Detection of Diabetic Retinopathy Using Deep Learning Models

Syed Vasim Fathima,
Student, waseemfathima1012@gmail.com

S K N S Surya Varma,
Student, suryavarmaaei043@gmail.com
A Pavan Kumar, Student, pavankumarakula2001@gmail.com

V Naga Prudhvi Raj,
Associate Professor, nagaprudhvi@gmail.com

G. Geetha,
Asst.Professor, Department of Information Technology
Department of Electronics and Instrumentation Engineering, V R Siddhartha Engineering College
(Affiliated to JNTU, Kakinada), Kanuru, Vijayawada, India.

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Abstract

Diabetic retinopathy occurs due to vascular complications in diabetics. It consists of different stages which do not have any early-stage symptoms. An ophthalmologist can identify some disease in the retina but they can't tell how that disease occurs and at what stage it is present. So, ophthalmologists suggest retina specialists for curing disease.We are proposing a computer-aided diagnosis (CAD) system for the development of quick screening of diabetic retinopathy. By the proposed method ophthalmologist can classify the stage of diabetic retinopathy which can identify within less time and is easy for the ophthalmologist. In this paper, we are going to develop a convolutional neural network (CNN) using python language to predict whether the patient is diabetic or not and to identify its stage.

Keywords — Diabetic Retinopathy, Nonproliferative, Proliferative, Deep Learning, Convolutional Neural Network, Transfer Learning.

I. INTRODUCTION

Diabetic retinopathy is a diabetic consequence and a primary cause of blindness. Diabetes affects the small blood vessels inside the retina, causing it to swell. If diabetic retinopathy occurs for the first time there will be no changes to the vision. Diabetic retinopathy, on the other hand, can worsen over time and result in visual loss. Both eyes are generally affected by diabetic retinopathy. Diabetic retinopathy affects persons of all ages who have diabetes. This condition mostly affects diabetic pregnant women. They should go to the hospital at least once a week for a checkup. If it happens to a pregnant woman, there is a high risk of harming the infant kid. This condition can be treated without medication in its early stages. If the condition has progressed to a more advanced state, it can be treated with significant procedures. Diabetic Retinopathy can also be treated with laser treatments such asscatter laser treatment, vitrectomyand Focal laser therapy. Surgery isoften degraded orelse’s prohibits the development of the diabetic retinopathy in fundus.But this is not a complete cure for the DR. As it is a lifetime condition, future retina gets damage and vision loss is also possible. As the result, a correct diagnosis of disease condition is required. Diagnostic method such as like optical coherence tomography andfluorescein angiographyare involved in external fluid or dies to be applied to the patient’s eye after the retinal imagesare taken. But an automated system which immediately predict the diabetic retinopathy without any external agent and is more convenient andcomfortable method for both patients and ophthalmologist.

Diabetic Retinopathy consists of different stages, they are as follows:

Stage-1: Mild NonProliferative Retinopathy

Stage-2: Moderate NonProliferative Retinopathy

Stage-3: Severe NonProliferative Retinopathy

Stage-4: Proliferative Retinopathy

Mild Non-Proliferative Retinopathy: Microaneurysms occur in the early stages of diabetic retinopathy, known as retinopathy. In tiny places near the retina blood vessels, a balloon-like swelling will ensue.

*Moderate Non-Proliferative Retinopathy:*Blood arteries that supply to the retina are clogged at this stage, and there will be symptoms. And a vast number of little blood vessels swell.

*Severe NonProliferative Retinopathy:*Lack of blood flow's through the retina, the blood vessels get clogged at this stage. As a result, these blood vessels send a signal to the brain, instructing it to build new blood vessels in these places.

*Proliferative Retinopathy:*There will be an increase in the number of new aberrant blood vessels around the retina and vitreous gel. These irregular blood vessels are unstable and cause blood leakage in the eye, which can cause sudden blindness, or these blood clots in the eye and migrate inside the eye, causing them to appear in front of the iris, which is also a major issue of diabetic retinopathy.

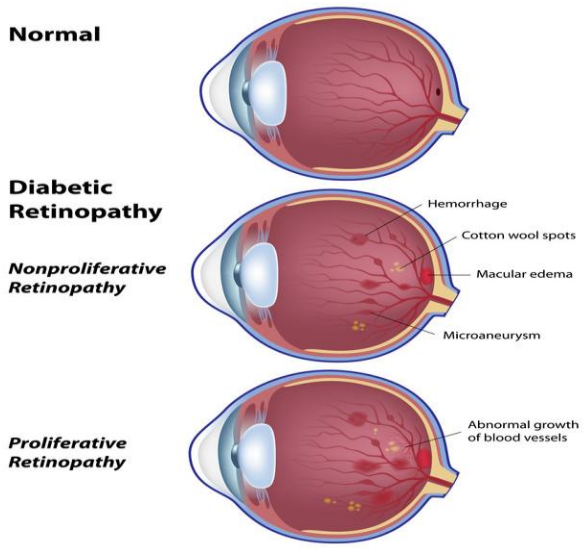

Fig.1 With and Without Diabetic Retinopathy

In this work, we will create a computer-aided system that will be used to classify diabetic retinopathy. We shall classify five distinct stages to indicate the illness categorization. We are employing the deep learning approach, which employs many algorithms for categorization. There are several categorization techniques. We employ sequential learning and transfer learning in this paper: Dense Net, InceptionResNetV2, VGG19, EfficientNetB1, EfficientNetB4.

Table-1. Classes of Diabetic Retinopathy

DEGREE OF DR	CLASS NAME
Normal	0
Mild	1

Moderate	2
Severe	3
Proliferative	4

II. LITERATURE REVIEW

There have been a few methods that have been tried in the past that aimed to detect Diabetic Retinopathy

Navoneel Chakrabarty developed an offbeat method for detecting diabetic retinopathy utilizing a convolutional neural network and a computer vision methodology. They used image processing techniques to obtain 91.6 percent accuracy, 100 percent sensitivity, and 100 percent specificity on their picture datasets [1].

