# Lung Tumor Image Segmentation from CT images using Deep Learning


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**2022**

# Lung Tumor Image Segmentation from CT images using Deep Learning

A Thesis submitted in partial fulfillment of requirement for the degree of

Master of Science

In

Biomedical Engineering

By

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Islamabad-Pakistan

2022

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# Dedicated to

*My parents, whose tremendous support and cooperation led me to this wonderful accomplishment.*

# ACKNOWLEDGMENTS

I am thankful to my Creator Allah Subhana-Watala to have guided me throughout this work at every step and for every new thought which You setup in my mind to improve it. Indeed, I could have done nothing without Your priceless help and guidance. Whosoever helped me throughout the course of my thesis, whether my parents or any other individual was Your will, so indeed none be worthy of praise but You.

I am profusely thankful to my beloved parents who raised me when I was not capable of walking and continued to support me throughout in every department of my life. I would like to thank my siblings, who stood by me and bore with me the many challenges that came with this work and offered their complete belief and support in every matter.

I would also like to express special thanks to my supervisor, Dr. Syed Omer Gilani for his tremendous support and cooperation. Each time I got stuck in something, he came up with the solution. Without his help I wouldn't have been able to complete my thesis. I appreciate his patience and guidance throughout the whole thesis. I would expend my gratitude to my GEC members Dr. Asim Waris, Dr. Mohsin Jamil and Umer Ansai for their presence and support.

My special thanks to my friend Abida Nazir for being with me in the long run, wherever life may take me. And my gratitude to Maria Qubtia, who inspired me with his faith to achieve more and be more. Finally, I would like to express my gratitude to all the individuals who have rendered valuable assistance to my study.

**- Zainab Riaz**

# CONTENTS

# LIST OF ACRONYM

| | |
|---|---|
| CT | Computer Tomography |
| MSD | Medical Segmentation Decathlon |
| NSCLC | Non-Small Cell Lung Cancer |
| TCIA | The Cancer Imaging Archive |
| SCLC | Small Cell Lung Cancer |
| ROI | Region of Interest |
| ML | Machine Learning |
| COPD | Chronic Obstructive Pulmonary Disease |
| WHO | World Health Organization |
| VOI | Volume of Interest |
| IARC | International Agency for Research on Cancers |
| RF | Random Forest |
| LDCT | Low Dose Computed Tomography |
| DLC | Deep Learning-based Classifier |
| LSE | Line Structure Enhancement |
| BSE | Blob-like Structure Enhancement |
| CNN | Convolutional Neural Network |
| CAD | Computer Aided Diagnosis |
| KNN | K-Nearest Neighbors |

| | |
|---|---|
| SVM | Support Vector Machine |
| LIDC | Lung Image Database Consortium |
| DSC | Dice Score Coefficient |
| GLCM | Grey Level Co-occurrence Matrix |
| TP | True Positives |
| MRI | Magnetic Resonance Imaging |
| FP | False Positive |
| FN | False Negatives |
| LSTM | Long Short-Term Memory |

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# ABSTRACT

Automated segmentation of lung tumor from CT scan images is an essential for analyzing the progression of the lung cancer as it is one of the most widespread disease in the world. Therefore, prompt detection of malignant tumor can hence increase the possibility of patients' survival and can help in decrease the mortality rate. In this regard, proper segmentation of suspicious lesions in computerized-tomography (CT) images is the primary step towards achieving completely automated diagnostic system for lung cancer detection. Therefore, transfer learning techniques outperform on tasks of semantic segmentation as it is an optimization that allows improved performance, saving training time and not demanding a lot of data. Models are trained on large ImageNet Datasets, and these pre-trained models are performed exceptionally well in comparison with network trained from scratch. UNET extensively used for biomedical image segmentation and have significantly improved state of the art performance. Objective of this paper is to develop an integrated architecture of two segmentation networks: MobileNetV2 and UNET, an efficient segmentation technique based on light weighted neural network developed by depth-wise separable convolutions. We trained our model on lung dataset (MSD Challenge 2018) provided by The Cancer Imaging Archive (TCIA). The suggested integrated architecture achieved dice score of 0.8793, recall of 0.8602 and precision of 0.9322 which are comparable to the results of current available techniques. Additionally, other segmentation algorithms require a lot of labeled data, while, our algorithm allows more efficient training and more generalizability to other medical image segmentation.

**CHAPTER 1**

# INTRODUCTION

# INTRODUCTION

Computer Tomography (CT) is considered as one of the best imaging modalities and it becomes standard modality for analyzing and assessing tumors in lungs. Accurate segmentation of cancerous nodules from CT scan images is very important as it provides necessary information which strongly associated with early diagnosis of the lung cancer, in result it becomes most successful treatment and enhances the possibilities of patients' survival [1]. Lung cancer falls into the most deadly cancers and malignant tumors characterized by uncontrolled growth of cells [2]. Usually, symptoms of lung cancer do not appear until it is already at an advanced stage [3]. Most common cancer that starts in lungs is carcinoma, whereas, lung cancer is classified histologically as small cell lung cancer (SCLC), non-small cell lung cancer (NSCLC), and common sub-types of non-small cell lung cancer (NSCLC) are adenocarcinoma, large-cell carcinoma and squamous cell carcinoma [4]. Small cell lung cancer (SCLC) develops in airways, however, progress more quickly and difficult to treat [5]. Non-small cell lung cancer (NSCLC) evolves slowly, remains disappointingly low and most importantly it depends on where it starts in lungs [6]. Lung carcinoma is the most prevalent form, diagnosed as malignant lung tumor which further can affect other organs of the body through the process of metastasis [7], [8].

At early stage, there are no prominent symptoms but eminent factors for the progression of this pathology include tobacco exposure, breathing in asbestos fibers [2], air pollution, exposure of radon gas, Long standing cough that become worse with time, Consistent breathlessness and family history. Cigarette smoke remains highest probability factor for the evolution of lung cancer [9]. Airway obstruction is a pervasive cause of danger for the progression of lung cancer, typically linked with chronic obstructive pulmonary disease (COPD) as well as emphysema. Detection of pulmonary nodules on time is a worth of attention, therefore, early treatment is mandatory to avoid its spreading to rest of the body and for clinical management as well [10].

## STATISTICS OF LUNG CANCER

According to survey of World Health Organization (WHO) in 2018, Cancer accounting for an estimated 9.6 million deaths, where lung cancer is responsible of 13% of entire deaths annually worldwide [11]. Therefore, WHO enhances awareness and promote education related to cancer in following fundamental sections such as early detection, diagnosis and treatment, control-prevention, and palliative care.

