

# **Comparative Analysis of UNET-Based and Transformer-Based Medical Image Segmentation Models on Lungs X-rays**



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Comparative Analysis of CNN-Based and Transformer-Based Medical  
Image Segmentation Models on Lungs X-rays

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A thesis submitted in partial fulfillment of the requirements for the degree of  
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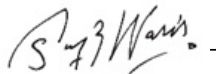
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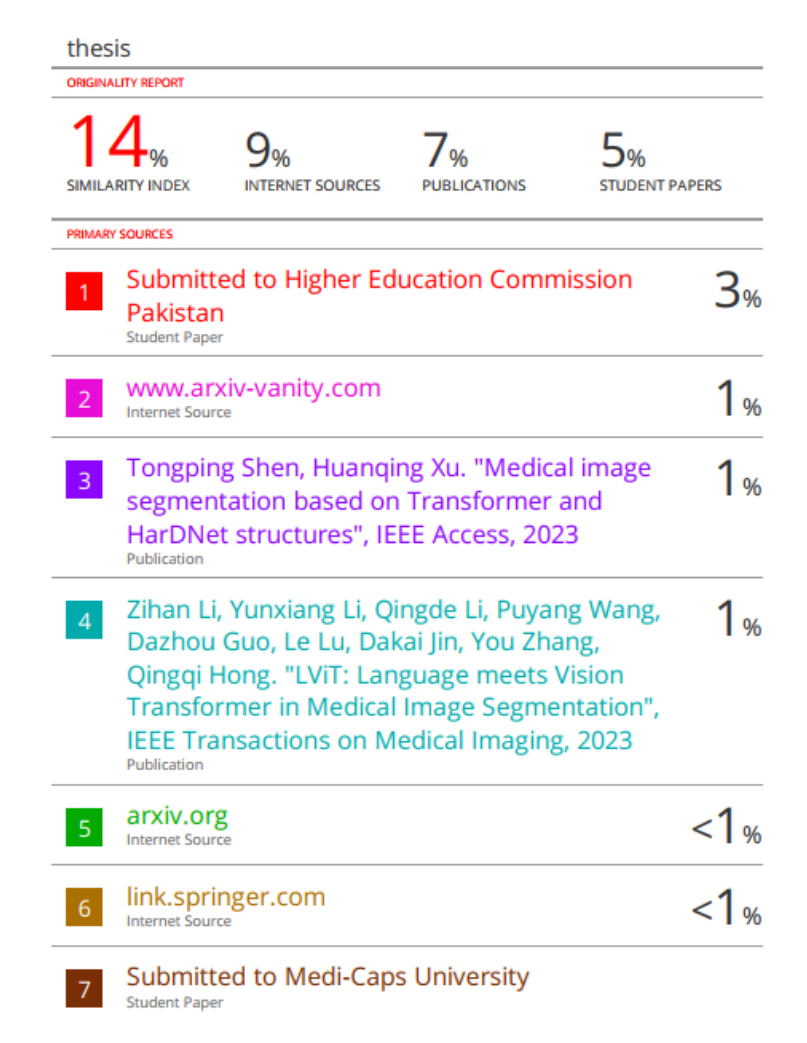
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## **Abstract**

In this Research we did to a comparative analysis of UNET based segmentation models and Transformers based Segmentation model on Chest X ray images in medical imaging domain. The parameters for study were Jaccard Index (IoU) Foreground accuracy, Inference time, and Model size. The Hyper parameters such as Augmentations, learning rate, batch size and image size were kept similar. We used three augmentations, batch size of 32, and image size of 256x256. The experimentation environment for all models was Google Collab Pro, and for training Transformers Hugging face was used for loading dataset, models and Fine tuning. The training dataset was used as 80% training, 10% validation and 10% testing. The Jaccard Index (IOU) for UNET was 92.7 and foreground accuracy was 94. The Jaccard Index (IOU) for U2NET was 94 and foreground accuracy was 95. The Jaccard Index (IOU) for Segformer was 97 and foreground accuracy was 97.9. The Jaccard Index (IOU) for DPT was 97 and foreground accuracy was 97.8. The transformers beat accuracies of UNET based models and also performed better in Inference, and model size was insignificant and did not have any effect on performance. Overall performance of Transformers in same environment was better than UNET based models, and we recommend using transformers for medical image segmentation tasks.

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## List of Acronyms

<b>Abbreviation</b>	<b>Definition</b>
AI	Artificial Intelligence
CiI	Coefficient Index
CNN	Convolutionary Neural Network
CT	Computed Tomography
DL	Deep Learning
DPT	Data-efficient Image Transformer
GPU	Graphics Processing Unit
GSA	Global Spatial Attention
IOU	Intersection Over Union
ML	Machine Learning
MRI	Magnetic Resonance Imaging
ReLU	Rectified Linear Unit
SETR	Segmentation Transformer
TB	Tuberculosis
TSA	Transformer Self Attention
ViT	Vision Transformer



## CHAPTER 1: INTRODUCTION

Image segmentation methods have proved to be a prominent way for the acquisition of features for image processing applications. Basic purpose of image segmentation is to search for objects of interest in the image by assigning labels to pixels so that entire image doesn't need to be processed, thereby increasing the efficiency in terms of inference time.

Image segmentation techniques can be categorized into traditional image processing methods i.e. edge-based segmentation, threshold-based segmentation and region-based segmentation, and Machine Learning (ML) and Deep Learning (DL) based methods i.e. instance based segmentation, panoptic segmentation and semantic segmentation.

As far as the traditional techniques are concerned, Region based segmentation recursively groups the pixels of similar characteristics using gray scale values of the neighboring pixels [1]. Another simpler image processing segmentation method is based on the concept of thresholding. In this method, pixel are differentiated based on their intensity in comparison to a specified threshold. A prominent example of this method is Otsu's method that finds the suitable threshold using interclass variance maximization [2].

In case of edge detection, different image objects are identified using their boundary or edge values as they differ from their surrounding pixel. An example of edge detection is Marr-Hildreth algorithm [3] that detects the edges by convolution of the image with Gaussian or Laplacian function.

As image segmentation tasks primarily focus on categorization of pixels, ML and DL based pipelines stand out because of their extraordinary performance in data classification and clustering tasks.

Instance segmentation involves classification of pixels as per instances of a given object (contrary to the idea of object classes).

Panoptic segmentation is the hybridization of semantic and instance segmentation, predicting object identity and then classifying all the instances of objects in a given input image. This method is specifically effective in real-time applications in which accuracy and speed are simultaneously required such as cruise control applications [4].

The basic idea of semantic segmentation revolves around the concept of semantic classes. In this method, each pixel belongs to a specific class and final segmentation model doesn't depend on

any other information. For instance, an input image containing trees, buildings and other landmarks, using this technique, will generate a mask that classifies each entity in a unique class.

Studies have shown that DL based semantic segmentation algorithms outperform the ML based methods [5]. For the purpose of this study, Convolutionary Neural Networks (CNN) have been selected as a comparison to the proposed approach, specifically U-NET and U2NET.

The U-NET architecture, initially designed for biomedical image segmentation, has now emerged as a prevailing standard for various image segmentation tasks across diverse domains. Conceived by Olaf Ronneberger, Philipp Fischer, and Thomas Brox in 2015, this architecture has been an exemplar of how DL can transform traditional imaging techniques, specifically with a paucity of training data [17].

Central to the design of U-NET is its symmetrically expanding and contracting structure, which is reminiscent of the letter 'U', thereby providing its moniker. The architecture essentially comprises two main parts: the contracting (or encoder) path and the expansive (or decoder) path.

**The Contracting Path:** This initial phase is structured similarly to a conventional convolutional network. It consists of repeated application of two 3x3 convolutions (unpadded), each trailed by a rectified linear unit (ReLU) and a 2x2 max pooling operation with stride 2 for down-sampling. As one progresses deeper into the network, the number of channels doubles at every step, capturing intricate details and contextual information from the input image [18].

**The Expansive Path:** Mirroring the contracting path, the expansive segment seeks to upscale the feature maps. Each step in this phase involves an up-sampling of the feature map, followed by a 2x2 up-convolution, reducing the number of channels by half. This is succeeded by a concatenation with the correspondingly cropped feature map from the contracting path, and two 3x3 convolutions, each succeeded by a ReLU. The symmetric expansion allows the network to consider the context from the contracting path, leading to precise localization [19].

A crucial advantage of U-NET lies in its ability to perform end-to-end training and produce high-resolution outputs, which obviates the need for post-processing stages.

From a practitioner's viewpoint, U-NET provides a harmonious blend of depth and architectural nuances, facilitating efficient training even with limited data. Its modular nature allows for adaptability; researchers and developers can incorporate modifications tailored to specific

challenges. For instance, by integrating additional regularization techniques or loss functions, U-NET can be calibrated for various imaging scenarios beyond its original biomedical remit.

Furthermore, real-world deployments of U-NET have been marked by a noticeable diminution in inference times, particularly pivotal for applications necessitating swift responses, such as medical emergencies or real-time surveillance [20].

However, as with any DL model, the success of U-NET is contingent on judicious parameter tuning and the quality of training data. But, with due diligence, the architecture has proven its mettle in delivering state-of-the-art results in numerous image segmentation tasks.

Transformers, originally proposed for natural language processing tasks, have recently manifested their prowess in computer vision challenges, particularly in image segmentation. This evolution epitomizes the adaptability of transformer architectures, marking a significant deviation from the typical convolutional paradigms that have dominated the domain [21].

Transformers operate based on self-attention mechanisms that weigh input features differently, thereby offering the model the ability to focus more on specific features over others. This makes them exceptionally adept at modeling long-range interactions and contextual dependencies in data, which are crucial for precise image segmentation [22].

In the context of images, while Convolutional Neural Networks (CNNs) operate on local patches, transformers consider global relationships, permitting every pixel or patch in the image to interact with every other. This global receptive field is a game-changer in tasks that require understanding comprehensive image semantics [23].

Several pioneering works have surfaced, accentuating the significance of transformers in image segmentation tasks:

**ViT (Vision Transformer):** Initially designed for image classification, ViT tokenizes images into fixed-size patches, linearly embeds them, and then processes these tokens using transformer encoders [24]. Although not directly a segmentation model, the adaptability of ViT to segmentation has been explored, revealing promising results.

**SETR (Segmentation Transformer):** SETR utilizes the power of transformers to process entire image tokens, benefiting from the global self-attention to produce segmented outputs with fine-grained details. It exemplifies the potential of end-to-end transformer architectures for segmentation [25].

Swin Transformer: A recent innovation, the Swin Transformer subdivides images into local patches and hierarchically processes them with shifted windows, making it a highly flexible and efficient model suitable for dense prediction tasks like segmentation [26].

Transformers' significance in image segmentation lies in their ability to capture intricate patterns and long-range dependencies without being constrained by the localized nature of convolutions.

This has led to:

**Improved Performance:** In many benchmarks, transformer-based architectures have matched or even surpassed the state-of-the-art models traditionally based on CNNs.

**Flexibility:** Transformers are inherently more adaptable, allowing for easier integration into hybrid models or other vision tasks.

**Enhanced Context Understanding:** For segmentation tasks where understanding context is vital (e.g., distinguishing similar objects in crowded scenes), transformers offer a clear advantage due to their global self-attention mechanism.

In conclusion, while CNNs have been the linchpin of image segmentation for years, the advent of transformers and their demonstrated competence in segmentation tasks heralds an era of enriched possibilities and refined performance in the domain.

## **CHAPTER 2: RESEARCH AIM**

The aim of the current study is to investigate the performance of CNN based segmentation models for Lung X-rays and doing a comparative analysis against Transformers for the two datasets used in study. One is going to be used for training and validation, and other one for test. The evaluation is going to be based on Accuracy, Inference speed and performance of the models. The aim is to find out which Deep Learning architectures are better for the Segmentation of X-rays images based on criteria described above, and this will help in gauging if Transformers are giving results closer to state of the art Deep Neural Networks or not.

## CHAPTER 3: LITERATURE REVIEW

Deep learning is being used a lot to help separate different parts in images taken in medical imaging. The writers studied an important aspect of diagnosing illnesses. They found that using statistical methods to automatically separate different parts of an image has been very effective in a variety of serious medical situations. This study aimed to make the system process better in accuracy and speed compared to traditional auto segmentation methods. They also compared how well different algorithms in deep learning methods did in terms of accuracy, sensitivity, specificity, precision, and the ability to reproduce results. The researchers compared different methods for separating lung CT images, and found that a deep learning model was much better than traditional methods. The deep learning model had an accuracy rate of 99.6%. The test images are picture grids that are 512 by 512 pixels. The images are in shades of gray and each pixel has 16 bits of information. The images show a range of distances between 0.7mm to 12mm. The images are of lung CT scans and some of them may show signs of lung cancer. The collection of images is called LIDC and it is managed by the U. S. The National Cancer Institute is an organization that focuses on researching and finding treatments for cancer. The writer compared the technique and tried it out with different types of information collections. He also showed the measurements that compare how well the two methods performed. In simpler words, he believes that deep learning algorithms are really good at dividing images into sections and are measured using different methods than statistical methods. The deep learning approach is used to accurately segment a variety of medical images. In the future, we should build and compare various deep learning algorithms for the process of dividing images. [6]

Although Convolutional Neural Networks (CNNs) are currently the best technique for automatically dividing medical images into different parts, their accuracy and reliability have not been proven for actual medical practice. CNNs have some limitations. They struggle to adjust to specific images and they cannot categorize objects they have never seen before (zero-shot learning). The writers suggest a new way of segmenting images using deep learning. They use CNNs in a box and also a scribble-based approach. The writers suggest adjusting a CNN model so it can better fit and understand a specific test image. The test image can be done either without any help from users (unsupervised) or with some help from users (supervised by adding scribbles). To improve the model, the authors suggest using a special formula that considers uncertainty in both

the network and how different things interact with each other. They used this template for two tasks:

We want to separate different organs from images of a baby's MRI scans, but we only have training data for two types of organs. We also want to identify and separate the tumor core from MRI scans of different sequences, but we only have training data for the tumor core in one sequence.

