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Stratification of Chest Diseases through Convolution Neural Network

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Abstract: For Diagnosis of any problem or condition which is clearly be affecting the lungs or the nearby areas of it, Chest radiographic images are the common used images used by the doctors or radiologist for detecting the type of disease in every medical field. As it is most common and heavily used technology but due to shortage of good and proficient doctors or radiologist the applicability of this application is limited. To rectify this problem a computer based diagnosis by chest radiographic images is designed using Convolution Neural network (CNN) by 109,762 front view Radiographic images of 33,816 different patients having multiple scans and each of the patient is diagnose with the any one of the 14 lung diseases which are there in the dataset provided by the National Institute of Health(NIH) . Hence a CNN model can be developed to classify the disease using the given dataset.

Keywords: Deep Learning, Convolution Neural network, CNN, Chest Radiography.

1. INTRODUCTION

Subdivision of lung radiographic images are being greatly used in the medical field for example enhancing pixels of images and other tasks. For all those works the image has to be subdivided into three categories 1. Open beam 2. Soft tissues 3.Bones. Although use of machine learning have provided many advantages over our traditional methods. As the use of machine learning in the medical field increased noticeably now-a-days and along with this the open source databases are easily available. As we know that we can't use any publically available dataset of radiograph images to training a neural network for segmentation task represented in this paper. Hence if the company or organization willing to train a labelled network the it has to provide and label their own images by theirselves.

To obtain a large varied database is difficult or not possible because obtaining x ray images and performing it manually takes a lot of time and it is expensive; it is a common concern for the feasibility of neural networks for X-Ray subdivision.

In this paper we are constructing a Convolutional Neural Network (CNN) model to achieve subdivision through mining fine features, and also restricting the training parameter to avoid the overfitting. If we study the graph we get to know that there are million adults who are suffering from pneumonia and around 52,000 deaths are occurred due to this every year. According to the report of World Health organization, 2001 the Chest Radiographic images are the best method to for diagnosing pneumonia currently available. This technique is playing an important role in healthcare and in the study of diseases in humans. In spite of this diagnosis of pneumonia with the help of X-Ray technique is a big challenge which depends on the availability of trained radiologist. Hence we are introducing a model which can detect pneumonia with the help of chest X-ray at a step ahead of practicing radiologist. A report of the convolutional neural network (CNN) used for analyzing the lung diseases and its working principles is presented.

We used 109,762 front view Radiographic images of 33,816 different patients having multipal scans and each of the patient is diagnose with the any one of the 14 lung diseases which are there in the dataset provided by the National Institute of Health(NIH) for training of our Convolution neural network (CNN) model and we uses the image classification method to diagnose the diseases. We defined every disease as a class and we have to classify every image into one or more classes. we allow many disease label for every image. We trained our model to We train our model to check many things such as the X-ray image is normal or nor ? , Is the image is labelled with a disease or not ? , The image is labelled with how many disease?. Our model is capable identify the disease label with 57.8% accuracy.

2. BACKGROUND

Convolutional Neural Network (CNN) belongs to deep learning. It is an algorithm which receive the inputs in the

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form of image and assign some biases and weights to different objects of the image and make the images different or unique from one another. This process is the combination of three layers:-

1. Convolution Layer
2. Pooling Layer
3. Fully Connected Layer

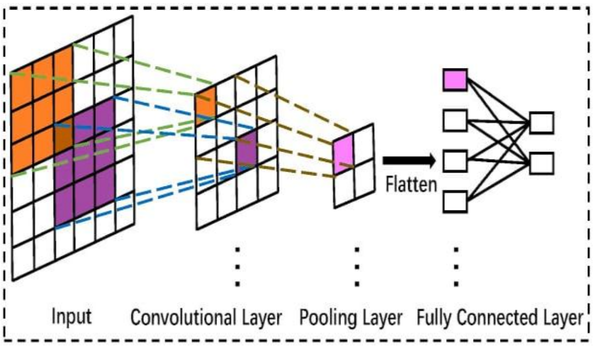

Figure 1. The diagram of Convolutional Layer and Pooling Layer

A. Convolutional Layer

Convolutional layer contains a set of kernals (independent filters) which is convolved with the input image and by performing multiplication of matrix between portion I and k we get convolved feature matrix as given in fig. Shifting of each filter/kernel is dependents on its stride value. Shifting is started and its parsing is continue until it parses the complete width and then again it started from the extreme left by moving down according to its stride value until full image is covered. We use padding to preserve the convolved feature . in padding process we add extra pixels at the image border. An activation layer is usually attached after the convolutional layer. Generally we use Rectifies Linear Unit (ReLU) function .

