A LIGHTWEIGHT CNN FOR LUNG NODULE DETECTION AND CLASSIFICATION FROM CHEST RADIOGRAPHS

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***Abstract* - Lung cancer is one of the most common diseases and the leading cause of mortality in many nations. Early identification of lung cancer can improve people's chances of survival. When lung cancer is identified early, the 5-year survival rate jumps from 14 to 49 percent. Although Computed Tomography (CT) can be more efficient than chest radiographs, they are used in this study as it is economically feasible and easily available in all the testing centers and in hospitals. In this paper a lung cancer detection system using Deep Learning approach is used to classify the presence of lung cancer in Chest X-Ray images from the JSRT Database which is grouped into three classes i.e., Benign, Malignant and Non Nodule. The images are initially segmented by creating a mask using UNet based Convolutional Neural Network. The mask is then multiplied with the original image to get the segmented lung part from the original chest X-Ray images. A lightweight CNN based 15 layer network has been used as the model. This model has been optimized by using Particle Swarm Optimization, which is used to find the number of filters to be used in the model. The average accuracy observed for this model is 90%.**

Index Terms – Convolutional Neural Network, Particle Swarm Optimization, UNet, Chest Radiographs.

I. INTRODUCTION

According to the World Health Organization, cancer claimed the lives of approximately 10 million people in 2020[1]. Lung cancer is responsible for about 20% of all deaths, or 1.69 million people. As a result, numerous countries are working on early detection measures for lung cancer. Considering cancer is most treatable when found early, cancer screening is an important part of preventative care.

Lung Cancer develops when abnormal cells in the lungs grow out of control. They have the ability to infiltrate surrounding tissues and create tumors. Lung cancer can begin in any section of the lungs and spread to other parts of the respiratory system. The cancer cells can travel to the lymph nodes and other regions of the body, which is known as metastasis. Lung cancer is caused mostly by smoking, secondhand smoke, exposure to specific chemicals, and in rare cases it may be due to family history.

The two types of lung cancer are small cell lung cancer (SCLC) and non-small cell lung cancer (NSCLC)[2]. This classification is based on how tumor cells appear under a microscope. It is critical to distinguish between these two types of cancer because they grow, spread, and are treated differently.

SCLC accounts for approximately 10% to 15% of all lung cancers. This is the most aggressive and rapidly spreading type of lung cancer. Tobacco use is strongly linked to SCLC. SCLCs spread quickly throughout the body and are typically discovered after they have spread widely. Non-small cell lung cancer

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(NSCLC) is the most common type of lung cancer, accounting for approximately 85 percent of all cases. Cancers that have spread from other primary tumors in the body are frequently found in the lungs. Tumors can spread to the lungs from anywhere in the body, via the bloodstream, the lymphatic system, or directly through surrounding organs. Lung Cancer treatments may vary but primarily includes surgery, chemotherapy, radiation therapy, targeted drug therapy and immunotherapy.

While treatments are available, they are only effective when lung cancer is detected in time. Cancer detection can be performed using various invasive and noninvasive procedures. The invasive procedures include: Thoracentesis where pleural liquid accumulated in the lung cavity is drained and tested for cancer, Needle Biopsy where a sample of suspicious mass is removed and tested for possibilities of cancer etc.,. These invasive tests pose a threat of pneumothorax which can cause further problems. The noninvasive techniques consist of X-Ray, Computed Tomography(CT) scan, Magnetic Resonance Imaging (MRI) scan, Positron Emitted Tomography (PET) scan, Bronchoscopy, Sputum Cytology etc.,

Mostly a combination of Invasive and Noninvasive procedures is used to detect Lung cancer and the extent of its spread. In this work, a CAD system is proposed to identify lung nodules from chest radiographs and to classify them into benign and malignant. Chest Radiographs are primarily used in this work as they are easily available and cost effective in comparison to CT and other imaging methodologies.

II. Literature Survey

Worawate Ausawalaithong et.al, [3] in their work proposed a method to use transfer learning twice to classify and detect Lung cancer from chest X-Rays. They trained DenseNet 121 with Imagenet Dataset and modified the final fully connected layer. The method of transfer learning twice on various datasets has helped them to attain better results when compared to a single transfer learning method.

