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Segmentation of the Lung CT using UNet for the Diagnosis of COVID-19 Cases

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Abstract: The COVID-19 pandemic, with its rapid, widespread global impact, has highlighted the urgent need for efficient, accurate diagnostic tools. Among the various diagnostic methods available, Computed Tomography (CT) imaging has proven to be especially valuable for identifying and monitoring lung abnormalities in COVID-19 patients. CT scans provide highly detailed views of pulmonary structures, enabling the detection of characteristic lesions and other pathological changes. However, manual analysis of CT images can be slow and prone to inter-observer variability, underscoring the importance of automated approaches for lung segmentation and lesion identification.

The lung segmentation method discussed in this study employs a U-Net architecture enhanced with pre-processing techniques such as Contrast Limited Adaptive Histogram Equalization (CLAHE) and targeted cropping. This approach achieved an average Dice coefficient of 97.73% on a COVID-19 CT dataset. CLAHE improves the uniformity of contrast across the images, making key lung features more distinguishable, while precise cropping reduces computational overhead and ensures that the model focuses on the most relevant regions. The high Dice coefficient reflects the model's accuracy and reliability, supporting its suitability for clinical-grade applications involving COVID-19 imaging features.

Furthermore, the strong performance of this segmentation technique suggests its potential for generalization to other lung pathologies. By offering a robust and efficient approach to automated lung CT analysis, this method contributes meaningfully to the development of advanced medical imaging and diagnostic tools.

Keywords: *UNet, COVID-19, Lung CT, CLACHE, dice coefficient.*

1. Introduction

The emergence of the SARS-CoV-2 virus in late 2019 triggered a global pandemic that has profoundly impacted public health, clinical practice, and biomedical research. The respiratory system constitutes the primary target organ for COVID-19, with pneumonia and associated pulmonary complications frequently manifesting as secondary manifestations of the infection (World Health Organization, 2022). During the acute phase of the pandemic, the rapid and accurate diagnosis of COVID-19 became paramount for timely patient management, isolation protocols, and therapeutic intervention. CT imaging has demonstrated exceptional utility in this context, providing superior spatial resolution and three-dimensional anatomical representation compared to conventional radiographic techniques.

Computed Tomography (CT) imaging possesses the unique capability to acquire detailed cross-sectional images of pulmonary structures, rendering it an indispensable imaging modality for assessing the extent and severity of lung involvement in COVID-19 patients (Bernheim et al., 2020). The characteristic radiological findings—including ground-glass opacities, consolidations, and other pathological indicators observable on CT scans—provide clinicians with quantitative and qualitative information essential for evidence-based clinical decision-making. Ground-glass opacities represent areas of slight increase in density that preserve underlying vascular and bronchial structures, while consolidations manifest as regions of increased opacity obscuring internal structures (Shi et al., 2020).

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These findings, when combined with clinical and laboratory data, significantly enhance diagnostic accuracy and prognostic assessment. Despite the diagnostic utility of CT imaging, the manual interpretation of volumetric CT datasets by radiologists presents significant challenges and limitations (Wynants et al., 2020). The analysis of multiple sequential CT slices (often exceeding 500 images per examination) is time-intensive and subject to substantial inter-observer and intra-observer variability. Multiple factors contribute to this variability, including radiologist fatigue, experience heterogeneity, individual interpretive bias, and the subjective nature of lesion delineation. Furthermore, the exponential surge in COVID-19 cases during peak pandemic phases frequently overwhelmed radiological infrastructure, creating bottlenecks in diagnostic throughput. These limitations have catalyzed significant research interest in developing automated computational approaches for intelligent image analysis.

The application of deep learning methodologies to medical image analysis has revolutionized diagnostic imaging. Deep learning architectures, particularly Convolutional Neural Networks (CNNs) (LeCun et al., 2015) have demonstrated remarkable capability in pattern recognition, feature extraction, and tissue classification across a wide range of medical imaging tasks, including disease detection and segmentation. These computational approaches can process vast image datasets, learn complex feature hierarchies, and generate pixel-accurate segmentation maps without explicit programming of diagnostic rules. Segmentation, in the context of medical image processing, represents the process of partitioning an image into meaningful, non-overlapping regions that correspond to anatomically or pathologically distinct structures (Shan et al., 2020). The automated delineation of lung boundaries and identification of infected regions.

