الجامعة الإسلامية العالمية ماليزيا
INTERNATIONAL ISLAMIC UNIVERSITY MALAYSIA
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Garden of Knowledge and Virtue

PREMIER INTERNATIONAL ISLAMIC RESEARCH UNIVERSITY

FINAL PROGRESS REPORT

Final Year Project 1

Semester 1, 2019/2020

Bachelor of Computer Science

A. Project Information

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Project ID

424R

Project Title

Automated Diabetic Retinopathy Detection using Deep Neural Network

Project Category

Research

Supervisor

Assoc. Prof. Dr. Amelia Ritahani Ismail

Table of Content

B. Introduction

Project Overview

Automated Diabetic Retinopathy Detection is a tool to predict the level of diabetic retinopathy that occurs in patients with diabetes. It is a condition that happens as a result of blood vessels damaged in the retina among people who have diabetes. Diabetic retinopathy are able to develop in people in type 1 or 2 diabetes with a long history of uncontrolled high blood sugar levels. It starts out with only mild vision problems, however the ignorance of diabetic retinopathy will eventually lead to blindness and it is the most common eye disease in people with diabetes.

Problem Statement

The diagnosis of diabetic retinopathy(DR) is difficult for patients in the early stage since it relies on the presence of microaneurysms, small saccular outpouching of capillaries, retinal hemorrhages, ruptured blood vessels on the fundoscopic images. It is also hard to diagnose DR requires a skilled reader and i's opens to the inconsistency of the diagnosis.

Project Objective

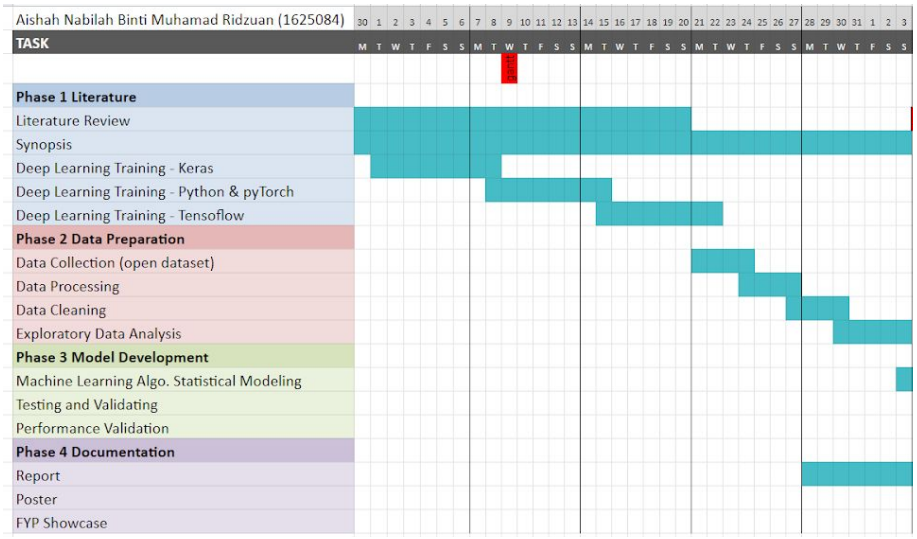
1. To detect diabetic retinopathy level.
2. To construct diabetic retinopathy into image model
3. To evaluate and test the constructed model.
4. To develop an interface for detecting the diabetic retinopathy of patience.

Significance of Project

Diabitic Retinopathy(DR) diagnosis currently using typical retinal fundus photography that requires and depends on a skilled reader for the manual DR assessment. However, according to Goh et al. (2016), this method opens to the inconsistency of the diagnosis. Therefore, Automated Diabetic Retinopathy Detection aims to reduce the burden on opthamologists and mitigate diagnostic inconsistencies between manual readers.

Project Schedule

Show the timeline (Gantt Chart and milestone) of the execution of this project, including FYP1 and FYP2.



