

# End to End System for Pneumonia and Lung Cancer Detection using Deep Learning

Venkata Tulasiramu Ponnada, S.V. Naga Srinivasu



**Abstract:** *The Deep learning solutions for medical image analysis are offered a promising alternative solution to self-learning problem-specific features and gave a new facet for computer vision challenges. The early detection of pneumonia and lung cancer plays big role in saving the life. Any method or system contributing to early disease detection is likely to reduce the dearth rate of diseases. Our previous work [3] proposed an efficient CNN (EFFI-CNN) for Lung cancer detection. This paper presents a system to detect the pneumonia and lung cancer using deep learning techniques (ESPLDUDL). The system leverages the EFFI-CNN, Raspberry Pi and Tensor processing Unit (TPU). The system configuration raises the bar in detection results and technology front.*

**Index Terms:** *Pneumonia detection, Lung cancer detection, deep learning, Machine learning, Neural networks, CN, Raspberry Pi, TPU*

## I. INTRODUCTION

In recent days, the statistics of lung cancer and pneumonia cases are grabbed a lot of research attention. The medical image analysis using deep learning techniques are stand out of traditional methods as getting promising results. National Institutes of Health (NIH) cancer statistics [6], indicating that lung cancer cases are 12.9% of overall cancer cases. The lung cancer death is 23.5% of overall cancer deaths. The pneumonia is equally dangerous and accounts for toddlers. The pneumonia is resulting in 16% of all deaths of children fewer than five years. The proposed system uses the EFFI-CNN [3] to address the pneumonia and lung cancer detection challenges.

EFFI-CNN is the efficient CNN for medical image analysis which is 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 [4] and Mendeley[5] data sets.

This paper is structured as follows. Related work is described in Section 2. In Section 3, we discuss proposed system end to end system for pneumonia and lung cancer detection using deep learning (ESPLDUDL).

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In section 4, we discuss the research results and results comparison with previous work. In Section 5, we discuss conclusion and future work.

## II. RELATED WORK

In our present paper, we discuss first about our previous research work in lung organ disease detection methods. We have three works published to address the pneumonia and lung cancer detection methods. Our first work is “Integrated Clinician Decision Supporting System for Pneumonia and Lung Cancer Detection”[1], the second one is “Edge AI System for Pneumonia and Lung Cancer Detection”[2] and the third one is “Efficient CNN for Lung Cancer Detection”[3].

The first work proposed a ICDSSPLD-CNN [1], second proposed a EASPLD-CNN [2] and third one proposed advanced EFFI-CNN [3]. In our third work we applied EFFI-CNN for only lung cancer detection. As the results are shown significant change, we leveraged the EFFI-CNN for pneumonia and lung cancer in our present work ESPLDUDL.

ICDSSPLD-CNN contains the three sets of CNN layers. Each set contains two convolution layers and one max pooling layer. The three set of Convolution layer, Convolution layer and Max pooling layer; Convolution layer, Convolution layer and Max pooling layer and Convolution layer, Convolution layer and Max pooling layer.

EASPLD-CNN uses 3X3 and 5X5 convolution layers. It consists of below given eight convolution layers.

1. Convolution, 3X3
2. Convolution1, 3X3
3. Convolution6, 3X3
4. Convolution6, 5X5
5. Convolution6, 3X3
6. Convolution6, 5X5
7. Convolution6, 5X5
8. Convolution6, 3X3

EFFI-CNN uses below listed 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

### III. ESPLDUDL SYSTEM

The proposed system for psoriasis and lung cancer detection (ESPLDUDL) consists of 3 sub-systems. The sub systems are Tensor processing unit (TPU), Raspberry Pi and a LED display unit. The LED display unit and TPU are connected to Raspberry Pi using USB ports.

Tensor Processing Unit (TPU) is a Google ASIC to accelerate the linear algebra computation performance. It is widely used machine learning applications. It minimizes the time-to-accuracy. To train the ML models usually CPUs takes weeks to train and run the model, where TPUs are bring it down to hours.

The LED display is used to provide the user application interface which supports inputting the CT scan image and to display the results.

