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Automatic Segmentation of Lung X-Ray Images Using U-Net Convolutional Neural Network

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ABSTRACT

Medical imaging, particularly chest X-ray analysis, plays a vital role in diagnosing and treating lung diseases such as pneumonia, pulmonary fibrosis, and lung cancer. Despite its importance, accurate interpretation of these images faces several challenges, including low quality, noise, illumination variations, and the high cost and effort of manual annotation. Moreover, the complex anatomy of the lungs requires advanced algorithms to achieve precise delineation.

This study presents an automatic lung segmentation approach based on the U-Net convolutional neural network. With its encoder–decoder architecture, U-Net effectively integrates compressed and expanded feature representations to produce accurate segmentation. The model was trained on 563 annotated chest X-ray images and evaluated on 141 independent cases.

Experimental results demonstrate 91% accuracy on the training set and over 84% accuracy on the test set, confirming its strong performance in extracting lung regions. The findings reveal that U-Net can reliably detect lung structures and lesions, even with limited training data or varying image quality. This reduces dependence on manual interpretation, lowers associated costs, and minimizes human error while accelerating the diagnostic process. The model's high generalizability further supports its potential for use across diverse clinical settings.

In summary, this research emphasizes the value of deep learning architectures such as U-Net for precise medical image segmentation. The proposed method enhances diagnostic efficiency and accuracy, providing a reliable tool for supporting clinicians. Future extensions, including integration with complementary deep learning techniques, may further advance intelligent healthcare applications.

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1. Introduction

In recent years, medical imaging has emerged as a key tool for disease diagnosis and treatment improvement (Huang et al., 2024; Kordnoori et al., 2024). Imaging modalities, including radiography, CT, and MRI (Laousy et al., 2023), are employed not only for clinical diagnosis but also for education and research across different medical domains. With the rapid growth of digital medical data, there is an increasing need for fast and accurate analysis to ensure timely and precise disease detection (Wang et al., 2023). Specifically, in respiratory medicine (Rashid and Türker, 2024), chest X-ray images (Gupta et al., 2024) are widely used for disease identification, making precise image segmentation critical (Sumathi & Phamila, 2024). Deep learning models, particularly architectures like U-Net, have demonstrated significant progress in this field (Turk, 2024).

Despite these advancements, several challenges remain in medical image analysis (Ding et al., 2024; Le et al., 2024), limiting achievable accuracy in clinical settings. These challenges include the requirement for large and diverse datasets, the complexity of acquiring high-quality annotated data, limited interpretability of models, and high computational demands (Savaş & Damar, 2024; Gu & Lee, 2024; Mukhlif et al., 2023). Moreover, domain shift, where model performance drops when exposed to data from different distributions, is a fundamental concern (Ding et al., 2024), particularly when models are applied to unseen anatomical regions or alternative imaging modalities. Addressing such issues often requires retraining, which is both time-consuming and costly (Butoi et al., 2023).

Deep learning models such as U-Net and Deeplabv2 rely heavily on high-quality annotated datasets (Alhussan et al., 2023). However, acquiring these data is practically challenging due to time and cost constraints (Mukhlif et al., 2023; Junia & Selvan, 2024). Multi-source or weakly supervised models, including MedSAM and MIScnn, are also vulnerable to noise and low-quality data (Ijaz et al., 2023; Tareq et al., 2023). Approaches like knowledge distillation, transfer learning, and self-supervised learning can mitigate such effects and enhance segmentation accuracy (Jiang et al., 2024; Waheed et al., 2024), although substantial and diverse datasets are still often required.

U-Net, originally developed for biomedical image segmentation (Saimassay et al., 2024), features a distinctive encoder–decoder structure (Mukhlif et al., 2023) that efficiently extracts features and reconstructs image details (Atasever et al., 2023). Its U-shaped design, enriched with skip connections, preserves fine details while maintaining global context, accelerates convergence, and improves robustness to input variations (Kordnoori et al., 2024). In this study, the U-Net was applied to lung X-ray images. The model was trained on 563 annotated images and evaluated on 141 additional cases, achieving over 84% accuracy, demonstrating its capability for reliable and precise segmentation without resorting to more complex methods such as transfer learning (Lee et al., 2024).

