 https://doi.org/10.24191/jeesr.v17i1.006

# Designation of Thorax and Non-Thorax Regions for Lung Cancer Detection in CT Scan Images using Deep Learning

Mohd Firdaus Abdullah*, Siti Noraini Sulaiman, Muhammad Khusairi Osman, Noor Khairiah A. Karim, Iza Sazanita Isa, Ibrahim Lutfi Shuaib

***Abstract*—Lung cancer is a common cause of death among people throughout the world. Lung cancer detection can be done in several ways, such as radiography, magnetic resonance imaging (MRI) and computed tomography (CT). These methods take up a lot of resources in terms of time and money. However, CT has good for lung cancer detection, offers a lower cost, short imaging time and widespread availability. Early diagnosis of lung cancer can help doctors to treat patients in order to reduce the number of mortalities. This paper presents designation of thorax and non-thorax regions for lung cancer detection in CT Scan images using deep learning. The primary aim of this research is to propose an intelligent, fast and accurate method for lung cancer detection. As initial stage we proposed a thorax and non-thorax slice detection for CT scan images using deep convolutional neural network (DCNN) so that later it can be used to simplify the process of lung cancer detection. The proposed method involved the development of DCNN network architecture. It comprises the following steps which involves designed the convolution layer, activation function, max pooling, fully-connected layer and output size. We present three DCNN structures to find the most effective network for thorax and non-thorax region detection. All networks were trained using 12866 images and validate the performance using 5514 images. Simulation results showed that DCNN 2 and DCNN 3 were able to classify the thorax and non-thorax regions with good performance. The most efficient network is the DCNN with five-layer structure (DCNN 2). This DCNN model achieved an accuracy of 99.42% with moderate duration of training time.**

***Index Terms*—Deep Learning, Thorax, Non-Thorax, CT Scan Images, Lung Cancer, Classification**

## I. INTRODUCTION

LUNG CANCER is one of the main causes of cancer death in the U.S and worldwide [1]. Based on the studies from [2], cancer is the second leading cause of death in the world and contributed to 8.8 million deaths in 2015.

This manuscript is submitted on 16th May 2020 and accepted on 5th October 2020. Mohd Firdaus Abdullah, Siti Noraini Sulaiman, Muhammad Khusairi Osman and Iza Sazanita Isa are with the Faculty of Electrical Engineering, Universiti Teknologi MARA, 40450 Shah Alam, Selangor (email: firdausabdullah84@gmail.com).

Noor Khairiah A. Karim is from University of Malaya and Ibrahim Lutfi Shuaib is with Universiti Sains Malaysia.



In Malaysia, cancer is the fourth leading cause of death, accounting for 12.6% of all deaths in government hospitals and 26.7% in private hospitals [2]. Moreover, according to the latest World Health Organisation report released in April 2011, in Malaysia, the number one cause of death among men is lung cancer[4].

The human body is made up of cells. Each cell is often divided by its DNA (by genetic order) to form a tissue. When cells begin to divide uncontrollably out of the order in the lungs, the tumour is generated. The lungs are located in the chest on both sides of the heart in the ribs. The lungs are a pair of spongy, air-filled organs located on either side of the chest. Lung cancer is tumour that grows up fast and has the capability to spread or invade other organs [5]. The addiction to cigarette smoking, carcinogenic environments such as radioactive gas, and air pollution are the main factors of lung cancer. In addition, genetic factors also contribute to the cause of lung cancer [3].

According to Khin and Aung [6], the progression of lung cancer disease can be divided into four stages. The classifications are as follows; stage I is when the cancer is confined to the lung. The cancer is confined to the chest in stage II and III, but when the tumour grows larger and more invasive, the tumour is classified as stage III. Stage IV is when the cancer spreads from the chest to other parts of the body. There are two major types of lung cancer i.e. Small Cell Lung Cancer (SCLC) and Non-Small Cell Lung Cancer (NSCLC) [7].

Detection of lung cancer can be done in several ways, such as using computed tomography (CT) and radiography [5][8]. All these methods take a lot of resources in terms of time and money. The diagnosis and treatment of lung cancer are dependent on the type of lung cancer. Based on randomised controlled trials (RCTs) reported in the 1980s and 1990s, low-dose multidetector computed tomography (LDCT) of the chest has been intensively investigated in the last two decades [9]. Chest CT is more sensitive than chest radiography for early detection of lung cancers presenting as small, non-calcified, solitary pulmonary nodules. CT is the most reliable method for early detection of the cancer, and this modality is mostly used

in treatment method e.g. radiotherapy. Besides, CT has good detection of classification, low cost, short imaging time and widespread availability. Using CT scan, several types of tissues such as lung, bone, soft tissues, and blood vessels can be shown with great clarity, which cannot be seen in conventional radiographs [10].

Recently, the development of intelligent screening and detection system of the lung cancer using deep convolutional neural network (DCNN) shows an increasing trend among researchers [11][12][13][14]. DCNN is the most commonly used class of deep neural network learning algorithms for analysing visual imagery. DCNN involves very little pre-processing as it learns the image features that in traditional algorithms were hand-engineered. This independence from human effort and prior knowledge in complex feature design is a major advantage. DCNN is part of fundamental problems in computer vision which is the image classifications, that can be described as the task of categorising image into one of several predefined categories. It forms the basis for other computer vision functions such as location, segmentation and detection [6]. This task is considered by human copy for an automated system, and it is much more challenging. Some of the problems encountered include variations in perspectives depending on the objects and the class variance of many objects [7].

