A computational framework based on convolutional neural network for classifying interstitial lung disease in computed tomography scans

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Introduction
Chest Computed Tomography (CT) Scans are a form of X-ray that provide detailed images of organs so that they can be diagnosed as either healthy or diseased. CT scans are commonly used in the analysis of a lung to classify whether an Interstitial Lung Disease (ILD) is present or not. Computer Aided Diagnostic (CAD) systems are often used in conjunction with CT scans during the diagnosing process in an attempt to get quicker results. Convolutional Neural Networks (CNN) have proven to be a reliable method of choice in the use of CAD systems thanks to their diverse ability to learn and categorize different images based on what the network is being trained on. CNNs normally require large amounts of data in order to be accurate but the use of tools like transfer learning and our image patch extraction framework have allowed us to work with a smaller set of data.

Convolutional Neural Networks

- They have Convolutional layers.
- All the layers of pre-trained CNN can have features.
- Either the more generic or detailed new layers appended to them to utilize information from a certain image to figure out what is present.
- This speeds up the process since the whole network may not need to be trained.
- Features learned from that previous training can be used to train and test on a new data set.

Neural Networks (CNN) have proven to be a reliable method of choice in the use of CAD systems thanks to their diverse ability to learn and categorize different images based on what the network is being trained on. CNNs normally

Datasets

ImageNet
- 14,197,122 total images
- 21,841 Categories of images which include animals, plants, crops, people, cars, and many others which creates a diverse dataset to be used for different purposes.
- The large amount of images makes it a very appealing option to perform transfer learning when training various different Convolutional Neural Networks.
- All 1,946 Region of interests (ROI)
- Disease Labels used for testing: Emphysema, Fibrosis, Ground Glass, Healthy, Micro nodules.
- Allows us to try working with different types of Interstitial Lung Diseases and is closer to the type of data that a neural network would be interacting with in a real world application.

MedGIFT
- 128 patients
- 1,846 Region of interests (ROI)
- 12 different potential disease labels for CT images (including healthy).
- Disease Labels used for testing: Emphysema, Fibrosis, Ground Glass, Healthy, Micro nodules.
- Allows us to try working with different types of Interstitial Lung Diseases and is closer to the type of data that a neural network would be interacting with in a real world application.

Transfer Learning:
- Using a model that has been trained with an alternative dataset. (ImageNet)
- Features learned from that previous training can be used to train and test on a new data set.
- Additional layers can be added to a network to train new data while utilizing the features from the previously trained model.
- Speeds up the process since the whole network may not need to be trained.
- Leads to greater accuracy if there is only a small amount of original data to use.

ImageNet

MedGIFT Dataset: Image Patch Framework

Purpose of the Framework:
- Extract patches from CT scan that are from the ROI to avoid passing unnecessary CT info to the CNN.
- Convert the patches that are in single channel Hounsfield Unit to 3 channel red, green, blue png images.
- Use good naming conventions so that the patch names contain important information like disease label, CT series number, slice number, patch number (relative to the label), and patient number.
- Provide a framework with configurable values so that the user can get patches of a specific size, frequency, ROI concentration, and disease label.

Why Use MedGIFT?
- The amount of diseases available means testing can be done to create a CNN framework that is more dynamic.
- Interacting with full CT scans is closer to a real world application.
- Using a full set of CT scans from a single patient opens up the door for the possibility of using multiple CT scans at once to gain some intuition of how a disease presents itself. This could lead to more accurate classifications of diseases from CT scans.

Conclusions
- Patches extracted using an even distribution of HU to RGB yield the best results even above methods which were meant to highlight lung tissue.
- Larger datasets using 25% shifts proved to yield much better F1 scores when compared to a full shift data set.
- Class accuracy seems largely dependent on how different the class is compared to other classes being tested.
- While the larger dataset is more accurate it comes at a cost; running tests take substantially longer.