DETECTION OF DIABETIC RETINOPATHY USING DEEP NEURAL NETWORK WITH KERAS

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Abstract

Diabetic Retinopathy (DR) also known as Diabetic Eye Disease (DED) is a commonly caused eye illness in diabetic adults due to poor maintenance of diabetes. DR caused due to high sugar or glucose level in blood which damages blood vessels in the retina. These damaged vessels form Lesion which eventually causes vision problems. If ignored it may lead to complete vision loss. The Manual procedures done by ophthalmologists to find DR is time-consuming and hence this paper focuses on detecting different stages of DR using DenseNet, which is a Deep Learning (DL) model. This model is trained with dataset of 3662 images. These images are high-resolution fundus images and are classified into 5 types which represents the 5 different stages of DR. The dataset is available in Kaggle (APTOS 2019 Blindness Detection). The proposed model uses a deep learning model called DensNet which is used for extracting features from the images of eye (angiograms) and for classifying different stages of DR. After configuring the activation function weights of the model, the proposed model achieved an accuracy of 0.9633.

Keywords – Angiogram, Dataset, Deep Learning (DL), DenseNet121 Architecture, ResNet50 Architecture, AlexNet Architecture, VGG16 Architecture and InceptionNet V3 Architecture.

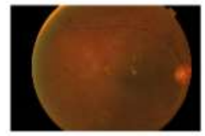
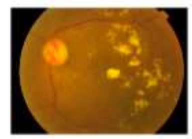
INTRODUCTION

Vision loss is not new to diabetic patients. The vision of millions of people is being affected because of high glucose levels. One of the main causes of vision loss is Diabetic Retinopathy (DR), It is also called Diabetes Mellitus. This disease is commonly seen in Diabetic adults. Worldwide, approximately 420 million people have been diagnosed with DR.

DR occurs due to damaged blood vessels in the retina because of high sugar and glucose levels. These damaged blood vessels will cause disturbances in the blood flow by forming Lesions and Haemorrhages which eventually cause vision problems. If ignored, it may lead to complete vision loss. People with high cholesterol levels are prone to be diagnosed with DR. Early detection of DR protects patients from losing their vision.

Manually DR is checked by a doctor with the help of an Angiogram. An angiogram shows the blood vessels by highlighting them. Angiograms help the doctor see the problem in the eyes. In the case of DR, Angiograms help the doctor to see any lesions and Haemorrhages. With the intensity of Lesions and Haemorrhages DR is classified into five stages.

Here are the details of the five DR stages:

Level	Type	Damage	Images
0	No DR	Absence of Lesions	
1	Mild non-proliferative DR	Small red round dots appear on the retina due to weakness of the vessel's walls	
2	Moderate non-proliferative DR	More than just small red round dots (microaneurysms) but not as severe as servere non-proliferative DR	
3	Severe non-proliferative DR	Any of the following: • more than 20 intraretinal Haemorrhages in each of 4 quadrants. • definite venous beading in 2+quadrants. • Prominent intraretinal microvascular abnormalities in 1+ quadrant.	
4	proliferative DR	One or more of the following: vitreous/ pre-retinal Haemorrhages, neovascularization.	

Each stage of DR can be detected by its own symptoms and properties. Most common symptoms for DR are

- Eye floaters
- Blurry Vision
- Dark spots in Vision
- Difficulty in distinguishing colors
- Difficulty seeing at night
- Vision loss

To detect DR doctors used fundus camera which produce angiograms that have picture of nerves and veins behind the retina. As each stage has different symptoms and properties, sometimes doctors can't specify the DR stage using angiograms, even though if they do, the process of diagnosing DR is time-consuming, due to which the treatment will be inefficient and ineffective.

Literature Survey

A. Automated diabetic retinopathy grading using ResNet

In reference [4], the author applied a supervised ResNet, it is used for DR grading. The architecture is enhanced to achieve better accuracy. The proposed model uses ResNet which is a 50-layer deep network with cascading classifiers. In this proposed model each classifier has variable amount of convolution layers. Each classifier in the cascading classifier uses different classification technique.

The ResNet-50 architecture achieved a classification accuracy of 86.67%. But better accuracies can be obtained by deeper ResNet or by modifying the architecture.