2. Related work

Computational analysis of medical images has undergone remarkable advancements, with deep learning models becoming central to many complex tasks, such as radiological image segmentation (Rashid & Türker, 2024). This section reviews prior studies and models that form the foundation of the present research, providing an overview of achievements in lung segmentation, the evolution of U-Net architectures, and the existing challenges in segmenting lung structures from medical images.

2.1. Deep Learning in Medical Imaging

Deep learning has significantly transformed medical image segmentation, with models such as U-Net, Deeplabv2, and SwinUNet demonstrating outstanding performance (Mukhlif et al., 2023; Zhang et al., 2024). In particular, U-Net, with its encoder–decoder structure, has achieved high accuracy in delineating boundary regions in medical images (Mukhlif et al., 2023; Atasever et al., 2023). These models have shown promising results in detecting diseases such as cancer (Saimassay et al., 2024) and respiratory conditions (Rashid & Türker, 2024).

Studies on deep learning-based medical image segmentation have reported substantial improvements in both accuracy and efficiency. For lung cancer detection, an enhanced U-Net with multi-scale convolutional blocks was evaluated on CT images from the OSIC dataset, achieving an average Dice score of 93.29% (Zhu et al., 2024). The RDAG U-Net model also performed successfully in analysing SARS-CoV-2-induced pneumonia CT scans, maintaining a Dice score of 93.29% while reducing processing time by 45% (Lee et al., 2024). In X-ray segmentation, the Attention U-Net achieved 98.54% accuracy, and the MobileViT model reached 98.52% for pulmonary disease classification (Gupta et al., 2024). Explainability techniques such as Grad-CAM++ and LRP further enabled detailed analysis of model decisions.

For COVID-19 detection from X-ray images, the ENNSA model, leveraging features extracted via IGLCM, achieved 99.25% accuracy (Junia and Selvan, 2024). The L-UNet model showed high accuracy in segmenting lungs, liver, skin cancer, and chest X-rays, with 93.45% for COVID-19 (Alafer et al., 2024). In tuberculosis detection, RNGU-Net, which combines ResNet, attention, and non-local blocks, reported a Dice score of 97.21% and accuracy of 98.56% (Lee et al., 2024). Other applications include Swin U-Net for pelvic segmentation, achieving 98.03% accuracy and 96.32% Dice (Lee et al., 2024), and dental image processing using Vanilla U-Net and Dense U-Net, attaining 95.56% and 95.94% accuracy depending on convolutional depth (Zannah et al., 2024). These results highlight the substantial impact of deep learning in enhancing the accuracy and efficiency of medical image segmentation methods.

2.2. Challenges in CT and Chest X-Ray Segmentation

One of the major challenges in segmenting CT and chest X-ray images is the inherent complexity of the images and the precise delineation of anatomical boundaries (Saimassay et al., 2024). Medical images often exhibit intricate features that require models with high accuracy to correctly identify these boundaries (Khaniki & Manthouri, 2024). Furthermore, the need for high-quality annotated datasets presents another significant challenge, as access to such data is often limited in practice (Ding et al., 2024).

2.3. Evolution of U-Net and Its Variants

The emergence of the U-Net model marked a significant milestone in medical image segmentation, particularly due to its symmetric encoder–decoder structure and extensive use of skip connections. The original U-Net architecture was designed for biomedical image segmentation and laid the foundation for the development of various specialized variants. For instance, V-Net introduced the capability to process three-dimensional images, which is essential for analysing CT and MRI scans, while Attention U-Net (Gupta et al., 2024) incorporated attention gates to guide the model's focus toward specific regions of the image. Despite these advancements, these models still face challenges in performing certain fine-grained segmentation tasks, particularly in complex anatomical regions such as the lungs (Saimassay et al., 2024).

