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Automated Detection of Diabetic Retinopathy Using Deep Learning

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Abstract - *Diabetic retinopathy is one of the prevalent causes of blindness among working-age adults. Diabetic retinopathy or DR is an ailment because of diabetes mellitus that can harm the patient image retina and also cause blood spills It is the fastest growing cause of blindness. We have used Deep learning classification techniques, Convolutional Neural Network (CNN), pre-trained VGG-16, ResNet to detect the severity level of Diabetic Retinopathy from the color fundus image. Fundus photography technique is used to take these photographs.*

Key Words*: *Diabetic Retinopathy, Convolutional Neural Network, VGG-16 and ResNet

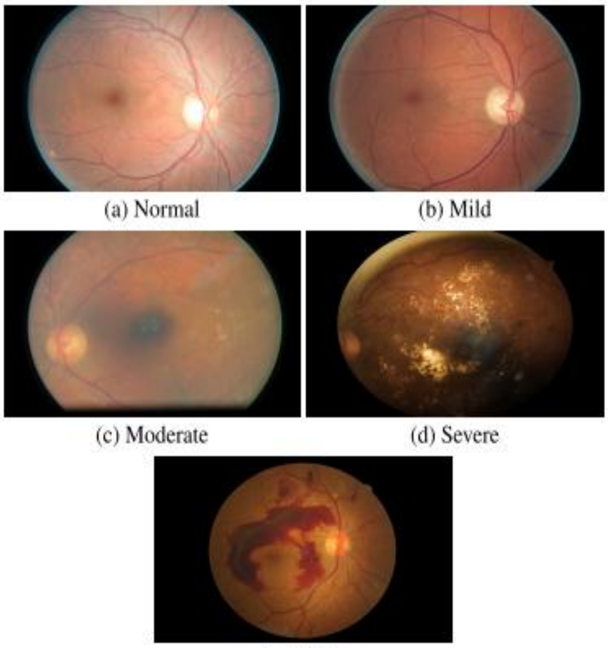
1. INTRODUCTION

Diabetic retinopathy is a medical complication that is caused by the damage to the blood vessels of the light-sensitive tissue which is present at the back of the eye, retina, which can gradually lead to complete blindness and various other eye problems depending on the severity of Diabetic Retinopathy.

It is observed that 40% – 45% of diabetic patients are likely to have DR in their life, but due to lack of knowledge and delayed diagnosis, the condition escalates quickly.

Diabetes was once thought of as a disease of the affluent but it's now reached epidemic proportion in both developed and developing countries. Currently, a minimum of 366 million people worldwide has diabetes, and this number is probably going to extend as a results of an aging global population

Globally, the quantity of individuals with DR will grow from 126.6 million in 2010 to 191.0 million by 2030, and that we estimate that the quantity with vision-threatening diabetic retinopathy (VTDR) will increase from 37.3 million to 56.3 million, if prompt action isn't taken.



(a) Normal (b) Mild (c) Moderate (d) Severe (e) PDR

1.1 METHOD AND METHODOLOGY

1.2 DATA SET

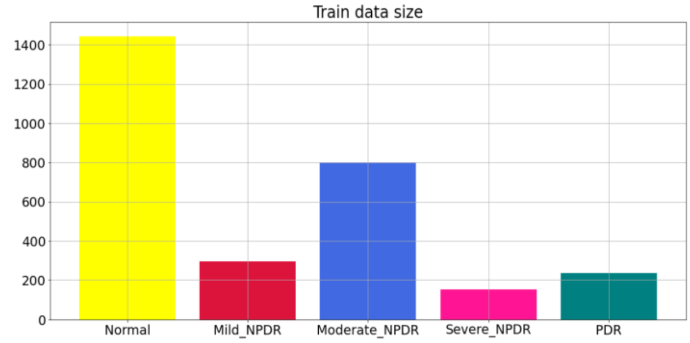
We have used the data collected by the Asia-Pacific TeleOphthalmology Society (APTOS) available on the Kaggle platform.

