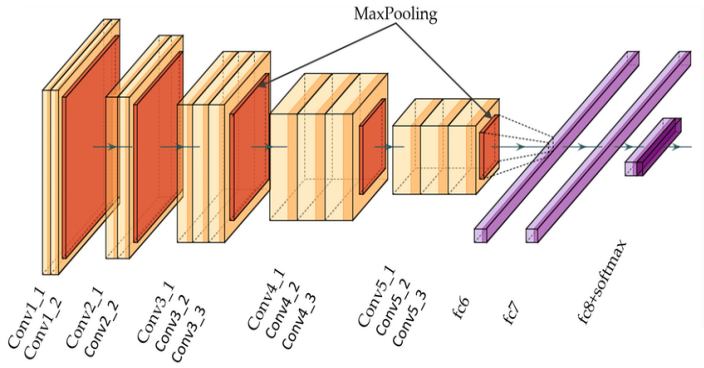


Figure 4: Architecture of VGG16

The dataset is used to retrain the VGG-16 model and fine-tune it in order to get the classifications. It follows that in order to employ the VGGNet as a feature extractor until the final fully connected layers that were fine-tuned in order to meet the number of classes in the dataset, this model falls into the third situation as outlined above. Details of the proposed architecture are displayed. Each of the four convolution layers is followed by a ReLU, Maxpooling, and dropout layer, and then two Fully Connected Layers (FCL) and SoftMax are added on top of that. Although there was a substantial difference in performance, it was still evident. A comparison of the two is included in the findings section[14]

4.5 Classification of Diabetic Retinopathy using DenseNet121:

DenseNet structure (Figure 5) contains dense block, transition layer, convolutional layer, and fully connected layer.Dense block consists of densely connected dense units with nonlinear mapping functions of BN, ReLU, and Conv, which are designed with pre-activation strategy to make network training easier and generalization performance better. Dense unit input is spliced and merged with all outputs of the previous dense units, and new features generated also need to be passed to subsequent dense units, so that shallow features of dense block are repeatedly reused and effectively utilized, which can alleviate gradient disappearance to a certain extent, and a large number of features can be generated with a small number of convolution kernels; final DenseNet model is relatively in scale. Transition layer is the structure between adjacent dense blocks, which consists of convolution and average pooling layer, compressing dense block input and all extracted feature information, reducing feature map size and dimensionality, which can effectively reduce the number of dense block parameters and prevent network from overfitting.

The fully connected layer is classification prediction layer, which reduces the influence of feature location on classification by integrating category feature information in network features, and classifies feature information after weighting. Feature map sizes are the same within the dense block so that they can be concatenated together easily. At the end of the last dense block, global averaging is performed and then SoftMax classification is applied. The error signal can easily be passed to earlier layers more directly. This is a form of indirect depth inspection, as earlier layers can receive direct inspection from the final classification layer. Because each DenseNet layer receives input from all previous layers, richer features and usually richer patterns. The model receives an image and it is determined whether or not she has an eye disease. [15].

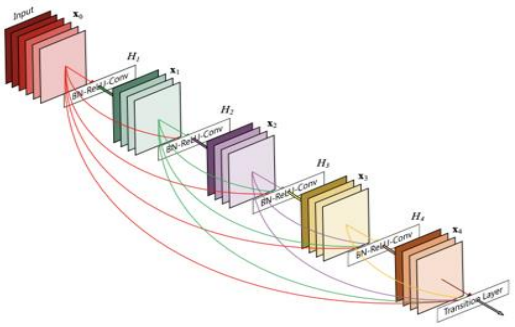


Figure 5: Architecture of Densenet121

5. RESULTS AND DISCUSSIONS

In order to show the generalization ability of the proposed system, the performance of the proposed system is evaluated using the fundus images dataset that is collected from LVPEI Hospital, which consists of several diabetic retinopathies affected retinal images about of 415 images. Results after pre-processing of images by applying Image-resizing and image scaling are shown in Figure 6 & Figure 7.