B. Convolutional neural network-based transfer learning for diabetic retinopathy fundus image classification

In reference [3], a CNN classifier based on transfer learning is applied for DR image classification. Author proposed two methods and compared them. In the first method, fine-tuning CNN classifier is applied to all the layers of the pre-trained model. The other proposed method is the fine-tuning CNN classifier applied to a few selected layers of the pre-trained model. This model is used to preprocess and extract features from DR fundus images then a SVM classifier is trained for detecting the severity of DR images.

The fine-tuned CNN classifier applied to specific layers performed better than the method where all layers are fine-tuned with an accuracy of 92.01%. Better results can be achieved by fine-tuning the deeper and advanced architecture of CNN. Instead of using a specific classifier at the end, activation functions of the layers can be used for classification after feature extraction.

C. Diabetic retinopathy stage classification using convolutional neural networks

In reference [2], Various CNN classifiers are applied for DR image classification. Author proposed three architectures for the detection of severity of the DR fundus images which are AlexNet, VGG16 and InceptionNet V3. These three architectures are trained using the cross-validation process.

The accuracies of proposed architectures are as follows: 37.43%, 50.03% and 62.23% for AlexNet, VGG16 and InceptionNet V3 respectively. The accuracies of proposed architectures are very low. Using advanced architectures produces better results.

DATASET

The fundus images used for training the DL model are from an open dataset which means this dataset can be used by anyone. The dataset is available in Kaggle APTOS Blindness Detection which is collected by ARVIND EYE HOSPITAL. The Data has high resolution DR fundus images (angiograms) which are captured using fundus camera. These images are used by the doctors to detect the DR condition of the patient.

The doctors divided the DR condition into 5 classes as described in the table earlier. The Kaggle dataset has different folders and files like train_images, test_images, train.csv, test.csv and sample_submission.csv.

The CSV (comma separated values) contains information and can be opened in the form of spreadsheet. train.csv has information about the fundus images. It contains the labels of train_images and their DR severity levels. Similarly, for test.csv it contains labels of the images but it doesn’t include DR severity level because the images have to be tested. Here is the sample of DR fundus image:

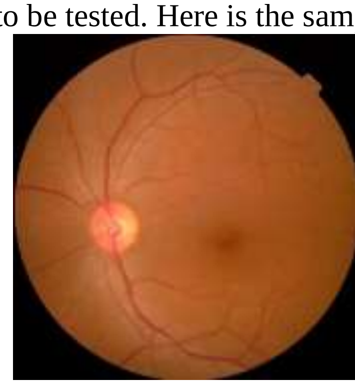


Fig 1: Sample Fundus Image

In the above figure, blood vessel can be observed behind the retina, all the images in the dataset have 3 channel which is RGB channel and classified into 5 DR severity levels. The dataset contains 3662 training images and 1928 testing images. The below image Fig2 show the number of images belong to each class (DR stage). The image describes that the training dataset contains

- Class 0 (No DR) has 1805 images
- Class 1 (Mild DR) has 999 images
- Class2 (Moderate DR) has 370 images
- Class 3 (Severe DR) has 295 images
- Class 4 (Proliferative DR) has 193 images

```
Out[4]: 0    1805
        2     999
        1     370
        4     295
        3     193
        Name: diagnosis, dtype: int64
```

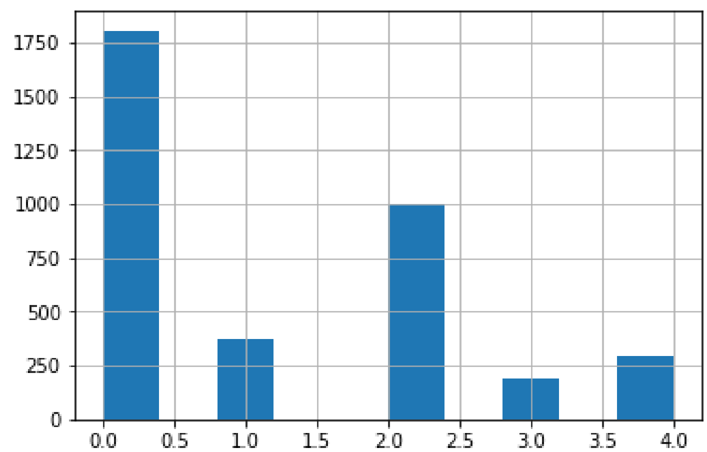


Fig 2: number of images in each DR class

METHODOLOGY

Diabetic Retinopathy is common and main issue for diabetic patients. Early detection of DR is the only way to prevent it easily. For the early detection of DR, a Deep Convolutional Neural Network (DCNN) Architecture is used which is called "DenseNet 121".

