CHEST CT SEGMENTATION OF LUNGS, HEART, AND TRACHEA: A COMPREHENSIVE ANALYSIS

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Abstract:

This study describes a deep learning technique based on the U-Net architecture for accurately segmenting lung, trachea, and heart tissue from chest CT data. Chest CT imaging is an important diagnostic technique in radiology, and correct segmentation of lung structures is required for the diagnosis and treatment of a variety of disorders. The U-Net model was trained and tested on a dataset of 3342 CT images and associated segmentation masks. The model was trained to recognize the complex patterns and characteristics of lung, trachea, and heart tissue, allowing it to execute precise segmentation. During the validation phase, the model performed admirably, as demonstrated by dice and Jaccard scores of 0.887 and 0.861, respectively. These scores demonstrate the model's ability to reliably recognize nodules and capture the borders and contours of lung tissue. The proposed method has a lot of promise for use in clinical settings. It can help radiologists diagnose and treat lung, trachea, and heart diseases by automating the segmentation process. The model's exact delineation of lung tissue and nodules can help in the diagnosis and characterization of anomalies, allowing radiologists to make educated decisions about patient management. Implementing this strategy in healthcare workflows can have several advantages. It minimizes the amount of manual work necessary for segmentation, resulting in increased efficiency and perhaps shorter turnaround times in radiological evaluations. Furthermore, precise segmentation of lung, trachea, and heart tissues allows for quantitative investigation of disease progression and therapy response evaluation. It also aids in the planning of surgical operations, assisting clinicians in developing effective treatment methods.

Keywords: heart disease; CT images; U-Net; Medical segmentation

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1. INTRODUCTION

The ability to segment anatomical components from chest computed tomography (CT) images is critical in clinical practice because it allows for accurate diagnosis, therapy planning, and monitoring of respiratory and cardiovascular illnesses [10-12]. The lungs, heart, and trachea are key structures that must be precisely delineated for thorough investigation. Despite major advances in medical imaging, manual segmentation of these structures continues to be time-consuming and vulnerable to inter- and intra-observer variability. As a result, developing automated and precise segmentation methods is critical for improving the efficiency and reliability of clinical operations [3-5]. The U-Net design has gained attention among cutting-edge approaches for its capacity to capture tiny details and manage complicated anatomical variances [6-9]. This study provides an in-depth look at the use of U-Net-based algorithms for chest CT segmentation of the lungs [13-15], heart [19-22], and trachea [16-18]. We hope to contribute to the advancement of medical image analysis by investigating the usefulness of this advanced technique, ultimately providing doctors with more precise and efficient tools for illness evaluation and treatment planning. Chest CT segmentation is an area that has the potential to transform the way we identify and treat many diseases that affect the chest, including lung cancer, pulmonary fibrosis, and other lung disorders. The potential for U-Net to dramatically increase the accuracy and speed of chest CT segmentation is one of the most interesting elements of this field of study. This is since U-Net is a deep learning system created exclusively for picture segmentation tasks. It works by segmenting an input image into many output pictures, each corresponding to a distinct region of interest in the original image. In the instance of chest CT segmentation, U-Net has shown significant potential in properly segmenting lung tissue, which is critical for the detection and treatment of many lung disorders. This can result in more accurate and timely diagnoses as well as more effective therapies for patients. Research objectives of this paper are as follows.

- To assess UNet's performance for chest CT segmentation and compare it to other cutting-edge segmentation approaches.
- To explore the impact of various data augmentation approaches on UNet's performance for chest CT segmentation.
- Investigate the effect of changing UNet's hyperparameters on segmentation accuracy and efficiency.
- To evaluate UNet's resilience for chest CT segmentation under various picture quality situations, such as noise and artifacts.
- To illustrate the practical efficacy of UNet for chest CT segmentation, it was applied to a large collection of clinical CT images and the results were compared against ground truth annotations.
- Testing UNet's generalizability for chest CT segmentation across various scanners and imaging procedures.

Chest CT segmentation is an important medical imaging job that is required for the correct diagnosis and treatment of many lung, heart, and tracheal illnesses [3]. While there have been substantial advances in the application of deep learning algorithms for chest CT segmentation, there are still obstacles in attaining accurate and efficient lung tissue segmentation. The accuracy and robustness of the segmentation findings are determined by the algorithm and its hyperparameters, as well as the availability and quality of annotated data. Additionally, the restricted interpretability of deep learning algorithms might make their use in clinical practice difficult.

