Detection of Pneumonia from X-Ray Imaging using Faster RCNN

M.K.Dharani[1], S.Santhoshkumar[2], T.Balaji[3], B.Dhayaneshwar[4], S.Arunbarathy[5]
[1,2] Assistant Professor, Department of Computer Science and Engineering, Kongu Engineering College, Erode, India
[3,4,5]Student, Department of Computer Science and Engineering, Kongu Engineering College, Erode, India
[1]dharani.cse@kongu.edu,[2]santhosh.cse@kongu.edu,[3]balaji.thangaraj@yahoo.com, [4]dhayaneshwarb@gmail.com, [5]arunbarathys@gmail.com

Abstract

Pneumonia is a disease which occurs in the lungs caused by a bacterial infection. Early diagnosis is an important factor in terms of the successful treatment process. Generally, the disease can be diagnosed from chest X-ray images by an expert radiologist. The diagnoses can be subjective for some reasons such as the appearance of disease which can be unclear in chest X-ray images or can be confused with other diseases. Therefore, computer-aided diagnosis systems are needed to guide the clinicians. In the division of health care artificial intelligence plays a vital role to perform better diagnosis with less error rate. Deep learning techniques can be employed to predict the disease with higher accuracy. Previously a comparative analysis was made on Xception vs vgg16 and CNN(Convolutional Neural Network) VGG19, ResNet, Inception V3. The main disadvantage of CNN is that it doesn't encode the position and orientation of object. In order to overcome the existing disadvantage the proposed system was compiled using Faster RCNN (Region Convolutional Neural network). In RCNN method selective search is done based on the bounding box values. The system has been trained and tested with the 10000 images of x-ray dataset and it shows a higher accuracy when compared to the existing models.

***Keywords**: Deeplearning, Pneumonia, Health care, Convolutional neural network, Region Convolutional Neural network*

1. Introduction

In today's world artificial intelligence plays a vital role in almost all the field of science. In the health care industry it shows the level of advancement in diagnosis of disease at the various levels. In terms of accuracy it rates higher and reduces the human error. As medical industries are one of the prominent industries the deep learning is majorly used in the tumor detections and lesions in medical images [10]. Pneumonia is a lung disease or inflammation that is caused by the bacteria fungi or viruses. It can occur to people at any age level[11]. It becomes a life threatening factor for the infants, elderly people and then people having very weak immune system. According to survey in 2017 more than one million adults are getting affected by pneumonia and average of 50000 people are died per year[8]. In the diagnosing of pneumonia x- rays are well thought-out as the most effective method to determine the level and location of the septic region in lungs [9]. Treating pneumonia mainly involves taking an x-ray of the chest area further diagnosis may require CT scan, MRI scan, ultrasound of the chest depending upon physician treating techniques. Mostly x-rays were used because it is cost-effective and

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affordable for all class of people. The main obstacle involved here is interpreting x-ray which is not as easy as normal x-rays taken from non-complicated body parts. So the interpretation of x-ray requires experts not by all physicians. However, examining chest radio-graphs is not a relaxed task for radiotherapists. In chest X-ray images, appearance of pneumonia can be unclear and can be a chance of misapprehended with other diagnoses. So by employing deep learning techniques, pneumonia can be detected with much greater accuracy.

2. Related work

Zahra Sobhaninia et al., has proposed a work on deep learning techniques. In that work different angles of brain images are used to detect the brain tumors. The comparison was done between single network diagnosis and the different network diagnosis with separate network for image segmentation. It has been identified from the work that the network with separate network for the image segmentation gives the higher accuracy with the score of 0.79[1]. Deep neural network has been developed by Lindsey R et al., to detect the fractures using the radiographs. The method has been tested and compared with the manual work. It has been proved that the neural network formed under the deep learning techniques provided more accurate detection than manual work. In the extension of the study they suggested that it will provide a substantial improvement for patient care[2]. Shaoqing Ren et al., introduced a framework called Region Proposal Network (RPN).it is a network that shares the full image convolutional features and enables the costfree region proposals. Faster RCNN used the end to end trained regions for detection. Both RPN and Fast – RCNN are trained to share the convolutional features[3].Okeke Stephen et al has developed a complete neural network from the scratch to identify the pneumonia using the chest x-ray images. Since it had designed from scratch its performance level in feature extraction and classification were high. It outperformed all the other traditional approaches. This network helped to diminish the reliability and interpretability challenges which are often faced in medical images[4]. Deniz Yagmur Urey et al., worked on a problem to find the efficient deep learning technique to find the pneumonia at the early stage using the x-ray images. They studied the various stages of pneumonia and designed architecture for classification task. The architecture has been trained and tested for classification using the using the convolutional neural network and residual network architecture[5]. Xiaotong Zhao et al., proposed a model using Faster R-CNN to detect the pedestrian in the road. The proposed system was capable to take the un uniform images and produce the boundary box for that image. Since it produces a correct mapping of boundary it can able to detect the pedestrians with higher accuracy and with the greater speed[6].Kalyani Kadam et al.developed a model for the doctors to predict the pneumonia in minimal time with higher efficiency. The model was developed using a deep neural network based convolutional neural networks and residual network. The network is defined along with techniques of identifying optimum differential rates using cosine annealing and stochastic gradient[7].

