A Novel Approach for Lung Nodule Classification in Lung CT Images using Convolutional Neural Network (CNN)

Gaurav D. Chibde[#1], Maruska F.C Mascarenhas[#2]

[#]Department of Computer Engineering, Goa College Of Engineering, Farmagudi-Goa.

[1]gaurav73c@gmail.com

[2]maruskha@gec.ac.in

Abstract - **Lung cancer is a growing cancer in the world; the cancer needs to be treated with right method at the right time. The early detection of cancer is better than the last stage treatment that can help in a high decrease in the lung cancer mortality rate. This will result in more than 17% percent of the total cancer related deaths. There are different methods for early diagnosis of lung cancer. CT scan is one of the methods used to view the inside of human body. This image helps doctors to get an idea of what is wrong with the human organs. CT scans of lung are used by doctors to get a better insight of the patient. We have proposed a method to classify the lung cancer that uses a convolution neural network (CNN). This classification is done from the Lung CT images. The nodule is the important factor to detect the lung cancer. The module belongs to one of the category, benign or malignant. Taking into consideration the difficulties of the current scenario, we have proposed a convolution neural network(CNN) model to classify the lung CT image in either one of categories that is, malignant or benign. The model takes normal 512 x 512 CT images with original pixel and inverted pixels. This images are passed to the two different subCNN . It was tested on SPIE lung dataset from cancer imaging archive.**

Keywords: **Lung Cancer, Convolution Neural Network, Neural Network, Lung Nodule Classification, Lung CT Image.**

I. INTRODUCTION

Lung cancer is one of the cancer among other cancers that being recognized by the doctors or experts in the field. It is also known as lung carcinoma. This is the uncontrolled cell growth in tissues of the lung which starts and spreads from the lung. Lungs are two spongy organs which are responsible for taking in air and releasing air. Lungs filter air and take oxygen from air and mixed in blood. Carbon dioxide, a waste product of metabolism (carbon dioxide), travels from the blood to the alveoli to exhale from lung. Lung cancer is being the leading death in parts of world for both men's and women's. The smoking is the most common reason for lung cancer, but now a day a person who is not smoking also suffers lung cancer. People standing or sitting next to the smoker will also get lung cancer as the smoke in the air. Some other causes of the lung cancer are the increasing air pollution in the world.

There is sudden increase in the lung cancer cases [1].One of the medical solutions is that we have to diagnose the patient at early stages. Lung cancer is the most common cancer that cannot be ignored and cause death with late health care. Currently, CT can be used to help doctors detect the lung cancer in the early stages[2].This will give a patient and doctor better information whether patient about to develop cancer or not in upcoming days. Early detection can save patients life and it will be much simpler for the doctors to get decision and diagnose the patient rather than last moment or the stage where cancer is difficult to cure or couldn’t be cured. This may result in loosing life of patient. Motivation behind the automating the system or computerize the system is that there are large number of cases everyday which the radiologist has to face and there is a constant pressure build up on them to analyze this huge data and take a quick decision based on the analysis for betterment of the patients[3].

