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Efficient CNN for Lung Cancer Detection

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Abstract: ***The machine learning based solutions for medical image analysis are successful in detection of wide variety of anomalies in imaging procedures. The aim of the medical image analysis systems based on machine learning methods is to improve the accuracy and minimize the detection time. The aim in turn contributes to early disease detection and extending the patient life. This paper presents an efficient CNN (EFFI-CNN) for Lung cancer detection. EFFI-CNN consists of seven CNN layers (i.e. Convolution layer, Max-Pool layer, Convolution layer, Max-Pool layer, fully connected layer, fully connected layer and Soft-Max layer). EFFI-CNN uses lung CT scan images from LIDC-IDRI and Mendeley data sets. EFFI-CNN has a unique combination of CNN layers with parameters (Depth, Height, Width, filter Height and filter width).***

Index Terms: ***Lung Cancer Detection, Machine learning, Edge AI System, CNN, deep learning and neural networks.***

I. INTRODUCTION

According to the National Institutes of Health (NIH) cancer statistics [6], the estimated new lung cancer cases in USA for 2019 are 228150 which are 12.9% of overall cancer cases [6]. The estimated lung cancer death in USA for 2019 is 142670 which are 23.5% of overall cancer deaths [6]. Medical image analysis using deep learning is paid a lot of attention in researchers. Deep learning technology is advanced version of the artificial neural networks. The technology contains the several layers to extract the image features and classification tasks. Convolutional neural network(CNN) is proven that it could provide promising results in medical image analysis.

Motivated by CNN results, we propose a new CNN (EFFI-CNN) which is more efficient compared to current literature. EFFI-CNN is the efficient CNN for Lung cancer detection using CT scan images. EFFI-CNN consists of seven layers to achieve the best in class results. In our research, we have used the lung CT scan images from LIDC-IDRI [3] and Mendeley[4] data sets.

This paper is structured as follows. We briefly describe the CNN layers used in Section 2. In Section 3, we discuss proposed CNN(EFFI-CNN). In section 4, we discuss the research results and results comparison. In Section 5, we discuss conclusion and future work.

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II. CNN LAYERS

In our paper, we have used the convolution layer, Max Polong layer, Fully connected layer and Soft max layer. In this section, it is briefly described the all used layers.

A. Convolution Layer

The Convolution layer purpose is to abstract the features from input image. Convolution conserves the spatial relationship between pixels and it is achieved by learning image features using small squares of input image. Fig.1 describes the how convolution works. In Fig.1 the input image considered as 5X5 matrix of pixel values. A 3X3 matrix is used as kernel or filter.

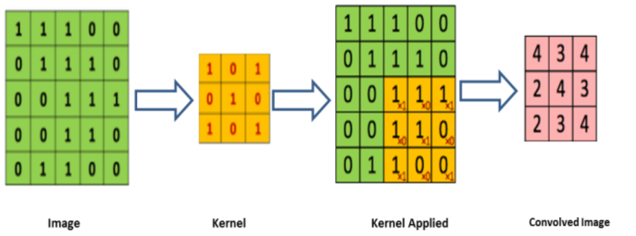

Fig.1 Convlution Layer Demo

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B. Max-Pool Layer

Max Pooling is one type of spatial pooling. Max Pooling reduces the dimensionality of each feature map and preserves the critical information. The other types of spatial Pooling Max, Average and Sum.

Here input image is 4X4 matrix of pixel values. A 2X2 filter with stride 2 is used for Max pool operation. Fig.2 describes the Max pool functionality.

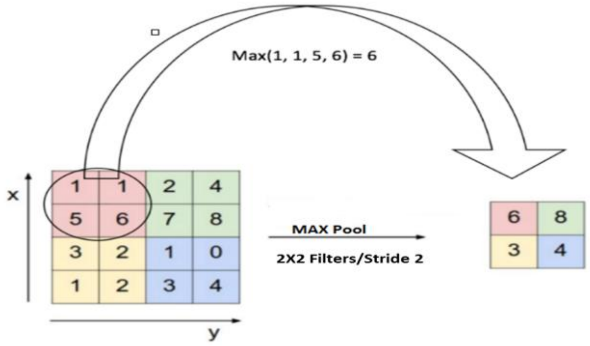

Fig.2 Max Pool Layer Demo

C. Fully Connected Layer

The Fully Connected layer is a multi-layer perceptron. It ensures that the every neuron in the previous layer is connected to every neuron on the sub sequent layer. The objective of this layer is to classify the input image based on the preserved features. Fig,3 shows the four possible outcomes with given data set and extracted features.