The International Agency for Research on Cancers (IARC) handed over a report about burden of cancer globally by approximating prevalence and fatality for 36 cancers in 93 countries [7]. Every year, The American Cancer's Society evaluates the number of new cases and deaths in the United States and collects most recent data on mortality and survival [12]. Prevalence rate of lung cancer in USA gets higher and higher with no time, and it is 2$^{nd}$ most dominant cause of cancer deaths in both men and women. In 2020, about 228,820 new cases of lung cancer were diagnosed, out of which 116,300 are men and 112,520 are women, however, almost 135,720 deaths are due to this fatal disease.

## DIAGNOSTIC TOOL AND IMAGING MODALITY

Computerized Tomography (CT) is a noninvasive technique that currently considered as the best diagnostic tool for the identification of small pulmonary nodules, employed by the radiologists for the analysis and evaluation of lung tumor, utilizes low dose xrays from multiple angles to screen lungs and provides more fine and detailed images of lungs in which it reveals an abnormal growth rate of lung nodules thus indicating malignancy [13]. Computed Tomography (CT) is a special type of medical imaging modalities that is intrusive in nature and it has prolonged imaging duration as well [14]. LDCT (Low Dose Computed Tomography) scan is frequently and widely recommended imaging modality that takes multiple cross sectional images of inside of the body which provides more information related to location of tumor, adversity of the cancer and cancerous lesions that can be distinguished from benign lesions using up to 90 percent less ionized radiations than a standard.

## DEEP LEARNING

Medical Segmentation Decathlon (MSD) is a platform to analyze and evaluate the development of deep learning models for generalizable 3D semantic segmentation. They provide huge amount of dataset of 3D CT scan images of lung cancer and corresponding annotated ground truths to public for evaluation of models' robustness. The given CT scans are then used for training as well as validating the developed model for particular segmentation task. However, manual delineation of lung tumor regions from CT scans is therefore prone to inter- and intra-variability and time-consuming.

Traditional methods generally demand handcrafted features for instance pixel thresholding, voxel clustering and morphological features [15]. These approaches to medical image segmentation also revolve around edge detection, active contours, template matching techniques and statistical shape models as well [16]. Therefore, deep learning-based classifiers (DLCs) have changed the research objectives from traditional image processing techniques for feature engineering to network architecture design for obtaining high segmentation accuracy.

Although, deep learning approaches have shown power to effectively extract out prominent features of input image for successful segmentation and classification of variety of tasks [17]. Additionally, studies of Transfer Learning (TR) found out that Convolutional Neural Networks (CNNs) are one of the most advanced deep learning techniques, that are capable of being applied to other tasks as well even without any alteration of its network structure, as it can be utilized as generic image representation. Moreover, U-NET set a new benchmark in biomedical image segmentation by achieving promising results.

Biomedical image processing is an emerging area of research and transfer learning [18] has established most practical paradigms in the field of semantic segmentation, instance segmentation [19] and image classification [20], and to make use of knowledge acquired from source domain while solving one supervised learning task and employing it to other novel but related target domain. However, fine tuning is a way of employing or utilizing transfer learning, particularly, a process that takes a model that already been trained for a specific task and then tuning or tweaking that model to make it execute second similar task without having to build a model from scratch.

There are certain limitations in embracing machine learning techniques due to distinctive characteristics of medical image database such as missing parameters owing to incompleteness and in particular, lack of sufficient amount of labeled dataset [21]. Therefore, to overcome the aforementioned constraint, many transfer learning-based strategies have presented in a comprehensive way to overcome such limitations while processing medical image datasets [22].

Due to heterogeneity of tumour in terms of size, shape and appearance of tumor remains a challenge, therefore, automated segmentation of lung tumour from CT scan images, can ultimately enable the physicians to provide an accurate solutions for further monitoring the disease progression. Whereas, classical methods of automatic tumor segmentation mainly depends on feature engineering, which requires extraction of features from input images for further training of the classifier [23]. However, Convolutional Neural Networks (CNNs) considered as one of the advance techniques for accurate pattern classification of tumour as they automatically learn the relevant features [24].

In this work, we present a novel strategy of deep learning-based for semantic segmentation of malignant lung tumour from computed tomographic (CT) images. The employed technique is basically the traditional U-NET, utilizing the pre-trained MobileNetV2 as an encoder of U-NET. The introduced network is trained and fine-tuned with optimized hyperparameters on the training dataset acquired from the Medical Segmentation Decathlon (MSD) 2018 challenge. Results indicate that proposed approach is robust and significantly improve the segmentation accuracy.

## AIMS AND OBJECTIVES

The aim of the work is to propose an automated lung tumor segmentation method with high efficiency and accuracy, for precise delineation of tumor in order to accurate detection of tumor.

Prime objectives are:

- To develop an algorithm that automatically segment out the region of interest (ROI) from CT scans with greater accuracy.
- To determine the efficiency by contrasting it with other available methods for accurate diagnosis of lung cancer.

## CHAPTER 2

# LITERATURE REVIEW

# LITERATURE REVIEW

Medical image segmentation as an emerging biomedical image processing technology has made huge contributions to facilitate and improve quality of human practices and decision making in diagnosis. Fueled by latest advancements in Machine Learning (ML), especially related to deep learning are justifying instrumental in identification, segmentation and quantification of patterns in medical imaging. The key element to these improvements is the inevitable capability of deep learning techniques to prevail prime features explicitly from images, which in result, minimizing the demand for hand-crafted features.

## RELATED WORK

Precisely assessment of lung tumour is essential to scrutinize its malignancy and probability of lung cancer. Therefore, extensive efforts have been made to establish a robust lesion segmentation system that can aid radiologists in determination of cancer stage. Herein, this paper demonstrated the Computer Aided Diagnosis (CAD) system based on 3D CNN as well as modified UNET, used for the detection and classification of benign and malignant tumor with an accuracy of 86.6%, suggested system was not deep enough in order to locate the exact position of the tumor [25]. Igor Rafael S. Valente *et al.* [26] presented automated 3D techniques for detection and segmentation of cancerous nodules from Computed Tomographic (CT) scans, which were optimized for the detection of various types of tumor with different but effective size and shape and reducing number of false positives.