Based on previous studies, the most common way to detect lung cancer is by using CT image. CT has already become a necessity for humans in medical imaging throughout the world. The CT image is used to record images and for the radiologists to perform diagnosis. Based on CT scan image, the image will detect the overall parts of the body that include thorax and non-thorax parts. There are many slices that need to be evaluated and radiologists have to evaluate non-thorax as well. Therefore, there is a need to separate slices of thorax and non-thorax to automatically identify the correct region for further analysis. To the best of the authors' knowledge, no study has attempted to detect thorax and non-thorax slices from CT scan images prior to the process of lung cancer detection, which is the gap that this paper attempts to address by employing deep learning method. This study proposes an intelligent, fast and accurate method for thorax and non-thorax detection using DCNN. The proposed method was developed using the MATLAB to identify the thorax and non-thorax regions. Section II consists of the related work for lung cancer disease, computed tomography (CT) scan, and deep convolutional neural network. Section III includes the research methodology, which involve the ethical approval and data collection, image classification and performance evaluation. Meanwhile, Section IV consists of the results and discussion that highlight the data collection and image classification using DCNN. The final part is the conclusion for the overall results.

## II. Related Work

### A. Lung Cancer Disease

The main cause of lung cancer is cigarette smoking addiction [15], [16], [17] carcinogenic environment such as radioactive gas as well as air pollution. In addition, genetic factors also contribute to lung cancer. Lung cancer can develop gradually over a short period of time. Symptoms can vary depending on the location of the nodule [18]. Lung cancer grows and compresses the other structures in the thorax and prevents part of the lung from functioning normally. The incidence of cancer in Malaysia, from 2007 to 2011 in men was 86.9 and in women, it was 99.3 per 100,000 population. Cancer puts a huge economic burden on the patients, families and communities they live in. In addition to financial costs, cancer has important psychosocial effects on patients and their families. Based on the analysis that has been conducted among Malaysians [2], a total of 72884 cases were analysed which consisted of 64302 of solid cancers, and 8582 of haematological malignancies. From the total cases, lung cancer was found to be the second highest of cancers, with 11.22%, which is the number one cause of deaths among men.

There are two kinds of tumour, benign tumour and malignant tumour. Benign tumour is a tumour that do not invade surrounding tissue or spread throughout the body. While, malignant tumour is a tumour that can invade surrounding tissues or spread throughout the body. There are two types of lung cancer, in the lung cancer diseases, which are small cell lung cancer (SCLC) and non-small cell lung cancer (NSCLC). Generally, lung cancer is of two types:

1. Small Cell Lung Cancer (SCLC)

SCLC cancer usually grows faster than non-small cells, but is more likely to respond to chemotherapy. Small cell cancers are divided into "limited levels" (generally limited to the chest) and "extensive stages" (cancer that has spread beyond the chest) [5][10].

2. Non-Small Cell Lung Cancer (NSCLC)

NSCLC constitutes 75%-80% of lung cancers. More than 70% of non-small cell lung cancers are in stage III and IV. There are three types of NSCLC lung cancer. They respond in similar ways, and respond to treatment differently compared to SCLC [5][10].

a) Adenocarcinoma:

The most common type of NSCLC is Adenocarcinoma and it is the most common form of lung cancer in women. Like other forms of lung cancer, adenocarcinoma can spread to other parts of the body and usually, it appears on the outer edge of the lungs in the mucous glands that cover the airways.

b) Squamous Cell Carcinoma:

Squamous cell carcinoma is the most common lung cancer in men that usually appears in the larger respiratory tract. Squamous cell carcinoma is a relatively slow cancer compared to other NSCLCs.

c) Large Cell Carcinoma:

Large cell carcinomas occur more rarely and have larger cells compared to other NSCLCs. They normally appear in the smaller respiratory tract and can spread faster. Large cell carcinomas are diagnosed after other types of lung cancer are eliminated. They tend to grow quickly and spread at a much earlier stage than other non-small cell lung cancers.

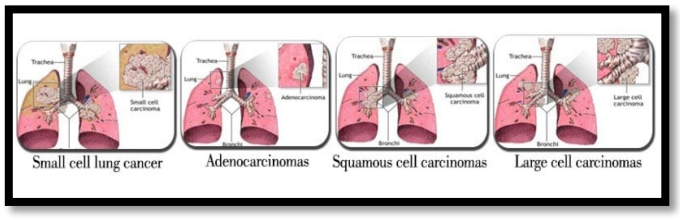



Figure 1: The difference between small cell lung cancer, adenocarcinomas, squamous cell carcinomas and large cell carcinomas. Courtesy of [15]

### *B. Computed Tomography (CT) Scan*

Prior to any treatment, lung cancer patients will undergo a doctor's diagnosis to determine the location, shape and size of the tumour using imaging modalities. The imaging modalities include computed tomography (CT) scan and magnetic resonance imaging (MRI). MRI is a type of scan that uses strong magnetic fields and radio waves to produce detailed images of the inside of the body. An MRI scanner is a large tube that contains powerful magnets that need to lie inside the tube during the scan. It is used to examine almost any part of the body, including the brain and spinal cord, bones and joints, breasts, heart and blood vessels and internal organs such as liver, womb, or prostate gland. According to Isa et al. [19], MRI is a very effective but non-invasive medical imaging technique for clinical diagnosis and for monitoring neurological abnormalities. In addition, they also proposed a new technique for cavity imaging on MRI images for the cerebrovascular disease [20].