2. Literature Survey

Segmentation methods can mainly fall into two classes:

- Threshold-based Segmentation: (Hu et al., 2001) used this method is based on setting a threshold value or a range of threshold values, distinguishing two regions based on pixel intensities. Pixels with intensity values under the threshold were assigned to one region, while pixels with intensity values exceeding the threshold were assigned to the other region. Thresholding is a straightforward and common method, especially for binary image segmentation.
- Advanced Segmentation Techniques: These techniques are used in situations where more advanced algorithms are required to segment images based on factors such as color, texture, edges, or the shape of their objects.

Some notable advanced segmentation techniques include:

- Region-based Segmentation (Qian & Guirong, 2014): In region-based segmentation, pixels are clustered into regions based on applying predefined criteria (intensity similarity, proximity, etc.)
- Edge-based Segmentation: In edge-based segmentation, the boundaries between objects are identified and pixels are grouped based on the information of the edge.
- Cluster-based Segmentation (Xiao et al., 2012) : In cluster-based segmentation, clustering algorithms such as K-means clustering (Kumari et al., 2022) or fuzzy clustering are performed to group pixels.
- Contour-based Segmentation (Babu & Chandrasekaran, 2018): In contour-based segmentation techniques, we locate the boundaries of the object or the object contour using techniques like edge detection or gradients.

Segmentation plays a crucial role in various image processing applications, including medical imaging, object detection and recognition, scene understanding, and computer vision tasks. It provides a foundation for subsequent analysis and processing steps by isolating regions or objects of interest within an image. The following is a study of the literature on several lung CT segmentation techniques employed in COVID- 19 detection, as well as the names and authors of pertinent research articles to our knowledge (Shan et al., 2020) has defined a VB-Net deep learning model to obtain segmentation of the infection area with a human-in-the-loop method used to help radiologists improve the automatic

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annotation of each case in the diagnosis of COVID-19 cases and obtained Dice similarity coefficient of 91.6%±10.0% between automatic and manual segmentations. Shaoping proposed (Hu et al., 2020) a Multiview UNet architecture was used for Segmentation with sliding window method for identification of COVID-10 infection. Ait Skourt et al., 2018 have used UNet for accurate lung segmentation with 0.9502 Dice-Coefficient index.(Saood & Hatem, 2021) compared the segmentation result obtained from two deep learning models SegNet and Unet with dice coefficient of 0.95 and 0.954 respectively. To extract Low-level specifics and high-level semantics from feature maps at various scales are combined in the full-scale skip connections in model UNet3+ by (Huang et al., 2020) in their study and obtained dice coefficient of 0.9568. A Swin-Unet model is proposed by (Cao et al., 2022) which is Pure Transformer architecture similar to Unet for medical image segmentation to learn global and long-range semantic information with accuracy 0.917. Another machine learning approach used by (Kumari et al., 2022) for lung segmentation using K-Means method. UNet was also used by (Diniz et al., 2021) and (Qiu et al., 2021) in their study for the segmentation of the lung CT with dice value of 77.28% and 96% respectively.

Ding *et al.* proposed CDSE-UNet (Ding et al., 2025), which integrates Canny edge detection and dual-path squeeze-and-excitation feature fusion into the U-Net framework to enhance boundary awareness in COVID-19 CT segmentation. The proposed model achieved Dice similarity coefficient of approximately 0.89**.** CAD-UNet defined by Dang et al. enhanced standard UNet with capsule networks (Dang et al., 2025), designed to preserve spatial hierarchies and orientation information in lung infection segmentation with Dice score of approximately 0.88**.** Shen et al. proposed an enhanced U-Net architecture (SHEN, 2025) incorporating optimized convolutional blocks and improved feature aggregation strategies for COVID-19 CT image segmentation and achieved a Dice coefficient of approximately 0.86. (Zhang et al., 2024) presented a comprehensive review of deep learning-based COVID-19 CT segmentation techniques, focusing on U-Net variants, attention mechanisms, and multi-scale learning strategies. The review reported that state-of-the-art U-Net-based models commonly achieve Dice scores in the range of 0.85–0.90**.** Lahchim and Davic developed an attention-enhanced U-Net (Lahchim & Davic, 2025) that employs attention gates within skip connections to emphasize infected lung regions while suppressing irrelevant background features The proposed approach reported a Dice similarity coefficient exceeding 0.90**.**