Even in the diagnosis a nodule is found, it may or may not be a cancerous. The every nodule is not cancerous. Lung cancer majorly classified as a malignant and benign, benign does not spread but malignant may spread around the body. Although we say the early lung detection is better but if there is only a dime-sized lesion growth known as nodule that can lead to failure in detecting lung cancer in early stages, and by the time it is detected it is already too late for the patient. Also, these small lesions cannot be detected by X-rays and are only detectable by a CT scan. Even after the detection, it takes a high amount of determination and experience for radiologists to identify and label the nodules as benign or as a probable case of malignancy. The systems designed to help doctors to make a better decision for lung cancer detection the cancer, which focusing on higher accuracy in this task. There are different types of architecture in neural network which can be used for doing this same task. Which could be a fully connected neural network alone or other defined architectures. QingZeng Song et al. have studied a comparison of deep neural network such as CNN, DNN and SAE. These networks were evaluated on LIDC-IDRI database which showed that CNN architecture performs best, with accuracy of 84.15% followed by DNN with accuracy of 82.37% and SAE with accuracy of 82.59% [2]. Computer aided system (CAD) based on deep feature that can be used to classification lung nodule, a CAD system was given by Devinder Kumar et al. The system was tested on LIDC dataset having 1010 CT images of 157 patients having rating of nodule as 0, 1, 2 and 3 as unknown, benign, primary malignant and malignant respectively. Autoencoder extracted Features from data, the result showed that deep feature has accuracy of 75.01% and belief decision has 68.66% [3]. The model has to be faster so we can get quick result. Caffe architecture was designed by Yangqing Jia et al. provided a modifiable framework for state-of-the-art deep learning algorithm. The framework is a BSD licensed C++ library with python on MATLAB binding. Caffe processing over 40 million images a day on a single k40 which gives approx. 2.5ms per images on Titan GPU. The architecture of caffe is simple sequential model with convolution pooling layer followed by Inner product layer with ReLU layer [5]. There neural network correct itself by back propagation correcting the error. Optimizer are used to perform this task, ADAM was the most used optimizer in models. Zijun Zhang et al. have introduced ND-ADAM which is a tailored version of ADAM which can be used in training of DNN. This bridge the gap between Adam and SGD [4]. There are many architecture that exist in the deep neural network Dmytro Mishkin et al. have given systematic evaluation of CNN advances on the ImageNet. Evaluation testing was done using no-linearity, pooling variants, network width, classifier design, image pre-processing and learning rates. 128x128 pixel image was used as the input. Top-1 accuracy comparison was done for CaffeNet, GoogleNet and VGGNet . this paper shows how the alteration in parameter affect the accuracy [6]. CNN can be trained using smaller batch size and learn features equally well, as done by Haarburger et al. by predicting lung cancer patient survival based on tomographic medical images using CNN. Features were extracted from the pre trained ResNet18 model [12]. Xiangyu Zhang et al. have introduced ShuffleNet which is an extremely computation efficient CNN architecture. This architecture is specially design for mobile devices with consideration of very limited computing power. Theoretically shuffleNet is ~18x faster but this paper model works ~13x faster than AlexNet still the it is much more faster than AlexNet [8]. Moitra et al. specified a hybrid of CNN and RNN. The objective was to give a simple yet fast model. Feature extraction used two methods Maximally stable external regions (MSER) and Speeded up robust features (SURF).The overall staging accuracy of the CNN-RNN was approximately (97 ± 2) % which was higher than its nearest competitor random forest (88 ± 10) %.It was also found that, the model accuracy of the proposed CNN-RNN model was always higher than the other machine learning algorithms under consideration. [10]. Zuo, Wangxia, et al, worked on Multi-Resolution CNN which had accuracy of 0.9733 [9] and Moradi et al. found a new approach in deep neural network to classify the lung cancer data. Multilevel contextual CNNs were used to reduce false positive. Their Proposed method gives accuracy of 91.23% for 3.99 false positive per scan [11]. Some of the method discussed above are complex and it may not run on simple hardware we have proposed a method aiming a simple model with better accuracy for classification.

II. MODEL

The proposed method is based on the CNN (convolutional neural network) model, a family of neural network. The model was designed aiming for simple and faster network with high accuracy. The model is a simple CNN, learning feature from the original CT image and the negative of the CT image. The main aim giving the negative image to the model is that, as human we cannot see some things in the normal images but same thing can be observed well in negative images. Depicting this learning style we have introduced two networks which are parallel to each other.

Each of these networks is sequential network of convolution and pooling layers. One network is provided the original image and another is given the inverted of the original CT image. The inverted image is sometimes also referred as negative image in image processing term. At the end of convolution layers, we get two vector of extracted feature from each of the network. Combining these vectors into a single vector becomes an input to fully connected layer. The whole model works on 512 x 512 lung CT image. The input data is available on cancer imaging archive which is a public access website for medical dataset.

