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Lung Segmentation in Chest X-ray Images using Edge Attention-based U-Net

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***Abstract*— Accurate lung segmentation from chest X-rays is crucial for early disease diagnosis and monitoring of pulmonary diseases. For lung segmentation, CNN-based architecture plays a crucial role but still lacks some edge boundary detection issues while working with low-feature images. Previous research shows that there is still an issue in proper image segmentation with proper edge detection as in earlier methods like TVAC, Active Spline, Random Walker, U-Net as they focus on only high-level feature extraction from images and not low-level features, resulting in poor boundary detection. This research addresses this gap by proposing an Edge Attention-based U-Net architecture for proper edge boundary detection. This Edge Attention-based U-Net uses edge attention mechanisms to precisely locate lung boundaries while working with noisy and challenging X-ray imaging conditions. This improves segmentation accuracy and works efficiently in noisy situations, making it suitable for real-world clinical applications. Unlike previous methods the EA-U-Net surpasses them significantly. This superiority is evident through comprehensive comparisons conducted on the same Montgomery dataset of X-ray images during the training, validation, and testing phases. The EA-U-Net consistently outperforms its predecessors, demonstrating higher accuracy metrics, including Dice mean, Jaccard Mean, and Pixel accuracy, while exhibiting superior boundary detection capabilities. The EA-U-Net's exceptional performance in lung segmentation enhances reliability and paves the way for advancements in computer-aided diagnosis and personalized healthcare. By providing clinicians with more accurate and reliable tools for analyzing chest X-rays, the EA-U-Net contributes significantly to improving patient care and medical decision-making processes.**

Keywords*— *Chest X-ray Images, Convolutional Neural Networks, Deep Learning, Edge Attention-based U-Net, Lung Segmentation, Medical imaging

I. Introduction

In recent years, medical imaging has become a really important way for doctors to see inside our bodies and find out what might be wrong. This helps doctors make quicker and more accurate diagnosis which helps for better treatments and care of patients. These imaging methods have improved a lot over time giving better result with clear pictures.

Chest X-rays (CXRs) are widely used for cost-effective radiological imaging for pulmonary disease diagnosis and treatment. They play important role in various clinical conditions including screening, diagnosis, treatment monitoring and for research purpose. Segmentation of the lungs in CXRs is a fundamental step in computer-aided diagnosis (CAD) systems, providing qualitative and quantitative analysis in disease prediction and analysis. However, achieving efficient lung segmentation remains a significant challenge due to the complexities of CXRs.

Medical imaging plays an important role in modern healthcare problems, providing valuable observation for the diagnosis and treatment of various diseases. Among the various methods, chest X-ray imaging remains one of the most commonly used techniques for examining pulmonary conditions. Accurate segmentation of lung area from chest X-ray images is an essential step in the analysis process forming the base source for diagnosis and analysis tasks. However, the essential challenges introduced by complex anatomical structures, variations in imaging conditions, and the presence of pathological abnormalities require the development of refined and efficient segmentation techniques.

However, there is a new challenge as we have so many images to look at as it becomes difficult for the radiologists to check them all within a limited time period which creates a bottleneck to them. There are not enough radiologists to go through all the X-ray images for proper diagnosis [1]. The population of smokers as well as pulmonary disease patients are increasing rapidly and for diagnosis X-ray image is the first step for doctors to examine their internal lung conditions. The most common type of imaging for taking pictures of the chest is X-rays [2].

X-ray image examination is becoming a bottleneck for doctors and radiologists as they are few in number. So, to deal with this challenge there are new computer tool algorithms and models that can automatically look at these images and help the radiologists in analysis and diagnosis. In the past, making these tools involved a lot of complicated steps, like designing specific features and teaching computers how to recognize them. This was hard and time-consuming. However, a new approach called deep learning changed all of that. This method could make it much easier for computers to understand these images and help radiologists do their job better.

Deep learning is a rapidly advancing subfield of artificial intelligence that has gained immense popularity in recent

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years. With the increasing availability of large amounts of medical imaging data and computing power, deep learning has become a valuable tool for the automatic segmentation and analysis of chest X-rays for the diagnosis of lung diseases. Chest X-rays are widely used for the diagnosis of various lung conditions, including pneumonia, tuberculosis, and lung cancer[3]. However, the decoding chest X-rays demands a significant level of skill and requires a high degree of expertise which is susceptible to subjectivity and variations between different observers[4].