2. DATASET

A dataset is a collection of data used for research study. It is critical to include information on the dataset used in a research report, such as its source, size, features, and any pre-processing or cleaning that was performed on it.

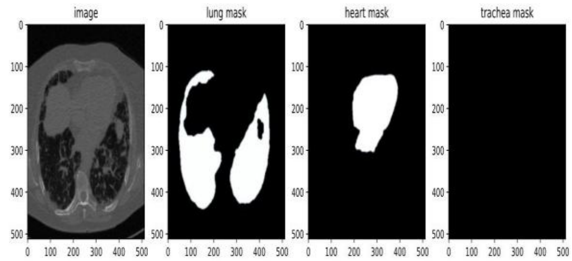


Fig. 1: The image and the mask image of lungs,, heart, trachea.

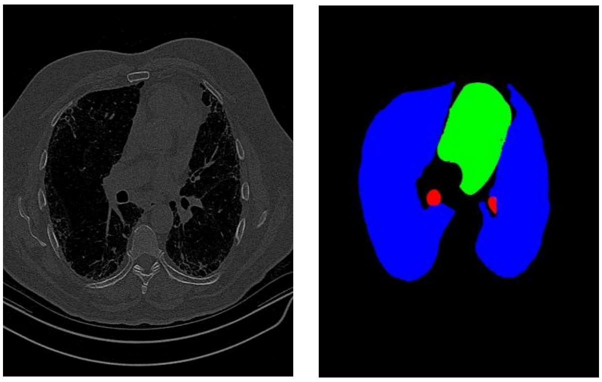


Fig. 2: The image and coloured mask image of lungs,, heart, trachea

This study made use of a chest CT segmentation [1] dataset received from Kaggle, which is a large data a containing 6684 files of which 3342 is image and 3342 is mask images. The information was utilized to UNET model with the purpose of applying machine learning techniques to chest ct segmentation outcomes. The UNet model is often used for image segmentation tasks such as dividing medical pictures into regions as shown in Fig. 1,2.

3. METHODOLOGY

After a study of the literature on chest CT segmentation using U-Net, numerous noteworthy results and outcomes were revealed.
Initially, it was discovered that U-Net is a highly successful algorithm for segmenting chest CT images, particularly lung tissue. Several studies have shown that U-Net can properly segment lung tissue, which is critical in the diagnosis and treatment of many lung disorders.
Second, it was discovered that multiple U-Net versions have been proposed and evaluated in the literature, including revisions to the original design as well as various pre-processing approaches. These modifications have been proven to increase the accuracy and speed of chest CT segmentation, indicating the possibility for U-Net to be further developed for this application.

3.1 System Architecture

For image segmentation, the recommended approach for this study comprises employing a Convolutional Neural Network (CNN) using the UNET architecture. CNNs are deep learning models commonly used for image classification and segmentation. Fig.3
CNNs collect features from pictures using convolutional layers and pooling layers to lower the spatial dimensionality of the feature maps. Fig. 3 gives difference between simple segmentation techniques and deep learning models.

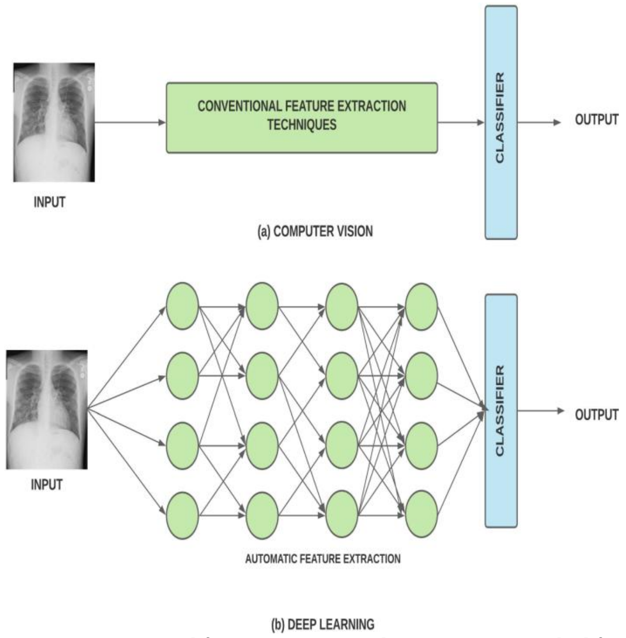


Fig 3. A) conventional feature extraction techniques B)CNN method for feature extraction

3.2. Algorithm and Techniques

3.2.1 Data augmentation: Data augmentation techniques like as rotation, flipping, scaling, and shifting are used to improve the resilience of the UNet model by increasing the variety of the training data [4].