Computed tomography (CT) is the name given to a diagnostic imaging procedure where anatomical information is digitally reconstructed from X-ray transmission data obtained by scanning areas from multiple directions in the same plane to visualise the information in that plane[21] . Tun et al. [6] reported CT scan images are suitable for lung cancer diagnosis. Ignatious et al. [16] used CT scan imaging to provide more information about the type and extent of disease. By using image processing techniques within the CT scan images, the disease can be properly identified. According to Makaju et al. [17], CT scan is the best imaging technique for the diagnosis of lung cancer as it can reveal any suspected or unsuspected lung cancer nodules.

### *C. Deep Convolutional Neural Network for Computed Tomography (CT) Scan Images*

There are several researches about lung cancer detection using different methods of deep neural networks [13][22][23]. Deep learning is a machine learning technique that teaches computers to do what comes naturally to humans: learning by example. This is a new method in biomedical engineering that has been started around 2017 for lung cancer detection. In the past few years, deep learning (DL) is a new machine learning technique using neural network architecture that learns the features directly from the data training. The term "deep" refers to the number of layers in the network as the use of more layers will deepen the network. For the past several years, some researchers introduced these machine learning for this DR screening technique method known as Convolution Neural Network (CNN). Comparing to previous machine learning, DL helps to reduce engineering effort in order to perform manual feature extraction, since the features are learned automatically by CNN. The time needed to manually design filter and extract feature can be concluded as "the time used on annotating image vs training the CNN to almost negligible". DL takes a longer time during training compared to traditional training (ANN, KNN, SVM,). Once the training is complete, the testing time efficiency is very fast. However, deep learning has its own challenge as it requires large datasets and high- performance GPUs to train the datasets. The more input of dataset to be trained, the higher accuracy on CNN is able to be developed. Among the main challenges of CNN are the inclusion of low variation among classes in several datasets , erroneous data labelling by the expert, the existence of noise, inaccuracy of sensor equipment, overlapping of plants, crop occlusions and low resolution.

Recently, the deep neural network has been developed as a new method for lung cancer detection since 2017 [14][24][23][25]. Shaziya et al. [26], proposed the U-Net method, which is a special kind of convolutional network designed for biomedical image analysis. In the present study, U-Net ConvNet was developed to be used to segment lung regions. The accuracy obtained for lung segmentation using U-Net is 0.9678. However, this system does not classify the cancer as benign or malignant. Yan et al. [27] categorised the collection of lesions using an unsupervised deep mining scheme to generate clustered pseudo lesion labels. They adopted a regional-CNN method to detect lesions of multiple categories, regardless of missing annotations. The benefit of this approach is that it is able to build a large-scale Radiology lesion image database for lung cancer detection. P. Mohamed Shakeel et. al [28] applied deep learning instantaneously trained neural network for predicting lung cancer. It involved with the improvement of the quality of lung image and diagnosis of lung cancer by reducing misclassification. The system ensures that 98.42% of accuracy with minimum classification error of 0.038.

Based on the systems developed by previous researchers using DCNN, there are room for improvement can be done therefore a bestter method for the cancer detection is hence proposed in this research so that the accuracy can be improved, and the lung can be classified as the thorax or non-thorax region using CT scan images.

## III. METHODOLOGY

There are three major parts of this project which are i) ethical approval and data collection, ii) image classification of thorax and non-thorax using DCNN and iii) performance evaluation. The first part of this study is ethical approval and data collection of the sample collected from the Advanced Medical and Dental Institute (AMDI), Universiti Sains Malaysia (USM) database. The next part is image classification using DCNN, and the final part is performance analysis that was used to analyse the thorax region for lung cancer detection. Figure 2 shows the block diagram of the overall methodology. The details of the methodology are briefly described in the subsections below.

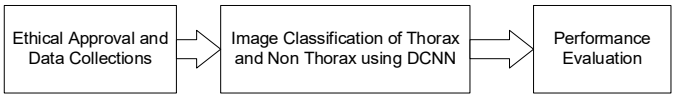



Figure 2: Block Diagram of the Overall Methodology

### *A. Ethical Approval and Data Collection*

This stage also involved the process of application for ethical approval from the Human Research Ethics Committee of USM (JEPeM) under the School of Medical Sciences, USM, IPPT, Bertam, Pulau Pinang. This ethical approval is a provision to conduct clinical research on a human since it uses CT scanning on human subjects. Basically, the data from 30 subjects with underlying lung cancer were collected in retrospective from 2010 until 2020. Patients scanned at the Imaging Unit, Advanced Medical and Dental Institute (AMDI), USM with underlying lung malignancy were included as the samples for this study. Images from Picture Archiving and Communication systems (PACS) at AMDI that show evidence of nodule and tumor but had entirely normal CT Scans study (reported by a radiologist as having no nodule or any other imaging evidence of lung cancer) will also be included as a control group subjects. To comply with ethical regulation that has been used, the data is de-identified anonymized before being transfered to the public domain.

Based on the CT scan image, the image will detect the overall parts of the body that include thorax and non-thorax parts. From one patient, the images were taken 125mm and 1mm slices CT scanner that consisted of 1-281 images and 1-882 images respectively. The number of slices determines the distance between one scanned image of the body to the next. If there are more slices, the distance between each slice is smaller, but it can provide more information about the images. Figure 3 shows different angles of CT lung cancer images from one patient using soft tissues density.

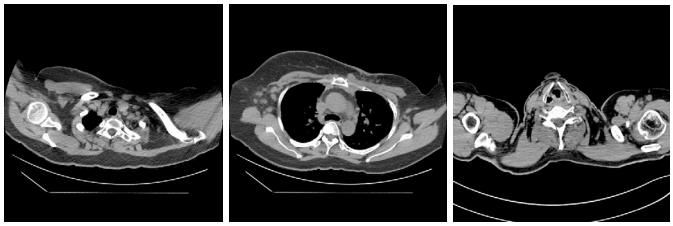


Figure 3. Different angles of CT lung cancer images.

