Classification of Diabetic Retinopathy

A report submitted to

JSS Science and Technology University

in partial fulfilment for the award of the degree of

Master of Technology

in

Data Science

by

Deepak B K

(01JST19PDS003)

Under the supervision of

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2020-21

July, 2021

DECLARATION

I certify that

(a) The work contained in this report has been done by me under the guidance of my supervisor.

(b) The work has not been submitted to any other Institute for any degree or diploma.

(c) I have conformed to the norms and guidelines given in the Ethical Code of Conduct of the Institute.

(d) Whenever I have used materials (data, theoretical analysis, figures, and text) from other sources, I have given due credit to them by citing them in the text of the thesis and giving their details in the references. Further, I have taken permission from the copyright owners of the sources, whenever necessary.

Date: (Deepak B K)

Place: Mysuru (01JST19PDS003)

DEPARTMENT OF INFORMATION SCIENCE AND ENGINEERING

JSS SCIENCE AND TECHNOLOGY UNIVERSITY

MYSURU - 570006, INDIA

CERTIFICATE

This is to certify that the project report entitled "**Classification of Diabetic Retinopathy**" submitted by **Deepak B K** (Roll No. 01JST19PDS003) to JSS Science and Technology University towards partial fulfilment of requirements for the award of degree of Master of Technology in Data Science is a record of bonafide work carried out by him under my supervision and guidance during 2020-21.

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Date:

Place: Mysuru

Abstract

Name of the student: **Deepak B K** Roll No: **01JST19PDS003**

Degree for which submitted: **Master of Technology**

Department: **Department of Information Science and Engineering**

Thesis title: **Classification of Diabetic Retinopathy**

Thesis supervisor: **Prof.T N Naghabushan**

Month and year of thesis submission: **July, 2021**

The classification of the Diabetic Retinopathy at the early stages is very important in order to stop the spreading of the disease.This proposed work, aims to detect the Diabetic Retinopathy at early stages accurately and quickly by using different CNN architectures . The Dataset that is used in this work is from IDRid dataset which consists of 413 training samples and 103 testing samples , the images is of 2848 X 4288 pixel.We can see there is a class imbalance in the dataset so appropriate measure have taken to overcome it. We have used CNN , ResNet-50 , DenseNet-121,Inception v3 for Classification of Diabetic Retinopathy . All the models were trained Individually and took the best model out of these for the final classification of the Diabetic Retinopathy. In this project we achieved an highest accuracy of 68.91 from DenseNet-121.

Acknowledgements

First and foremost, I consider myself privileged to express gratitude and respect towards all those who guided me throughout the completion of my Master's program.

I owe my thanks to the management of JSSSTU, for giving this wonderful opportunity for carrying out my course in this prestigious institution.

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I take immense pleasure and very deep sense of gratitude in conveying my special, sincere and heartfelt thanks to my guide **Dr. T N Naghabushan**, Professor, Department of Information Science and Engineering, JSS Science and Technology University, Mysuru.

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It is with deep sense of gratitude, I thank my parents, who have constantly encouraged,and continuously supported my entire academic life.

Contents

List of Figures

Abbreviations

CNN	**C**onvolution **N**eural **N**etwork
RGB	**R**ed **G**reen **B**lue
BGR	**B**lue **G**reen **R**ed **DR**
Diabetic **R**etinopathy **DME**	**D**iabetic **M**acular **E**dema

Chapter 1

Introduction

1.1 Introduction

Let us first know what is Classification before we talk about how we classify the images and so on. To keep it simple Classification is basically grouping the objects by using the known Label information. So, we need to send Label information along with the data for the model to Classify. In this paper we classify Diabetic Retinopathy images with the help of Deeplearning models which takes images and label as input. We provide Diabetic Retinopathi image with label as input for the model and train it to Classify the Diabetic Retinopathy images.

Diabetic Retinopathy (DR), also known as diabetic eye disease, is a medical condition in which damage occurs to the retina due to diabetes mellitus.Diabetic Retinopathy (DR) is the leading cause of blindness in the working-age group. 50 million Indians sufering from diabetes, the prevalence of those with DR is estimated between 18percent to 28percent.Regular eye examination among these vulnerable groups is necessary to diagnose DR at an early stage, when it can be treated with the best prognosis.

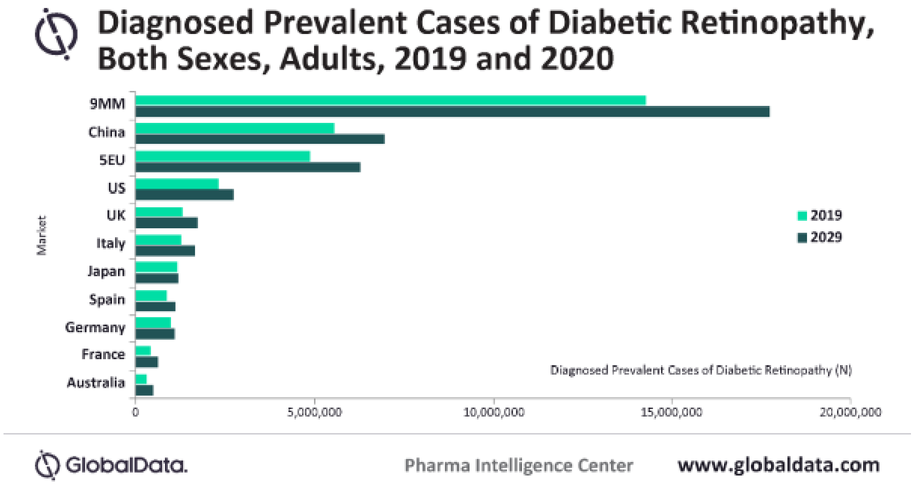

FIGURE 1.1: Cases of DR

As show in the Figure 1.1, According to the GlobalData, it is predicted to have the increase in the DR cases to 17.8 million in 2029 .Diabetic Retinopathy is the most prevalent cause of avoidable vision impairment, mainly affecting the working-age population in the world. Recent research has given a better understanding of the requirement in clinical eye care practice to identify better and cheaper ways of identification, management, diagnosis and treatment of retinal disease. Currently, detecting DR is a time-consuming and manual process that requires a trained clinician to examine and evaluate digital color fundus photographs of the retina. Automated analysis of retinal color images has such benefits as increased efficiency and coverage of screening programs, reduced barriers to access, and early detection and treatment. In this project we use Deep Learning models to detect referable Diabetic Retinopathy.

