Florida Institute of Technology

College of Engineering

Introduction to Artificial Intelligence

Specific Object/Tissue Detection From Shepp-Logan Phantom

Final Report

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Abstract

Current imaging techniques used to determine the location and other features of a brain tumor is magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET) scans are all methods used to find brain tumors. Though these are all very effective, all require the addition of a biopsy to determine the characteristics of the anomaly, which is an invasive process. With the addition of the neural network, many characteristics are able to be determined with very high accuracy. Not only does this create a noninvasive process, but it also improves the chances of a tumor being detected sooner. Studies have shown that when a neural network is used to accompany a neuroradiologist in analyzing MRI brain scans, the accuracy of tumor detection rises from 63.5 percent to 75.5 percent, as well as being able to detect cancer type, size, texture, and volume (14). For the scope of the class, tumor size and shape were the only characteristics being detected. We are determining how accurate U-Net is for tumor detection and image segmentation.

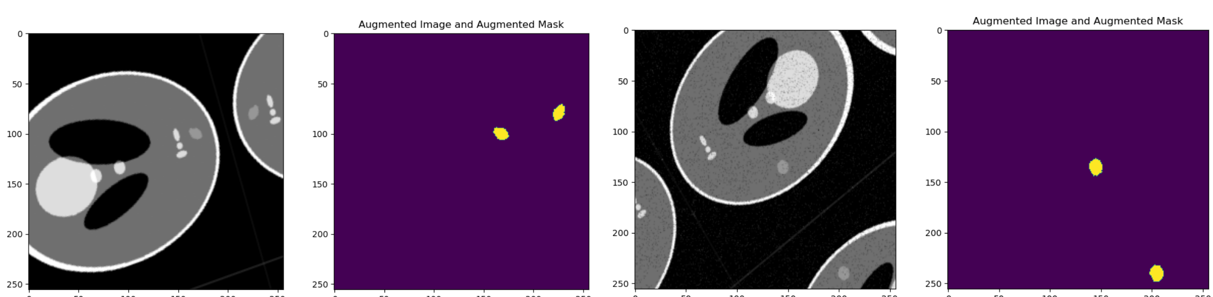
Introduction

Biomedical image segmentation is the process of extracting a feature from the background. This is important because by sectioning out and isolating an anomaly, more precise analyses and conclusions can be drawn. When looking at brain tremors, segmentation is very necessary to best determine what kind of tumor and what the size/ placement is. Brain surgeries are extremely difficult and sensitive, so producing the most information before invasive procedures is the most beneficial option. Recently, image segmentation using neural networks has been conducted by both comparing a variety of different networks and determining what characteristics can be found.

The aim of this project is to analyze medical imaging of the brain to find and segment tumors, or other anomalies, locations using a neural network powered by the U-Net architecture. U-Net is a convolutional neural network (CNN) specifically designed for biomedical image segmentation. More specifically, the U-Net is used to segment a tumor though feature extraction. Most studies have been done using MRI scans, but in our case, shepp-logan phantom images were used. These images function as a simple reconstruction of cranial space in order to test the ability of U-Net. By having a simplified image, we were able to focus on the changes in the output and have more distinct tumors for our first-time use. In this project, 50 tumor and image augmentations were created to make up the dataset for training the U-Net. After the U-Net was trained on the expanded dataset, the model was able to accurately segment the tumor.

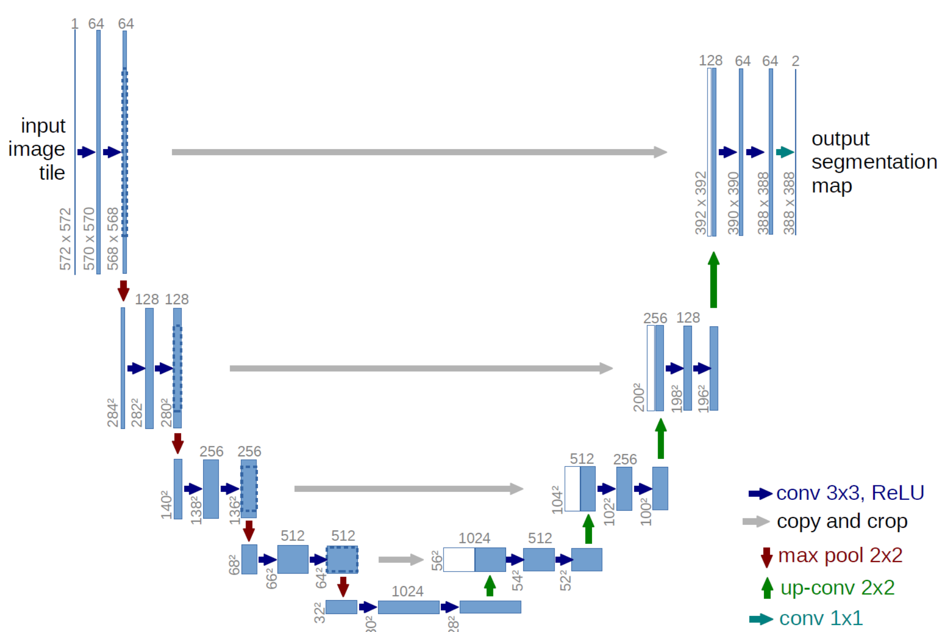
Data Pre-Processings / Image Augmentation