The basic idea of giving the inverted input along with the normal image is that we can learn different features from the image. For original image we know that a nodule is white pixel and the same nodule will be of black pixel in inverted image. This will give an idea to CNN which to consider from the original image and which values to discard from the inverted image and visa-versa.

The model uses max pooling function so it will extract the maximum value from the previous convolution layer.so the max values in CNN which takes original CT image input will get the features of the nodule, which has the higher HU. Now similarly in the CNN which uses the inverted CT image the values of nodule are darker and have lower HU. So this CNN will learn the feature other than the nodule. After we combine this two feature vectors by appending each other we will have one vector learning of a nodule or the high HU pixels and another learning pulmonary area or lower HU pixels.

Our base model uses 4 filter with 6 convolution pooling layer in each branch, as shown in Fig 1. A fully connected network is followed by a CNN having input layer of 72 neurons a hidden layer having 36 neurons and an output layer of single neuron which can be written as FC_72_36_1 in short. The model uses ADAM optimizer as back-propagation.We have used a 2D CNN although Xiaojie Huang et al. have shown advantages over 2D CNN the 3D CNN will increase complexity [7].Our aim was to design smaller, simple yet achieving high accuracy.

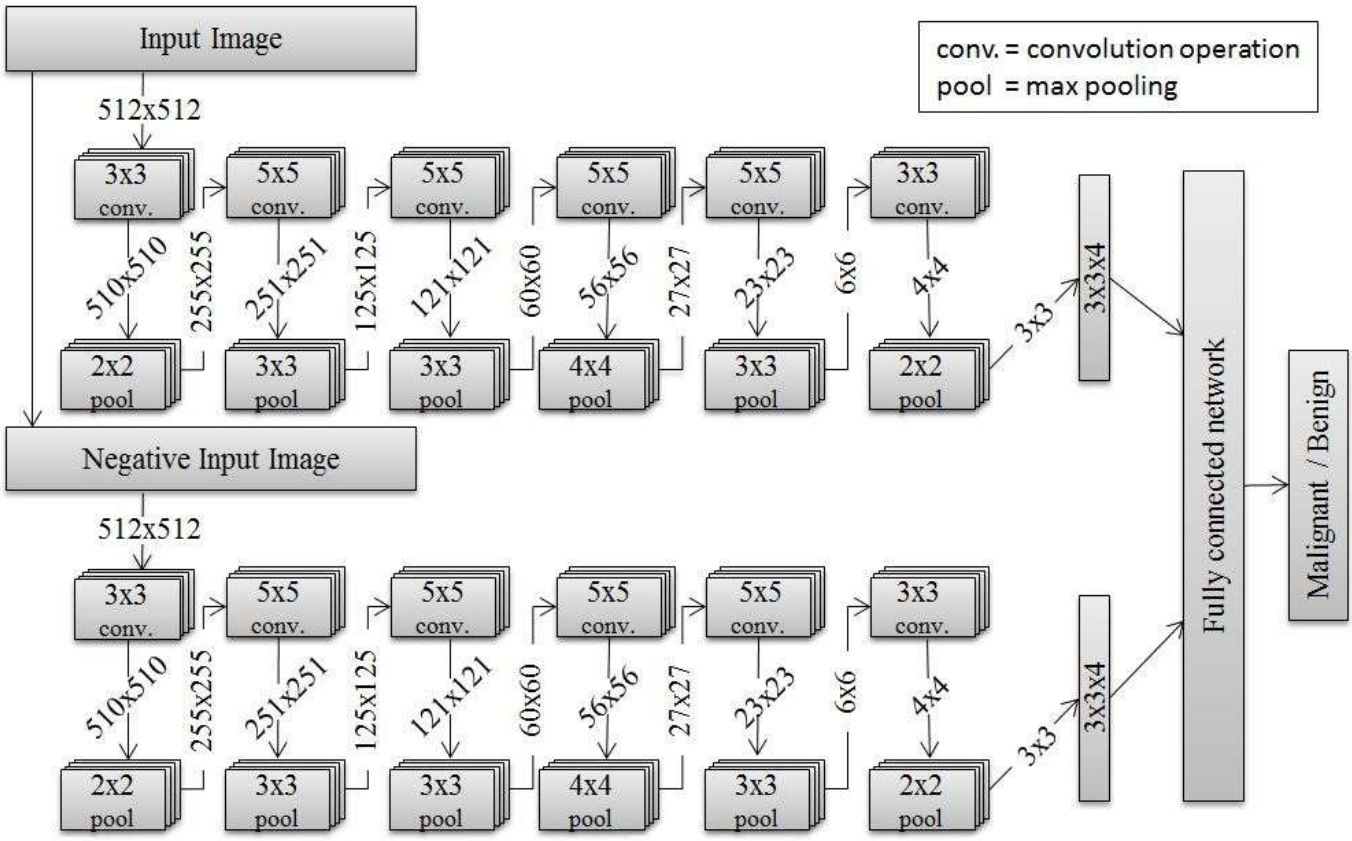

Fig 1: proposed model

III. RESULT