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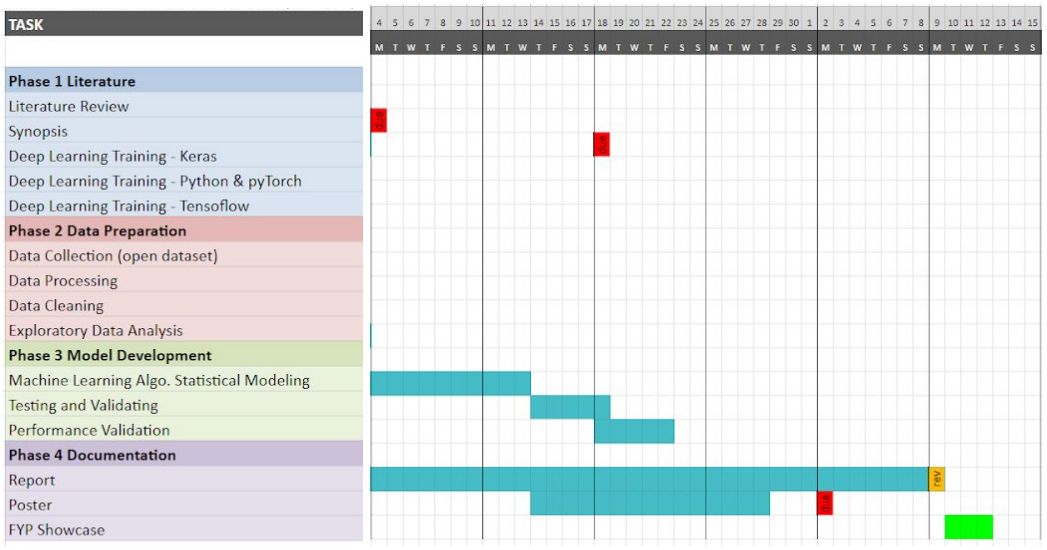


C. Review of Previous Work

Doshi, Shenoy, Sidhpura, & Gharpure(2017) in their paper explained the automatic diagnosis of the disease into its several stages using deep learning. Doshi et al. presents the design and implementation of GPU accelerated deep convolutional neural networks to automatically diagnose and thereby classify high-resolution retinal images into 5 stages of the disease based on severity. However, the single model that Doshi et al. created only produced accuracy of 0.386 on a quadratic weighted kappa metric and assembling three such similar models resulted in a score of 0.3996.

Lam, Yi, Guo, & Lindsey (2018) also use a deep convolutional neural network (CNN) but with a different approach of classification. They examined binary, 3-ary and 4-ary label classification to examine the weakness of CNN. They are using several CNN models, for example, AlexNet, VGG16 and GoogleNet. They found that binary models (normal or mild, moderate to end stage) achieved more accuracy and sensitivity than multiclass training. This might come from the noises from kaggle images or low fidelity of labelling the images. These are the results:

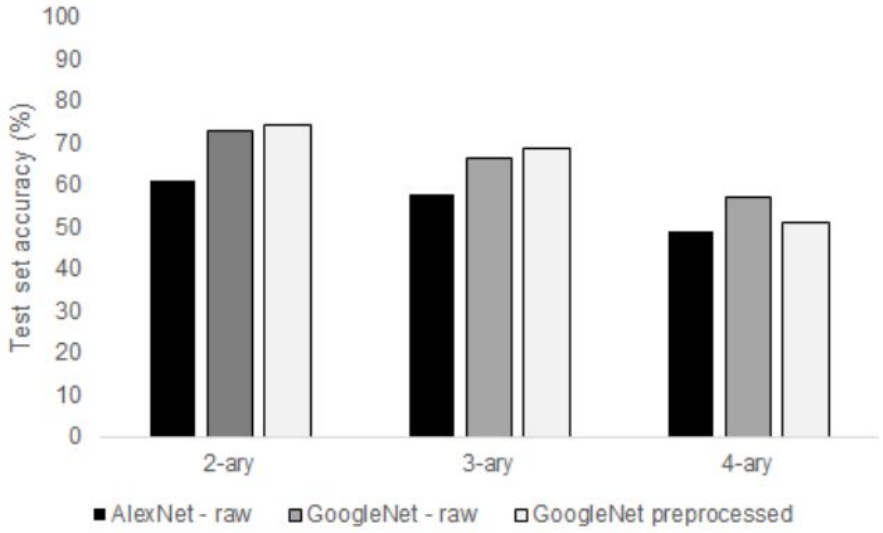


Figure 1 : Graph of accuracy based on model and number of classes

Abràmoff et al., (2016) doing "Improved Automated Detection of Diabetic Retinopathy on a Publicly Available Dataset Through Integration of Deep Learning". They were working on three classes {No DR, Vision threatening DR (vtDR), Macular edema}. They used AlexNet CNN model to train and managed to get this results:

IDx Output For	Disease Level	Sensitivity (95% CI)	Specificity (95% CI)	Negative Predictive Value (95% CI)	Positive Predictive Value (95% CI)	AUC (95% CI)
rDR	rDR	96.8% (93.3%–98.8%)	87.0% (84.2%–89.4%)	99.0% (97.8%–99.6%)	67.4% (61.5%–72.9%)	0.980 (0.968, 0.992)
rDR	vtDR	100% (96.1%–100%)	N.A.	N.A.	N.A.	N.A.
rDR	ME	100% (95.6%–100%)	N.A.	N.A.	N.A.	N.A.
vtDR	vtDR	100.0% (96.1%–100.0%)	90.8% (88.5%–92.7%)	100.0% (99.5%–100.0%)	56.4% (48.4%–64.1%)	0.989 (0.984, 0.994)

N.A., not calculated.

Figure 2 : The Result of models

The results are good with the integration of CNN.

A working medical device, iGradingM, had received its class 1 Conformité Européenne (CE) mark in 2013 and being used in Scottish Diabetic Retinopathy Screening Program(Sim et al., 2015). It is a product produced by Medalytix Group Ltd. However, the device could only detect diabetic retinopathy absent and diabetic retinopathy present instead of specifying the severity of the disease condition.

There are also a few companies that produce a system regarding this disease as shown in table 1 below, for example DR-RACS system is built based on Amplitude modulation-frequency modulation(AM-FM), k-means & partial least square classifier to predict the risk(low/high) for DR. Retmarker DR also produce a system that able to detect the presence or absence of DR using longitudinal analysis by comparing with baseline image and Singapore Eye Lesion Analyzer (SELENA) produced a system

SYSTEM	Algorithm & Strength	OUTCOME
DR-RACS	Amplitude modulation-frequency modulation(AM-FM), k-means & partial least square classifier	Low risk / high risk for DR
Retmarker DR	Longitudinal analysis by comparing with baseline image	Presence/Absence of DR : microaneurysm turnover
Singapore Eye Lesion Analyzer (SELENA)	Deep learning technology using CNN and region extraction	Grade of DR and referable / nonreferable

