Classification and Localization of Thoracic Diseases and Multiple Sclerosis Detection Using Deep Learning

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Abstract: Deep learning and large-scale image datasets in CAD systems have demonstrated rapid and enormous success in a variety of computer challenges. In this study, “ChestX-ray8” is presented, which consists of 108,948 frontal X-ray images of 32,717 patients with 14 disease labels. It is shown that these thoracic disorders can be noticed and spatially placed utilizing a unified weakly – supervised multi label image classification and disease localization framework. The approach taken is an automated approach for segmenting and 3D localizing multiple sclerosis (MS) lesions utilizing multi-modal brain magnetic resonance data provided. The method is based on a deep end-to-end convolutional neural network (CNN) for slice -based segmentation of 3D volumetric data. The architecture follows the original U-Net and enhanced variations. The proposed pipeline is tested on four different datasets: the 2008 MICCAI MS Lesion Segmentation Challenge dataset, that holds 20 figures for preparation and 24 representations for experiment; the Longitudinal Multiple Sclerosis Lesion Segmentation Challenge, that holds 40 concepts for preparation and 42 representations for experiment; and MSSEG 2016 challenge, which contains 15 images for training and 38 images for testing; and dataset provided by the NIH clinical centre containing more than 100,000 anonymized chest X-ray images.

Keywords: *Dice loss, CheXNet, Sclerosis, Cross Entropy, CNN, NN-UNET.*

1. Introduction

Chest X-ray is one of the most universally used radiological test for lung diseases. It reveals the fluid in and around the lungs. In many hospitals, a large amount of data from X-ray imaging tests are accumulated and archived. A chest radiograph is used to diagnose lung disorders in symptomatic patients. The most difficult aspect of this screening procedure is timely reporting and patient follow up for treatment commencement. Deep learning has demonstrated rapid and remarkable success in a variety of computer vision challenges. Sclerosis detection has become much easier with the advent of deep learning. However, there still exist many challenges that are yet to be overcome such as the varying symptoms amidst patients. Cardiothoracic and vascular surgery is divided into three subspecialties: cardiac, general thoracic, and vascular surgery. These three fields were performed by the same individuals in the early phases of evolution. This is still the situation in number of practice settings around the world. Specific training programs and academic departments resulted from the maturation of each profession. Due to extensive under reporting, India's disease burden numbers are insufficient. Despite these limitations, The Global Burden of Disease Study 2013 might provide some useful statistics. India has a significant burden of non-cancer lung pathology when compared to other parts of the world. COPD, pneumoconiosis, and other devastating ailments are the examples of chronic respiratory illness. Furthermore, lung diseases such as tuberculosis, which were once uncommon to the western world, still exists in India. Multiple Sclerosis has disadvantageous effects on lifestyle of patients due to its harmful characteristics. In order to perform automatic segmentation of the lesions MRI scans are significant. Detection of Multiple Sclerosis is a tedious process which in itself requires a lot of economic stability from patient's background. With the use of deep learning the physical cost of preliminary sclerosis detection is reduced. In this paper we have illustrated a deep learning model that can validate and test an automated approach for segmenting Multiple Sclerosis Lesion from multi modal brain MRI and we have also localized and identified fourteen common thoracic diseases observed in chest X-rays.

2. Related Work

In this paper [1], for the classification and localization of thoracic disease they have used new multi attention convolution neural network. This network as three attention modules that is feature attention module for cross channel feature recalibration, space attention module for including both global and local information and hard example module for alleviating class imbalance problem. They have used ChestX-ray14dataset.

In this paper [3], they have proposed lesion location attention guided network (LLAGnet). This network consists of two module that is region level attention (RLA) and channel level attention (CLA). They have used ChestX-ray14 dataset. They have got average AUC score of 14 pathologies is 0.824.

In this paper [4], they have proposed contralaterally enhanced network for localization of thoracic disease. They have used NIH chest X-ray dataset.

In this paper [11], they have proposed technique from 3D U-Net. This is a first deep learning framework which was adopted. This was able to detect and segment T2-weighted lesions from the MRI images taken from RRMS patient's brain MRI taken longitudinally. The mechanism was based on subtraction MRI which adapted the 3D U-Net technology. This network has achieved high overall accuracy in detection (area under curve=0.95). This method as also accurately classified patients as active or inactive with sensitivities of 0.69 and specificities of 0.97.