Research Motivation and Gap Identification: While numerous deep learning approaches have been proposed for COVID-19 CT segmentation, there exists a persistent need for methods that balance exceptional accuracy with computational efficiency and clinical applicability. Many existing approaches require substantial computational resources, extensive training datasets, or sophisticated ensemble methodologies. This study addresses the identified research gap by demonstrating that a well-optimized U-Net architecture, when combined with strategic preprocessing techniques (CLAHE and precision cropping) and appropriate data augmentation strategies, can achieve state-of-the-art performance metrics while maintaining computational efficiency. The specific novelty of this work resides in the systematic integration of these complementary techniques and comprehensive validation on a curated COVID-19 dataset, providing a reproducible and practical framework for clinical implementation.

The structure of the paper is as follows: Section 1 will provide an introduction to the study; Section 2 will summarize and highlight the previous work available in the literature; Section 3 will provide the detailed methodology of the work that was tested in the segmentation process; Section 4 will provide the findings of the situational study, while Section 5 will conclude the experiment with limitations and future plans.

3. Research Methodology

For segmenting lung CT scans for COVID-19 diagnosis, this study utilizes a deep learning architecture known as UNet (Ronneberger et al., 2015). UNet is a good candidate for segmenting lung regions and detecting irregularities associated with COVID-19 because of its capability to accurately delineate complex structures. A Convolutional Neural Network for Medical Image Segmentation: UNet Architecture, referenced paper by Ronneberger, Fischer, and Brox (Ronneberger et al., 2015) has been

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widely cited and served as the foundation for numerous subsequent studies and applications of the UNet architecture in medical image segmentation tasks, including COVID-19 diagnosis using lung CT scans. UNet architecture has been established and is widely used for multiple applications in medical imaging due to its competence of segmenting complicated structures with high accuracy.

The model is composed of Encoder-Decoder pooling layers that iteratively downscale the spatial dimension of the input image, capturing hierarchical features. Skip connections between corresponding layers in the encoder and decoder enable the network to retain high-resolution feature maps from the encoder while upscaling in the decoder, enhancing segmentation accuracy. The encoder path progressively reduces the spatial dimensions of feature maps through convolution layers and pooling layers, capturing hierarchical features. Conversely, the decoder path uses transposed convolutions and upsampling to recover spatial information. The structure of basic UNet layers is as described in Figure 1. All features of the UNet model collectively make it a versatile and powerful model for image segmentation tasks, especially in scenarios where accurate localization and preservation of fine details are critical.

3.1 Detailed description of UNet architecture for the detection of lung mask

Input Layer: The network accepts grayscale lung CT slices of size 224 × 224 × 1.

- Encoder: Four sequential convolutional blocks with filter sizes 64 → 128 → 256 → 512. Each block contains two 3×3 Conv2D layers (ReLU activation, same padding), followed by BN, 2×2 max pooling, and a dropout layer with rate 0.3.
- Bottleneck: The deepest layer contains two Conv2D layers with 1024 filters representing the most abstract features.
- Decoder: A symmetric structure that replaces pooling with Conv2DTranspose layers for upsampling. Each step halves the number of filters (1024 → 512 → 256 → 128 → 64) and concatenates the upsampled feature maps with the corresponding encoder outputs via skip connections. After concatenation, BN is applied, followed by two Conv2D layers to refine features.
- Output Layer: A 1×1 Conv2D layer with a sigmoid activation function generates the final pixel-wise segmentation mask of size 224 × 224 × 1.
-

The complete model has 34,523,713 trainable parameters (~131.70 MB)

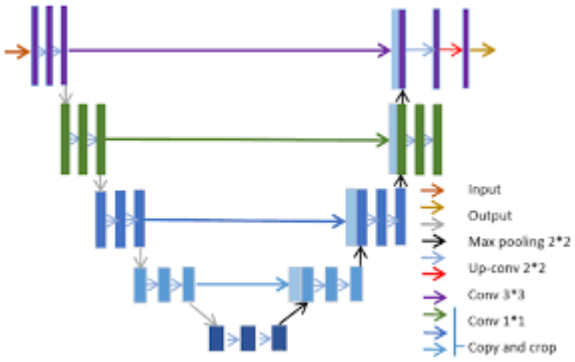


Figure 1: Basic U-Net Architecture (Adapted from Simple U-Net architecture (n.d.), ResearchGate)