### *B. Image Classification of Thorax and Non-Thorax using DCNN*

This is the main part of this work presented in this paper. Corresponding with the objective, this method focused on the classification of the range of thorax and non-thorax from CT scan images. The classification was done by using DCNN. Each step in the proposed image classification of thorax and non-thorax using DCNN procedure is discussed in detail in the following Figure 4.

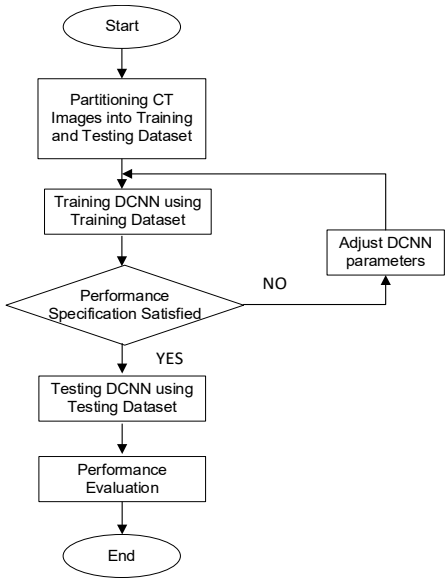



Figure 4: Image Classification of Thorax and Non-Thorax using DCNN

To develop CNN network architecture, three (3) convolution layers were designed. The rectified linear unit (ReLU) activate function was used in this research to avoid saturation and allowed it to compute faster than sigmoid. Convolutional layers were sometimes followed by a down-sampling operation that reduced the spatial size of the feature map and removed redundant spatial information. One way of down-sampling was using a max pooling that made it possible to increase the number of filters in deeper convolutional layers without increasing the required amount of computation per layer. Fully-connected (FC) layer is a layer in which the neurons connect to all the neurons in the preceding layer. This layer combines all the features learned by the previous layers across the image to identify the larger patterns. The last fully-connected layer combines the features to classify the images. Therefore, the number of DCNN outputs in the last fully connected layer is equal to the number of classes in the target data. In this network, the output size was 4, corresponding to the 4 classes which are lower thorax, middle thorax, upper thorax and non-thorax region. The softmax activated function normalised output result of FC would determine the classification probabilities by the classification layer. Figure 5 shows the DCNN training process structure for thorax and non-thorax region. Thorax region consists of lower thorax, middle thorax and upper thorax.

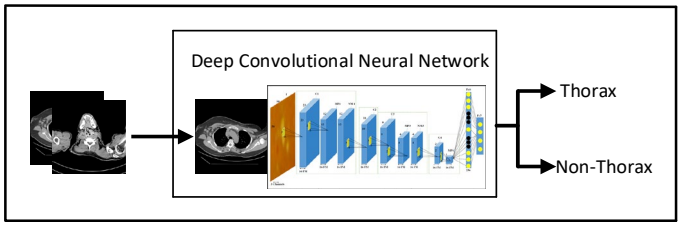



Figure 5: DCNN training process structure

To specify training option for the DCNN in MATLAB, the default parameters were set up as shown in Table I.

TABLE I
DCNN SETUP DETAILS

| CNN Parameter | Default Value |
|---|---|
| Learning Rate | 0.001 |
| MaxEpochs | 6 |
| Validation Frequency | 128 iterations |
| Mini Batch Size | 100 |
| Convolutional layer | 1/2/3 |
| GPU | GeForce RTX 2070 |
| Verbose | False |
| Activation Function | ReLU, Softmax |

In a convolutional neural network, there are 3 main parameters that need to be tweaked to modify the behavior of a convolutional layer. These parameters are filter size, stride and zero padding. The size of the output feature map generated depends on these 3 important parameters. Size of the filters play an important role in finding the key features. It was difficult to select an optimal size of the filter because its depends on the application. If a larger size kernel was used, it can overlook the features and could skip the essential details in the images whereas a smaller size kernel could provide more information leading to more confusion. Thus there was a need to determine the most suitable size of the kernel/filter. Stride can controls the number of steps that will move the filter over the input image.. The value of the stride can controls the size of the output volume generated by the convolutional layer. When the bigger the stride was set, it will reduced the output volume size. Next important parameter is the zero padding. Zero padding refers to padding the input volume with zeros around the border. The zero padding used to control the spatial size of the output volume. The output size of DCNN layer is calculated using the following equation:

$$O = \frac{W-K+2P}{S} + 1 \quad (1)$$

where O is the output height/length, W is the input height/length, K is the filter size, P is the padding, and S is the stride. Table II,III and IV shows network structure using learning rate=0.001 and dropout with 0.7 for DCNN 1, DCNN2 and DCNN 3 respectively. Three different network structure architecture was developed to find the best accuracy for the system. In Figure 6,7 and 8 shows the convolution neural network architecture design for DCNN 1, DCNN 2 and DCNN 3 respectively based on the network architecture that was set based on Table II, III and IV.

