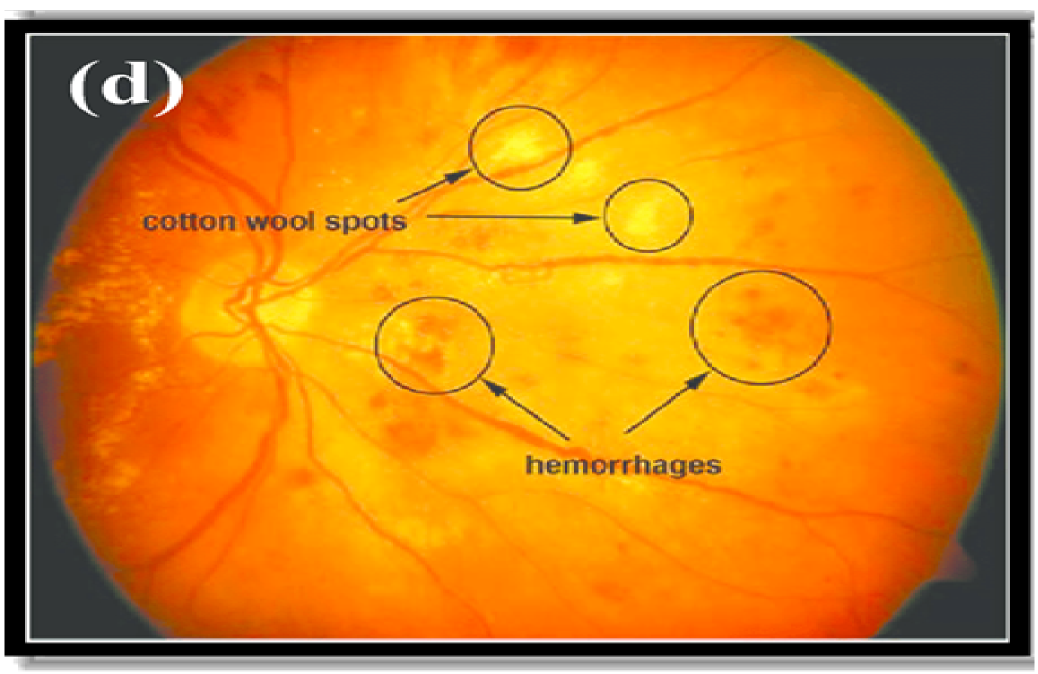
Retinal Image Analysis using Deep Learning
Report

Introduction to Hypertensive Retinopathy

Hypertension is a medical condition in which a person has elevated blood pressure. Hypertension can damage the delicate and tiny blood vessels of the eyes, and cause many diseases such as:

- **Retinopathy** (Damaging the retina): Causes bleeding in the eye, blurred vision, and can also lead to complete loss of sight.
- **Optic neuropathy** (Nerve damage): Damages the optic nerve due to blocked blood flow.
- **Choroidopathy**: Fluid buildup under the retina leading to distorted vision. [1]

Such diseases majorly damage the pathological lesions of the eyes, such as retinal haemorrhage, arteriolar narrowing, macular oedema, and cotton wool spots.



Cotton wool spots and haemorrhages seen through fundus images of the eye [2].

Work Done Till Now

Problem Statement:

- Given the fundus images of a person's eye, use a pre-trained model to detect whether the person is suffering from Hypertensive Retinopathy.
- Implement Vessel classification and segmentation of the Retinal Images.
- Study retinal image analysis algorithms, understand the various datasets available and come up with a novel approach to detect Hypertensive Retinopathy from the fundus image of the eyes.
- Further, applying a similar model to detect similar diseases which damage the pathological lesions of the eye.

Literature Review:

Hypertension is a prevalent medical condition that affects nearly 9.6 million people worldwide in a year. Symptoms of Hypertensive Retinopathy are visible in the fundus images, like Cotton wool spots (CWS), retinal haemorrhage (HE), haemorrhages and microaneurysms (HM). It is crucial to early detect HR because it may cause cardiovascular risk and retina microcirculation.

Early detection of HR-related eye disease is vital for human life prevention and proper treatment. The early detection of HR disease through fundus image analysis can save ophthalmologists a lot of effort and time. [2]

Earlier, complex image processing algorithms were used by researchers to pick features from the fundus images, but this task requires high computational power. Nowadays, researchers have started using deep learning models for the classification of such diseases.