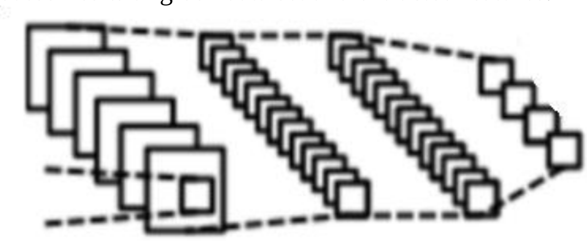

Fig.3 Fully Connected Layer Example

D. Soft-Max Layer

Softmax function is an activation function that turns numbers aka logits into probabilities that sum to one. This function outputs a vector that represents the probability distributions of a list of potential outcomes. This layer plays vital role in classification tasks. Fig.4 presents the soft max function.

$$S(y_i) = \frac{e^{y_i}}{\sum_j e^{y_j}}$$

Fig.4 Soft Max Function

Fig.5 and Fig.6 shows the soft-max examples. In Fig.5, *j* represents the *logit* that needs to be normalized by sum_of_exps. sum_of_exps is the sum of all the logits including itself.

```
softmax = [j/sum_of_exps for j in exps]
```

Fig.5 Soft Max Example-1

```
>>> softmax
[0.6590011388859679, 0.2424329707047139, 0.09856589040931818]
>>> sum(softmax)
1.0
```

Fig.6 Soft Max Example-2

III. EFFI-CNN

FigFig. 1 and Fig. 2 describe the EFFI-CNN architecture. NN-SVG architecture [5] tools are used to develop the EFFI -CNN. EFFI-CNN consists below listed seven CNN layers.

1. Convolution layer
2. Max-Pool layer
3. Convolution layer
4. Max-Pool layer
5. Fully connected layer
6. Fully connected layer
7. Soft-Max layer

EFFI-CNN described below in detail step by step input and output.

1. The input image is 224x224x3
2. Convolution 3X3 is applied
3. The output of Convolution 3X3 is 200X200X32
4. The output of Convolution 3X3 is input for Max-Pool layer
5. Max-Pool layer is applied
6. The output of Max-Pool layer is 100X100X32
7. The output of Max-Pool layer is input for Convolution 3X3
8. Convolution 3X3 is applied
9. The output of Convolution 3X3 is 50X50X32
10. The output of Convolution 3X3 is input for Max-Pool layer
11. Max-Pool layer is applied
12. The output of Max-Pool layer is 25X25X32
13. The output of Max-Pool layer is input for Fully connected layer
14. Two consequent Fully connected layers are applied
15. The output of last Fully connected layer is 25X25X16
16. The output of Fully connected layer is input for Soft-Max layer
17. Soft-Max layer is applied
18. The output of Soft-Max layer is 1X224

The seven layer combination has been chosen to improve the lung cancer detection results. EFFI-CNN is developed based on the experiments performed in ICDSSPLD-CNN [1] and EASPLD-CNN [2].