W. Choi and T. Choi [27] suggested an automatic approach of identification of lung tumor on the basis of feature descriptor which then differentiated by 3D shape of the tumor. In this approach, multi-scale dot enhancement filtering is utilized for the detection of potential nodules, followed by feature extraction and refinement of each nodule by applying eliminating edge detection technique. *Chen et al.* [28] introduced a new method that was based on analysis of intensity structure and surface propagation in 3D CT scans in order to separate pulmonary nodules and vessels. They utilized the Line Structure Enhancement (LSE) and Blob-like Structure Enhancement (BSE) filters, and that procedure known as Front Surface Propagation (FSP), which was used to perform precise segmentation of nodules and vessels with algorithms' improved sensitivity and 10.5 false positives (FP) per exam.

Authors [29] devised an approach that consists of two stages: initially, they estimated the 3d shape of nodule across axial axis to extract the VOI (Volume of Interest) and utilized that VOI to investigate the existence of malignant tumour along the coronal and sagittal axes. The algorithm proposed by A. Setio *et al.* [30] composed of three candidate detectors especially designed for the detection of cancerous lesions to enhance the detection sensitivity of lesions, the nodule candidates are computed and processed by ConvNets by averaging the position of the tumour and its probability.

Extensive research has been carried out towards the development of CAD that must be capable enough in order to detect, segment and analyze the malignancy of tumour for the prompt diagnosis of lung cancer. Performance of computer aided diagnosis (CAD) system immensely depends on the precise detection and segmentation of tumour region. Therefore, G. Niranjana & Dr. M. Ponnavaikko [15] suggested a CAD system that was primarily based on segmentation and classification of malignant and benign by learning the prominent features such as geometrical, texture, gradient and spatial features. U Kamal *et al.* [31] stated Recurrent 3D-DenseUNet, an architecture for the segmentation of volume of interest (VOI) from lung CT scans. The suggested approach comprised of

3d encoder block and recurrent block of ConvLSTM layers to bring out fine grained spatio-temporal details, and ultimately reconstruct the volumetric segmentation mask by introducing 3d decoder block.

Random transformation induce deliberate changes and can be used to create varied images from available images in order to enhance size of dataset for training the classifier. Deep convolutional neural networks (CNNs) have been performed exceptionally well on computer vision tasks, these networks are greatly reliant on huge data in order to avoid overfitting, and moreover, overfitting happens when a network understands a function with high variance such as to accurately model the training data. However, data augmentation increase the data size with class preserving transformation and standard of training datasets, so strengthening the generalization ability of deep learning model [32].

Tri Dao *et al.* [33] established a framework to understand the data augmentation and analyze the ways of augmentation that effects the models' learning. Data augmentation artificially enhance the training dataset by data warping such as geometric and color transformation and adversarial training. Furthermore, images and mask are randomly augmented which reduces possibility of the model to learn inherent pattern in data thus reducing over fitting.

## MACHINE LEARNING FOR TUMOR SEGMENTATION

Wang *et al.* [34] proposed a support vector machine (SVM) based on three-dimensional (3D) matrix pattern method to avoid the loss of local and structural information that usually happens in one-dimensional (1D) and two-dimensional (2D) approaches of tumor detection. However, three dimensional (3D) volume of tumors taking the whole Region of Interest (ROI) for analysis and used straightaway as an input image for training of the algorithm. Lung parenchyma segmentation technique using fast marching method was adopted in [35] to extract candidate nodules from segmented lung parenchyma. Then, a random forest (RF) algorithm was employed for the classification between benign and malignant tumour.

S M Naqi *et al.* [36] opted a strategy that was based on extraction of lung region by utilizing optimal threshold and connected component labeling in order to remove the background area. After their segmentation from computed tomographic (CT) images, geometric texture and 3d component connectivity were analyzed by novel hybrid 3d nodule detection. Based upon extracted feature, classification was performed by distinctive classifiers including K-Nearest Neighbors (KNN), Naïve Bayesian and Support Vector Machine (SVM). The validation and evaluation of mentioned approach was performed well on dataset acquired from Lung Image Database Consortium (LIDC).

N. A. Memon *et al.* [37] proposed machine learning based segmentation technique for the medical image analysis, where CAD system generally segment the lung from CT images and after that analyze the area of nodule detection to determine the malignancy of lesion and its progression. To detect lung cancer at its early stage K. Sebastian *et al.* [38] developed a grey level co-occurrence matrix (GLCM) algorithm for feature extraction to eliminate false minutiae and to enhance quality of image analysis.

## DEEP LEARNING FOR TUMOR SEGMENTATION

Deep Learning (DL) architectures with exceptional results on tasks of semantic segmentation in contrary to more conventional and context-based computer vision discriminative tasks. With the rapid advancements in Artificial Intelligence (AI), deep learning-based medical image segmentation methods have attained remarkable results in the field of medical imaging. Deep learning architectures have certain advantages in segmentations' accuracy and computation time as compared with traditional machine learning and computer vision methods. Novel Recurrent 3D-DenseUNet framework proposed by Udey *et al.* [2], and implemented convolutional LSTM block inside the transition region of UNET, trained to segment region of interest (ROI), utilizing tversky loss function in order to enhance dice score coefficient (DSC).

M. Havaei *et al*. [39] presented a Deep Neural Networks (DNNs) for brain tumour segmentation to fully automate the approach in which local features and global contextual features were utilized simultaneously to enhance the robustness of the network. Model was outperformed on the BRATS dataset as compared to currently published state of the art approaches. T. Brosch *et al.* [40] put forward a novel segmentation framework rely on deep 3d convolutional encoder networks along with shortcut connections and employ it to segment out the lesions from magnetic resonance images (MRI). The suggested network mainly comprised of two inter-connected pathways, a convolutional path, which ascertain more abstract and prominent image features, and a deconvolution path, which anticipate segmentation at the voxel level. Model was validated on publically available MICCAI 2008 dataset with comparable results. Hongtao Xie *et al.* [17] designed a classifier for the reduction of false positives (FPs), and to separate the malignant tumour from benign with high accuracy and sensitivity.

For hepatocellular carcinoma determination and its treatment planning, automatic liver tumour segmentation approach is exceptionally demanded in order to assist the surgeons. Therefore, Xiaomeng Li *et al.* [41] concentrated on Hybrid Densely Connected UNET, which was comprised of 2D DenseUNet for the extraction of features and a 3D counterpart for accumulating volumetric contexts to segment out the liver tumour. The proposed method was extensively evaluated on MICCAI 2017 dataset and it performed with competitive performance.

