Blindness Detection Using Deep Learning

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Diabetic Retinopathy (DR)

- DR is a condition that causes damage to blood vessels in the retina
- Some of the risk factors are:
  - Type 1 or type 2 diabetes
  - Poor control of blood sugar
  - High blood pressure
  - High cholesterol
  - Pregnancy
  - Tobacco use
- It can lead to blurry or complete loss of vision
- The Eye Diseases Prevalence Research Group determined that in the US, the crude prevalence rate of retinopathy in adults with diabetes is 40.3%; sight-threatening retinopathy occurred at a rate of 8.2% [1].

Diabetes Retinopathy

- Symptoms include:
  - Spots or dark strings floating in your vision (floaters)
  - Blurred vision
  - Fluctuating vision
  - Impaired color vision
  - Dark or empty areas in your vision
  - Vision loss
- A comprehensive dilated eye examination is conducted to diagnose DR and its progression.
- The pupils are dilated and fundus images are taken to assess blood vessels, optic nerves and retina

Healthy vs DR Eye

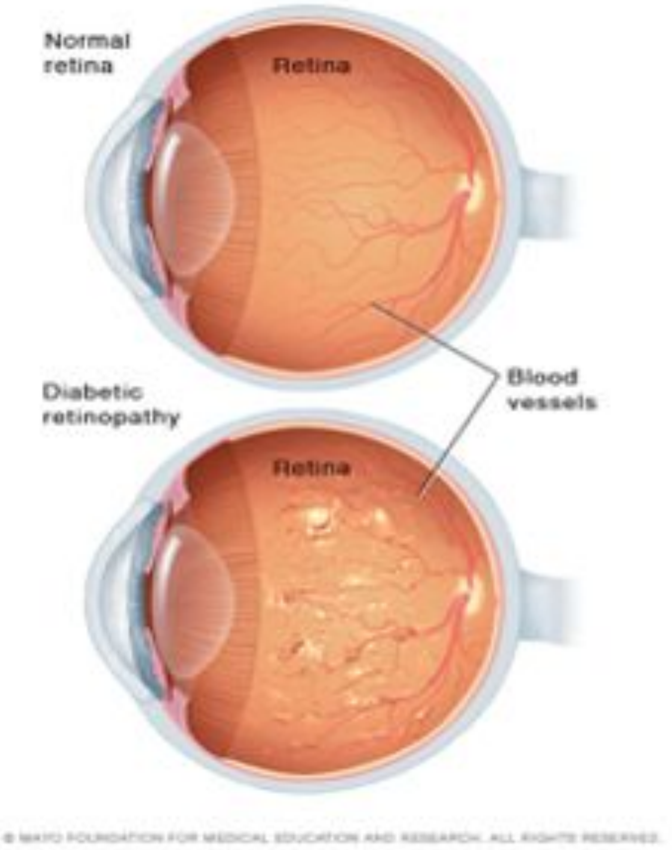


Image Courtesy: Mayo Clinic [2]

