BME 548. Machine Learning and Imaging: Final Project
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Classifying Carcinomas in Patient Noisy Images with Lung Cancer

Abstract

Lung Cancer is a very serious disease that causes the death of tens of thousands of people every year in the US and in the world. For this reason, there exists the need for better diagnostic tools to identify if a person has lung cancer, and if they do, what type to determine the severity of it. In this project, a neural network model is proposed to be able to classify CT-scan images into four different types of cancer cells. This can be done even if the images have noise due to a denoiser present in the model. The network showed potential in classification but needs more work in the denoiser component. For future work, an improvement in the denoiser model needs to happen.

Introduction

Lung Cancer is a major killer in today's world. For 2020, it was estimated that there would be 228,820 new cases and 135,720 deaths just in the US alone. There are four major types of lung cancer: Adenocarcinoma (in cells that secrete mucous-like substances, A classification), Squamous Cell Carcinoma (in cells that line the inside of the airways in the lungs, G classification), Small Carcinoma (which tends to spread much faster than the others, B classification), and Large Cell Carcinoma (in virtually any part of the lung cells, E classification). The causes and the symptoms vary so much for this disease, so it is really hard to detect and sometimes detection happens until it is very late. This is a big reason why early diagnostics for lung cancer is very important. In this project, a method of classifying these types of cancer even with the presence of image noise is attempted.

Related Work

Convolutional neural networks are already being used nowadays in medical settings. Radiology imaging, for instance, uses this tool very often. This machine learning technique is not only used in imaging, but it even helps in studying protein to protein interaction and uncertainty quantification. In imaging, it is already helping in studying neuropsychiatric disorders, brain segmentation, stroke imaging, and more. In cancer research, it is being used to study breast cancer. Neural networks are the state-of-the-art in terms of machine learning algorithms that are going to help us improve human lives.

Methods

A set of CT-scan images in DICOM format was obtained from the Cancer Imaging Archive. Here a total of 132GB worth of images was collected, but due to the size of the dataset, not all the images were used. The images were arranged in four folders to represent the different types of lung cancer. Then a special library to load DICOM images was used to load them and parse through all the folders to convert them into numpy arrays that could be stored to then be used for the training and evaluating of the convolutional neural network models being developed. At the end, a total of 45,808 images were being used. These images were split into training and validating images for noisy images and classification (plus an extra set for testing the final network). In total there were five sets of data used for the neural networks.

For the problem of classifying lung cancer images with noise, some neural network models needed to be developed. First, it is important to understand that there are two problems here: cleaning noisy images and classifying these cleaned images as one of the four types of lung cancer. First of all, some noise needed to be added to the original images. For this, I used a salt and pepper type of noise model. I basically randomly selected a percentage of the points in the images to be white dots and another percentage to be black dots. This created images with irregularities and patterns that can clearly be seen that are not part of the system. This physically represents how sometimes a CT-scanner (due to different factors like the patients position in the bed and just different irregularities in the capturing method) can create images with black or white dots where there should not be any (see Figure 1). With this in mind, the idea was to simulate a rapid denoiser, which usually filter the signal in the chip before sending the image to the computer. Once in the computer, the second part of this problem comes in. A classification neural network was needed to classify filtered and clean images into the four different categories of lung cancer (A, E, G, or B).

For the denoiser component, an encoder-decoder neural network was needed. This is a complex problem due to the size of each layer and the number of layers needed. The idea is that the noisy image was used as the input of the network and the desired output was the pure and original image without any noise. To add to the level of complexity of this problem, the noise itself was added in a random fashion to keep it more realistic and physically representative. The first few layers of this neural network worked as a funnel, putting together the important pixels and encoding the image. The last few layers were the decoding component. Here the size of the matrix representing the image expanded again through upsampling and convolution. At the end, a binary cross-entropy loss function was chosen with an Adam optimizer. The schematic for this network can be seen in Figure 2a. At the end, the weights potentially can become the denoiser component, cleaning up images from noise.

For the classification component, a simpler model was used. Four convolutional layers were used after the input layer; after this, a dense layer followed by a flattening and another dense layer were implemented. For this network, a categorical cross-entropy loss function was used. With this simpler network, the classification of the 4 different types of lung cancer cells could be classified. The schematic can be seen in Figure 2b. For the final joint model, the layers for the encoding and decoding of the first model were joined with all the classification layers of the second model. In this way, a third neural network that could take noisy images and clean them and classify them was created. The weights were initialized with the layers from the other models with the idea that that would make convergence to be achieved faster. The schematic for this final network is seen in Figure 2c.

Results and Discussion

The model yielded some interesting results. Since I was virtually doing three different models (the last one depending on the first two), accuracy and loss in each epoch of training was an important thing to look at for all the models.