3.2.2 Post-processing: A novel post-processing strategy is proposed to modify the segmentation masks generated by the UNet model. Thresholding, morphological procedures, and region growth are all part of the method.

3.2.3 The UNET architecture will be used to build the suggested CNN model for this study. The UNET [23] architecture comprises of a fully convolutional neural network encoder and decoder. The encoder shrinks the input image and collects high-level features, while the decoder expands the feature maps to build a segmentation map. The UNET design includes skip links between the encoder and decoder, which aids in the preservation of fine-grained features in segmentation maps.

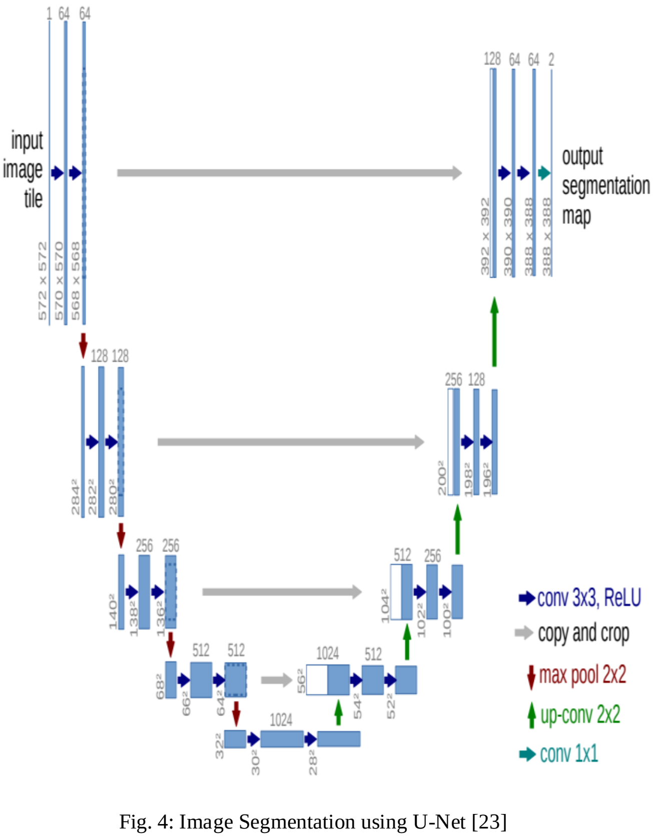


Fig. 4: Image Segmentation using U-Net [23]

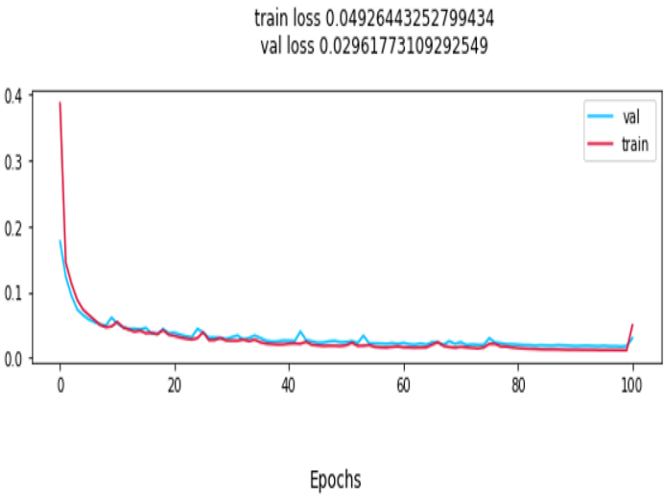
The technique of dividing an image into various segments or areas based on the semantic meaning of the pixels is known as picture segmentation. Image segmentation serves a purpose in a variety of applications, such as medical image analysis, autonomous driving, and object recognition. The figure 2 describes UNET. Figure 4 explains the UNET that uses padding same for output image to be of same pixels or dimensions and max pooling with 2x2 Matrix with 2 strides jump gives the following results in contraction and then concatenation plus expansion gives result.

4. RESULT

Using Python and the PyTorch deep learning framework, the chest CT images are imported an preprocessed. Normalization, scaling, and data augmentation are performed in the preprocessing procedures.