1. Framework of proposed model for DR detection

The Framework of the model contains 4 major steps and it is as follows:

a. *Loading and exploring DR fundus images*

DR fundus images are imported into the working environment.

b. *Preprocessing*

There are various steps to be followed during preprocessing:

i. Taking imported fundus images as input.
ii. cropping and resizing the images.
iii. Data cleaning or adding noise as per the model needs.
iv. Applying techniques to highlight features of the images.
v. Conversion of Images into NumPy arrays.

c. *Training DCNN model*

After preprocessing, the images will convert into NumPy array of values in RGB channel which are suitable for training. The images data is then loaded into the proposed Deep Learning model for training.

d. Validation

After training DCNN model, unseen image is given to the model for detecting the DR severity of the image.

2.Detailed flowchart of DR detection using proposed model.

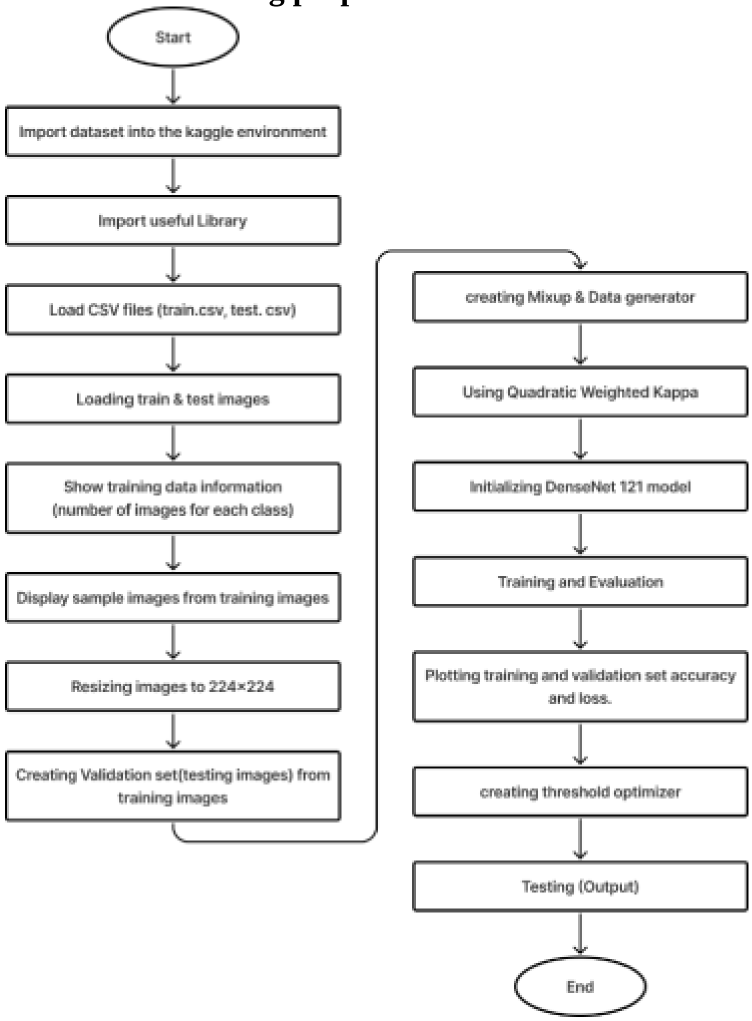


Fig 3: Detailed flowchart of proposed model

Fig3 is the detail flowchart of the proposed model which is DenseNet 121 architecture pre-trained on ImageNet. ImageNet database improves the accuracy of our DenseNet 121 architecture. ImageNet has a database of large set of Images which are used for developing and improve AI and Machine & Deep learning models.

First, dataset and dependencies are imported and loaded into the environment. Then CSV files are loaded which contains the DR severity levels and the training images. After loading the training images, a graph is plotted that shows number of images in each class, then samples of training images are displayed with their class as shown in Fig4 to check if there are labeled correctly as per train.csv file.

