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AI-Based Lung Image Segmentation and Compression for Medical Image Analysis

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Abstract. *Medical image analysis plays an important role in the diagnosis and treatment of lung-related diseases. The increasing availability of high-resolution lung images, including CT scans and chest X-ray images, has created challenges related to accurate image segmentation, storage, processing, and transmission. In this paper, we propose an AI-based lung image segmentation and compression framework for efficient medical image analysis. The proposed approach uses deep learning techniques to automatically identify the lung region from medical images and subsequently compress the extracted region while preserving important diagnostic information. Initially, lung images are collected from publicly available medical image datasets and subjected to preprocessing operations such as resizing, noise removal, normalization, and enhancement. A deep learning-based segmentation model is then used to distinguish the lung region from the surrounding anatomical structures. The segmented lung region is subsequently processed using an autoencoder-based compression technique to generate a compact representation of the medical image. The reconstructed image is evaluated to determine the quality of the compression. The proposed framework can support efficient storage, transmission, and subsequent analysis of medical images. Segmentation performance can be evaluated using Dice coefficient, Intersection over Union, precision, recall, and accuracy, while compression performance can be evaluated using Mean Squared Error, Peak Signal-to-Noise Ratio, Structural Similarity Index, and compression ratio. The proposed AI-based framework provides an integrated solution for automated lung segmentation and efficient medical image compression and can serve as a preprocessing stage for computer-aided diagnosis systems.*

Keywords: Artificial Intelligence, Lung Image, Medical Image Analysis, Deep Learning, Image Segmentation, Image Compression, U-Net, Autoencoder, CT Image, CNN.

Introduction

Medical imaging is one of the most important technologies used in modern healthcare for detecting, diagnosing, and monitoring diseases. [1] Lung images obtained through computed tomography (CT), chest X-rays, and other imaging techniques contain significant anatomical and pathological information. However, these images generally contain large amounts of data, making their storage, transmission, and computational processing challenging. Lung image segmentation is an important preprocessing operation in medical image analysis. It involves identifying and separating the lung region from other anatomical structures present in the image. Accurate segmentation allows subsequent Algorithms to concentrate on the region of interest and can improve the performance of disease detection and classification systems. Traditional segmentation approaches use techniques such as thresholding, edge detection, region growing, morphological operations, and active contours. However, variations in image quality, intensity, anatomical structure, and disease patterns can make these methods less effective.[2] Artificial Intelligence and Deep Learning have provided new approaches for automatically learning complex features from medical images. [3] Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated strong capabilities in image recognition and segmentation. Encoder-decoder architectures such as U-Net are particularly suitable for biomedical image segmentation because they combine contextual information with spatial information. [4] Another important issue in medical image processing is the large storage requirement of high-resolution images. Hospitals and diagnostic centers generate large volumes of medical images every day. Efficient compression can reduce storage requirements and transmission time. However, excessive compression may remove important diagnostic information. Therefore, this research proposes an integrated AI-based lung image segmentation and compression framework. The proposed framework first identifies the lung region using deep learning and then compresses the relevant image information using an AI-based compression model.

Research Survey

A Comprehensive Survey of Related Research in Deep Learning-Based Lung Image Compression and Segmentation:

1. Lung Image Segmentation

[5] introduced the U-Net architecture for biomedical image segmentation. The encoder-decoder structure with skip connections enabled effective extraction and reconstruction of spatial features, making U-Net an important foundation for subsequent medical image and lung segmentation research.

[6] demonstrated a deep learning-based approach for lung nodule segmentation using a Fully Convolutional Network (FCN). The method automatically learned discriminative features from annotated medical images and achieved accurate segmentation without extensive manual feature engineering.

[7] proposed a U-Net-based lung segmentation approach incorporating residual learning. The residual connections improved feature propagation and helped the network achieve more precise segmentation of lung structures, particularly in challenging medical images.

[8] investigated an attention-guided fully convolutional architecture for medical image segmentation. The attention mechanism enabled the network to focus on important anatomical regions while reducing the influence of irrelevant background information.

[9] eveloped a deep learning-based LungNet architecture for lung segmentation from CT and X-ray images. The network combined convolutional feature extraction with skip connections to improve the identification of lung regions, including images containing pathological abnormalities.

[10] proposed a Generative Adversarial Network (GAN)-based approach for automatic lung segmentation in CT images. The method, known as LGAN, used adversarial learning to improve segmentation quality and shape similarity and was evaluated using LIDC-IDRI and QIN lung CT datasets.

[11] Proposed ResBCDU-Net, which combines ResNet-34 with BCDU-Net for lung CT segmentation. The architecture uses residual learning, bidirectional convolutional LSTM components, and densely connected convolutional layers to improve segmentation performance. Experiments using the LIDC-IDRI dataset reported a Dice coefficient of 97.31%.