**Findings from the experiment:** The authors' model can more accurately identify new objects than existing CNNs.

- 2) Using their suggested weighted loss function helps improve the accuracy of segmenting images.
- 3) Their method gives correct results with less need for users to do things and less time spent by users compared to traditional methods for separating things.

Their suggested plan includes using boxes as a way for users to interact, along with the possibility of using scribbles if they want to. Users or automatic detection can give bounding boxes in test images to make it faster. The authors of the research found that by making small adjustments to an image, they were able to improve how well the computer program could divide the image into different parts. This adjustment was done after the initial division was already made, and they found that it worked better than a different method called CRF. When the automated performance is good enough, unsupervised fine-tuning can fix small mistakes in segmentation. However, in certain complicated situations, when the distribution of data used for training is different from the distribution of data used for testing, it can cause the performance to be lower than expected. To solve this problem, the authors use BIFSeg. It can be adjusted with the help of the user to make it more accurate and reliable. Because the scribbles are only placed in specific areas, the scribbles found in these areas have limited variations in position and length. This is different from traditional methods like Random Walks or Slic-Seg where freely drawn scribbles are used, which have greater variations. The BIFSeg output also changes a little bit when there are different scribbles, as demonstrated below:

In their tests, the researchers adjusted certain settings (e.g. during the testing phase, the problems ( $\lambda$ ) of BIFSeg were fixed everywhere. One way to improve the accuracy of segmenting images is by adjusting parameters specific to the object being segmented. Another way is to let the

user make small adjustments for each test image while using an interactive method. [7]

New technology is creating better health systems that help healthcare workers. In the past ten years, studying proactive diagnosis with AI and related technologies has become a very interesting area of research. Doctors often look at X-rays of the lungs to check for tuberculosis (TB). Deep learning algorithms can accurately detect TB, similar to how doctors do. However, using classification algorithms can improve the chances of finding tuberculosis (TB) if the lungs are separated and analyzed individually instead of looking at the whole X-ray image. The writers describe the false information in a careful study and talk about the outcomes of using U-Net for separating the lungs in X-ray scans. They also compare U-Net to three other commonly used models for segmentation and talk about how segmentation can be helpful in identifying diseases in the lungs, such as tuberculosis or other lung-related illnesses. As per authors' knowledge, nobody has previously tried to use x-ray technology to implement U-Net pulmonary segmentation. The authors used a method called U-Net and were able to accurately segment the lungs with over 98% accuracy. They also found that the average values for lung segmentation were 0.95. This comparison analysis has been proven to be effective. The writers divided the data to make it safer and help the classification process focus on important parts, thus increasing its accuracy. The authors carefully examined and talked about the performance of SegNet and U-Net, two different architectures. We tested the performance of FCN, U-Net, SegNet, and U-Net on the Shenzhen and Montgomery datasets. The U-Net does much better than the other architectures and gets an accuracy of 98%. FCN did not do well with 78% and was not suggested to continue exploring image segmentation. [8]

Finding the boundaries or outline of lungs on CT scans is an important step in Lung cancer detection and other related uses. Segmentation is seen as a tricky issue because lung structures in images have similar density, and a diverse range of scanners and methods of scanning make it even more challenging. Many segmentation methods are dependent on human factors and may not always be accurate. Another disadvantage of these methods is that they often give inaccurate results by incorrectly identifying something as positive. In the last few years, many successful methods using deep learning have been used to segment medical images. The U-Net is a highly successful type of artificial intelligence that is used to separate different parts of medical images. In this paper, they suggest using a special computer program called Deep Neural Network to automatically separate and analyze parts of the lungs in CT scans. In their plan, they used different



techniques to prepare the CT images before using them for deep learning. They also found the accurate information to match these images by using certain operations and making changes manually. We used a special U-Net model called Res BCD U-Net to analyze images. The U-Net model had a ResNet-34 network instead of its regular encoder. In architecture, BConvLSPM is a special module that combines feature maps from the contracting path with the previous up convolutional layer. In the shrinking process, they used a closely connected Convolutional layer. Using lung CT images from the lidc-IDRI database, the new method achieved a dice coefficient index (CiI) of 97.31% In the method being suggested, there are three main actions. The first step is a partially automated process to collect accurate information for each lung. One of the main benefits of this method is that all mask images can be created by it cleverly without needing a radiologist and is time efficient. The next step is creating a new channel of three images. The new method we suggest has a much lower chance of wrongly detecting something (false positive) and has a better measurement for accuracy (dice coefficient). This is because it uses better images as input for the network. The third step is to use a special technology called Res BCD U-Net to separate the lung area from the CT images accurately without human intervention. Additionally, the framework for this process was created using a new type of computer network architecture called bdcdu-net, with the help of a pre-trained resnet-34 encoder. The model was given the name Res bdcu-net. This model did a good job as proven by many tests on a big lidc-idri dataset. The computer program used for the dataset was the same as the one used for making labels. The time it takes for this algorithm to finish is much less than the time it takes for the mask production method. This is one of the main advantages of this method. So, the medical community has decided to use the new algorithm in their everyday work. It is very important to accurately and reliably separate lung tissue in various medical uses like assisting with bronchoscopy, measuring emphysema, and diagnosing lung cancer. So, the main aim of this work is to use it in real-life medical situations for doctors and healthcare professionals. [9]

During the coronavirus outbreak, doctors use CT scans to figure out what is wrong with patients. The most recent studies about this subject mainly concentrate on big, private, detailed information. This kind of data is hard for an organization to obtain, especially as radiologists are currently dealing with the COVID situation. It was hard to compare these techniques because they use different datasets, learned with different training sets, and evaluated with different measurements. In this study, the authors used a special computer program called Deep Learning Semantic

Segmentation Architecture. They used it to find COVID damage in a small collection of chest CT scans. The planned model structure consists of two parts: an encoder and a decoder. In the part called encoder, there are 3 layers of convolutions and 3 layers of pooling. In the decoder, there are 3 layers of undoing image compression and 3 layers of making the image bigger.

**The dataset contains:** There are 20 pictures of patients' lungs in two different collections.

There are 3520 CT images along with their specified images.

The dataset is divided so that 70% goes into training and 30% is reserved for testing. The image dataset are changed in size and made to look similar before they are used.

This study examines five tests done, where they used different pictures to teach and assess in each test. The model performed very well, with an overall accuracy of 0.993. It also had a weighted IOU (intersection over union) score of 0.799 and a mean BF (boundary F1) score of 0.799. The model was better at correctly identifying positive and negative results, and it had a higher overall score for accuracy. The findings were better than other studies using the same data, but the similarity and amount of images affected the results. The design they suggested for DS3 had the best scores for IOUs, Mean IoUs, and Mean BF. The scores were 0.8700, 0.7700, 0.7800, and 0.7800 respectively. These measurements demonstrated that the model was better at accurately identifying and locating COVID-19 spots in CT lung images compared to other models.

When checking how well the model can tell if a pixel belongs to the COVID-19 or background category, it had the best accuracy for DS1 and was almost as accurate for DS3. The overall accuracy was 0.9932 and for DS3 it was 0.9930. So, we decided to use the proposed model for the DS3 based on the main findings of this research.

The overall accuracy of the suggested model was 0.9930, with a weighted Intersection over Union (IOU) score of 0.9886. The Weighted IOU was measured to be 0.7990, while both the Mean IOU and the Mean BF Score were determined to be 0.874. The predicted mask and the actual mask are very similar, with a similarity score of about 0.9930 based on the weighted IOU being 0.9886. [10]. Medical image segmentation has made significant progress in the past few years. Deep learning networks that can fully analyze images have been important, but they only identify small details and do not consider the complete context of medical images. This paper suggests two deep

learning models called USegTransform and USegTransform-S. These models use a combination of transformer encoder and convolution encoder to accurately divide medical images into different sections. The findings are good. USegTransform-P is better than other recent models in tasks like separating brain tumors, lung nodules, skin lesions, and nuclei. This could be very helpful for doctors and radiologists worldwide. They examined the forecasts made by these models on various sets of data.

We analyzed the above metrics to measure their quantities. However, we only used one metric to compare with previous models because most datasets were part of a competition that focused on that specific metric. The proposed model also gives visual predictions to help understand how well it performs.

The scientists suggested a new way to use deep learning technology to divide and analyze medical pictures. The new deep learning systems were called USegTransform-P and USegTransform-S. They helped doctors and made medical diagnosis faster. They also showed that combining transformer-based encoding with FCN based encoding is an effective approach in the model. They also showed two ways to combine FCN models with transformer models for segmentation.

Also, they showed that the suggested model performed well when tested on different benchmark datasets like LGG dataset, LUNA dataset, ISIC dataset, and data science Bowl 2018 dataset. USegTransform-P had better accuracies (99.71, 99.13, 95.14, 97.61%) compared to existing models, while USegTransform-S had better accuracies at 99.54, 98.94, 94.31, and 97.53%. In addition, they showed that features taken from FCN-based networks and transform-based networks work together to improve a model's ability to separate different parts in medical data. Based on these improvements that can be measured and observed, the suggested models were considered reliable and appropriate for use in actual clinical settings. Their predictions could be used in a diagnostic system to analyze medical images and reports. This would help medical workers to make sure that health services are available, easy to reach and effective for people who need them. [11]

Medical image segmentation has been extensively used in deep learning for a variety of purposes, but the performance of current medical segmentation models is limited due to the high cost of data annotation and the difficulty of obtaining high quality labeled data. To address this issue, the author proposes a new language-based medical segmentation model (LViT). The LViT integrates medical

text annotation to address the quality deficiency of image data. The text information can also be used to guide the generation of pseudo labels of higher quality in semi supervised learning. The authors also suggest an Exponential Pascal-Epy (PPE) label iteration mechanism (EPI) to help PLAM maintain local image feature in semi supervised LViT settings. In the model, LV loss is designed to oversee the training of unlabeled images using directly text information. The authors construct three multidimensional medical segmentation data sets (X-ray + text) with X-ray and CT images for testing. Experimental results show that the model being proposed, has comparatively improved segmentation performance than conventionally designed models in both fully supervised and semi supervised settings. [12]

It is important to accurately identify and outline organs and abnormalities in medical images to correctly diagnose diseases and measure the size and shape of organs. Convolutional encoder decoder techniques have made significant progress in automatically segmenting medical images. Previous models mainly focused on the close-up visual clues made by nearby pixels because of the built-in partiality of convolution operations, but they did not completely analyze the faraway relationships between visual elements.

In this article, we suggest a new neural network called TransAttUnet. The network uses attention and skip connections to enhance the way we analyze and understand images.

Based on the Transformer, we include three modules called self aware attention (SAA), Transformer Self attention (TSA), and Global spatial attention (GSA) in TransAttUnet. This allows us to better understand how different parts of the encoder connect with each other. We also connect different parts of the decoder blocks together to make the image clearer and more detailed. This helps us to better understand the different image layers and perform final image quality enhancement.

**Advantages of complementary parts:** TransAttUnet improves the quality of segmentation in medical images by reducing the loss of fine details caused by stacking convolution layers and successive sampling operations. Many tests were done on different medical images to see how well the method works compared to other techniques. The results showed that the method did better than the current standard methods. In this paper, the authors proposed a new attention-guided u-net based on transformer called TransAttUtet, which integrates multilevel guided attention and

multilevel skip connections into the U-Net to improve segmentation strength in biomedical images. In particular, the multilevel focused attention block maximizes the utilization of global context information by learning about long-distance interactions as well as global spatial links among encoder semantic features. The multilevel skip connection scheme flexibly aggregates contextual feature maps of different semantic scales decoders to produce the discriminate feature depictions. When compared to previously done advanced work, TransAttU<sub>tet</sub> greatly benefits from long-distance feature dependencies and multiscale context information, which guarantees semantic consistency in feature representations. By doing so, they effectively reduce the inherent bottlenecks that are present in legacy Ushape architecture. In fact, extensive testing on various benchmark datasets showed that the proposed transAttUnet can deliver consistent performance improvements by incorporating the above-mentioned innovations [13].