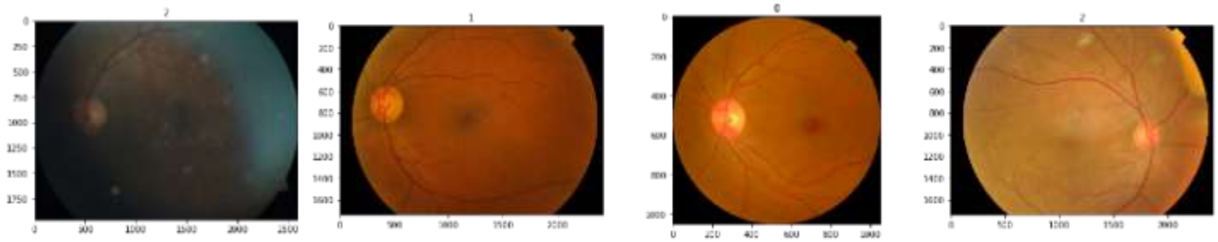


Fig 4: sample of training images

Later the training images are cropped and resized to the dimensions of 224x244 to decrease the processing time. Later the processed training dataset is split into 2 sets namely training set and validation set. From the original training images (APTOS dataset) which has 3662 images, 3112 images which is 85% of 3662 images are used for training and the rest 550 images which is 15% of 3662 images are used for validation.

After creating validation set from the training dataset, a data generator is used for feeding DR fundus images to train the DL model. Data Generators are used when the system doesn't have enough memory space to load and feed all the images to the DL model. If conventional method for feeding images to the model are used where all images in the dataset are loaded at once then in the case of larger datasets system don't have enough memory space to load and feed them into the DL model. So, in these cases, data generators will be an effective tool for loading the images and helping in DL model training. Some of the advantages of Data generators are

- It allows the usage of multiple GPU cores to parallel load the data which the process much faster.
- It allows loading and feeding of smaller batches of images to train the models, the proposed model using the same process.
- It allows data augmentation by raising diversity of training data available without adding new data by using techniques like cropping, padding or flipping the images.

Using generator, training images are can be fed into DL model in fast and efficient way.

Now, Quadratic Weighted Kappa (QWK) is used as an evaluation metric. It is used with a custom callback to observe the kappa score during the training of the model. QWK is used for measuring agreement between two ratings. In our case, it measures the agreement between results from the human rater and predicted scores from the model. The metric varies from 0 to 1 were

- 0 is minimum agreement between raters
- 1 is complete agreement between raters

$$\kappa \equiv \frac{po - pe}{1 - pe}$$

κ is the Cohen's kappa score. po is the agreement observed in Confusion matrix (pictorial representation of agreement among raters). po is also identical to accuracy. pe is the agreement that occurs by chance.

$$p_0 = acc = \frac{t_P + t_n}{all}$$

$$p_e = \frac{1}{N^2} \sum_k n_{k_1} n_{k_2}$$

This is the concept of Cohen's Kappa when applying the same concept to a multi-class model by introducing the concept of Weights. Weights are used here because they are ordinal variables. If two scores disagree, then the disagreement depends on how far their agreements are apart. It means that agreement between classes 0 and 1 is better than the agreement between classes 0 and 2 because the former classes are nearer. So, in our DR detection model, fundus images are classified into 5 classes, for this case, a quadratic scale is introduced which can work with 5 classes. The closer the classes, the higher are their weights.

After using the QWK, DenseNet 121 architecture is initialized. The full form of DenseNet 121 is "Densely connected convolutional neural networks" and 121 refers into number of layers in the model. The sole reason to choose DenseNet is, it needs less parameters than others architectures like ResNet. Compared to other architectures, DenseNet has very narrow layers and every layer contributes while training the model. With DenseNet there is no need of learning large sets of redundant feature maps.