The Raspberry Pi is used to achieve a low cost, mobile sized computer that can replace the traditional laptops and ensures the better performance. ESPLDUDL uses the Raspberry Pi to run the User interface application and EFFI-CNN model to provide the results and to re-engineering the model periodically. The User Interface application (SPLDUDL) is used by the end user (Clinician/Patient) to input the CT scan image to the system to detect the pneumonia and lung cancer. EFFI-CNN [3] model is generated using Tensor flow and deployed in Raspberry Pi as an edge service. EFFI-CNN is generated with option TPU as processing unit. It means that Raspberry Pi give high priority to run the model on TPU rather than using the internal memory. Raspberry Pi configured for Docker Container. Docker container manages the interaction between user interface (SPLDUDL) service and EFFI-CNN model service. The given input in SPLDUDL passed through the Docker container and provided as an input service to EFFI-CNN model service. The output of disease detection is displayed in user interface.

The Docker container takes care of re-engineering the EFFI-CNN model. Part of continuous improvement, it uploads the inputs images to cloud on regular interval using the internet service. The uploaded input images are added to data sets. The EFFI-CNN model is re-engineered in cloud using the Tensor flow. Once the re-engineered model is available it can be deployed in Raspberry Pi using the Docker container.

Fig.1 describes the ESPLDUDL Theory of Operation. The main tasks of ESPLDUDL system in view of the user are described.

Fig.2 describes the ESPLDUDL system and its sub systems. It gives the block box vies and its interfaces to communicate with each other sub-system.

Fig.3 describes the UI user guide for SPLDUDL-Pneumonia Detection. It is used to show the UI Flow for pneumonia detection initiation, detection status and detection result.

Fig.4 describes the UI user guide for SPLDUDL-Lung cancer Detection. It is used to show the UI Flow for pneumonia detection initiation, detection status and detection result.

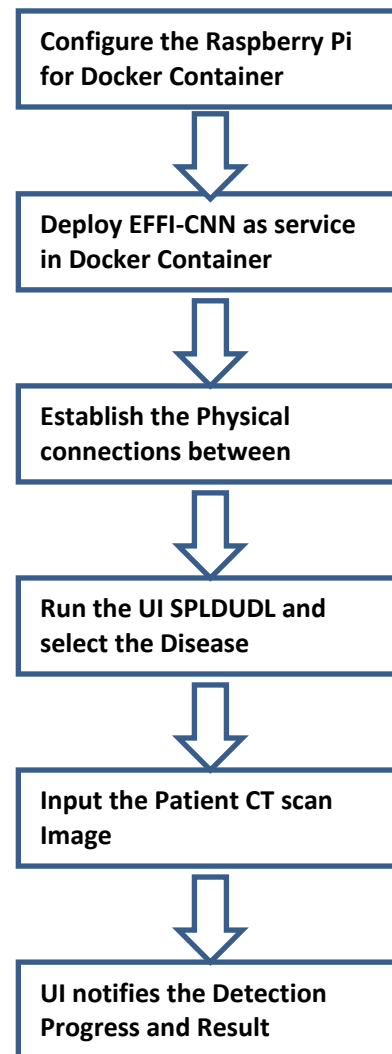
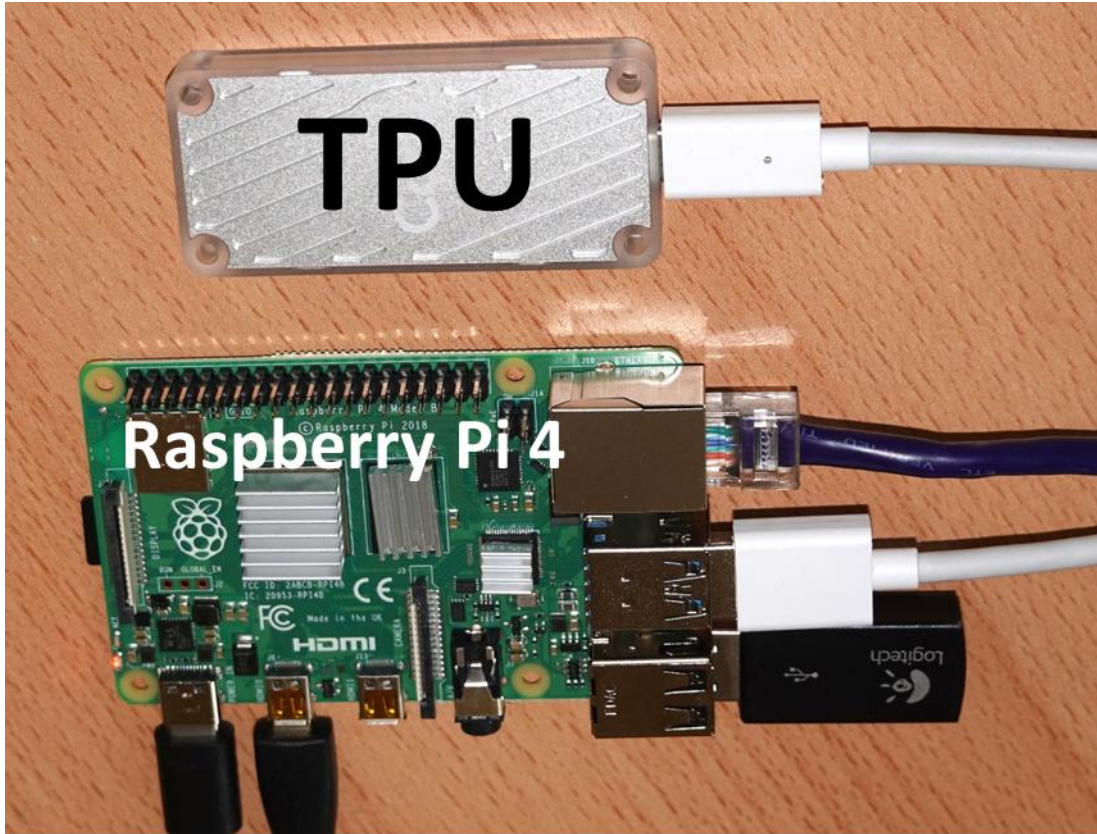