Yashal Shakti Kanungo proposed an algorithm using a programming language with “a deep learning approach involving a convolutional neural network” using different batch sizes and epochs and achieved high accuracy, high sensitivity, and high specificity [2].

Deepika Vallabha proposed the “automated detection of vascular changes that are seen clearly in the moderate to severe stages of diabetic retinopathy”. Gabor filters are used for the analysingthe images at different orientations and the scales. This will distinguish the mild Nonproliferative and severe proliferative [3].

Anovel method was proposed by kanikaverma which consist of blood vessel extraction, hemorrhages and its detection, and classifying the retina disease cases using the advanced nonparametric methods with the higher classification accuracy, specificity, and sensitivity [4].

Y.V. Venkatesh recommends utilizing image processing to classify the different phases of Diabetic Retinopathy, and they categorised with 90% sensitivity and 100% specificity [5].

Subhasis Chaudhuri proposed a method of “Detection of blood vessels in retinal images” and this algorithm is efficiently implemented in many machine vision systems and they all analyze the minor modifications [6].

ChilukaNagaraju proposes a method on Canny Scale Edge Detection and is simulated in MATLAB and this method gives the better result comparison with Sobel, Roberts [7].

Yuji Hatanaka proposes a novel method for “Automated lesion detection in the retinal images”. A double-ring filter was used to remove blood vessels and haemorrhages. This filter will calculate the difference in between the average pixel’s value of inside and outside regions and also detects the abnormal cases with 83% sensitivity and 67% specificity [8].

Using keras, numpy, and opencv in Python, Hare Shyam Sharma, Ajith Singh, and Amit Singh Chandel suggested a technique for the categorization of diabetic retinopathy. They used their CNN model, which consists of six convolutional layers, one flattens layer, and one fully connected layer, to train on 1200 photos from Kaggle. They reached 74.5 percent accuracy and suggested that if the dataset is expanded, greater accuracy may be attained[9].

AbinayaRamaiyan P Meenalaxmi P Vignesh T Kuralamuthan D proposed a “Survey on Detection of Diabetic Retinopathy”. In the paper they have made the survey on diabetic retinopathy and their aim is to provide information for researchers [10].

M. Aeri, M. Manwal, and M. Gupta offered a study on the comparison of several diabetic retinopathy detection methods. In this study, they developed SVM and KNN algorithms to classify diabetic and non-diabetic eye illness, concluding that this approach provides the best categorization of spots in the disease. [11].

Lam. C, Yi. D, Guo. M, and lindsey proposed ancomputer aided approach for detecting DR. In this study, they identified preprocessing using adaptive histogram equilization and employed transfer learning techniques from GoogleNet and AlexNet to achieve 74.5 percent and 64.8 percent accuracy, respectively [12].

An article on the detection of diabetic retinopathy using OP-BPN was proposed by Devi, R. M., Keerthika, P., Devi, K. v., Suresh, P., Sangeetha, M., Sagana, C., and Devendran. For detection, an improved back-propagation neural network is utilised in this article, and it is compared to an existing back-propagation network (BPN). And they came to the conclusion that conventional approaches generate 89.28 percent accuracy for 1250 epochs, whereas their method delivers 96.81 percent accuracy for 1098 epochs [13].

Rosline Mary and A Kavitha suggested a publication on diabetic retinopathy diagnosis using stochastic coordinate descent deep learning architectures. In this research, they apply several techniques such as DenseNet, XceptionNet, VGG19, and InceptionResnet, and they train the model using various epochs. They discovered that decreasing the epoch size by 1.5 percent reduced accuracy, and they concluded that DenseNet and XceptionNet give more than 90% accuracy when the dataset is modified when compared to other techniques [14].

A. Dutta, P. Agarwal, A. Mittal, and A. Khandelwal suggested a journal on detecting diabetic retinopathy and extracting retinal lesions from digital fundus pictures. They employed the transfer learning technique and the VGG-19 algorithm for retinal extraction and eye lesions in this study. On the classification task, the model outperforms existing CNN algorithms by 37%. [15].

A. Bora, Virmani, B. Babenko, and S.Balasubramanian developed the 2 deep learning algorithms for predicting the development of the diabetic retinopathy over the course of two years and validated them using internal and external validation. They identified the individual hazards in the two datasets using InceptionNet and numerous algorithms. [16].

A work on automated identification of diabetic retinopathy using fundus pictures was proposed by Xu, K., and Feng, D. In this study, the CNN algorithm is used for detection, and the augmentation approach is used to boost accuracy to 94.5 percent [17].

The convolutional neural network is proposed by Kamal Kumar,Rahul Chauhan, R.C Joshi, andGhanshala for image detection and identification. The technique was built for the MNIST dataset for image identification and detection, and it produced an accuracy of 99.6% and droupout on the CPU unit [18].

Takayuki, Fukushima, Sei Miyake, and Kunihiko presented a new technique for recognising visual patterns. In the beginning, they used the neocognitron approach, which was quite effective. When the input pattern differs from the training pattern, the neocognitron successfully detects it [19].

Z. Wang and J. Yang suggested a deep convolutional network-based technique for detecting diabetic retinopathy. In the deep learning model, they introduced a regression activation manslayer (RAM). They concluded that by monitoring pathogenesis, the RAM layer can provide a robust inter-probability for the suggested detection model, which can then be extended to additional medical applications in the future [20].