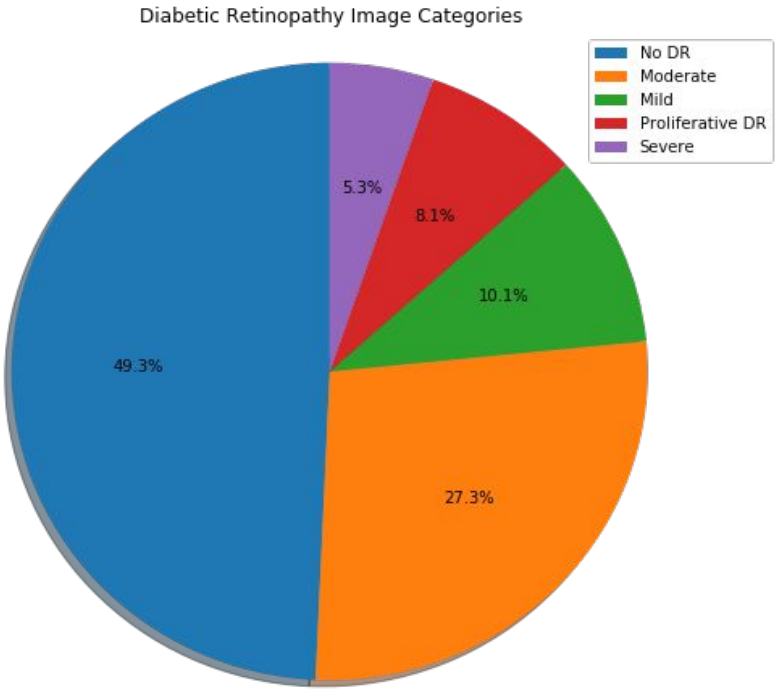
Objective

The goal of the project is to develop a deep learning model that can effectively identify the severity of diabetic retinopathy from fundus images and classify it into the following categories:

0 - No Diabetic Retinopathy (DR)
1 - Mild
2 - Moderate
3 - Severe
4 - Proliferative DR

The dataset was made available via Kaggle competition, hosted by Aravind Eye Hospital and APTOS (https://www.kaggle.com/c/aptos2019-blindness-detection/overview)

Dataset



Total number of images	3622
No DR	1805
Mild	370
Moderate	999
Severe	193
Proliferative DR	295

Building the dataset

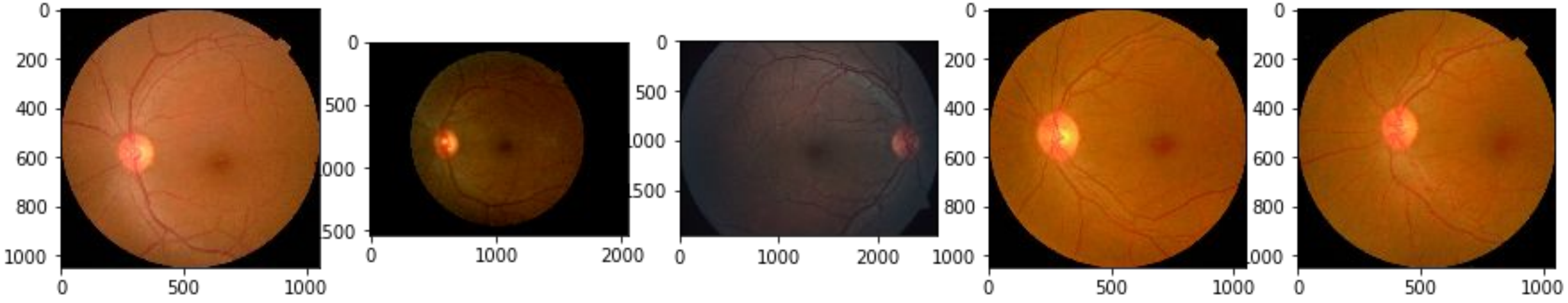
- We divide the dataset into 70:30 split for training and testing, respectively. 10% of the training data will be used for validation during model training.
  Number of train images= 2563 ; Number of test images= 1099

- These images were generated from multiple clinics. The data collection process is not completely standardized. Thus, variation in image size is expected. We load the training set of images and get some summary statistics on the size of the training set.

  Min Dimensions: [480, 640, 3]
  Max Dimensions: [2848, 4288, 3]
  Average Dimensions: [1528.826, 2018.985, 3]
  Median Dimensions: [1536, 2144, 3]