In recent years, there has been a growing increase in research on deep learning algorithms and models for the automatic analysis of chest X-rays for lung disease segmentation and diagnosis. One of the key advantages of deep learning algorithms is their ability to learn complex patterns in the data, allowing them to automatically extract features that are suggestive for specific diseases [5] .This can lead to improved accuracy and reduced different observer variability compared to traditional diagnostic methods [3]. One of the most widely used deep learning techniques for chest X-ray analysis is convolutional neural networks (CNNs)[2]. CNNs are particularly well-suited for this task due to their ability to learn local features from the images and build increasing complex representations of the data easily[5].

Similarly, another popular technique, which is growing interest for chest X-ray analysis is Generative Adversarial Networks (GANs). GANs consist of two neural networks: a generator that produces synthetic data, and a discriminator that determines whether the data is real or fake. GANs can be trained on chest X-rays to generate artificially created visual images of lung diseases, which can be used to upgrade the training dataset and improve the performance of the deep learning algorithms[6]. In addition to improve the accuracy of lungs image segmentation and diagnosis process deep learning can help to reduce the workload of radiologists and healthcare providers by automating the analysis of chest X-rays.

This opens up a valuable opportunity to shift our focus. With more time and resources at our disposal, we can redirect our efforts towards providing better patient care and diligent follow-ups. The swifter and more accurate pace of deep learning algorithms can notably enhance healthcare outcomes by facilitating early detection and treatment of lung diseases. It remains crucial to stay committed to ongoing research and development. This involves crafting novel algorithms and models to deepen our grasp of how these deep learning models operate. Expanding our training datasets ensures the efficiency and adaptability of these algorithms. Moreover, it's imperative to delve into clinical studies, scrutinizing how well these models perform in real-world scenarios and assessing their impact on patient outcomes and healthcare costs.

It leads to free up time and resources which can be shifted for patient care and follow-up activities. Furthermore, the speed and accuracy with the help of deep learning algorithms can lead us in improved patient healthcare outcomes. It helps us in the early-stage detection and treatment of lung diseases. It is important to continue various research and development activities by developing new algorithms and models for improving the ability of deep learning models and increasing the training datasets to check that the algorithms are efficient and usable. Also, it is important to conduct clinical studies to test the performance of deep learning models in real-world scenarios for analyzing the impact on patient results and healthcare margins.

Despite the many advantages of deep learning for chest X-ray analysis, several challenges and limitations must be considered. For example, deep learning models require large amount of high-quality training image datasets to obtain the best result[7].

Deep learning techniques have shown outstanding results in medical image segmentation including lung segmentation in chest X-ray images. The U-Net architecture is a widely used in deep learning-based approach for medical image segmentation tasks. As it has shown higher accuracy in medical image segmentation tasks such as tumor detection in MRI images, retinal vessel segmentation in fundus images and lung cancer detection[8]. However, the U-Net architecture has some boundary limitations when it comes in context to lung segmentation in chest X-ray images. The U-Net architecture can miss a small portion of the lung and over-segment regions that contain other structures such as bones or the diaphragms. To figure out these limitations of the U-Net architecture, researchers have proposed various modifications of the U-Net architecture such as the improved U-Net, ResU-Net, U-Net++, Nested U-Net etc.[9]. On going through our research, we observed that it still lacks in proper edge boundary detection with X-ray image segmentation. So, to clearly focus on noticeable lung boundaries which misleads to inaccuracies in the presence of overlapping structures or intensity, we introduce a new lung segmentation framework named Edge Attention-based U-Net approach to address the limitations of existing methods and achieve efficient segmentation in challenging CXRs.

II. Literature Study

Lung segmentation plays a vital role in the analysis of chest X-ray images for the proper diagnosis and treatment of various lung diseases. Higher accuracy of lung segmentation can provide radiologists and healthcare professionals with valuable information of the location, size and shape of lung structures, density, and texture helping in disease detection and assessment enabling them to detect and monitor lung diseases. Manual lung segmentation is a time-consuming and tedious task and it is prone to inter-observer variability. Therefore, the development of automatic lung segmentation methods is essential for efficient and reliable analysis of chest X-ray images. Deep learning-based approaches have shown remarkable performance in medical image segmentation tasks, including lung segmentation in chest X-ray images. The U-Net architecture introduced by Ronneberger[8], is a widely used deep learning-based approach for medical image segmentation. The U-Net architecture has an encoder-decoder structure, which allows for the extraction of high-level features from the input image and the reconstruction of the segmented image. However, the U-Net architecture has some limitations in lung segmentation in chest X-ray images including difficulties in capturing exact lung boundaries and handling the irregular class distribution of lung and non-lung pixels.