Fabian Isensee *et al.* [42] introduced the robust no-new-Net (nnU-Net) framework, where ReLU activation function is replaced by leaky ReLU and use of instance normalization instead of batch normalization. Furthermore, they evaluated the model on medical segmentation decathlon challenge (MSD) dataset and achieved highest mean dice score. The same architecture [43] with certain modification of automatically adapt the new dataset, however, whole procedure is completely human driven except pre-processing, batch size, patch size and inference settings. Remarkably, out of the box, nnU-Net obtained state of the art performance.

## MINDMAP

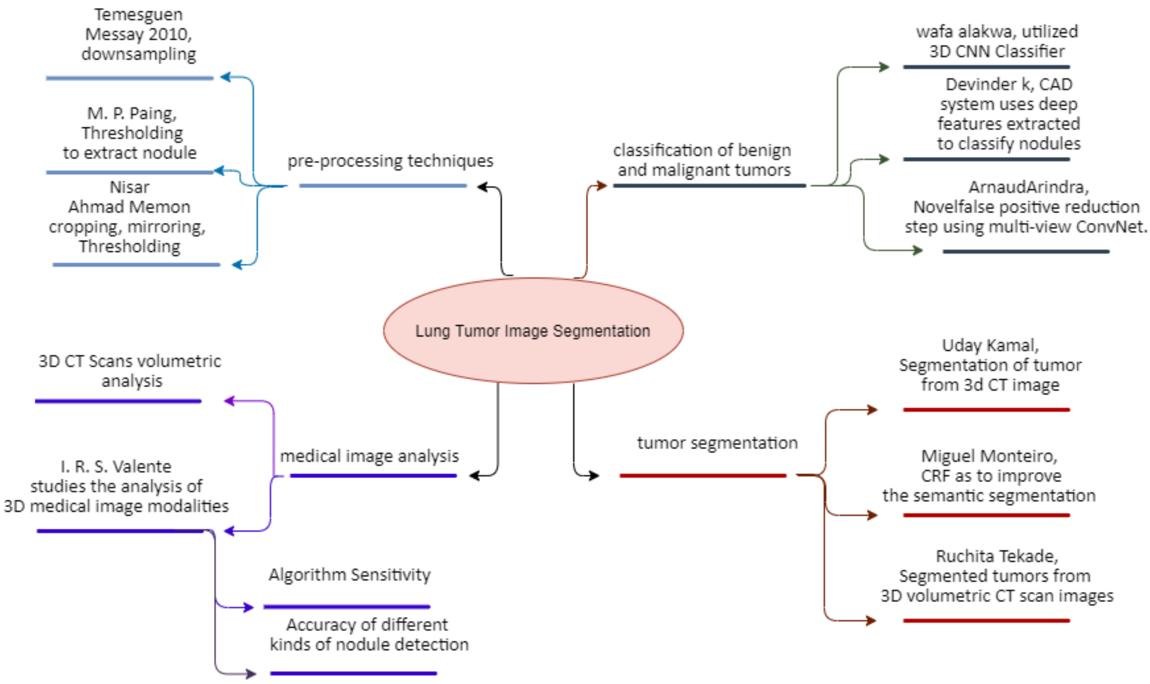


***Figure 1.*** *Pictorial description of literature review*

## CHAPTER 3

# METHODS & MATERIALS

# MATERIALS & METHODS

## DATASET

We use the 2018 Medical Segmentation Decathlon Challenge (MSD) dataset for the training, validation and evaluation of the proposed algorithm. The 3-dimentional computed tomographic (CT) images dataset, acquired from The Cancer Imaging Archive (TCIA) that are made available to the public through Medical Segmentation Decathlon Challenge (MSD). Briefly, 96 preoperative thin-section CT images were obtained with the following parameters: automatic tube current modulation range, 100-700mA; helical pitch, 0.9-1.0; tube rotation speed, 0.5 s; section thickness, < 1.5mm; 120kVp; and a sharp reconstruction kernel [44].

Expert thoracic radiologists indicated tumor region on Computed Tomographic (CT) cross section by utilizing OsiriX. Training set used here is comprised of 64 heterogeneous Computed Tomographic (CT) images with accurately annotated ground truths, from which 25% of training set utilized to check the validity of the proposed architecture. Each CT scan volume has a dimension of 512 × 512 × X, where X denotes the variability in voxel size of each CT scan, from which segmentation of tumoural subregion is performed. Therefore, dataset is processed to overcome the inconsistency of the voxel of each 3D scan by splitting into 2D images, wherein, lung nodules also have huge variations in tumour size and morphological characteristics. Different 2D slices from 3D CT scans, and its corresponding ground truth are shown in Figure 1, as an example images from training section.

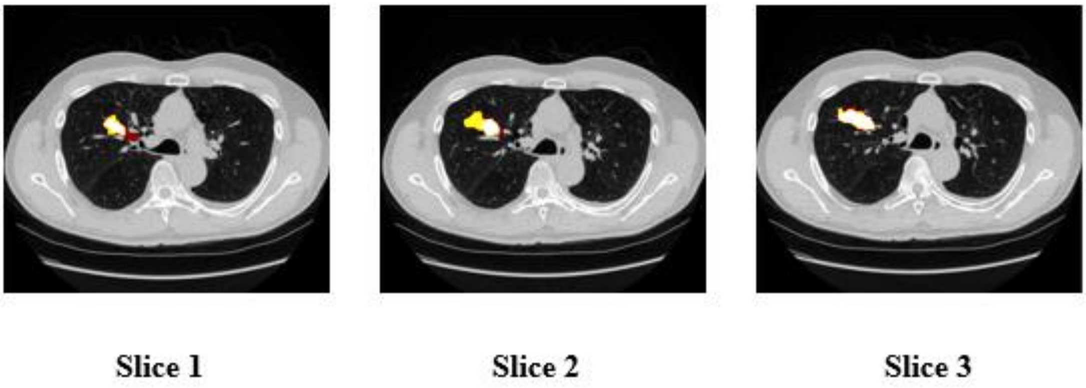


***Figure 2.*** *Image slices of CT scan of a single patient in MSD-2018 Training Set, along with manual annotation overlaid on the image.*

Manually delineating of lung tumour subregions from CT scans is a prone to variability and time consuming task, therefore, automated segmentation of pulmonary nodules from 3d computed tomographic (CT) images can help the clinicians to accelerate the precise diagnosis in order to provide accurate solutions for further monitoring the disease progression. As visualized in Figure 2, manual annotations of tumoural subregions indicated by experienced radiologists inclusive in training set.