Table 1. : List of systems

D. Methodology

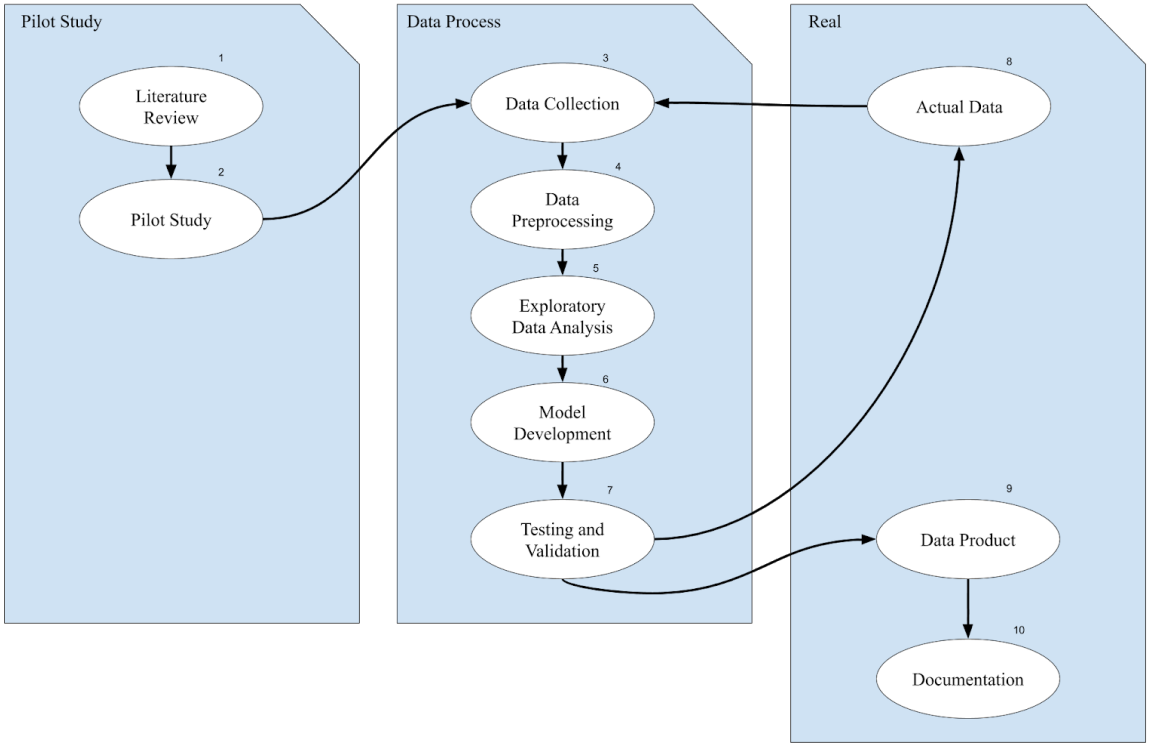
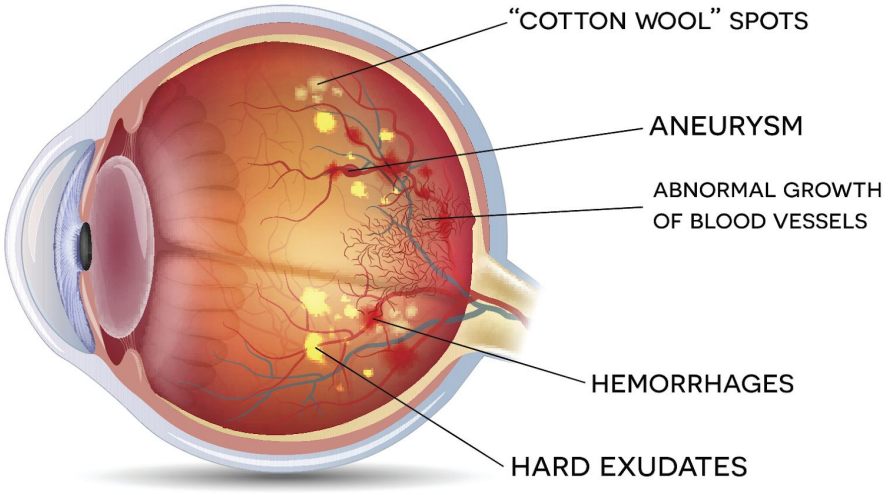


Figure 3 : Methodology flowchart

E. Literature Review

Diabetic Retinopathy



***Source**: Getty Images*

Diabetic retinopathy(DR) is a disease that occurs in patients with a long period history of diabetes. It happens when high levels of blood sugar damage blood vessels in a part of the eye called the retina. This eye disease starts out with only mild vision problems such as blurriness and will eventually lead to blindness. DR mainly has four stages including Mild Nonproliferative Retinopathy, Moderate Nonproliferative Retinopathy, Severe Nonproliferative Retinopathy and Severe Nonproliferative Retinopathy.

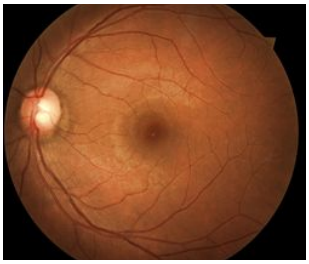
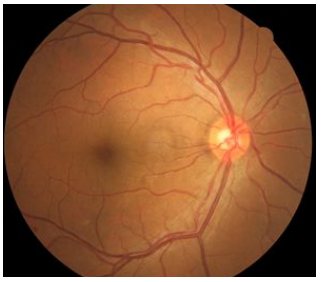
During the Mild Nonproliferative Retinopathy stage, **microaneurysms** occur. Microaneurysms are the earliest changes of diabetic retinopathy that are clinically visible. They appear as small red dots, balloon-like swelling in the retina's tiny blood vessels which are often in clusters. Dot and blot **hemorrhages**, Flame-shaped hemorrhages and **hard exudates** also occur as the result of microaneurysms.