More recent transformer-based models are getting a lot of attention, especially when used with U-Net (or variants of it) which has been really successful for medical image segmentation. Most current 2D-based methods either just swap out the convolutional layers for pure transformers or think of a transformer like an additional encoder that resides between U-Net and the encoder. But these methods only look at the attention encoding in single slice and don't take into account the axial axis information that's naturally given by the 3D volume. Plus, in 3D, both convolution on volume data and transformers use up a lot of GPU memory, so you have to either downsize the image or just use cropped local patches, which slows it down. So, in this paper, they came up with a new model called AXIAL FUEL TRANSFORMER UNET (AFTER-UNET), which takes advantage of both the power of convolution layers' ability to extract comprehensive features and the strength of transformers to perform long sequence modeling, taking into account both single-slice as well as multiple-slice and long-range indications for segmentation. In addition, the model has less parameters and requires less GPU memory for training compared to the models based on transformers in the past. The extensive experimentation results on three multidimensional segmentation datasets prove that their method surpasses the present best-in-class methods. The researchers present AFTer-Unet, an all-in-one framework for segmentation process of medical images. The framework being proposed uses the axial fusion mechanism for fusion of single slice, and multiple-slice context information and guides the end-of-segmentation process. Demonstrations on three datasets. [14]

Medical Segmentation is one of the most important tools to help doctors to diagnose diseases accurately. However, medical Segmentation needs to be more accurate due to the noisy nature of medical images and background regions being quite similar to target region. Current mainstream Segmentation Networks like TransUnet have provided better performance in segmentation tasks but the encoder of these Segmentation Networks does not take into account the localized fusion of adjacent chunks and does not realize the information communication between channels while upsampling the Decoder. In this paper, we proposed a Dual Encoder Image Segmentation Network including HarDeepNet68 & Transformer branch that can be used to extract localized feature information and global Segmentation Information of the input Image allowing the Segmentation Network in acquiring better information about the image thereby enhancing Segmentation Networks accuracy and efficacy. We propose a Feature Adaptation Fusion Module to merge the Channel Information of Multi-Level Segmentation Networks and realize the Information Interaction between Channels and then improve Segmentation Network accuracy.

The results from the experiment, for the proposed model are based on four evaluation metrics: Dice (4), Iou (5), Prec (6), and Sens (7). The proposed model outperforms the existing model in terms of internal filling as well as edge prediction for imaging applications in medical field. Better segmentation can help doctors to make a well-informed diagnosis for cancerous areas ahead of time, provide targeted treatment for cancer patients, and improve survival quality. As the transform module in the current image segmentation network doesn't take into account the local connection of adjacent blocks, channel information having low interaction during upsampling, the authors propose a dual module (HarDNet68) and transformer (Transformer) for simultaneous image segmentation at the same time. HarDNet68 is an improved version of the existing network structure, DenseNet, which runs faster and extracts information about localized features. The transformer module can take global information into account and uses it to get global feature information from medical images. It's designed to combine information about image features, from different dimensions into a dual stage of coding and decoding. To do this, it's proposed to combine channel information from multiple-level features, realize information interactions between channels, and after doing that, use that to enhance the accuracy of segmentation networks. The Dice for this method was 0.932, the Dice for the comparison method was 0.775, and the Dice for the method for the medical images was 0.953. The Mean Out of Unit (OOU) was 0.822, the Mean Out of Mean (71) was 0.691, and the Mean Out of Out of Out (974) was better than the

segmentation effect. [15]

The problem with analyzing detailed medical images is that the transformer's ability to analyze them is still being developed. The main reason for the UNet's great success is its ability to understand segmentation, which current transformer-based models are not good at. To fill this gap, they suggested a new transformer model that can divide medical images of various types. FCT combines the strong image learning abilities of CNNs with the efficient long-term dependency capturing abilities of Transformers. FCT is the first type of model in medical imaging research that combines convolutional and transformer techniques. FCT learns how to handle its input in two steps. First, it first learns how to find and understand important information that is far away in the picture. Then, it learns how to find and understand important features that make up the big picture. This is small, very precise and very strong. The study shows that FCT is better than all existing transformer models by a big difference. It works well on various medical image segmentation datasets without any pre-training. FCT performs better than its competitor on multiple datasets, like ACDC, Synapse, Spleen, ISIC 2017, and the dice metric. It achieves this with fewer parameters, up to 5 times less. On the ACDC dataset, FCT performs better than all other models, even though it has 5 times fewer parameters. FCT's model size is also 5 times smaller than its closest competitor, nnFormer, which has a size of 158.9 million parameters and 157.8 gigaflops. The author's model achieved better results than the previous best models on hidden MRI test cases, even though it had fewer parameters compared to large ensemble models and nnUnet. FCT has the best results among all the methods, with fewer parameters and a higher measure of operations performed per second. The researchers taught the computer program using two different sizes of pictures. Using a larger input image size of  $384 \times 384$  for FCT gives better results compared to the smaller input image size of  $224 \times 224$  because it has higher spatial resolution. They also looked at the difference between using deep supervision on all sizes of the image and not using it at all when comparing their model. The researchers found that the deep supervision configuration stands to be the ideal setting for the model. To prove that their results were important, they also did a 5-fold cross validation of ACDC and calculated p-values that showed their results were important compared to nnFormer. The experiments used FCT224. By using 5-fold CV, the average dice score was 92.43 with a standard deviation of 0.38. The tests were done 5 times using ACDC, and the average result was  $92.88 \pm 0.09$ . This dataset was very advanced compared to nnFormer, which had an average of  $91.78 \pm 0.18$ . They also looked at their findings along with the

previous ones and found that there was a significant difference in both cases. The results on Synapse were mostly similar to TransUNet(5), LeViT(UNet(39)), and SwinUNet(3) because they used the identical data-splitting scheme and pre-processing as TransUNet(4).

They looked at all three models and found that their model was much better than all of them. This means that their model can be used as a good base for making multiple-layer semantic segmentation. They discovered that TransUNet has ViT+12 main structures, which implies it consists of approximately 100 million parameters (and 49 billion floating-point operations per second). You can find all the results in the table below. When comparing the segmentation of the Spleen, they outperform SETR and CoTr, as well as TransUNet, by over 1.2% in terms of accuracy, with a significantly lower number of parameters. They also did better than the Boundary Aware Transformer, a new program made to identify skin cancer, by around 1.1%. They also studied sensitivity, which is a good way to measure how accurately a model can find the boundaries of cancer. Usually, models made from ISIC 2017 data can detect many things, but the BA Transformer model can only detect a few things. That's why they talked about it here. The ablation studies found that the main reason for this was because their Wide-focus module could accurately gather important information from various parts of the image. They created a new type of block called fully convolutional transformer block. This block can perform binary and semantic segments without using as many parameters as current models. They discovered that FCT was much smaller than nnFormer, about five times smaller. It was also three times smaller than TransUNet, and even smaller than TransViT-Unet. The FCT layer has two main parts – first being convolutional attention and second being wide focus. Convolutional attention eliminates the any requirement for positional encoding while generating patches for your model. Their medical image processing algorithm used a technique called depthwise-convolution to analyze spatial information and identify connections between different parts of the image. This approach was the first of its kind in the field of medical imaging. Using a wide-focus approach in the ablations helped us make use of detailed information in medical images, which was important for enhancing the performance of our transformer block. They showed that their model works well by producing good results on several large datasets with different types of data and sizes [16].



## CHAPTER 4: IMPLEMENTATION AND METHODOLOGY

### 4.1. Research Objectives

The essence of this study lies in the comparative assessment of various computer vision models' capabilities in lung segmentation, a critical task within medical image analysis. We have selected four prominent models for evaluation: UNet, U2Net, SegFormer, and DPT. Our overarching goal is to gain insights into their performance across multiple dimensions.

1. **Jaccard Index Assessment:** Our foremost objective is to gauge the precision of each model's lung segmentation. The Jaccard Index, often referred to as the Intersection over Union (IoU), serves as a robust metric for this purpose. It quantifies the degree of overlap between the predicted lung regions and the ground truth, offering a measure of segmentation accuracy.
2. **Dice Score Evaluation:** Complementing the Jaccard Index, we aim to assess the Dice Score for each model. This metric provides a nuanced perspective on segmentation quality by accounting for both false positives and false negatives. A high Dice Score indicates a closer alignment between the model's predictions and the actual lung boundaries.
3. **Inference Speed Analysis:** In a clinical setting, time is of the essence. Therefore, we seek to determine the real-time performance of these models. This entails measuring the time required for each model to process a lung image and generate a segmentation output. A faster inference speed signifies a model's suitability for time-sensitive applications.
4. **Model Size Investigation:** Computational resources are valuable assets. We will investigate the size of each model in terms of memory and storage requirements. Understanding the trade-off between model size and performance is pivotal, as it influences deployment feasibility and scalability.
5. **Robustness to Noise Testing:** In the medical domain, images are often afflicted with noise due to various factors. To assess the models' practical utility, we will subject them to lung images corrupted by noise. The objective is to ascertain the extent to which these models can maintain accurate segmentation in challenging, real-world scenarios.

In summary, this study transcends the mere selection of a superior model; it delves into the multifaceted aspects of model performance in the specific context of lung segmentation. These objectives drive our research, providing a comprehensive evaluation framework for these state-of-the-art models.

### 4.2. Data Collection

The foundation of any robust research lies in the quality and relevance of the dataset employed. In this study, we leveraged an openly accessible dataset specifically designed for lung segmentation tasks namely Pulmonary Chest X-Ray Defect Detection and for testing dataset we used a subset



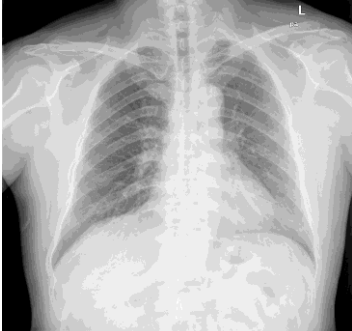
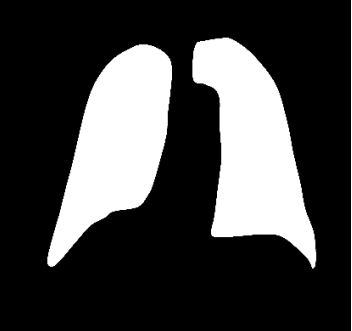

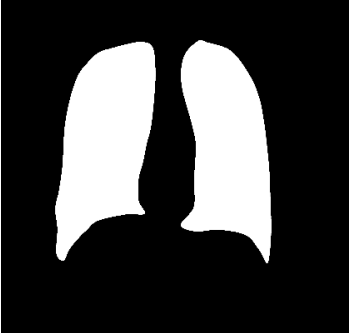
of Shenzhen Chest x-ray dataset. This dataset is a valuable resource in the realm of medical image analysis, facilitating our comparative study of computer vision models.

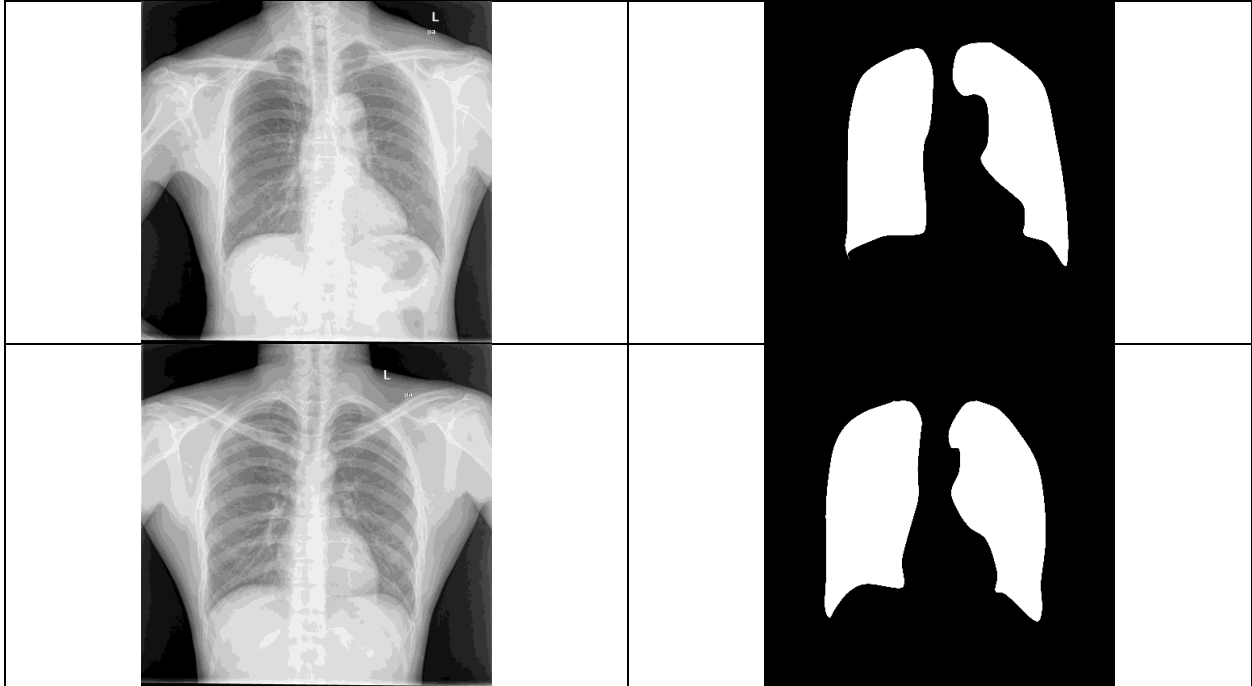
### 4.3. Dataset Description

The dataset consists of a diverse array of medical images, each of which focuses on the pulmonary region. These images were meticulously curated to encompass variations in anatomy, pathology, and image quality. Importantly, the dataset includes ground truth annotations that delineate the precise boundaries of the lung structures within each image. These annotations serve as the reference standards against which the model's segmentation outputs are evaluated.