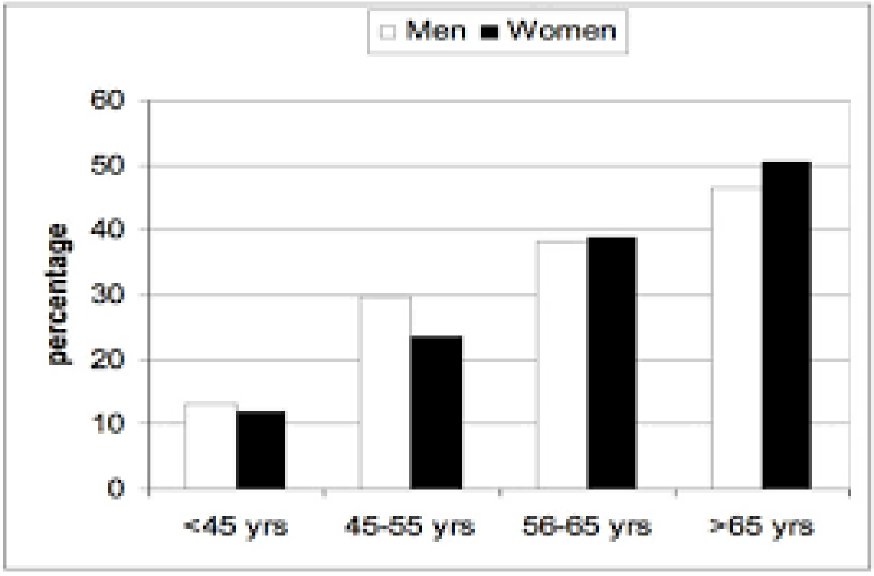

FIGURE 1.2: Gender wise DR Cases

As we can see in the Figure 1.2 as the age increases the person with the Diabetics are more prone to be affected by the Diabetic Retinopathy Disese. Diabetic Retinopathy affects up to 80 percent of those who have had diabetes for 20 years or more. Diabetic retinopathy often has no early warning signs. Retinal (fundus) photography with manual interpretation is a widely accepted screening tool for diabetic retinopathy, with performance that can exceed that of in-person dilated eye examinations. An automated tool for grading severity of diabetic retinopathy would be very useful for accerelating detection and treatment. Recently, there have been a number of attempts to utilize deep learning to diagnose DR and automatically grade diabetic retinopathy.

In the Figure 1.3 we can see the changes in the eye when the person is affected by the Diabetic Retinopathy and we can see what are the different type disease we can find in the DR affected Eye.

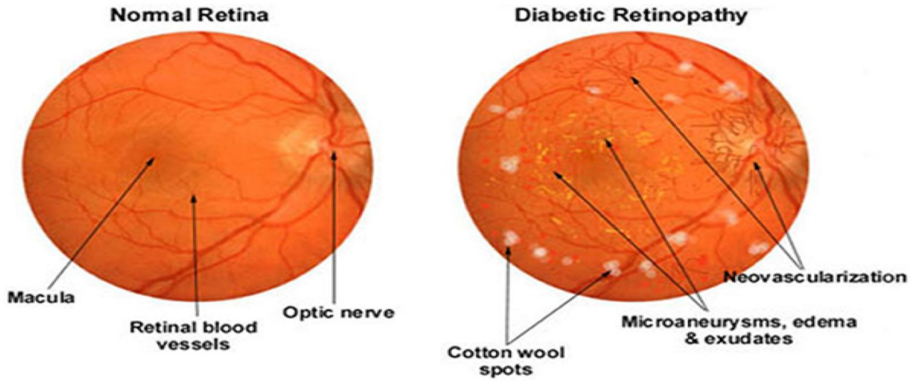

FIGURE 1.3: DR affected and unaffected eye

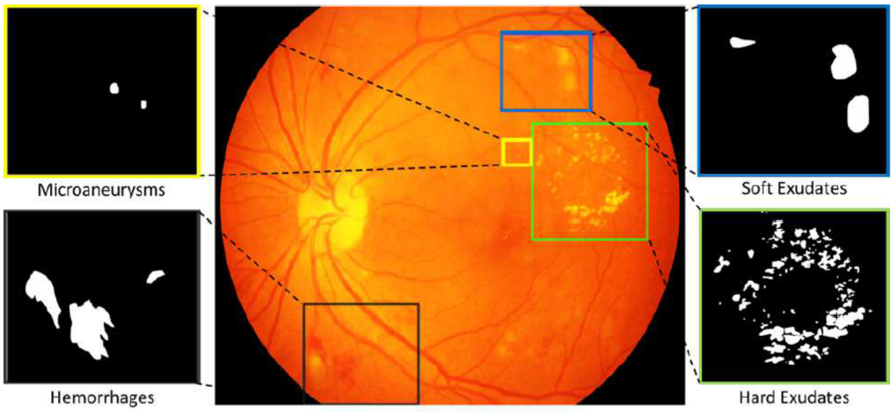

FIGURE 1.4: Image of EYE containg different retina leison

In the Figure 1.4 we can see what are the disease that can be found in the Diabetic Retinopathy affected eye.

Literature Survey i)Indian Diabetic Retinopathy Image Dataset (IDRiD): (Porwal et al., 2018) In this paper the authors explained about how they created the IDRiD (Indian Diabetic Retinopathy Image Dataset), this is the first database representative of an Indian population. It constitutes typical diabetic retinopathy lesions and normal retinal structures annotated at a pixel level. The dataset also provides information on the disease severity of diabetic retinopathy, and diabetic macular edema for each image.

ii)Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs (Gulshan et al., 2016) In this paper the audthors focused on applying deep learning to create an algorithm for automated detection of diabetic retinopathy in retinal fundus photographs on EYEPACS-1 dataset and Messidor-2 dataset. The EYEPACS dataset contains

9963 images and the Messidor-2 dataset contains 1748 images. They have achieved the sensitivity of 97 for EYEPACS-1 , 96.1 for Messidor-2 and they achieved the specificity of 93.4 for EYEPACS-1 , 93.9 for Messidor-2 datasets.

iii)Diabetic Retinopathy detection through integration of Deep Learning classification framework (Rakhlin, 2018) in this paper they created the deeplearning CNN -model for Kaggle data and messidor-2 data set . They use 81670 retinal images for training and 40835 retinal images for modelevalutation of the Kaggle dataset .The Messidor-2 dataset contains 1748 retinal images of 874 subjects, the images were taken by color video 3CCD camera on a Topcon TRC NW6 non-mydriatic funfus camera with a 45 degree field of view.