Deep learning models like Convolutional neural networks have proved quite effective in picking up features during their training process. [2]

Epidemiological studies have shown that the diameter of retinal blood vessels change when a person is suffering from cardiovascular disease or high blood pressure (leading to Hypertensive Retinopathy). Retinal arteriolar narrowing and venular widening are independently associated with an increased risk of hypertension. [3]

Dataset Details:

There are many publicly available datasets of fundus images. The details of some of them are given below:

1. DRIVE

   The Digital Retinal Images for Vessel Extraction (DRIVE) dataset is a dataset for retinal vessel segmentation. The DRIVE dataset consists of 40 fundus images, all with a resolution of 584 × 565, with eight bits per colour channel(3 channels). These images were randomly selected from a diabetic retinopathy screening set of about 400 Dutch participants suffering from diabetes. In this subset of 40 images, 33 of them are considered healthy, and the remaining 7 have early signs of diabetic retinopathy.

2. HRF

   The High-Resolution Fundus Image Database contains 45 fundus images, equally distributed into three classes: healthy, glaucoma, diabetic retinopathy. These images have a high resolution of 3504 × 2336. They are about six times the height and four times the width of DRIVE dataset images.

3. STARE

   The STARE dataset has images from the Structured Analysis of the Retina project, initiated in 1975. The images and clinical data were provided by the Shiley Eye Centre at the University of California, San Diego, and the Veterans Administration Medical Center in San Diego. It contains 20 equal-sized (700×605) colour fundus images.

4. IOSTAR

   The IOSTAR vessel segmentation dataset includes 30 images with a resolution of 1024 × 1024 pixels, acquired from scanning laser ophthalmoscope.

5. RITE

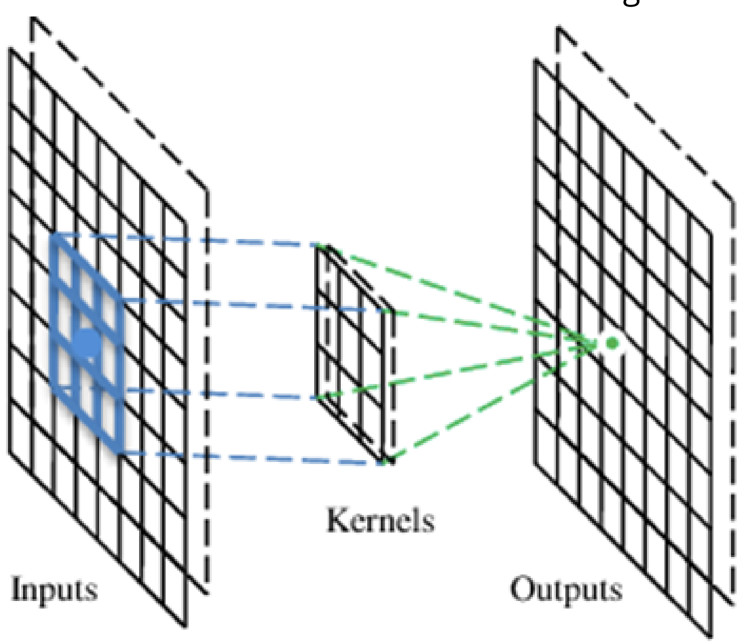
   RITE(Retinal Images Vessel Tree Extraction) dataset is mainly used for comparative studies on segmentation or classification of arteries and veins on retinal fundus images. This dataset consists of 40 images inherited from the DRIVE dataset and also has arteries and veins individual masks for each image in the DRIVE dataset.

6. AVRDB

   AVRDB (Annotated Dataset for Vessel Segmentation and Calculation of Arteriovenous Ratio) dataset consists of 100 fundus retinal images which are captured through TOPCON TRC-NW8 and annotated with the help of expert ophthalmologists from Armed Forces Institute of Ophthalmology (AFIO), Pakistan. These 100 images having dimensions of 1504 x 1000 contain retinal arteries, veins, AVR and whole vascular structure for ground truths. This dataset is mainly used for retinal vessel classification.

Understanding and Learning CNN model:

A CNN is a neural network with some convolutional layers (and some other layers). A convolutional layer has several filters that do the convolutional operation and thus extract different features from the image.