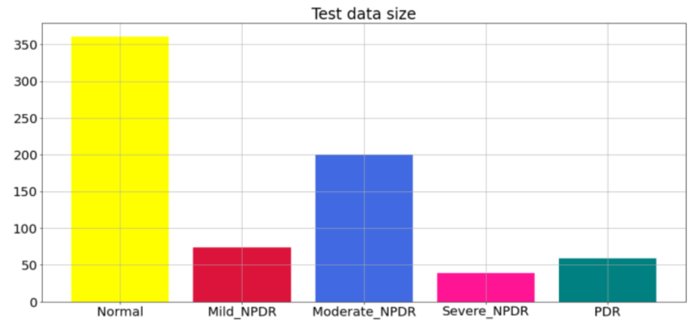
The data set consists of 3,662 color fundus images. We have used the dataset of such images for the training and testing of our model. Each image in the dataset has been assigned an integral value on the scale of 0 to 4 according to the severity of the disease by a professionally trained clinician as shown in Table-1.

Class	Name	No. of images
0	Normal	1805
1	Mild NPDR	370
2	Moderate NPDR	999
3	Severe NPDR	193
4	PDR	295

Table -1

In order to induce a more balanced date, we have split the dataset into 80:20 for training and validation purpose. Totally for training purpose we have considered 2,929 color fundus images and 733 color fundus images for validation.





0 – Normal: The person is not suffering from Diabetic Retinopathy.

1 – Mild Non-Proliferative DR (Mild_NPDR): Within the Retina's minute blood vessels, small areas of balloon like inflammations.

2 – Moderate Non-Proliferative DR (Moderate_NPDR): The blood vessels that sustain the retina are blocked at this stage. Within the retina, there might also be haemorrhages.

3 – Severe Non-Proliferative DR (Severe_NPDR): More blood vessels are blocked in this particular stage, denying several areas of retina of blood supply. The number of haemorrhages in the retina also increases drastically.

4 – Proliferative DR (PDR): New and abnormal blood vessels developed on the surface of retina. These new blood vessels are delicate and have the tendency to bleed, causing vision threatening haemorrhages to fill the eye. They can also turn into connective tissue which will contract over time, causing the retina to detach and cause blindness.

2. PREPROCESSING

We are resizing the images for pre-processing the data before providing it to the model first, keeping in view the aspect ratio to 256 × 256. It helps us to avoid features loss from images. The dataset is distributed into training, validation sets with a ratio of 80% and 20% respectively.

CNN ARCHITECTURE:

Convolutional Neural Network, is commonly used to breaking down of visual imagery and thus used for retinal images. A Convolutional Neural Network or CNN is a general multilayered neural framework with an outstanding plan to perceive complex features in the data. The pre-processing required in a CNN is much lower as compared to other classification algorithms. CNN architecture consists of these main layers: convolutional layer, pooling layer, Dropout layer and fully-connected layer.

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 256, 256, 64)	1792
max_pooling2d (MaxPooling2D)	(None, 128, 128, 64)	0
conv2d_1 (Conv2D)	(None, 128, 128, 64)	36928
max_pooling2d_1 (MaxPooling 2D)	(None, 64, 64, 64)	0
conv2d_2 (Conv2D)	(None, 64, 64, 128)	73856
max_pooling2d_2 (MaxPooling 2D)	(None, 32, 32, 128)	0
conv2d_3 (Conv2D)	(None, 32, 32, 128)	147584
max_pooling2d_3 (MaxPooling 2D)	(None, 16, 16, 128)	0
dropout (Dropout)	(None, 16, 16, 128)	0
flatten (Flatten)	(None, 32768)	0
dense (Dense)	(None, 1024)	33555456
dense_1 (Dense)	(None, 5)	5125

Total params: 33,820,741
Trainable params: 33,820,741
Non-trainable params: 0

We have built the sequential CNN model. Firstly, Conv2d layer with parameters: 64 filters and kernel of size (3,3) which is a 2-tuple specifying width and height of the 2D convolution window.

The input shape parameter is passed with train's shape and with padding value to be the same to preserve the spatial dimensions along with activation parameter to be Relu.

Max pooling is considered as the pooling layer, which down-samples the resulting feature maps and increases the receptive field on the filters [2,2].

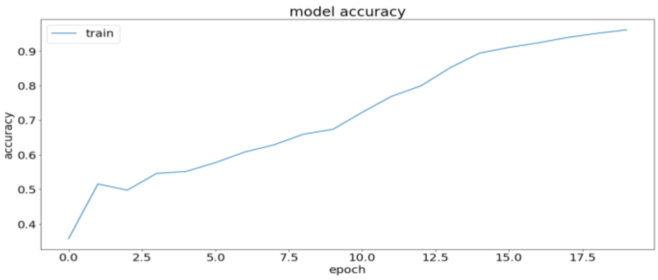
These 2 layers are re-layered in the same manner once more.