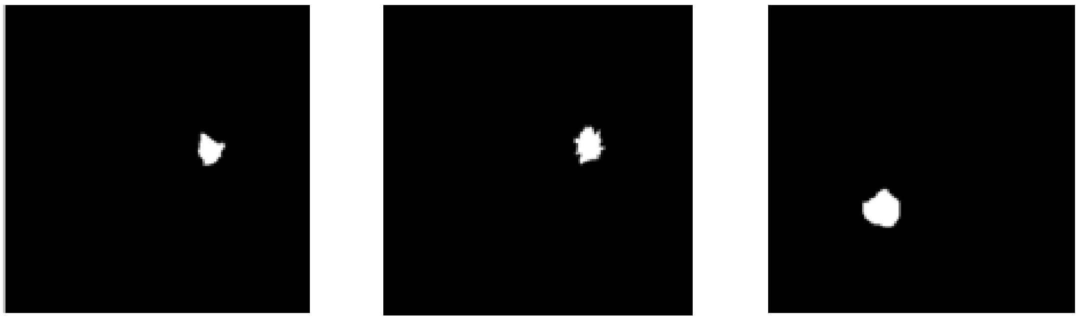

***Figure 3.*** *Manually annotated lesions from CT scans of different patients, expertly marked by radiologists, as ground truths labels, in Training Set.*

Dataset other than mentioned dataset is not used in the experiments. In addition to that, access to MSD-18 is limited to participants of the challenge. We report the segmentation results of the suggested model on validation set and compare it to existing state of the art networks. We provide further details on the utilized methods in the following sections.

## METHODOLOGY

In this section, we begin by describing the common representation of the architecture that we employed. MobileNetV2 is usually adapted for resource-constrained environment to accurately solve the problem of semantic segmentation and has advantage of modifying both results and performance. We propose a computationally light weighted network with less trainable parameters and it achieves perfect balance between performance results and implementation efficiency. Approach is schematized in Figure 3.

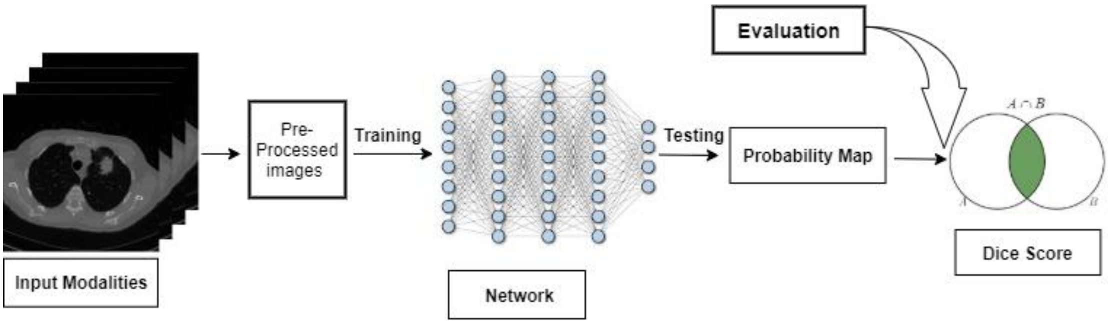


***Figure 4.*** *Generalized pipeline of nodule segmentation framework. Model is trained on input CT scans and then tested to generate predictions.*

A 2d image containing the nodule is provided as an input in order to investigate the presence of suspicious lesions using proposed algorithm. Output of this network is a segmentation map (illustrated in Figure 7), from which dice score coefficient is calculated. In the following section, we provide further details on the pipeline that has several phases which are described in the subsequent sections along with detailed explanation of network architecture.

**Preprocessing**

We converted the 3D Computed Tomographic (CT) images to 2D and resized them to 256 × 256 in order to reduce the size of the CT slices owing to memory consideration. Afterwards, standardize the image by utilizing the following technique (Equation 1) of intensity normalization. Furthermore, only those images carrying tumours are selected to train the proposed network (shown in Figure. 4).

$$Image\ Normalization = \frac{image - mean\ of\ image}{Standard\ deviation\ of\ image} \quad (1)$$

**Data Augmentation**

When training the neural network from limited training data, particular attention has to be taken to minimize overfitting.

- Augmentations induce deliberate changes and hence, can be used to create varied images from available images.
- Greater variation in training data ensures model generalization ability.
- Images and masks are randomly augmented which reduces the possibility of model to learn inherent pattern in data thus reducing overfitting.

Following augmentations are employed to the model to prepare enough data for training that will assist to increase the generalizability.

**Table 1.** Random transformations applied on the initial dataset

| Augmentation | Description |
|---|---|
| **Blur** | Blur the input image using random sized filter. |
| **Transpose** | Transpose the input by swapping rows and columns. |

| | |
|---|---|
| **Crop** | Crop the random part of input image, crop the central part of input image. |
| **Rotate** | Rotate the input image by an angle selected randomly from the uniform distribution. |
| **CLAHE** | Apply Contrast Limited Adaptive Histogram Equalization to the input image. |
| **Random Grid Shuffle** | Random shuffle grid's cell on input image. |
| **Hue Saturation Value** | Randomly change the Hue, saturation and value of input image. |
| **RGB Shift** | Randomly shift values for each channel of input RGB image. |
| **Random Contrast** | Randomly change the contrast of input image. |
| **Median Blur** | Blur the input image using a median filter with a random aperture linear size. |
| **Channel Shuffle** | Randomly rearrange the channels of the input RGB image. |
| **Invert Image** | Invert the input image by subtracting pixel values from 255. |
| **Gaussian Blur** | Blur the input image using a Gaussian filter with random sized kernel. Also apply the Gaussian noise to the input image. |
| **Resize** | Resize the input image to $256 \times 256$ |
| **Random Sized Crop** | Crop a random part of input image and rescale it to some dimensions. |