In this paper, [18] they have proposed two contrastive abnormal attention models and a dual-weighting graph convolution to improve the performance of thoracic multi-disease recognition. First, a left-right lung contrastive network is designed to learn intra-attentive abnormal features to better identify the most common thoracic diseases, whose lesions rarely appear in both sides symmetrically. Moreover, an inter-contrastive abnormal attention model aims to compare the query scan with multiple anchor scans without lesions to compute the abnormal attention map.

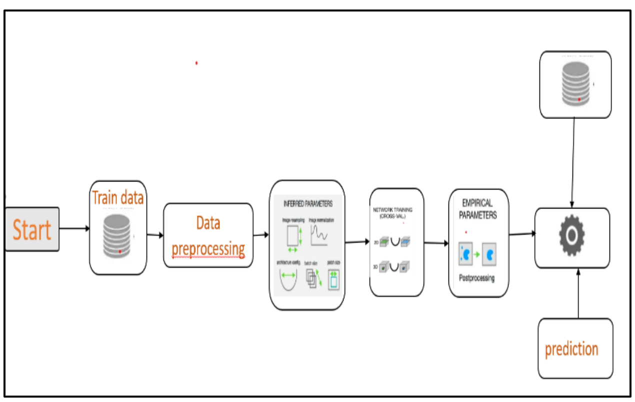
In this paper, [21] Accurate labeling and localization of irregularities from radiology images play an necessary part in dispassionate diagnosis and situation preparation. Building a well accurate forecast model for these tasks mostly requires a lot of figures manually remarked with labels and judgment sites of irregularities. In reality, however, afore mentioned defined dossier is expensive to achieve, exceptionally the one with region annotations.

3. Proposed Methodology

Given below are the working flow chart for thoracic and sclerosis detection depicted in Figure 1& 2. The approach is same for both the disease detection. The following are the steps involved in the prediction of outcome and with respect to the working flow chart:

- Raw data is processed
- Data is entered into datasets
- Data is run through neural networks
- Data set is tested through various parameters
- Efficiency of the system is noted at each stage as well as checking for errors
- Final predictions are made

Fig 1. Sclerosis Working Flow Chart



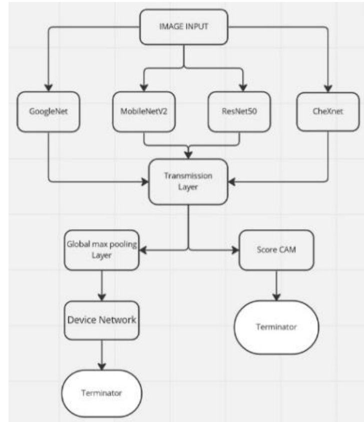


Fig 2. Thoracic Working Flow Chart

3.1 Collecting Dataset

Over 100,000 anonymized chest X-ray images and their related data were provided into the scientific community by the NIH Clinical Centre. Researchers from all over the world were able to freely access this data enhancing their potential to train computers to diagnose diseases. The dataset used to build the NN-UNET model consists of 189 different MRIs taken from varied sources and challenges. The MSSEG 2016 Segmentation Challenge, the 2015 Longitudinal Multiple Sclerosis Lesion Segmentation Challenge and the 2008 MISSAI Segmentation Challenge, all have MRIs are in “. nii.gz” layout that has existed split into preparation and experiment in percentage of 70:30. The Slicer software is used to generate the MRI image as shown in Figure 3. The dataset used to build the CNN network is anonymized chest X-ray images provided by the NIH clinical centre which consists of 100,000 images.

