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Background research on using convolutional neural networks to analyze frontal and lateral chest x-rays

Chest x-rays are commonly used by many radiologists to determine what inside the patient’s lung and chest area is causing problems. Certain ailments, such as pneumonia, edema, atelectasis are able to be seen through x-rays, but it takes a very long time to provide an accurate diagnosis. Some people may have conditions that require a fast diagnosis, and they may miss out on crucial medical treatment because of how long it takes to reach a diagnosis. Researchers have started to develop computer aided detection system to recognize these diseases much faster than radiologists would, potentially saving the life of anybody who used it. Several studies have been done on creating different types of image detection systems based off of chest x-rays, and each of these systems is able to analyze frontal and/or lateral x-rays and associate a probability with each of the assigned diseases. Many recent studies created neural networks to analyze the chest x-rays, while others created a more refined version of a neural network called a convolutional neural network. Neural networks consists of layers of input neurons that take in input vectors that contain certain value, like the grayscale value of the pixel it is analyzing. Once each neuron has analyzed the value it was given, it passes that value on to every other neuron in the layer below it. These connections between neurons are known as weights, and a connection with a higher weight will be given greater importance when being analyzed by the neuron it was transmitted to. Once the data has passed through and been analyzed by all of the layers between the input layer and last layer, called the hidden layer, it is ready to be processed into its final values. The data pass into the final layer of neurons, the output layer, and in the case of using neural networks for chest x-ray image recognition, will be analyzed and made into a percentage that correlates to a disease. In the output layer, each disease will be associated with one neuron, and whichever disease has the highest percentage is output as the predicted disease(A Beginners Guide to Neural Networks and Deep Learning, n.d.). Studies have been switching from regular neural networks to convolutional neural networks, since they are more optimized for image recognition. Convolutional neural networks scan the image with filters of specific pixel sizes to search for specific features such as edges or sharpness. Additionally, convolutional neural networks use the fact that pixels nearby to the one that it is currently analyzing have more importance than pixels that are much farther away. These allow convolutional neural networks to be far more efficient than just regular ones, as they require less weights, which in turn makes the program faster as it doesn’t have to adjust as many weights as a regular neural network would have to. Other studies used dual convolutional neural networks, one was used to analyze the frontal chest x-rays and the other was used to analyze the later ones, and the outputs were later merged for the final prediction (Peng et al., 2017).

The two datasets that will be used in this experiment are the MIMIC-CXR database and the Indiana database. The MIMIC-CXR database consists of 371,920 chest x-rays associated with 227,943 imaging studies. This database contains paired frontal and lateral x-rays along with disease labels, but does not have any corresponding radiology reports. This is the largest publicly accessible database of chest x-rays at the moment, and the large amount of training data will increase the effectiveness of the model(Johnson et. al, 2019). The second dataset that will be used in this experiment is the Indiana dataset. This contains 7470 chest radiographs including both frontal and lateral x-rays with disease labels, and it also contains radiology reports that outline some of the patient symptoms and history(Qin et. al, 2018).

In 2018, Rajpurkar et al. published a paper comparing a convolutional neural network they had created, called CheXNeXt, to several practicing radiologists. Their model was first trained on the ChestXray-8 dataset, the second largest chest x-ray database after MIMIC-CXR. Both the convolutional neural network and the practicing radiologists were tested on 420 validation images. On average, it took the radiologists 240 minutes to analyze and assign a label to the images, while it took CheXNeXt only 1.5 minutes. The researchers computed an AUC score for how well the radiologists and model performed on the validation set. The radiologists performed better than the model on 3 of the diseases, but there was no statistically significant difference between the model and the radiologists on the other 10(Rajpurkar et al., 2018)

Researchers from Philips published a paper in 2018 detailing their methods of using dual convolutional neural networks as previously described to analyze both frontal and lateral x-rays and the outputs were associated with one of 14 different disease classifications. This study was unique from other as it analyzed the frontal and lateral chest x-rays separately, while the other studies analyzed them both at the same time. The researchers found that separating the convolutional neural networks allowed for their model to be more efficient than those that had analyzed the images together (Rubin et. al, 2018).

All of these studies have one big limitation; they fail to take into account patient history and symptoms. When making clinical diagnosis, it is important to factor in both of these as relying on the images alone will not give an accurate diagnosis 100% of the time. The researchers in the Philips study noted this, saying that the model could be made more accurate if patient history and symptoms were factored in. These both can be found in radiology reports, and factoring in this information could lead to the prevention of many unnecessary deaths and false diagnosis. With a model that is able to analyze both frontal and lateral x-rays and patient history, radiologists will be able to greatly improve their diagnosis speed and accuracy and save many more lives.

This research will first focus on replicating the experiment done by the Philips researchers through creating dual convolutional neural networks, one to analyze lateral chest x-rays and one to analyze frontal x-rays, and training it on the MIMIC-CXR database. Once the model has been adequately trained, the ability to factor in patient history and information found in the radiology reports will be added, and the improved model will be trained on the Indiana dataset, which contains not only frontal and lateral chest x-rays but also matching radiology reports.

References:

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