Unfortunately, the denoiser did not work as planned. It yielded only around 21% accuracy, which is not very high (see Figure 3). This is probably due to the complexity of the problem itself combined with the size of the images. Because in the dataset many of the images had very different sizes, I had to reshape the images to a standard smaller size (150x150). This affects percentage and presence of noise, but at the same time the image is still pretty big and would need many weights to process its information. For the encoder and decoder, I had to have many neurons in each layer, but it is possible it would still need more and that's why it's still not giving good accuracy values. These layers need refinement in terms of the number of neurons needed, and it might need some more layers in both the encoder and decoder to make this denoiser work, but I think the concept is still correct.

Fortunately, the classifier network worked well. It gave a good accuracy over 90% (see Figure 4). This can be seen in its accuracy and loss plots. This means that the classification is being done well with this simple network, but this only works in images that are not noisy. Like mentioned before, if the denoiser worked well, the final joined network would probably work well. As of now, the accuracy vs. epoch plot can be seen in Figure 5. At the end, with more layers, more neurons, and a trained architecture after many epochs, the joined network could clean images and classify them so the accuracy could be higher than 32%.

This has a lot of potential for other types of images as well. CT-scans are done for more than just lung cancer diagnosis; this imaging technique can also be used for breast cancer, brain cancer, kidney cancer, and so much more. Networks like this can be a helping tool for physicians to diagnose patients in clinical settings. The potential of deep learning for medical imaging and diagnosis is becoming more and more powerful every year.

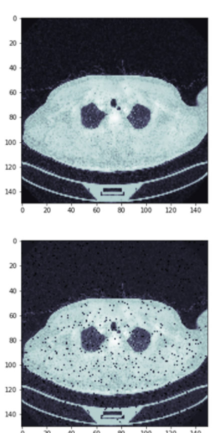

Figure 1: Original image can be seen on top, while the noisy image can be seen at the bottom

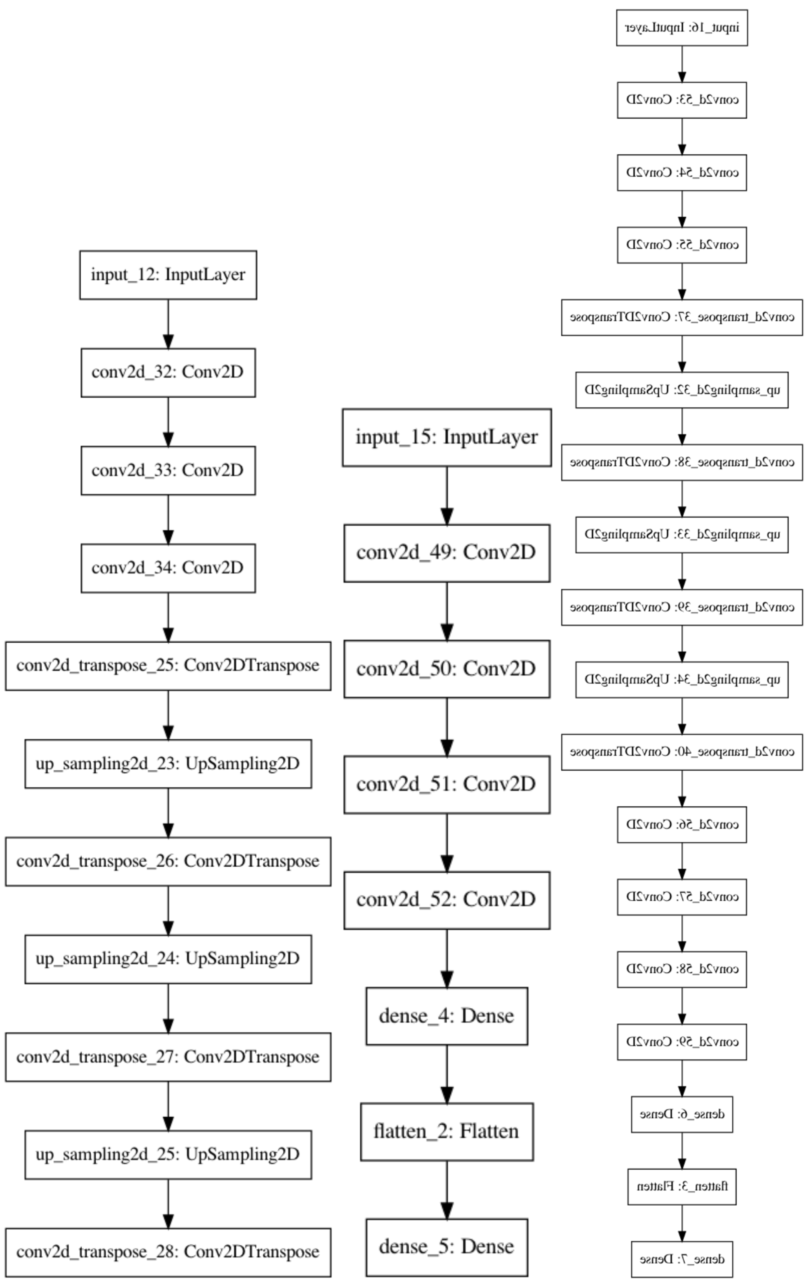

Figure 2: a) left side, model schematic for denoiser; b) middle, model schematic for classifier; c) right side, model schematic for joined network