III DIFFERENT METHODS FOR DIABETIC RETINOPATHY DETECTION

A. Spatial Domain Method

The spatial domain deals with images as they are. In this method, normal image space is converted into a 2-dimension matrix. It is operated on pixels like transformation. In the special domain, the input image is compared with the output image then a two-dimensional matrix is formed where each element is the intensity of the pixel. The input image is the diabetic retinopathy eye and the output image is the normal eye which is free from diabetic retinopathy [22].

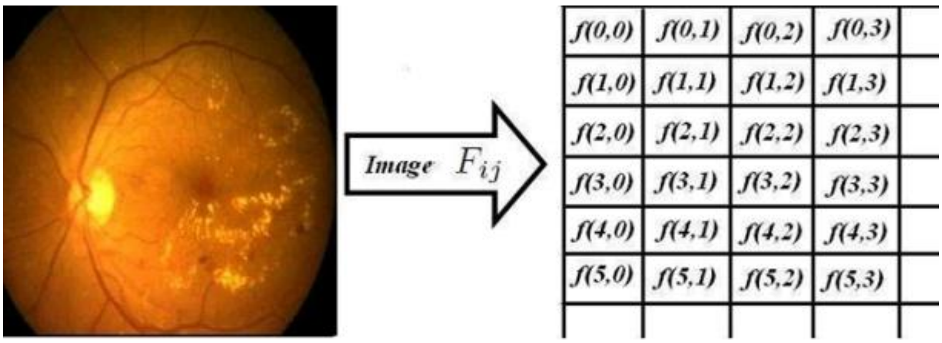

Fig.2 Example of image conversion into a 2D array

Digital image or a fundus image is a two-dimensional with a function f (x, y) of the brightness(light intensity) at a point in the space, where (x, y) are the coordinates of the point. Since a fundus image is a function of f (x, y) which is discretized in both brightness andspatial coordinates, and also commonly represented in a 2D matrix Fij = (fij) m n, where n and m are the picture dimensions and fij = f (xi, xj). Each element of the array is called a picture element or pixel. The spatial domain refers to the image plane itself, and techniques in this category are based on the direct manipulation of the pixels in the image [23].

B. Filtering Method

Gabor filter is also known as Gaussian filter it eliminates noise in images. Gabor filter represents the texture description. Gabor filters reveal the major blood arteries as well as any anomalies. The abnormalities appears at smaller scales or high frequencies [24].

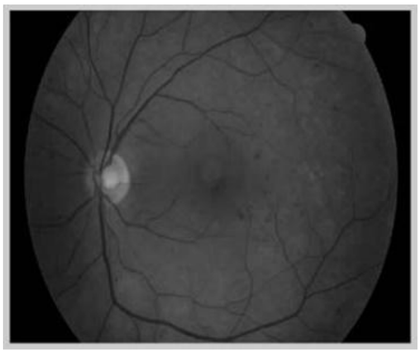

Fig.3 Example of Gabor filtering

The above image is called the Gabor response image. Here lambda and delta maintain false positive values. In this strategy, the rotation phase is always maintained at (2π)

A 2-D Gabor filter is centered at some location in a 2-D space that can be represented in a complex equation as follows:

$$g_{\theta}(x,y) = \exp\left\{-\frac{1}{2}\left(\frac{{x_{\theta}}^{2}}{\sigma_x} + \frac{(\gamma y_{\theta})}{\sigma_y}\right)\right\}\cos\left(2\pi\frac{x_{\theta}}{\lambda} + \varphi\right)$$

C. Grey Level Thresholding

Grey level Thresholding is used for changing RGB images into the grey level. So that it identifies the exudates. The threshold level is used to process the image. This threshold is a value of the intensity of the color [25].

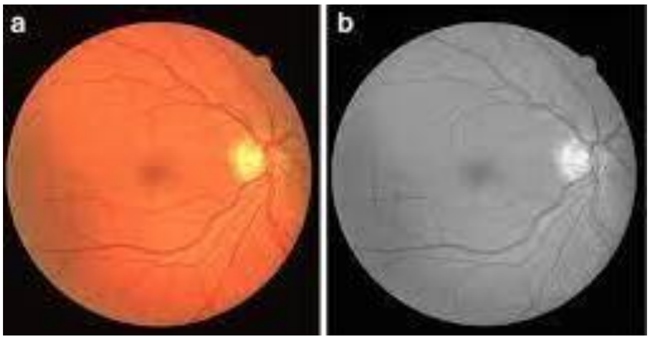

Fig.4 Example of Grey Level Thresholding

Thresholding is the most basic approach of the image segmentation and the most often used method of converting a gray-scale picture to a binary image. We pick a threshold value in Thresholding, and then all grey level values that are less than the threshold value is classed as 0, and all grey level values that are equal to or more than the threshold value are classified as 1.

In previously discussed methods there are some disadvantages like time taking, not applicable when low-frequency information is available, less efficient, need cross verification. Those are long processes that are difficult to identify exudates if they are in the same size and also difficult to find true positive and true negative values.

III. PROPOSED METHOD

A. Dataset

The database consists of captured imageset consists of 8-bits per color plane at 2304*1536,2240*1488, or1440*960 pixels with 1200 fundus color numerical images. These 800 images were acquired with pupil dilution and 400 images were acquired without pupildilution.

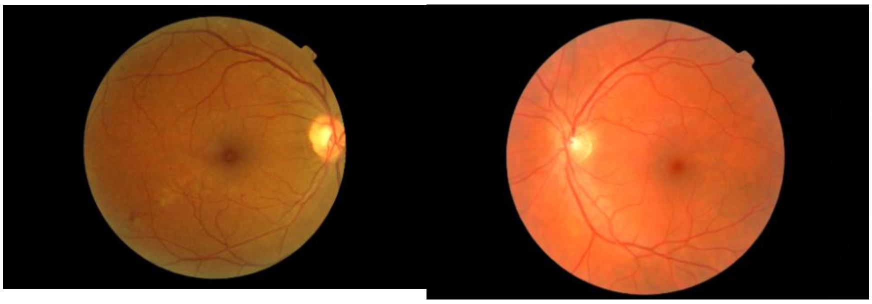

Fig.5 Dataset with pupil dilution

Fig.6 Datasets without pupil dilution

75% of the images in the 8-bit dataset are utilized for training, while 25% are used for assessing diabetic retinopathy in the eye. We require all of the photographs to be the same size, so we transform the dataset's width, height, and depth.