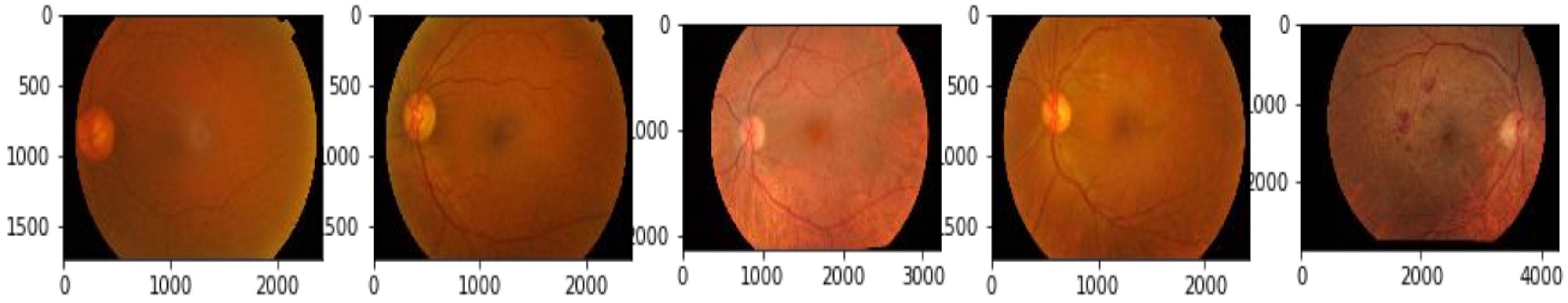
- We resize all images (train and test) to standard size [224, 224,3]. Resizing images to these standard dimensions make it easy to be used for our deep learning network and also any pre-trained network that we will use during transfer learning. We then normalize the dataset by dividing it by 255.