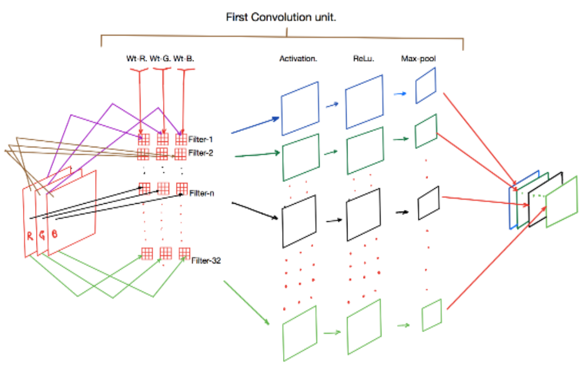

Figure 2. The illustration of Convolution layer having 3 kernal,R,G,B.

B. Pooling Layer

Pooling layer's role is to gradually decrease the three-dimensional size of the demonstration to lessen the quantity of constraints and computation in the network and it also useful to control overfitting. The operation of Polling layer is independent on every depth slice of the input and resize it by means of the Max operation. The pooling is done by two ways max pooling and min pooling generally Max pooling is used in which max value is covered from the different portions of the image by kernel and returned and performs noise reduction.

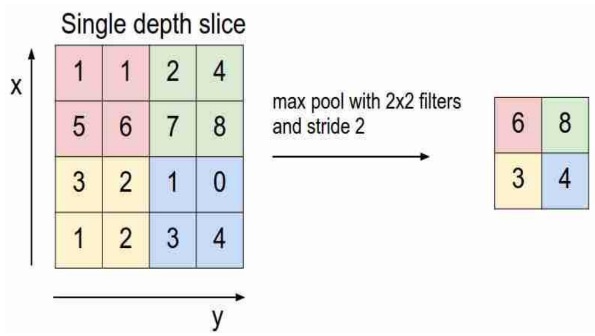

Figure 3. The illustration of Pooling Layer

C. Fully Connected Layer

Fully Connected layer is the layer where neurons of this layers have full connection to the all the activations in the previous layer, same as there in a regular Neural Networks. Hence their activations can be calculated by a Matrix multiplication along with a bias offset.

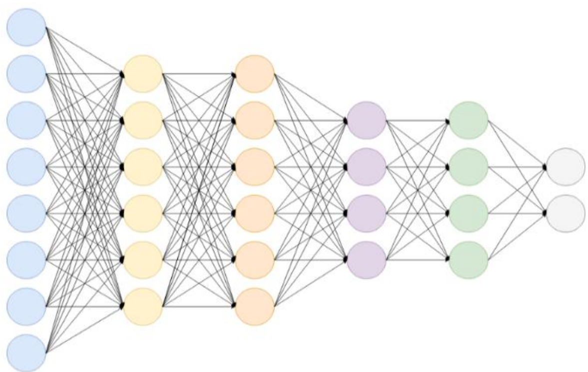

Figure 4. The illustration of Fully Connected network

3. METHOD

A. Dataset And Pre-Processing

We obtained the dataset from the kaggle which was provided by National Institute of Health (NIH). It

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contains 109,765 front view Chest radiology images of 33,816 different patients having multiple scans and the images are of size 1024 * 1024 pixels.

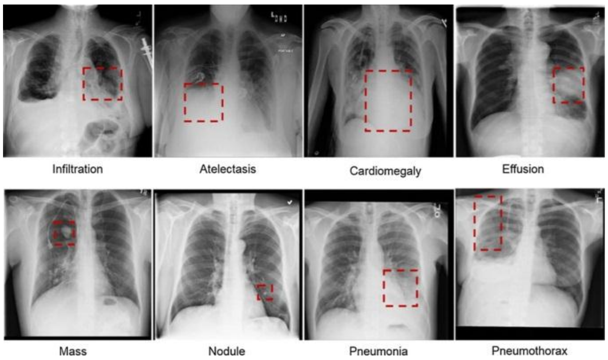

Figure 5. Chest diseases diagnosed from Chest X-ray

Some additional structural data is also given in which we have following data for each chest radiographic image such as image index , original image size, original image height, original image width, finding labels, original image pixel spacing x axis , original image pixel spacing y axis in which the information provided which has less relevancy or minimal information about the patient diagnosis is removed.

In case data has extra days or moths then to get homogeneous data we removed extra months and days from patient age column. After that we resize the images to 256 * 256 pixels. Due to fully connected layer convolutional neural network classification must be completed in fix-sized inputs.