2.4. Emergence of Advanced CNN Architectures for Segmentation

Recently, convolutional neural networks [1] have been recognized as powerful tools capable of automatically extracting hierarchical features from images, making them a central focus in image processing and computer vision research (Alafer et al., 2024). With recent advances in deep learning, new architectures leveraging techniques such as Pyramid Pooling have demonstrated strong performance in complex environments, while SwinUNet, utilizing Vision Transformers, has achieved significant progress, particularly in handling large and intricate images (Mukhlif et al., 2023; Iman et al., 2023).

2.5. Addressing Class Imbalance and Data Diversity

In many medical applications, datasets face challenges in terms of both quantity and diversity (Ding et al., 2024). Class imbalance can lead to reduced model accuracy (Alhussan et al., 2023). Particularly in scenarios with limited access to annotated data, models such as Med SAM and MIScnn have employed weakly supervised learning and multi-source data strategies to reduce reliance on manually labelled datasets (Salehi et al., 2023).

2.6. Advances in Post-Processing for Enhanced Segmentation

One recent trend in improving medical image segmentation involves the use of post-processing techniques. These methods have been particularly effective in enhancing model accuracy and performance under complex conditions. Models employing self-regulation mechanisms have been able to improve precision by optimizing supervisory signals across different parts of the network (Atasever et al., 2023).

2.7. Importance of Model Interpretability in Clinical Applications

One of the main challenges in applying deep learning models in medicine is model interpretability (Salehi et al., 2023). For clinical applications, models must provide their results clearly and understandably for physicians and specialists. This is especially important in sensitive tasks, such as the diagnosis of cancers and brain tumors, where correct interpretation of model outputs can play a significant role in clinical decision-making (Dhakshnamurthy et al., 2024).

2.8. Computational Efficiency in Model Deployment

In addition to accuracy, computational efficiency is a critical factor in deploying deep learning models. Lightweight models and domain-specific optimizations (Laousy et al., 2023) can help reduce resource consumption and processing time. Techniques such as IoT and Fog Computing can be particularly useful for deploying fast and precise diagnostic systems in clinical environments (Dhakshnamurthy et al., 2024; Fateh et al., 2024).

Consequently, given the high efficiency of the U-Net architecture in precise image segmentation, this study also leverages this model as an effective tool for lung X-ray image analysis.

3. Methodology

3.1. Data Used

Medical imaging provides critical information about the respiratory system for diagnosis, consultation, and analysis in healthcare. X-ray imaging is recognized as the most common and cost-effective medical imaging modality. Chest X-ray images are used across various medical settings, from emergency rooms to laboratories. Conditions such as pneumonia, respiratory infections, pulmonary nodules, and pulmonary edema are typically detected through chest X-ray examinations. Accurate interpretation of lung X-rays is essential, as misdiagnosis or incorrect treatment may lead to more severe complications. Researchers continue to explore computational approaches to assist radiologists in interpreting chest X-ray images,

[1] CNNs

primarily through image processing and machine learning, due to the clinical significance and complexity of chest X-rays. Computer-aided detection systems often integrate these methods to support radiologists in identifying abnormalities (Sumathi and Phamila, 2024).

Masks associated with these images are designed to segment different regions of the lungs, enabling the model to accurately identify areas such as healthy tissues and regions affected by disease. In this study, the dataset of chest X-ray images, along with corresponding masks and labels, was obtained from Kaggle. The dataset includes X-ray images with masks indicating various lung regions. Approximately 80% of the images with masks were used to train the model, while the remaining 20% were reserved for evaluating the model's prediction accuracy. An example of these images, along with their corresponding masks, is shown in Figure 1.

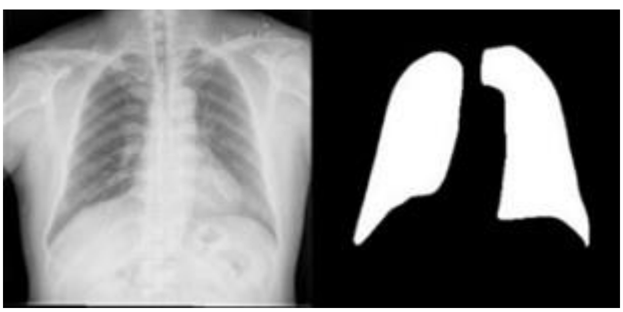

Figure 1. Example of a Chest X-ray Image with Corresponding Mask

3.2. Proposed Method

The workflow of this study is illustrated in Figure 2.