No DR



0 200 400 600 800 1000
0 500 1000
0 500 1000 1500
0 1000 2000
0 500 1000 1500
0 1000 2000
0 200 400 600 800 1000
0 500 1000
0 200 400 600 800 1000
0 500 1000

Mild



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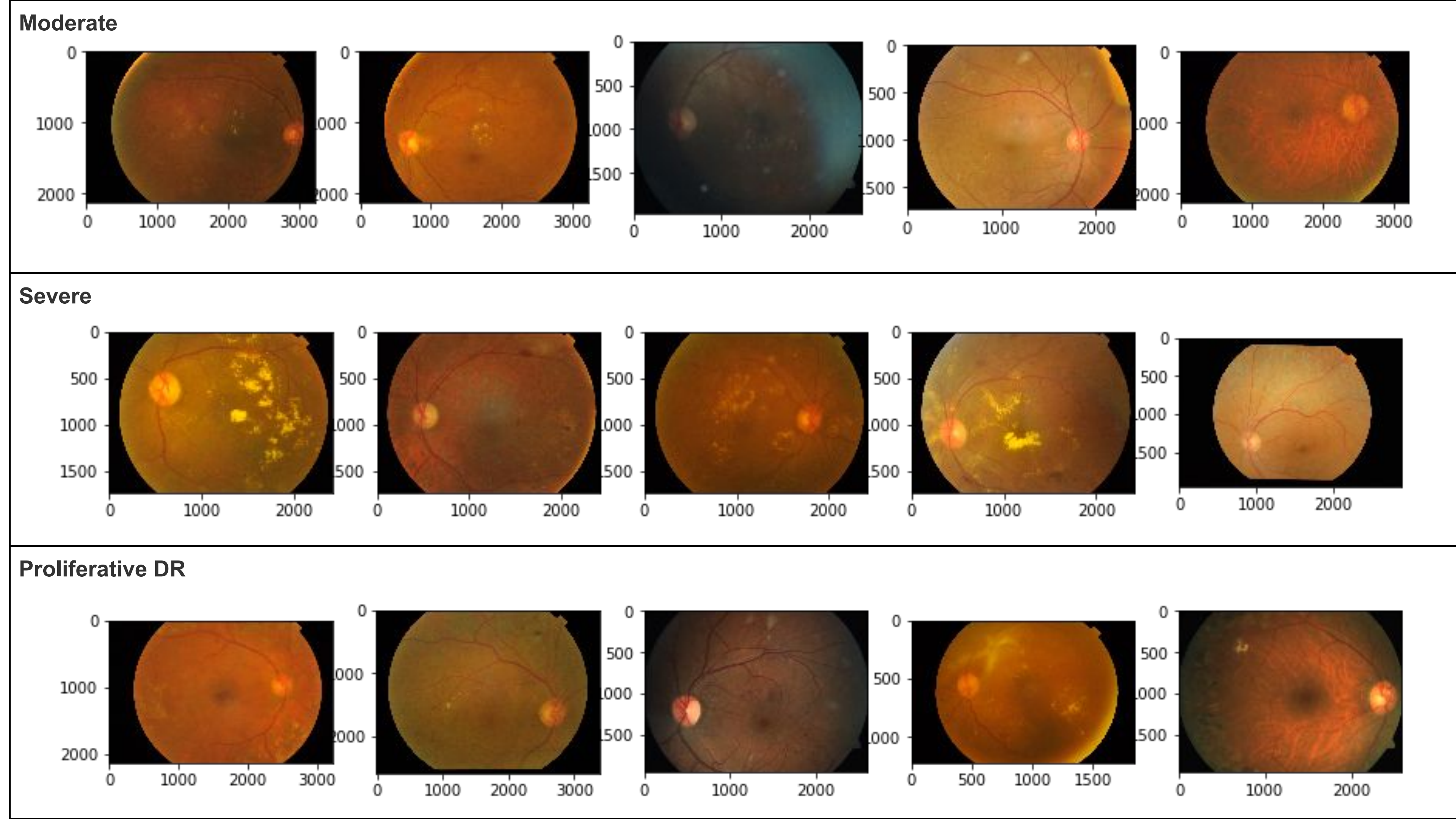
0 1000 2000
0 2000 4000