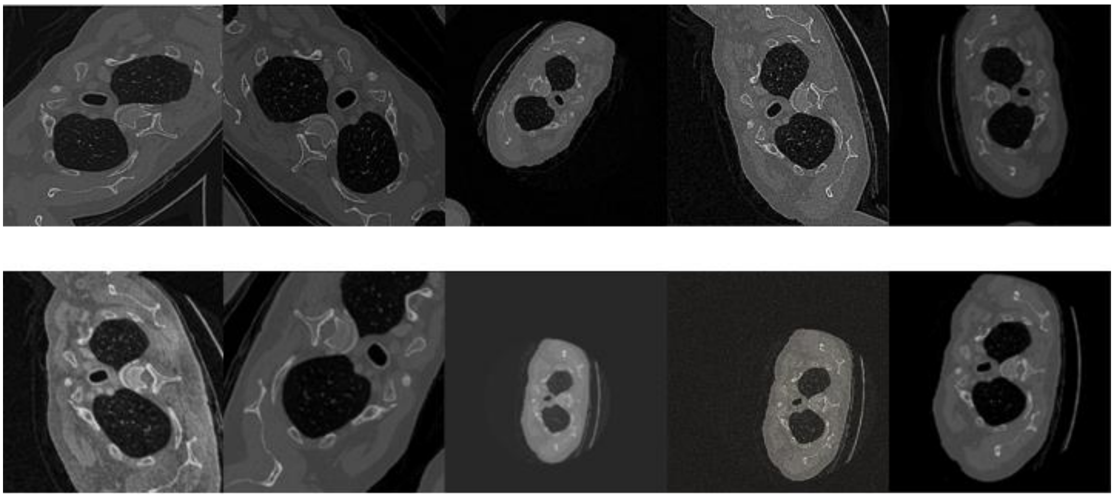

***Figure 5.*** *Visualizations of random augmentation of CT images.*

**Network Architecture**

The encoder decoder-based architecture is a classical U-NET with MobileNetV2 as pre-trained encoder, however, U-NET is a fundamental convolutional neural network (CNN), initially developed by Olaf Ronneberger *et al.* [45] for biomedical image analysis and got tremendous attention in medical imaging community by obtaining remarkable segmentation results, and won the international symposium on biomedical imaging (ISBI) competition 2015. On the other side, MobileNetV2 [46], [47] introduced light weighted convolutions in encoder part of the network, and achieves perfect balance with much fewer parameters. Encoder takes image as an input of the model and extracts necessary features and relevant information, wherein, decoder learns to generate the proper segmentation map and provides binary classification. Furthermore, skip connections in down sampling path are then concatenated with feature maps during up sampling path in order to provide local information to global information.

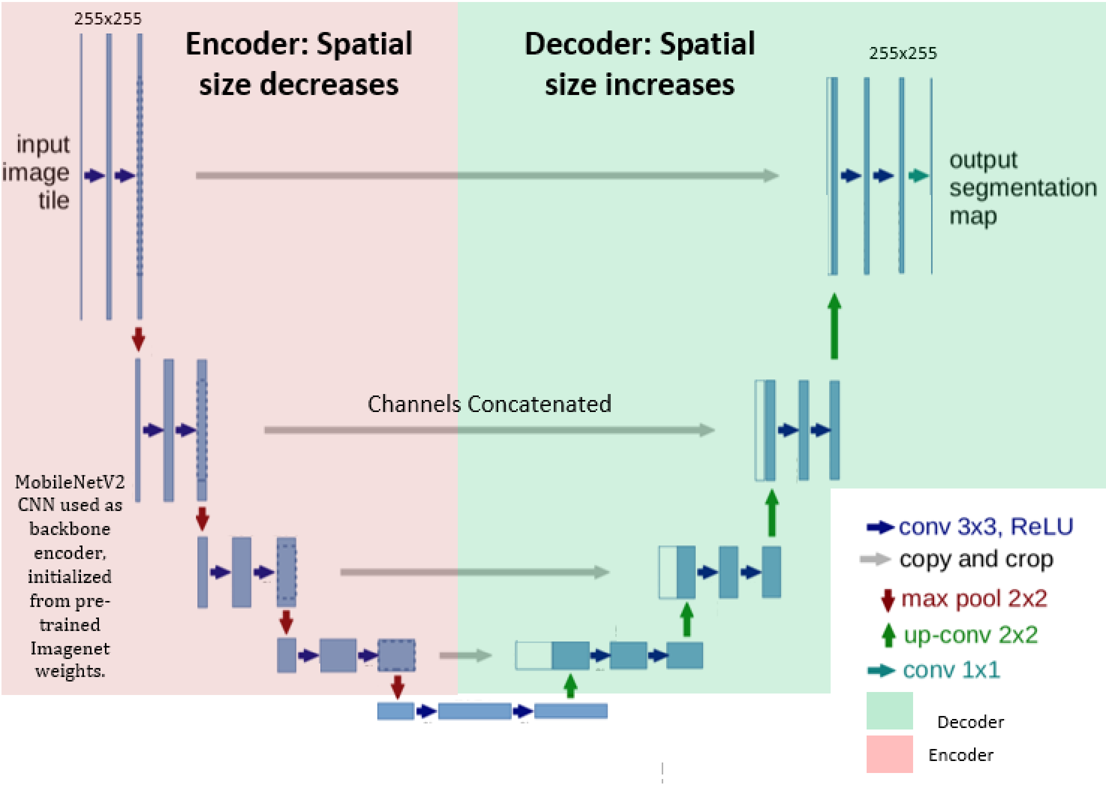


***Figure 6.*** *A structural visualization of the network architecture, where encoder exhibited on left side is MobileNetV2 and U-NET decoder shown on the right side. Input of patch size 256 x 256 are given into the model. Convolutional units are used with batch normalization and ReLU function activations. Upsampling along with concatenated feature channels is employed to obtain the output of the same spatial size as that of input.*

### Model Training

For training of the network, we provide the input patch size of 256 × 256 and batch size of 8 to the model and trained the model for 90 epochs on our dataset and training converges quickly as compared to the networks that are trained from scratch. Loss of information might be happened by employing ReLU, therefore, linear activation in the bottleneck introduced to mitigate the loss of information. Several schemes of data augmentation (shown in Table 1) are applied to dataset during runtime to show different data to our network during each iteration in order to prevent overfitting and to increase the predictability and segmentation accuracy. Fine-tuned hyperparameters are demonstrated in Table 2.

**Table 2.** Hyperparameters used for CNN training

| NAME | VALUE |
|---|---|
| Input size | 256 x 256 |
| Batch size | 8 |
| Learning Rate | $1 \times 10^{-4}$ |
| Epoch | 90 |
| Optimizer | Adam |
| Loss Function | $L_{dice}$ |

The employed dice loss performs the best as it gives more preference to true positives (TP) as compared to jaccard loss, on the other side, binary cross entropy loss saturated too quickly owing to large black pixels area in medical images. Nonetheless, the network has shown significantly better results on the medical image segmentation, and we trained as well as fine-tuned the model for highly improved segmentations.

**Evaluation Parameters**

The performance of the model is illustrated by certain parameters and following matrices are extremely important to evaluate the models' performance and accuracy.

***Dice score coefficient (DSC):*** it is pixel wise resemblance of true positives between the two images and pivotal to calculate that similarity between actual label and corresponding predicted segmentation results, however, when there is complete overlap its value is 1, 0 denotes no overlap and its value falls between this range $0<DSC<1$.