TABLE II
NETWORK STRUCTURE ARCHITECTURE FOR DCNN 1
(LEARNING RATE=0.001, DROPOUT WITH 0.7)

| Layer | DCNN 1 | | | |
|---|---|---|---|---|
| | Kernel | Stride | Pad | No. Output |
| conv1 | 3 | 1 | 1 | 8 |
| ReLu | - | - | - | - |
| pool1 | 2 | 2 | 0 | 8 |
| fc | - | - | - | 4 |

TABLE III
NETWORK STRUCTURE ARCHITECTURE FOR DCNN 2
(LEARNING RATE=0.001, DROPOUT WITH 0.7)

| Layer | DCNN 2 | | | |
|---|---|---|---|---|
| | Kernel | Stride | Pad | No. Output |
| conv1 | 3 | 1 | 1 | 8 |
| ReLu | - | - | - | - |
| pool1 | 2 | 2 | 0 | 8 |
| conv2 | 3 | 1 | 1 | 16 |
| ReLu | - | - | - | - |
| pool2 | 2 | 2 | 0 | 16 |
| fc | - | - | - | 4 |

TABLE IV
NETWORK STRUCTURE ARCHITECTURE FOR DCNN 3
(LEARNING RATE=0.001, DROPOUT WITH 0.7)

| Layer | DCNN 3 | | | |
|---|---|---|---|---|
| | Kernel | Stride | Pad | No. Output |
| conv1 | 3 | 1 | 1 | 8 |
| ReLu | - | - | - | - |
| pool1 | 2 | 2 | 0 | 8 |
| conv2 | 3 | 1 | 1 | 16 |
| ReLu | - | - | - | - |
| pool2 | 2 | 2 | 0 | 16 |
| conv3 | 3 | 1 | 1 | 32 |
| ReLu | - | - | - | - |
| pool3 | 2 | 2 | 2 | 32 |
| fc | - | - | - | 4 |

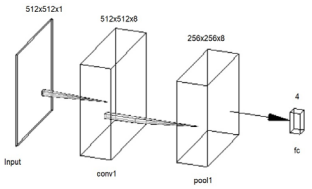



Figure 6: Convolution neural network architecture design for DCNN 1. CONV: convolution, pool: Max Pooling FC: fully connected layer

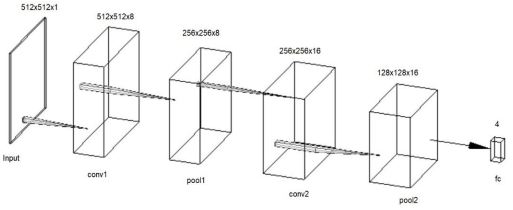



Figure 7: Convolution neural network architecture design for DCNN 2. CONV: convolution, pool: Max Pooling FC: fully connected layer

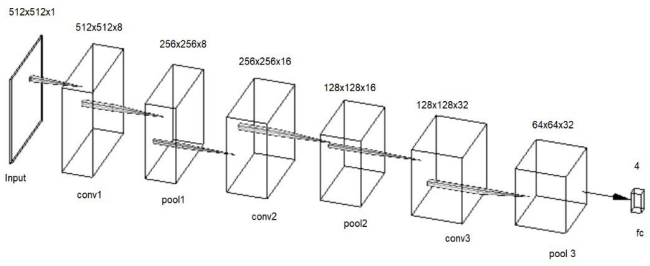



Figure 8: Convolution neural network architecture design for DCNN 3. CONV: convolution, pool: Max Pooling FC: fully connected layer

### C. Performance Evaluation

Initial testing and validation were carried out to test and validate the formulated method and to assess its performance evaluation. The evaluation were conducted both in qualitative and quantitative manners. Minor modifications and improvements may be required at this stage based on the recommendation from the radiologist to further improve the implementation of this method and to justify the proposed technique. In this study, the performance of the system was evaluated based on accuracy. Accuracy of a clinical test refers to how correct a diagnostic test identifies and excludes a given condition. This performance validation is validated based on the following equation:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

*TP: True Positive, TN: True Negative, FP: False Positive, FN: False Negative

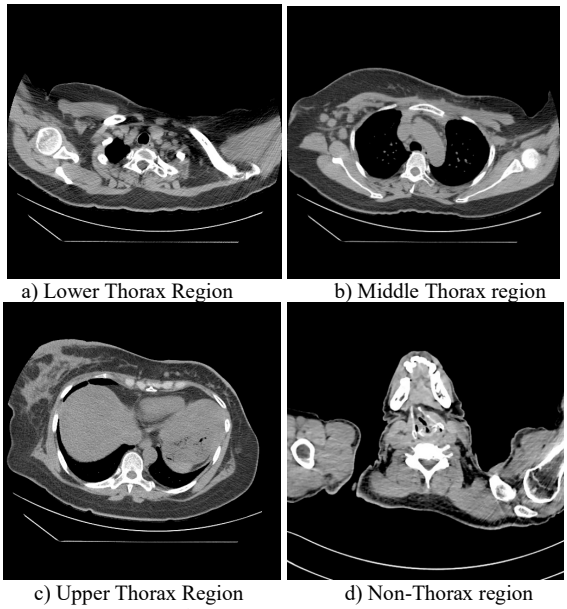
## IV. Results And Discussion

### A. Data Collection

Total images collected from 30 subjects with underlying lung cancer were 18,380 images altogether. From the total of these images, they were grouped into two groups, which were thorax and non-thorax, with 6541 images and 11839 images respectively. Then, the data were divided into training and validation data sets. 12866 images or 70% of the total images were used for training while 5514 images were used for validation as tabulated in Table V. Figure 9 shows an example of CT scan images for thorax and non-thorax regions.