Following are few samples' images from the dataset:

**Table 1: Original x-ray images and their corresponding masks**

Image	Mask
	
	
	



#### 4.4. Data Preprocessing

To prepare the dataset for model training and evaluation, a series of preprocessing steps were performed:

1. **Random Augmentations:** Random brightness, random contrast, and random RGB shift augmentations were applied to the images. These augmentations are essential for introducing variability into the training data, thereby enhancing model generalization.
2. **Image Resizing:** The dataset includes images with varying dimensions. To ensure consistency and compatibility with the input requirements of each segmentation model, all images were resized to a standardized resolution.

The meticulous handling of the dataset, including ethical adherence and preprocessing, lays the groundwork for the subsequent stages of this research, which involve the training, evaluation, and comparison of the selected computer vision models. These steps will be elucidated further in the subsequent sections of this methodology chapter.

#### 4.5. Model Architectures

The crux of this study hinges on the selection and utilization of diverse model architectures tailored to the task of lung segmentation within medical images. Four distinctive architectures have been chosen for evaluation: UNet, U2Net, SegFormer, and DPT. Each architecture offers unique features and characteristics contributing to the breadth of this comparative analysis.

## 4.5.1. Convolutional Neural Networks (CNN) Based Models

### 4.5.1.1. UNet

UNet, a pioneering architecture in the realm of semantic segmentation, constitutes the first pillar of our study. Known for its remarkable success in biomedical image analysis, UNet is revered for its expansive architecture, incorporating a contracting path followed by an expansive path. It possesses the capability to capture intricate image features while preserving spatial information, making it an ideal candidate for lung segmentation.

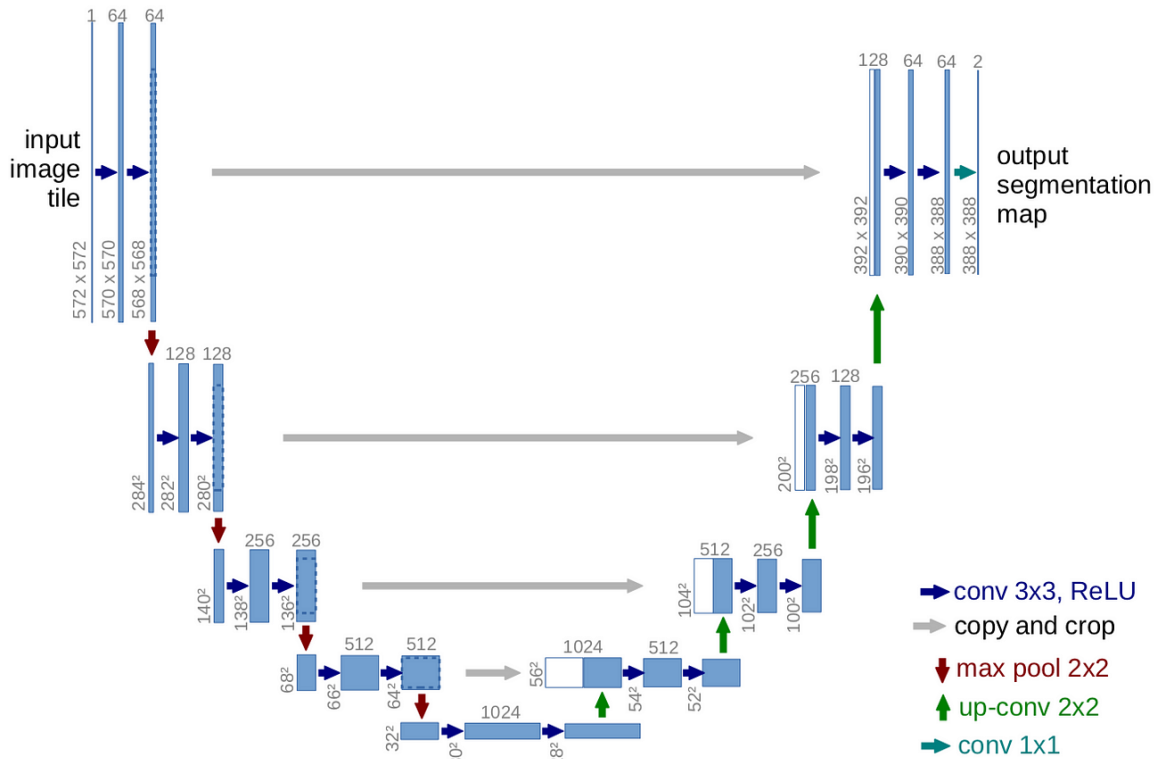


Figure 1: UNet Architecture Diagram

### 4.5.1.2. U2Net

U2Net represents a more recent advancement in the field, tailored for precise object boundary delineation. With its intricate architecture, including nested U-shaped pathways and a focus on saliency prediction, U2Net aims to provide superior segmentation accuracy, particularly in challenging scenarios.

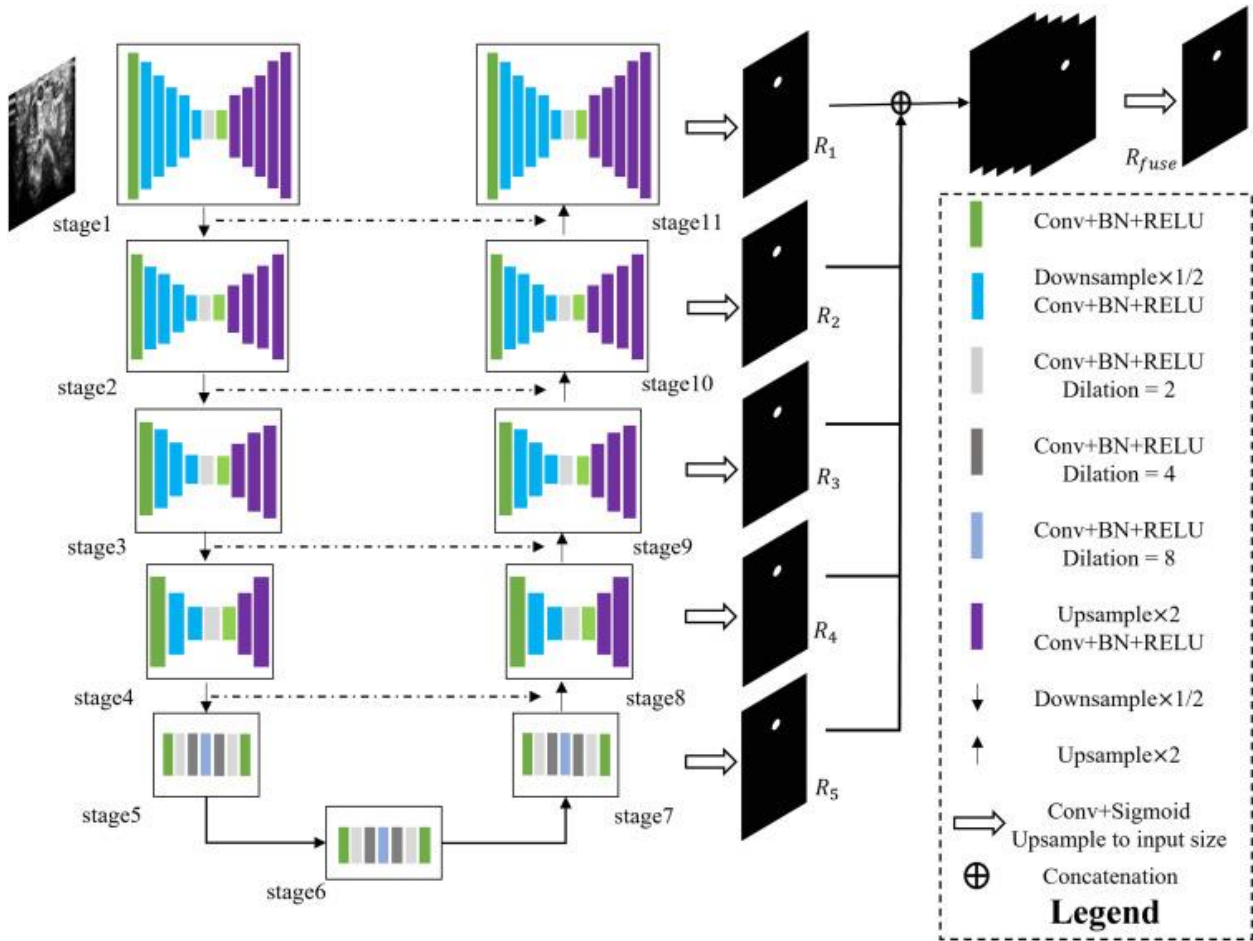


Figure 2: U2Net Architecture Diagram

## 4.5.2. Transformer-Based Models

### 4.5.2.1. SegFormer

SegFormer, in contrast to the conventional CNN-based models, harnesses the power of transformers. Originally conceived for natural language processing, transformers have recently made inroads into computer vision tasks. SegFormer, being one of the pioneers in this endeavor, seeks to demonstrate the potential of transformers in semantic segmentation. Its unique architecture prioritizes image patch processing and hierarchical feature extraction, revolutionizing the field.

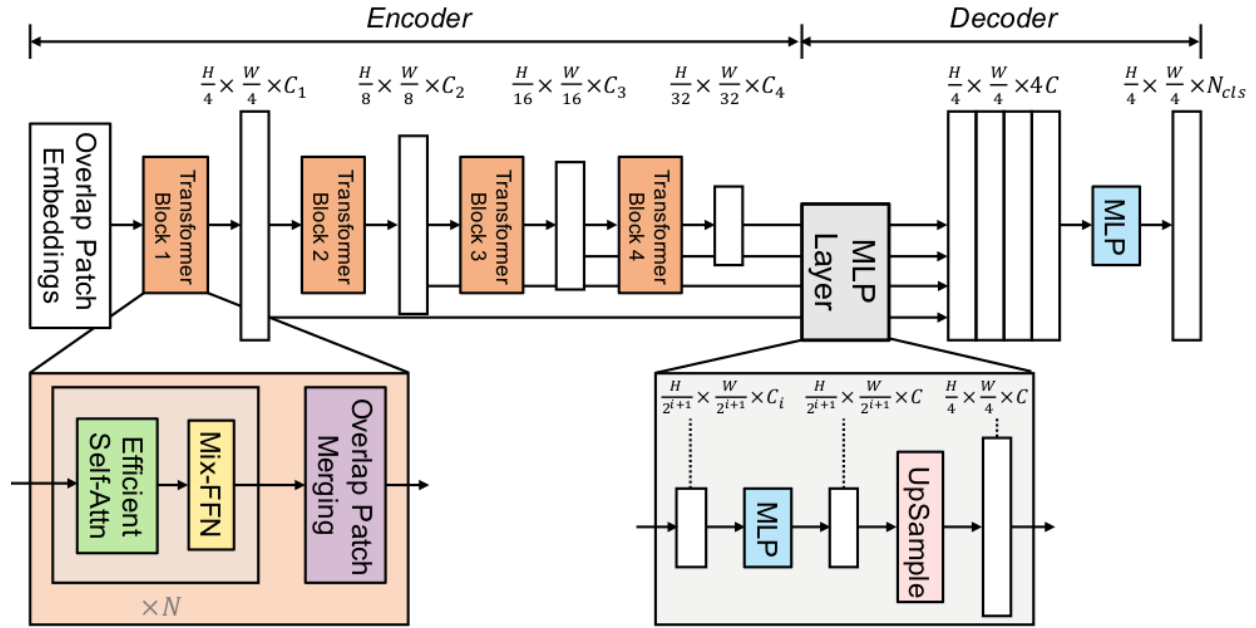


Figure 3: Segformer Architecture Diagram

#### 4.5.2.2. Data-efficient Image Transformer (DPT)

DPT, another revolutionary transformer-based architecture, explores the paradigm of data efficiency. In the era of ever-increasing model sizes, DPT strives to strike a balance by employing transformer principles for accurate lung segmentation while ensuring a more compact model footprint. Its focus on patch-based processing aims to optimize both performance and computational resources.

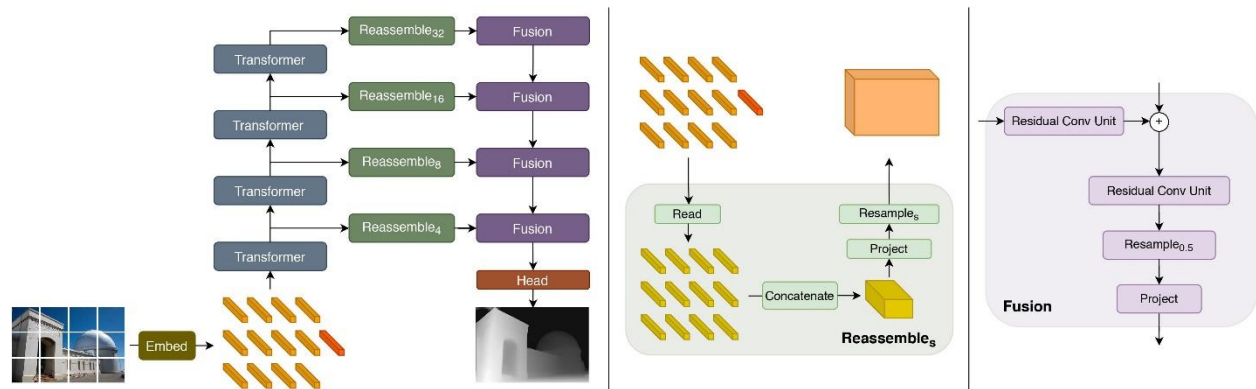


Figure 4: DPT Architecture Diagram

## 4.6. Model Customization

It is imperative to note that, in this study, we adhere to the original architectural designs of these models. No modifications have been made to the architectures themselves. Instead, the emphasis

is placed on leveraging transfer learning and fine-tuning strategies, harnessing the inherent capabilities of these architectures while respecting the integrity of their designs.