Abdelilah Bouslama et.al, [4] in their work developed an end-to-end technique for detecting Cardiomegaly disease that uses a Deep Convolutional Neural Network U Net based architecture. Chest X-ray images collected from the “ChestX-ray 8” open source medical dataset are used in the learning phase. The Equalization of Adaptive Histograms (AHE) is used to improve the contrast and brightness of the original images. To reduce computing time, these are compressed before going through a training stage. Accuracy of more than 93 % has been achieved.

Md. Ibrahim Ullah et.al, [5] in their work proposed a Computer-Aided Detection (CAD) system for detection of lung cancer. In the nodule detection part, the CT images are processed through Adaptive Histogram Equalization (AHE), thresholding, and edge detection. To extract features Gray Level Co-occurrence Matrix (GLCM) is used [6]. Features such as Energy, Entropy, Correlation, Homogeneity, Dissimilarity,Contrast are extracted. This proposed model is able to label the nodule as benign or malignant with 88.25% of accuracy. LIDC and Kaggle databases are used for this experimental procedure.

Yang Churnan et al, [7] proposed a lung nodule detection and segmentation method based on a fully convolutional network (FCN), the level set method, and other image processing techniques in their study. First, lung CT images are loaded into the FCN for lung segmentation. After which, using the threshold method and other image processing techniques, lung nodules are detected inside the lung area. Finally, based on the coordinate system transformation, the detected lung nodules and their speculation are segmented using the level set method and the threshold method. An accuracy of 100% has been obtained.

Amrit Sreekumar et al, [8] presented a method for detecting malignant pulmonary nodules in CT scans using Deep Learning in their work. To mask out the lung regions from the scans, a preprocessing pipeline was used. Following that, the features were extracted using a 3D CNN model based on the C3D network architecture. The final model had an 86 percent sensitivity for detecting malignant Lung Nodules and predicting their malignancy scores.

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III. METHODOLOGY

A. Structure of CNN

Convolutional Neural Networks (CNNs)[9] are powerful deep learning techniques that can be trained on large datasets. From these large collections, CNNs can learn rich features for a wide range of images. The features extracted from CNNs frequently outperform hand-crafted features like Histogram Oriented Gradients (HOG)[10], Local Binary Patterns (LBP)[11], Harlick features etc.,. Fig 3.1 represents the basic block diagram of Convolutional Neural Network.

As the convolution kernel slides along the input matrix for the layer, a feature map is generated, which then contributes to the input of the next layer. Following that, additional layers such as pooling layers, fully connected layers, and normalization layers are added. Pooling Layers reduce data dimensions by combining output from a group of neurons in the previous layer with that of a neuron in the current layer. The fully connected layer is a multi-layer perceptron neural network that processes the flattened input image and produces the classified output image.

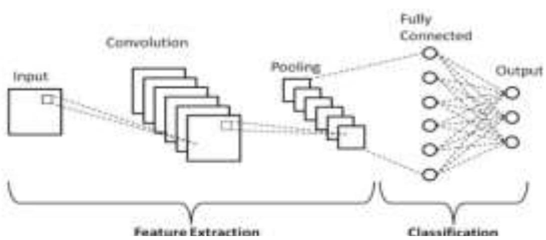

Fig 3.1 Basic block diagram of a Convolutional neural network

B. Dataset

The dataset utilized in this study is the publicly available JSRT (Japanese Society of Radiological Technology)[12]. There are 247 posteroanterior chest radiographs in all, 154 of which contain lung nodules (100 malignant cases, 54 benign instances), and 93 of which do not contain nodules. Each radiograph is a grayscale image with a resolution of 145 ppi and a size of 2048 by 2048 pixels.

A nodule can be seen in the images in a variety of locations within the rib cage, including the upper, middle, or lower lobe on either the left or right side. The nodules range in size from 30 to 170 pixels. CT scans were used to confirm all radiograph classifications as nodule or non-nodule in the dataset.