In the Moderate Nonproliferative Retinopathy stage, blood vessels that supply blood to the retina swell and block. **Cotton wool spots** that appear as fluffy white patches on the retina will occur together with microaneurysms, nerve fiber layer hemorrhages (also called flame-shaped hemorrhages) and/or exudates during this stage.

Next, the stage of Severe Nonproliferative Retinopathy occurs when many more blood vessels are blocked, damaging several areas of the retina with their blood supply. Then,

Venous beading and *Intraretinal microvascular abnormalities (**IRMA**)* occur as the results of those areas of the retina send signals to the body to grow new blood vessels for blood supply. However, if the blood vessels close off completely, it can lead to blurry vision with dark spots that are often described as "floaters."

The advanced stage of Proliferative Retinopathy happens when the signals sent by the retina for blood supply trigger the growth of new blood vessels where the new blood vessels are in a form of **abnormal** and fragile. They will grow in the retina area and along the surface of the clear, vitreous gel that fills the inside of the eye. Luckily, these blood vessels would not lead to vision loss but their thin and fragile walls may leak and will eventually lead to severe vision loss and even blindness.

Stage	Name	Details
1	**Normal** 	A normal condition of an eye.
2	**Mild** 	The initial stage of DR. - micro aneurysms(small swelling) appear that may cause a leak of fluid into the retina
3	**Moderate**	The progressive stage that cause swell and distortion of blood vessels that are connected to retina(for blood and nourishment)

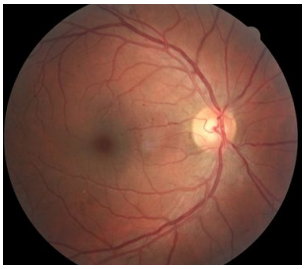
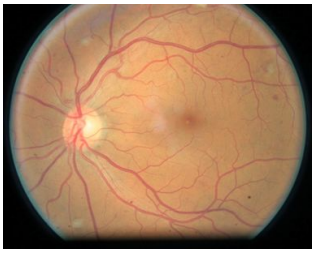
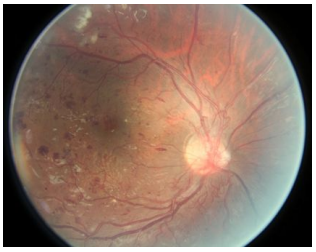
		
4	**Severe** 	The severe condition of DR where many blood vessels blocked making less supply of blood to retina(new blood vessels appear)
5	**Proliferative** 	The advanced stage of DR is caused by blockage of tiny blood vessels(that grow inside). It damages the retina

Table 2 : Information of each level

Source:

1. https://www.reliasmedia.com/articles/142738-diabetic-retinopathy-associated-comorbidities-and-treatment-considerations
2. https://www.webmd.com/diabetes/diabetic-retinopathy-stages#1

CNN Architecture

It is based on neural network architecture with extra layers which are made to process images. The major difference between CNN and the usual NN, it takes input right away with images without flattening the images while NN needs to flatten the image first as the input. Thus, it reduces tons of parameters during the process.