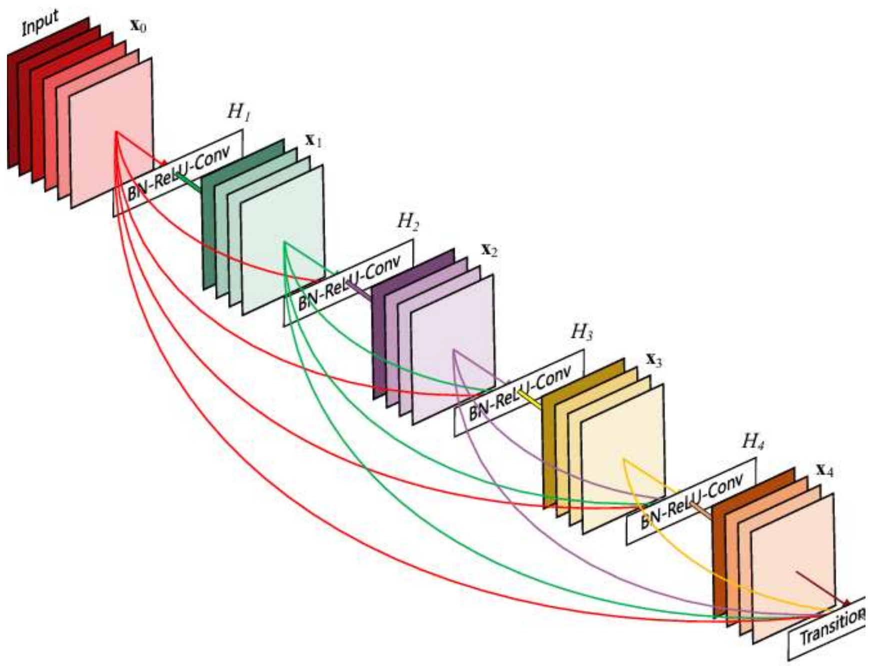


Fig 5: structure of DenseNet block.

DenseNet 121 architecture is divided into Dense Blocks. Between the Dense Block there will variable amount of composition of different layers. The layer composition between Dense Block contains Transition and pooling layers. Features remains unchanged and constant within the Dense Block but the features are halved after passing through every Transition Block

.

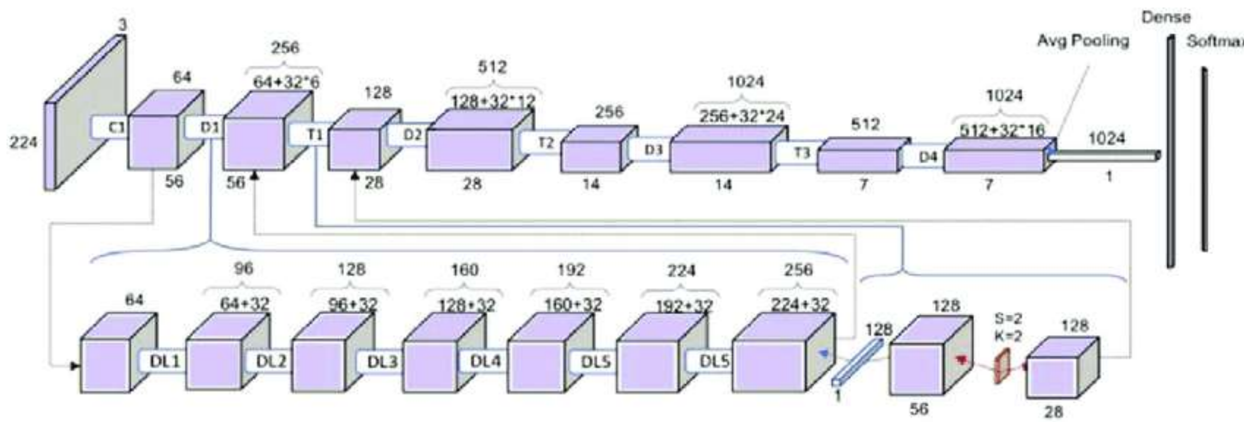


Fig 6: Level 1 deep structure of DenseNet 121

In Fig6, Depth and width measurements are representing on each volume. The number on top of each volume represents the dimensions of features. The volume of the features after every Dense Block increase by the growth rate times the number of Dense Layers within that Dense Block. In the reference [1], the growth rate is 32, every layer has 32 new features with the features of previous volume. By 32 for 6 Dense Layers, the feature maps increase from 64 to 256. As mentioned earlier there is composition of layers between Dense Blocks. In the Composition, the transition block contains 1x1 convolution layer with 128 layers with a 2x2 pooling layer which results in dividing the amount of feature map of the Dense Block by half.

Therefore, this is the structure of the proposed model DenseNet 121. With new feature maps being added at each Dense Block, it will greatly improve the accuracy of the model. Now the model will be trained with training set, after training results are generated which contains the accuracy of the model on seen and unseen data.