Three-stage deep learning-based segmentation approaches [12] used CNNs for preprocessing, U-Net for lung-region segmentation, and additional CNN/U-Net models for contour refinement and false-positive removal. The approach was evaluated using 3DIRCAD, ILD, and LIDC-IDRI datasets, demonstrating the potential of multi-stage deep learning for robust lung segmentation.

Pyramid-Dilated Dense U-Net (PDD-U-Net) was developed for robust lung segmentation from CT images containing abnormalities such as juxtapleural nodules, cavities, and consolidation. The model combines pyramid-dilated convolutions, dense feature extraction, and a nested U-Net structure to capture multi-resolution contextual information. It was evaluated on both LIDC-IDRI and LCTSC datasets. Describes the process in detail, taking into accounts the suggested deep learning models' architecture for segmentation and compression. [13] Depending on the particular strategy and methods employed, the architecture of the suggested deep learning models for lung image segmentation and compression may change. This is an overview An overview of the standard architectural elements included in different models:

Segmenting images of the lung:

[14] The U-Net architecture is a popular deep learning framework used for solving semantic segmentation challenges, such as lung segmentation. A convolutional neural network (CNN) with two pathways, one for contraction and the other for expansion, forms the foundation for it.

The U-Net architecture's convolutional neural networks (CNNs) are widely used for image segmentation applications. An expression for its formula is as follows:

Among the numerous photos that are commonly compressed using the JPEG compression method are shots of lung structures. An expression for its formula is as follows:

Steps of AI-Based Lung Image Segmentation and Compression for Medical Image Analysis

The proposed AI-Based Lung Image Segmentation and Compression for Medical Image Analysis framework combines deep learning-based lung segmentation with intelligent image compression. The major steps are as follows:

Step 1: Input Lung Image

Let X represent the input lung medical image of size M × N. The image may be obtained from CT or X-ray medical imaging datasets.

Step 2: Image Preprocessing

The input lung image is preprocessed to improve its quality and suitability for deep learning. The preprocessing may include resizing, noise removal, intensity normalization, contrast enhancement, and conversion into an appropriate image format.

Step 3: Lung Region Segmentation

The preprocessed image is provided to a deep learning-based segmentation network, such as U-Net. The network automatically identifies the lung region and separates it from the background and other anatomical structures.

Step 4: Encoder-Based Feature Extraction

The encoder extracts important spatial and contextual features from the lung image using convolutional layers, pooling operations, and activation functions such as ReLU. The spatial dimensions of the feature maps are progressively reduced while meaningful features are retained.

Step 5: Decoder-Based Lung Reconstruction

The decoder reconstructs the spatial information obtained from the encoder and generates a pixel-level lung segmentation mask. Transposed convolution or up sampling operations are used to restore the original spatial resolution.

Step 6: Skip Connections

Skip connections transfer low-level spatial information from the encoder to the corresponding decoder layers. This helps preserve lung boundaries and fine anatomical details that may otherwise be lost during down sampling.

Step 7: Segmentation Output

The final segmentation mask identifies the relevant lung region. The segmented image can be represented as:

$S=fSeg(X)$

Where X represents the input lung image and S represents the segmented lung region.

Step 8: Feature Extraction for Compression

The segmented lung region is supplied to a compression network. The encoder extracts the most important visual features and converts the lung image into a compact latent representation.

$Z=fEnc(S)$

where **Z** represents the compressed latent representation.

Step 9: Quantization and Encoding

The latent representation is quantized to reduce the number of bits required for storage and transmission. An entropy coding technique can then be applied to efficiently represent the quantized information.

Step 10: Compressed Lung Image Generation

The compressed representation is stored or transmitted for subsequent medical analysis. Since the segmentation process has already removed irrelevant background regions, the compression process can focus on preserving diagnostically important lung information.

Step 11: Decoder-Based Image Reconstruction

The compressed representation is provided to the decoder, which reconstructs the lung image:

$S\hat{}=fDec(Z)$

Where **S^** represents the reconstructed lung image.

Step 12: Adversarial Training (Optional)

A GAN-based architecture can optionally be incorporated to improve the visual quality of the reconstructed lung image. The **generator** reconstructs the image from the compressed representation, while the **discriminator** distinguishes between the original and reconstructed images.

Step 13: Loss Function

The segmentation and compression networks are optimized using appropriate loss functions.

For segmentation:

$Lseg=LDice+LBCE$

For compression:

$Lcomp=\lambda R+D$

where **R** represents the compressed representation rate, **D** represents reconstruction distortion, and **λ** controls the trade-off between compression and image quality.