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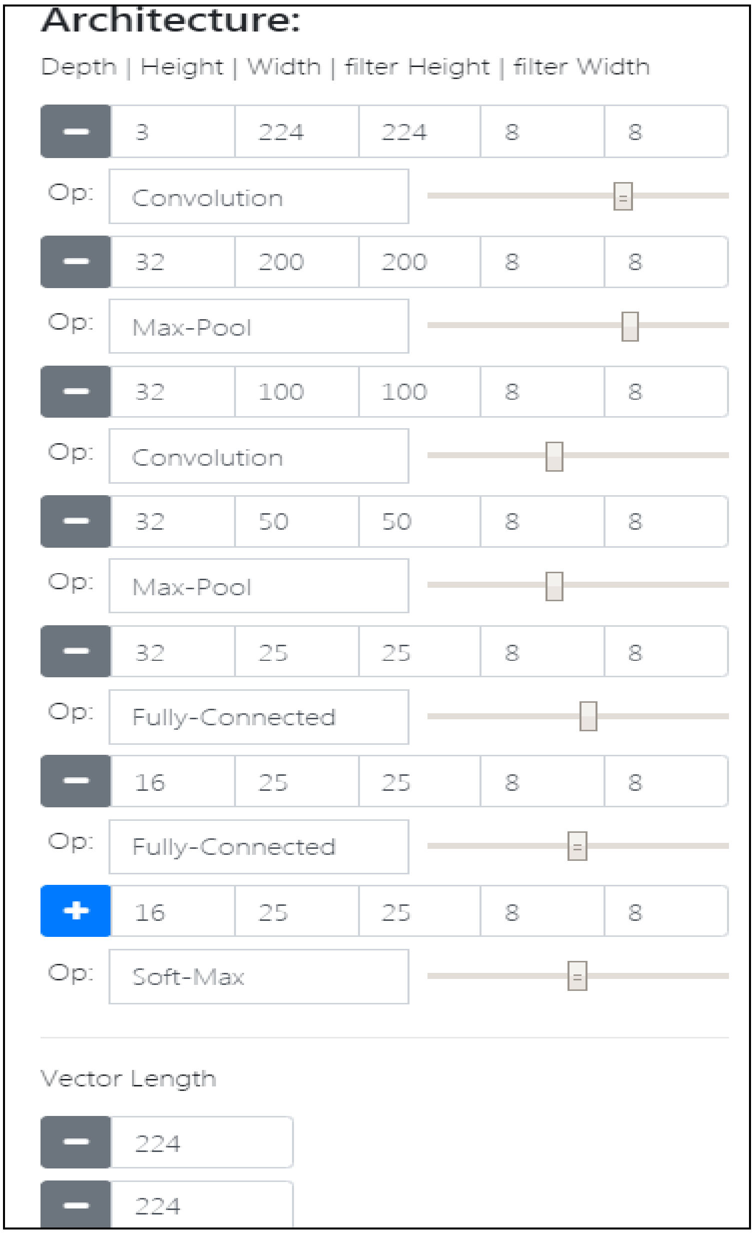