The experiment result was tested for the different number of feature extractor (filter) and two different full connected neural networks was used as the output vector for the 4 filter and 16 filter are different. As per the vector obtain the full connected layer was modified accordingly. For a 4 filter the fully connected layer was designed as FC_72_36_1 and for a 16 filter the fully connected layer was designed with 288 neuron in the input layer followed by 3 hidden layers, hidden layer 1 having 144 neuron, hidden layer 2 having 72 neuron, hidden layer 3 having 36 neuron and a output layer with 1 neuron which can also be written as FC_288_144_72_36_1 in short.

The base model was run for 10 epochs and 50 epochs with the variation of parameter for the batch sizes of 1, 32, 50, 100, 150, 195 and 200. The following graphs have been obtained showing the result. ADAM optimizer used for back propagation and a binary cross-entropy as the loss function (tf.keras.losses.BinaryCrossentropy) was used to calculate the loss. The model was run on the Google COLAB for evaluation. The model was trained and tested on Lung CT images from the cancer imaging archive (TCIA) which contains different challenges dataset. We have chosen “SPIE-AAPM Lung CT Challenge” having dataset of 70 patients.

A. Base Model Without Preprocessing

1) Epoch=10

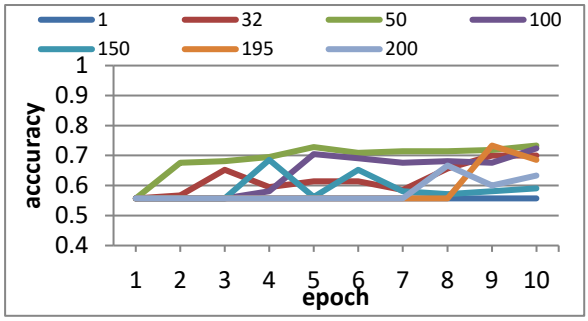

Fig 2 : Test accuracies of 4 filter model for 10 epochs

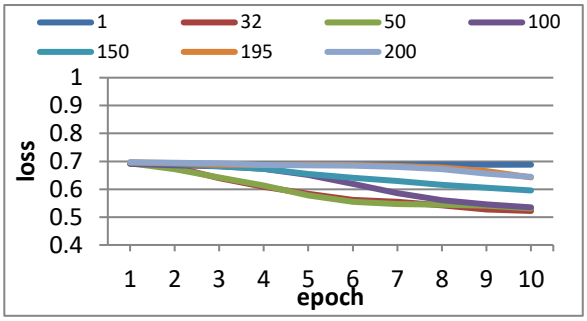

Fig 3 : Train loss of 4 filter model for 10 epochs

Above Fig 2 shows the accuracy and Fig 3 shows loss for different batch sizes for 4 filter model run for 10 epochs. As we can observe batch size of 50 gives good accuracy above 70% and more stable graph also having low loss among other batch sizes. Also other batch sizes have lower loss but it could not attain higher accuracy than the accuracy of batch size 50. At end of 10th epoch highest accuracy is 73.33% with the loss of 53.13%.