They have used the VGG16 model and have achieved the AUC of 97 for Messidor-2 , 92 for Kaggle dataset. They also achieved the sensitivity of 99 and specificty of 71 for Messidor-2 dataset

iv)Fastai: A Layered API for Deep Learning (Howard and Gugger, 2020) , fastai is a deep learning library which provides practitioners with high-level components that can quickly and easily provide state-of-the-art results in standard deep learning domains, and provides researchers with low-level components that can be mixed and matched to build new approaches. It aims to do both things without substantial compromises in ease of use, flexibility, or performance. This is possible thanks to a carefully layered architecture, which expresses common underlying patterns of many deep learning and data processing techniques in terms of decoupled abstractions. These abstractions can be expressed concisely and clearly by leveraging the dynamism of the underlying Python language and the flexibility of the PyTorch library. fastai includes: a new type dispatch system for Python along with a semantic type hierarchy for tensors; a GPU-optimized computer vision library which can be extended in pure Python; an optimizer which refactors out the common functionality of modern optimizers into two basic pieces, allowing optimization algorithms to be implemented in 4ndash;5 lines of code; a novel 2-way callback system that can access any part of the data, model, or optimizer and change it at any point during training; a new data block API; and much more. We used this library to successfully create a complete deep learning course, which we were able to write more quickly than using previous approaches, and the code was more clear. The library is already in wide use in research, industry, and teaching.

v)CANet: Cross-disease Attention Network for Joint Diabetic Retinopathy and Diabetic Macular Edema Grading (Li et al., 2020)where they have used the IDRid dataset which consists of 413 training samples and 103 testing data ,In the IDRiD dataset, each image contains both DR and DME severity grading labels. DR grade is annotated into five classes according to the severity scale, and we perform 5 class classification for DR. DME is annotated based on the shortest distance d between the hard exudates location and the macula. The annotation criteria of DME grading is the same as that in the IDRiD dataset, and they have made use of the CANet and have achieved the joint accuracy of 65.1.

1.2 Research gaps

only one or two have worked on the same topic in which they have worked on same dataset and have achieved the Accuracy of 65 which is the current highest who has achieved on this dataset for classifying both Diabetic Macular Edema and Diabetic Retinopathy Grade.

1.3 Observations

It was observed that the dataset consist of very less number of samples and the dataset also consist of the class imbalance , which will affect in building the model and getting the required accuracy . In most of the papers they have used they have used the dataset that consist of huge number of sample , and in IDRid challenge the top team that participated have achieved the overall percentage of 63.

1.4 Motivation

The main motivation for doing this project is to give a more appropriate classification model just by using the less number of samples and achieve more accuracy in identifying the diabetic retinopathy.

1.5 Problem Statement

Building the deep learning classification model to classify the diabetic retinopathy affected eye and classify them according to their subclasses in Macular Edema and Retinopathy Grade. The aim of this is to classify the Diabetic Retinopathy images automatically. The given system is designed around the different deeplearning model and choosen the best model that is good for this data and result is evaluated . The objectives of this system is to Classify the Diabetic Retinopathy images

Chapter 2

PROPOSED METHODOLOGY

2.1 Input Unit

We use the Diabetic Retinopathy IDRid datset images to train the model.

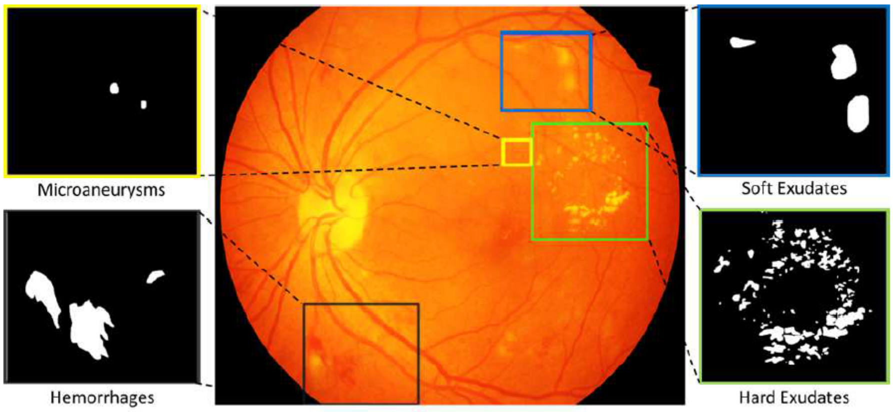

Figure 2.1: Eye image

The Images in the IDRid dataset were acquired using a Kowa VX-10 alpha digital fundus camera with 50-degree field of view (FOV), and all are centered near to the macula. The images have a resolution size of 4288×2848 pixels and are stored in .jpg file format. The size of each image is about 800 KB.

2.2 Data set formulation

Data set formulation unit designed to perform the task to check the input and store it into data set with their appropriate attributes. This unit is designed to choose correct class label for a given data input.

```
x=df.dropna(axis=1)
x
```

	Image name	Retinopathy grade	Risk of macular edema
0	IDRiD_001	3	2
1	IDRiD_002	3	2
2	IDRiD_003	2	2
3	IDRiD_004	3	2
4	IDRiD_005	4	0
...	...	...	...
408	IDRiD_409	2	1
409	IDRiD_410	2	0
410	IDRiD_411	2	0
411	IDRiD_412	2	0
412	IDRiD_413	2	0

413 rows × 3 columns

FIGURE 2.2: Training set

The Figure 2.2 represent the total number of the images in the training set along with the labels in the csv format.Here we store the images into the folder of their respective subclasses of Macular Edema and Retinopathy grade which will be helpful in building the model in the later stage.

```
sns.countplot(data=x,x=df['Retinopathy grade'])
<matplotlib.axes._subplots.AxesSubplot at 0x7fa7e943a0f0>
```

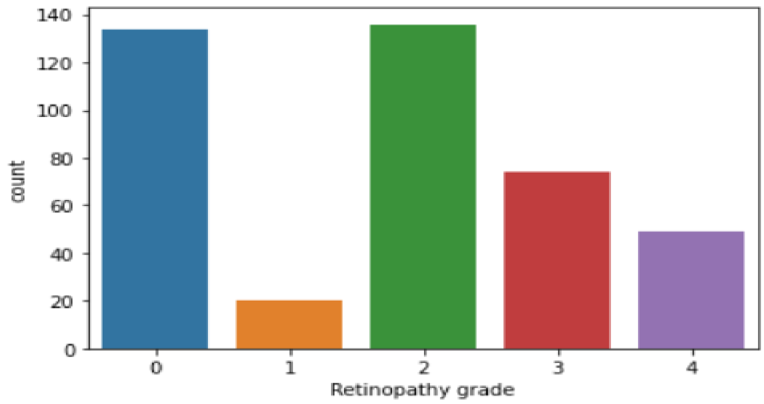

Figure 2.3: Exploratory Data Analysis 1

In the Figure 2.3 we can see that there is an clear class imbalance in the dataset for the classes of 1,3 and 4 of Retinopathy grade.

```
sns.countplot(data=x,x=df['Risk of macular edema '])
<matplotlib.axes._subplots.AxesSubplot at 0x7fa7ea7eff98>
```