Fig.1 ESPLDUDL Theory of Operation



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Fig.2 ESPLDUDL System

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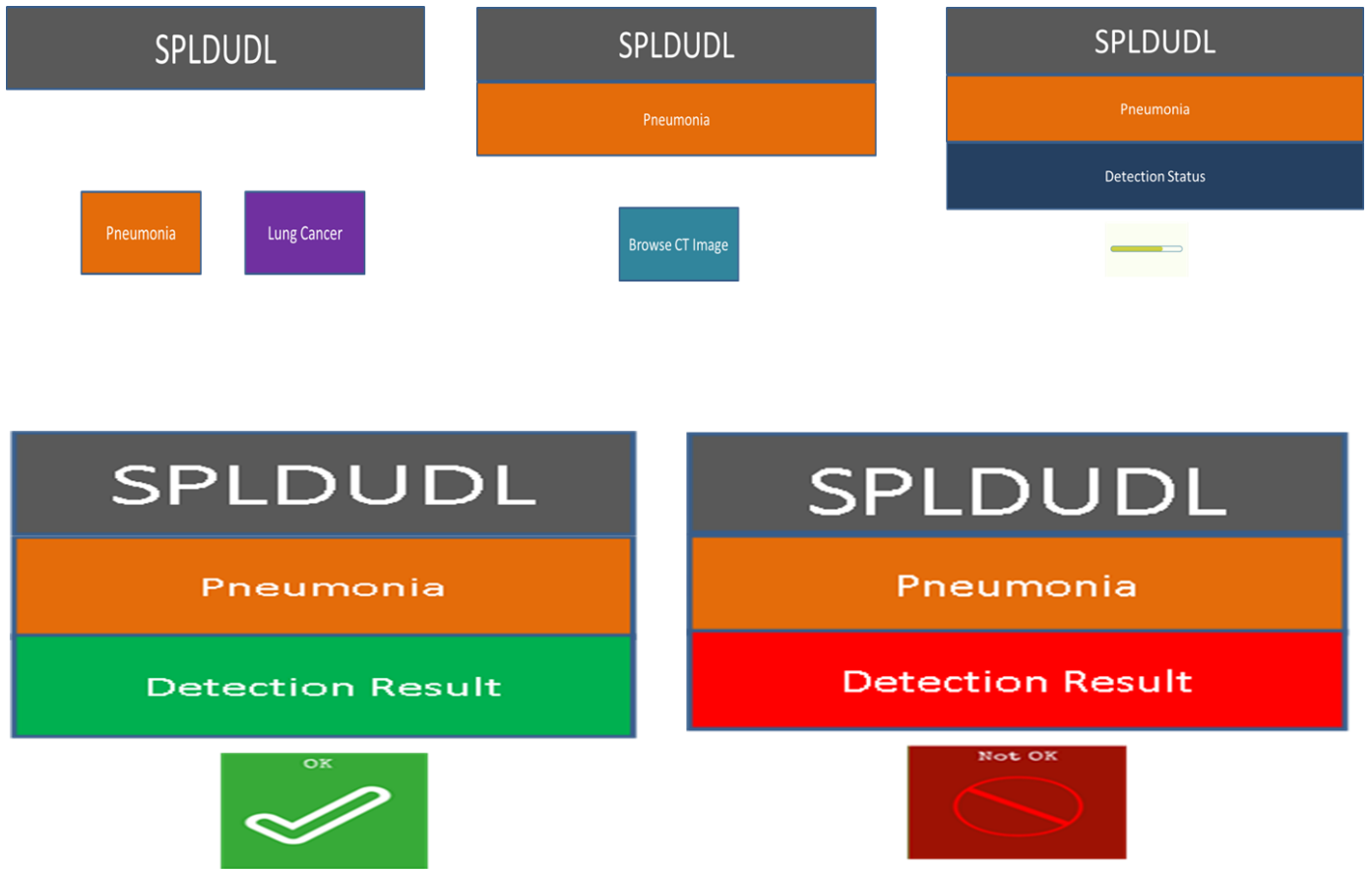