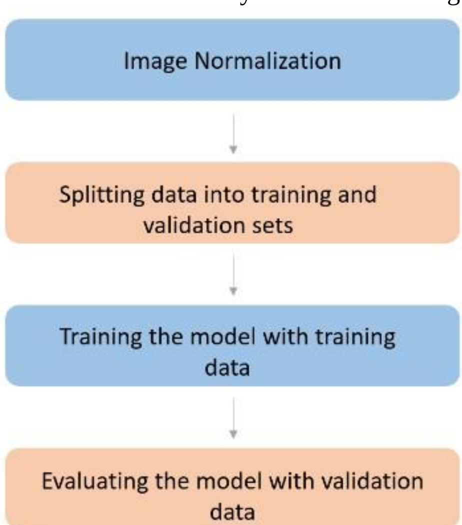

Figure 2. Flowchart of the Project

According to the workflow, first, the data related to chest X-ray images and their corresponding masks were collected and loaded for training the U-Net model. The data were then normalized, and the U-Net model was designed for lung image segmentation. The model was trained using the training data, and its performance was evaluated with the validation data. Finally, the trained model was saved, its accuracy was calculated on the test data, and predictions were made for new images, with the results visualized.

3.2.1. Data Collection and Processing

In this step, a set of chest X-ray images and their corresponding masks were collected from various sources. The images and masks were loaded separately from different folders and resized to uniform dimensions (256×256 pixels). Subsequently, data normalization was performed to scale the pixel values to the range [0, 1]. These pre-processing steps were essential to ensure data consistency and to enhance the model's performance during training.

3.2.2. U-Net Model Design

In this section, the U-Net model was designed as the primary architecture for performing image segmentation. This architecture utilizes contracting and expanding blocks to extract features from images and reconstruct important regions during the segmentation process. The model employs convolutional layers, activation functions, and pooling operations to achieve more accurate detection of lung structures.

3.2.3. Model Training

In this stage, the training data were divided into images and their corresponding masks, and the model was trained to identify and segment lung structures. The training was carried out over multiple epochs using the training dataset, and the model's performance was regularly evaluated using the validation data. Techniques such as Dropout were employed to improve the model's performance and prevent overfitting.

3.2.4. Model Evaluation

After training, the model was tested using the validation data to measure its prediction accuracy. This evaluation was performed using metrics such as accuracy and loss function. Additionally, the model's results on the validation data were visualized through images showing the predictions, inputs, and masks, allowing for the assessment of the segmentation quality.

3.2.5. Model Saving and Utilization

After the training was completed, the final model was saved for future use. The saved model was loaded to make predictions on new data, and its accuracy was evaluated. In this stage, the model effectively identified lung structures in the X-ray images, and the prediction results were compared with the ground truth data to verify the model's performance.

4. Results Presentation

In this section of the code, the model's performance during training and evaluation is presented using various plots. First, the model's accuracy and loss over the training and validation epochs are plotted. These charts, displayed separately for accuracy and loss, clearly illustrate the changes in performance over time. Figure 3 provides a more detailed assessment of the model's performance, showing the trend of improvement or lack thereof throughout the epochs.