The dataset we took from the open source consist of 1200 images and these images are divided into 75:25 ratio with the code and these images have different size and shape and it shape is changed to (128,128) shape.

B. CNN Architecture

Feature extraction and a detection/prediction algorithm make up the majority of prior automated methods. The focus is on feature extraction because typical machine learning techniques may be employed directly as detection/prediction algorithms. This sort of strategy is effective to some extent, but it has a number of flaws.

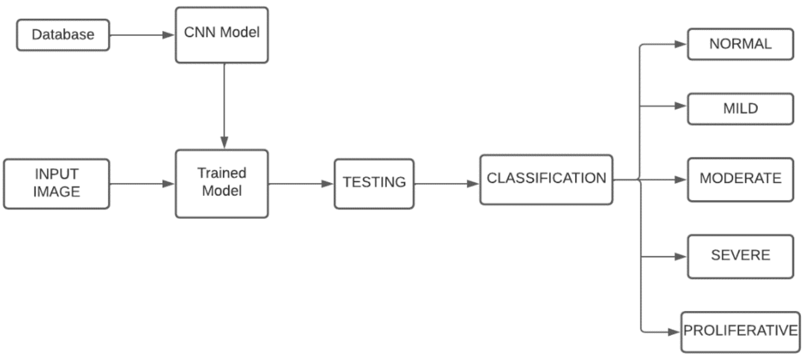

Fig.7Block Diagram of common CNN Model for Diabetic Retinopathy

The RGB color image is converted into the greyscale image and then converted into the 2D array and then that images undergone into the CNN network. The RGB image is converted with one hot encoding method in python so that we can convert the image into the 2D array.

***1)Convolutional Layer*:** Convolution is a two-function integration. The input images is convoluted with the feature detector to generate a convoluted feature map. The convolutional layer is constructed with the following formula:

$$(f * g)(t) \stackrel{\text{def}}{=} \int_{-\infty}^{\infty} f(\tau)g(t-\tau)d\tau$$

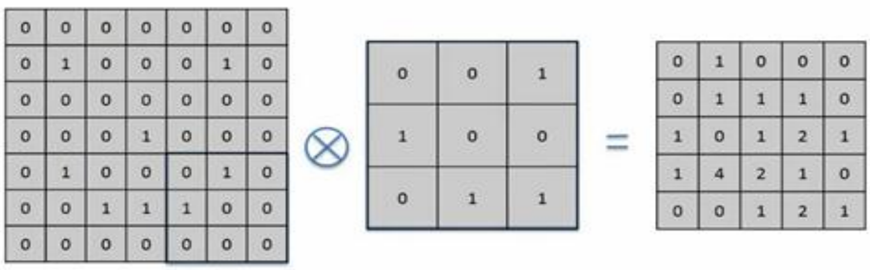

Fig.8 Example of Convolution Layer

Feature detector reduces the size of the input image pixel. It acts as a filter and detects the features which tell about the image. We use different feature detectors so that for detecting the features of the eye. Every feature detector produces a feature map. So, we identify every feature in the eye.

2) Max Pooling Layer:Max pooling layer will help to get rid of unwanted features. Max pooling is done with (2 x 2) dimensions to preserves the features and make the CNN Network, spatially independent. We apply max pooling for differentfeature maps so that we can identify the maximum number of features from the image.

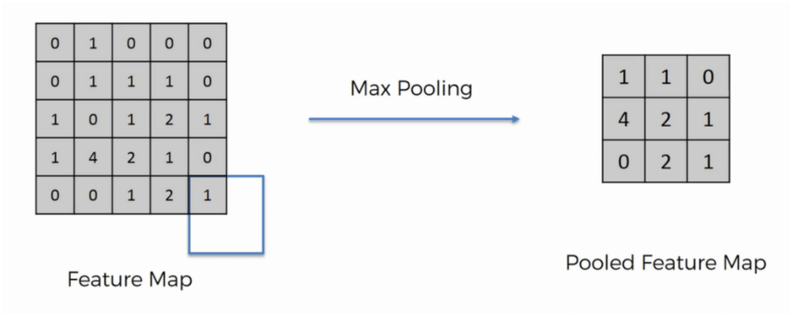

Fig.9 Example of Max pooling Layer

3) Flattening Layer:Pooled feature map is flattened into a column. It takes numbers from a row place them in a column and continues its second row in the same column. This layer iseasy to construct in python.

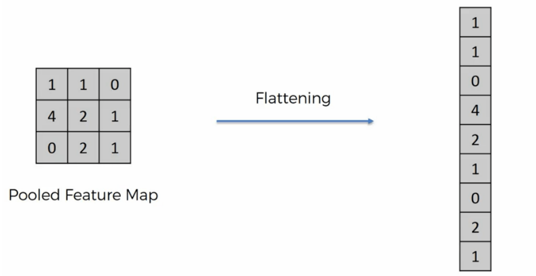

Fig.10 Example of Flatten Layer

4)Fully Connected Layer:The Fully Connected layer consists of the biasesand weightsalong with neurons and are used to connect the neurons between different layers. So that we can train the model by its features. Now the model is ready for testing. In a fully connected layer, the user identifies the weights and biases that are assigned to the neurons.

In diabetic retinopathy disease classification, the output layer size is four. Each neuron represents the stages of diabeticretinopathy.