[4]

Each convolution can be assumed to be some kind of feature extractor on the image. The CNN architecture majorly consists of the following type of layers:

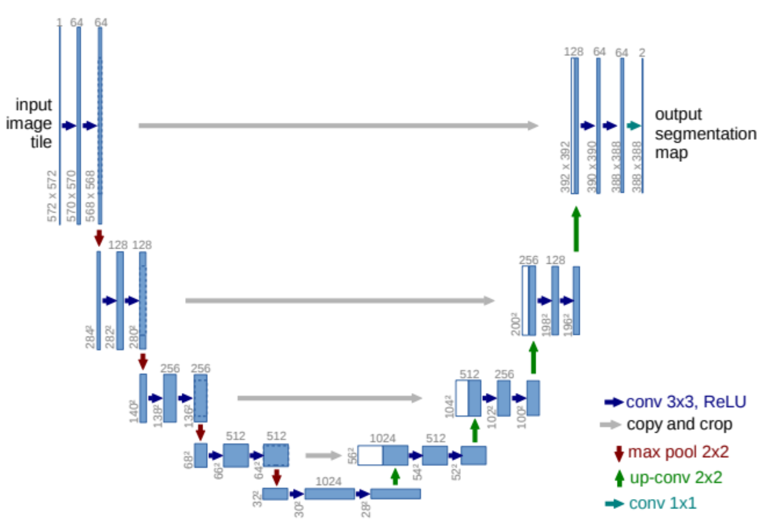
- Convolution
- Pooling
- Flattening
- Fully Connected Layer(Softmax layer)

In pooling, we consider the pixel values in a small neighbourhood and replace them with a single pixel value, thus reducing the number of pixels. It can be of three types: Min pooling, Max pooling and average pooling. But max-pooling generally gives better results. In max-pooling, the final value of the single-pixel is taken to be the maximum value of the pixels in its neighbourhood. Mainly, pooling is done to reduce the computation as the size of the input is reduced without much alteration in the input features(characteristics).

After the feature extraction(convolution) and pooling operations are performed various times, then the final 2D image is flattened into a 1D array and is fed to a fully connected layer(neural network) for the task of classification.

In conclusion, CNN is able to take into account the spatial distribution of the input image(due to convolution) and also the pooling layers help to reduce the computation of training the model. Thus, effectively extracting features from the input image.

A similar architecture is used in the elastic U-Net model, which is a fully connected convolutional neural network, which was used in vessel segmentation in [3].In a U-Net model, after many convolution and pooling operations, the image obtained is upscaled back to its original size using the method of transposed convolution.[5]



U-Net Architecture. [5]

Implementing Vessel Segmentation

The fundamental step towards automated retinal image analysis is vessel segmentation and artery/vein classification, which provide various information on potential disorders.

Epidemiological studies show that dimensions of retinal vessels change with ocular diseases, increased blood pressure, coronary heart disease and stroke. Thus, as the structure and function of retinal vessels change due to such cardiovascular diseases, they are a valuable biomarker for detecting such conditions and their severity. Thus, efficient Artery/Vein segmentation systems are of great importance.

Steps used in Image Segmentation:

1. Image Augmentation
2. Image enhancement/pre-processing
3. Training a U-Net model
4. Checking the performance of the model on the Validation Dataset

Image Augmentation:

Since we were using DRIVE dataset for image segmentation, we had only 20 images, in the training dataset, thus we used many data augmentation techniques, like horizontal flipping, vertical flipping, rotations of the images at angles of 90 and 270 degrees.

Below is an example of augmented image:

Original image Horizontal filp applied

Image Enhancement/Preprocessing

As we know that Retinal fundus images suffer brightness issues and also the contrast between the vessels and the background is pretty low, we applied local contrast enhancement, Contrast Limited Adaptive Histogram Equalization to the images(CLAHE). Also, we used to green channel of the images for training our model, as it has the most contrast between the background and the vessels. We also used gamma correction in the images, with the gamma value = 1.2 as it was giving the best results.

Training the U-Net model

While Training the model we have used the model similar to the one shown in U-net Architecture image[5]. We have used valid convolutions of 3*3 kernels in between layers, and Max Pooling layers of size 2*2 of stride=2. We trained the model for 20 epochs, as our local system were unable to handle a load greater that 20 epochs.

