Executive Summary

Problem Statement & Significance

According to NCBI, the number of people with Diabetic Retinopathy (DR) is estimated to grow from 126 Million in 2010 to 191 million in 2030, and an estimated growth of 19 million alone with vision threatening diabetic retinopathy, if immediate action is not taken.

What is Diabetic Retinopathy?

Diabetic Retinopathy (DR) is a complication that can be caused due to abnormalities in the blood vessels in anyone who has type 1 or type 2 diabetes. It involves four stages from mild to proliferative, which is the advanced stage leading to loss of vision and possibly complete blindness if not treated early.

The Problem:

50-70% of the associated blindness can be avoided with early detection and treatment. But lack of facilities in rural areas, shortage of medical experts and delay in the manual detection process leaves most of them undiagnosed at the appropriate time.

Our Solution

Our dataset has captured both the left and right eye of the tested individuals. Using this data, we train the model using CNN Architecture and Data Augmentation to identify the minute yet complex details and help detect the severeity of the damage.

Prior Work

This data was extracted from a competition on Kaggle, which showcased the implementation of Transfer learning using ResNet.

Key Benefits

- Our solution helps simplify the screening process with different levels indicating the extent of damage

  Level 0 – Healthy Eye
  Level 1 – Mild
  Level 2 – Moderate
  Level 3 – Severe
  Level 4 – Proliferative DR

- It is affordable, faster and reliable without the need for eye surgeons.
- Since they are affordable, they can be installed in small dispensaries in remote areas, making it accessible to the remote population.
- Longer waiting times are reduced as this can be easily predicted by regular clinicians.

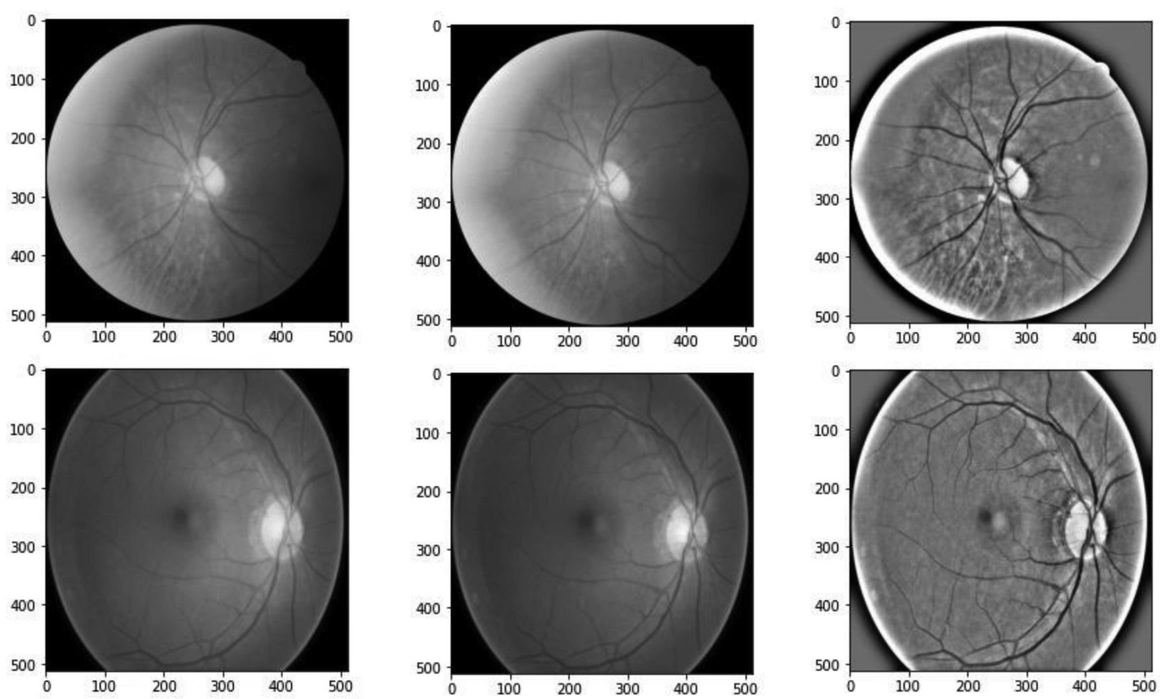
Data Analysis & Cleaning

Dataset Description

Our dataset consists of 40,000 high-resolution images of both the left and right eyes of the tested individuals. These images were taken in different types/models of cameras. Due to our machine processing limitations and the images being of very high resolution, for our project we have taken only two levels of retinol damage into consideration i.e. Level 0 indicating No DR and level 4 indicating Proliferative DR. We have taken 250 images each for either of the category. The dataset includes images that are out of focus, underexposed or overexposed.