Fig.1 EFFI-CNN High level architecture

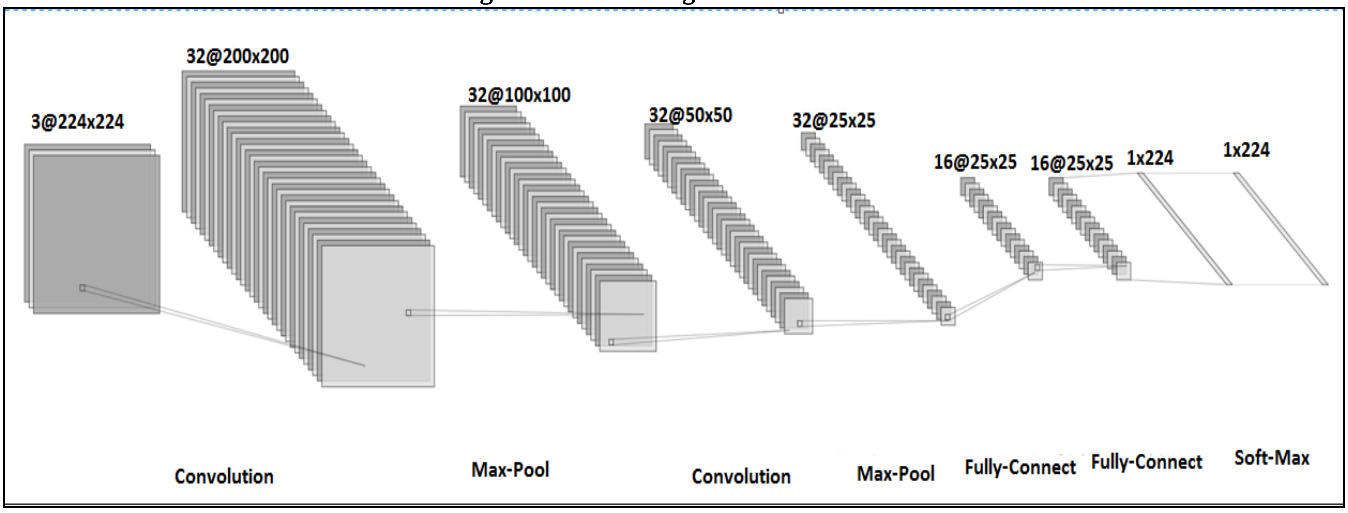

Fig.2 EFFI-CNN Detailed architecture

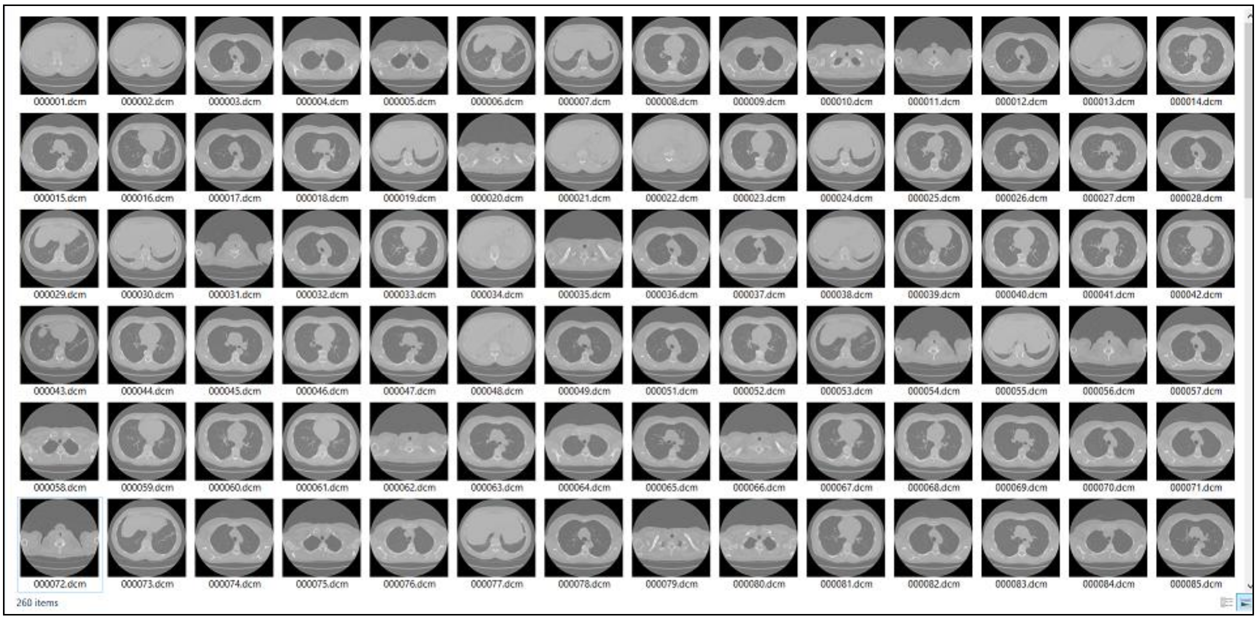

Fig.3 EFFI-CNN Lung Cancer Data set

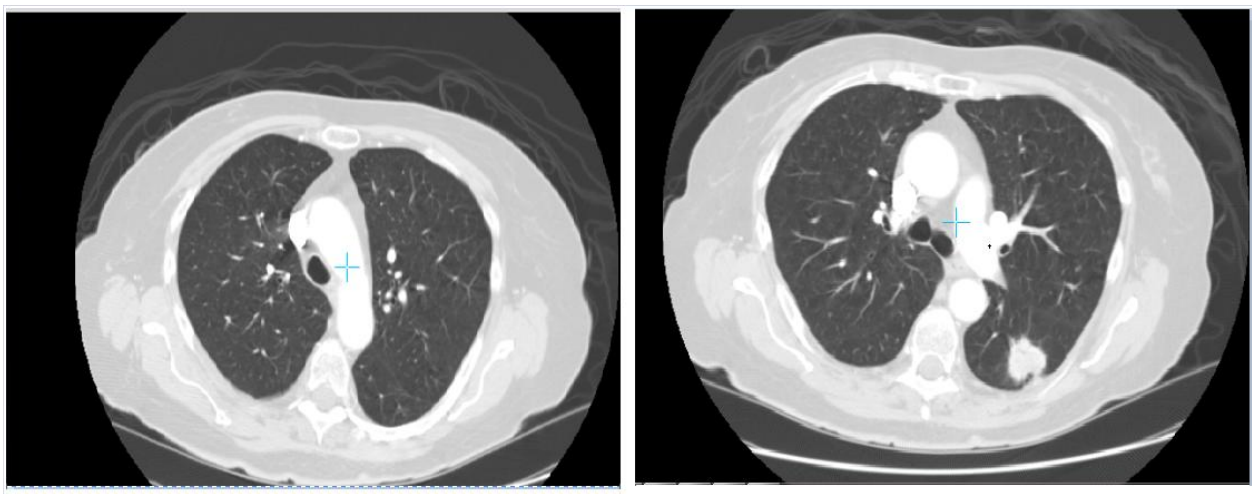

Fig.4 Normal Lung Image-Cancerous Lung Image

Fig.3 shows the Lung cancer data set taken from LIDC-IDRI and Mendeley[3][4]. Fig.4 shows the difference between normal lung and cancerous lung.

IV. RESULTS

The EFFI-CNN is implemented using TesnorFlow. Lung cancer detection results using EFFI-CNN is presented in Table-1. The EFFI-CNN results clearly indicating that the results are promising and standout of the existing methods [1][2]. In Table-2, the lung cancer detection results of ICDSSPLD-CNN, EASPLD-CNN and EFFI-CNN are compared. Fig.5 is plotted to compare the lung cancer detection results of ICDSSPLD-CNN, EASPLD-CNN and EFFI-CNN.

Parameters	EFFI-CNN Results
Sample Data set Size	1400/1400
Processing time for each step	410s 400ms
Loss on test set	0.8562345678
Accuracy on test set	0.8702340124
Recall rate of the model	0.98