RESULTS & ANALYSIS

After training the DenseNet model for 15 epochs and unseen validation set is loaded into the model for testing. From training and testing, the accuracy, loss and weighted kappa score of the model are observed and here are the results obtained.

Evaluation Type	Accuracy	Loss	Kappa Score
Training	0.9747	0.0676	0.9122
Validation	0.9633	0.1014	

The proposed model achieved training accuracy of 97.47% and the validation accuracy of 96.33% with our DL model. The model also achieved Weighted kappa score of 0.9122 which shows the agreement between the labeled data of training set and predicted values of validation set.

Now let's take look at accuracy, loss and QWK graphs through 15 epochs.

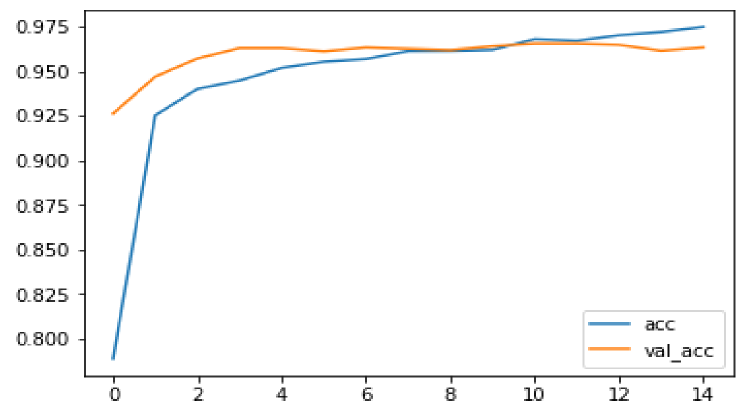


Fig 7(a)

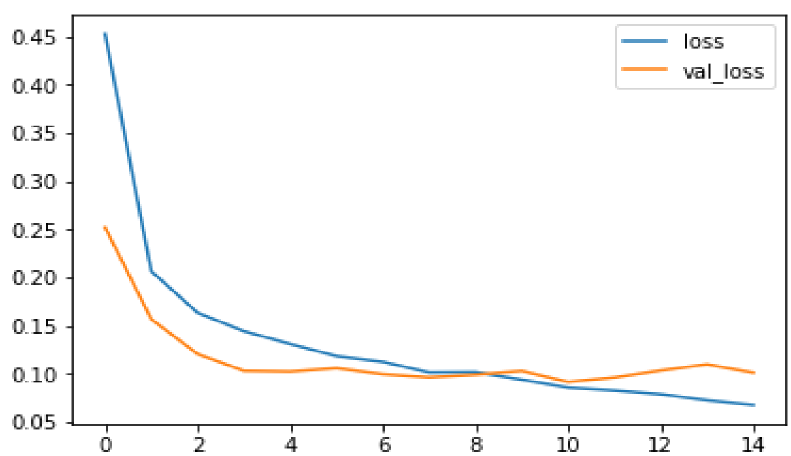


Fig 7(b)

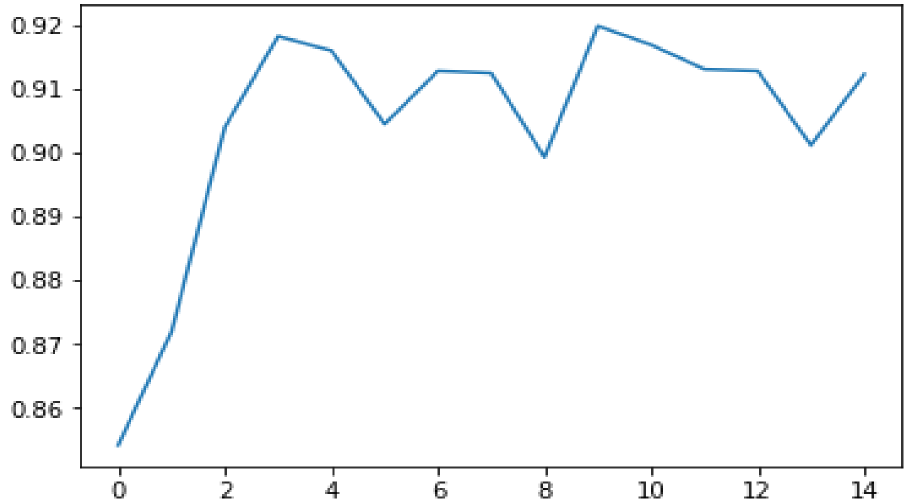


Fig 7(c)