Fig.3 SPLDUDL-Pneumonia Detection UI Flow

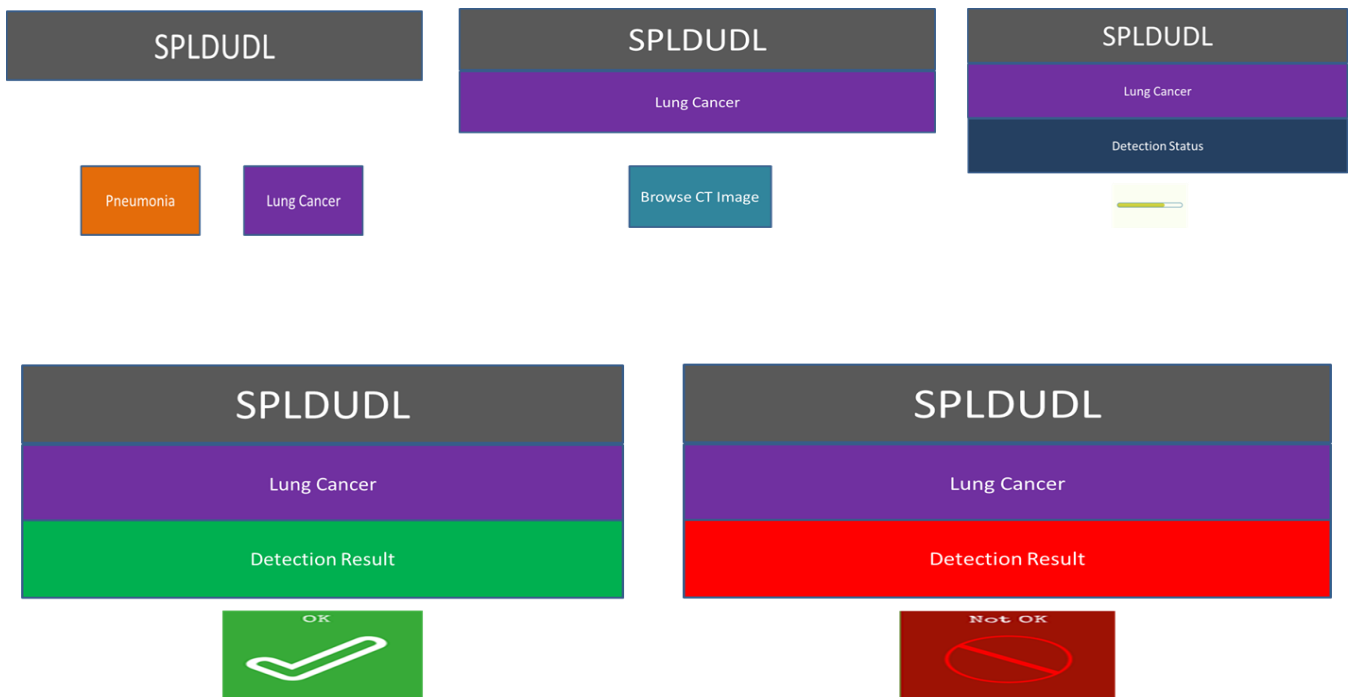


Fig.4 SPLDUDL-Lung Cancer Detection UI Flow



**IV. RESULTS**

ESPLDUDL uses the EFFI-CNN [3]. EFFI-CNN is implemented using TesnorFlow and deployed on Raspberry Pi. Lung cancer detection results of ESPLDUDL are described in Table-1. Pneumonia detection results of ESPLDUDL described in Table-2. The comparison matrix is presented in Lung cancer detection results using EFFI-CNN is presented in Table-3. In Table-4, the lung cancer detection results of ICDSSPLD-CNN [1], EASPLD-CNN[2], EFFI-CNN[3] and ESPLDUDL are compared. In Table-5, the pneumonia detection results of ICDSSPLD-CNN [1], EASPLD-CNN[2] and ESPLDUDL are compared. In Fig.5 and Fig.6, the pneumonia and lung cancer detection parameters sample data size and processing time are presented. In Fig.7 and Fig.8, the pneumonia and lung cancer detection critical parameters are presented. The results are evident that ESPLDUDL stands out of the existing methods.

Parameters	ESPLDUDL Results
Sample Data set Size	2020
Processing time for each step	402
Loss on test set	0.8789
Accuracy on test set	0.890345
Recall rate of the model	0.98567
Precision of the model	0.82

Table-1 ESPLDUDL Lung Cancer Detection Results

Parameters	ESPLDUDL Results
Sample Data set Size	2020
Processing time for each step	350
Loss on test set	0.856789
Accuracy on test set	0.930345
Recall rate of the model	0.973689
Precision of the model	0.85

Table-2 ESPLDUDL Pneumonia Detection Results

Parameters	ICDSSPLD-CNN	EASPLD-CNN	EFFI-CNN	ESPLDUDL
Sample Data set Size	880	1080	1400	2020
Processing time for each step	520	420	410	402
Loss on test set	0.799569726	0.819569726	0.85623457	0.8789
Accuracy on test set	0.852307692	0.861307692	0.87023401	0.890345
Recall rate of the model	0.97	0.98	0.98	0.98567
Precision of the model	0.78	0.79	0.81	0.82

Table-3 Lung Cancer Detection Results Comparison Matrix

Parameters	ICDSSPLD-CNN	EASPLD-CNN	ESPLDUDL
Sample Data set Size	624	880	2020
Processing time for each step	487	378	350
Loss on test set	0.905697255	0.935697256	0.856789
Accuracy on test set	0.826923076	0.856923077	0.930345
Recall rate of the model	0.98	0.98	0.973689
Precision of the model	0.79	0.81	0.85