Precision of the model	0.81

Table-1 EFFI-CNN Results

Parameters	ICDSSPLD-CNN	EASPLD-CNN	EFFI-CNN
Sample Data set Size	880/880	1080/1080	1400/1400
Processing time for each step	520s 820ms	420s 408ms	410s 400ms
Loss on test set	0.7995697255753682	0.8195697255753682	0.8562345678
Accuracy on test set	0.85230769230769	0.86130769230769	0.8702340124
Recall rate of the model	0.97	0.98	0.98
Precision of the model	0.78	0.79	0.81

Table-2 Lung Cancer Detection Results Comparison Matrix

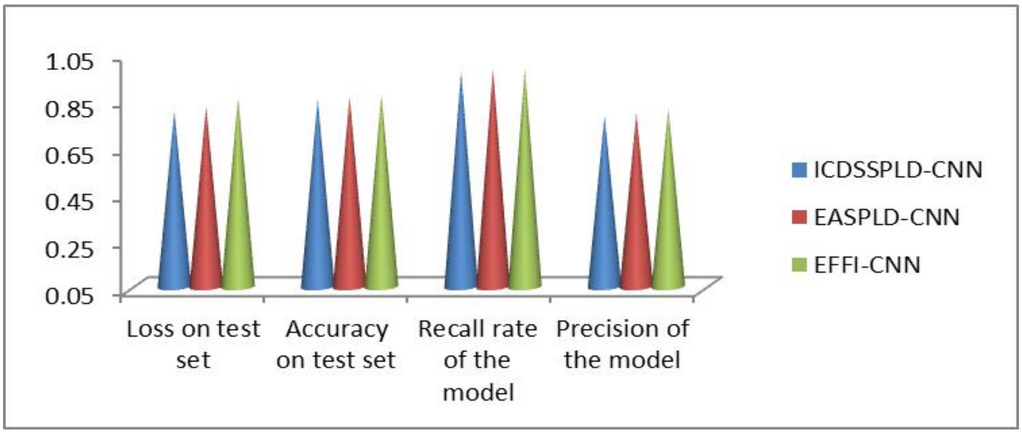

Fig.5 Lung Cancer Detection Results Comparison Graph

V. Conclusion And Future Work

Lung cancer is a one of the critical lung organ disease. Any method or technique contributing to early detection is likely to trigger the early diagnosis and leads extend the life. EFFI-CNN has shown promising results in lung cancer detection. The EFFI-CNN achieved best results comparatively with ICDSSPLD-CNN and EASPLD-CNN. We will leverage the EFFI-CNN to derive a generalized solution for majority of lung organ disease detection.

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