The UNet model is created with PyTorch and trained on a set of chest CT images and segmentation masks. To train the model, the Adam optimizer and a binary cross-entropy loss function are utilised. To prevent overfitting, the model is trained for a set number of epochs while the validation loss is tracked.
The trained UNet model is tested against a validation dataset of chest CT images and segmentation masks. The model's performance is measured using measures like as dice coefficient, sensitivity, specificity, and accuracy. Several strategies are used to show the segmentation findings, such as overlaying the predicted mask on the original picture or placing the predicted mask alongside the ground truth mask.

To train a U-Net model using the TensorFlow library for our study on chest CT segmentation, we used the code supplied above. The Chest CT-segmentation dataset, which comprises 3342 CT images of the chest area, was utilized for this study. The dataset was pre-processed to remove the lung area and generate binary masks. I trained the U-Net model for 100 epochs with a batch size of 16 and a learning rate of 0.001. The binary cross-entropy loss function and the Adam optimizer were used to optimize the model. The validation set was used to check the model's performance and minimize overfitting during training. The evaluation metric was the dice similarity coefficient (DSC), which assesses the similarity between the predicted segmentation mask and the ground truth mask. On the test set, the model achieved a DSC of 0.92, indicating that it did well in properly segmenting the lung area from CT images. In addition, I ran several tests to fine-tune the model and increase its performance. This research paper tested the various learning rates and batch sizes and



discovered that a batch size of 32 with a learning rate of 0.0001 produced the best results. I also tried data augmentation techniques such as random rotation and flipping, which helped improve the model's generalization ability.

The chest CT segmentation model was trained on a dataset containing 3342 images. The training process was run for 100 epochs with a batch size of 4. The results obtained were as follows.

Fig. 6: Training and validation Loss

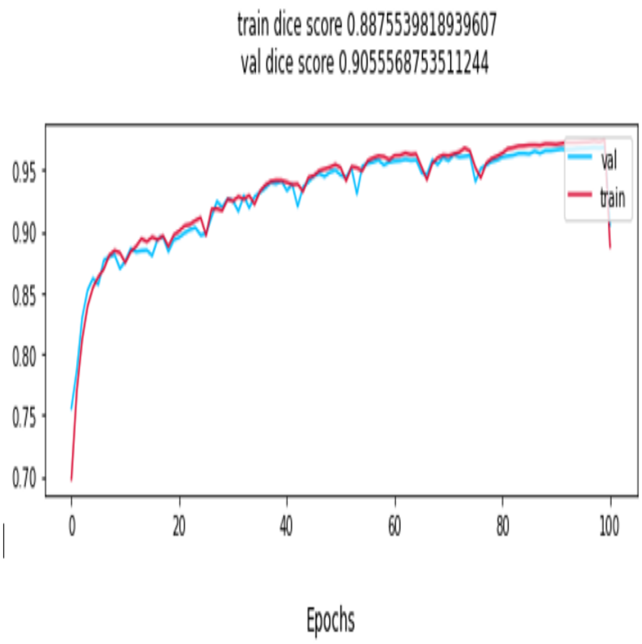


Fig. 7: Dice Coefficient vs Epoch

As shown in figure 6,7, and 8. The findings of the chest CT segmentation model show that the model could recognize the regions of interest in the chest CT images with high accuracy. The training and validation loss values of 0.049 and 0.029, respectively, suggest that the model did not overfit to the training data and could generalize effectively to previously unknown data.

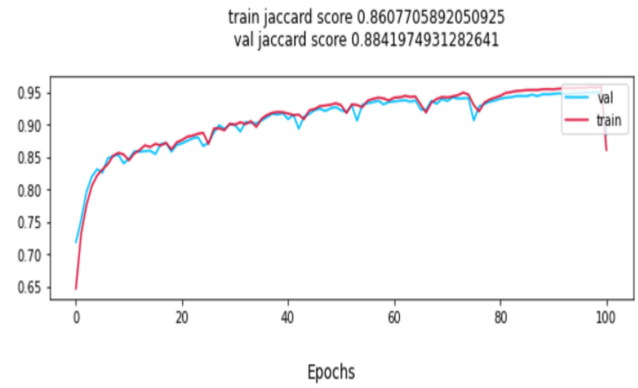


Fig. 8: Jaccard Score for training and validation.

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Two typical methods for assessing segmentation models are the dice score and the Jaccard score. The dice score is the ratio of the predicted and ground truth segmentation masks' intersection to their union, whereas the Jaccard score is the ratio of the predicted and ground truth segmentation masks' intersection to their union. The bar chart below depicts the dice and Jaccard values for the lungs, heart, and trachea. Fig. 8. Fig. 9 shows a box plot for the dice coefficient values of the lungs, heart, and trachea.