These carefully chosen model architectures serve as the instrumental tools in our quest to comprehensively evaluate lung segmentation performance. The subsequent sections will delve into the intricacies of training, evaluation, and the metrics applied to discern the effectiveness of each model.

## 4.7. Training

The training phase of our comparative study constitutes a pivotal aspect, as it imparts the models with the ability to discern and delineate lung regions within medical images. A systematic approach has been employed to ensure fair and effective training across all selected architectures, namely UNet, U2Net, SegFormer, and DPT.

## 4.8. Data Partitioning

Before initiating the training process, the dataset was judiciously partitioned into three distinct subsets: the training set, validation set, and test set. This partitioning ensures that the models are exposed to diverse data for effective learning, validation, and evaluation.

- **Training Set:** The largest subset, comprising a substantial portion of the dataset, serves as the primary source for model learning. It enables the models to grasp the intricacies of lung anatomy and variations in image characteristics.
- **Validation Set:** A dedicated validation set is vital for monitoring the models' performance during training. It provides an independent dataset against which the models' progress is evaluated, aiding in the selection of optimal hyperparameters and preventing overfitting.

## 4.9. Hyperparameter Settings

The training parameters for each model adhere to established standards and default settings as outlined in the respective original research papers and documentation. This consistency in hyperparameter selection ensures that the models are trained under comparable conditions, enhancing the reliability of the comparative analysis.

Key hyperparameters include:

- **Learning Rate:** A crucial factor governing the rate of model convergence.
- **Batch Size:** The number of samples processed in each training iteration.
- **Number of Epochs:** The total number of training cycles.
- **Loss Function:** A function that quantifies the disparity between predicted and ground truth segmentations.

## **4.10. Transfer Learning and Fine-tuning**

To expedite and optimize model training, a transfer learning approach is adopted. Pre-trained weights, obtained from models trained on large-scale image datasets, are initialized as the starting point for our models. These weights encapsulate valuable knowledge about low-level image features, which can be leveraged to expedite learning on the lung segmentation task.

Fine-tuning follows the transfer learning phase, allowing the models to adapt and specialize in lung segmentation. During fine-tuning, the models' weights are adjusted to align with the nuances of lung anatomy and image characteristics present in our dataset.

## **4.11. Training Environment**

All training procedures were conducted using the Google Collab platform. For CNN-based models (UNet and U2Net), PyTorch, a widely adopted deep learning framework, was employed. In the case of transformer-based models (SegFormer and DPT), the Hugging Face Transformers library was utilized, harnessing the power of transformers for computer vision tasks.

The training process was monitored meticulously to ensure convergence and to avoid potential issues such as overfitting. Model performance on the validation set was tracked to determine the optimal stopping point for training.

In the subsequent sections, we will delve into the metrics employed for model evaluation and the experiments undertaken to assess their performance effectively.

## **4.12. Evaluation Metrics**

The evaluation of our selected models, including UNet, U2Net, SegFormer, and DPT, hinges on a comprehensive set of metrics designed to gauge their performance in lung segmentation accurately. These metrics encompass a holistic assessment of their capabilities in delineating lung regions within medical images.

### **4.12.1. Jaccard Index (Intersection over Union - IoU)**

The Jaccard Index, also known as the Intersection over Union (IoU), is a pivotal metric in our evaluation framework. It quantifies the degree of overlap between the model's predicted lung region and the ground truth. Mathematically, it is calculated as the intersection of the predicted and ground truth regions divided by their union. A higher IoU score signifies a more accurate segmentation, with a perfect match yielding a score of 1.

### **4.12.2. Dice Score (F1 Score)**

Complementing the Jaccard Index, the Dice Score, or F1 Score, provides an additional perspective on segmentation accuracy. It balances the precision and recall of the model by considering both false positives and false negatives. The Dice Score is calculated as twice the intersection of



predicted and ground truth regions divided by the sum of their areas. Similar to the Jaccard Index, a higher Dice Score implies superior segmentation performance.

#### **4.12.3. Foreground Accuracy**

Foreground accuracy measures the model's ability to correctly identify and segment the lung regions within an image. It calculates the percentage of correctly predicted foreground pixels concerning the total number of foreground pixels in the ground truth. A high foreground accuracy score indicates that the model accurately identifies lung regions.

#### **4.13. Cross-Validation**

To ensure the robustness and reliability of our evaluation, we employ cross-validation. The dataset is divided into multiple subsets, and the models are trained and evaluated iteratively on different partitions. This process helps mitigate biases introduced by a particular dataset split and provides a more comprehensive assessment of model performance.

#### **4.14. Statistical Significance**

Statistical significance tests, such as the t-test or Wilcoxon signed-rank test, are applied to ascertain the significance of differences observed between model performances. These tests help validate whether observed variations in metrics are statistically significant or merely the result of random chance.

#### **4.15. Experiment Replication**

For each metric, experiments are replicated multiple times to reduce the impact of random variations and provide a more stable assessment of model performance. The replication process ensures that results are consistent and reliable.

In summary, our evaluation metrics encompass a multidimensional analysis of model performance, considering both accuracy and robustness. These metrics, combined with cross-validation and statistical testing, constitute a robust evaluation framework that enables an objective and comprehensive comparison of the selected lung segmentation models.

#### **4.16. Experiments and Setup**

The experiments conducted in this study are designed to rigorously evaluate the performance of our selected lung segmentation models, namely UNet, U2Net, SegFormer, and DPT. A systematic and controlled setup has been employed to ensure the reliability and reproducibility of our findings.

#### **4.17. Experimental Design**

1. **Data Partitioning:** As previously mentioned, the dataset is partitioned into three distinct subsets: the training set, validation set, and test set. This partitioning ensures that the models are trained on one subset, validated on another, and rigorously tested on a third,

independent subset. The random nature of the data split is controlled to minimize any potential bias.

2. **Model Training:** Each model is meticulously trained using the training set. Transfer learning, initialized with pre-trained weights, serves as the foundation for model training. Fine-tuning follows to adapt the models to the specific task of lung segmentation.
3. **Validation:** During the training process, the models' performance is monitored using the validation set. Early stopping criteria are employed to prevent overfitting and to identify the optimal model checkpoint.
4. **Testing:** The ultimate evaluation of model performance is conducted on the test set, which remains unseen by the models during the entire training and validation phases. This ensures an unbiased assessment of their capabilities.

## 4.18. Metrics and Measurements

The evaluation metrics outlined in the previous section, including the Jaccard Index, Dice Score, and Foreground Accuracy, are meticulously computed for each model's performance on the test set. These metrics provide quantitative insights into segmentation accuracy, precision, and recall.

## 4.19. Replication of Experiments

To ensure the robustness and reliability of our findings, all experiments are replicated multiple times. Replication helps mitigate the impact of random variations and provides a more stable assessment of model performance. The results are averaged over these replications to obtain more reliable performance measures.

## 4.20. Hardware and Software Environment

All experiments and model training were conducted on the Google Colab platform, which offers a cloud-based environment with access to high-performance GPUs. This ensures uniformity in the computational resources available to each model, facilitating a fair comparison.

- **CNN-based Models:** PyTorch, a widely adopted deep learning framework, was utilized for UNet and U2Net implementation. PyTorch's extensive ecosystem and ease of use make it a popular choice for deep learning tasks.
- **Transformer-based Models:** For SegFormer and DPT, we harnessed the Hugging Face Transformers library. This library provides pre-trained transformer models, streamlining the implementation of transformer-based architectures for computer vision tasks.

## 4.21. Model Training Parameters

Consistency in training parameters is a crucial aspect of our setup. All models were trained using default settings and hyperparameters as outlined in the respective original research papers and documentation. These include learning rates, batch sizes, and the number of training epochs.

## 4.22. Ethical Considerations

Ethical principles and responsible research practices are of paramount importance in the conduct of this study, particularly when working with medical data and sensitive patient information. We have meticulously addressed various ethical aspects to ensure the integrity and ethical soundness of our research.

### 4.22.1. Data Privacy and Anonymization

- **Patient Privacy:** The dataset employed in this study consists of medical images, potentially containing sensitive patient information. To safeguard patient privacy, all data used have undergone thorough anonymization and de-identification processes. Personal identifiers such as names, dates of birth, and medical record numbers have been removed or encrypted.
- **Institutional Approval:** Prior to data acquisition and usage, institutional approvals and ethical clearances, where applicable, have been obtained. Compliance with institutional protocols and guidelines is a fundamental aspect of this research.

### 4.22.2. Open Data Usage

- **Open Data Principles:** Wherever possible, we have prioritized the use of openly accessible and publicly available datasets. Utilizing open data sources ensures transparency and facilitates replication of our research by the scientific community.

### 4.22.3. Ethical Data Handling

- **Data Usage Agreement:** A strict data usage agreement has been upheld throughout this research. Data were accessed and used solely for the purpose of this study, with adherence to all terms and conditions stipulated by data providers.
- **Data Security:** Stringent data security measures have been implemented to protect against unauthorized access and data breaches. Data storage and access are restricted to authorized researchers involved in this study.

### 4.22.4. Informed Consent

- **Patient Consent:** In cases where patient consent was required for data usage, it was obtained following ethical guidelines and institutional procedures. Patient consent forms were carefully drafted to ensure comprehension of the research objectives and potential implications.

#### 4.22.5. Transparency and Reporting

- **Full Disclosure:** We commit to full transparency in reporting our findings. All methods, data sources, and procedures are clearly documented in this thesis, enabling readers to evaluate the research process comprehensively.

#### 4.22.6. Ethical Oversight

- **Ethical Review:** This research has undergone ethical review, where necessary, by relevant institutional review boards (IRBs) or ethics committees. Ethical oversight helps ensure that the research aligns with established ethical standards.

#### 4.22.7. Responsible Research

- **Responsible Conduct:** Throughout this study, we have adhered to the principles of responsible research conduct. This encompasses integrity in data handling, honesty in reporting, and adherence to ethical guidelines.

In conclusion, ethical considerations have been at the forefront of our research endeavors. We have rigorously upheld ethical standards, prioritizing patient privacy, data security, and transparency. These ethical foundations underpin the integrity and credibility of our study, allowing us to contribute responsibly to the field of medical image analysis.

## CHAPTER 5: RESULTS

In this chapter, we present the outcomes of our research, which include the performance of the selected lung segmentation models (UNet, U2Net, SegFormer, and DPT) based on various evaluation metrics.

### 5.1. Evaluation Metrics

Before delving into the results of individual models, we provide an overview of the evaluation metrics used in this study, including the Jaccard Index and Foreground Accuracy (Table 4.1). These metrics serve as the foundation for the comparative analysis of model performance.

**Table 2: Overview of Evaluation Metrics**

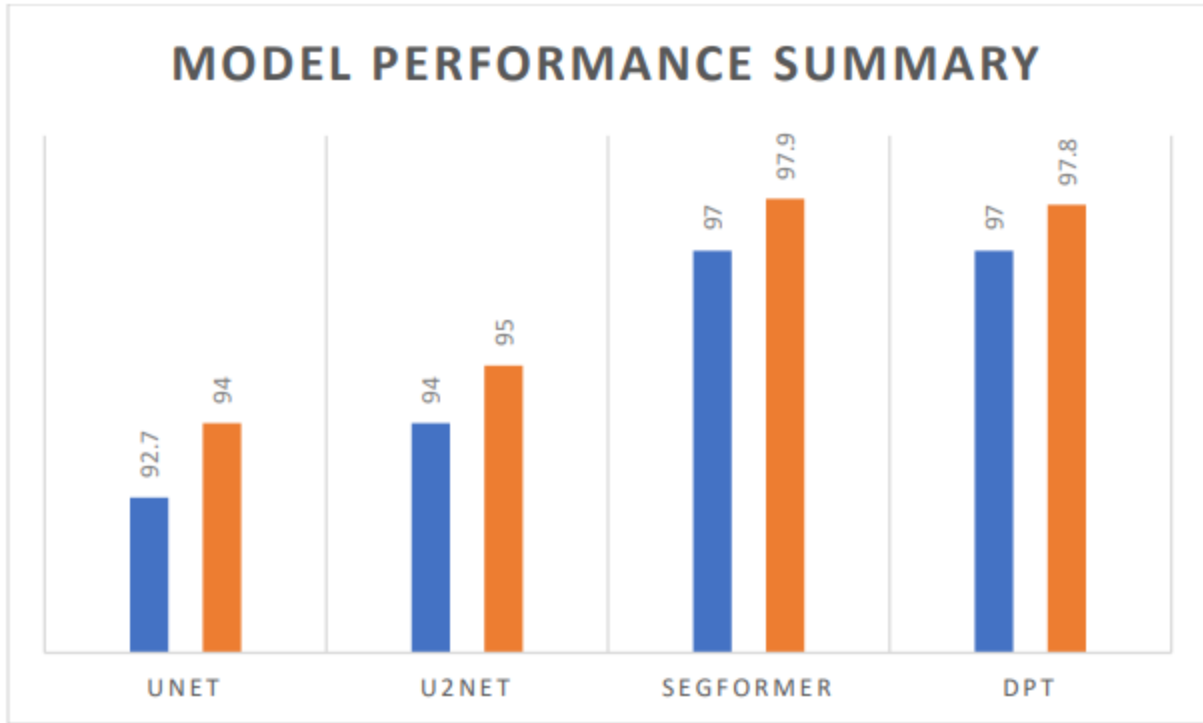
Metric	Description
Jaccard Index (IoU)	Measures the overlap between predicted and ground truth.
Foreground Accuracy	Measures the correctness of lung region identification.