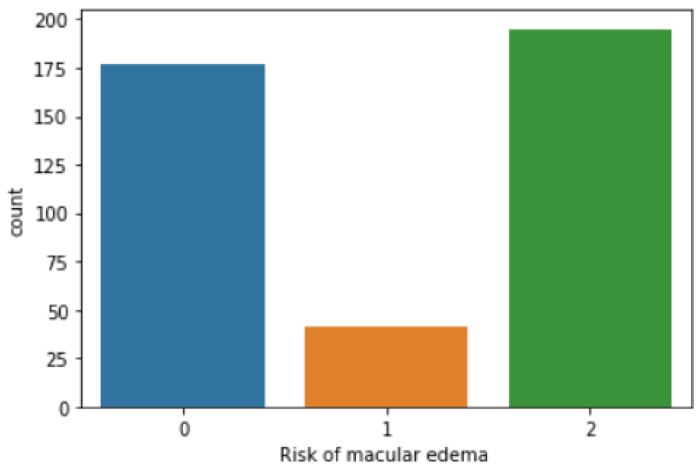

Figure 2.4: Exploratory Data Analysis 2

In the Figure 2.4 we can see that there is an clear class imbalance in the dataset for the classes of 1 of Macular Edema.The distribution of the data on retinopaty grade with respect to the macular edema is shown in the Figure 2.5

```
sns.histplot(x,y=df['Retinopathy grade'],x=df['Risk of macular edema '])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa7eac65b00>
```

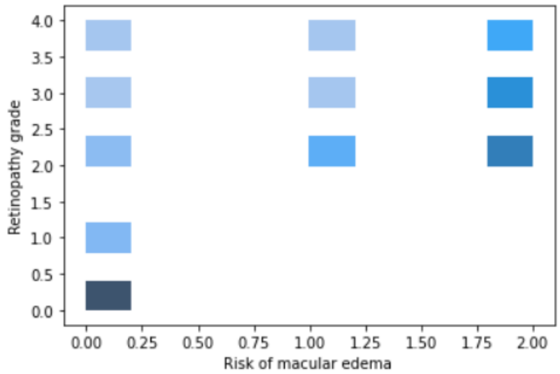

FIGURE 2.5: Exploratory Data Analysis 3

2.3 Work Flow

First things first we collect all the data that is required for this work and it is stored in one folder , those images that are stored is passed to the Pre- processing step where the required preprocessing techniques are used on the images .Here we have used the images resizing and the images should be read in RGB color instead of BGR color, as the preprocessing for the images then we pass the preprocessed images to the next stage that is for the CNN Architecture where we used the pretrained network and also custom build cnn model.The output of these images are then sent to the output stage where we can validate how god is our model is. These are the general workflow that is used in this work . The augmentation of the images based on the class is done when we were copying the images from the oringinal dataset to custom structured dataset. The custom structured dataset will be having the subclass names as their folder name and all the respective images of the subclass of both macular edema and retinopathy grade are stored seperately.

The Figure 2.6 represent the Generalized Work Flow that is used in building this model and the Figure 2.7 represent the common blocks or layers that is present in the model.

Here we use the different types of CNN model and the best model is used for the classification of Diabetic Retinopathy .CNN is a modified variety of deep neural net which depends upon the correlation of neighboring pixels. It uses randomly defined patches for input at the start, and modifies them in the training process. Once training is done, the network uses these modified patches to predict and validate the result in the testing and validation process. Convolutional neural networks have achieved success in the image classification problem, as the defined

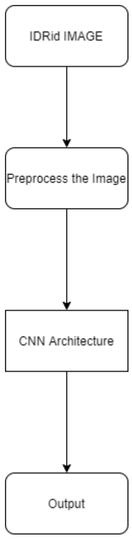

FIGURE 2.6: Work Flow

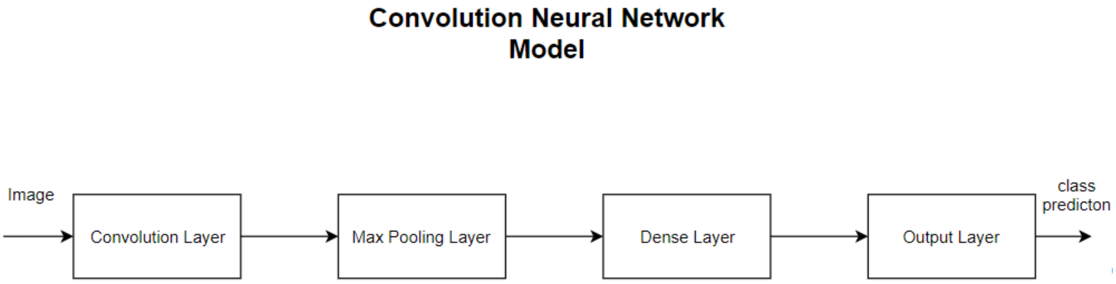

FIGURE 2.7: Convolution Neural Network

nature of CNN matches the data point distribution in the image. As a result, many image processing tasks adapt CNN for automatic feature extraction. CNN is frequently used for image segmentation and medical image processing as well. The CNN architecture has two main types of transformation. The first is convolution, in which pixels are convolved with a filter or kernel. This step provides the dot product between image patch and kernel. The width and height of filters can be set according to the network, and the depth of the filter is the same as the depth of the input.

A second important transformation is subsampling, which can be of many types (max pooling, min pooling and average pooling) and used as per-requirement. The size of the pooling filter can be set by the user and is generally taken in odd numbers. The pooling layer is responsible to lower the dimensionality of the data, and is quite useful to reduce overfitting. After using a combination of convolution and pooling layers, the output can be fed to a fully connected layer for efficient classification.Apart from the architecture of CNN, there is an additional key point, i.e., that simplicity to the user is helpful on the development side, as CNN requires a tremendous amount of data for training. It also requires more training time as compared to other supervised and unsupervised training approaches.

There are many CNN models that are readily available for the users in the Deep learning , those models are trained on the different kind of the dataset. We can make use of those model according to our dataset just by tweaking some hyper parameters and it will ready to use for our data. Here we are using the fastai and using the pretrained CNN models that are already available in it.

Here we used the Transfer learning. Transfer learning has become popular in the feild of image classification and Natural language Processing, Here we take the Pretrained model that is trained on other similar kinda data and then we retrain that model on our data. Transfer learning are more use when we have very less number of samples or data.