The algorithm for lung segmentation to obtain a lung mask from CT images is as follows:

Step 1: Download a publicly available dataset from Kaggle

Step 2: Apply preprocessing Steps for all images in the dataset (lung CT, lung mask)

i. Normalize pixel values
ii. NaN values? then drop both masks and their corresponding CT

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iii. Apply CLAHE enhancement to enhance image contrast
iv. Apply cropping using the lung mask
v. Split the dataset into Training (70%) and Testing (30%)

Step 3: Apply Data Augmentation, such as left-right flip and up-down flip of the original images and original masks.
Step 4: Build a segmentation model architecture
Step 5: Train the model using the Dice coefficient metric and Dice loss.
Step 6: Evaluate the performance of the model with the testing dataset

3.2 Data Acquisition

The proposed work is performed on the dataset (MvD, n.d.), publicly available on Kaggle in nii-format containing CT scans with corresponding lung masks and infection masks of 20 patients. These scans of the left and right lungs are obtained, labeled manually by radiologists, and confirmed by experts. A patient who tests negative for COVID-19 is indicated by the black mask. Sample CT slices with infection masks are shown below in Figure 2.

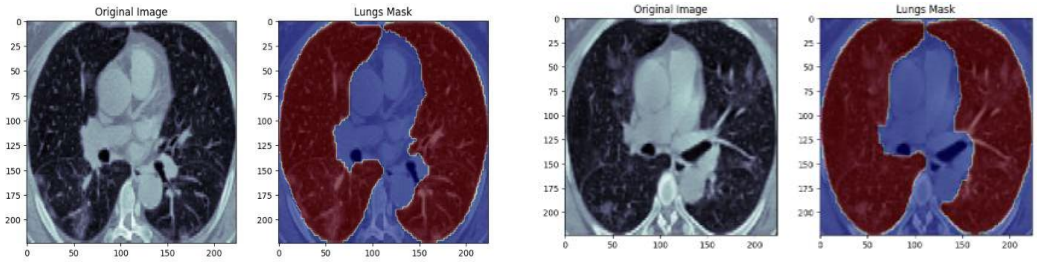


Figure 2: Sample images from the dataset

3.3 Data Preprocessing

- Data Cleaning: Dataset used in this study containing total 3520 number of slices of lung CT with 512x512 size. Some masks in the dataset contained only NaN values, so these masks and their corresponding CT scans were removed as part of the data cleaning process and some duplicate slices are also deleted from the dataset.
- Data enhancement & cropping: To improve contrast and quality, all lung CT slices were enhanced using the CLAHE algorithm (Salem et al., 2019). This preprocessing significantly boosts segmentation accuracy by enhancing contrast and focusing on relevant regions. Additionally, lung masks were used to crop and derive the region of interest (ROI) for each scan, improving processing time by targeting only the relevant lung areas.
- Data augmentation: Small dataset may add overfitting problem during training the DL model. Dataset size is further increased by applying traditional simple data augmentation method such as left-right flip and up-down flip of the original CT slice and its corresponding original masks.
- Data Split: Entire dataset is divided into training (70%) testing set (30%) with each image resolution of 224 x 224 for training segmentation model. The model is trained by applying hyper parameter tuning with different optimizers like Adam, RMSprop by selecting different initial learning rate. Final parameters selected for training and testing : Number of epochs 50, Adam (Adaptive Moment Estimation) optimizer with learning rate 0.0001, batch size 16 and dice coefficient to measure the accuracy of the model. the dice coefficient and dice loss. Dice coefficient is the ratio between 2 * intersection (of true mask and predicted mask) and the sum of true and predicted masks.

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Hardware and Software Tools for the experimental setup

- Hardware: Google Colab: The experiments were conducted on Google Colab. The use of GPU acceleration on Google Colab significantly reduced the training time of the UNet model, allowing for efficient processing of large datasets and complex computations.
- Software: Python was used for its extensive libraries and ease of integration with deep learning frameworks. TensorFlow/Keras: The UNet model was implemented using TensorFlow/Keras, providing a high-level API for building and training neural networks. Image Processing Libraries: OpenCV: Used for image preprocessing tasks such as cropping and applying CLAHE enhancement to CT lung images.