Data Pre-processing

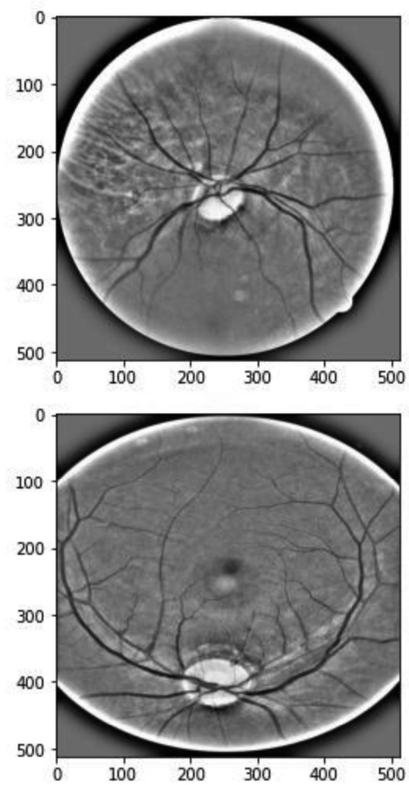
As the dataset was too large, and maybe due to the no of Kaggle API Call restriction, we could not run it in a loop, rather chose to import the data directly from the Kaggle website. Due to our machine processing capabilities and the high resolution of the images, we have considered 250 images each for two levels i.e. No DR or severe Proliferative DR. After we have loaded the images, we have resized all the images into 512*512 pixel format. We have then converted the images from RGB scale to Gray scale to increase the image clarity and reduce the image memory size. Finally, used the Gaussian Blur filter and tweaked the parameters to reduce the noise by blurring the edges and reducing the contrast, making the blood vessels clear and visible.

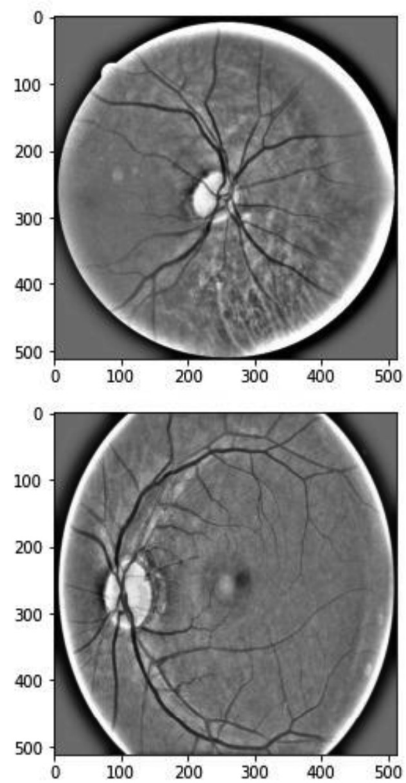


Original Image **RGB to Gray Scale** **Gaussian Blur**

Data Augmentation

With the limited data that we have taken, there is a chance of overfitting and also, the performance of deep learning models is enhanced using data augmentation. For our model, we have created new variants of the already existing images using two different augmentation techniques i.e. Titling the image by 90 degrees and Flipping the image vertically.





Data Augmentation – Tilting the image By 90 degrees

Data Augmentation – Flipping the image vertically

Models

MLP Classifier

We have tried the MLP classifier to classify the images of the diabetic retinopathic eyes. The images of the eye are very sensitive, and it was difficult for the MLP classifier to classify between both the labels. The model had an accuracy of 50 % and the model was able to classify only one label.

Keras

We also tried to do the classification using Keras. We came across the same problem of sensitivity of the images of the eye which was making it difficult to classify the images correctly. Even Keras was only able to classify one type of image with an accuracy of 50 %. To avoid these hinderances we have gone to the Convolutional Neural Network model

CNN Model

The CNN was trained on 500 images with 250 in each classification i.e. No Dr and DR. We defined the convolutional base with a stacked pattern of Conv2D and MaxPooling2D - with a size 2*2 and stride 2 and configured our CNN to process inputs of shape (512,512,1). We then flattened the three-dimensional output to one dimensional vector and added two hidden layers with relu activation, finally used a dense layer with 2 outputs and a softmax activation.