Formula comprehension of dice coefficient also known as F1 score is given below (shown in Equation 2).

$$DSC = \frac{2TP}{2TP + FP + FN} \tag{2}$$

Where TP stands for true positives, FP represents false positives and FN indicates false negatives.

***Dice Loss (DL):*** Loss function is employed to calculate the degree of inconsistency between the predicted value of model and ground truth value. In this work, we utilize the simple dice coefficient loss function, and simply, it is the negation of dice score coefficient, adapted to determine the measure of intersection between regions, which is particularly employable for the segmentation problems when ground truths are available. Therefore, higher the dice score coefficient is, lower the loss becomes and better predictability the model has.

$$Loss = L_{dice} = 1 - DSC \tag{3}$$

***Recall and Precision:*** These are two extremely imperative matrices for model evaluation, wherein, recall demonstrates the percentage of total relevant results correctly classified by the network.

$$Recall = \frac{True\ Positive}{Predicted\ Results} = \frac{nTP}{nTP + nFN} \tag{4}$$

On the other side, precision indicates the percentage of the results which are relevant.

$$Precision = \frac{True\ Positive}{Actual\ Results} = \frac{nTP}{nTP + nFP} \tag{5}$$

### Inference

We standardize the data by strategy of min-max normalization in order to weigh the pixel values between 0 and 1 and resized the data by clipping the patch size to $256 \times 256$, which is further ready to process by the network. The nature of model training is patch based and different data augmentation schemes are applied on data during training to increase the dataset size, thus, improves the networks' predictability and robustness. Furthermore, model is evaluated on independent test dataset and segmentation maps are generated and we discuss more details of the results in the following section.

## CHAPTER 4

# RESULTS

# RESULTS

## LUNG TUMOR SEGMENTATION

Herein, we present the prediction results from our devised segmentation model, evaluated on MSD-2018 lung tumour segmentation dataset provided by the cancer imaging archive (TCIA). We use traditional U-NET architecture by integrating down-sampling path of the U-NET with a pre-trained encoder entitled as MobileNetV2 that is trained on a large ImageNet dataset. Predicted segmentations from proposed network are shown in Figure 6. The dice score achieved by the network is 0.8793, in addition to this, accuracy and precision of the model is 0.8602 and 0.9322 respectively.

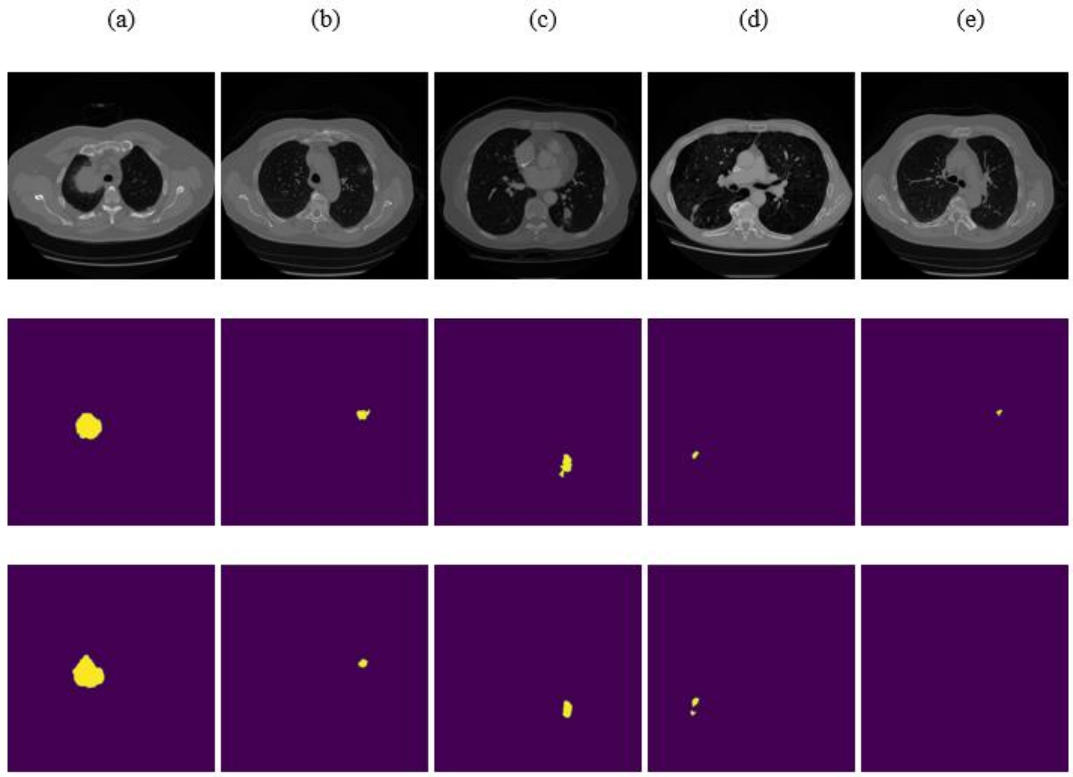


***Figure 7.*** *Example CT scans of different patients are exhibited in the form of rows. First row indicates the actual images, middle row is the visualization of true labels and last row is the segmentation predictions, wherein, most of the prediction results are correctly segmented as visualized in (a)-(d) and very few of them are omitted by the model as depicted in (e).*

Herein, distribution of dice score coefficient of each patient is illustrated in histogram, but average dice score that we have achieved is 0.8793 and most of tumours have dice coefficient above 80% which indicates the performance of the network.

