Predicting lung Cancer using Deep Learning Algorithm

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***Abstract*—Many kinds of diseases are there which affects human health and one among them is Lung cancer which is a deadly affecting disease and should be treated in its early stage and failing which may cause the death of an individual. It is caused due to the reluctant increase of cells in the lung tissues. It is cured only during its early stage, by starting the treatment. This is detected using the Computed Tomography (CT) scanning and blood test reports. By blood test, the tumor is detected after the humans affected with a minimum span of 4 years. So, to know the early stage of cancer, CT scanning is used. The CT images are classified into normal and abnormal. The abnormal image is detected by focusing on the tumor portion. The dataset in jpg format, composed of Computed Tomography (CT) images. The proposed model is trained by using the Convolutional Neural Network (CNN). Pertained ImageNet models including LeNet, AlexNet and VGG-16, are used to detect lung cancer.**

***Index Terms*—component, formatting, style, styling, insert**

I. INTRODUCTION

Cancer is a disease which is caused by abnormal growth of cells/tissues in the human body. Since many years' cancer is one of the deadly diseases that threatens human health. According to the latest WHO data published in 2020 Lung Cancers Deaths in Bangladesh reached 12,174 or 1.70% of total deaths [1]. However, the early detection of lung cancer significantly improves survival rate. Cancerous (malignant) and noncancerous (benign) pulmonary nodules are the small growths of cells inside the lung. Detection of malignant lung nodules at an early stage is necessary for the crucial prognosis [2]. Early-stage cancerous lung nodules are very much similar to noncancerous nodules and need a differential diagnosis on the basis of slight morphological changes, locations, and clinical biomarkers [3] . The challenging task is to measure the probability of malignancy for the early cancerous lung nodules [4].

The most suitable method used for the investigation of lung diseases is computed tomography (CT) imaging [5]. Results show that only 68% of the time lung cancer nodules are correctly diagnosed when only one radiologist examines the scan, and are accurately detected up to 82% of the time with two radiologists. The detection of cancerous lung nodules at an early stage is a very difficult, tedious, and time-consuming task for radiologists [6]. For that reason, one of the basic models favored for lung malignancy (carcinoma) determination is profound learning picture nets. We have used convolutional neural network models such as ResNet, DenseNet and VGG-16. In our study, the CT image dataset is classified as Cancer and Non- cancer dataset.

II. BACKGROUND AND RELATED WORK

Although the first computer-aided detection (CAD) system for lung nodule detection was designed in the late 1980s, these attempts were not appealing due to inadequate computational resources for advanced image analysis techniques at that time. After the invention of the graphical processing unit (GPU) and convolutional neural networks (CNN), the performance of computer-based image analysis and decision support systems got a high boost. A lot of deep learning-based medical image analysis models have been proposed by researchers, and a few of the most relevant lung nodule detection and classification methods are mentioned here [7].

R. Raja Subramanian et al. proposed a model which uses AlexNet model and the features obtained from the last fully connected layer of the model were separately applied as input to the softmax classifier[8].

Setio et al. proposed a 3D fully convolutional neural network for FP reduction in lung nodule classification [8]. A 3D network was used to analyze the 3D nature of the CT scans to reduce wrong diagnosis, and weighted sampling was used to improve results.

Masood et al. proposed a deep fully convolutional neural network (DFCNet) for the detection and classification of pulmonary lung nodules in a CT image [9]. Initially the nodule was classified as either benign or malignant; after that, the malignant nodule was further classified into four sub-classes on the basis of the CT image and metastasis information obtained from the medical IoT network.

Gu Yu et al. proposed 3D deep CNN with multiscale prediction strategies for the detection of lung nodules from segmented images [10]. The 3D CNN performs much better with richer features than 2D CNN.

After the popularity of convolutional neural networks (CNNs) in image analysis, different types of connectivity patterns were proposed by researchers to increase the performance of deep CNNs. Up until now, in the deep CNNs, dense topology structures ResNet, DenseNet performance is superior as compared to other ones, but there is still room for connection improvements in these topologies [11]. The MixNet architecture has improved connection structures with better features of extraction and reduced parameter redundancy .

III. Methodology

The aim of this research is to build a model which will predict the lung cancer from CT scan images. A publicly available image dataset has been used. The dataset is pre-processed so that it can be used by pertained models. The dataset was split into train set, test set and validation set. Fig1 represents the complete workflow of this work.