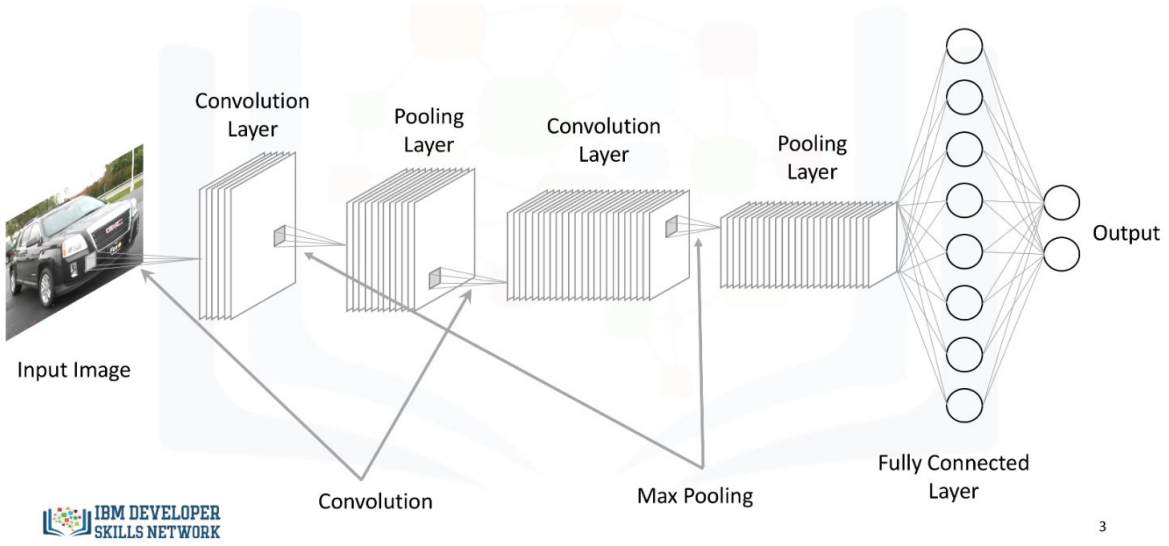


Figure 4 : Basic architecture of CNN

Based on Figure 4. It has additional relu layer, convolutional layer and pooling layer. During the input layer, it takes input from (n x m x 1) for grayscale images or (n x m x 3) for color images.

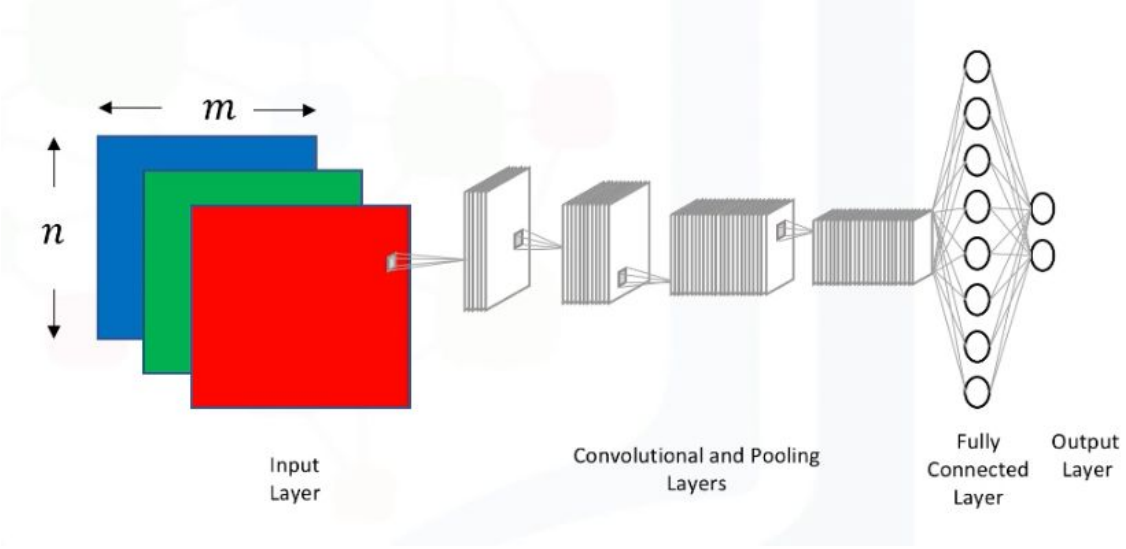


Figure 5 : Dimension for color image

In the convolutional layer, it filters the images by computing the dot product between the images and the filters. The more filters used, the more we can preserve the special dimension better. Convolution's way of handling images saves computing power rather than flatten the input which takes a massive amount of parameters. During this layer, it also

contains ReLU layers which filter the convolutional step which only allows positive values to be passed through forward propagation.