2) Epoch=50

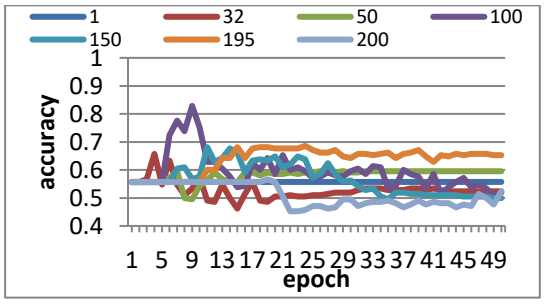

Fig 4 : Test accuracies of 4 filter model for 50 epoch

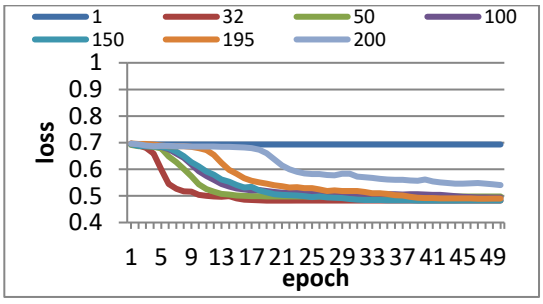

Fig 5 : Train loss of 4 filter model for 50 epoch

By increasing the epoch to 50 we can observe that 195 batch size gives better accuracy along with lower loss. Even batch size of 32 has lower loss but it could not achieve accuracy more than 48.24%. Although batch size of 100 gives higher accuracy but its keeps on decreasing even if loss is at lowest point. So we can consider batch size of 195 with 65.24% having loss of 48.99%, as shown in Fig 4 and 5.

B. Variation In Base Model Without Preprocessing

1) Epoch=10

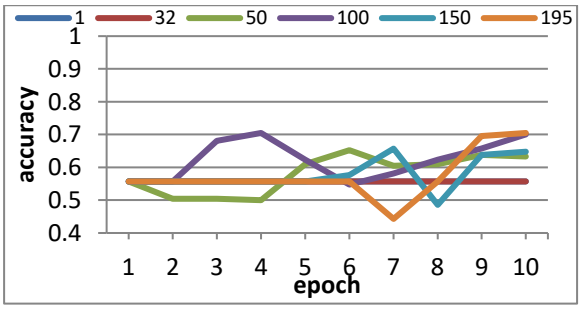

Fig 6 : Test accuracies of 16 filter model for 10 epoch

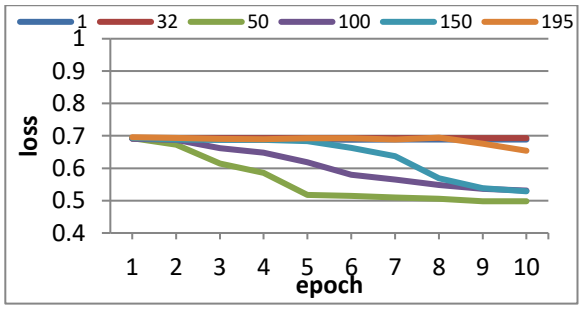

Fig 7 : Train loss of 16 filter model for 10 epochs

Fig 6 and 7 shows accuracy and loss for 16 filter model which is an variation of base model. The higher batch size of 195 shows the higher accuracy among the other batch sizes but we see that even loss is higher which is not good. But batch size of 100 gives accuracy of 70% at end of 10 epochs with lower loss function of 53.11%. Overall we can see batch size in between 50 to 150 has lower loss.