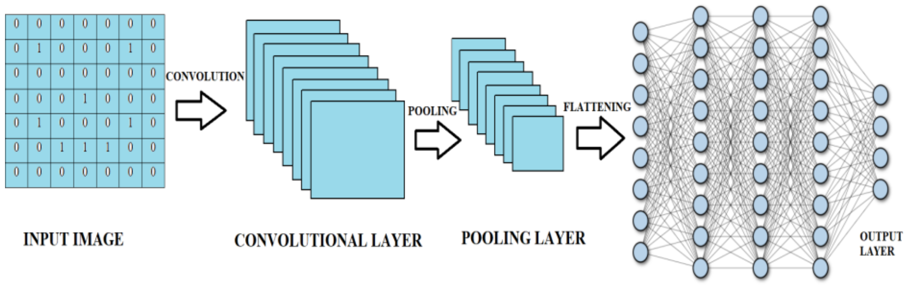

Fig.11 Schematic diagram of CNN

C. Activation Function

Back propagation is allowed with the Activation Function since the gradient is provided together with the error to update the error to update the biasesandweights. There are different activation functions used for hidden layers among them default activation function is rectified linear unit (RELU). Mathematical equation of activation function is as follows:

$$\text{net input} = \sum(\text{weight} * \text{input}) + \text{Bias}$$

RELU is used to break the linearity in the image. Every pixel of feature maps obtains in the convolutional layer is Rectified linear unit activated to introduce the nonlinearity in the feature maps. So that we can also find the maximum and minimum features of the image.

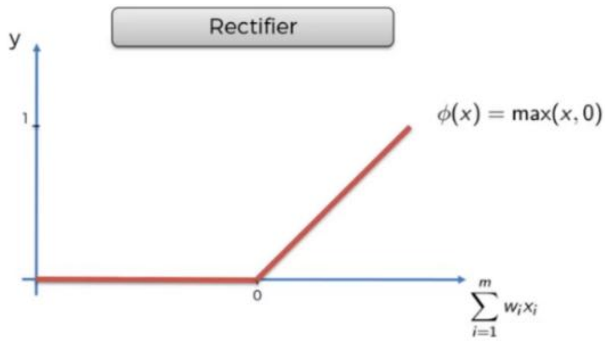

Fig.12 Rectifier Function

D. Backpropagation

Backpropagation is a method of comparing the predicted value with the actual value. If errors occur then those errors are backpropagated through the network and allow the user to train the model by adjusting their weights and using different feature detectors for better classification.

It is an advanced algorithm-driven by mathematics. The main advantage of the backpropagation method is that the user can adjust all the weights at a time.In classification, we have used the cross-entropy function as a loss function. This function is used for the difference between the actual valueand thepredicted value.

E. Optimizer

Optimizersare used to identify the features of the new image for testing. Because if the optimizer is not used while training the model it will considerthe features as default and then when the test image is given for testing the disease classification the model will give the default features while it was in the testing mode. So that the model is not able to identify the features of the test image and gives the wrong classification. So, the optimizer will overcome the feature detection while testing the image to the model.

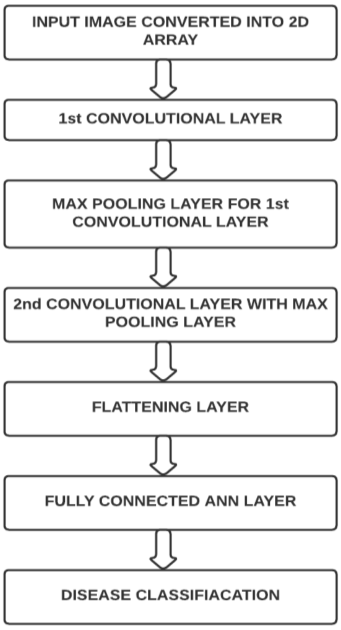

Fig.13 CNN Model

F. ConvNet configuration

In deep learning, there are multiple neural networks to choose from. For training and testing diabetic retinopathy, we employ convolutional neural networks and various convnets. The images are divided into five categories, with a width and height of (128,128) and a depth of 3. For the categorization of diabetic retinopathy, we employed sequential and transfer convnet algorithms, which are as follows:

i. Sequential Learning
ii. Transfer Learning
   a. VGG19
   b. EfficientNetB4
   c. DenseNet121
   d. InceptionResNetV2

i. Sequential Learning

We construct the classification model using the sequential convnet approach to categories diabetic retinopathy. To begin, we'll make three sets of standard layers, each with input layers, hidden levels, and SoftMax layers. We train and test the dataset after constructing the model, which is divided into 75:25 for classification.

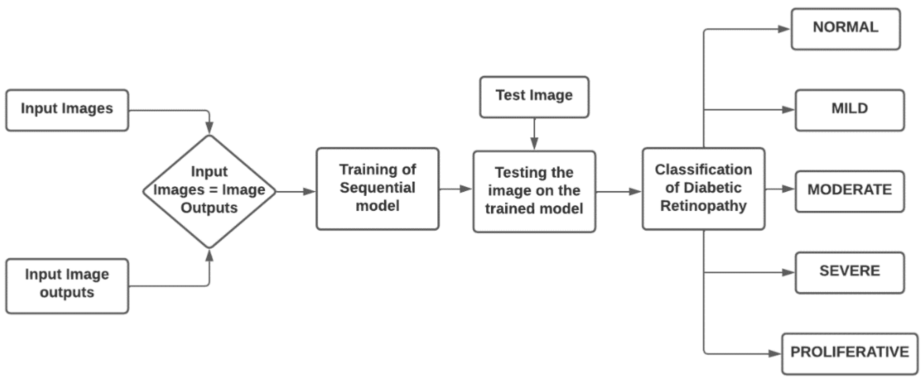

Fig.14 Block Diagram of the sequential model

To begin, all photos are imported and pre-processed, after which they are turned into an array and partitioned into training and testing datasets. Seventy-five percent of the photos are utilized for training, while twenty-five percent are used for testing. The sequential model has now been built, and the model has been trained.

