Medical Image Segmentation

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1 Problem Statement

Aim of this project is to learn Medical Image Segmentation and know about the field. There were many problem statements to choose from and train a model on it. Most of the problems were related to the human body, especially the retina, lungs, etc. I thought I was not gonna make better results than others or a better model. So, I decided to choose a different kind of statement to go with **Leaf Disease Segmentation**.

2 Dataset

The dataset I chose for Leaf Disease Segmentation is from Kaggle - kaggle.com/datasets/leaf-disease-segmentation-dataset. This dataset contains 588 images of disease leaf and 588 masks of the corresponding images. It is augmented to get 2940 total images, quite large to train the data.

The data collection is based on the PlantDoc images. The images are of several plant leaf-like Apple Scab Leaf, Apple rust leaf, Bell pepper leaf spot, Corn leaf blight, Potato leaf early blight, etc.

An example from the dataset (leaf with disease in the left, masks of disease spots in the right):

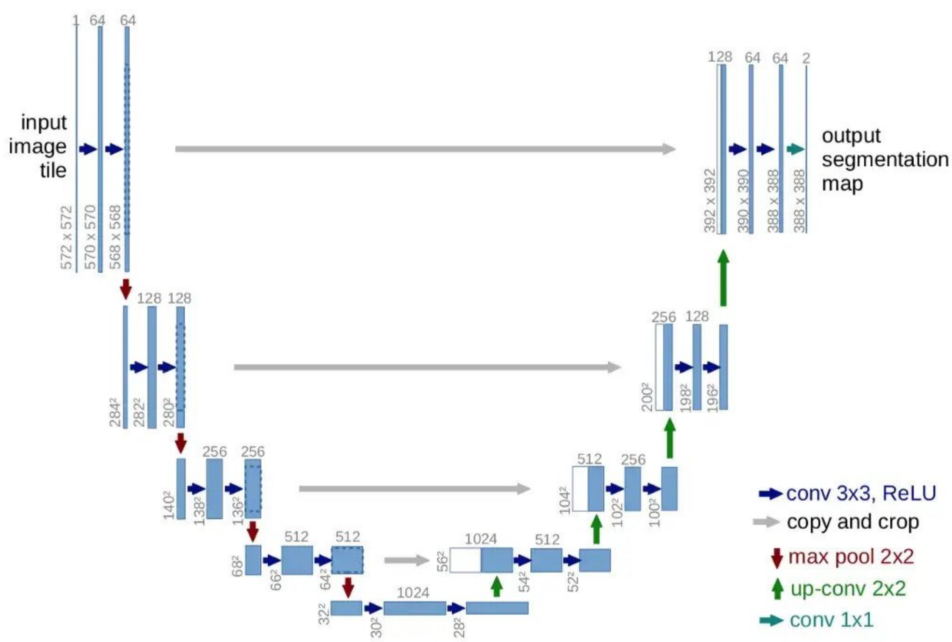
3 Preprocessing

Images were augmented to get five times the count. The more images, the more data the model can learn from and the better the model can perform. Images were resized to 256x256 to make training easier.

4 Architecture

The Architecture I wanted to start with first was the **UNET**. UNET was a U-shaped convolutional network that was specifically made for Medical Image Segmentation. I chose it as a start because it was made for Medical Image Segmentation, and the model was understandable and able to be implemented.

UNET architecture is built to focus on distinguishing whether there is a disease and also to localize the area of abnormality.



You can see the picture looks like a U shape, hence UNET. Left part is called the contracting path, which is constituted by the general convolutional process; the right part is the expansive path, which is constituted by transposed 2d convolutional layers. UNet can do image localization by predicting the image pixel by pixel.

5 Metrics

5.1 Intersection-Over-Union (IoU)

IoU is the area of overlap between the predicted segmentation and the ground truth divided by the area of union between the predicted segmentation and the ground truth. IoU is known to better than pixel accuracy metric. More the value of IoU, more closer and overlapped the predicted and actual masks are.

5.2 Dice Coefficient

Dice Coefficient is twice the Area of Overlap divided by the total number of pixels in both images. The more the value, the more overlapped the images are.

6 Loss Function

Since **Dice Coefficient** seems to be the appropriate metric for Image Segmentation, we will take **Dice Loss** function as **(1 - Dice Coefficient)**. The lower the loss, the more overlapped the masks are, and the prediction is better.

7 Results

After training it for 20 epochs, I achieved a loss of 0.2 (Dice Loss), which makes the Dice Coefficient 0.8. I also achieved IoU of 0.7 with a recall of 0.87 and a precision of 0.82. A sample result image can be seen below (Leaf with the disease at the left, actual diseased mask at the middle, predicted diseased mask at the end).

We can see that overlapping is not perfect. One main issue I faced was it failed to capture small spots and instead it captured the small spots as one big spot.