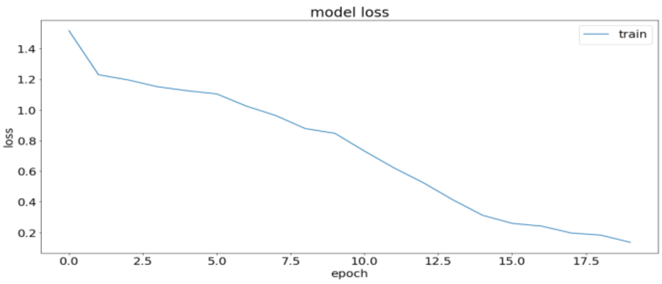
Now a conv2d layer with parameters of 128 filters and (3,3) kernel with padding and activation is to be the same and Relu respectively.

Then a pooling layer is added wherein max pooling is done. These 2 layers are re-layered in the same manner twice.

To maintain the effectivity of the data and avoid overfitting, a Dropout Layer (DL) is added succeeding to the fully-connected layer. Dropout usually randomly deactivates a fraction of the units or connections for example 50%, in a network on each training iteration.

After dropout and flattening the model, a dense layer is added with 1024 units and activation to be Relu.





CNN

VGG-16 ARCHITECTURE:

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 256, 256, 3)]     0

 block1_conv1 (Conv2D)       (None, 256, 256, 64)      1792

 block1_conv2 (Conv2D)       (None, 256, 256, 64)      36928

 block1_pool (MaxPooling2D)  (None, 128, 128, 64)      0

 block2_conv1 (Conv2D)       (None, 128, 128, 128)     73856

 block2_conv2 (Conv2D)       (None, 128, 128, 128)     147584

 block2_pool (MaxPooling2D)  (None, 64, 64, 128)       0

 block3_conv1 (Conv2D)       (None, 64, 64, 256)       295168

 block3_conv2 (Conv2D)       (None, 64, 64, 256)       590080

 block3_conv3 (Conv2D)       (None, 64, 64, 256)       590080

 block3_pool (MaxPooling2D)  (None, 32, 32, 256)       0

 block4_conv1 (Conv2D)       (None, 32, 32, 512)       1180160

 block4_conv2 (Conv2D)       (None, 32, 32, 512)       2359808

 block4_conv3 (Conv2D)       (None, 32, 32, 512)       2359808

 block4_pool (MaxPooling2D)  (None, 16, 16, 512)       0

 block5_conv1 (Conv2D)       (None, 16, 16, 512)       2359808

 block5_conv2 (Conv2D)       (None, 16, 16, 512)       2359808

 block5_conv3 (Conv2D)       (None, 16, 16, 512)       2359808

 block5_pool (MaxPooling2D)  (None, 8, 8, 512)         0

 global_max_pooling2d (Globa  (None, 512)              0
 lMaxPooling2D)

 dense (Dense)               (None, 1024)              525312

 dense_1 (Dense)             (None, 5)                 5125

=================================================================
Total params: 15,245,125
Trainable params: 530,437
Non-trainable params: 14,714,688
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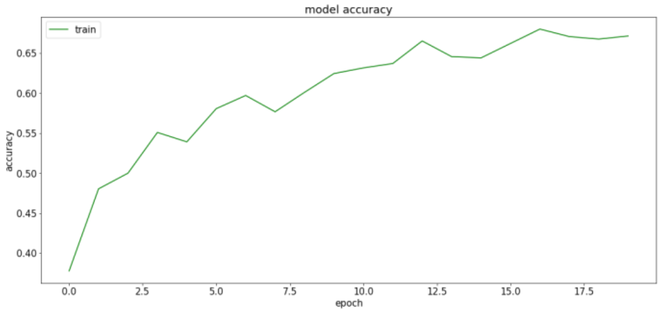
VGG16 is one of the best vision model architectures present. VGG16 is having a large number of hyper-parameters, focused on having convolution layers of 3x3 filter with stride 1 and has same padding and max pool layer of 2x2 filter of stride 2.

