Optimizing Early Lung Cancer Detection on Chest Radiographs: AI-Based Lung Segmentation for Enhanced Diagnostic Accuracy

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Abstract :**Early detection of lung cancer significantly improves survival rates, yet interpreting chest radiographs (CXR) remains challenging due to overlapping anatomical structures. This study proposes an AI-based segmentation framework using U-Net to isolate lung regions, enhancing the performance of subsequent nodule detection models. We trained and evaluated the model on publicly available Montgomery and Shenzhen datasets, achieving a Dice coefficient of 0.961 and IoU of 0.924. Further classification on the JSRT dataset demonstrated improved sensitivity and specificity in nodule detection when lung segmentation was applied. This work affirms that AI-based lung segmentation significantly improves early lung cancer diagnostic accuracy and provides a foundation for scalable computer-aided diagnosis systems.**

Index Terms: **Chest Radiograph,Deep Learning, Early Detection, Lung Cancer, Segmentation, U-Net.**

I. INTRODUCTION

Lung cancer remains one of the leading causes of cancer-related deaths globally. Early detection through chest radiographs (CXR) plays a crucial role in improving patient outcomes. However, the interpretation of CXR is often limited by overlapping anatomical structures, subtle lesions, and observer variability, making it difficult to identify early-stage cancer accurately.

Artificial Intelligence (AI), particularly deep learning techniques, has demonstrated significant potential in supporting radiological diagnosis. One effective method is image segmentation, where specific regions of interest such as lungs are separated from the background to help focus analysis. Segmenting the lung fields reduces noise from surrounding tissues and bones, making it easier to detect abnormal growths like nodules. This study introduces a deep learning-based segmentation approach using the U-Net model and explores its impact on improving nodule detection accuracy.

II. LITERATURE REVIEW

Recent developments in medical image analysis have shown the effectiveness of convolutional neural networks (CNNs) for segmentation and classification tasks. The U-Net architecture, specifically designed for biomedical image segmentation, uses a symmetric encoder-decoder structure and skip connections that allow precise localization.

The Montgomery and Shenzhen chest X-ray datasets have become standard benchmarks for evaluating lung segmentation methods, with reported Dice scores typically around 0.95. Other works have explored the integration of segmentation with classification, showing that isolating lung regions prior to diagnosis improves detection accuracy for nodules.

The JSRT dataset contains chest radiographs with and without lung nodules and has been used in many studies for developing and validating early lung cancer detection algorithms. Researchers report better performance when classification models are trained on segmented lung areas rather than full CXR images, which motivates the approach followed in this paper.

III. MATERIALS AND METHODS

A. Datasets:

- Montgomery County X-ray Set: Consists of 138 posterior-anterior X-ray images with manually annotated lung masks.
- Shenzhen Hospital X-ray Set: Contains 662 CXR images of patients with and without tuberculosis, also annotated for lung segmentation.
- JSRT Dataset: Comprises 247 X-rays, including 154 images with lung nodules and 93 control images without nodules. This dataset was used to evaluate the impact of segmentation on nodule classification.

B. Preprocessing:

- All images were resized to 256x256 pixels for uniform input.
- Histogram equalization improved image contrast.
- Normalization scaled pixel values to [0,1].
- The dataset was divided into 70% training, 10% validation, and 20% testing sets to train and evaluate the models fairly.

C. Segmentation Model:

- A U-Net model with 4 encoder and decoder blocks was implemented.
- We used a composite loss function: Dice loss (to handle class imbalance) and binary cross-entropy.
- Training was conducted using the Adam optimizer with a learning rate of 1e-4 over 50 epochs.
- Data augmentation techniques such as random flipping, rotation, and contrast adjustment were applied to improve generalization.

D. Classification Model:

- A simple CNN architecture was used to classify images as nodule-positive or negative.
- Two training conditions were tested: one with raw full CXR images, and another using only the segmented lung regions.
- Performance was evaluated using standard classification metrics: Accuracy, Sensitivity (true positive rate), Specificity (true negative rate), and Area Under the Receiver Operating Characteristic Curve (AUC).

E. AI Workflow for Lung Cancer Detection

To provide a clear understanding of the end-to-end process, we summarize the proposed AI pipeline for early lung cancer detection. The system begins with chest X-ray input, followed by preprocessing (resizing, contrast enhancement, normalization). Then, U-Net segmentation model isolates lung regions, eliminating background noise. The segmented output is used for focused classification using a CNN that identifies the presence of lung nodules.

This modular approach ensures that only relevant anatomical features are processed during diagnosis, improving sensitivity and specificity.