Here we use Densenet121(Huang et al., 2017), as we can see in the Figure 2.8 It introduces direct connections between any two layers with the same feature-map size.DenseNet is a convolutional neural network where each layer is connected to all other layers that are deeper in the network, that is, the first layer is connected to the 2nd, 3rd, 4th and so on, and it is showed that DenseNets scale naturally to hundreds of layers, while exhibiting no optimization difficulties.DenseNets tend

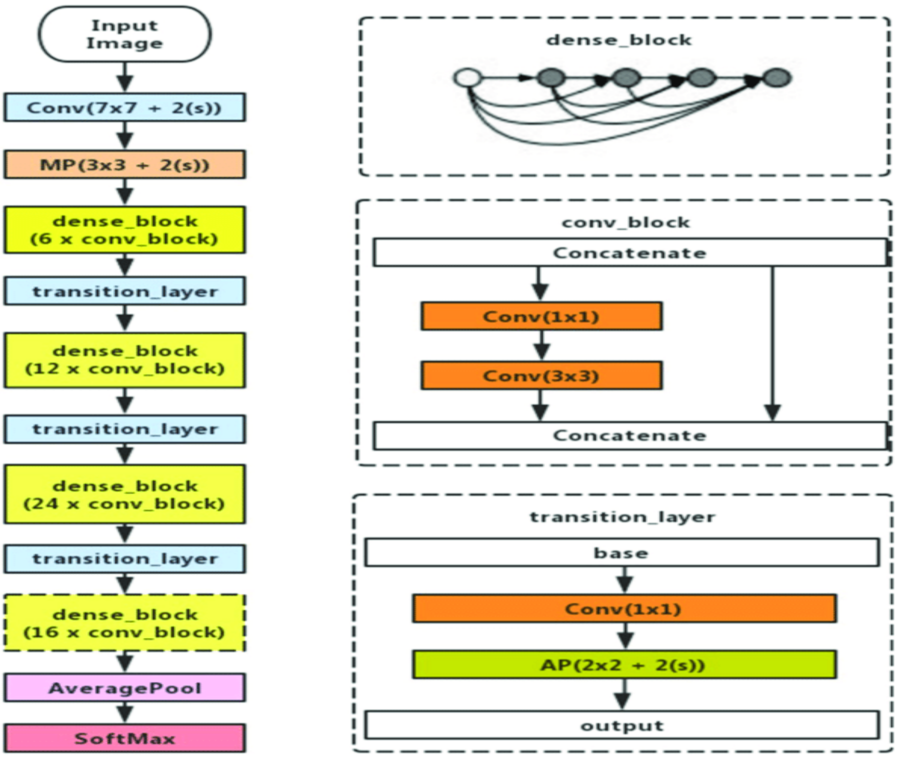

FIGURE 2.8: DenseNet121

to yield consistent improvement in accuracy with growing number of parameters, without any signs of performance degradation or overfitting. Under multiple settings, it achieved state-of-the-art results across several highly competitive datasets. Moreover, DenseNets require substantially fewer parameters and less computation to achieve state-of-the-art performances.The total parameters of Densenet121 is of 8,009,088.

DenseNet121 has one input layer followed by one Convolution layer of 7x7 stride2 followed by one Max Pooling layer of size 3x3 with stride 2, followed by Dense block 1 which has 6 times 2 convolution layer or size 1x1 and 3x3 respectively followed by the Transition layer which has 1 convolution layer of size 1x1 and one average pooling of size 2x2 with stride 2 after this we have same dense block of 2 convolution but with 12 times which is followed by the same transition layer which is followed by the dense block 3 which has same 2 convolution layer but with 24 time and it is followed by the transition block which is specified before and it is followed by one more dense block which has same 2 convolution layer with 16 times followed by classification layer with one global average pooling layer of size 7x7 and 1000D fully connected layer and then finally it is connected to a output layer.

Another pretrained network that is used is ResNet50 it has one input layer followed by the one convolution one convolution layer of 7x7 with kernel size of 64 followed by the convolution block which has the convolution size of 1x1 with kernel size of 64 followed by the convolution size of 3x3 with kernal size of 64 followed by the convolution size of 1x1 with kernel size of 256 followed by the sec cconvolution block which same convolution layer but with kernal size of 128,128,512 followed 3rd conv block which has same same convolution layers with kernel size of 256,256,1024 followed by 4th convo block with same convolution layer but with kernel size of 512,512,2048 followed by 1000 fully connected layer and then finally it is connected to a output layer. It has a total of 25,615,936 parameters.

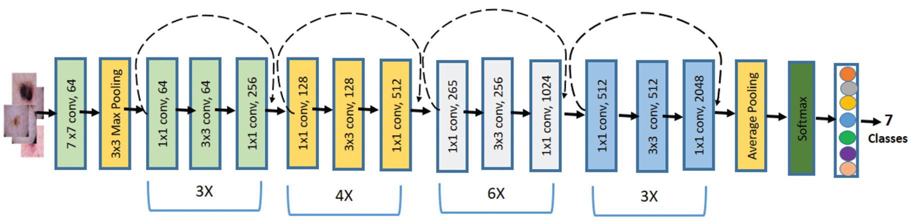

FIGURE 2.9: RestNet50

2.4 Implementation

First we pass all the collected training data from custom structured dataset as the input to the model , the necessary preprocessing and the rescaling of the images are done in next step.In preprocessing we will read the images in rgb channel and resize the images to 300x300. These images are passed to the imageDataloaders and need to specify the train and validation data , Then we create a learner which provides an abstraction combining an optimizer , models and the data to train the learner.

We freez the top layers of the model and train only on the final layer and we check the output of the model in which we can know whether we can use this model or not. By using this method we will minimise the number of trainable parameters which inturn reduces the amount of the time and resources that is required to train the model.Here we will monitor the accuracy and error rate of the model.Here we fit the model using the fit one cycle policy ,It annealing both learning rates , and momentums and print the metrics on the validation data.Once we can get confirm that we are getting good results then we move on to the next stage.

Then we unfreez the learner and then we fit the model and then we tune the hyper parameter and the train the model using fit one cycle policy and we measure the metrics on the validation data. Then we find learning rate based on the trained model in order to finetune the learning rate, we used the lrfind inbuilt function that is present in the fastai as shown in the Figure 2.10 and based on the result we will retrain the model with new learning rate .Then we find the trained model accuracy on the validation data and we plot the confusion matrix . When the results that is obtained it satisfied then we save the model for the final testing