2) Epoch=50

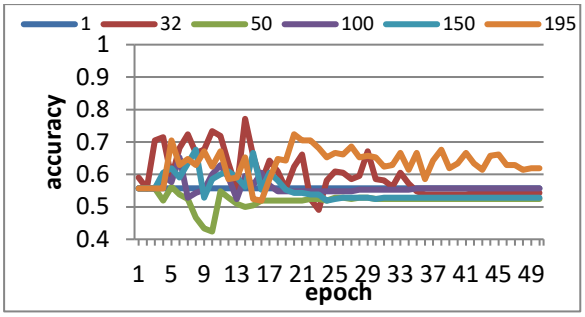

Fig 8 : Test accuracies of 16 filter model for 10 epochs

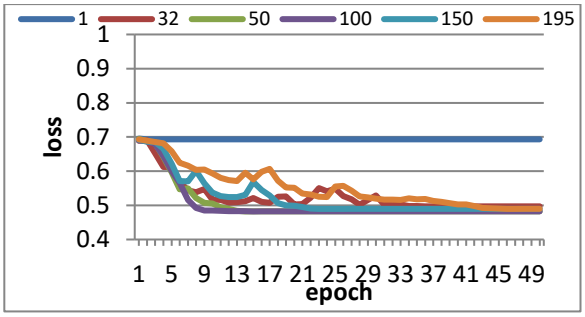

Fig 9 : Train loss of 16 filter model for 10 epoch

This run of 50 epochs for 16 filter showed very unstable accuracy even if it has lower loss functions. Batch size of 195 gives higher accuracy of 61.9% having lower loss of 48.97% among the other batches, as shown in Fig 8 and 9.

C. Base Model With Preprocessing

1) Epoch=10

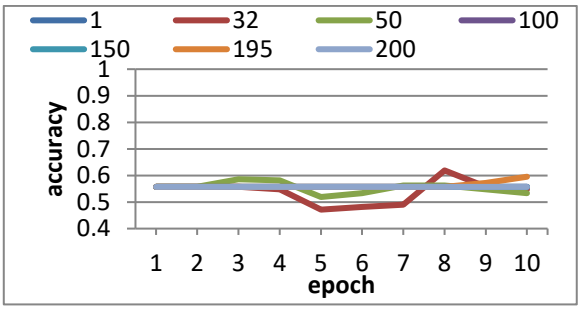

Fig 10 : Test accuracies of 4 filter model for 10 epochs

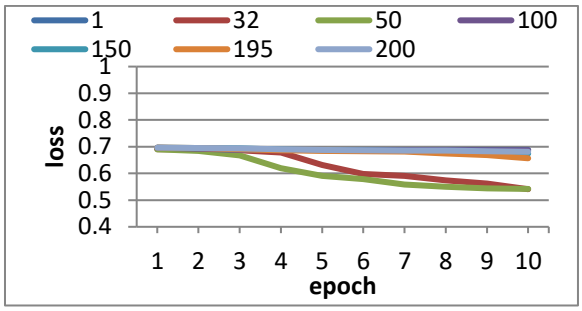

Fig 11 : Train loss of 4 filter model for 10 epoch

In preprocessed data the model has same accuracy of 55.71% for batch size of 1,100 and 200, whereas the batch size of 50 have lowest loss of 54.18% with Accuracy 53.33% at end of 10th epoch. The highest accuracy of 59.52% is given by the 195 batch size at end of 10th epoch, as shown in Fig 10 and 11.