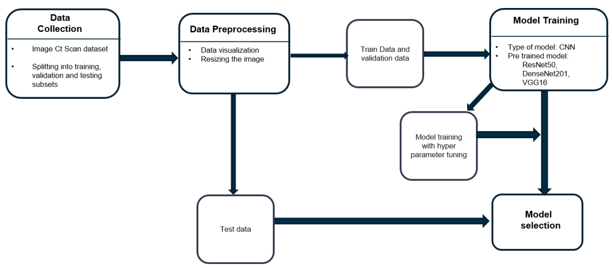

Fig. 1. System Design

A. Data Acquisition and descriptions

The dataset is obtained from kaggle. The dataset contains 2016 images. There are mainly 3 types of CT images- normal cell images, adenocarcinoma cell image, large cell image and squamous cell image. Adenocarcinoma cell, large cell and squamous cell are the cancer cells. And this dataset are split into 3 part's- test set, train set and valid set.

B. Image Preprocessing

When using Gradient Descent, We should ensure that all Features have a similar scale, otherwise, it will take much longer to converge. So, we resized all images into 305*430.

C. Proposed Models

The proposed model is a convolutional neural network approach based on lung segmentation on CT scan images. At first we preprocess the dataset from kaggle. Then we preprocessing the images, after that we trains the dataset in 3 different CNN models0- ResNet50, VGG-16, DenseNet201. Then we do the parameter hypertuning for getting the better accuracy

Our first model “Sequential” is the basic simple approach of using the 2 convolution layers, flatten fully connected layers, 2max pooling followed by the convolution layers and dropout in the middle layers. Summary of the model is given below.

Our Second model Resnet50 is followed by the first model. ResNet-50 is a pretrained convolution neural network that is 50 layers deep. It is comparable to VGG-16 accept that Resnet50 has an additional identity mapping capability. ResNet reduces the vanishing gradient problem by allowing this alternate shortcut path for gradient to fow through. The identity mapping used in ResNet allows the model to bypass a CNN weight layer if the current layer is not necessary. This helps in avoiding the over fitting problem to the training set [13]. Summary of model is given below:

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 305, 430, 8)       104
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 152, 215, 8)       0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 152, 215, 16)      528
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 76, 107, 16)       0
_________________________________________________________________
dropout (Dropout)            (None, 76, 107, 16)       0
_________________________________________________________________
flatten (Flatten)            (None, 130112)            0
_________________________________________________________________
dense (Dense)                (None, 300)               39033900
_________________________________________________________________
dropout_1 (Dropout)          (None, 300)               0
_________________________________________________________________
dense_1 (Dense)              (None, 4)                 1204
=================================================================
Total params: 39,035,736
Trainable params: 39,035,736
Non-trainable params: 0
```

Fig. 2. Model summary ”Sequential”

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
resnet50 (Functional)        (None, 2048)              23587712
_________________________________________________________________
dropout_2 (Dropout)          (None, 2048)              0
_________________________________________________________________
flatten_1 (Flatten)          (None, 2048)              0
_________________________________________________________________
batch_normalization (BatchNo (None, 2048)              8192
_________________________________________________________________
dropout_3 (Dropout)          (None, 2048)              0
_________________________________________________________________
dense_2 (Dense)              (None, 4)                 8196
=================================================================
Total params: 23,604,100
Trainable params: 14,988,292
Non-trainable params: 8,615,808
_________________________________________________________________
```

Fig. 3. Model summary ”ResNet50”

Our third model approach was to use transfer learning on VGG-16. The VGG-16 network was trained on the ImageNet database [14]. VGG-16 gives excellent accuracies even when the image data sets are small. The VGG-16 network consists of 16 convolution layers and has a small receptive feld of 3×3. It has a Max pooling layer of size 2×2 and has a total of 5 such layers. There are 3 fully connected layers after the last Max pooling layer. This is followed by three fully connected layers. It uses the softmax classifer as the fnal layer. ReLu activation is applied to all hidden layers. Fig.4 represents the summary of the model.