4. Results and Discussion

A complete segmentation model is implemented and tested using TensorFlow/Keras on Google Colab with a GPU to optimize pixel-wise segmentation accuracy.

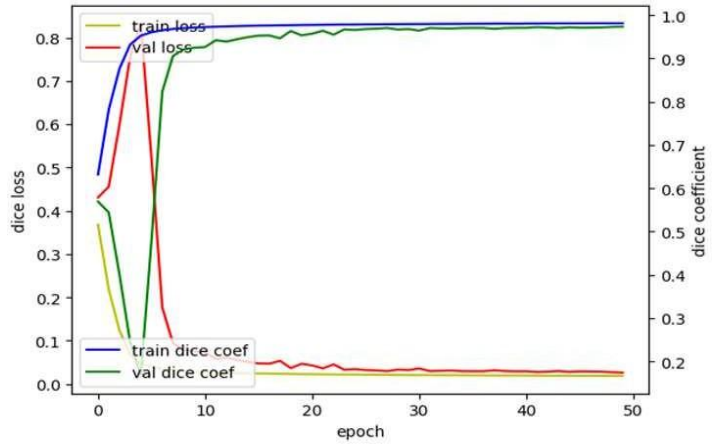


Figure 3: Behavior of the model in training and validation process for 50 epochs

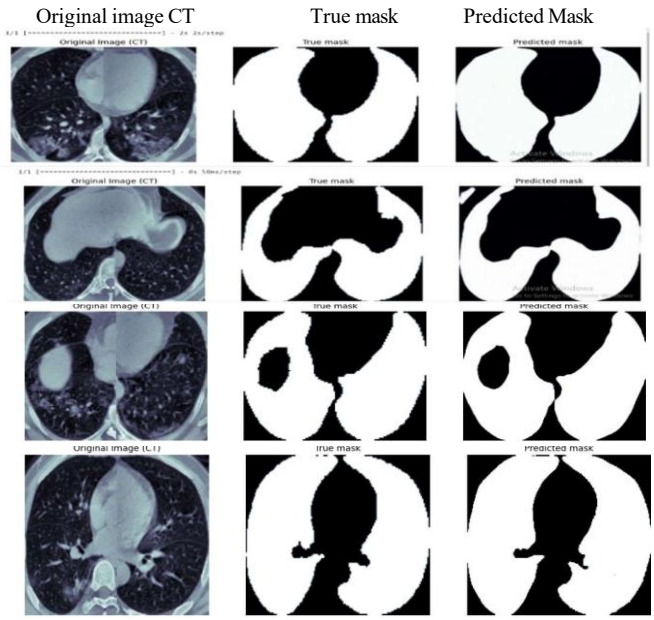


Figure 4: Comparison of True masks and predicted masks by the proposed model

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For the training step, the following parameters are set: number of epoch 50, batch size per epoch 16, optimizer=Adam (learning rate = $3e^{-5}$) (Kingma & Ba, 2014) yielding an impressive Dice score of dice_coeff: 0.9812 for training and 0.9735 for validation, as shown in Figure 3.

Segmentation results were visualized using the Matplotlib library in Python to perform a qualitative assessment of the model's performance. These visualizations included comparisons between the ground truth and the model's predictions as depicted below in Figure 4.

Table 1 compares the outcomes of the different UNet models published in the literature:

Table 1: Basic Deep Learning Architecture with its important features

Method	**Dice value**	**purpose**
Unet (Ronneberger et al., 2015)	95.53%	Biomedical image segmentation
Swin-UNet (Cao et al., 2022)	91.7%	Medical image segmentation
UNet Seg-Net (Saood & Hatem, 2021)	95% 95.4%	Lung CT segmentation
UNet (De Oliveira et al., 2021)	96%	Lung CT segmentation
Res-UNet (Zhou et al., 2022)	96.78%	Lung CT segmentation
Proposed UNet	**97.73%**	Lung CT segmentation

Lung mask segmentation is an essential step in the detection and management of COVID-19, providing healthcare professionals with crucial information for accurate diagnosis, treatment planning, and patient care. The proposed UNet model excelled in the segmentation process, achieving a high accuracy of 97.73%. This performance is comparable to the Res-UNet model used by Li, Z (Li et al., 2022), which achieved an average Dice coefficient of 96.78%, and the UNet model used by Diniz (Diniz et al., 2021), which achieved a Dice value of 95.53%.