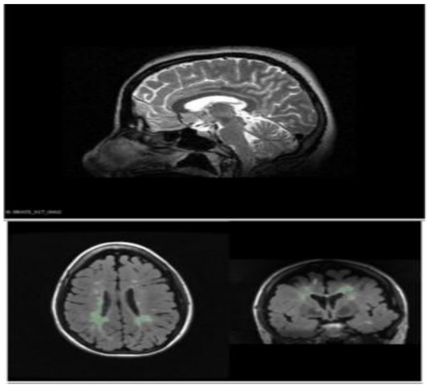


Fig 3. Sample Brain MRI

3.2 Data Pre-processing

Data pre-processing is the process of preparing the raw data and making it suitable for a model. The pre-processed raw data is taken in the form of X-Rays as well as MRI scans (for detection of sclerosis).As a first step in processing of data is done so that all the MRI files are arranged in a specified file-folder format. This is required so that the U-net can easily process the MRIs in batches. All files are binary NIFTI (. nii) files with two labels: 1 for lesions and 0 for background. Despite the fact that the NIFTI files are used as inputs to the evaluation software, the header orientation information is ignored.A sample MRI scan in coronal axis and its associated segmentation image are shown in Figure 4.

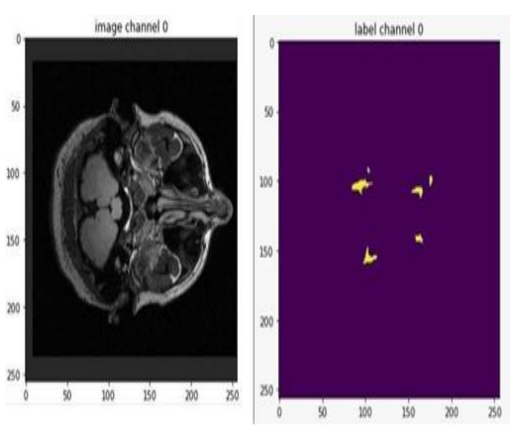


Fig 4. Sample brain MRI scan and Associated segmentation

Adaptive histogram equalization (AHE) is a computer image processing technique used to improve the contrast of images. However sometimes information can be lost from images due to over brightness. Therefore, to avoid this, the use of contrast limiting adaptive histogram equalization (CLAHE) is preferred. If a histogram curtain exceeds the specified contrast limit, those pixels will be clipped off and eventually distributed in later stages. Given below is an example image of CLAHE. Figure 5 shows before and after CLAHE on a chest X-ray image.

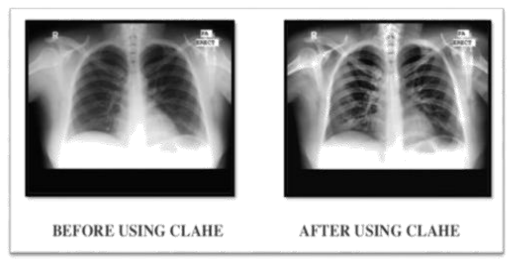


Fig 5. before and after CLAH

3.3 Model Selection

3.3.1 Convolution Neural Network

In deep learning a convolutional neural network is a class of deep neural networks that are most often used to analyse visual images. They are also known as space invariant artificial neural networks (SIANN), based on the weight shared architecture of convolution cores.They provide responses equivalent to the translation known as feature maps. Most convolutional neural networks are equivariant. It has various applications in image and video recognition. MRI pictures include a third dimension, a pool of basic U- Net architectures that include 2D U-Net and a 3D U-Net. The differences between the design and the original U-Net formulation are almost insignificant. The U-Net is a well-established encoder-decoder network. Its encoder function is similar to that of a typical classification CNN. It combines semantic information sequentially at the price of diminished spatial information. Figure 6 depicts the convolution operation on a MXNX3 image with a 3X3X3 kernel.

Fig 6. Convolution operation on an

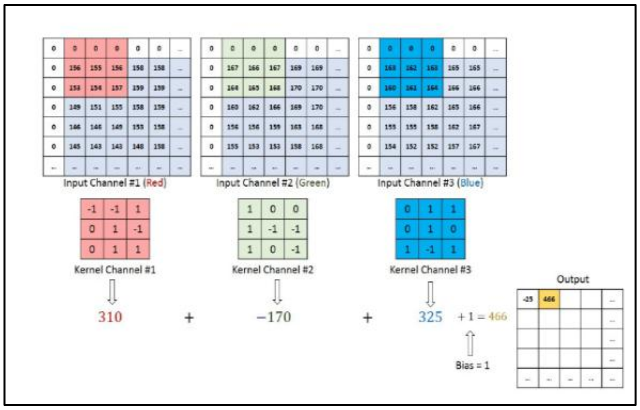


image matrix with 3X3X3 kernel

3.3.2 Unified DCNN

The objective is to see if there are one or more pathologies in each X-ray image and then one can locate them by activating and weighting from the network. A DCNN classification is used that inserts a transition layer, a global grouping layer, a prediction layer, and a loss layer at the very end. Network is performed on models like GoogLeNet, ResNet50, MobileNetV2, CheXNet.

