Medical Image Segmentation

Sankalan Baidya

January 2023

1 Problem Statement

After extensive research, the following problems have been identified where Medical Image Segmentation can be performed. In case of most of these problems, manual segmentation is a difficult process and the use of ML algorithms can heavily increase the speed of diagnosis of many such diseases which if not detected early can have lasting effects and can even be fatal.

- Retinal Blood Vessel Segmentation.
- Brain Tumor Segmentation
- Lung Segmentation
- Polyp Segmentation
- Cell Nuclei Segmentation

The problem statement that I have chosen for this task is **Retinal Blood Vessel Segmentation**. This involves the segmentation of the thin blood vessels present inside the human eye. For this retinal blood vessel segmentation, I have referred to the **ICDS 2018** paper **"Retina Blood Vessel Segmentation Using A U-Net Based Convolutional Neural Network"**. The datasets used here is the **DRIVE** dataset which has 20 training examples with annotated training labels, which can be augmented further and the **STARE** dataset. It's performance was significantly better than a skilled opthalmologist on the DRIVE dataset, but on practical datasets the results weren't that good due to noisy images, but the authors conclude that they can be improved by using various image processing techniques. For this project, I have decided to choose the problem(s) **Retinal Blood Vessel Segmentation**. I have chosen this problem because I was able to read a paper doing the same in detail. I have also found datasets related to it, the most famous one being **DRIVE Dataset** on Kaggle. I also feel that this field is a bit underrepresented, because retinal diseases are quite rare, yet extremely dangerous. I also feel I know a little bit about this field, because I had formed an unhealthy obsession with eye diseases, back in lockdown, simply because I was bored and noticed weird artifacts in my vision, which led me to a conclusion that I was going blind XD.

Figure 1: Original Image

Figure 2: Preprocessed Image

2 Dataset & Data Preparation

For the purpose of training the model I have chosen images from multiple datasets like **DRIVE**, **STARE**, **CHASE**, **HRF**, **RETA** for a total of 167 training images and manually annotated retinal blood vessels and 20 test images and manually annotated.

In the data preprocessing step, all the images were resized to 256x256(to make training easier), the green channel of each image was extracted, **CLAHE** was applied and the images were gamma corrected.

3 Architecture

For the purpose of Medical Image Segmentation, papers related to **Mask RCNN**, Segmentation Based on **Image Pixel Embeddings**, **U-Net**, and **Pix2Pix GAN** was looked into. In this case, Mask RCNN was actually not applicable because it required bounding box annotations for the objects in the image, which made little sense for Retinal Blood Vessels. The pixel embeddings approach was dropped because I felt it was too complex for the given time frame. UNET was dropped, because there existed many papers which had already tested UNET. Ultimately I chose a GAN based architecture because I wanted to learn more about GANs. For training the model, **Pix2Pix GAN** was used. Pix2Pix GAN is a **conditional GAN** which uses a U-NET like architecture for it's generator and a deep CNN which is also known as **PatchGAN** as it's discriminator. Pix2Pix GAN is used for image to image translation, from a source image to a target image. **IEEE 2018** Paper by Dan Popescu, Mihaela Deacon & others used this architecture for Retinal Blood Vessel Segmentation.