### 5.2. Model Performance

In this section, we present the detailed results of each model based on the defined evaluation metrics. We begin by summarizing the quantitative performance metrics in Table 4.2.

**Table 3: Model Performance Summary**

Model	Jaccard Index (IoU)	Foreground Accuracy
UNet	92.7	94
U2Net	94	95
SegFormer	97	97.9
DPT	97	97.8





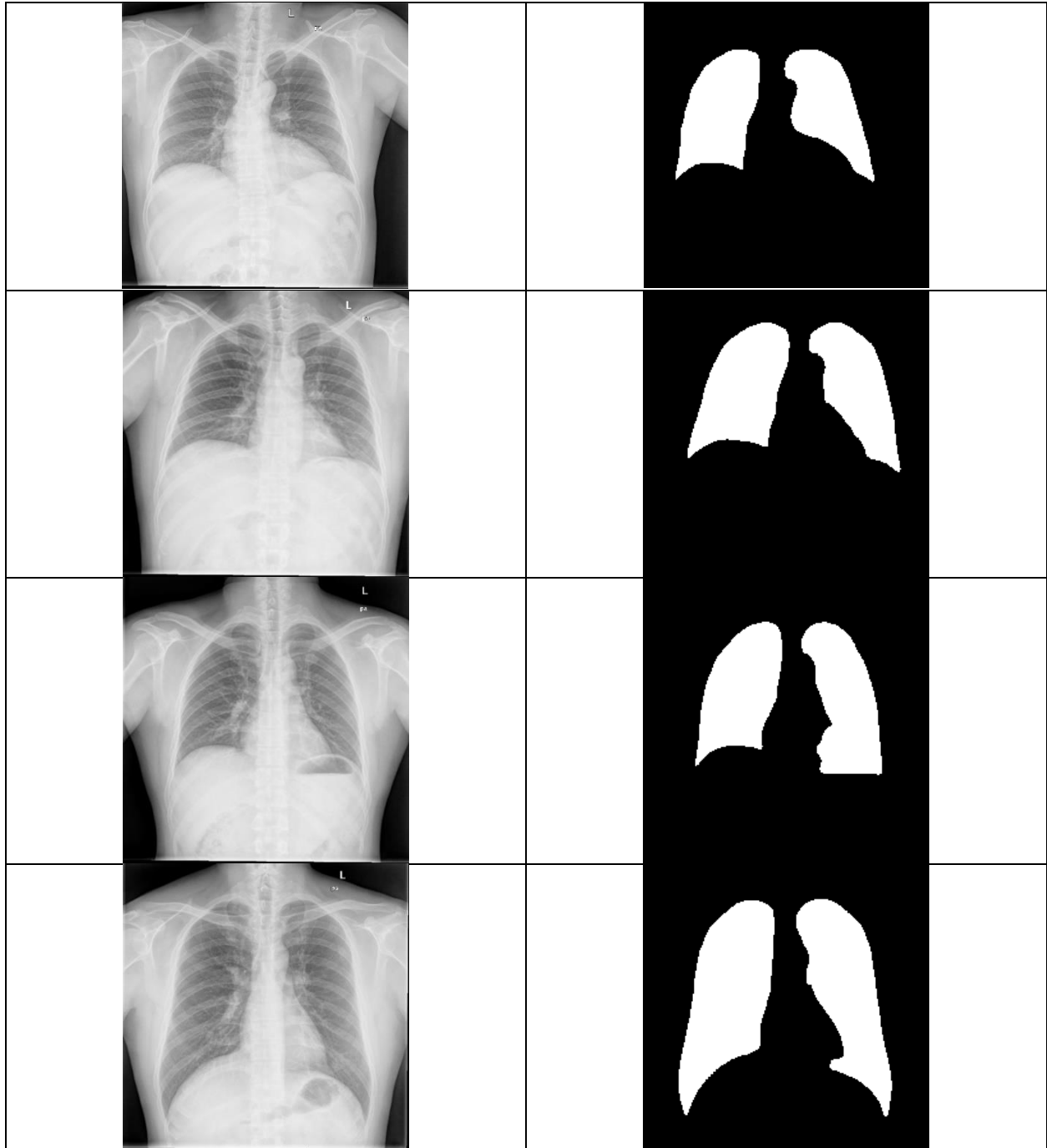
**Figure 5: Model Performance Summary using Accuracy as Criteria**

### 5.2.1. UNet

In this subsection, we provide a detailed analysis of UNet's performance based on the evaluation metrics. We include visual examples of segmentation results (Figure 4.1) to illustrate its capabilities.

**Table 4: Example UNet Segmentation Results**




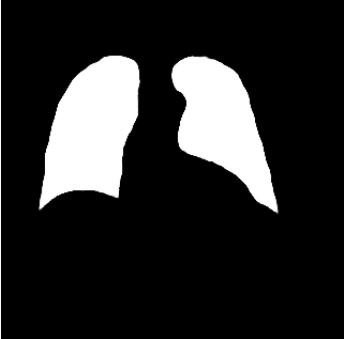



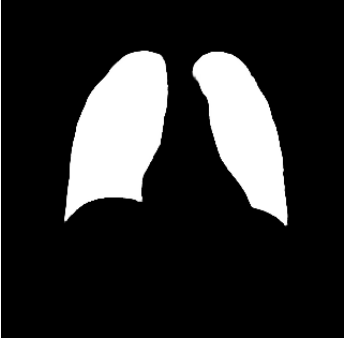
Image	Predicted Mask
	



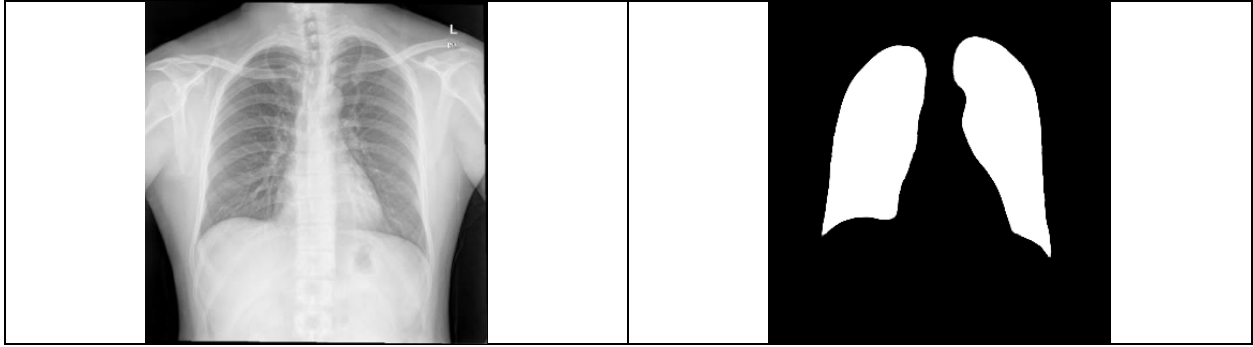
### 5.2.2. U2Net

Similarly, we present an in-depth examination of U2Net's performance, accompanied by visual segmentation examples (Figure 4.2).

**Table 5: Example U2Net Segmentation Results**

Image		Predicted Mask	
			
			
			
			




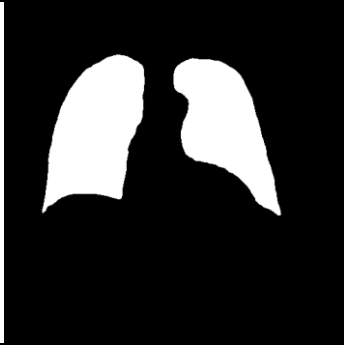




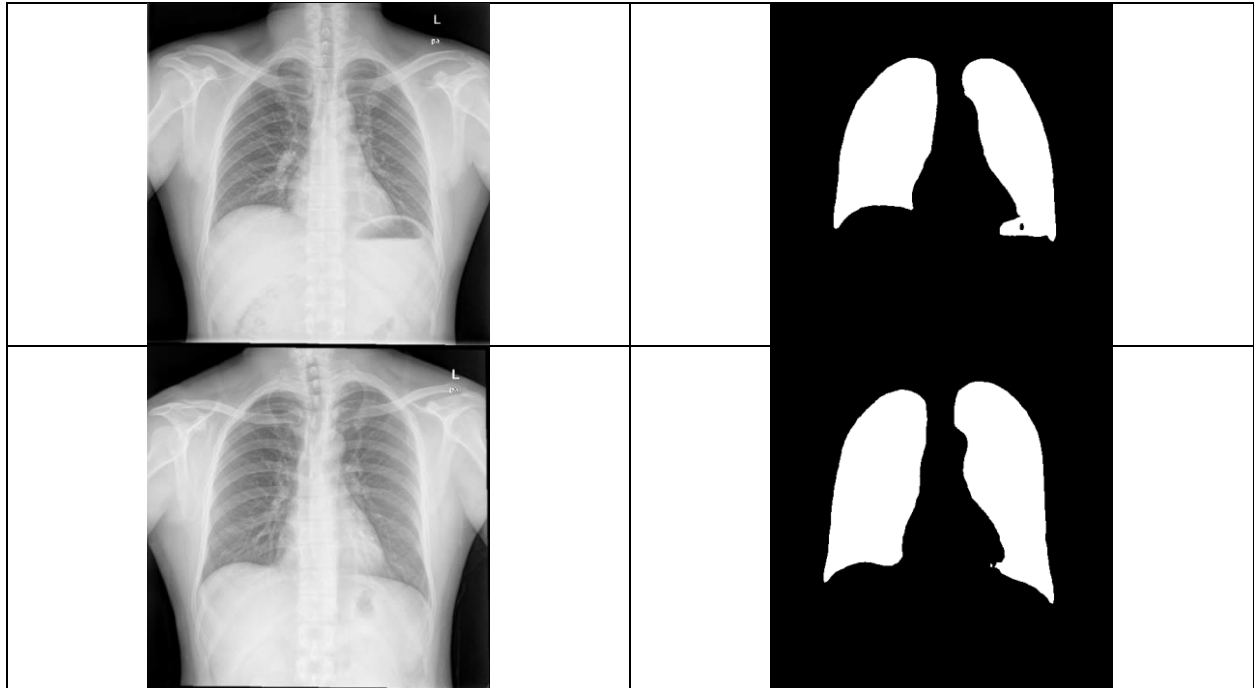


### 5.2.3. SegFormer

In this subsection, we delve into the performance of SegFormer and provide visual representation of its segmentation results (Figure 4.3).

**Table 6: Example SegFormer Segmentation Results**




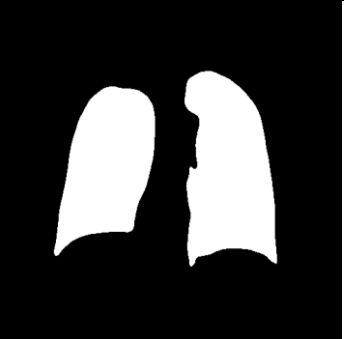
Image	Predicted Mask
	
	
	

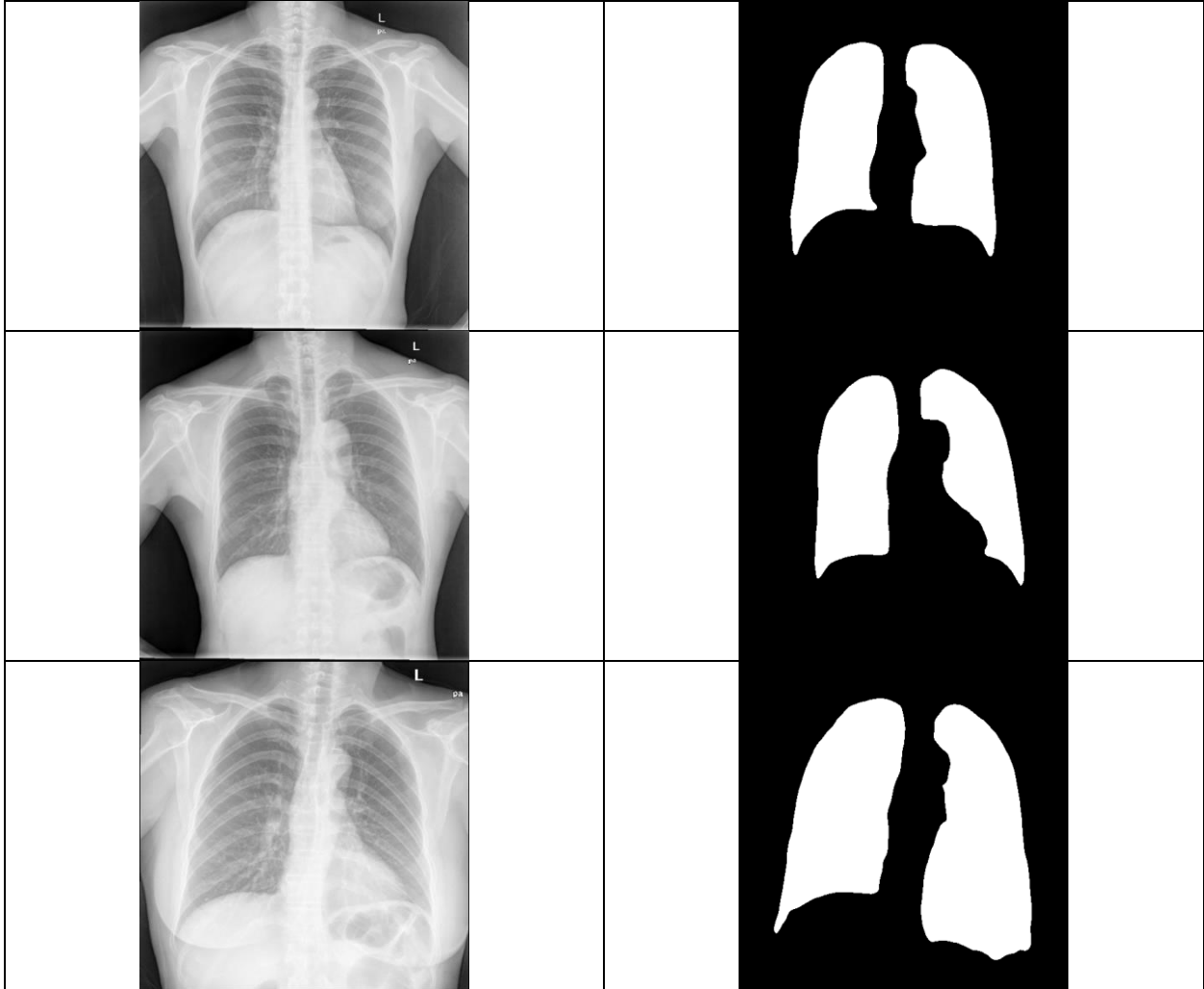


#### 5.2.4. Data-efficient Image Transformer (DPT)

Lastly, we analyze the performance of DPT, including visual examples of its segmentation results (Figure 4.4).