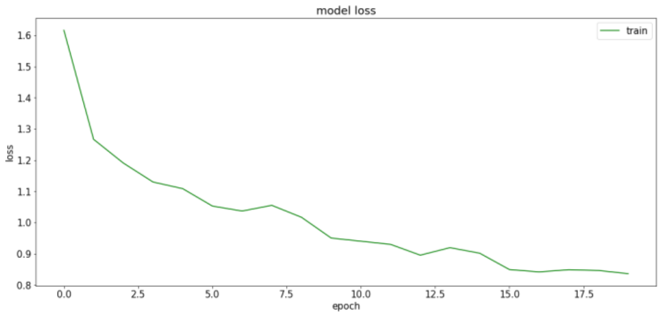
This arrangement of convolution and max pool layers is consistently followed throughout the entire architecture.

At the end, it has 2 fully connected layers followed by a SoftMax for output.

VGG16 has 16 layers that have weights.

We downloaded the VGG-16 model from TensorFlow Keras. Then added fully connected layer, dense layer with 1024 units and activation to be Relu.





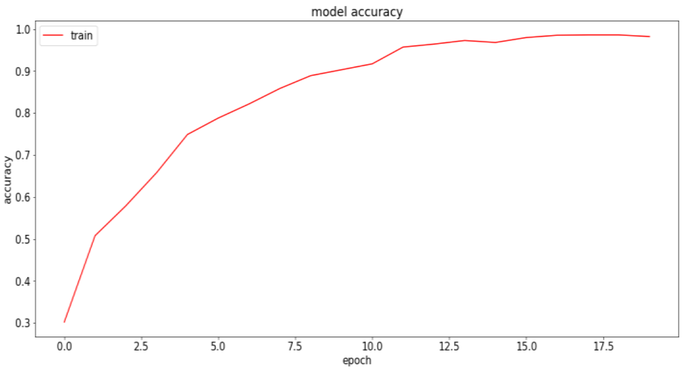
VGG16

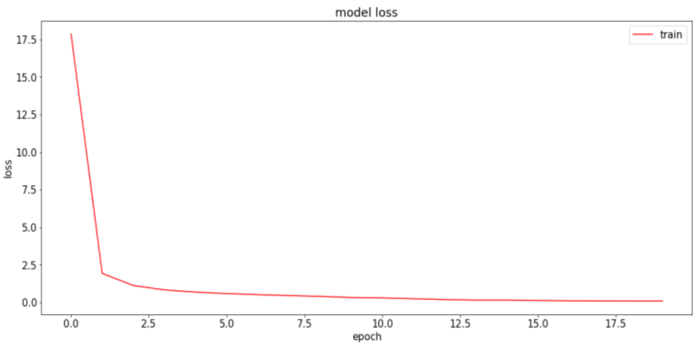
ResNet152V2 ARCHITECTURE:

ResNet-152V2, a convolutional neural network has 101 layers deep. we will load a pre-trained version of the network, trained on over 1,000,000 images.

The pre-trained network can classify images into 1000 object categories, as a result, the network has learned rich feature representations for a wider range of images. The network has a picture input size of 224-by-224.

We downloaded the ResNet152V2 model from TensorFlow Keras. Then added fully connected layer, dense layer with 1024 units and activation to be Relu.





ResNet152V2

For all the 3 models, epoch is defined to be once all images are processed once individually of forward and backward to the network. 1 epoch is counted to be:

(Number of iterations * batch size) / total number of images present in training.

While training the models, we checked for 20 epochs, with batch size 64. Each epoch as observed in the above graphs, the loss decreased simultaneously the accuracy accuracy increased.

GUI:

A web application has been developed, where the color fundus image can be uploaded as the input to the models by the user who can login with credentials.

The respective result according to the stage of Diabetic Retinopathy will be displayed along with accuracy. The email of the result shall be sent to the patient.