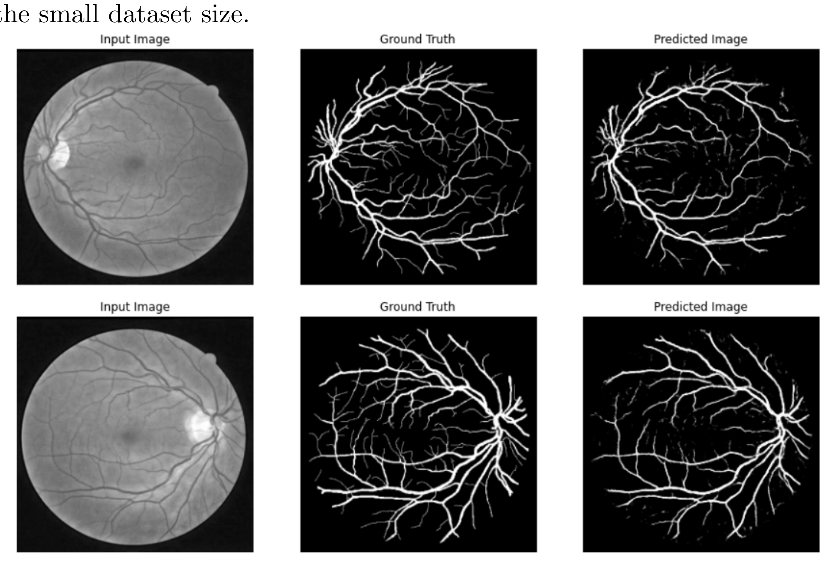
3.1 Loss Function

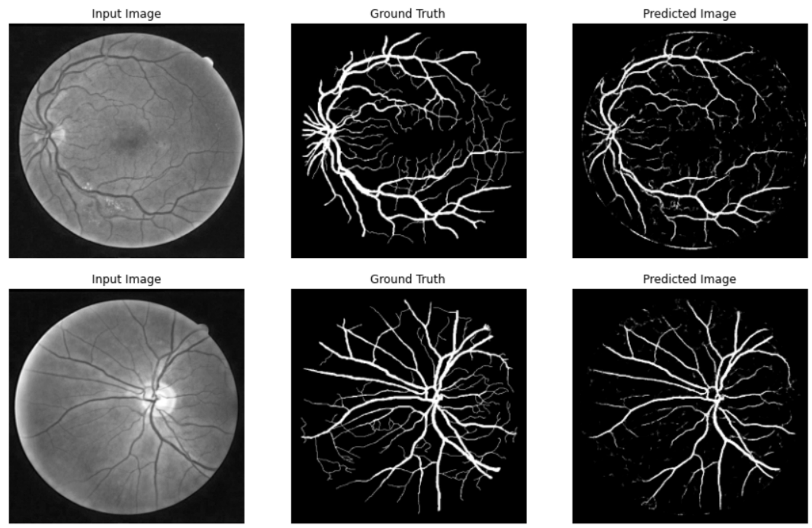
The loss function used for training the GAN is the sum of L1 loss(Mean Absolute Error between the generated image and the target) multiplied by a regularisation constant and the 'GAN' loss.

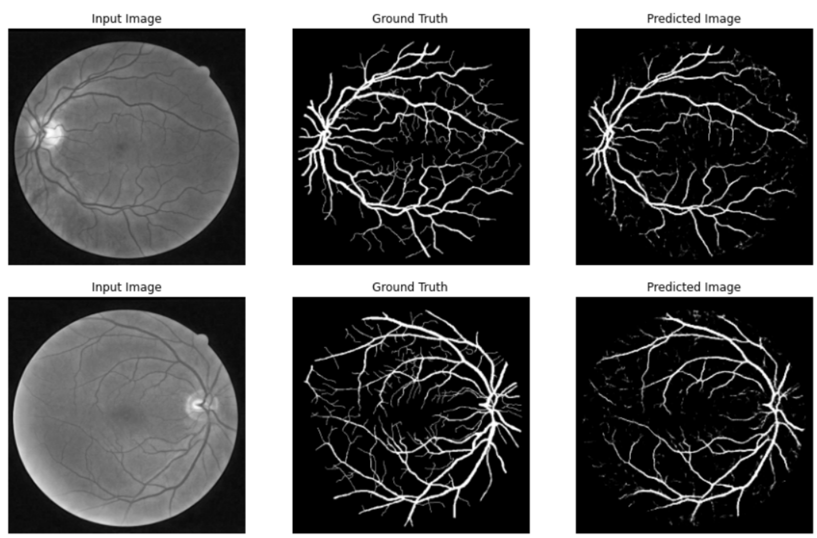
$$\mathcal{L}_{GAN}(G, D) = E_y[logD(y)] + E_{x,z}[1 - logD(G(x, z))]$$
$$\mathcal{L}_{L1}(G) = E_{x,y,z}[||y - G(x, z)||]$$
$$\mathcal{G}^* = arg\ min_G\ max_D\ \mathcal{L}_{GAN}(G, D) + \lambda\mathcal{L}_{L1}(G)$$