Previous research results show that in the context of chest X-ray (CXR) image analysis, Deep Learning (DL) has played an important role in offering promising results for the automated detection of diseases. This result suggests an overview of DL concepts in CXR analysis, including basic

DNN structures, transfer learning, and data augmentation. It systematically surveys recent literature on the application of DL models to detect common CXR abnormalities, evaluating their performance, including multi-class classification. The article also addresses challenges inherent in DNN models, their future implementation, and their implications for radiologists[20]. Another study presents an integrated weakly-supervised deep learning framework for thoracic disease classification and localization in chest X-rays, utilizing noisy multi-class disease labels. The model's strengths lie in its disease-specific feature learning via multi-map transfer layers and cross-channel feature recalibration with squeeze-and-excitation blocks. The generated heat maps which are commonly generated to highlight regions of interest or activation in an image as a by-product of weak supervision, enhance interpretability. Outperforming existing methods in both quantitative and qualitative assessments, this framework holds promise for future work in refining abnormal area localization with limited bounding areas[18].

To address these limitations, researchers have proposed various modifications of the U-Net architecture for lung segmentation in chest X-ray images. Liu et al.[17] proposed an improved U-Net model for lung segmentation in chest X-ray images, which includes skip connections between the encoder and decoder, a densely connected decoder, and a multi-scale feature fusion module. The skip connections allow for the direct transmission of low-level features from the encoder to the decoder, enabling the model to capture fine details in lung boundaries. The densely connected decoder enhances the feature reuse and gradient flow in the decoder, leading to improved segmentation accuracy. The multi-scale feature fusion module combines features from different scales to enhance the representation of lung structures[17].

Several studies have demonstrated the effectiveness of the improved U-Net model for lung segmentation in chest X-ray images. Wang et al. proposed a modified improved U-Net model, which incorporates a squeeze-and-excitation module and an attention mechanism, and achieved state-of-the-art performance on a publicly available dataset of chest X-ray images[21]. The squeeze-and-excitation module enables the model to learn channel-wise feature dependencies, while the attention mechanism focuses on the relevant regions of the input image. Zhang et al.[22] proposed a hybrid deep learning-based method for lung segmentation in chest X-ray images, which combines the improved U-Net model with a conditional random field (CRF) post-processing step. The CRF post-processing step helps to refine the segmentation results by enforcing spatial coherence and reducing the effects of noise and artifacts. Similarly, other deep learning-based approaches have also been proposed for lung segmentation in chest X-ray images, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and fully convolutional networks (FCNs). Xu et al. [23]proposed an RNN-based method for lung segmentation in chest X-ray images, which incorporates spatial and temporal information through a spatiotemporal convolutional LSTM network. Wang et al.[24] proposed a FCN-based method for lung segmentation in chest X-ray images, which uses a multi-branch architecture to extract features from different scales. The accuracy of lung segmentation algorithms is essential for various applications such as radiation therapy planning, pulmonary disease detection, and quantitative analysis of lung structures. In this context, recent research evaluated the performance of four different algorithms, including random walker, active spline model, TVAC (Total Variation Active Contour), and U-Net, on the Montgomery dataset. Narathip Reamaroon [25] provided summary statistics of Dice coefficient, a commonly used metric for segmentation accuracy for the Montgomery dataset. As presented in Table 1, TVAC, U-Net, Random Walker and Active Spline algorithms U-Net algorithm outperformed better than other methods with higher Dice coefficient mean and lowest standard deviation. This research focuses on selecting the best approach for lung segmentation algorithm with the aid of edge attention block. The U-Net algorithm, with a proper edge attention module attached to it results in impressive accuracy with edge boundary detection.

Hence, this paper proposes an Edge Attention-based U-Net architecture for the automated segmentation of lung in chest X-ray images.

III. METHODOLOGY

U-Net is a deep learning architecture for image segmentation tasks, which was proposed by Olaf Ranneberger, Philipp Fischer, and Thomas Brox in 2015[8]. It is named after its U-shaped architecture. The U-Net is a specialized convolutional neural network model designed for precise biomedical image segmentation. Its U-shaped architecture consists of an encoder and decoder block. The encoder captures features with convolutional layers and max-pooling and the decoder uses transposed convolutional layers and skip connections to recover details and produce segmented images. U-Net's symmetric design combines local and global feature learning, making it ideal for high pixel-level accuracy. U-Net have its more improved variants like U-Net++, ResU-Net, and Attention U-Net used for various tasks. An attention-based U-Net model, is an extension of the classic U-Net architecture having attention mechanism integrated to enhance its segmentation capabilities higher. The architectural difference between an Attention U-Net and an Edge-Attention U-Net primarily lies in the type of attention mechanism used. While both architectures enhance the U-Net framework with attention, an Edge-Attention U-Net specifically targets edge information, making it well-suited for tasks where precise boundary detection is crucial task. It consists of a contracting path and an expanding path. The contracting path is a traditional convolutional network that applies a series of convolutional and max pooling layers to reduce the spatial dimensions of the input image while increasing the number of feature channels. This process generates a high-level representation of the image. The expanding path on the other hand is a mirror of the contracting path, and it uses a series of deconvolutional and up-sampling layers to recover the original spatial dimensions of the input image while reducing the number of feature channels. This process combines the high-level feature representation obtained from the contracting path with the low-level feature representation obtained from the expanding path to generate a segmentation mask for the input image.