Table-4 Pneumonia Cancer Detection Results Comparison Matrix

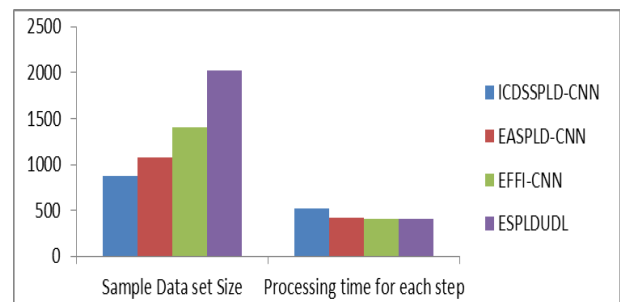


Fig.5 Lung Cancer Detection - Data Size and Processing Time Comparison

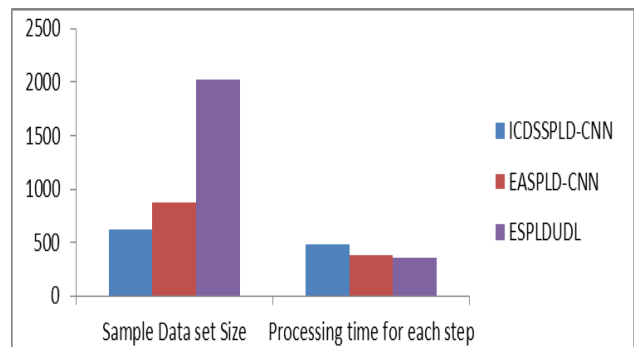


Fig.6 Pneumonia Detection - Data Size and Processing Time Comparison

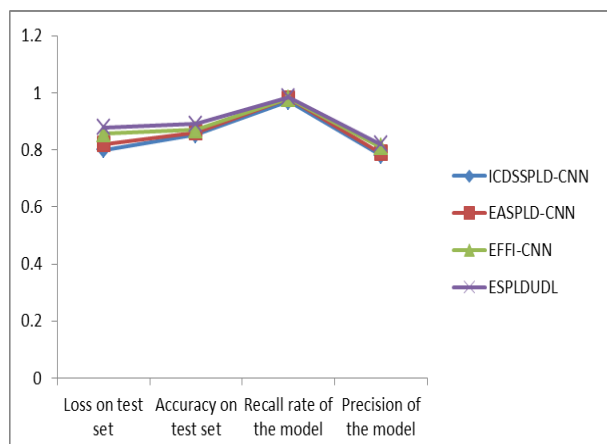
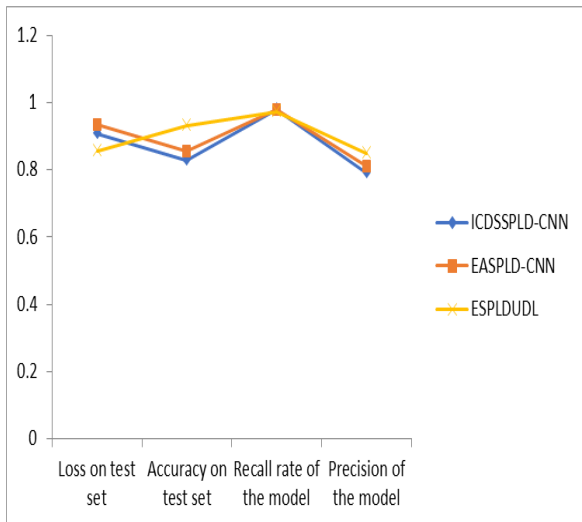


Fig.7 Lung Cancer Detection - Results Comparison



**Fig.8 Pneumonia Detection – Results Comparison**



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## V. CONCLUSION AND FUTURE WORK

ESPLDUDL system provides an end to end cost effective solution for lung organ diseases pneumonia and lung cancer. ESPLDUDL uses advanced technology like Raspberry Pi with EFFI-CNN. ESPLDUDL demonstrated the promising results for pneumonia and lung cancer detection. We would like to leverage the system to address the majority of lung organ disease detection.

## REFERENCES

1. Venkata Tulasiramu Ponnada, S.V.Naga Srinivasu, Integrated Clinician Decision Supporting System for Pneumonia and Lung Cancer Detection, International Journal of Innovative Technology and Exploring Engineering (IJITEE),2019, ISSN: 2278-3075, Volume-8, Issue-8
2. Venkata Tulasiramu Ponnada, S.V.Naga Srinivasu Edge AI System for Pneumonia and Lung Cancer Detection, International Journal of Innovative Technology and Exploring Engineering (IJITEE),2019, ISSN: 2278-3075, Volume-8, Issue-9