TABLE V
Description of Data Set for Thorax and Non-thorax Classification on DCNN Model

| | Thorax Region | | | Non-Thorax Region | Total |
|---|---|---|---|---|---|
| | Lower | Middle | Upper | | |
| Training | 421 | 3193 | 965 | 8287 | 12866 |
| Testing | 181 | 1367 | 413 | 3552 | 5514 |
| Total | | | | | 18380 |



a) Lower Thorax Region b) Middle Thorax region

c) Upper Thorax Region d) Non-Thorax region

Figure 9: CT scan Images

### B. Classification of Thorax and Non-Thorax using DCNN

Table VI records the validation performance of different iteration numbers with minibatch size = 100. From Table VI, it can be observed that the performance gradually improved along with the number of iteration. However, the performance shows degradation after a certain point, which is at 896 iterations. This is because, training for too many iterations may result in overtraining/overfitting problems. From the results, the best 768 iterations were chosen for the next analysis.

TABLE VI
Validation Performance of Different Iteration Numbers with Minibatch 100

| Iterations | Accuracy (%) |
|---|---|
| | Minibatch (100) |
| 128 | 98.01 |
| 256 | 98.2 |
| 384 | 98.7 |
| 512 | 99.11 |
| 640 | 99.17 |
| 768 | 99.42 |
| 896 | 99.27 |

Table VII consists of the results after the data set was implemented on the DCNN model using different layers. The best iterations from the previous simulations were chosen and this analysis was conducted to find the best layer for the DCNN model when the learning rate was set to 0.001 and dropout=0.7. A dropout layer randomly sets input elements to zero with a given probability. This operation effectively changed the underlying network architecture between iterations and helped prevent the network from overfitting. The table shows the classification performance such as training accuracy and time taken to train the input image. All of the results are based on the variable parameters set earlier in Table I using different network structure architecture as in Table II,III and IV.

TABLE VII
The Results For data Implementation on DCNN Model

| Layer | Dropout | Training Time | Accuracy |
|---|---|---|---|
| DCNN 1 | 0.7 | 10min 53sec | 64.42% |
| DCNN 2 | 0.7 | 13min 20sec | 99.42% |
| DCNN 3 | 0.7 | 13min 38sec | 99.13% |

From Table VII, the DCNN2 layer achieved the best accuracy of 99.42% as set in Table III for Convolution neural network architecture design as in Figure 7. Based on the graph for DCNN 2 layers illustrated in Figure 10, a graph showed the training and validation accuracy for CT scan images for lung cancer data. The black line and blue graph represent training accuracy and validation accuracy. Based on the graph, it can also be observed that the validation accuracy increases promptly in the earlier iterations but shows a slower pace of increment after 512 iterations.

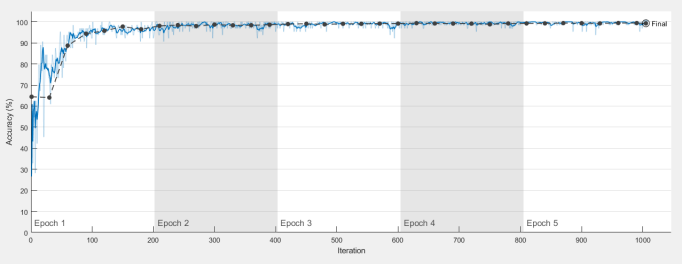



Figure 10: Training and validation accuracy against number of epoch for DCNN 2.

Based on the graph illustrated in Figure 11, the training and validation loss for CT scan images for lung cancer data. The black line and red graph represent training loss and validation loss. Based on the graph, it can be concluded that the training process is limited until 2 epoch, and then it would be constant too. This showed that the training process was decreasing in terms of the number of its loss. The losses were found to be constant at epoch 2. This result is crucial to prevent overfitting the data with the networks.

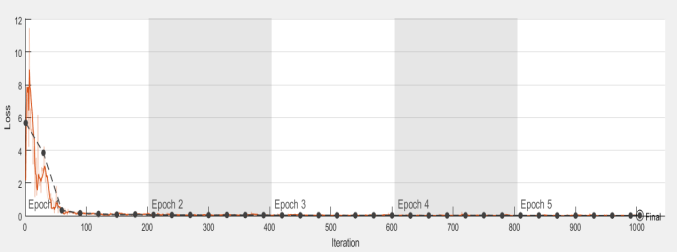



Figure 11: Training and validation loss against the number of epoch for DCNN 2.

## V. CONCLUSIONS

This study was successfully carried out for the designation of thorax and non-thorax regions of CT scan images for lung cancer detection using deep learning method. The validation performance of different iteration numbers with minibatch size = 100 was performed to find the best iterations numbers for the DCNN models. All networks were trained using 12866 images and validate the performance using 5514 images. From the results, the best iterations from the previous simulations were chosen, which consisted of 768 iterations and analysis was done to find the best DCNN model when the learning rate was set to 0.001 and dropout=0.7. Simulation results showed that DCNN 2 and DCNN 3 were able to classify the thorax and non-thorax regions with good performance. The most efficient network is the DCNN with five-layer structure (DCNN 2). This DCNN model achieved an accuracy of 99.42% with moderate duration of training time. The results of the experiment found clear support for the next stage of this research. With the excellent result obtained here, future work is to apply the outcome from this work i.e. used the identified thorax region only to classify the tumor for lung cancer detection purposes. This may be considered a promising aspect in realizing an intelligent, fast and accurate method for lung cancer detection.

## ACKNOWLEDGMENT

This research work was financially supported by the Ministry of Higher Education Grant Scheme (FRGS) " Formulation of A New Watershed-based Segmentation Method for Features Extraction of Lung Cancer Nodule in CT-scan Images" (Ref: FRGS/1/2019/TK04/UITM/02/15) and ethics from Universiti Sains Malaysia (USM/JEPeM/19040231). The authors are grateful to Research Group Advanced Rehabilitation Engineering in Diagnostic and Monitoring (AREDiM) and Advanced Control System and Computing Research Group (ACSCRG) for their contribution that led to the completion of this study.