For training a neural network, a large amount of data is typically needed to infer any solution of substance, but for this project, a single Shepp-Logan Phantom image served as the base image. Though there is no specific value for how many images can be considered as a sufficient amount, the more unique samples the model is given to train on, the better it is able to learn and generalize on new information which is particularly important to the nature of the project to create a robust segmentation model in analyzing medical scans.The initial steps of pre-processing involved adjusting the base image size to 512x512 pixels to fit the format of the U-Net model where the input size should be a multiple of 32. Then, to expand the data set, a series of augmentations were applied to the base image that included varying levels of high noise, max filtering, min filtering, speckled noise, along with varying the shape and size of the anomaly. After this first stage of processing and augmentation, these 50 images were resized as 256x256 pixel images to decrease the complexity of the problem allowing for faster performance in training and simplicity. After these preliminary processing functions, each image instance went through further augmentation as part of a generator. Generators with similar parameters were made for the sample images and for the masks of these images. The generators were given the same seed so that the augmentations would run in parallel applying the same modifications to the corresponding samples and masks. These augmentations involved a measure of image rotation, width shifting, height shifting, shearing, zooming, horizontal and vertical flips to increase the sample size.



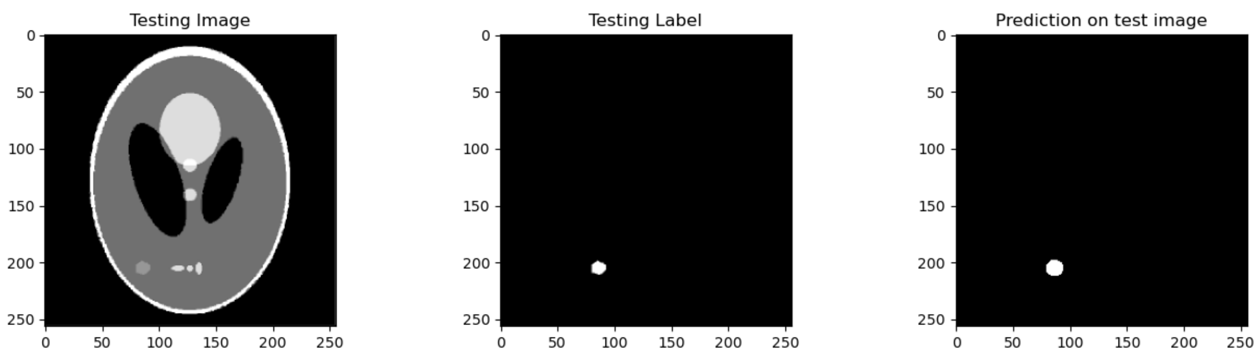
U-Net Architecture

The U-Net is an architecture of convolutional neural networks typically used for fast and precise image segmentation. This implementation utilizes a contracting and expanding path typically referred to as the encoder and decoder respectively. The encoder section of the unet, which is the first section that the data passes through, is responsible for capturing the context and important sections of the image. This is done through the combination of convolutional 3x3 layers, max pooling 2x2 layers and a copying operation that feeds into the decoder. The convolutional layer involves the simple application of a filter to the image. Repeated actions of this application of the filter create a feature map which is an indication of the strength of a detected feature. The max pooling layer then reduces the size of the feature map so there are less parameters in the network. This is done by extracting the maximum value within a portion of the image, typically done using a 2x2 window. The decoder enables precise localization that finds where the important features to be segmented is. This is done similarly to the encoding layer but opposed to the max pooling function, an up convolutional function is applied. An additional factor is the decoder accepts a copy of the corresponding layer from the encoder and appends it to its own layer. The training of this network over the image dataset then involves the model tweaking the values in the convolution layer filter so it can find a better configuration to segment the targets in the image.



Results

Using the 50 augmented images as our new base, these images are put through a generator that applies multiple further augmentations which are a rotation with a range of 90 degrees, a width shift with a range of 0.3, a heigh shift with range 0.3, shear range of 0.5, zoom range of 0.3, and the option to flip horizontally or vertically. Because these augmentations are dynamically applied to each of the 50 images one by one as they pass through the generator, there is no static size of the dataset but given the number of steps and epochs, we can gain an understanding of how many possible unique samples the model has trained on. Using 20 epochs to train, a batch size of 8 images and steps per epoch given by $3 * (len_{X_{train}} // batch)$ where $len_{X_{train}}$ is the number of training values in the split training dataset and batch is the batch size. Given that we have 50 images, the number of unique images given as input to the model over all epochs is 2880 assuming there were no repeated configurations of the parameters in the generator.



Future Work

Firstly, with any neural network model, by providing more unique clean data, the accuracy and ability to make a prediction on a wider set of problems will be improved. Therefore, one area of improvement in future work is analyzing what other augmentations or sources of data we can give to the model to serve the purpose of training it to accomplish the goal set out. Furthermore, this project aims to tackle the problem of identifying anomalies in medical scans but this implementation uses the Shepp-Logan phantom as a replacement for actual scans to serve for a valid stand in image so naturally the next step is to apply medical imaging scans to the model to measure its performance an a more nuanced image to see how well it can gather context in higher complexity imagery. Additionally, some of these medical scans come are given as a sequence of images of different layers such as scans of the brain. The current implementation works on a single image but to fully utilize the sequential nature of the brain scans, the idea of a recurrent neural network can be introduced to maximize the efficiency and accuracy of our model.

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