In the sequential model we have used the convolution net, max pooling net and flatten layer are used for input, convolution and output layers in the model and the dropout layer is used for the back propagation of the error. This is used to find out the error and the weights of the neurons in the model.

Sequential model is the most widely used convnet in the architecture. This model can be developed by the user in the user defined manner. As this can be developed by the user and trained with the datasets for increase in accuracy and the true positive and true negative values.

RESULTS

After transforming the images from hash to data frame, we construct the columns of image, data, level, and patient id in this model. Figure 12 shows an example image that has been turned into an array.

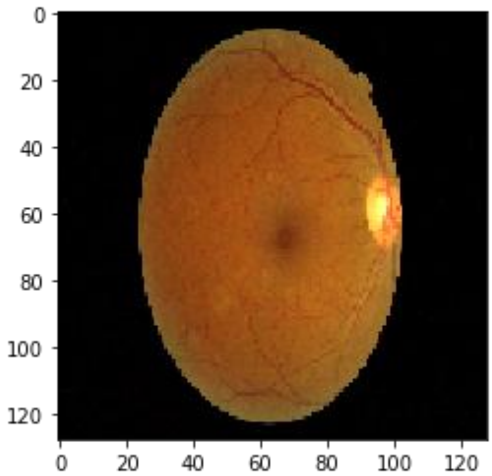

Fig.15 numpy. ndarray

The model's accuracy is 45 percent, and validation loss reduces with epoch size of 15. However, there is an overfitting issue that may be addressed by increased number of photos in our dataset. When we raise the epoch size from 15 to 30, the accuracy only rises by 3%.

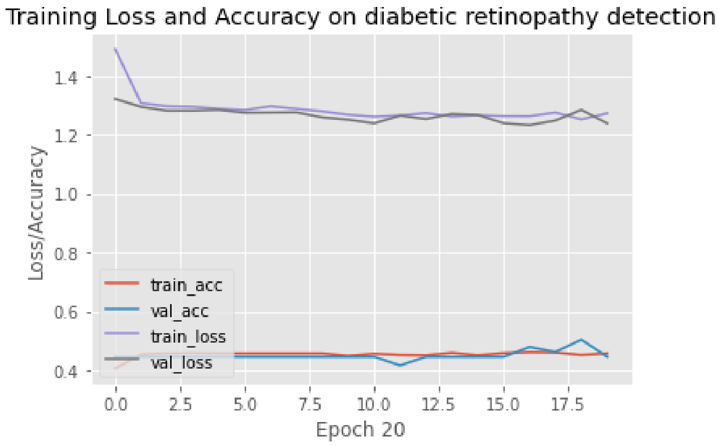

Fig.16 Result of Sequential Model

ii. Transfer Learning

Transfer learning saves a substantial amount of computing power. These learning-based strategies employed pre-trained models such as EfficientNetB1, EfficientNetB4, DenseNet, and InceptionResNet architectures. While extracting image attributes, transfer learning keeps the initial pretrained model weights. We freeze all of the layers save the last one and use these models to categorize the disease.

a. VGG19

It is a part of convnet family. VGG19 uses in many ways as the weights are easily available with other frameworks like keras so they can be tinkered with and used for as one wants. This architecture is trained with large number of image datasets, so that when we want to test the diabetic retinopathy with the trained set then the accuracy increases by 37%.

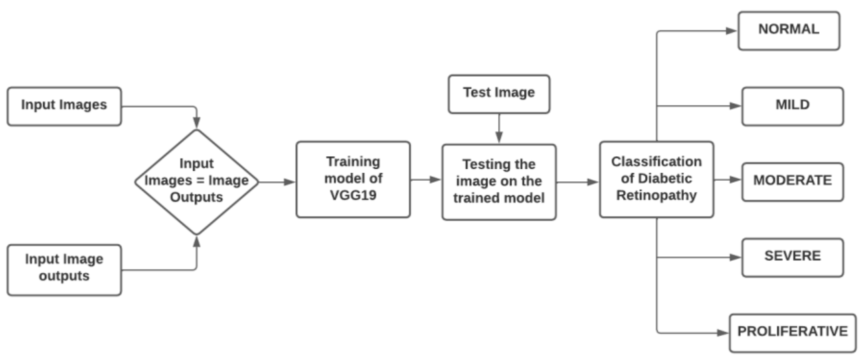

Fig.17 Block Diagram of VGG19

RESULTS

When we give the dataset to the trained VGG model with a batch size of 32 and with a size of 128 and depth with 3. As we give RGB colour images to the model this will be converted into binary array and the model will produced the accuracy of 77% and losses also decreases.

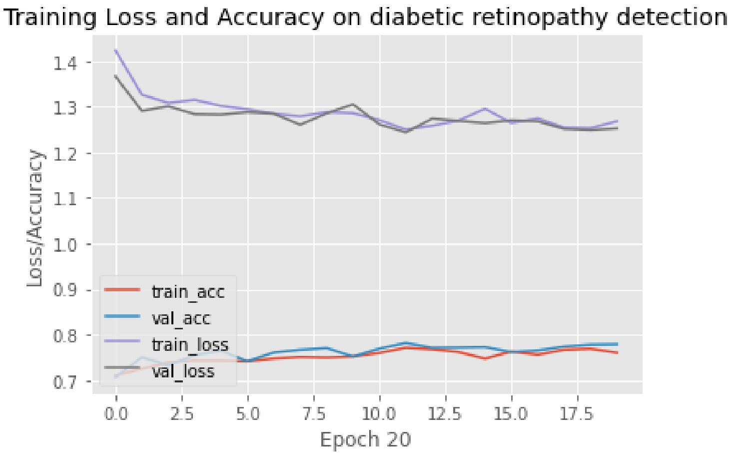

Fig.18 Result of VGG19

b. EfficientNetB4

It is also a member of the convnet family. The detection backbone is Efficient Net. It goes a step further by localising and categorising objects/images. This model scales up efficiently in terms of layer breadth,, input resolution,layer depth, or a combination of these factors. EfficientNet enables us to generate features from photos that can then be fed into a classifier. This is especially beneficial when utilising deep learning on the edge since it minimises compute costs, battery utilisation, and training and inference speeds. This level of model efficiency enables the application of deep learning on smartphones and other edge devices in the long run.