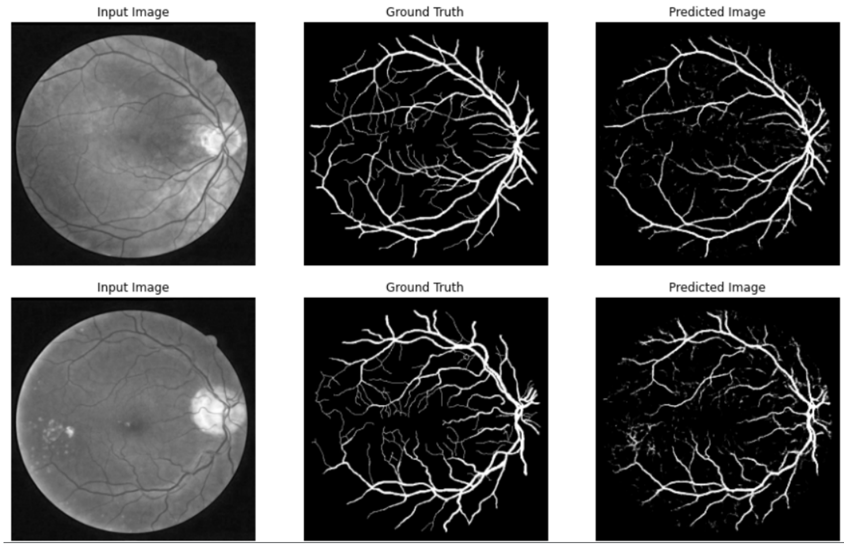
4 Results

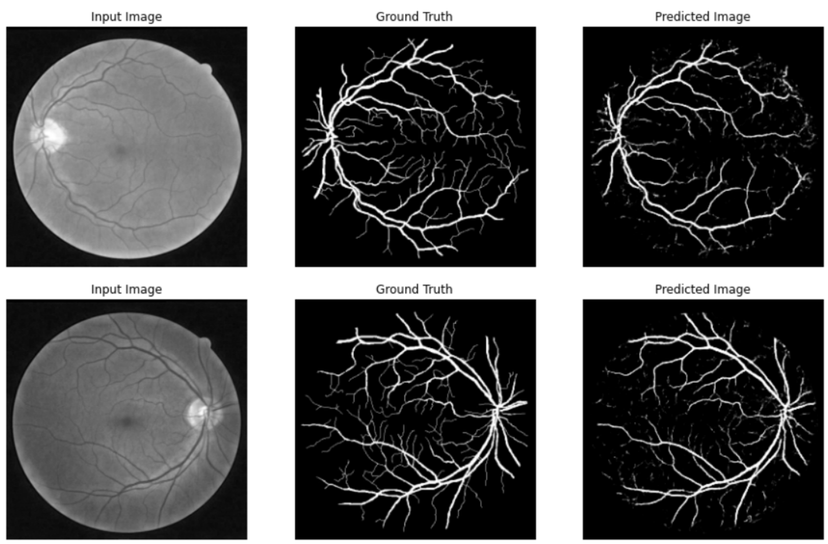
The Pix2Pix GAN was able to properly segment the larger retinal blood vessels quite accurately. It however struggled with the smaller and finer blood vessels. This can be attributed to the fact that the model was probably overfitting due to the small dataset size.

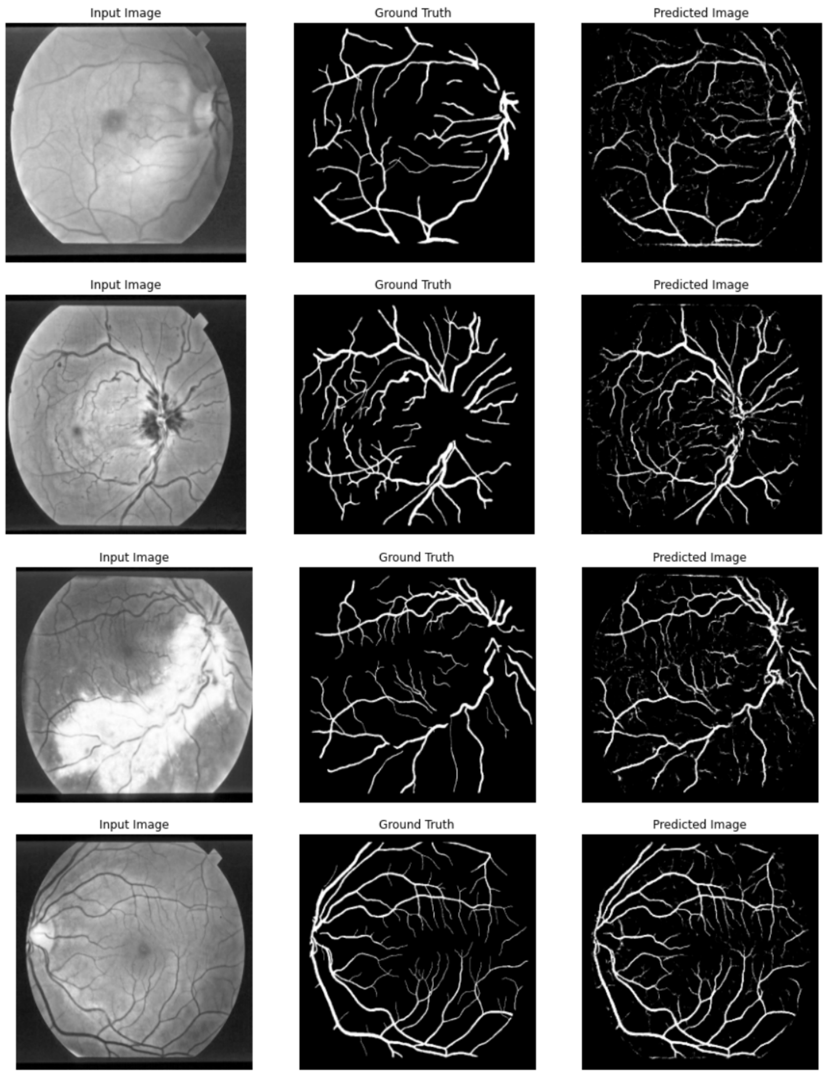



Input Image
Ground Truth
Predicted Image
Input Image
Ground Truth
Predicted Image


Input Image
Ground Truth
Predicted Image
Input Image
Ground Truth
Predicted Image


Input Image
Ground Truth
Predicted Image
Input Image
Ground Truth
Predicted Image


Input Image
Ground Truth
Predicted Image
Input Image
Ground Truth
Predicted Image



5 Issues Faced

There were difficulties in finding a dataset with a good amount of training images for this problem statement. As the dataset size was small there was overfitting in the training set, possibly leading to poorer results. Due to the unavailability of a GPU with large VRAM, I had to rely on Kaggle to train my model, which increased the training time by a lot. Also, I wasn't able to upload larger datasets on Kaggle due to it's limitations.