Nodule classifications of benign or malignant were made not only through their appearance in this dataset and the CT scans, but also through testing of tissue samples and monitoring for nodule changes over time. In addition to classification labels for each image, the JSRT dataset also includes the size and (x, y)-coordinate of the center of the lung nodule, if present.

C. Methodology

Chest radiographs contain images of lungs and other parts like heart, rib cage bones etc. For detecting the nodules in lungs and to reduce the computational power required for computing, the lung part of the radiographs is to be segmented. There are various ways to segment lung from the chest radiographs. They are based on active shape models[13], active appearance models[14], and a multi-resolution pixel classification method[15]. In this work we are using UNet-based convolutional neural network to obtain the masks for the chest radiographs. This CNN is a 7 layered network which approximately detects the boundaries of the lungs and creates a mask[16]. The mask thus obtained when multiplied with the original image gives segmented Lung image from the X-Ray. These images are used for training and testing

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the network model. Once the images are segmented, they are used for training the network. Segmented images are grouped into three classes viz., Nonodule, Benign, Malignant. Various pretrained networks such as Resnet50[17] and Resnet101[18] are used for classification. A light weight customised CNN with 15 layers is the network that is primarily used. The efficiency of the model greatly depends on various hyperparameters and its tuning. Hyperparameters like number of filters used in the convolutional layer of the model, momentum, maximum number of epochs, minibatch size, and initial learning rate are primarily used in this work. Particle Swarm Optimization(PSO)[19] is used to optimize the number of filters used in the convolutional 2D layer of the model. While, the other hyperparameters are fixed by trial and error method. The proposed method is described in figure 3.2

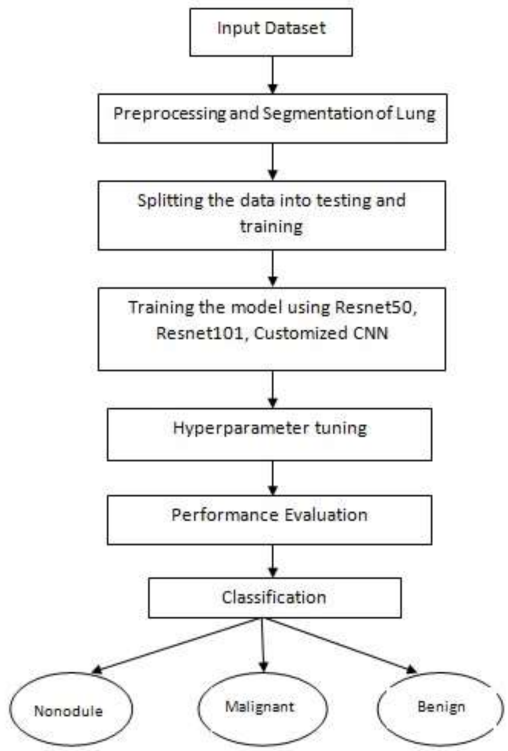

Fig 3.2 Proposed method

D. Pre-Trained Deep neural Networks

ResNet is a powerful backbone model that is widely used in computer vision tasks.

ResNet-50 is a deep residual network with 50 layers. The vanishing gradient problem plagues deep networks. As the model back propagates, the gradient becomes very small. Smaller and smaller gradients can make learning difficult. The skip connection enables the network to learn by allowing it to skip through layers that are less relevant in training.

ResNet-101 is a 101-layer deep. To reduce the vanishing gradient problem, ResNet employs skip connections to add the output from an earlier layer to a later layer.

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E. Light weight CNN

In This work, a fifteen layer CNN network consisting of input layer, three convolution layers, three clipped ReLU layers, three batch normalization layers, two max pooling layers, one fully connected layer, one softmax layer followed by one output layer has been used to classify the chest radiographs. The light weight CNN model is depicted in Fig 3.3.

Fig 3.3: Light Weight CNN Model

IV. Results and Discussion

Transfer Learning approach has been applied on various pre-trained models discussed in section III D. The models are trained on JSRT Dataset and metrics such as Accuracy, Precision, Sensitivity, Specificity, Recall and F-score have been evaluated.