Moderate
Severe
Proliferative DR

Deep Learning Models

1. Convolutional Neural Network from scratch

Transfer Learning using:

2. ResNet-50
3. VGG-19

Model 1: CNN Architecture

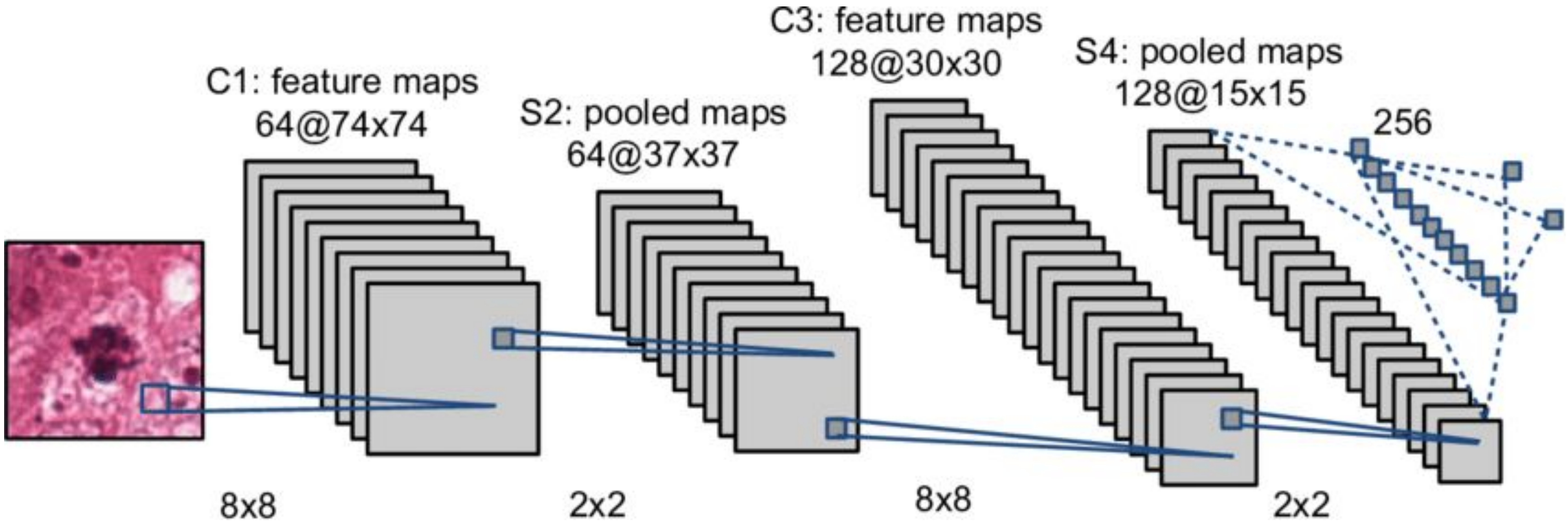
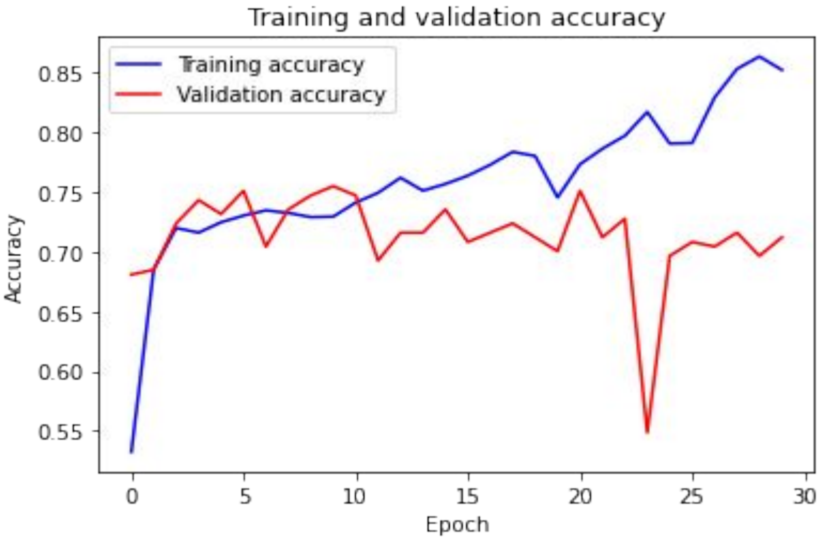
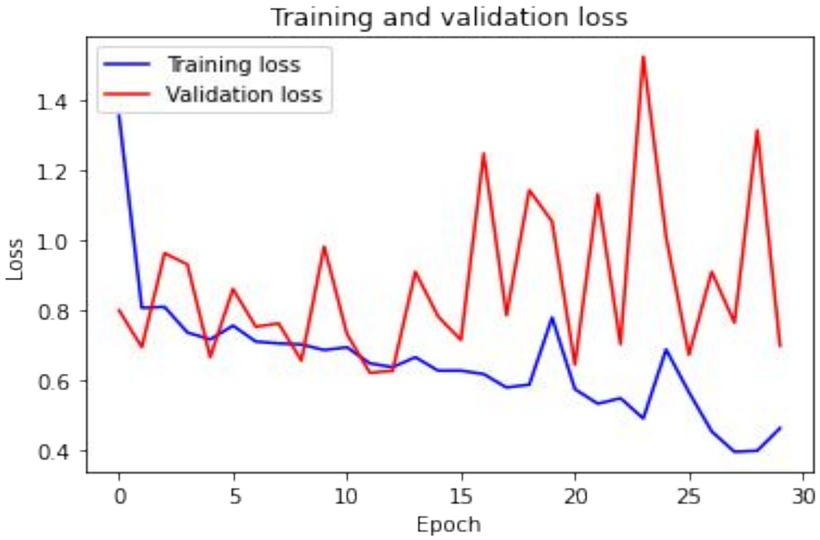