The above images Fig 7(a), Fig 7(b) and Fig 7(c) shows the accuracy, loss and weighted kappa scores of DenseNet 121 architecture. Using the validation data, Using the results of training and testing the model with training and validation sets, a confusion matrix (Fig8) is generated

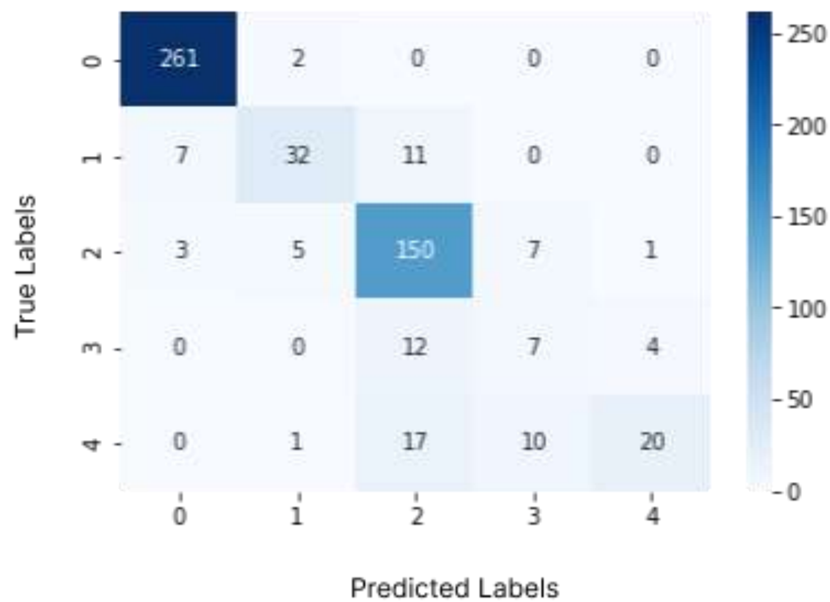


Fig8: Confusion Matrix

The matrix shows the agreement between true DR severity levels and predicted DR severity levels of validation set which taken from training images.

Later, test_images from APTOS dataset which contains 1928 DR fundus images are used, The DL model uses these images and predicts their DR severity level, here are the model predictions plotted on a graph.

```
Out[32]: 2    1048
         3     298
         0     274
         1     236
         4      72
         Name: diagnosis, dtype: int64
```

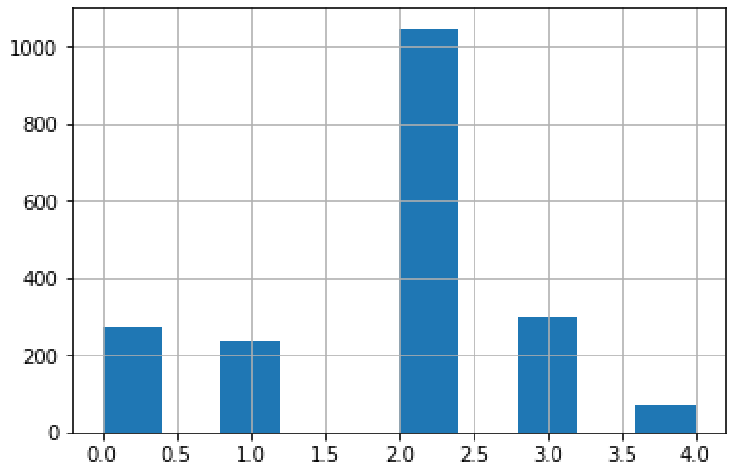


Fig 9: Number of images from test_images in each class

CONCLUSION

Henceforth, a Deep Learning architecture "DenseNet 121" is developed for automatic detection of Diabetic Retinopathy which has an accuracy of 96.33%. It allows detection of DR for multiple images at once. The model has confidence of accuracy (QWK) of 91.22%. With the proposed model we can detect Diabetic Retinopathy in its early stages. It will save lot of time for the ophthalmologist in detecting retinopathy.

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