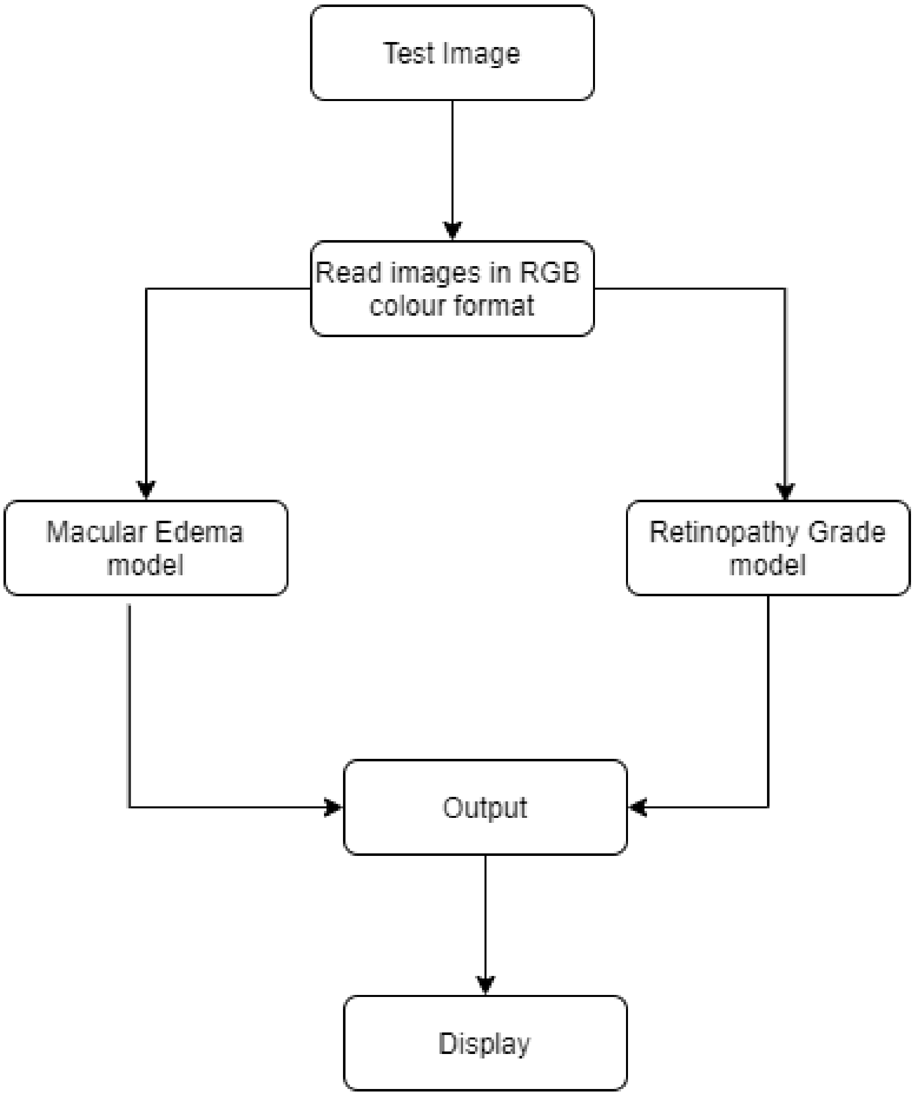

FIGURE 2.10: final Model Design

purpose. Two such models were created one for Macular Edema classification and the other is for Retinopathy Grade classification.

We create one more model in which we will read all the test data in it and load the both saved models of Macular Edema and Retinopathy Grade. then we finally pass the testing images and as the result we get the output with both macular edema and retinopathy grade result

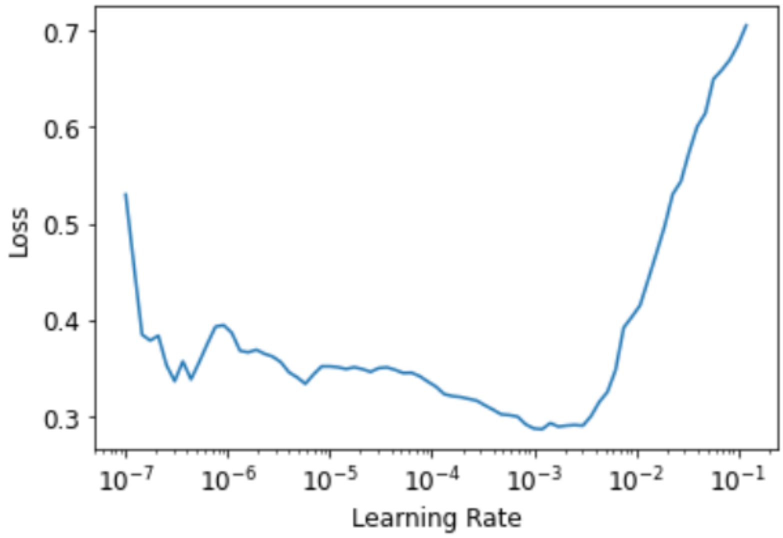

FIGURE 2.11: Learning rate

2.5 Dataset

The Diabetic Retinopathy is the most prevalent cause of avoidable vision impairment, mainly affecting working age population in the world. Recent research has given a better understanding of requirement in clinical eye care practice to identify better and cheaper ways of identification, management, diagnosis and treatment of retinal disease. The importance of diabetic retinopathy screening programs and difficulty in achieving reliable early diagnosis of diabetic retinopathy at a reasonable cost needs attention to develop computer-aided diagnosis tool. Computer-aided disease diagnosis in retinal image analysis could ease mass screening of population with diabetes mellitus and help clinicians in utilizing their time more efficiently. The recent technological advances in computing power, communication systems, and machine learning techniques provide opportunities to the biomedical engineers and computer scientists to meet the requirements of clinical practice. Diverse and representative retinal image sets are essential for developing and testing digital screening programs and the automated algorithms at their core. To the best of our knowledge, the database for this challenge, IDRiD (Indian

Diabetic Retinopathy Image Dataset), is the first database representative of an Indian population. Moreover, it is the only dataset constituting typical diabetic retinopathy lesions and also normal retinal structures annotated at a pixel level. This dataset provides information on the disease severity of diabetic retinopathy, and diabetic macular edema for each image. IDRiD (Indian Diabetic Retinopathy Image Dataset) consists of 413 labeled images for training each image is of the size 2848 X 4288 pixel.

2.6 EXPERIMENTAL RESULT

In this we can see the result of the three model. In the First model that is the Macular Edema classification model we have achieved the accuracy of the 87 percent and the ROC is about 91.

In the Figure 2.12 we have the confusion matrix of the validation of macular edema model which has 3 classes 0 ,1 ,2 which represents the stages of severity of the macular edema. As we can see if have classified efficiently for all class even with having less number of samples in the dataset . We have very less number of the miss match except in the class 1.