Image Courtesy: Wang et.al[3]

Model 1: CNN Learning Curves





The model consisted of 3 convolution layers and pooling layers, followed by 3 dense and 2 dropout layers for regularization.

Model 2: ResNet-50 Architecture

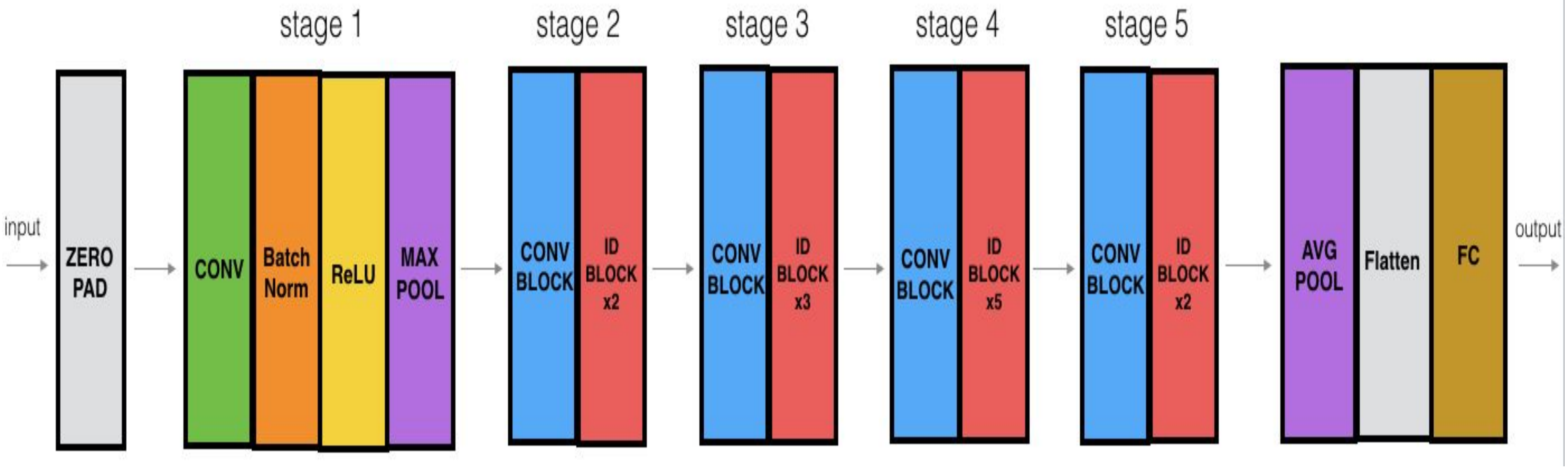
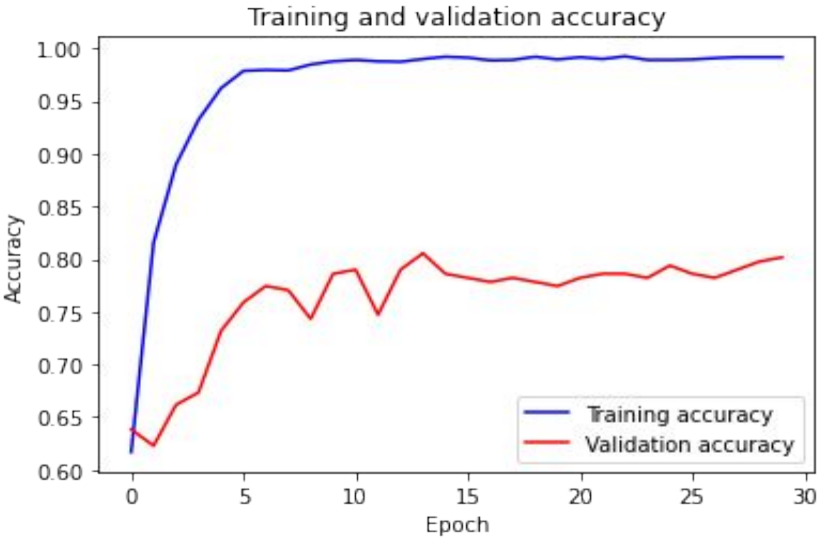
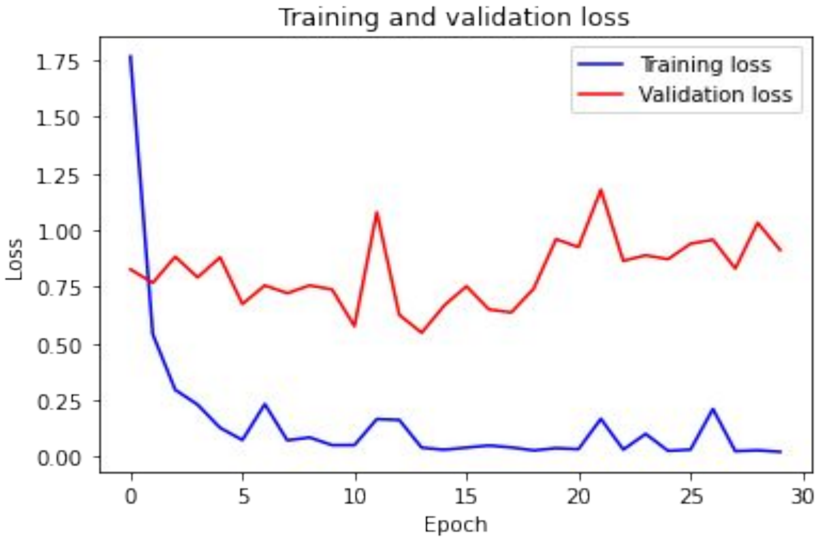