In the Pooling layer, the main objective of this layer is to reduce the dimension of the images propagating to the network. It has two most popular pooling techniques which are max pooling and average pooling. It takes the maximum or average value for each section of the images and stores them to the desired pooling dimension. Max pooling technique provides spatial variance which enables the NN to recognize objects in an image even if the object does not resemble the original object.

After the last convolution and pooling layer, the outputs are flattened to the fully-connected layer which connects every node of the current layer with every node of the next layer. It outputs an n-dimensional layer according to the number of classes we want to work on.

F. Progress

Data Collection

The first phase of this research are by doing pilot study of Diabetic Retinopathy Detection using kaggle dataset {https://www.kaggle.com/tanlikesmath/diabetic-retinopathy-resized} to create and analyze a good model in preparation for actual data. There are two types of images which are cropped and uncropped images. The cropped images means the images of DR have been cropped to remove the black area of the images:

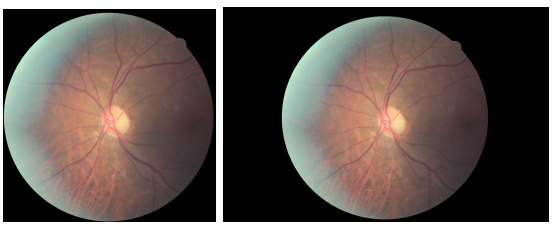


Figure 6 & 7 : Cropped image and uncropped image

The left side is a cropped image and the right side an uncropped image.

Data Preprocessing & Data Cleaning

Since the dataset provides cropped versions of retinal images. We took cropped retinal images to fit in the initial model. However, the size is too big to be fit in the training as to process high resolution images requires much computing power. Therefore, the images need to be resized. The actual size is approximately around 1024x1024 pixels. The retinal images are then resized to 64x64 pixels. We used open-cv python to resize the retinal image.

Exploratory Data Analysis

Based on Table 3 , the normal class of retinal images is way too much that the other classes. In figure 8 , we can see different levels of retinal images. Some are very hard to differentiate and some can be distinguished, for example, the proliferative level of the retinal image, there is something like a blood coat covering the retinal image.

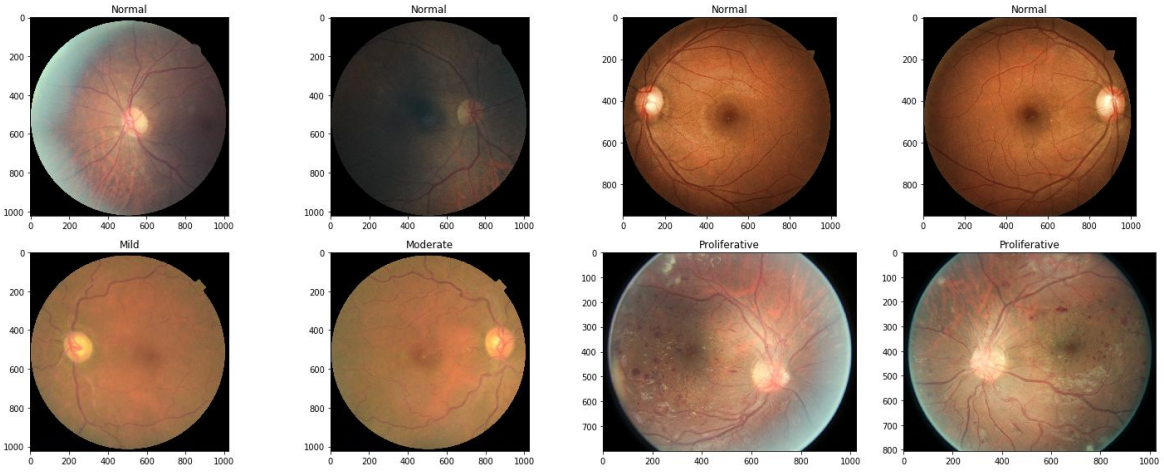


Figure 8 : Different levels of retinal image

Level	Type of DR	No. of sample	Percentage
0	No Diabetic Retinopathy	25802	73.49%
1	Mild Diabetic Retinopathy	2438	6.94%
2	Moderate Diabetic Retinopathy	5288	15.06%
3	Severe Diabetic Retinopathy	872	2.48%
4	Proliferative Diabetic Retinopathy	708	2.02%