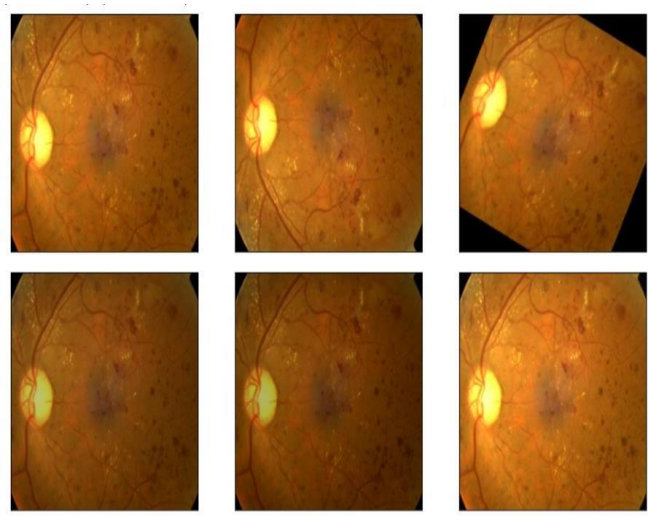


Figure 6:.1 Retinal image after flip and brightness contrast

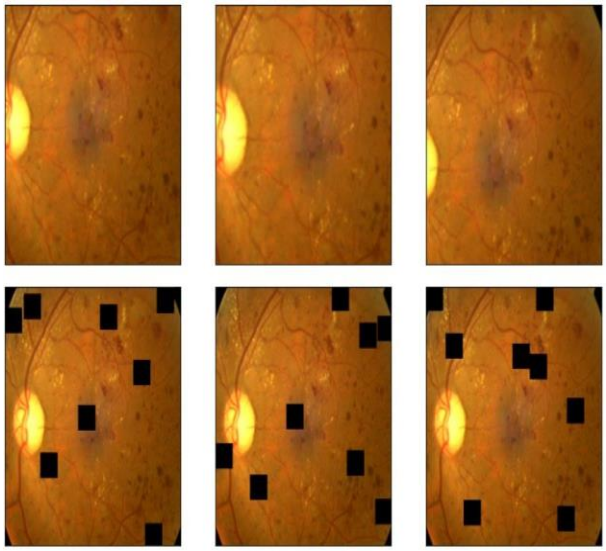
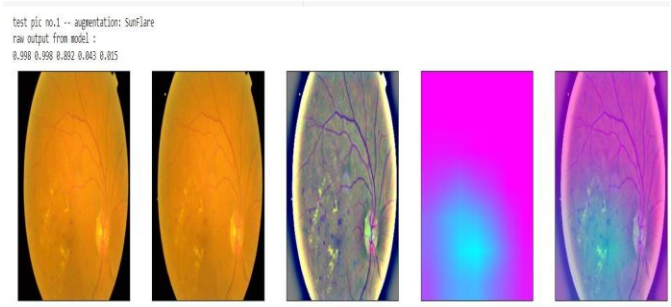


Figure 7: Retinal image after resize

After pre-processing is done the preprocessed images will be given to DCGAN-adaptive generator for augmentation of images in which the number of images will be increased. For every one image DCGAN will produce five augmented images as shown in figure 8.