3. Venkata Tulasiramu Ponnada, S.V.Naga Srinivasu, Efficient CNN for Lung Cancer Detection, International Journal of Recent Technology and Engineering (IJRTE), ISSN: 2277-3878, Volume-8 Issue-2, July 2019
4. <https://wiki.cancerimagingarchive.net/display/Public/LIDC-IDRI>
5. <https://data.mendeley.com/datasets>
6. Cancer Stat Facts: Lung and Bronchus Cancer <https://seer.cancer.gov/statfacts/html/lungb.html>
7. <http://alexlenail.me/NN-SVG/LeNet.html>
8. Kim SK, Allen-Auerbach M, Goldin J, Fueger BJ, Dahlbom M, Brown M, et al. Accuracy of PET/CT in characterization of solitary pulmonary lesions. J Nucl Med. 2007;48:214–20.
9. L. Bottou. Stochastic gradient tricks. Neural Networks, Tricks of the Trade, Reloaded, 7700:430–445, 2012.
10. <https://www.kaggle.com/nih-chest-xrays/datasets>
11. G. Veronesi, P. Maisonneuve, L. Spaggiari, C. Rampinelli, A. Pardolesi, R. Bertolotti, N. Filippi, and M. Bellomi. Diagnostic performance of low dose computed tomography screening for lung cancer over five years. Journal

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Venkata Tulasiramu Ponnada, completed his M.Tech(Software Engineering) and pursuing PhD in Computer science and engineering from Acharya Nagarjuna University, Nagarjuna Nagar, Guntur, Andhra Pradesh 522510, India. He has published 8 research papers. His area of interest includes Software engineering, safety critical system implementations, software project management and System engineering, machine learning, deep learning and artificial intelligence.