The primary task of EA-U-Net is the introduction edge attention block in between skip connections of the contracting and expanding paths for capturing important edge features within the input data keeping more attention on edges allowing the network to extract high resolution feature maps which is important for image segmentation and improve boundary detection. The skip connections concatenate the feature maps of the corresponding contracting and expanding paths at the same spatial resolution, which allows the network to refine the segmentation result at a more detailed level for better segmentation with higher accuracy in edge detection.

U-Net has found wide coverage in the field of medical image segmentation tasks with different state-of-the-art performances on different datasets. This architecture follows high modularity and capability for different image segmentation tasks.

Below diagrammatic representation shown is the general framework of proposed architecture of Edge-attention based U-Net used in this research. Who's each block and layers are explained below.

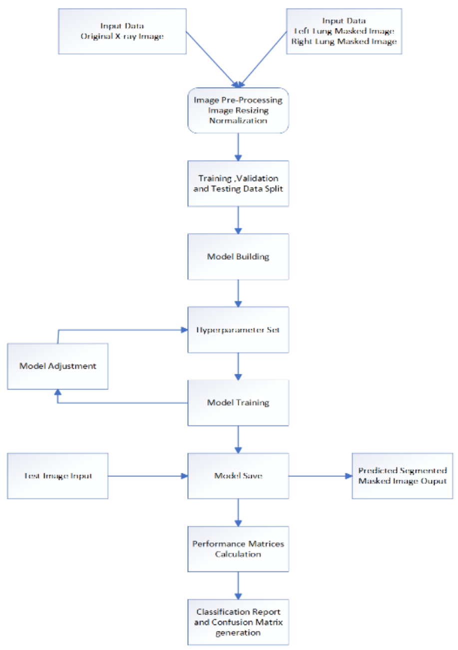


Fig. 1. Proposed Framework

The proposed methodology for lung segmentation in chest X-ray images using an Edge Attention-based U-Net follows a structured workflow to ensure accurate and efficient results. The process begins with the acquisition of input data, comprising original X-ray images along with left and right lung masked images. This initial data set undergoes image pre-processing steps, which include resizing the images to a consistent dimension to standardize input size for the neural network, and normalization to scale pixel values, enhancing model training efficiency and convergence. The pre-processed data is then split into three subsets: training, validation, and testing, ensuring that the model can be properly trained and evaluated.

Next, the model building phase involves constructing the Edge Attention-based U-Net, a specialized neural network architecture designed to enhance edge detection and improve segmentation accuracy. Hyperparameters are carefully set, including learning rate, batch size, and number of epochs, which are critical for optimizing the model's performance. Model training follows, during which the network learns from the training data, and periodic adjustments are made based on the validation set performance to avoid overfitting and improve generalization.

Upon completion of training, the final model is saved for future inference. For testing, a new X-ray image is input into the trained model, which generates a predicted segmented masked image as output, highlighting the lung regions. The performance of the model is then evaluated using several metrics, such as Dice coefficient, Intersection over Union (IoU), and accuracy, to quantify the segmentation quality. Finally, a comprehensive classification report and confusion matrix are generated, providing detailed insights into the model's performance, including precision, recall, F1-score, and the distribution of true positive, false positive, true negative, and false negative predictions. This structured workflow approach shows the process of lung segmentation in chest X-ray images using proposed EA-U-Net model.

Image Resizing: Resize all input chest X-ray images to a fixed resolution.

Normalization: Normalization is a pre-processing technique used to normalize pixel values to a standard range to improve training stability for easier convergence. The pixel values of the image were scaled to the [0, 1] range. Batch normalization applies normalization to the batch of samples for each feature map at each layer, which reduces the dependency on the gradients.

Activation Function: U-Net uses the ReLU activation function in all of its layers except for the output layer, where it uses the sigmoid activation function. The ReLU activation function helps to prevent the vanishing gradient problem. The range of the ReLU function is $[0, \infty)$. Any positive input will result the same positive value as the output, and any non-positive input will result zero. The function saturates at zero and allows the positive values to pass.