2) Epoch=50

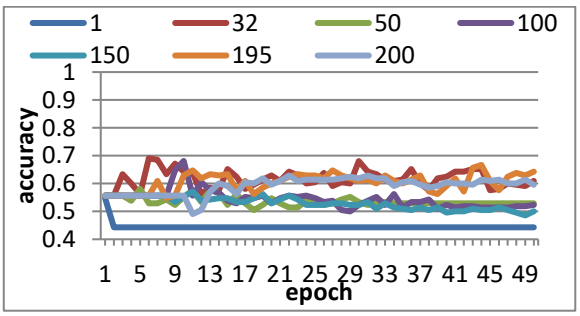

Fig 12 : Test accuracies of 4 filter model for 50 epoch

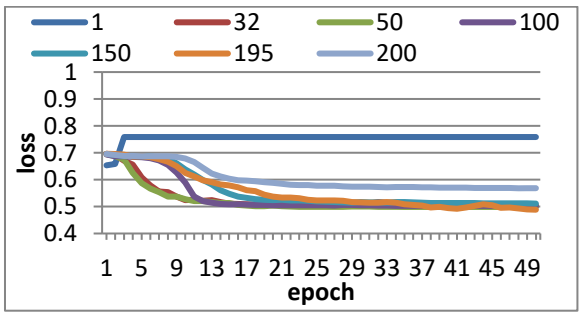

Fig 13 : Train loss of 4 filter model for 50 epoch

As we observe in above graphs Fig 12 and 13 of 4 filter for 50 epoch, the batch size 195 gives higher accuracy of 64.29% with loss of 48.84%.

D. Variation In Base Model With Preprocessing

1) 10 Epochs

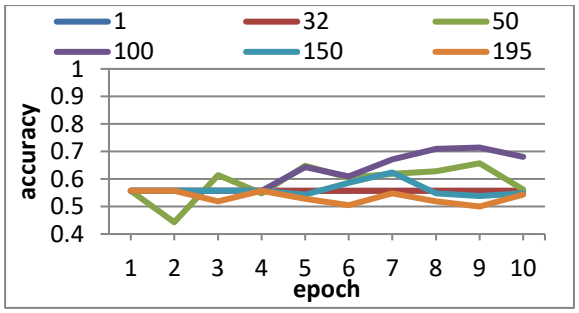

Fig 14 : Test accuracies of 16 filter model for 10 epoch

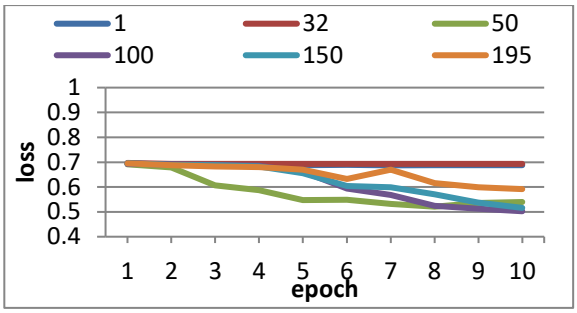

Fig 15 : Train loss of 16 filter model for 10 epoch

In preprocessed data for 16 filter model, the batch size 100 gives higher accuracy of 68.1% having loss of 50.24% among other batch sizes, as shown in Fig 14 and 15.

2) EPOCH=50

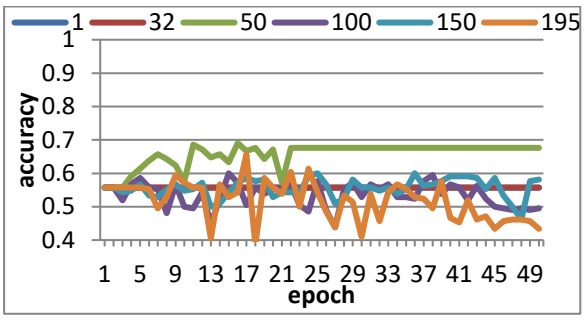

Fig 16 : Test accuracies of 16 filter model for 50 epoch

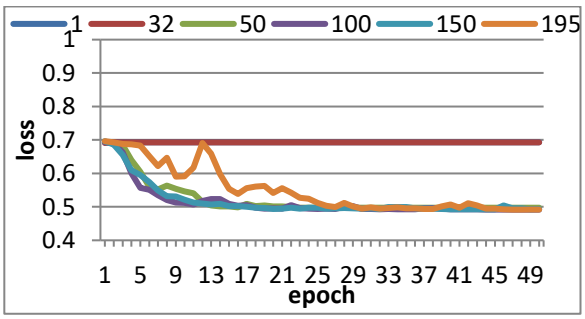

Fig 17 : Train loss of 16 filter model for 50 epoch

As show in Fig 16 and 17 we can observe that the batch size of 50 gives better accuracy of 67.62% with loss of 49.74%.