The database consisting of the patient's records are maintained using MySQL

3. IMPLEMENTATION

$$\text{True Positive Rate} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{True Negative Rate} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

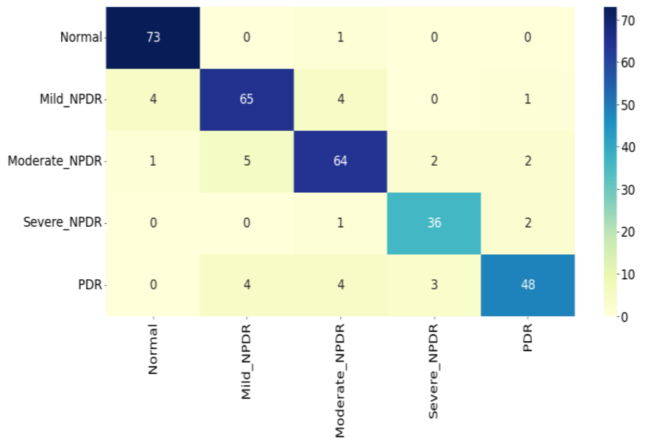
The true positive rate also referred to as hit rate or recall of a classifier is estimated by dividing the correctly classified positives by the full positive count.

The false positive rate of the classifier is estimated by dividing the incorrectly classified negatives by the overall negatives.

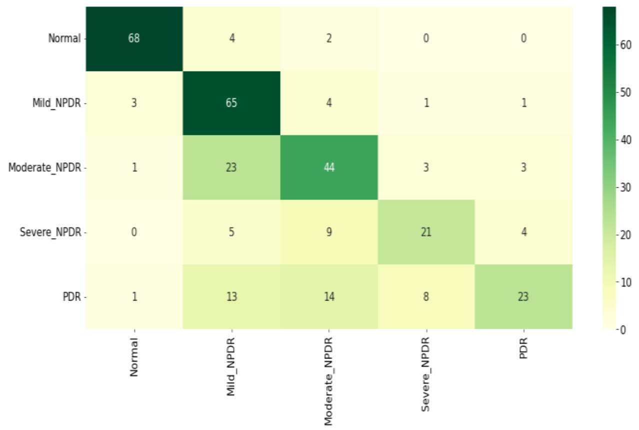
The accuracy of a classifier is estimated by dividing the full correctly classified positives and negatives by the overall number of samples.

Precision is one indicator which tells the quality of positive predictions made by the models.

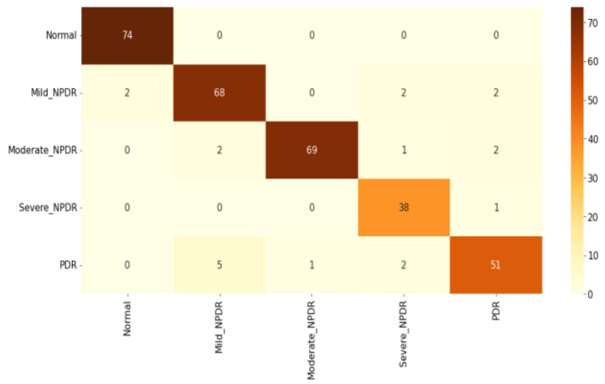
Recall is the ratio of True Positive by the sum of True Positive and False Negative.



CNN



VGG16



ResNet152V2

4. CONCLUSION

Out of 3,662 images, 733 images from the dataset are spitted for validation purpose. Loading the validation images into the models for predicting the label took 188 seconds.

We define accuracy as the number of patients with an accurate classification rate.

In this five-class problem, the accuracy of CNN model was 96%, ResNet152V2 was 98% and that of VGG-16 was 67%. Thus, ResNet152V2 performs better than the other two models.

	precision	recall	f1-score	support
Normal	0.94	0.99	0.96	74
Mild_NPDR	0.88	0.88	0.88	74
Moderate_NPDR	0.86	0.86	0.86	74
Severe_NPDR	0.88	0.92	0.90	39
PDR	0.91	0.81	0.86	59

CNN

	precision	recall	f1-score
Normal	0.93	0.92	0.93
Mild_NPDR	0.59	0.88	0.71
Moderate_NPDR	0.60	0.59	0.60
Severe_NPDR	0.64	0.54	0.58
PDR	0.74	0.39	0.51

VGG16

	precision	recall	f1-score	support
Normal	0.97	1.00	0.99	74
Mild_NPDR	0.91	0.92	0.91	74
Moderate_NPDR	0.99	0.93	0.96	74
Severe_NPDR	0.88	0.97	0.93	39
PDR	0.91	0.86	0.89	59

ResNet152V2

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BIOGRAPHIES

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