Input Layer: The input to the U-Net is typically an image that we want to perform segmentation on.

Output Layer: The output is a segmented image of corresponding input image which has the same dimensions as the input, where each pixel is classified into lung and non-lung region.

Encoder: The encoder is the contracting path consisting of convolutional layers and max pooling layers. It captures hierarchical features and reduces spatial dimensions.

Decoder: The decoder is the expanding path consisting of up-sampling layers and convolutional layers. It reconstructs the spatial information and generates the final segmented images.

Pooling Layers: Pooling layers are used in the contracting path of the U-Net to reduce the spatial dimensions of the feature maps keeping increasing the number of feature channels. U-Net uses max pooling to reduce the spatial dimensions of the feature maps in the contracting path. The pooling operation size determines the amount of down-sampling applied to the feature maps. A larger pooling operation size leads to more down-sampling and a higher reduction in spatial dimensions. U-Net supports two types of pooling layers:

a. Max Pooling: Max pooling is a down-sampling operation which reduces the spatial dimensions of the input image by selecting the maximum value from the pool. Max pooling is used to capture the most important features in each region while rejecting irrelevant information.

b. Convolution: Convolutional layers are used to extract features from the input data. They slide a filter over the input to perform element-wise multiplications and produce feature maps.

Concatenation: Concatenation is a process of combining feature maps from different layers. In U-Net, it is used to combine the feature maps from the encoder (contracting path) with the corresponding feature maps in the decoder (expansive path).

Skip Connection: Skip connections are used to concatenate feature maps from the encoder block to the decoder block helping to preserve spatial information during up-sampling.

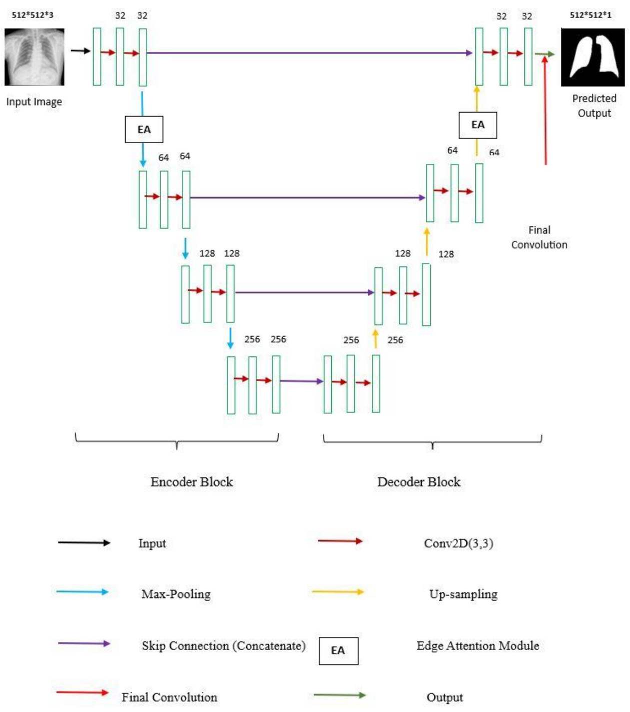


Fig. 2. Model Architecture

In this research, we proposed a U-Net architecture to automate lung segmentation in chest X-ray images introducing Edge-Attention U-Net. This model enhances the standard U-Net's performance by prioritizing edge detection and segmentation in X-ray images. The EA-U-Net integrates the U-Net architecture with an edge attention module. This module plays a vital role in identifying object edges and boundaries within the input X-ray image. It achieves this by calculating weighted sums of feature maps from various encoder levels performing operations like 2D convolution, batch normalization maxpooling using ReLU activation function which determines similarity between feature maps and a predefined set of edge templates. Which is a collection of patterns that the algorithm recognizes as edges. These templates serve as reference guides, helping the algorithm to figure out where important edges are in the image by comparing them with the patterns it already knows. It is like having a set of templates for recognizing the outlines or borders of objects in an input image. Focusing object boundaries, the edge attention module facilitates the learning of more discriminative features, significantly improving segmentation accuracy, especially for objects with thin or poorly defined boundaries. The proposed architecture focuses on preserving edge features by placing the edge attention module between skip connection layers in encoder and decoder section of the U-Net. While conventional U-Net architectures use skip connections to prevent gradient loss and retain spatial information, our approach is to focus on edge preservation. The edge attention module follows an encoder-decoder path, where high-resolution features extracted during the contracting path while in expanding path inputs are combined with upsampled, convolution, batch normalization to get final masked outputs image corresponding to input images. This integration of edge attention module enhances the precision of segmentation capturing fine details which is important for accurate lung boundary detection.