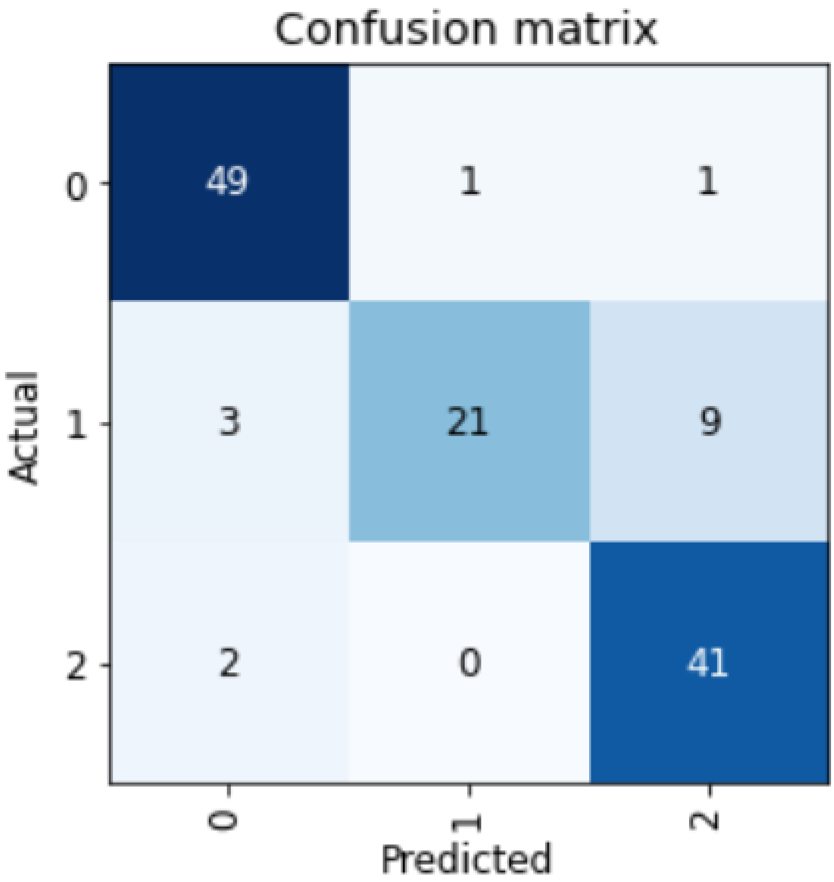

FIGURE 2.12: confusion matrix of macualar edema model

In the Figure 2.13 we are seeing the ROC curve of the Macular Edema model.As we can see we have achieved the 91 which specifies that the given model works good on the given data.

```
The accuracy is 87.40157318115234 %.
ROC area is 0.9119922630560928
<matplotlib.legend.Legend at 0x7f6d98b04910>
```

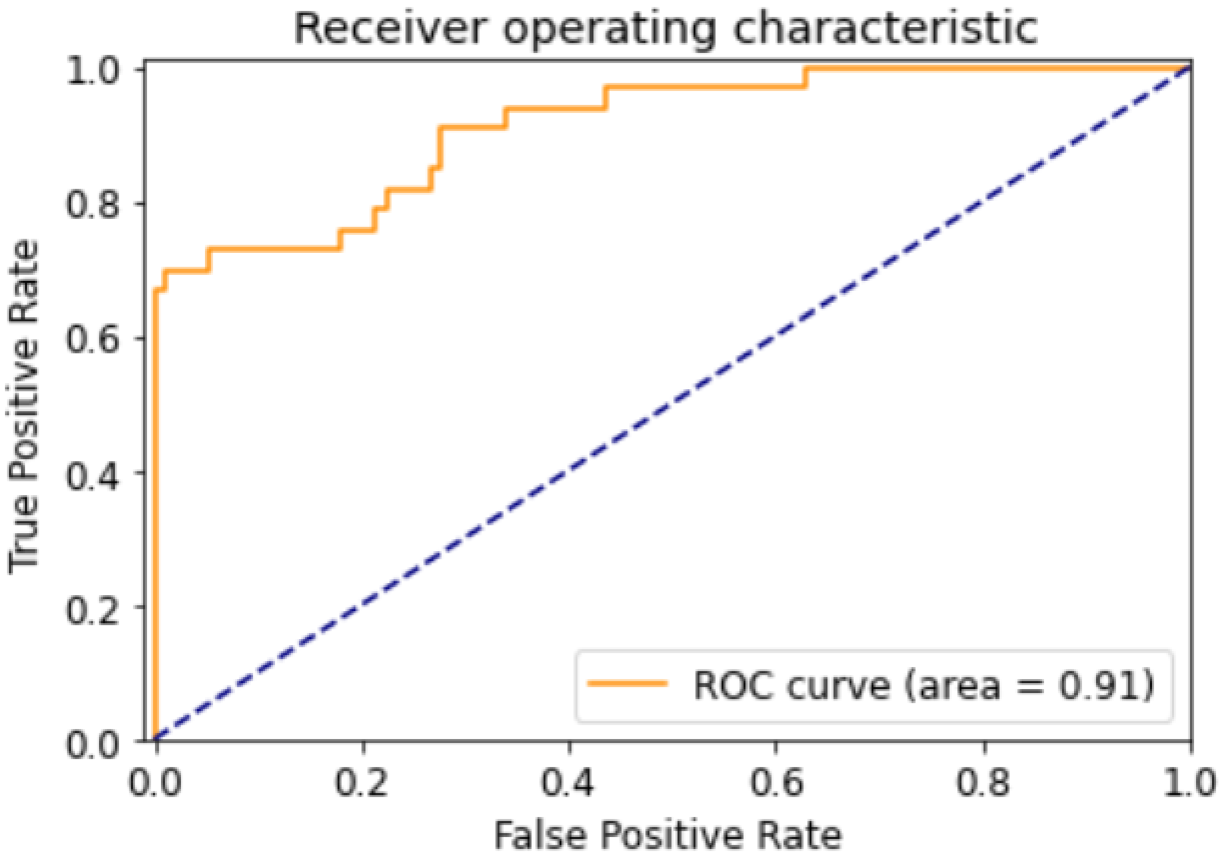

FIGURE 2.13: ROC of macualar edema model

In the second model that is the classification of the Retinopathy Grade we have achieved an accuracy of the 76 and the ROC is 100.

As we can see in the confusion matrix we have the total of 5 classes in the Retinopathy Grade where each class represents the severity of the retinopathy grade where 0 represents no normal eye and the class 4 represent the highest level of retinopathy diesease grade. If we look closely we can see that there is a good classification