F. U-Net Architecture Overview

The U-Net model used in this study features a symmetric encoder-decoder architecture designed for biomedical image segmentation. The encoder captures contextual features through successive convolution and max-pooling layers, while the decoder reconstructs the spatial details via transposed convolutions. Skip connections between corresponding encoder and decoder layers help retain fine-grained information essential for accurate segmentation.

This architecture is particularly suitable for medical images with limited training data due to its efficient use of feature reuse.

IV.A. Visualization of Lung Segmentation Results

To qualitatively evaluate the segmentation model, we visualized its output alongside the ground truth and the original CXR image. The U-Net successfully isolated lung fields while minimizing inclusion of irrelevant areas like bones and soft tissue.

Visual inspection supports the high Dice and IoU scores, confirming the model's ability to delineate lung boundaries accurately.

C. Evaluation Metrics Explained

To evaluate the segmentation performance, we use two key metrics: Dice Coefficient and Intersection over Union (IoU).

- Dice Coefficient measures the overlap between the predicted and true segmentation masks. It is calculated as: $\text{Dice} = \frac{2|A \cap B|}{|A| + |B|}$
- IoU quantifies the area of overlap divided by the area of union:

$$\text{IoU} = \frac{|A \cap B|}{|A \cup B|}$$

Both metrics range from 0 to 1, where values closer to 1 indicate better overlap. The high Dice and IoU values in our results indicate robust lung segmentation.

V.Potential for Real-Time Clinical Integration

Given the promising results, the proposed system has potential for real-time deployment in clinical settings.

The segmentation-classification pipeline can be integrated with hospital Picture Archiving and Communication Systems (PACS) or mobile applications for rapid second-opinion generation.

Further extensions could adapt this framework for large-scale datasets like MIMIC-CXR or NIH ChestX-ray14, enabling it to function as a clinical decision support system in telemedicine or underserved areas.

VI. Results

A. Lung Segmentation Performance:

Dataset	Dice Coefficient	IoU
Montgomery	0.963	0.927
Shenzhen	0.960	0.921

The U-Net model demonstrated high accuracy across both datasets. Average Dice Score was 0.961 and average Intersection over Union (IoU) was 0.924, indicating excellent overlap between predicted and ground truth lung masks.

B. Nodule Classification (JSRT):

Model Variant	Accuracy	Sensitivity	Specificity	AUC
Without Segmentation	84.1%	80.5%	87.2%	0.891
With Segmentation	89.6%	87.7%	91.1%	0.938

When lung segmentation was applied before classification, the model showed noticeable improvements in accuracy and AUC. This confirms that removing irrelevant background features allows the classifier to focus on relevant pathological regions.

VII. DISCUSSION

The experiments confirm that AI-based segmentation helps improve the performance of early lung cancer detection. Specifically, segmentation acts as an intelligent filter to extract meaningful regions from CXR images. This leads to better training for classifiers and enhances the overall diagnostic quality.

The segmentation model generalized well across two datasets, and its integration with classification further demonstrated its clinical value. However, we acknowledge limitations such as the relatively small number of annotated images and the need to test on more diverse datasets.

Future research could explore applying this segmentation-classification pipeline to large-scale data such as MIMIC-CXR and adapting it to real-time applications in hospitals.

VIII. CONCLUSION

This paper presents a deep learning framework that significantly enhances lung cancer detection on chest radiographs by combining lung segmentation with nodule classification. The U-Net-based segmentation showed high accuracy, and its integration into a diagnostic pipeline led to superior classification results. This approach demonstrates the potential of AI to support radiologists in early cancer diagnosis and to lay the groundwork for real-world clinical tools.

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IV.B. Comparative Performance with and without Segmentation

Table X presents the performance metrics for the nodule classification model trained with and without prior segmentation. The segmented input version achieved a higher AUC (0.938 vs. 0.891), accuracy, and sensitivity. These results illustrate the effectiveness of segmentation in guiding the classifier's focus toward relevant regions, reducing false positives and false negatives.

This confirms the hypothesis that segmentation enhances the interpretability and performance of the diagnostic model.

IV.C. Evaluation Metrics Explained

To evaluate the segmentation performance, we use two key metrics: Dice Coefficient and Intersection over Union (IoU).

- Dice Coefficient measures the overlap between the predicted and true segmentation masks. It is calculated as:

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- IoU quantifies the area of overlap divided by the area of union:

  IoU=∣A∩B∣∣A∪B∣\text{IoU} = \frac{|A \cap B|}{|A \cup B|}IoU=∣A∪B∣∣A∩B∣

Both metrics range from 0 to 1, where values closer to 1 indicate better overlap. The high Dice and IoU values in our results indicate robust lung segmentation.

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Further extensions could adapt this framework for large-scale datasets like MIMIC-CXR or NIH ChestX-ray14, enabling it to function as a clinical decision support system in telemedicine or underserved areas.