Our fourth and final model is DenseNet201.DenseNet201 was proposed by Huang et al. [15], and is known for its excellent performance on four object recognition benchmark datasets such as CIFAR-100 and ImageNet [16]. To maximize the information fow between the layers in the network, the DenseNet architecture uses a simple connectivity pattern

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
vgg16 (Functional)           (None, 512)               14714688
_________________________________________________________________
flatten_2 (Flatten)          (None, 512)               0
_________________________________________________________________
batch_normalization_1 (Batch (None, 512)               2048
_________________________________________________________________
dense_3 (Dense)              (None, 4)                 2052
=================================================================
Total params: 14,718,788
Trainable params: 3,076
Non-trainable params: 14,715,712
_________________________________________________________________
```

Fig. 4. Model summary ”VGG16”

that connects all layers directly to each other in a feed-forward fashion, i.e., each layer obtains additional inputs from all previous layers and passes its own feature-maps to all subsequent layers[26]. With this architecture, DenseNet has several impressive advantages, including mitigating the vanishing gradient problem, strengthening feature propagation, encouraging feature reuse, and substantially reducing the number of parameters. Fig.5 represents the summary of the model.

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
densenet201 (Functional)     (None, 1920)              18321984
_________________________________________________________________
flatten_3 (Flatten)          (None, 1920)              0
_________________________________________________________________
batch_normalization_2 (Batch (None, 1920)              7680
_________________________________________________________________
dense_4 (Dense)              (None, 4)                 7684
=================================================================
Total params: 18,337,348
Trainable params: 6,990,084
Non-trainable params: 11,347,264
_________________________________________________________________
```

Fig. 5. Model summary ”DenseNet201”

IV. Result

Before doing the hypertuning the Acuuracy of the three models IS given below.

TABLE I
TEST, TRAIN AND THE VALIDATION ACCURACY OF THE MODELS

Model Name	Test Accuracy	Train Accuracy	Validation
ResNet50	88%	98%	80%
VGG-16	47%	30%	39%
DenseNet201	81%	99%	90%

So here we can see that ResNet50 and DenseNet201 gives the better accuracy. So then we applied parameter hypertuning on this two model for the better accuracy.

The fig6 represents the Training and Validation Accuracy of ResNet50. Now the train accuracy is 99% , Validation Accuracy 90% and test accuracy reach to 89%.

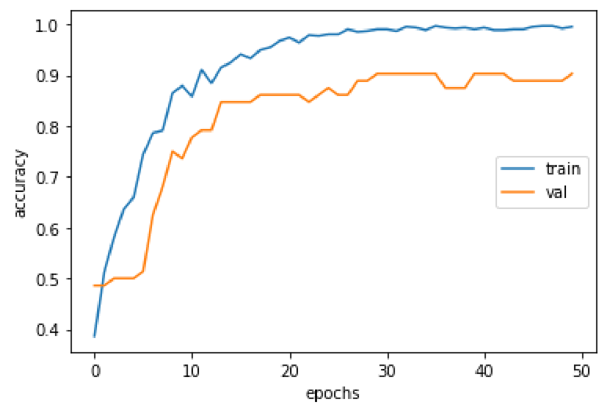

Fig. 6. Training and Validation Accuracy of ResNet50

The fig7 represents the Training and Validation Accuracy of DenseNet201. Now the train accuracy is 100%, validation accuracy 94% and test accuracy reach to 90%.

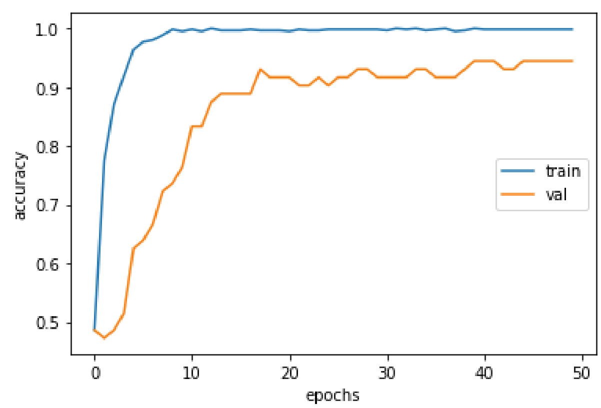

Fig. 7. Training and Validation Accuracy of DenseNet201

So, from the above result the DenseNet201 performs best.

V. Conclusion

Cancer is considered to be one of the main sources of mortality around the world. So a model lung cancer disease prediction system is developed using deep learning image classification techniques. A deep learning model leveraging DenseNet201 pretrained model combined with a softmax layer is developed and used to efficiently classify the lung CT images for cancer. The proposed model is compared with two other models ResNet50 and VGG16. With an best accuracy level , the analyses of the suggested model show that it performs better than other, comparable models that are available in the literature.

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