## REFERENCES

[1] P. Su, J. Yang, K. Lu, N. Yu, S. T. Wong, and Z. Xue, “A fast CT and CT-fluoroscopy registration algorithm with respiratory motion compensation for image-guided lung intervention,” *IEEE Trans. Biomed. Eng.*, 2013, doi: 10.1109/TBME.2013.2245895.

[2] A. A. M. Asmayani Khalib, *Malaysian Study on Cancer Survival (MySCan)*, vol. 4. National Cancer Institute, Health Education Division, 2018.

[3] Y. F. Riti, H. A. Nugroho, S. Wibirama, B. Windarta, and L. Choridah, “Feature extraction for lesion margin characteristic classification from CT Scan lungs image,” in *Proceedings - 2016 1st International Conference on Information Technology, Information Systems and Electrical Engineering, ICITISEE 2016*, 2016, doi: 10.1109/ICITISEE.2016.7803047.

[4] M. Assefa, I. Faye, A. S. Malik, and M. Shoaib, “Lung nodule detection using multi-resolution analysis,” in *2013 ICME International Conference on Complex Medical Engineering, CME 2013*, 2013, doi: 10.1109/ICCME.2013.6548290.

[5] S. Sindhu Priya and B. Ramamurthy, “Lung cancer detection using image processing techniques,” *Res. J. Pharm. Technol.*, 2018, doi: 10.5958/0974-360X.2018.00379.7.

[6] K. M. M. Tun and A. S. Khaing, “Feature Extraction and Classification of Lung Cancer Nodule using Image Processing Techniques,” *Int. J. Eng. Res. Technol.*, vol. 3, no. 3, pp. 2204–2210, 2014.

[7] A. Tartar, N. Kilic, and A. Akan, “Classification of pulmonary nodules by using hybrid features,” *Comput. Math. Methods Med.*, 2013, doi: 10.1155/2013/148363.

[8] A. K. Tiwari, “Prediction of Lung Cancer Using Image Processing Techniques: A Review,” *Adv. Comput. Intell. An Int. J.*, vol. 3, no. 1, pp. 1–9, 2016, doi: 10.5121/acii.2016.3101.

[9] J. Vansteenkiste, C. Dooms, C. Mascaux, and K. Nackaerts, “Screening and early-detection of lung cancer,” *Ann. Oncol.*, vol. 23, no. SUPPL. 10, pp. x320–x327, 2012, doi: 10.1093/annonc/mds303.

[10] K. Varalakshmi, “Classification of Lung Cancer Nodules using a Hybrid Approach Percentage %,” *J. Emerg. Trends Comput. Inf. Sci.*, vol. 4, no. 1, pp. 63–68, 2013.

[11] H. Wang, “Deep Convolutional Neural Networks for Lunc Cancer Detector,” no. November, pp. 1–9, 2009.

[12] O. Ronneberger, P. Fischer, and T. Brox, “U-net: Convolutional networks for biomedical image segmentation,” *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 9351, pp. 234–241, 2015, doi: 10.1007/978-3-319-24574-4_28.

[13] M. Z. Alom, C. Yakopcic, M. Hasan, T. M. Taha, and V. K. Asari, “Recurrent residual U-Net for medical image segmentation,” *J. Med. Imaging*, vol. 6, no. 01, p. 1, 2019, doi: 10.1117/1.jmi.6.1.014006.

[14] S. Bhatia, Y. Sinha, and L. Goel, “Lung cancer detection: A deep learning approach,” *Adv. Intell. Syst. Comput.*, vol. 817, pp. 699–705, 2019, doi: 10.1007/978-981-13-1595-4_55.

[15] T. S. Roy, N. Sirohi, and A. Patle, “Classification of lung image and nodule detection using fuzzy inference system,” *Int. Conf. Comput. Commun. Autom. ICCCA 2015*, pp. 1204–1207, 2015, doi: 10.1109/CCAA.2015.7148560.

[16] S. Ignatious and R. Joseph, “Computer aided lung cancer detection system,” *Glob. Conf. Commun. Technol. GCCT 2015*, no. Gcct, pp. 555–558, 2015, doi: 10.1109/GCCT.2015.7342723.

[17] S. Makaju, P. W. C. Prasad, A. Alsadoon, A. K. Singh, and A. Elchouemi, "Lung Cancer Detection using CT Scan Images," *Procedia Comput. Sci.*, vol. 125, no. 2009, pp. 107–114, 2018, doi: 10.1016/j.procs.2017.12.016.

[18] S. Moreno, M. Bonfante, E. Zurek, and H. S. Juan, "Study of medical image processing techniques applied to lung cancer," *Iber. Conf. Inf. Syst. Technol. Cist.*, vol. 2019-June, no. June, pp. 1–6, 2019, doi: 10.23919/CISTI.2019.8760888.

[19] A. S. Tajudin *et al.*, "An improved watershed segmentation technique for microbleeds detection in MRI images," *2017 Int. Conf. Electr. Electron. Syst. Eng. ICEESE 2017*, vol. 2018-Janua, pp. 11–16, 2018, doi: 10.1109/ICEESE.2017.8298394.

[20] A. S. Tajudin, I. S. Isa, Z. H. C. Soh, S. N. Sulaiman, N. K. A. Karim, and I. L. Shuaib, "A new technique of flow voids segmentation on MRI image for cerebrovascular disease," *ICSET 2018 - 2018 IEEE 8th Int. Conf. Syst. Eng. Technol. Proc.*, no. October, pp. 144–150, 2019, doi: 10.1109/ICSEngT.2018.8606365.