**Table 7: Example DPT Segmentation Results**

Image	Predicted Mask
	
	

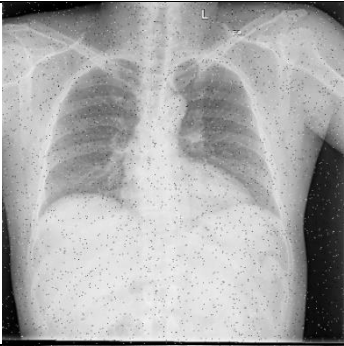

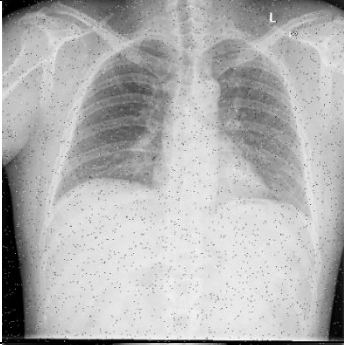

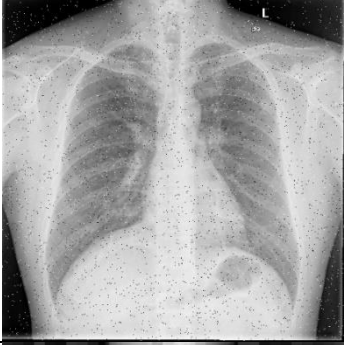





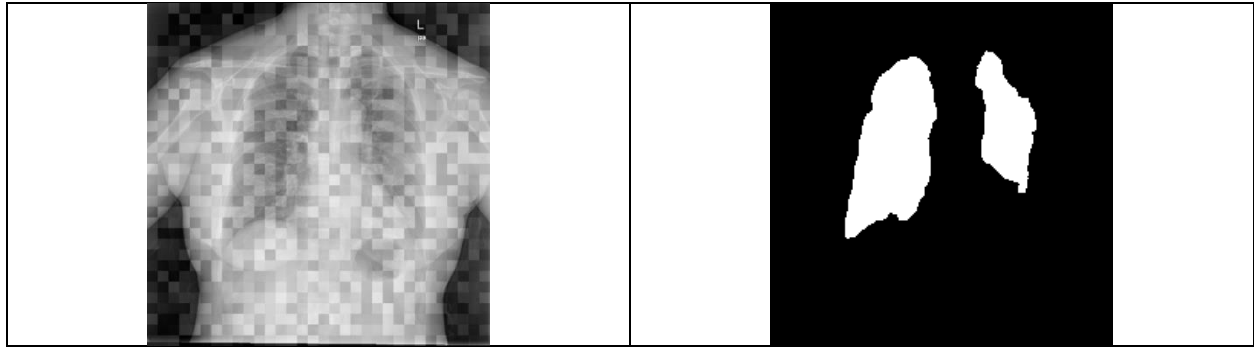
### 5.3. Comparative Analysis

With the individual model performances assessed, we proceed to conduct a comparative analysis. This section discusses the relative strengths and weaknesses of the models, highlighting key findings and insights derived from the results. We randomly added noises from 4 following type to images and ran the analysis for noise robustness.

### 5.3.1. UNet

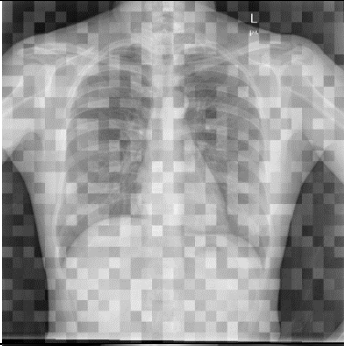



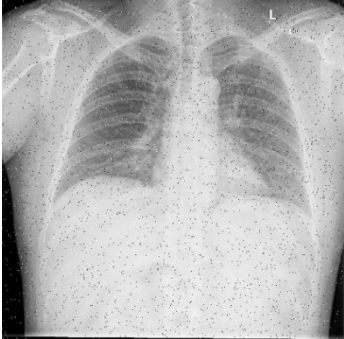

Table 8: UNet Results

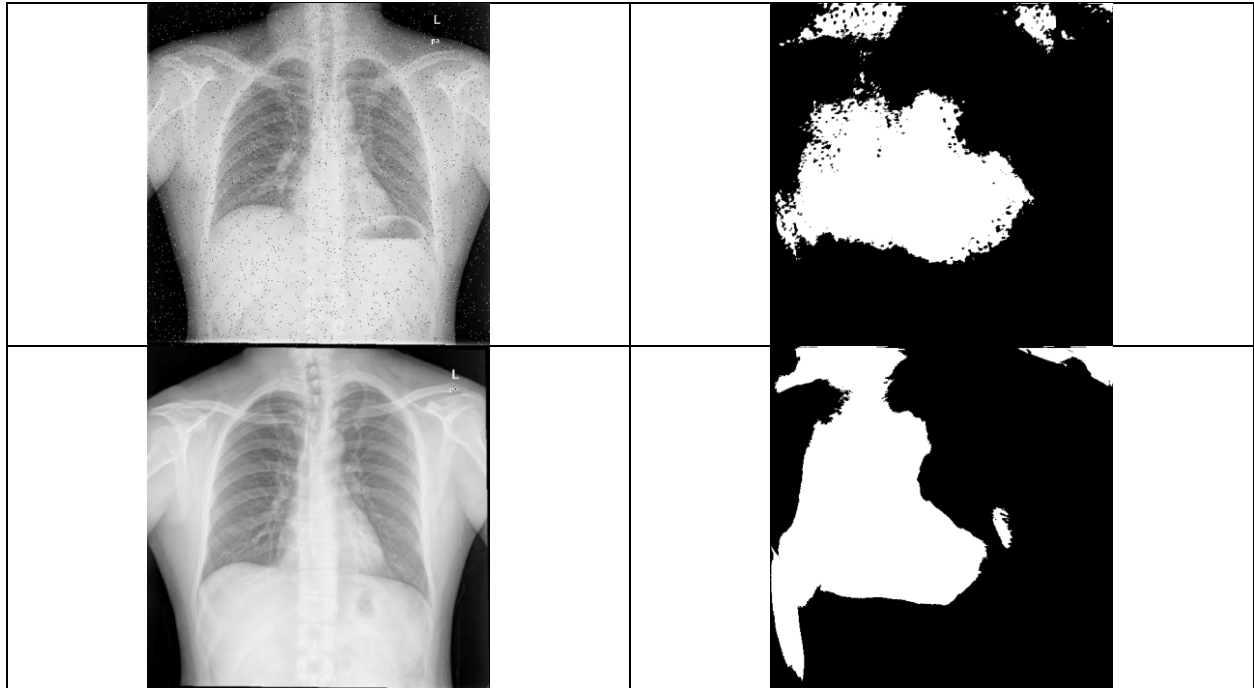
Image	Predicted Masks
	
	
	
	



### 5.3.2. U2Net

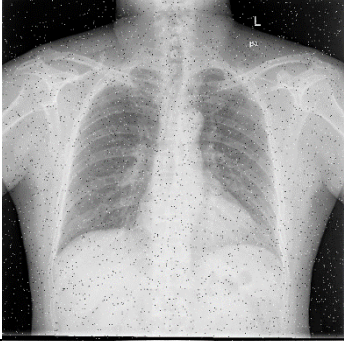



Table 9: U2Net Results

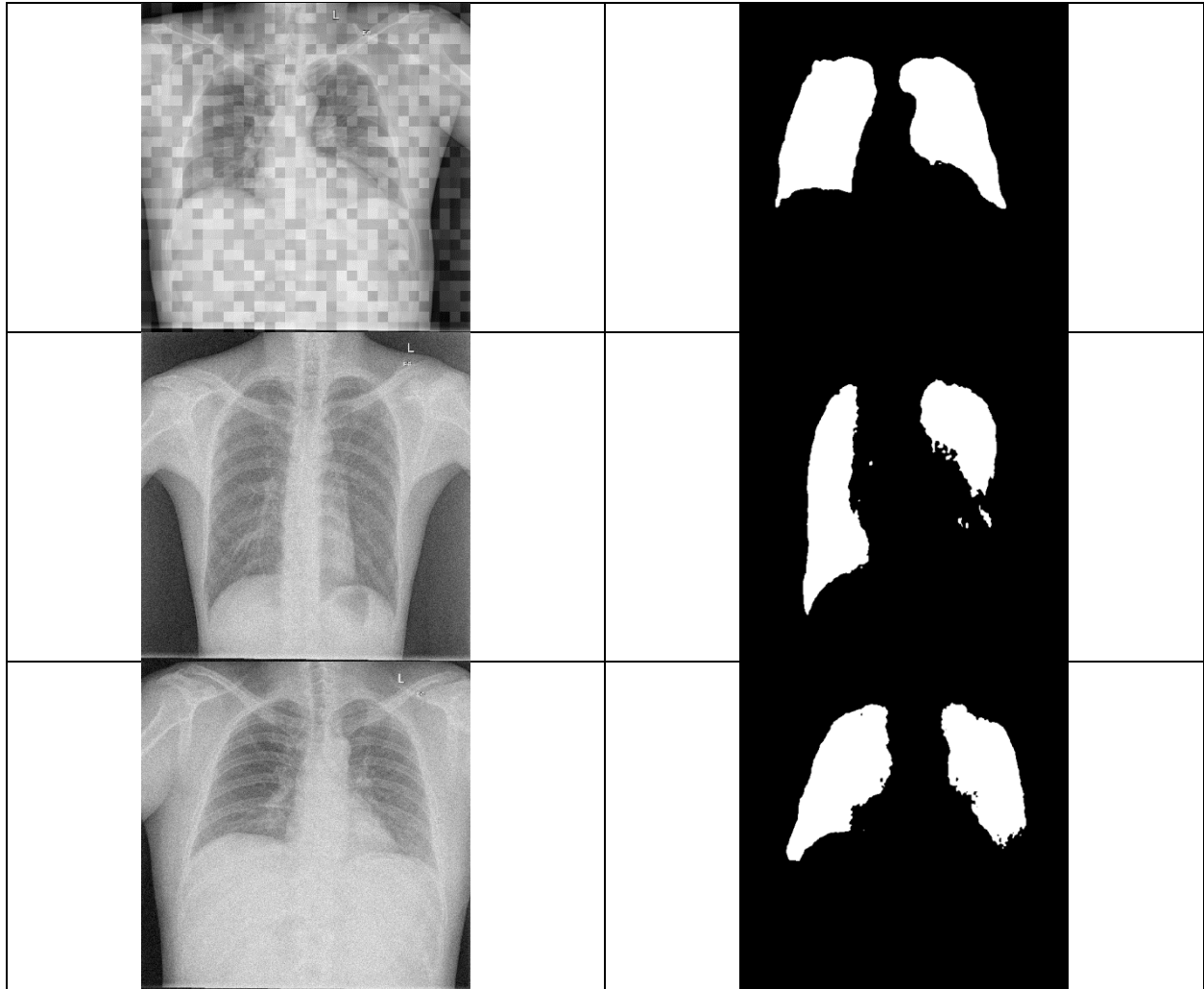
Image	Predicted Mask
	
	
	



### 5.3.3. Segformer

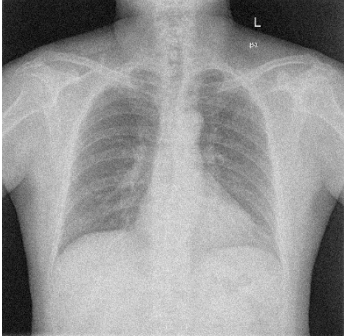

**Table 10: Segformer Results**

Image	Predicted Mask
	
	



### 5.3.4. DPT

Table 11: DPT Results

Image	Predicted Mask
	



**Table 12: Inference Time Comparison**

Architecture	Average Inference Time(s)
UNet	0.68
U2Net	0.04
SegFormer	0.062
DPT	0.04