3.4 Network Architecture

3.4.1 GoogLeNet

GoogLeNet a 22-tier convolutional interconnected system is established. One can load a pre- prepared tale of the network on ImageNet or Places365 dossier sets. Images are top-secret into 1000 object classifications, to a degree rodent, mammals etc. These networks have various feature likenesses for expansive range of representations.

3.4.2 ResNet50

ResNet50 is a neural network that is 50 layers deep. An individual can upload more than a million images from the ImageNet database. Similar to GoogLeNet images are classified into 1000 object categories. The networks input size is 224X224 pixels.

3.4.3 CheXNet:

This method uses X-ray pictures to diagnose and localize 14 different diseases. It is a 121-layer convolutional neural network that takes chest X-ray image and outputs the probability of pneumonia.

2D U NET**:** Runs on full resolution information.

3D FULL RESOLTION U NET**:** Runs on full resolution data. Patch size is limited by availability of GPU memory. It is overall the best performing configuration.

4. Result and Discussion

The following figures 7 -12 shows the deep learning model which was trained having the following characteristics. Figure7 depicts the improvement of network when presented through transfer learning and second pass.

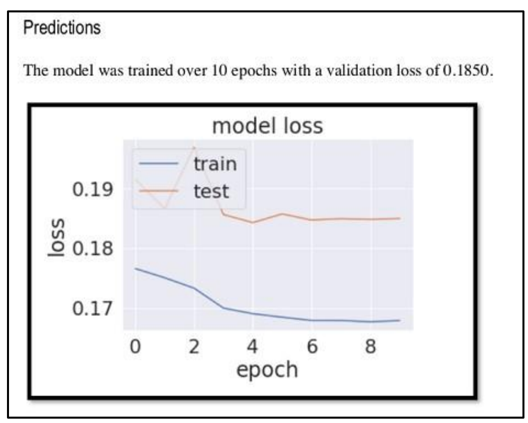


Fig 7. Model Accuracy vs Loss

Tests for validation loss of the algorithm was carried out and it was found to be at

0.1850. It is represented in the above graph for over 10 epochs. Figure 8 depicts the confusion matrix of the test predictions.

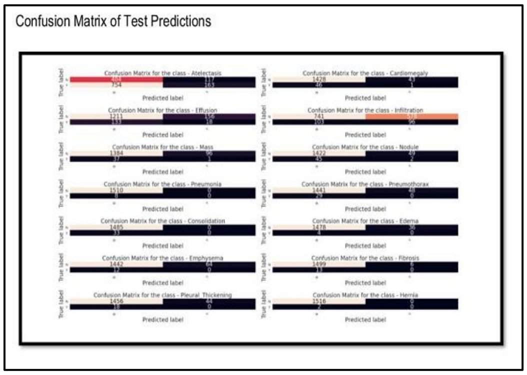


Fig 8. The confusion matrix of the test predictions.

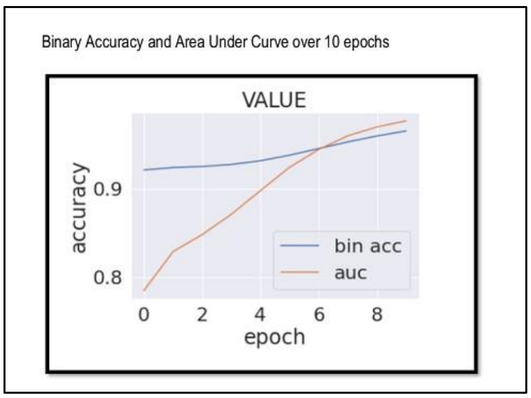


Fig 9. Accuracy vs epoch graph

Figure 9 that the individual class accuracy is also good and high while the False Positive rates are lower as well which signifies that the model has been trained well and can perform classification accurately on real-time data as well.