Accuracy is defined as defined as the number of correct predictions divided by the total number of predictions, multiplied by 100. It indicates how often the given classifier is correct.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{TP + TN + FP + FN} * 100 \ldots \ldots \ldots \ldots (1)$$

Precision represents the possibly correct classification if the classifier predicts the class as Yes and is defined as the ratio between the total no. of correctly classified inputs to total no. of predicted inputs.

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$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \qquad \ldots\ldots\ldots\ldots\ldots(2)$$

Sensitivity is a measure of the proportion of actual positive cases that got predicted as positive (or true positive). Sensitivity is also termed as Recall defined as the ratio between the total numbers of correctly classified inputs to the total number of correctly predicted inputs.

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad \ldots\ldots(3)$$

Specificity is defined as the proportion of actual negatives, which got predicted as the negative

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}} \qquad \ldots.(4)$$

Recall is the measure of how correctly the model is identifying true positives

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \qquad \ldots\ldots\ldots\ldots\ldots(5)$$

F-score is the measure of test accuracy which is the harmonic mean of the precision and recall.

$$\text{Fscore} = \frac{2}{\text{Sensitivity}^{-1} + \text{Precision}^{-1}} \quad \ldots\ldots(6)$$

TP =True positive, TN=True negative, FP=False positive, FN=False negative

Table 4.1: Performance of pre-trained Networks

Parameter	**Resnet50**	**Resnet101**
% Accuracy	65.722%	78%
Precision	0.4834	0.714
Sensitivity	0.4833	0.714
Specificity	0.73575	0.333
Recall	0.4833	0.4736
F-score	0.47835	0.714

The light weight CNN model is trained on JSRT dataset and the results of Accuracy are promising.

Table 4.2 Classification results using lightweight CNN

Parameter	**Nonodule**	**Benign**	**Malignant**
% Accuracy	96%	94%	90%
Precision	0.94736	0.9	0.85714
Sensitivity	0.94736	0.81818	0.9
Specificity	0.96774	0.97	0.9
Recall	0.94736	0.81818	0.9
F-score	0.94736	0.85714	0.87804

The hyper parameters for this network uses Momentum=0.9, MaxEpochs=60, MiniBatchSize=64 and and an initial learning rate as 0.01.

Fig 4.1: Original Radiograph, Lung Mask, Segmented Lung

Fig4.2: Classification results

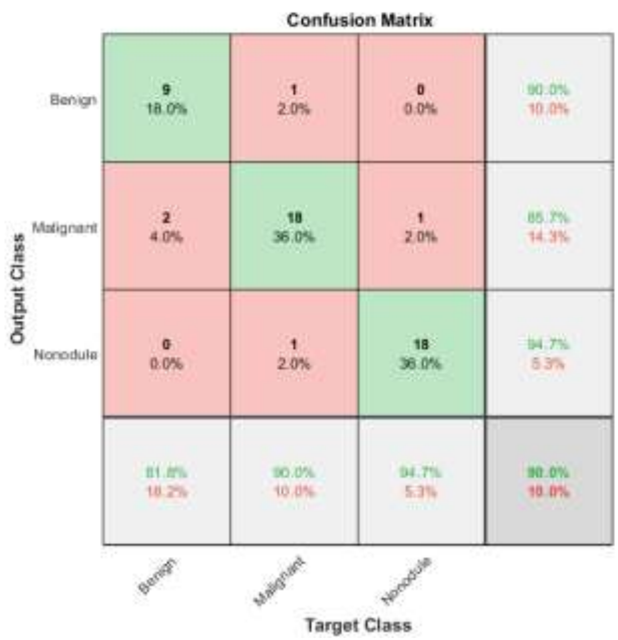

Fig 4.3: Confusion Matrix for light weight CNN

V. CONCLUSION AND FUTURE SCOPE

The custom convolutional neural network's performance in detecting lung cancer from chest radiographs was investigated. Optimal number of features has been extracted using the PSO and used in the network layers. The proposed training strategy outperformed the standard method, resulting in increased test accuracy of 90%.

The amount of data used for training in deep learning frequently boosts classification accuracy, therefore employing a larger dataset for training could be a useful study direction to continue improving our classification accuracy of lung nodules.

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