5. Conclusion

The segmentation of the lung mask is a crucial step in the identification and treatment of COVID-19. It provides medical practitioners with critical knowledge for accurate diagnosis, treatment management and patient care. The lung segmentation method proposed with the UNet model has shown high accuracy, with a Dice coefficient average of 97.73% evaluated on a COVID-19 dataset. The CLAHE enhancement and cropping, together with the SMOTE method, handle data imbalance, with the preprocessing steps successful in increasing the accuracy of the CT lung images and yielding excellent performance related to segmentation.

Limitations and Potential Challenges: Although favorable results were attained using the suggested lung segmentation methodology, there were various limitations and challenges involved in applying it. Limited Data size and generalization of the model: The dataset size was small, which could have impacted how applicable the results would be for the general population. The dataset was composed of lung CT scans from COVID-19-positive patients and may not represent all lung pathologies. There is also a risk of overfitting due to the model's high capacity and low dataset.

Data Preprocessing: While the respective preprocessing steps, CLAHE enhancement and cropping, were helpful, the use of these steps would introduce variability that would impact consistency across datasets. Resource requirement: The complexity of the UNet model required substantial computational resources and training time, which may not be readily available in all settings. Also, the evaluation predominantly based on the Dice coefficient might overlook other aspects of model performance.

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Following are the future recommendation can help to implement more effective model for Lung segmentation : Expanding and diversifying the dataset involves increasing the quantity and variety of data used to train and test the model such as Collecting Data from Multiple Sources, Augmentation Techniques, Ensuring that the dataset has a balanced representation of different classes such as COVID-19 positive and negative cases, to prevent the model from becoming biased towards the more prevalent class, Exploring Additional Preprocessing Techniques such as Noise Reduction, Advanced Image Enhancement, integration of multimodal data.

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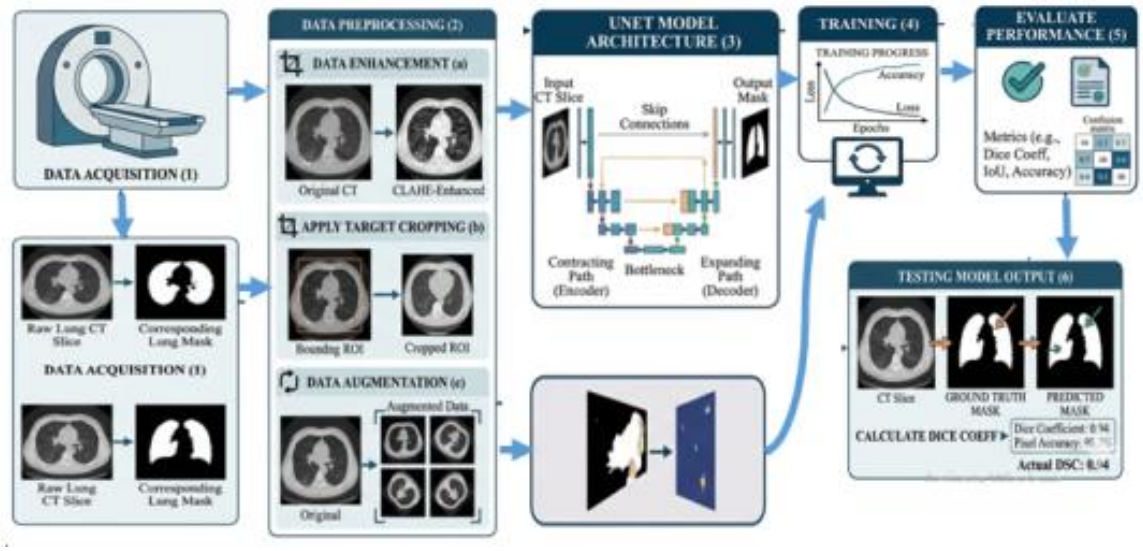
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Graphical Abstract





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