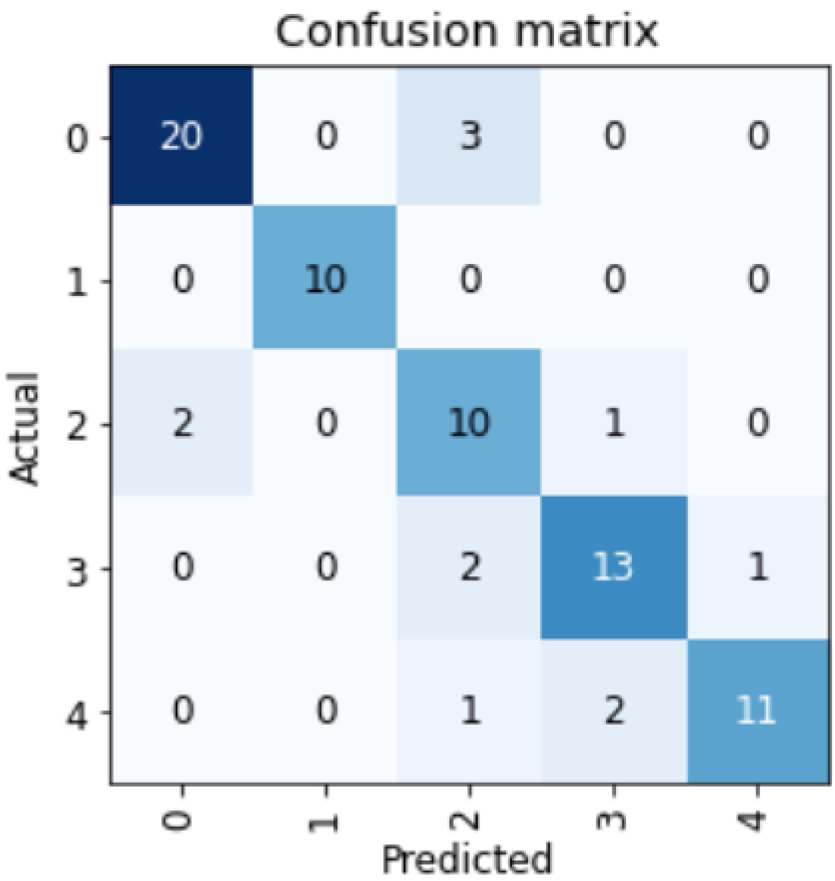

FIGURE 2.14: confusion matrix of Retinopathy Grade model

and we can find only few miss classification so this model is pretty good in its performance and the ROC curve is also looks pretty good.

```
The accuracy is 76.31578826904297 %.
ROC area is 1.0
<matplotlib.legend.Legend at 0x7feaa4358b50>
```

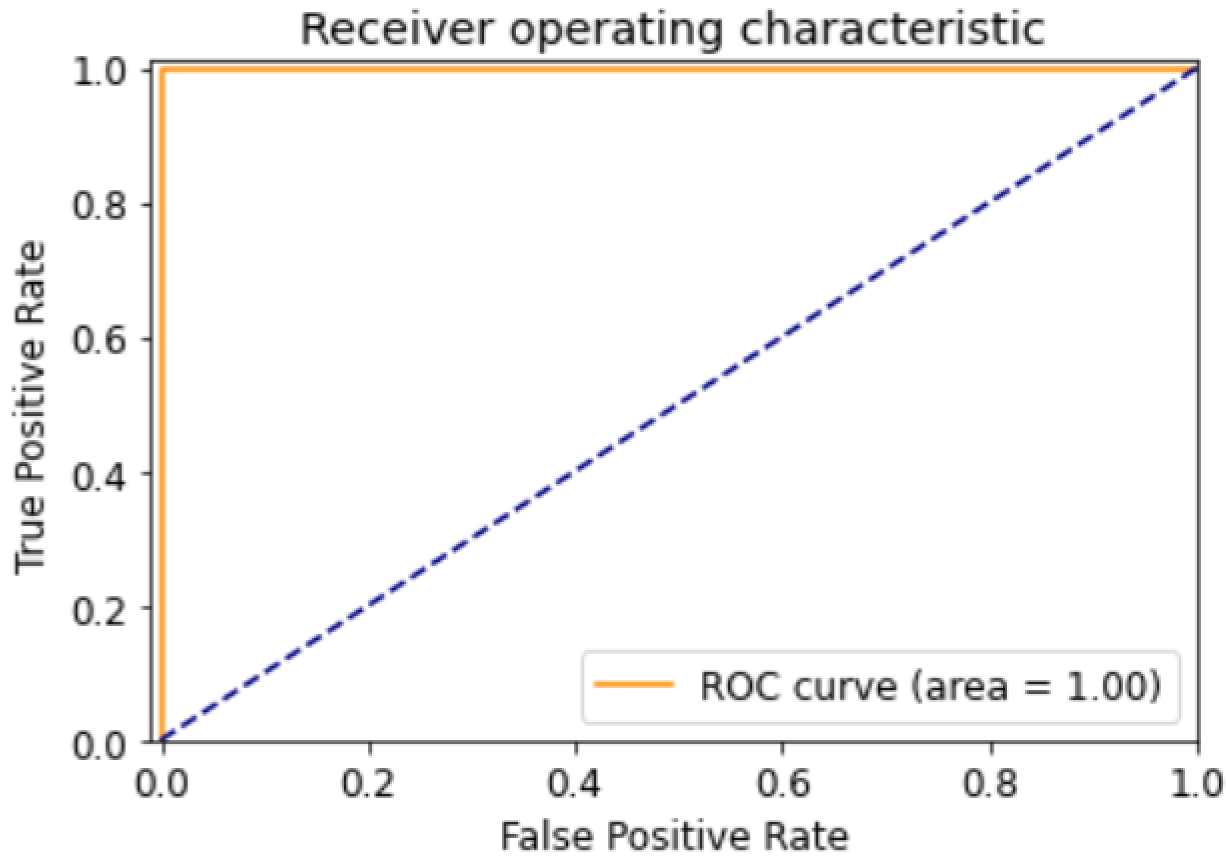

FIGURE 2.15: ROC of macualar edema model

In then final model we used both the Macular Edema and Retinopathy Grade saved models and we used the test images to check how well our model is working on the test data and as you can see in the Figure 2.16 we have achieved the accuracy of 69

```
acc_both_true = cnt/103 * 100
print(acc_both_true)
```

```
68.93203883495146
```

FIGURE 2.16: Final model Accuracy

Here in Figure 2.17 are few results that we have achieved for Macular Edema classification using different models.

Model (DME)	Accuracy
CNN	52
2nd CNN model	32
Resnet 50 (batch size=10)	34
Resnet 50(batch size=40)	61
Inception v3	59
Dense Net	87

FIGURE 2.17: Macualar edema model Accuracy

In the Figure 2.18 are the few results than is achieved for Retinopathy Grade classification using different models.

Model (DRG)	Accuracy
CNN	33
2nd CNN model	32
Resnet 50 (batch size=10)	28
Resnet 50(batch size=40)	37
Inception v3	35
Dense Net	76

Figure 2.18: Retinopathy Grade model Accuracy

The Figure 2.19 represent the Accuracy for the classifying both Diabetic Retinopathy Grade and Diabetic Macular Edema correctly that is achieved by the Top Leaderboard in the Idrid Challenge and our model

Model (DRG+DME)	Accuracy
LzyUNCC	63
VRT	55
Mammoth	51
HarangiM1	48
AVSASVA	48
HarangiM2	41
Our Model	69

FIGURE 2.19: Retinopathy Grade model Accuracy

Chapter 3

CONCLUSION

The detection of the Diabetic Retinalimages at the early stages is very important in order to stop the spreading of the disease which may he very severe.We designed and implemented IDRid Diabetic Retinopathy classification using different Deeplearning Model, which uses the retinal images and we used the best model , and we tried to classify the changes in the Retinal image during different stages.The Deep CNN model that gave us the best result for the given data. We got the best result for DenseNet121 which gave us the result of 87.40 for Macular Edema and 76.31 for Retinopathy Grade model and with both we achieved the accuracy 68.92 which is good when compared to others that have done on this Dataset only, Even though we have only less data samples, if we have more number of samples and have balanced in data then we can have achieve more accuracy .The results exhibits that we can use this model for detecting the Diabetic Retinopathy. Our future aim is to make image segmentation for each eye image and understand the disease and then apply classification for that images.

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https://idrid.grand-challenge.org/Leaderboard

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