3. Faster RCNN

FASTER RCNN (Region convolutional neural network) is a deep learning technique that has an important advantage i.e., it uses RPN (Region proposal network). The normal CNN layers (Convolutional, ReLu, Pooling, and Fully connected layer) were involved in this method followed by some additional features that play a major role here. RPN is a major player produces a number of proposals from the feature map which was the output of CNN layers.

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RPN uses classifier and regressor which tells whether the particular proposal is the desired one or background. The proposals are called anchors. After ROI (region of interest) pooling was applied to produce a fixed size feature map and then the SoftMax layer and regressor suggest bounding boxes. The pros of this method are it avoids selective search and avoids feeding of 2000 regions for each layer.

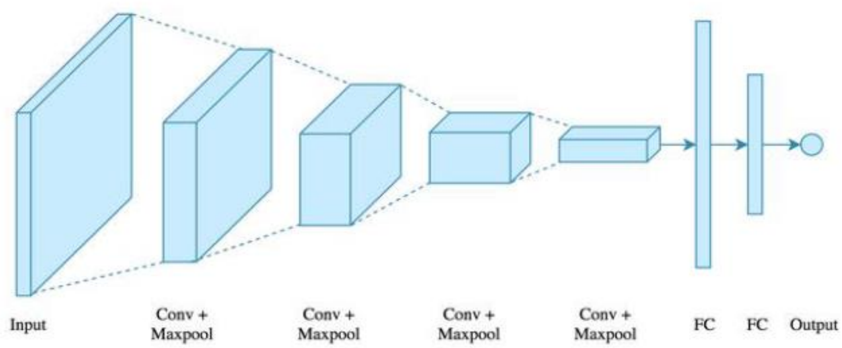

Figure 3.1: CNN Architecture

4. Methodology

4.1 Dataset Collection

In this research, the pneumonia x-ray image dataset was collected from the Kaggle platform consists of around 26000 images in DCM format and a CSV file with a bounding box and patient information. This dataset was published under RSNA pneumonia detection challenge in Kaggle platform. Around 10000 images were used for this study and these images were classified as three classes namely Normal, Lung opacity, infected presented in Figure 4.1, Figure 4.2 and Figure 4.3. Dataset images were in 1024 X 1024 dimension and the desired region for each image was available in the Kaggle platform.

Figure 4.1: Normal Condition

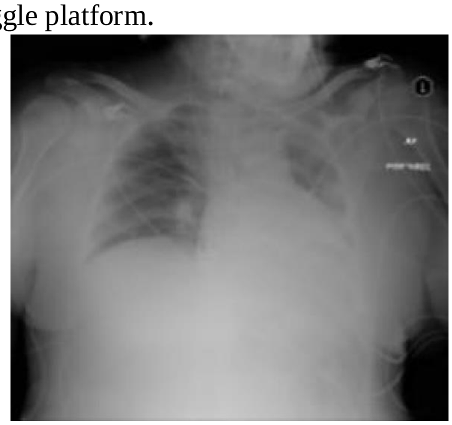

Figure 4.2: Lung Opacity

Figure 4.3: Infected Condition

4.2 Data Preprocessing

The images collected from the Kaggle dataset were in DCM format. It has to be converted to DICOM format (Digital Imaging and Communications in Medicine) is a standard for handling, storing, printing, and transmitting information in medical imaging. It includes a file format definition and a network communications protocol. The bounding boxes further images were collected for the images of normal, not normal and lung opacity classes. Some images desired bounding coordinates were drawn manually and those bounding box values were updated in CSV file to train images.