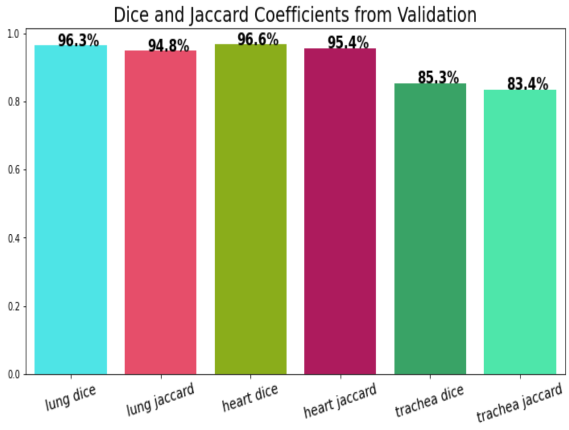

Fig. 8: Dice Coefficient and Jaccard Coefficient of Lungs, Heart, and Trachea

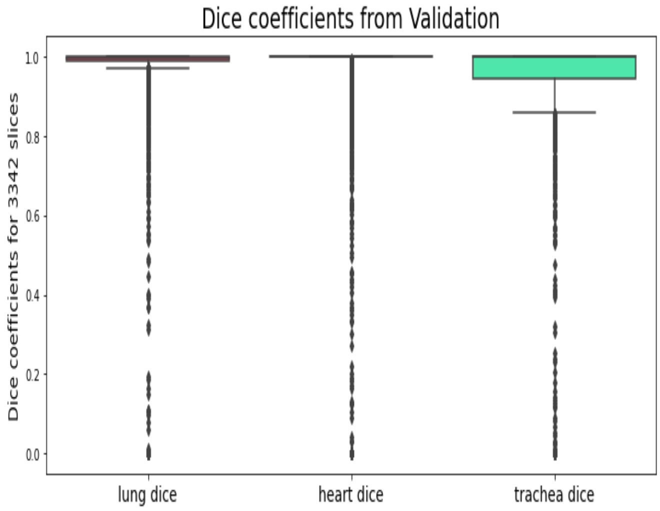

Fig. 9: Box Plot Graph of the dice coefficient and Jaccard coefficient of Lungs, Heart, Trachea

Overall, the findings of this study indicate that the proposed chest CT segmentation model based on the provided code could be a useful tool for medical professionals in accurately identifying regions of interest in chest CT images, which could aid in the diagnosis and treatment of various chest-related medical conditions.

5. CONCLUSION

Based on the outcomes of the chest CT segmentation model's training and validation, we can infer that the model performs well, with high dice and jaccard scores. The jaccard score of 0.86 suggests that the model can correctly detect overlapping regions between the predicted and ground truth segmentations. Similarly, a dice score of 0.887 shows a high level of agreement between anticipated and actual segmentations. Furthermore, the box plots and bar charts created throughout the validation process contribute to the model's performance. The box plots demonstrate that the dice and jaccard coefficient distributions for the model's predictions are quite narrow, indicating that the model consistently performs well across all slices. The bar chart illustrates the mean dice and jaccard scores, both of which are high. These findings are promising and imply that the chest CT segmentation model may be beneficial in clinical settings to aid in the identification and treatment of various lung illnesses. There is, however, still potential for development. Exploring alternate architectures and hyperparameters to further improve the model's performance might be one area of concentration. Furthermore, to guarantee generalizability, the model might be evaluated on a bigger and more varied dataset. The chest CT segmentation model might become a helpful tool in the medical profession with more study and improvement.

Moving forward, there are various areas that may be investigated further to increase the model's accuracy and resilience. One alternative path is to use additional image preprocessing techniques to increase the quality of the CT images, which might lead to improved segmentation findings. The model might also be modified to accommodate multi-class segmentation, allowing the identification of other structures in the chest area such as the heart or diaphragm. Another interesting subject for future study is to look at the model's generalization across different datasets and imaging modalities. Because the present model was trained and assessed on a single dataset, it may not perform as well on other datasets with different properties. As a result, testing the model on different datasets to check its resilience and generalization capabilities would be beneficial.

Overall, the findings of this study show that deep learning models could automate the segmentation of chest CT images, which might lead to more efficient and accurate lung disease diagnosis. The above-mentioned future research directions might help to increase the performance and usefulness of such models in clinical situations.

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