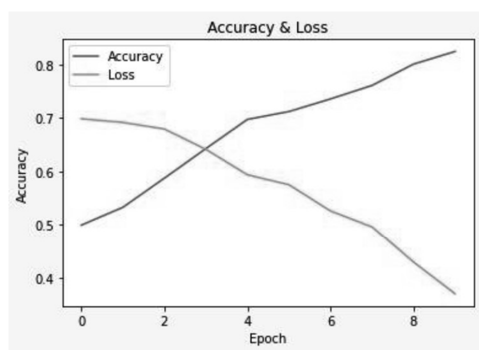
Model Evaluation

This shows that out of 149 Non-DR images, our model was able to successfully predict 97 images as Non-DR and out of 159 DR-images, it was successfully able to predict 112 images as DR.

```
[[115  34]
 [ 59 100]]
              precision    recall  f1-score   support

           0       0.66      0.77      0.71       149
           1       0.75      0.63      0.68       159

    accuracy                           0.70       308
   macro avg       0.70      0.70      0.70       308
weighted avg       0.70      0.70      0.70       308
```

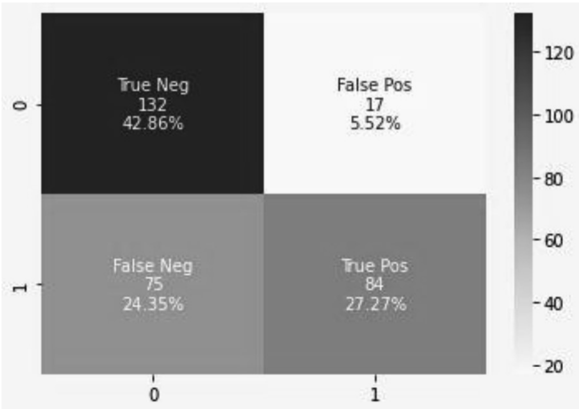


The accuracy of our model is 70% which seems quite good.

Grid Search:

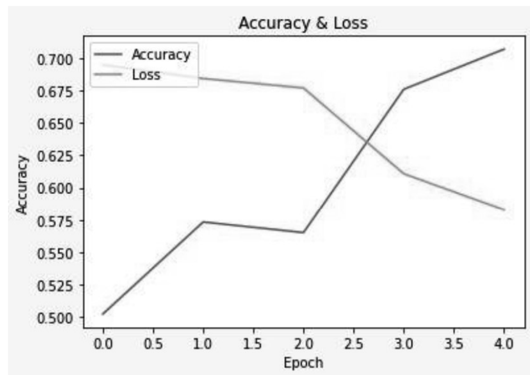
We ran Grid search to determine the best parameters for our model and have tweaked the model accordingly. We have made significant changes in the no of epochs and batch size from (20,10) to (10,5). We have illustrated clearly illustrated our model's performance after the modifications.

Model Evaluation:



With the tweaking we see that the rate of True negatives has increased from 97 to 132 and the successful predictions of DR as DR is 84 out of a total of 159 images.

	precision	recall	f1-score	support
0	0.77	0.64	0.70	149
1	0.71	0.82	0.76	159
accuracy			0.74	308
macro avg	0.74	0.73	0.73	308
weighted avg	0.74	0.74	0.73	308



We see a slight increase in the accuracy of the model from 70 to 74. But in case of a larger dataset, the difference could be larger.

Conclusion & Future Scope:

We have currently trained the model with 250 images each for two of the classifications i.e. No DR or DR, from each of the two classes and later resized them into 512*512 pixel format. Then converted them from RGB scale to gray scale to improve the picture clarity and then implemented gaussian blur to blur the edges and reduce the contrast thereby elevating the focus and clarity of the blood vessels in the image. Next, augmented the data to reduce data overfit and increase the no of images making it a better fit to run over deep learning algorithms. This data was then trained using CNN model, used grid search to tweak the parameters and successfully increased the accuracy of the model from 70-74%.

Future Scope: We can use Transfer Learning based approach so that we can train the model with a greater number of images so that the machine can learn well and can avoid overfitting leading to a higher accuracy. The accuracy of the image can be improved by using results of both the eyes together. We have done the classification for only 2 levels. We can extend our models to train on all the four levels of images.

References:

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