In image segmentation tasks, especially medical image segmentation, EA-U-Net is undoubtedly one of the most successful methods as Compared with FCN, SegNet and Deeplab. The architecture we proposed is implemented in Python, utilizing the TensorFlow deep learning framework. It is characterized by an encoder-decoder structure enhanced with an Edge Attention Module. This architecture comprises three essential components: the encoder, decoder, and Edge-Attention module. An overview of these components is explained below:

Encoder Block: The encoder plays a pivotal role in extracting hierarchical features from the input image. It is composed of the following elements:

Input Layer: The model preprocesses any dimensions input image to dimensions of (512, 512, 1), representing height, width, and channels.

Convolutional & Max Pooling Layers: Four sets of 2D convolutional layers of size (3,3) are applied at each layer with increasing image feature extraction channel employing different filter sizes for convolution operations. Maxpooling layers of size (2,2) are employed for down-sampling operations. Rectified Linear Unit (ReLU) serves as the activation function.

Decoder Block: The decoder path is responsible for up-sampling and generating the final segmentation of input images. It consists of the following components:

Convolutional Layers: Following the up-sampling operation four sets of convolutional layers having filter size (3,3) are applied in each layer and ReLU is employed as the activation function to avoid overfitting.

Up-sampling: For up-sampling and feature map concatenation from the corresponding encoder path, the Conv2DTranspose function is used. The up-sampling is done with filter size (2,2).

Output Layer: This layer outputs final image images with dimensions of (512, 512, 1). The final convolutional layer employs a 1x1 convolution with a SoftMax Sigmoid activation function to output the mask. This layer generates the pixel-wise segmented output image providing the segmented image.

Skip connections: It directly bypass the down-sampling layers and connect corresponding feature maps from the encoder to the decoder. However, this down-sampling process also loses some spatial information which is important for accurate segmentation of image especially with detailed boundaries.

Edge-Attention Module: This Edge-Attention module is positioned after the first max-pooling and up-sampling layer in encoder-decoder section and connected via the skip connection of encoder and decoder section in first layer. Its role is to prevent the loss of fine-grained edge information which is essential for accurate image segmentation. Therefore, the Edge-Attention module is placed in between encoder and decoder section of skip connection phase. This module helps in capturing and enhancing edge-related features while preserving spatial information which lost during down-sampling process. By doing so, our model can more precisely detect lung boundaries, resulting in enhanced segmentation accuracy and overall performance.

A. *Training Dataset*

The Montgomery X-ray dataset, collected from Montgomery County's tuberculosis control program, includes 138 frontal chest X-rays. Captured with a Eureka stationary X-ray machine, these 12-bit grey level images are in PNG format. Expert radiologists provided labeled masks for these images, enabling researchers to use the dataset for developing and evaluating lung segmentation methods in medical image analysis.

B. *Optimizer*

The Adam optimizer, known for combining momentum and adaptive learning rates, is used to enhance the performance of our deep learning model for lung segmentation in chest X-rays. In training the Edge Attention-based U-Net (EA-U-Net) model, we set a learning rate of 0.00001, which adjusts automatically if validation loss doesn't improve over five epochs. This optimizer is crucial for efficiently guiding the neural network towards an optimal solution.

C. *Training Procedure*

During training, the Adam optimizer with a learning rate of 0.00001 adjusts if validation loss stagnates for five epochs. Data is split into 80% training and 20% validation/testing. The model is trained in mini-batches of 1 image over 200 epochs to ensure accurate lung segmentation.

D. *Performance Matrices*

Here is a table that summarizes these evaluation metrics for automatic lung segmentation in chest X-ray images using Edge Attention-based U-Net:

TABLE I. RESULTS OBTAINED USING EA-U-NET

Matrices	Formula
Jaccard Coefficient (IoU)	Jaccard = (predicted mask ∩ ground truth mask) / (predicted mask ∪ ground truth mask)
Dice coefficient	Dice = (2 * predicted mask ∩ ground truth mask) / (predicted mask + ground truth mask)
Pixel Accuracy	Pixel Accuracy= (Number of Correctly Classified Pixels)/(Total Number of Pixels)
Precision	Precision = true positives / (true positives + false positives)
Recall	Recall = true positives / (true positives + false negatives)
F1-score	F1-score = 2 * ((Precision * Recall) / (Precision + Recall))

IV. IV. RESULT AND DISCUSSION

Our research on lung segmentation in chest X-rays using the Edge Attention-Based U-Net (EA-U-Net) showed promising results. The model achieved high Jaccard, Dice coefficients, pixel accuracy, precision, recall, and F1-score, outperforming previous models, especially in outlining thin or unclear boundaries. Visual inspection confirmed its ability to capture detailed boundaries. The EA-U-Net's robustness across various images suggests its potential for diverse clinical applications, providing reliable support for diagnosing and analyzing pulmonary conditions. Overall, EA-U-Net is a valuable tool for precise lung segmentation in chest X-ray images.