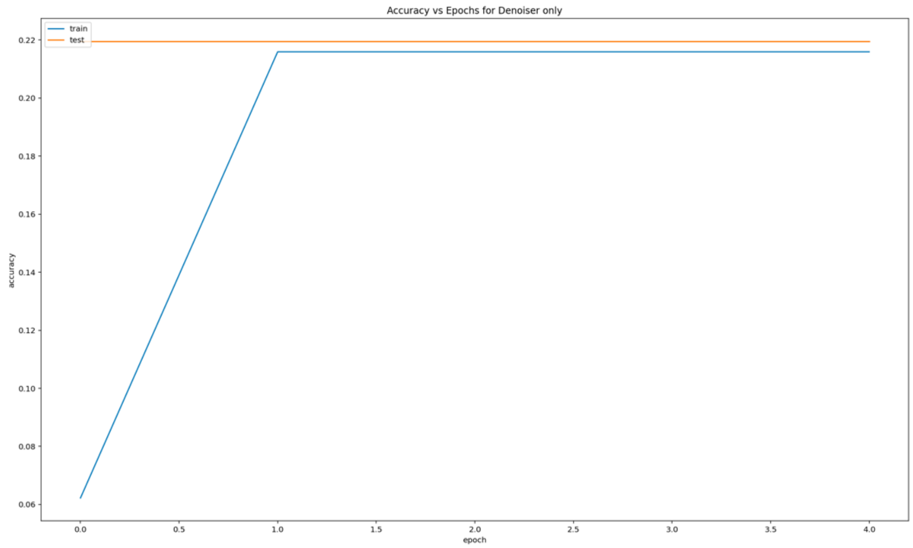

Figure 3: Denoiser network accuracy over each epoch

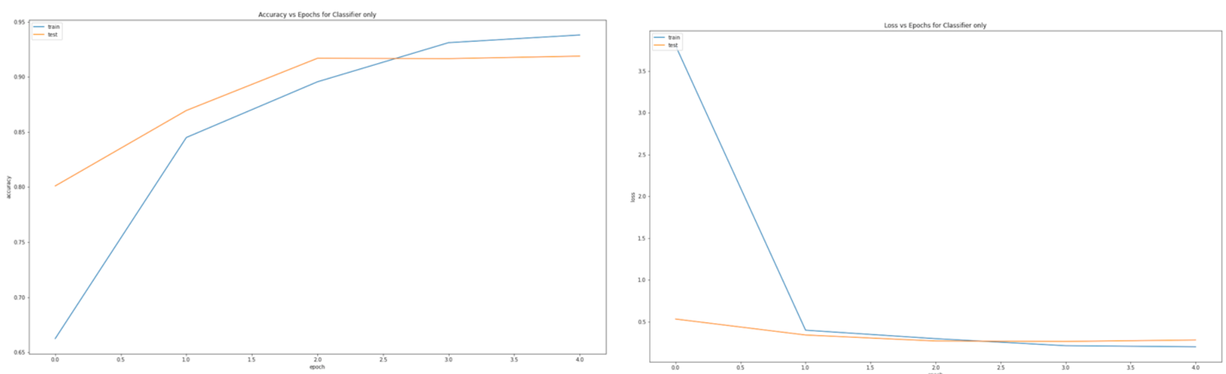

Figure 4: Classifier network accuracy and loss function over each epoch

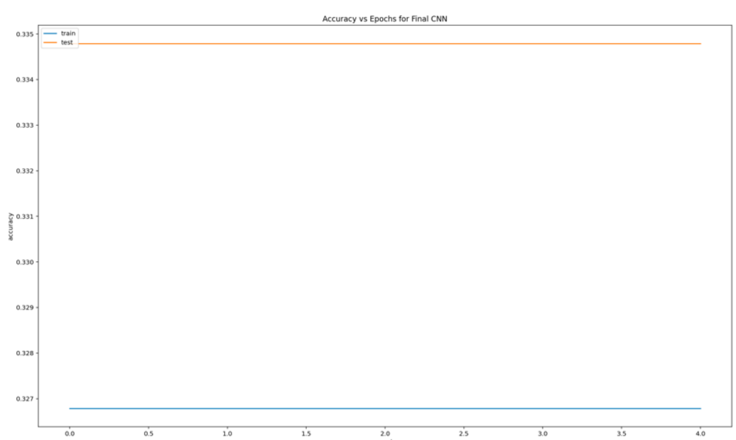

Figure 5: Complete network accuracy function over each epoch

References

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