[21] E. Adetiba and O. O. Olugbara, "Lung cancer prediction using neural network ensemble with histogram of oriented gradient genomic features," *Sci. World J.*, vol. 2015, 2015, doi: 10.1155/2015/786013.

[22] M. Z. Alom, M. Hasan, C. Yakopcic, T. M. Taha, and V. K. Asari, "Recurrent Residual Convolutional Neural Network based on U-Net (R2U-Net) for Medical Image Segmentation," 2018.

[23] A. M. Rossetto and W. Zhou, "Deep Learning for Categorization of Lung Cancer CT Images," *Proc. - 2017 IEEE 2nd Int. Conf. Connect. Heal. Appl. Syst. Eng. Technol. CHASE 2017*, pp. 272–273, 2017, doi: 10.1109/CHASE.2017.98.

[24] W. Alakwaa, M. Nassef, and A. Badr, "Lung Cancer Detection and Classification with 3D Convolutional Neural Network (3D-CNN)," *Int. J. Adv. Comput. Sci. Appl.*, vol. 8, no. 8, 2017, doi: 10.14569/ijacsa.2017.080853.

[25] G. Jakimovski and D. Davcev, "Using double convolution Neural Network for lung cancer stage detection," *Appl. Sci.*, vol. 9, no. 3, 2019, doi: 10.3390/app9030427.

[26] H. Shaziya, K. Shyamala, and R. Zaheer, "Automatic Lung Segmentation on Thoracic CT Scans Using U-Net Convolutional Network," *Proc. 2018 IEEE Int. Conf. Commun. Signal Process. ICCSP 2018*, pp. 643–647, 2018, doi: 10.1109/ICCSP.2018.8524484.

[27] K. Yan, X. Wang, L. Lu, and R. M. Summers, "DeepLesion: Automated Deep Mining, Categorization and Detection of Significant Radiology Image Findings using Large-Scale Clinical Lesion Annotations," pp. 1–9, 2017.

[28] P. M. Shakeel, M. A. Burhanuddin, and M. I. Desa, "Lung cancer detection from CT image using improved profuse clustering and deep learning instantaneously trained neural networks," *Meas. J. Int. Meas. Confed.*, vol. 145, pp. 702–712, 2019, doi: 10.1016/j.measurement.2019.05.027.

**Mohd Firdaus Abdullah** received his MSc Degree in Science (Electrical Engineering) from Faculty of Electrical Engineering, Universiti Teknologi MARA, Malaysia in 2012. Currently, he is doing his PhD at Universiti Teknologi MARA, Malaysia. His research focus is on the image processing of medical imaging, specifically in analysing CT scan images and deep learning.

**Siti Noraini Sulaiman** received PhD degree in image processing from School of Electrical and Electronics Engineering, Universiti Sains Malaysia in 2012. She is currently an Associate Professor at Faculty of Electrical Engineering, Universiti Teknologi MARA, Malaysia. She is now attached as the chair of Advanced Rehabilitation Engineering in Diagnostic and Monitoring (AREDiM) and the deputy chair of Advanced Control System and Computing Research Group (ACSCRG), Faculty of Electrical Engineering, Universiti Teknologi MARA, Penang Branch Campus in Permatang Pauh, Penang, Malaysia. Her main research interest is biomedical engineering focusing on image filtering, image clustering and algorithm for image processing

**Muhammad Khusairi Osman** obtained his B.Eng degree in Electrical and Electronic Engineering in 2000 and MSc in Electrical and Electronic Engineering in 2004 from Universiti Sains Malaysia. In 2014, he obtained his Ph.D. in medical electronic engineering from Universiti Malaysia Perlis (UniMAP), Malaysia. He is currently a senior lecturer at Faculty of Electrical Engineering, Universiti Teknologi MARA (UiTM), Malaysia. His research interest is in image processing, pattern recognition and artificial intelligence.

**Noor Khairiah A. Karim** received the Bachelor Degree in Medicine, Bachelor Degree in Surgery (MBBS) and Master of Radiology (MRad) from the University of Malaya, Malaysia. She then obtained her Fellowship in Cardiac Imaging from the National Heart Center Singapore. She is currently a Senior Medical Lecturer of the Regenerative Medicine Cluster, and a Consultant Radiologist at the Advanced Medical and Dental Institute, Universiti Sains Malaysia. Her current research areas include medical image processing and analysis with special interest in cardiac, breast and brain imaging.

**Iza Sazanita Isa** received MSc Degree in Electronics System Design Engineering from School of Electrical and Electronics Engineering, Universiti Sains Malaysia in 2009. She received her PhD Degree from Universiti Teknologi MARA, Malaysia. Her research focus is on the image processing of medical imaging, particularly in the segmentation of MRI Images and deep learning.

**Ibrahim Lutfi Shuaib** received FRCR (UK) in 1992 and started his career as a medical lecturer in 1993 at Universiti Sains Malaysia, Health Campus, Kubang Kerian. He became an Associate Professor in 2000 and later in November, 2004, he was transferred to Advanced Medical and Dental Institute, USM, Penang. In 2007, he was appointed as a Professor. His main research interest is in musculoskeletal radiology, and in 1995, he had the opportunity to undergo training in musculoskeletal radiology in Austin Hospital, Melbourne, Australia. USM is proud to be a national referral centre for musculoskeletal and soft tissue oncology. Being part of the team, he was involved in several research projects to explore in early diagnosis, accurate staging and management of tumours. His other interest includes Health Informatics.