The Edge-Attention U-Net model was trained to 200 epochs with a batch size of 1. The results obtained from our experiment are summarized below:

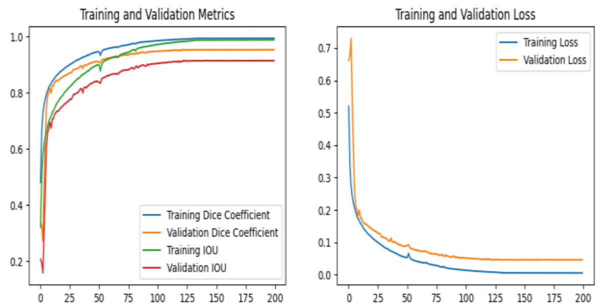


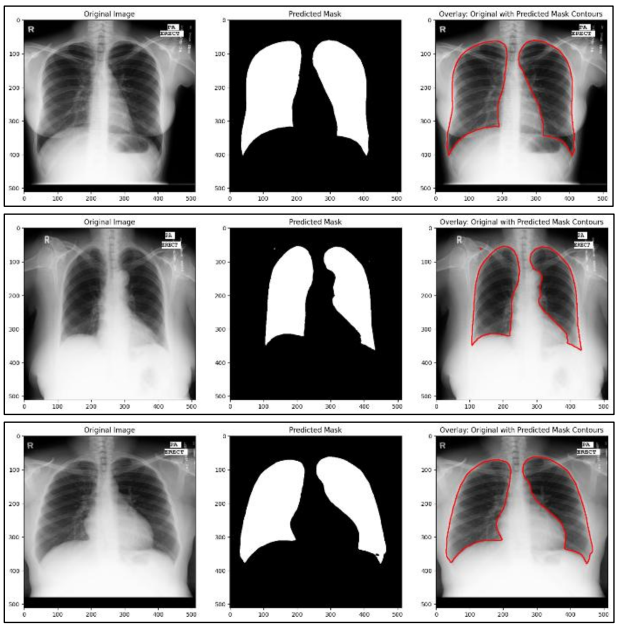
Fig. 3. Training and validation accuracy curve

TABLE II. RESULTS OBTAINED USING EA-U-NET

Dice Coefficient Accuracy	IOU Accuracy	Pixel Accuracy
Mean: **0.9376**	Mean: **0.8986**	Mean: **0.9800**
Max: 0.9830	Max: 0.9666	Max: 0.9957
Min: 0.3237	Min: 0.1949	Min: 0.9360

TABLE III. RESULT COMPARISON WITH DIFFERENT MODELS

Montgomery dataset Result			
Model	Dice (Mean)	Dice (Min)	Standard Deviation
TVAC	0.9269	0.7466	0.0251
Random Walker	0.8783	0.5084	0.0729
Active Spline	0.8672	0.3835	0.0826
U-Net	0.8725	0.3300	0.0396
EA-U-Net	**0.9376**	**0.3237**	**0.0642**