EfficientNet models (or approaches) have achieved new state-of-the-art accuracy for 5 of the 8 datasets, with an average of 9.6 times fewer parameters.The success of model scaling is also largely dependent on the baseline network; the EfficientNet models achieve more accuracy and better efficiency than previous CNNs, lowering the parameter size.

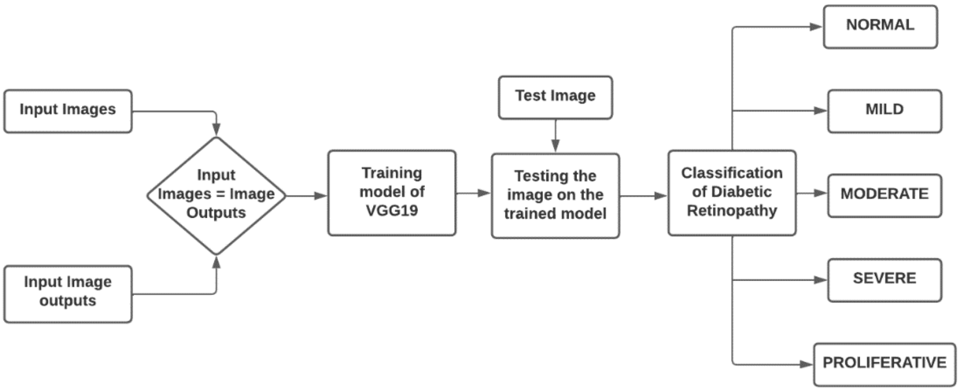

Fig.19 Block Diagram of EfficientNetB4

RESULTS

This net is used in conjunction with keras. When compared to the previous model, this model achieves 82 percent accuracy and lowers losses while decrease in precision and validation accuracy also increases with increase in accuracy.

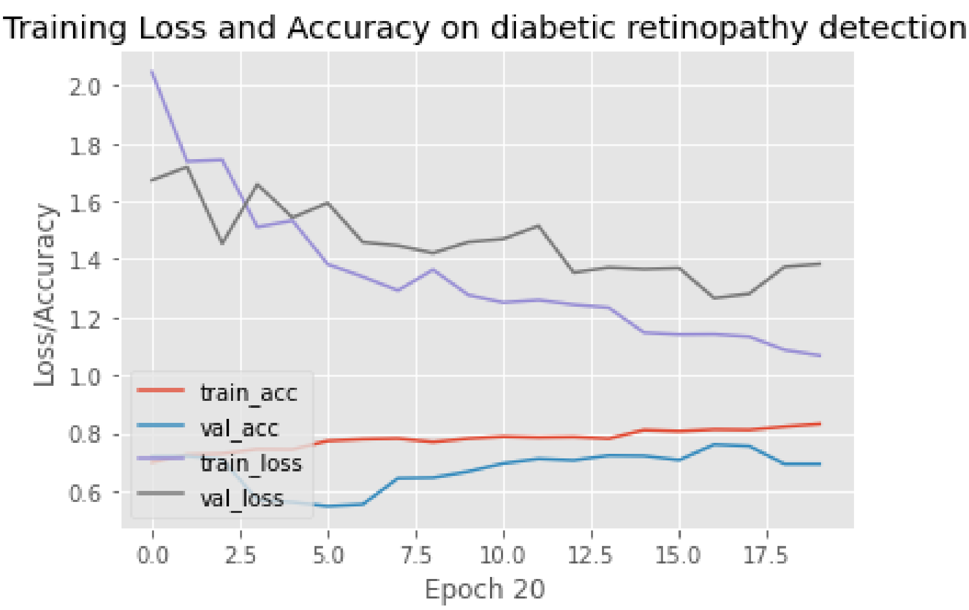

Fig.20 Result of EfficientNetB4

c. *DenseNet121*

DenseNet is one type of transfer learning method which consist of a trained model on a large number of datasets on different images. It is developed specifically for improving the declined accuracy which is caused by vanishing the gradient in high-level networks. In simpler words, due to longer path between the input layer and the output layer, the information vanishes before reaching its destination.

DenseNet operates in such a way that each layer receives extra inputs from all preceding levels and passes on its own feature-maps to all subsequent layers. It is seperatd into dense blocks, each of which has a different number of filters but the same dimensions. DenseNet offer numerous appealing advantages: they solve the vanishing-gradient problem, improve feature propagation, increase feature reuse, and reduce the number of parameters significations.

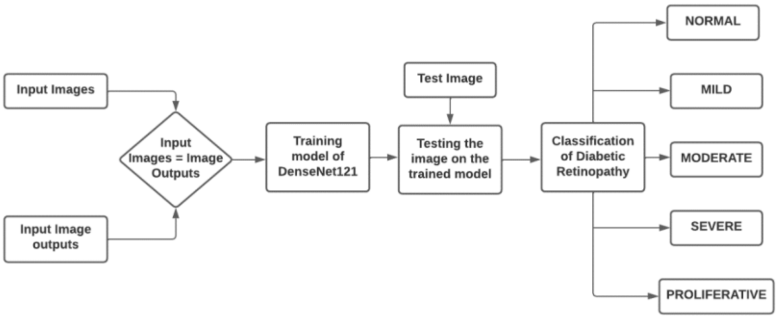

Fig.21 Block Diagram of DenseNet121

Results

It consists of trained and proven accuracy that has been enhanced to 95 percent, as well as a reduction in losses. However, because there are fewer photos in the dataset, overfitting occurs; this may be avoided by improving the number of images in the dataset.