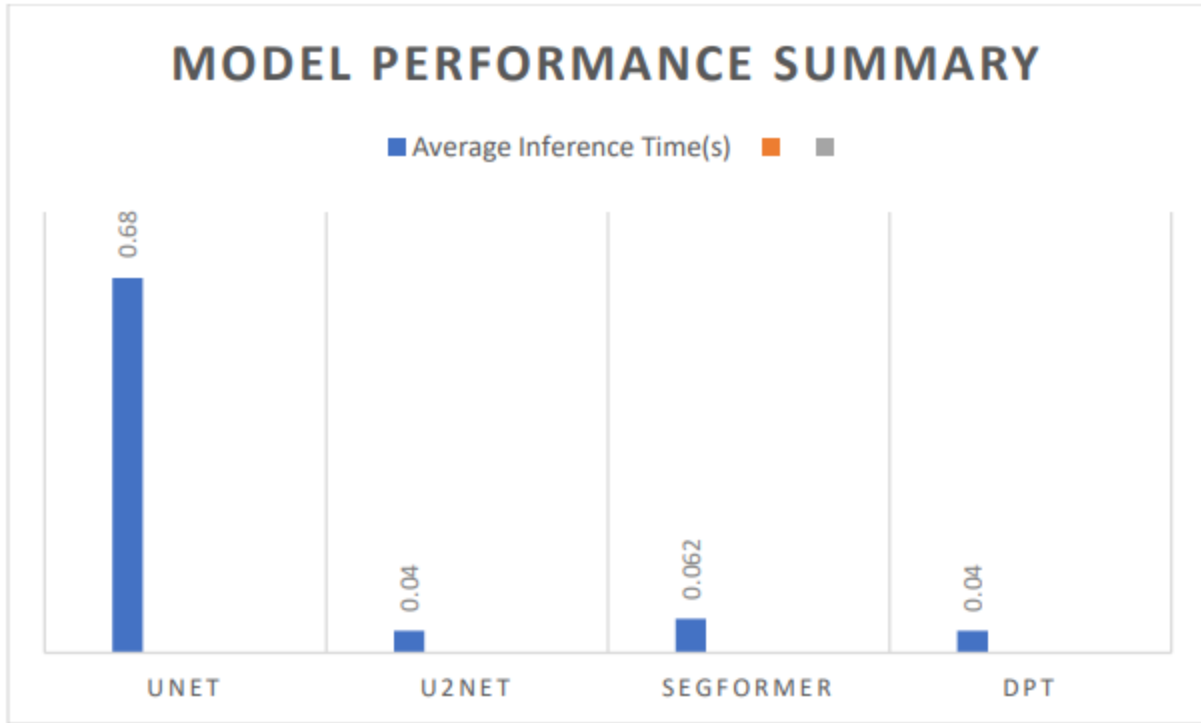
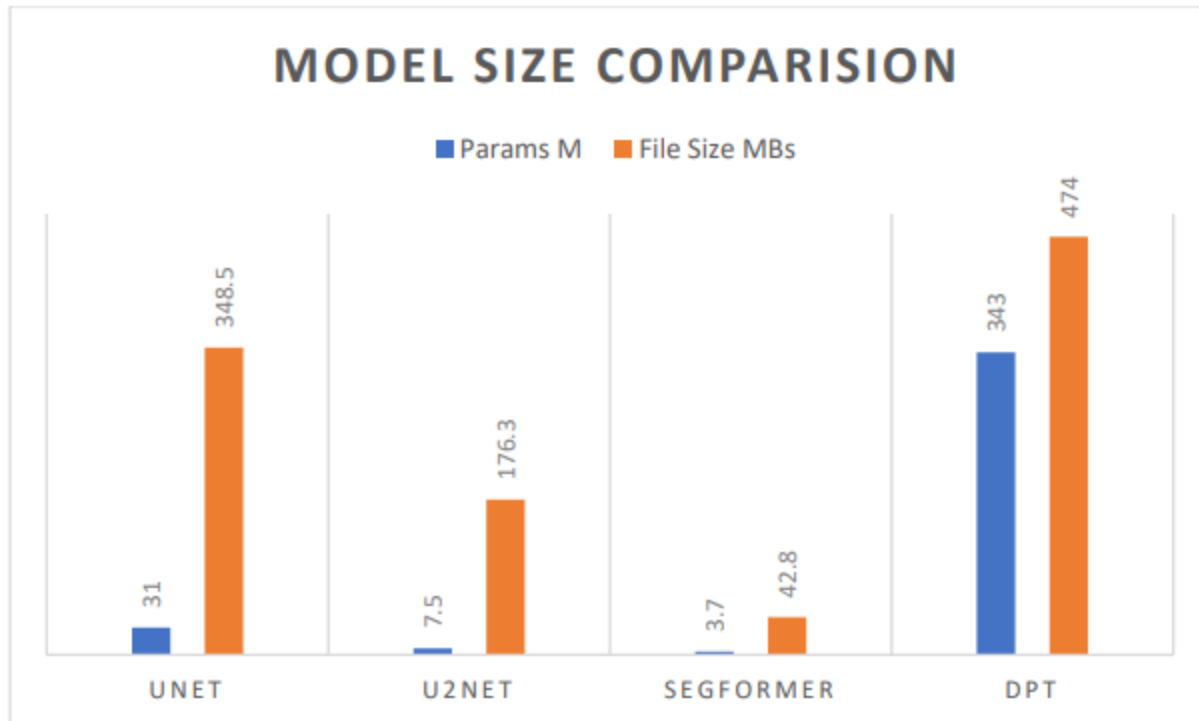


Figure 6: Model Performance Summary using Average Inference Time

Table 13: Model Size Comparison

Architecture	Params M	File Size MBs
UNet	31	348.5
U2Net	7.5	176.3
SegFormer	3.7	42.8
DPT	343	474



**Figure 7: Model Size Comparison using Params and File Size as Criteria**

## 5.4. Limitations

While our study yields valuable insights into the performance of lung segmentation models, it is important to acknowledge several limitations that may have influenced our findings.

### 5.4.1. Limited Dataset Size

One notable constraint of our study is the relatively small dataset used for training and evaluation, consisting of approximately 700 images. The dataset's size, though carefully selected, might not fully capture the diversity of lung images encountered in clinical practice. This limitation could potentially affect the generalizability of our results to larger and more diverse datasets.

### 5.4.2. Limited Noise Variation

Our evaluation of model robustness to noise is another area where limitations exist. While we introduced noise intentionally to assess the models' resilience, we acknowledge that the scope of noise types and levels tested was limited. The use of only four types of noise and random noise addition may not fully replicate the complexity and diversity of noise patterns encountered in real-world medical images.

### 5.4.3. Variability in Training Parameters

In our experiments, we employed consistent training parameters, with the exception of U2Net, which required an extended training duration (30 epochs) to achieve optimal performance. This

variability in training duration may introduce some inconsistency in model comparisons and affect the overall fairness of the evaluation.

#### 5.4.4. Limited Data Augmentation

We applied a limited set of data augmentations during model training, such as random brightness, random contrast, random RGB shift, and resizing. While these augmentations are common in image segmentation tasks, the scope of data augmentation techniques explored in this study was restricted. Exploring a broader range of augmentations could further enhance model performance and robustness.

Despite these limitations, our study provides valuable insights into the comparative performance of lung segmentation models. These findings serve as a foundational exploration in the field and offer a starting point for future research endeavors.

### 5.5. Summary

Our research presents a comprehensive evaluation of lung segmentation models, encompassing UNet, U2Net, SegFormer, and DPT. This investigation is founded on a rigorous analysis of performance metrics, robustness to noise, inference speed, and model size. The following key findings and contributions emerge from our study:

- **Performance Analysis:** Transformer-based models, specifically SegFormer and DPT, exhibit remarkable proficiency in lung segmentation. They consistently achieve Jaccard Index scores ranging between 97-98, demonstrating their precision and effectiveness. DPT, in particular, excels in generating high-quality segmentation masks, followed by SegFormer, UNet, and U2Net.
- **Robustness to Noise:** DPT shines in terms of robustness, demonstrating resilience even in the presence of added noise. UNet also exhibits robustness but with a slight decline in mask quality. SegFormer and U2Net, however, struggle to maintain accuracy when noise is introduced.
- **Inference Efficiency:** U2Net and DPT emerge as the fastest models, with an average inference time of 0.04 seconds. This efficiency is vital for real-time applications. In contrast, UNet lags with an average inference time of 0.68 seconds.
- **Model Size and Complexity:** DPT boasts the largest model size, while SegFormer maintains a more compact footprint. U2Net and UNet fall in between, both in terms of model size and computational requirements.
- **Zero-Shot Learning Capabilities:** Transformer-based models' exceptional performance highlights their potential in zero-shot learning scenarios. Their ability to generalize to lung segmentation tasks with minimal fine-tuning underscores their versatility.

Despite these valuable findings, it is crucial to acknowledge the limitations of our study, including the relatively small dataset, limited noise variation, variability in training parameters, and a restricted set of data augmentations.

In conclusion, our research contributes a comprehensive comparative analysis of lung segmentation models, shedding light on their respective strengths and weaknesses. The exceptional performance of DPT and SegFormer, coupled with their robustness and efficiency, positions them as promising tools for medical image analysis. These insights provide a solid foundation for future research endeavors aimed at further enhancing lung segmentation techniques and advancing the field of medical image analysis.

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## CHAPTER 6: DISCUSSION

In this section, we delve into a comprehensive discussion of the results obtained from the evaluation metrics, shedding light on the performance of the selected lung segmentation models—UNet, U2Net, SegFormer, and DPT.

### 6.1. Performance Analysis

Our evaluation, based on metrics such as the Jaccard Index and Foreground Accuracy, provides valuable insights into the proficiency of these models in the task of lung segmentation. One striking observation is the considerable disparity in performance between traditional Convolutional Neural Network (CNN)-based models and Transformer-based models.

#### 6.1.1. Transformer Models Excel

The Transformer-based models, SegFormer and DPT, exhibited exceptional performance across the board. Their Jaccard Index scores consistently ranged 97 to 98, demonstrating their remarkable ability to delineate lung regions with precision. Among them, DPT emerged as the frontrunner, producing high-quality segmentation masks that faithfully represented the lung anatomy. SegFormer followed closely, delivering competitive results, while maintaining a slightly lower computational overhead.

#### 6.1.2. CNN-Based Models Lag Behind

In stark contrast, the CNN-based models, UNet and U2Net, while still achieving respectable Jaccard Index scores of 92-94, fell behind their Transformer counterparts. UNet showed a slight edge over U2Net, but both struggled to match the segmentation accuracy demonstrated by SegFormer and DPT. These disparities can be attributed, in part, to the inherent capabilities of transformers in zero-shot learning scenarios, which appear to excel in lung segmentation.

#### 6.1.3. Robustness to Noise

Robustness to noise is a critical aspect of model evaluation, mirroring real-world scenarios where medical images may contain artifacts or imperfections. Here, we introduced noise intentionally to assess the models' resilience.

#### 6.1.4. DPT Shines in Robustness

DPT stood out as the most robust model in the face of added noise. Even under these challenging conditions, it continued to produce reliable segmentations. UNet, while still demonstrating robustness, saw a degradation in mask quality. SegFormer, on the other hand, seemed to struggle in the presence of noise, with performance comparable to UNet. U2Net, unfortunately, struggled the most and exhibited a notable decline in segmentation accuracy.

### **6.1.5. Inference Speed and Model Size**

The efficiency of a model extends beyond performance metrics and encompasses inference speed and model size—crucial considerations for practical applications.

### **6.1.6. Efficient Inference**

In terms of inference speed, U2Net and DPT emerged as the fastest performers, with an average inference time of 0.04 seconds. This efficiency bodes well for applications requiring real-time or near-real-time analysis. Conversely, UNet, with an average inference time of 0.68 seconds, lagged behind, potentially limiting its applicability in time-sensitive scenarios.

### **6.1.7. Model Footprint**

Considerations of model size and weight are pivotal, particularly in resource-constrained environments. DPT, with its transformer architecture, boasts the largest model size, while SegFormer maintains a relatively compact footprint. U2Net and UNet fall in between, both in terms of model size and computational requirements.

### **6.1.8. Zero-Shot Learning Capabilities**

The remarkable performance of transformer-based models, particularly DPT and SegFormer, underscores the potential of transformers in zero-shot learning scenarios. Their ability to generalize and adapt to the task of lung segmentation with minimal fine-tuning is a testament to the versatility of transformer architectures.

In conclusion, our discussion highlights the strengths and weaknesses of each model, providing valuable insights into their suitability for specific lung segmentation scenarios. The exceptional performance of DPT and SegFormer, coupled with their robustness to noise and efficient inference, positions them as formidable contenders in the field of medical image analysis. Meanwhile, UNet and U2Net, while still competent, may require additional fine-tuning to match the prowess of their transformer counterparts.

## **CHAPTER 7: CONCLUSION**

It can be concluded that the Transformers are beating specifically designed Models in Medical Imaging domain. The DPT transformer is not a segmentation based algorithm, but its performance was exceptional, even after adding noise. There is need of doing more research in the area with Transformers. Transformers have few shot learning capabilities, and can be used for performing different tasks. UNET based models can still perform well as was evident in the study, but they are not flexible for enough. Transformers feel like the key in near future.

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