Table 3 : Distribution of each level of Diabetic Retinopathy

Modelling

The initial models are done using convolutional neural networks (CNN) which is a derivative of deep neural networks. The overall architecture is as stated in Figure 9.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 60, 60, 32)        2432
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 30, 30, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 26, 26, 64)        51264
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 13, 13, 64)        0
_________________________________________________________________
flatten_1 (Flatten)          (None, 10816)             0
_________________________________________________________________
dense_1 (Dense)              (None, 100)               1081700
_________________________________________________________________
dense_2 (Dense)              (None, 5)                 505
=================================================================
Total params: 1,135,901
Trainable params: 1,135,901
Non-trainable params: 0
```

Figure 9 : Architecture of model

The model is built using tensorflow, and keras library and with the help of google collab tool.

Testing and Validating

The dataset is split into two sets which are training and testing set on ratio 8:2 for validating purposes. The final accuracy of the model is 73% while the final validation accuracy is 74%. The model ran with 10 epochs in total. Throughout the training phase the overall accuracy is stated in Figure 10.

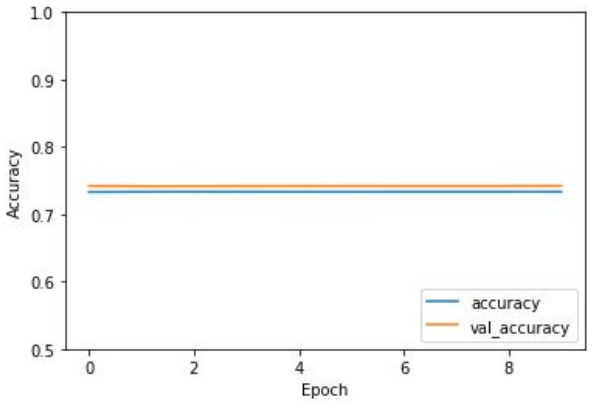


Figure 10 : Epoch vs Accuracy graph

Performance Validation

	Normal	Mil	Mod	Sev	Prol
Nor	5212	0	0	0	0
Mil	481	0	0	0	0
Mod	1023	0	0	0	0
Sev	159	0	0	0	0
Prol	147	0	0	0	0

Figure 11 : Confusion Matrix of the model

Based on Figure 11 , We can see the levels other than normal tend to learn normal levels rather than learn their own levels which is, the model is not very good enough for deliverability. This problem might occur because imbalance classes on datasets. We can see the distribution of classes on Table 3.

INTERFACE

We were building a platform for predicting the Diabetic Retinopathy so that it can see the model in a nice view.

The interface is built using html, css, javascript and flask web framework and runs on local hosts.

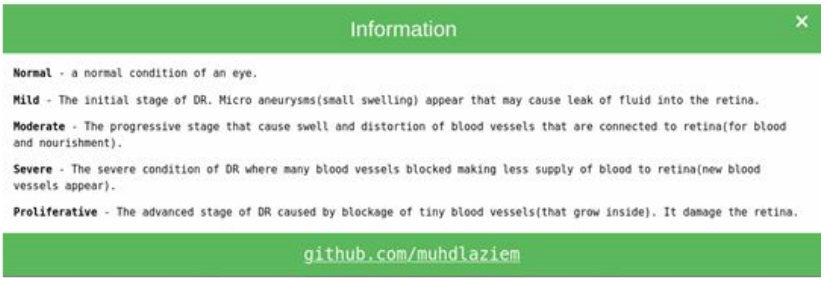


Figure 12 : Interfaces

G. Conclusion

It is crucial to take good care and treatment regarding this disease as it can cause more and more damage to the eyes. However, there are a lot of weaknesses on our initial model that we can identify. Afterall, that is the reason initial models are conducted, to find what are essential to create a sophisticated model. Imbalance class contributed a lot of drawbacks of models, which made the class other than normal learn normal class instead of their own class. One of the future work on creating a complete model is, to have two separate models, which is classifying 'Normal' and 'DR' first. If it has DR, proceeds to classify the classes of DR.

H. References

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