Image Courtesy: Priya Diwedi [4]

Model 2: ResNet-50 Learning Curves





Model 3: VGG-19 Architecture

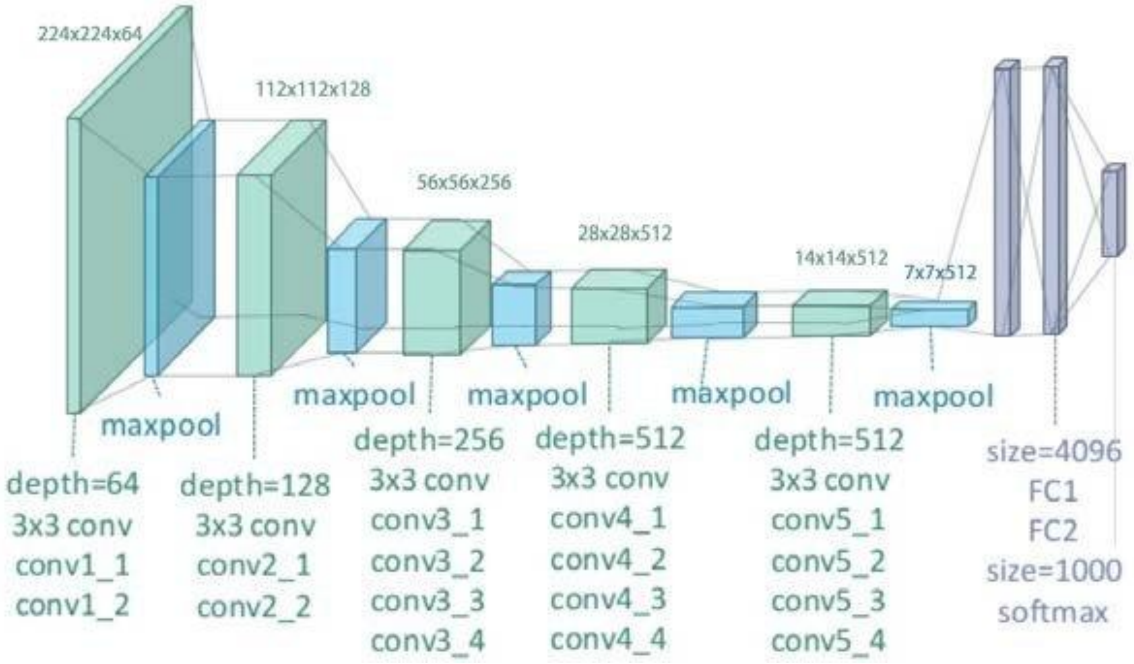
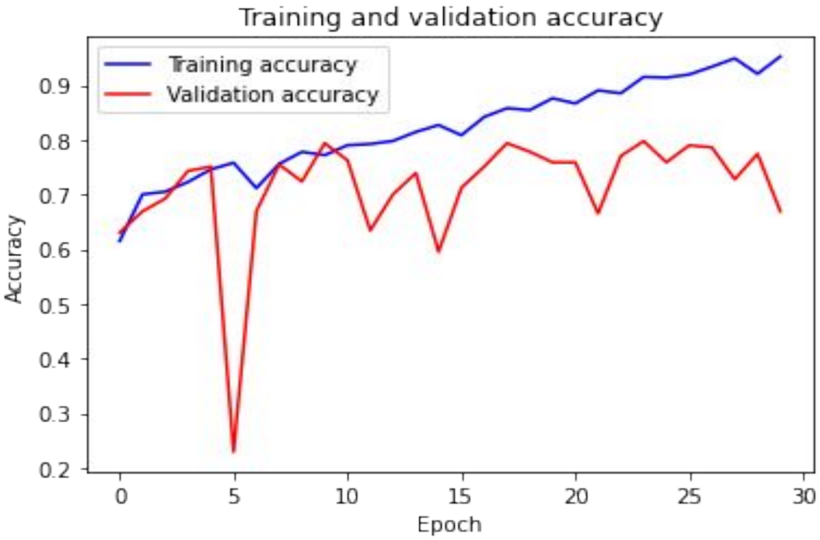
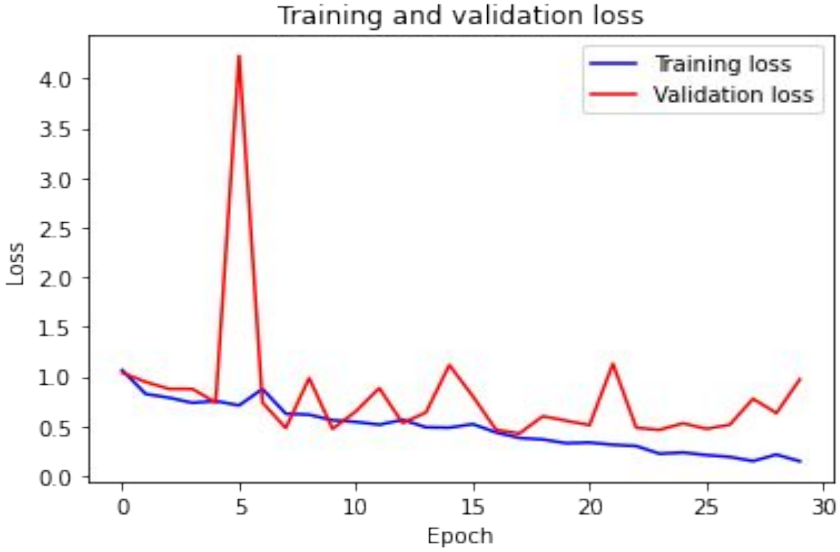