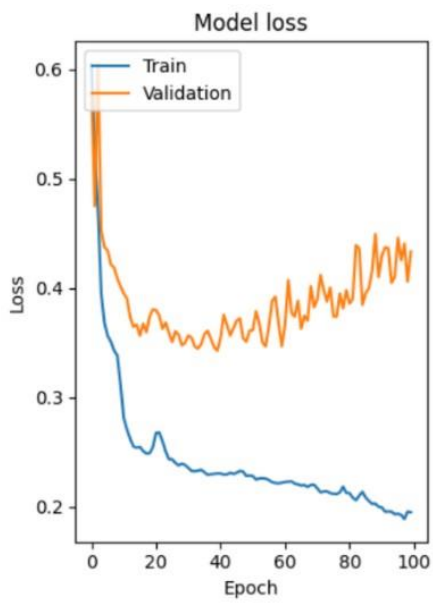

Figure 3. Model Loss Chart over Training and Validation Epochs

In the next step, the model's accuracy on the validation data is measured using the model evaluation function. The prediction accuracy is reported based on this evaluation and is numerically presented in Figure 4. This final assessment, conducted with the validation data, serves as a measure of the model's ability to correctly predict new images.

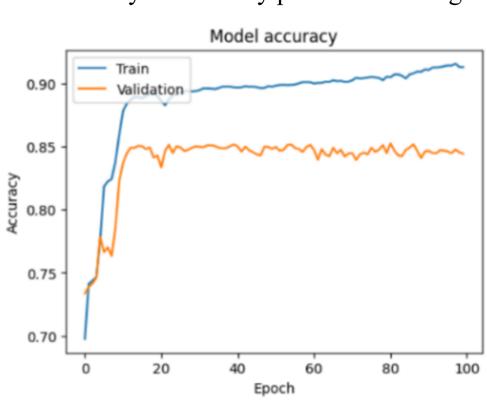

Figure 4. Model Accuracy Chart on the Validation Data

In the final section, images of the input data, ground truth masks, and the model's predictions are displayed for several samples from the validation dataset. These visualizations provide a direct graphical comparison between the input images, the original masks, and the model's predictions (Figure 5). Since these images clearly demonstrate the model's ability to detect and segment lung structures, they contribute to a better analysis and evaluation of the model's performance.

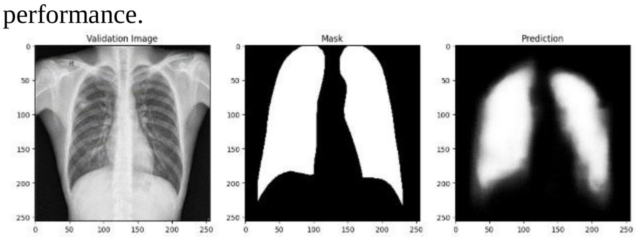

Figure 5. Input Images, Ground Truth Masks, and Model Predictions for Validation Samples

Finally, the model's results were evaluated using the validation data. The final evaluation demonstrated that the model achieved strong performance in simulating and segmenting lung structures from X-ray images. Based on the accuracy and loss charts during the training and evaluation process, the model showed steady progress toward achieving satisfactory accuracy. In the final assessment, the model's prediction accuracy on the validation data was reported to exceed 84%, indicating its high effectiveness in detecting and segmenting the images.

5. Conclusion and Recommendations

Medical image segmentation, particularly of lung images, has become a fundamental tool in diagnosing pulmonary diseases. X-ray images are highly valuable due to their availability, relatively low cost, and ability to provide critical information, especially for detecting conditions such as lung cancer, pneumonia, and tuberculosis. The use of deep neural networks, particularly the U-Net architecture, has significantly enhanced the accuracy and efficiency of the segmentation process. In this study, a U-Net–based model was developed for lung X-ray image segmentation, and the results demonstrated the model's remarkable performance in accurately simulating lung structures. To prevent overfitting, Dropout was incorporated into the model architecture, which represents one of the innovations of this approach. The model's high accuracy, especially when effectively trained with masked data, highlights the potential of this method for clinical applications. These findings also underscore the importance of selecting an appropriate architecture, utilizing precise data, and applying regularization techniques to achieve optimal results in medical image analysis.

Given the limitations of available training data and computational resources, transfer learning can further enhance model accuracy for specific tasks. By leveraging pre-trained models, this approach allows the transfer of general features from one domain to another, thereby improving performance in complex tasks such as medical image segmentation. In addition to reducing training time, particularly when training data are limited, transfer learning can lead to more robust and accurate results.

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