4.3 Faster RCNN in Pneumonia Detection

In this study, a faster R-CNN inception v2 coco model was used to train the dataset. Pneumonia analysis mainly insists on the lung portion where only major interpretation takes place so R-CNN plays a major role by taking only the desired area or region for analyzing. Usually, an x-ray of chest contains neck, shoulder region those all are not required in the analysis. This method is an apt one for analyzing pneumonia by using all parameters efficiently. Figure 4.4 represents architecture of faster R-CNN. In Figure 4.4 four CNN layers were involved namely convolutional, ReLu, pooling, and fully connected layer. All these layers produce a feature by interpreting from the input x-ray image and RPN suggests proposals from the input image and then region of interest pooling applied to make all proposals to a fixed size. After that classifier tells whether the particular part infected with pneumonia or not.

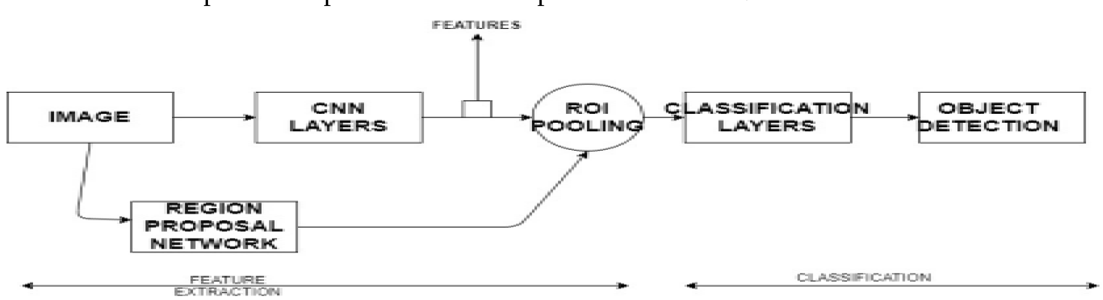

Figure 4.4: System Architecture

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Region of Interest (ROI) pooling is used for utilizing single feature map for all the proposals generated by RPN in a single pass. ROI pooling solves the problem of fixed image size requirement for object detection network. The number of output channels is equal to the number of input channels for this layer. The layer infers the number of classes from the output size of the previous layer.

4.4 Training and Testing

Faster R-CNN makes further progress than Fast R-CNN. Search selective process is replaced by Region Proposal Network (RPN). RPN is a network to propose regions. For instance, after getting the output feature map from a pre-trained model (VGG-16), if the input image has 600x800x3 dimensions, the output feature map would be 37x50x256 dimensions. Next, RPN is connected to a Conv layer with 3x3 filters, 1 padding, 512 output channels. The output is connected to two 1x1 convolutional layer for classification and box-regression. The dataset were classified as normal, not normal and lung opacity classes. The images were trained using the google colab platform. The virtual machine cache is cleared every 12 hours. Since, high computing Nvidia Telsa GPU is used, the training time is notably reduced. It takes about 7 hours to train 5000 steps. The Tensor Board page provides information and graphs (figure 4.5)that show how the training is progressing. The loss is calculates by RPN loss function (1).The training routine periodically saves checkpoints about every five minutes. The checkpoint at the highest number of steps will be used to generate the frozen inference graph. For testing, 100 images were used. Images were classified into three classes' lung opacity, normal and not normal. Lung opacity and not normal indicates pneumonia infection and normal represents free from pneumonia infection. Random images were tested and checked whether it correctly classifies or not. During this phase a second set of data is loaded. This data set has never been seen by the model and therefore its true accuracy will be verified.