Checking the performance of the model on the Validation Dataset

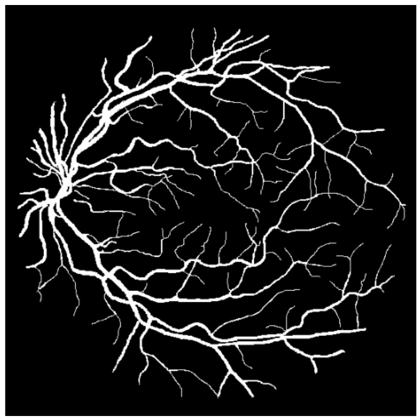
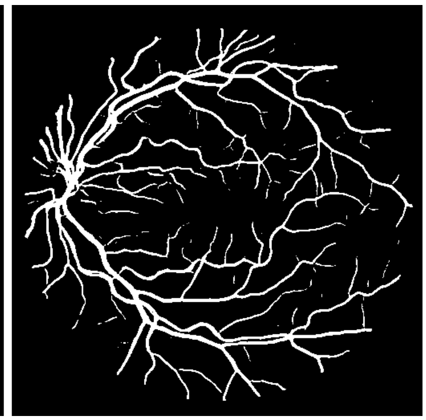
After Training the model and checking the performance on the validation dataset, we obtained the following scores:

Accuracy: 94.46%

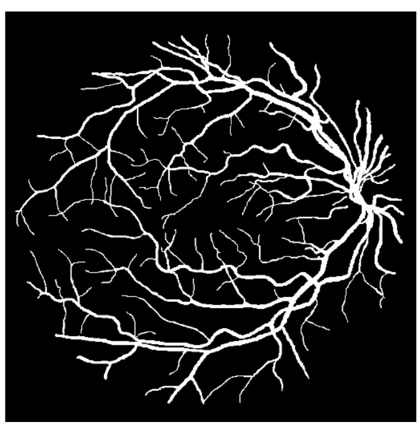
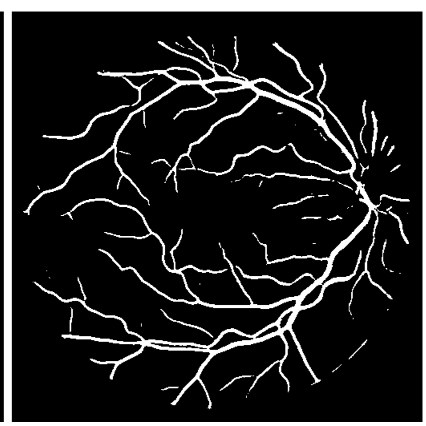
IOU score: 60.79%

Below are some prediction images:

Original Image | Original Mask | Prediction

Original Greyscale Image (Green Channel) | Original mask | Prediction

As we can see, the narrow vessels are not being segmented, thus we need to run our training for more number of epochs, and also work on using some better enhancement/pre-processing techniques in our image to get better results.