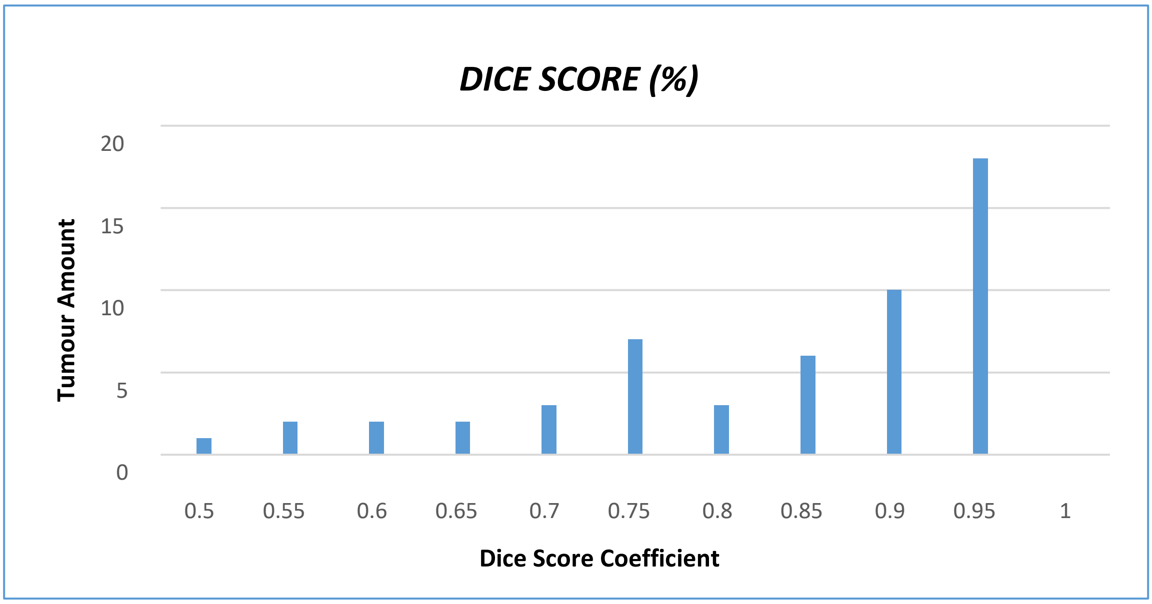


***Figure 8.*** *DSC distribution of the test dataset DSC distribution of the test dataset, where histogram shows number of tumours that achieve particular dice coefficient.*

Therefore, we propose a method to train the deep neural network and validate it with medical segmentation decathlon (MSD) lung CT scan dataset, showing competitive results as compared with state of the art methods.

## RESULT COMPARISON WITH DIFFERENT FRAMEWORKS

We compared our results with various state of the art deep learning methods (shown in Table 3) that are validated on lung CT scan dataset. These approaches utilized complex pipelines of training and achieves comparable results, whereas, our framework is computationally light, less algorithm execution time, gives better accuracy and performed reasonably well in capturing the whole nodule shape. Following table depicts the results of mentioned techniques in terms of dice score coefficient (DSC).

Thus, the proposed strategy rigorously evaluated and results in better segmentation irrespective of the other available segmentation models.

**Table 3.** Dice Score Coefficient (DSC) comparison with different architectures

| Approach | DSC |
|---|---|
| Central Focused CNN [48] | 0.821 |
| Multichannel ROI based on Deep Structured Algorithm [49] | 0.7701 |
| Multi-Crop CNN [50] | 0.7751 |
| Multi-View Deep CNN [51] | 0.7767 |
| Cascaded Dual-Pathway Residual Network [52] | 0.8158 |
| Unsupervised Metaheuristic [53] | 0.8235 |
| **Proposed Method** | **0.8793** |

We confirmed the effectiveness and efficiency of our fine-tuned model with extensive experiments and it can be applied to other medical segmentation tasks with required modifications according to the particular task. In comparison with several widely implemented lung tumour segmentation approaches, our proposed method showed superior performance in segmentation accuracy.

# CHAPTER 5

# DISCUSSION

# DISCUSSION

In this study, we have considered transfer learning based approach for the task of Lung Tumour Image Segmentation, in which we utilized MobileNetV2 as an encoder of traditional UNET for medical image segmentation. Our suggested method outperforms by achieving dice coefficient of 0.8793, accuracy of 0.8602 and precision of 0.9322. Nonetheless, substantial amount of training instances are given to the network to avoid overfitting, and hence, model exhibits efficient and vigorous segmentation as compared with other models that trained from scratch. Above all, much smaller memory requirements and faster execution than any other similar networks.

Specificity of the proposed technique is that it is applicable to other medical image segmentation tasks as well. It achieves perfect balance with much fewer parameters, much more accurate results, much faster execution than any similar nets and much smaller memory requirements. However, as suggested by Oliver Rippel *et al* multi-scale approach can be integrated into the presented algorithm to enhance the accuracy on the problem of label imbalance. Furthermore, hyper-parameter searching techniques can also be incorporated to our approach to facilitate automatic parameter tuning [54].

Our model performs favorably on lung tumour segmentation, however, accuracy can be improved by employing the technique presented by U Kamal *et al.* [2]. They implemented an interesting dynamic thresholding scheme which counts the histogram of predicted images and calculates the intensities associated with highest peaks, intensities then averaged using empirical parameters to predict particular threshold for each patient.  However, Results demonstrate that our proposed network performs better for segmenting the tumour region.

In current study, certain limitations still exist. The proposed segmentation method is only evaluated on validation set of the challenge and the robustness of the method can be evaluated further by testing on other medical image segmentation tasks, independent of the challenge's dataset. We did not extensively post-process our segmentation results, however, use of Conditional Random Fields (CRF) [55] can also amplify the segmentation accuracy. Additionally, by extending training for more epochs and further extensive hyperparameters tuning can improve models' generalization ability.

# CHAPTER 6

# CONCLUSION & FUTURE PROSPECTS

# CONCLUSION & FUTURE PROSPECTS

In this study, we have presented a network that successfully generates highly accurate predictions of lung tumors from Computed Tomographic (CT) scans provided by Medical Segmentation Decathlon (MSD) 2018 Challenge. We use an approach of deep learning by integrating light weighted MobileNetV2 encoder into classical UNET model to successfully generate highly accurate segmentations in order to achieve best scores. Thus, proposed model is a different yet straightforward, offers an automated way of generating lung tumor segmentation to aid in knowing the state of the disease and managing patients clinically. Results indicate the performance of proposed model by comparing with results of existing state of the art methods. Hence, it is an optimized architecture that improves performance of the network on various tasks. Certain key elements of this model are less parameters, converges much faster than the models trained from scratch.

In future, extensive research work is still required to develop robust CAD model or to optimize the existing networks that aids the clinicians to detect accurately and quantitatively assess the lung tumour timely. For example, evolution of an approach to enhance the model sensitivity and to maintain the small number of false positives (FPs). We also have an opinion that the distance between medical imaging community and researchers should be narrowed to overcome the challenges of not using the CAD systems in daily practice.

However, in this paper, we did not make any prior assumption to segment suspicious lesion and the essential features are exclusively learned from training data which permit us to apply on various 2d types of pathology segmentation when suitable data is available. Additionally, our proposed framework is quite resilient and can be easily amended, for instance, multi scale Gaussian distribution can be employed to CT images for the sake of smoothening the feature evolution process. In our future works, we have also an intention to modify the model architecture to 3D convolutional neural network in order to explore its performance to other medical imaging tasks.

## CHAPTER 7

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