IV. CONCLUSION

Our proposed model of CNN learns the data feature from the original CT image and a negative CT image. The model was tested by altering different parameters. Although our base model achieves accuracy of 73.33 % having 4 filter and the variation in the number of filter attain the highest accuracy of 68.1% with 16 filter. The model was also tested by providing preprocessed image as input but accuracy was not higher than without preprocessing. The proposed model has the future scope as this method is general enough that with small modification it will work for other dataset including other medical CT images. Accuracy can be improved with further modification to achieve state-of-the-art performance.

REFERENCES

[1] Noronha, V., Pinninti, R., Patil, V.M., Joshi, A. and Prabhash, K., 2016. *Lung cancer in the Indian subcontinent. South Asian journal of cancer*, *5*(3), p.95.

[2] Song, Q., Zhao, L., Luo, X. and Dou, X., 2017. *Using deep learning for classification of lung nodules on computed tomography images. Journal of healthcare engineering*, *2017*.

[3] Kumar, D., Wong, A. and Clausi, D.A., 2015, June. *Lung nodule classification using deep features in CT images*. In *2015 12th Conference on Computer and Robot Vision* (pp. 133-138). IEEE.

[4] Zhang, Z., Ma, L., Li, Z. and Wu, C., 2017. *Normalized direction-preserving adam. arXiv preprint arXiv:1709.04546*.

[5] Jia, Y., Shelhamer, E., Donahue, J., Karayev, S., Long, J., Girshick, R., Guadarrama, S. and Darrell, T., 2014, November. *Caffe: Convolutional architecture for fast feature embedding*. In *Proceedings of the 22nd ACM international conference on Multimedia* (pp. 675-678).

[6] Mishkin, D., Sergievskiy, N. and Matas, J., 2017. *Systematic evaluation of convolution neural network advances on the imagenet*. *Computer Vision and Image Understanding*, *161*, pp.11-19.

[7] Huang, X., Shan, J. and Vaidya, V., 2017, April. *Lung nodule detection in CT using 3D convolutional neural networks*. In *2017 IEEE 14th International Symposium on Biomedical Imaging (ISBI 2017)* (pp. 379-383). IEEE.

[8] Zhang, X., Zhou, X., Lin, M. and Sun, J., 2018. *Shufflenet: An extremely efficient convolutional neural network for mobile devices*. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 6848-6856).

[9] Zuo, W., Zhou, F., Li, Z. and Wang, L., 2019. *Multi-resolution CNN and knowledge transfer for candidate classification in lung nodule detection*. *Ieee Access*, *7*, pp.32510-32521.

[10] Moitra, D. and Mandal, R.K., 2019. *Automated AJCC staging of non-small cell lung cancer (NSCLC) using deep convolutional neural network (CNN) and recurrent neural network (RNN)*. *Health information science and systems*, *7*(1), p.14.

[11] Moradi, P. and Jamzad, M., 2019, March. *Detecting Lung Cancer Lesions in CT Images using 3D Convolutional Neural Networks*. In *2019 4th International Conference on Pattern Recognition and Image Analysis (IPRIA)* (pp. 114-118). IEEE.

[12] Haarburger, C., Weitz, P., Rippel, O. and Merhof, D., 2019, April. *Image-Based Survival Prediction for Lung Cancer Patients Using CNNS*. In *2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019)* (pp. 1197-1201). IEEE.