Classification Report

```
print("\nClassification report : \n", classification_report(y_true_argmax, y_pred_argmax,target_names=CLASS_NAMES))

Classification report :
                    precision    recall  f1-score   support

       Atelectasis       0.58      0.18      0.27       917
      Cardiomegaly       0.02      0.02      0.02        47
          Effusion       0.10      0.12      0.11       151
      Infiltration       0.14      0.48      0.22       199
              Mass       0.01      0.03      0.01        38
            Nodule       0.04      0.04      0.04        47
         Pneumonia       0.00      0.00      0.00         8
      Pneumothorax       0.00      0.00      0.00        29
     Consolidation       0.00      0.00      0.00        33
             Edema       0.00      0.00      0.00         4
         Emphysema       0.00      0.00      0.00        12
          Fibrosis       0.00      0.00      0.00        13
Pleural_Thickening       0.00      0.00      0.00        18
            Hernia       0.00      0.00      0.00         2

          accuracy                           0.19      1518
         macro avg       0.06      0.06      0.05      1518
      weighted avg       0.38      0.19      0.21      1518
```

Fig 10. Classification Report

Figure 10 illustrates the classification report produced by the algorithm explaining the disease detection and prediction of which thoracic disease is prevailing in the host. The precision provides us with the information of which disease is most likely to be prevalent.The following deep learning model was trained for 200 epochs, which accounts to 12 hours of training, and was followed by examining against standard test dataset. The following were the results obtained during training and testing. The training and validation cross-entropy loss was noted down, which could be visualized as shown in Figure 11.

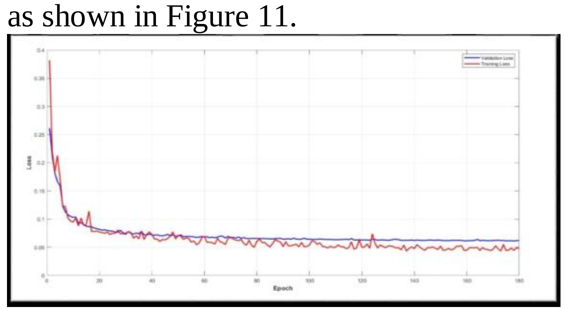


Fig 11. Cross-Entropy Loss Output

The training and validation losses were 5 and 5.5 percent respectively. A clear reduction in cross-entropy loss is deduced in the above graph. Lower the entropy-loss better would be the model trained.

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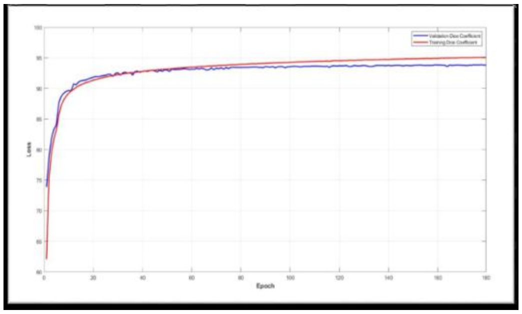

Fig 12. Training and validation dice loss output characteristics

The training and validation dice coefficients were 0.9 and 0.85 respectively. This shows a steady increment in dice coefficient value after each epoch. This indicates proper segmentation was observed throughout the training and testing.

5. Conclusion

Reading and diagnosis of chest X-ray pictures may appear to be a simple task for radiologists but in reality, requires careful observations and thorough understanding of pathology, physiology. As a result, finding a consistent and automated technique for reading chest X-ray becomes tedious. As in terms of sclerosis detection the dataset used to build NN-UNET model consists of 189 different MRI taken from various sources. Overall, it is illustrated, that is, the concept of deep learning in the study for detection of thoracic and sclerosis by designing an effective algorithm. This helps in reducing the burden on economy and makes diagnosis easier in hospitals.The trained CNN model had good pattern recognition accuracy and can be used for real-time implementation as it doesn't need much pre-processing. The CNN model out performed with 96% classification accuracy. In future the aim is to retrieve more data which helps to build more efficient and effective segmentation. One can also utilise the model to help screening of other diseases. The objective is to increase the accuracy in order to aid medical specialists for speedy diagnosis.

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