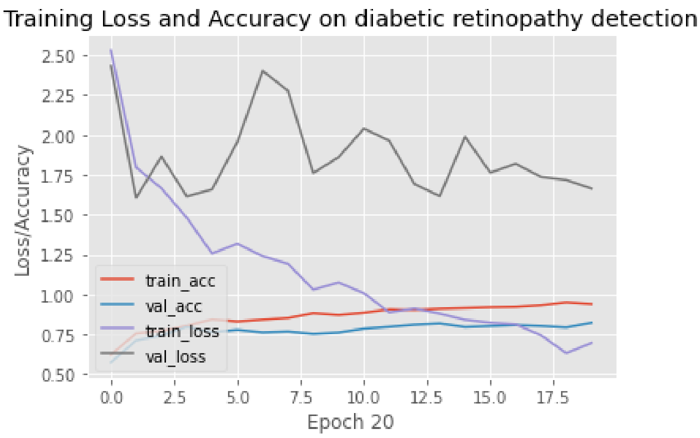

Fig.22 Result of DenseNet121

d. InceptionResNetV2

The neural network has 164 layers and can also categorize photos into 1000 different types. In this InceptionResNetV2 architecture, memory optimization on back-propagation is performed to reduce memory needs. This method returns the Keras image model classificationthat may be loaded by ImageNet-trained weights. For more information on images, it categorizes the use of cases. In this transfer learning and fine-tuning for transfer learning use cases. This method returns the Keras image classification model that may be loaded with ImageNet-trained weights.

Inception-ResNet-v2 is a CNN architecture that buildsthe Inception family of architectures but incorporates residual connections and replaces the filter concatenation stage of the Inception architecture. Inception-ResNet combines the two InceptionNet and ResNet to improve performance even more. (1 x 1 convolution without activation) which is used to match the depth of the input by scaling up the dimensionality of the filter bank before the addition. This method returns the Keras image classification model that may be loaded with ImageNet-trained weights.

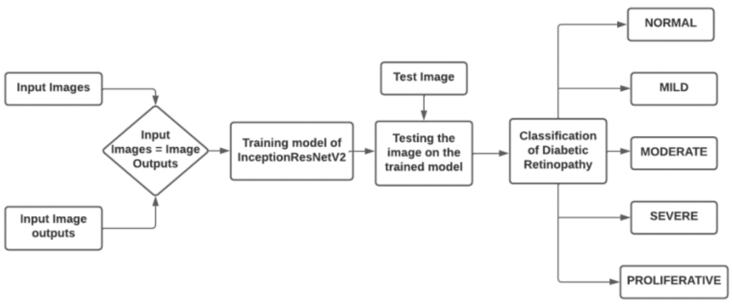

Fig.23 Block Diagram of InceptionResNetV2

RESULTS

InceptionResNetV2 produces good accuracy compared to other models. Where this model produces 97% accuracy and 82% of validation accuracy and losses and validation losses also decreases.

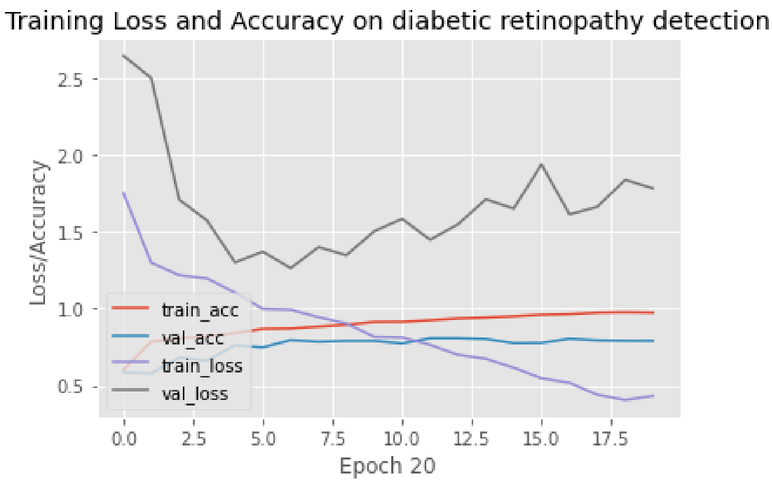

Fig.24 Result of InceptionResNetV2

CONCLUSION

In this paper, we discussed about the different techniques used for detection and classification of the diabetic retinopathy. Where the aim of the paper is to improve the efficiency, accuracy and to decrease the time with respect to ophthalmologists. This will help the eye specialist for disease detection. This is a computer-aided device/system. We mainly used the convolutional neural network (CNN) method in deep learning. We have used the different models in CNN which are shown above. From the models of sequential learning and transfer learning, we concluded that transfer learning will give the efficient values than sequential learning. The transfer learning models are the models which have been already trained with a large number of datasets or images. In transfer learning we have used VGG19, EfficientNetB4, DenseNet121, and InceptionResNetV2 which gives the accuracy of 46%, 82%, 95%, and 97% and there are fewer losses in every model and the precision is up to 82%. We have taken only 1200 images in our dataset so, as our dataset is small there is an issue of overfitting which can be rectified by the increase in terms of image count. The validation accuracy also increases and validation losses also decrease in InceptionResNetV2 which gives the good model performance with respect to all other models.

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