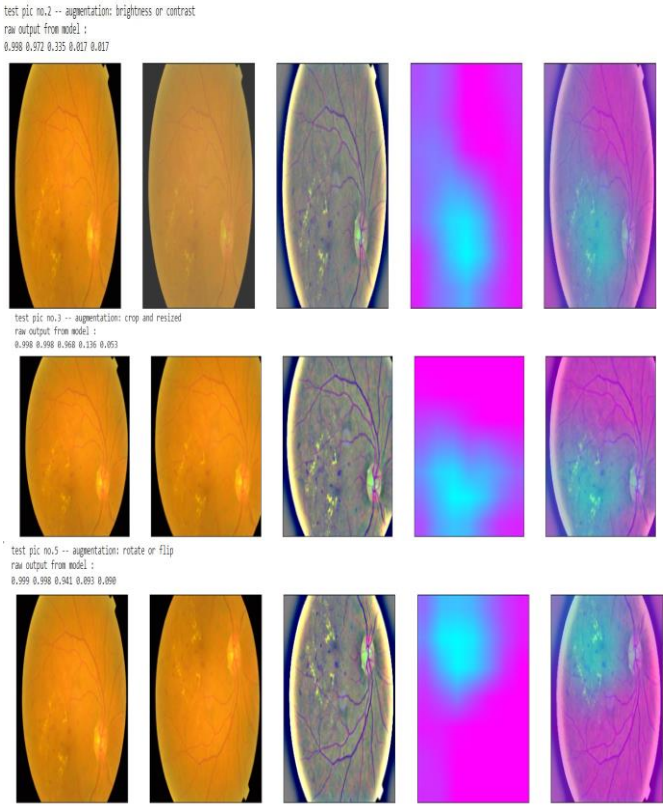


Figure 8: Augmented images from one to five

The pre-processed image after augmentation will be given to VGG16 model and DENSENET121 model for the training. 50 epochs were taken and trained the models.The Accuracy vs no. of epocs graph was shown in Figure 9.

VGG16

val_accuracy: 0.9457

DENSENET121

val_accuracy: 0.7975

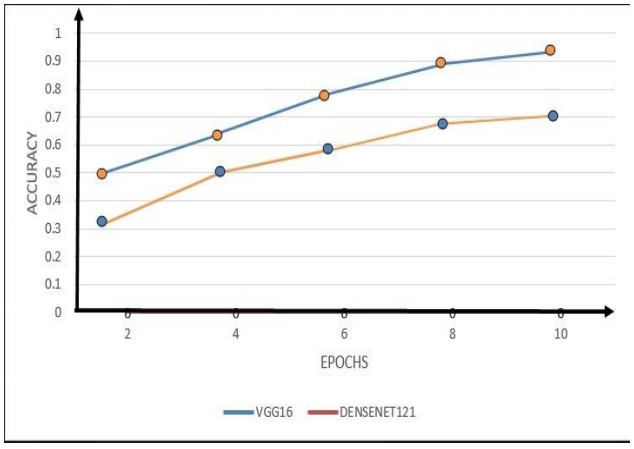


Figure 9: Accuracy graph of VGG16 and Densenet121

As in the proposed system it can be observed that Vgg16 gives 94.57% accuracy and Densenet121 gives 79.75% accuracy. It can be concluded that based on the results obtained by Deep Learning model i.e., VGG16 model of CNN architecture gives better results when compared to DENSENET121 model of CNN architecture. After training, the retinal image classification of disease will be done into normal and abnormal classes (Figure 10).

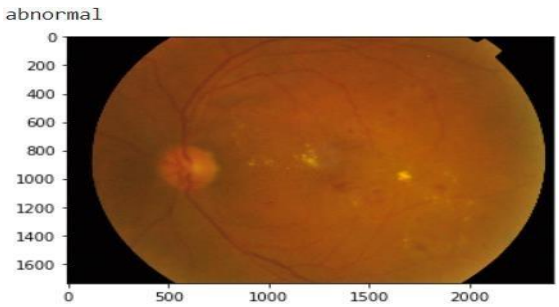


Figure 10: Retinal image classification into normal or abnormal classes

Analysis of Results:

The results of the model are measured using performance metrics such as accuracy, precision and recall.

The accuracy, precision and recall measures remains constant over the 415 images.
The Accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, the proportion of true positive and true negative in all evaluated cases should be calculated.

Mathematically, this can be stated as:

Accuracy = (True Positives +True Negatives) / (True positives + True Negatives +False Positives +False Negatives)

Accuracy=(TP+TN)/ (TP+TN+FP+FN)

6. CONCLUSION

The proposed system focuses on detecting diabetic retinopathy in retinal fundus images using Deep Learning technology. The proposed method has several unique properties. First, the retinal fundus images undergo preprocessing. The data collected may be insufficient and unbalanced. Therefore, Data Augmentation or DCGAN technology is used to balance the data and increase the number of retinal images. Using the VGG16 and DENSENET121 models, the image is divided into two different categories, normal and abnormal. The two architectures are compared at the end to find out which architecture is the best in DR detection. Accuracy is 94.57% for VGG16 and 79.75% for DENSENET121. Therefore, based on the obtained results, it can be concluded that the CNN architecture model VGG16 gives more accurate results than the CNN architecture model Densenet121.

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