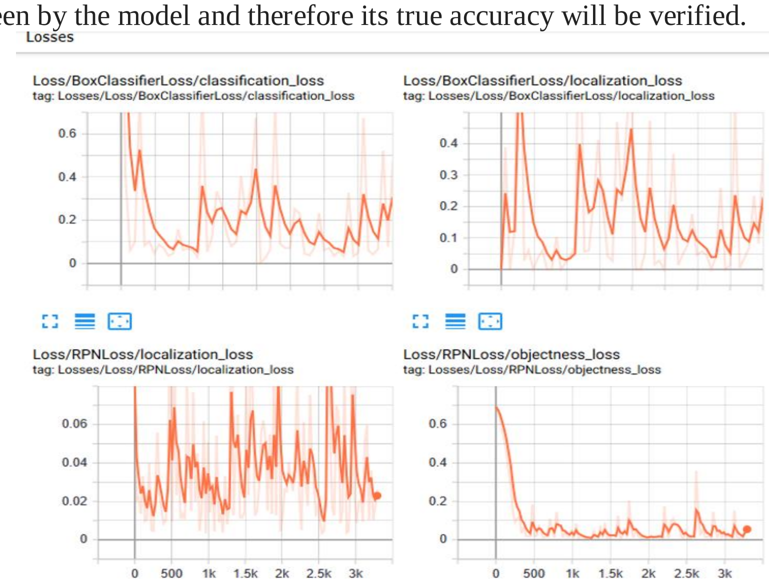

Figure 4.5: System Architecture

$$L(\{p_i\},\{t_i\}) = \frac{1}{N_{cls}}\sum_i L_{cls}(p_i,p_i^*) + \lambda\frac{1}{N_{reg}}\sum_i p_i^* L_{reg}(t_i,t_i^*) \quad (1)$$

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5. Results and Discussion

The dataset was trained using faster R-CNN inception v2 coco which is an open source model and the Tensor Flow library was used. All images were in 1024 X 1024 dimensions to avoid low-quality image problems the images were used as it is and no images were compressed and the images used are taken from RSNA pneumonia detection challenge. The threshold value for training was set to around 20000 steps to maintain a decent loss percentage. Training loss and RPN loss were illustrated graphically using tensor board. To reduce the loss percentage number of iterations were carried out until the loss value comes under 0.099. Faster R-CNN requires training time a little more compared with other deep learning techniques. The main problem faced was more training time required. Training images around 10000 were used and test images were around 100 randomly picked from the dataset. Images were classified into three classes lung opacity, normal and not normal. Lung opacity and not normal indicates pneumonia infection and normal represents free from pneumonia infection. Random images were tested and checked whether it correctly classifies or not. Figure 5.1 represents normal i.e., pneumonia not affected and Figure 5.2 represents not normal i.e., pneumonia affected.

Table 5.1 Evaluation

Evaluation	
Validation	Number of images
True Positive	85
True Negative	2
False Positive	10
False Negative	3

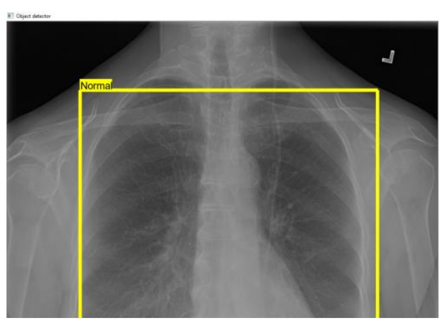

Figure 5.1: Normal Detected

Figure 5.2: Pneumonia Detected

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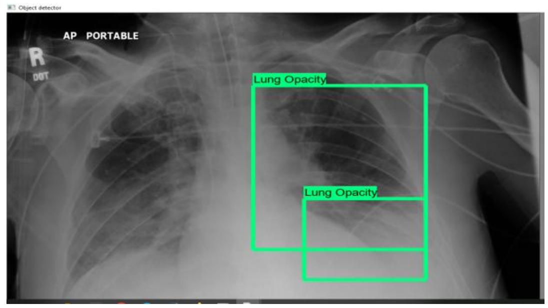

Figure 5.3: Lung Opacity

6. Conclusion and Future Work

Presence of expert radiologists is the topmost necessity to properly diagnose any kind of thoracic disease. This paper primarily aims to improve the medical adeptness in areas where the availability of radiotherapists is still limited. The proposed system provided a solution to automate pneumonia detection from x-ray images using faster R-CNN without depending on physician analysis. This work not fully replaces the need for physician analysis but helps in analyzing the pneumonia. The results were obtained using the faster R-CNN inception v2 coco model and it provides the result without any loss up to 99%. According the to the accuracy level of detection is up to 90%. The development of algorithms in this domain can be highly beneficial for providing better health-care services. Future work can be carried out based on analyzing pneumonia using x-ray along with person environment and body physical conditions. In this way, by using multiple features the accuracy of detection of pneumonia can be improved and diagnosed effectively.

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