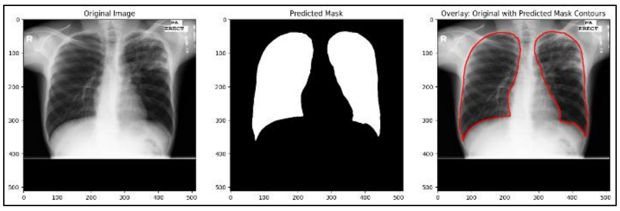


Fig. 4. Output Results

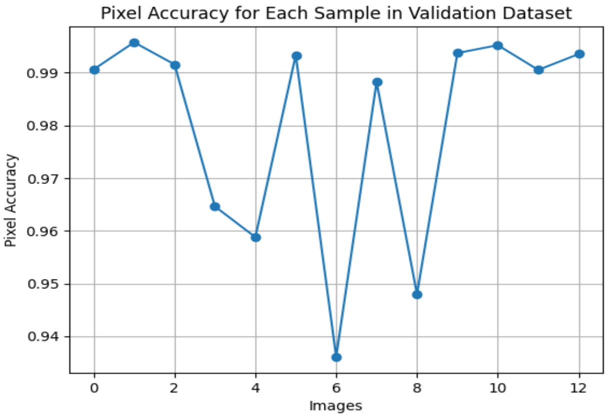


Fig. 5. Pixel accuracy vs sample Validation

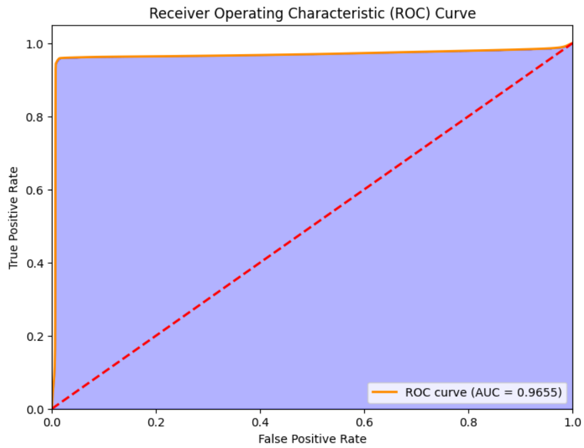


Fig. 6. ROC-AUC Curve

Our Edge Attention-Based U-Net (EA-U-Net) model for lung segmentation in chest X-rays demonstrated excellent quantitative performance. It achieved a high mean Dice coefficient of 0.9376 and a mean IoU of 0.8986, indicating precise lung boundary delineation. The model's pixel accuracy of 0.98 underscores its reliability in pixel-level segmentation. Additionally, the ROC and AUC metrics further validated the model's effectiveness, with an AUC of 0.9655, indicating superior classifier performance. These results highlight the model's robustness, stability, and potential clinical relevance in pulmonary image analysis.

A. Classification Report and Confusion Matrix

Classification report of testing data using EA-U-Net model is:

TABLE IV. CLASSIFICATION REPORT RESULT

Classification Report				
	Precision	Recall	F1-Score	Support
Background	0.9843	0.9889	0.9865	2547708
Lung	0.9668	0.9534	0.96	860164

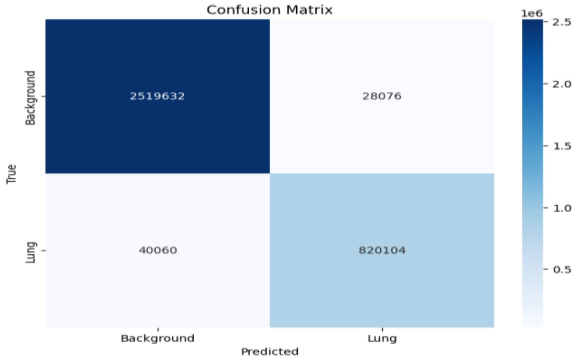


Fig. 7. Confusion Matrix of testing data

The testing results also supports with high accuracy with testing data as shown in classification report results as shown in Table 4. which confines the model capability and robustness in lung segmentation in chest x-ray images. Likewise, in Fig.4. confusion matrix is shown which offers a detailed breakdown of the model's performance in classifying the background (non-lung region) and the lung region within the dataset. It reveals the number of true positive, true negative, false positive and false negative for these two classes providing valuable insights into the model's ability to distinguish these two classes which confines the robustness of the model. Thus, when compared with baseline models, the EA U-Net exhibited superior performance, confirming its potential as an advanced solution for lung segmentation in medical imaging. These results surpass existing state-of-the-art methods, highlighting the effectiveness of the proposed architecture in healthcare applications for disease diagnosis and treatment planning.

V. CONCLUSION AND FURTHER WORK

In this research, the Edge-Attention-Based U-Net, exhibited robust performance in automated lung image segmentation. Edge-Attention U-Net demonstrated commendable generalization with the highest testing accuracy by a Jaccard coefficient of 89.86%, Dice coefficient of 93.76% and pixel accuracy of 98%. The selection of EA-U-Net performed best results for the desired application.

For future work in the field of medical science Chest X-ray lung segmentation is an important task for disease diagnosis and computer-aided diagnosis. The main key areas for further research include addressing the scarcity of high-quality data with accurate annotations through data augmentation, incorporating anatomical knowledge about lung shape, texture, and location for model predictions supporting better segmentation accuracy while developing interpretable AI models and creating efficient tools for real-time clinical deployment. Similarly, exploring alternative modalities like CT scans, combining lung segmentation with multi-organ segmentation, and implementing lifelong learning for continuous model improvement based on new data and clinical feedback. Focusing on these aspects can lead to more efficient, reliable, and clinically precise lung segmentation methods, enhancing patient care in medical practices.

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