B. CNN Classification Model

We developed a CNN model but before that we have to convert all the images which are resized, into a single array which will added to a Numpy array. We use Tensor flow as backend and Keras for training CNN model. We use VGG architecture for this model [12]. In the model we divide the Numpy array which was created previously into two part i.e. training and testing model and we create and train the model using training data. We use 2 to 3 convolution layers followed by ReLu activation Function and a pooling layer with it. To reduce overfitting we use dropout at the last fully connected layer which also improve the result.

4. CONCLUSION

In this Paper, we demonstrated our initial research of training the model for diagnose the disease from the chest radiography images using Convolution Neural network (CNN). We use Jupiter notebook with 8 titan x GPU to implement experiment. We done out experiment with the data as conferred above. 58.3 % accuracy of the result the argument of the proves Luke Oakden-Rayner that the model learned to pass inaccurate result in spite of rectification of class imbalances and regularization of data. Meanwhile the convolution neural network model is created on Chest radiography labels being precise and true the result varies.

5. FUTURE WORK

In Future we will form a larger dataset by adding more radiograph images to train the the model especially adding the images of rare lung diseases. For the better simulation of how the doctors and radiologist reads there images we will also include the medical history in the model. Moreover we can also diversify the classification category so that we can also identify the different bones and tissue materials. We will make a greater change in the medical field by identifying the tissue abnormality because it is a very tough task in the medical field using radiographic images.

REFERENCES

[1] H. C. Shin, H. R. Roth, M. Gao, L. Lu, Z. Xu, I. Nogues, J. Yao, D. Mollura, and R. M. Summers, “Deep convolutional neural networks for computer-aided detection: Cnn architectures, dataset characteristics and transfer learning,” IEEE Transactions on Medical Imaging, vol. 35, no. 5, p. 1285, 2016.

[2] K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” Computer Science, 2014.

[3] H. Chen, C. Shen, J. Qin, D. Ni, L. Shi, J. C. Y. Cheng, and P. A. Heng, Automatic Localization and Identification of Vertebrae in Spine CT via a Joint Learning Model with Deep Neural Networks. Springer International Publishing, 2015.

[4] Xiaosong Wang, Yifan Peng, Le Lu, Zhiyong Lu, Mohammadhadi Bagheri, Ronald M. Summers, “ChestX-ray8: Hospital-scale Chest X-ray Database and Benchmarks on Weakly-Supervised Classification and Localization of Common ThoraxDiseases”, 19 July 2017.

[5] H. Noh, S. Hong, and B. Han, “Learning deconvolution network for semantic segmentation,” pp. 1520–1528, 2015.

International Innovative Research Journal of Engineering and Technology
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[6] L. C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, and A. L. Yuille, “Semantic image segmentation with deep convolutional nets and fully connected crfs,” Computer Science, no. 4, pp. 357–361, 2016.

[7] E. Shelhamer, J. Long, and T. Darrell, “Fully convolutional networks for semantic segmentation,” IEEE Transactions on Pattern Analysis & Machine Intelligence, vol. 39, no. 4, p. 640, 2017.

[8] M. Mostajabi, P. Yadollahpour, and G. Shakhnarovich, “Feedforward semantic segmentation with zoom-out features,” in IEEE Conference on Computer Vision and Pattern Recognition, 2015, pp. 3376–3385.

[9] S.Yang, W. Cai, H. Huang, Z. Yun, W.Yue, and D.D.Feng,“Locality-constrained subcluster representation ensemble for lung image classification,” Medical Image Analysis, vol. 22, no. 1, pp. 102–113, 2015.

[10] F J. M. Wolterink, T. Leiner, M. A. Viergever, and I. Isgum, “Automatic coronary calcium scoring in cardiac ct angiography using convolutional neural networks,” Medical Image Analysis, vol. 9349, pp. 589–596, 2016.

[11] H. Roth, L. Lu, J. Liu, J. Yao, A. Seff, K. Cherry, L. Kim, and R. Summers, “Improving computer-aided detection using convolutional neural networks and random view aggregation.” IEEE Transactions on Medical Imaging, 2015.

[12] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “ImageNet classification with deep convolutional neural networks,” in International Conference on Neural Information Processing Systems, 2012, pp. 1097–1105.

[13] C. Szegedy, W. Liu, Y. Jia, and P. Sermanet, “Going deeper with convolutions,” pp. 1–9, 2014.

[14] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” pp. 770–778, 2015.