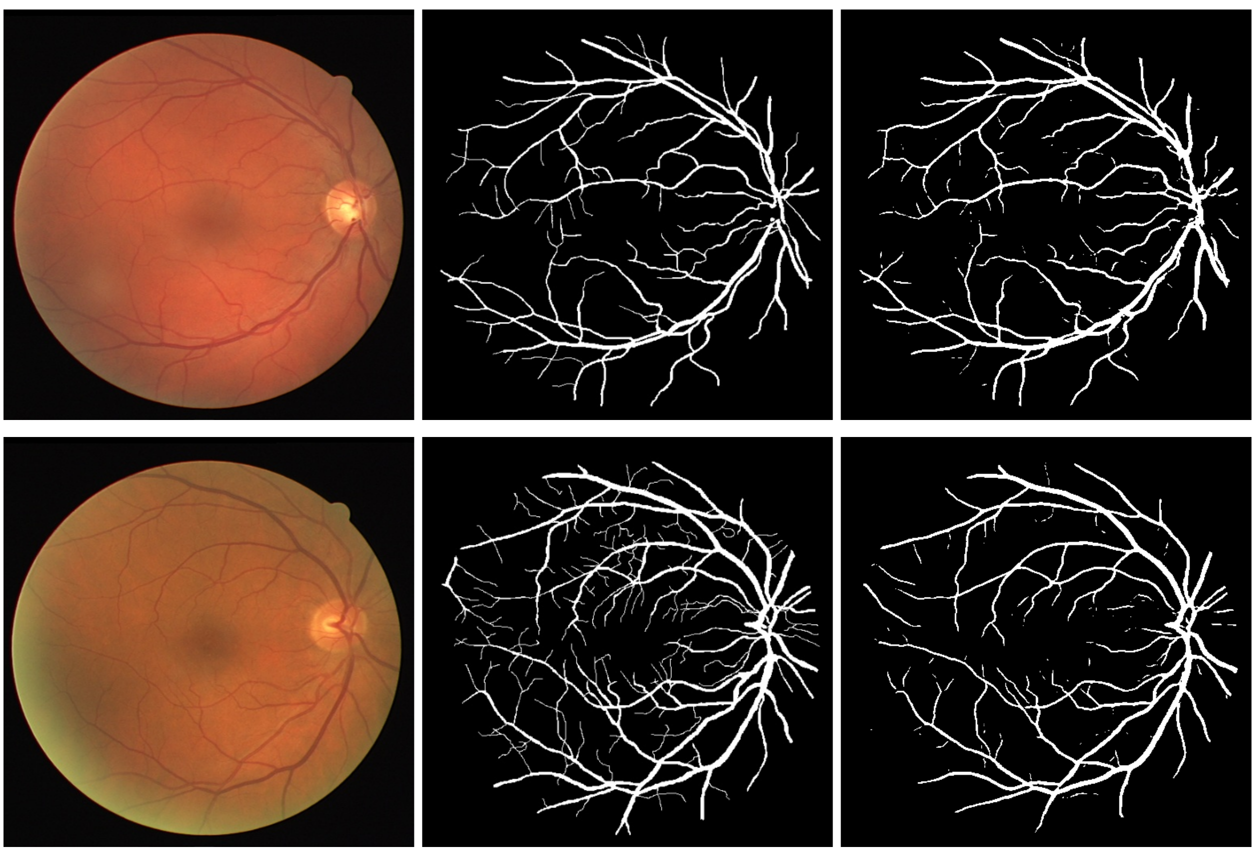
As we have realised that we need to use some pre-processing techniques, we have used some Morphological Operations after applying Local Contrast Enhancement techniques on the images. (Credits: Supriya ma'am, for providing the source code of enhancement of images.)

But still the results were not that good, in fact they were nearly the same as the previous results.

Results after using the Morphological pre-processing operations:

Accuracy: 92.4%

IOU Score: 57.36%



Conclusion

As we can see, that, we were unable to improve the segmentation accuracy of our model, even after using morphological operations. This can be due to several factors, that the pre-processing methods(CLAHE, and Top-Hat transformation) were enhancing the vessels, but also introducing some noise/blurring of the image.

References

[1] Rosendorff C, Lackland DT, Allison M, Aronow WS, Black HR, Blumenthal RS, Gersh BJ (2015) Treatment of hypertension in patients with coronary artery disease: a scientific statement from the American Heart Association, American College of Cardiology, and American Society of Hypertension. J Am Coll Cardiol 65(18):1998–2038

[2] Abbas, Q., Ibrahim, M.E.A. DenseHyper: an automatic recognition system for detection of hypertensive retinopathy using dense features transform and deep-residual learning. *Multimed Tools Appl* 79, 31595–31623 (2020).

https://doi.org/10.1007/s11042-020-09630-x

[3] Ruben Hemelings, Bart Elen, Ingeborg Stalmans, Karel Van Keer, Patrick De Boever, Matthew B.Blaschko, Artery–vein segmentation in fundus images using a fully convolutional network, Computerized Medical Imaging and Graphics, Volume 76,2019,101636, ISSN 0895-6111

https://doi.org/10.1016/j.compmedimag.2019.05.004

[4] Understanding the structure of a CNN

[5] Olaf Ronneberger, Philipp Fischer, and Thomas Brox, U-Net: Convolutional Networks for Biomedical Image Segmentation, Computer Science Department and BIOSS Centre for Biological Signalling Studies, University of Freiburg, Germany.

https://arxiv.org/pdf/1505.04597.pdf

Group Members:

Chakshu Dhannawat, Jaimin Gajjar and Arjun Singh.