Image Courtesy: Zheng et.al [(5)]

Model 3: VGG-19 Learning Curves





Model Evaluation

Model	Accuracy	Loss	Precision (weighted avg)	Recall (weighted avg)
CNN	0.70	1.08	0.66	0.70
Resnet50	0.72	2.03	0.66	0.72
VGG-19	0.62	1.55	0.71	0.62

ResNet50 performs the best on the test dataset. It gives an accuracy of 72%. This is followed by the CNN model at 70% and VGG-19 at 62% accuracy. In all three models, the precision was highest in the No DR class. It could be because there were more images in that category. For future work, utilizing advanced preprocessing techniques, such as image augmentation, can help enhance the performance of these model.

Conclusion

- Diabetic Retinopathy detection is not an easy process.

- It requires trained personnel and regular screening.

- Availability of trained professionals and screening equipment are a serious concern. However, it is very encouraging to see the potential of deep learning models to achieve some automation in the detection process. Collaboration of clinicians and deep learning experts would be crucial to take this project to the next level and help elevate the standard of care for patients.

References

1. Diabetes Canada Clinical Practice Guidelines Expert Committee. Diabetes Canada 2018 Clinical Practice Guidelines for the Prevention and Management of Diabetes in Canada. Can J Diabetes. 2018;42(Suppl 1):S1-S325. (http://guidelines.diabetes.ca/cpg/chapter30#sec1)
2. Diabetic Retinopathy, Mayo Clinic, 2018 (https://www.mayoclinic.org/diseases-conditions/diabetic-retinopathy/symptoms-causes/syc-20371611#dialogId8139015)
3. Wang, Haibo & Cruz-Roa, Angel & Basavanhally, Ajay & Gilmore, Hannah & Shih, Natalie & Feldman, Mike & Tomaszewski, John & González, Fabio & Madabhushi, Anant. (2014). Mitosis detection in breast cancer pathology images by combining handcrafted and convolutional neural network features. Journal of Medical Imaging. 1. 1-8. 10.1117/1.JMI.1.3.034003.
4. Understanding and coding a ResNet in Keras, Priya Diwedi, Towards Data Science
5. Zheng, Yufeng & Yang, Clifford & Merkulov, Aleksey. (2018). Breast cancer screening using convolutional neural network and follow-up digital mammography. 4. 10.1117/12.2304564.)