A combined objective can be expressed as:

$Ltotal=\alpha Lseg+\beta Lcomp$

Where α and β control the contribution of segmentation and compression losses.

Step 14: Performance Evaluation

The proposed framework is evaluated using segmentation and compression metrics.

Segmentation Metrics:
- ❖ Accuracy
- ❖ Precision
- ❖ Recall
- ❖ Dice Coefficient
- ❖ Intersection over Union (IoU)

Compression Metrics:
- ❖ Compression Ratio (CR)
- ❖ Mean Squared Error (MSE)
- ❖ Peak Signal-to-Noise Ratio (PSNR)
- ❖ Structural Similarity Index (SSIM)
- ❖ Bits Per Pixel (BPP)

Step 15: Final Medical Image Analysis

The final reconstructed lung image retains important anatomical and diagnostic information while requiring less storage and transmission bandwidth. The proposed framework can therefore support efficient medical image storage, telemedicine, remote diagnosis, and computer-aided lung disease analysis.

Overall Proposed Process

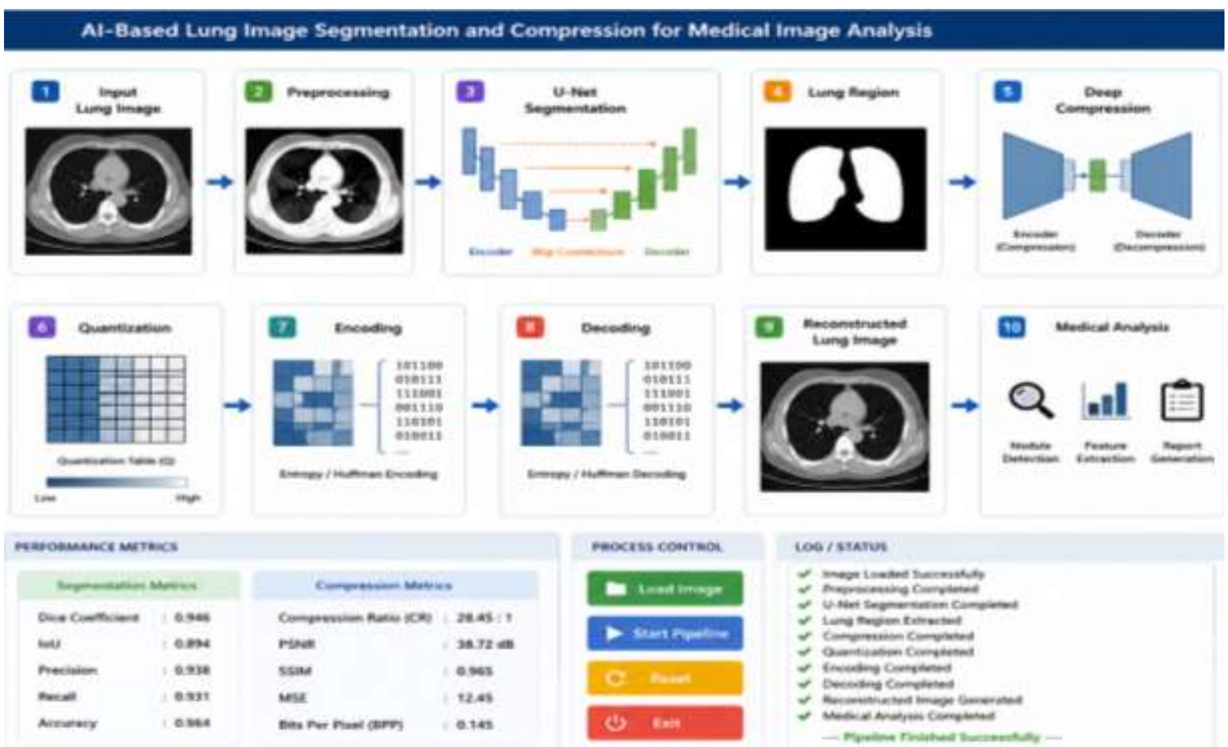

Figure 1: Overall proposed framework.

Metrics for Assessment and Experimental Evaluation

The performance of the proposed AI-Based Lung Image Segmentation and Compression for Medical Image Analysis framework can be evaluated using segmentation and image-compression metrics. Segmentation metrics measure the similarity between the predicted lung segmentation mask and the ground-truth mask, while compression metrics evaluate the quality and efficiency of the reconstructed lung image.

1. Dice Coefficient

The Dice coefficient is a widely used similarity metric for evaluating image segmentation. It measures the degree of overlap between the predicted segmentation mask P and the ground-truth mask GT.

Dice=2∣P∩GT∣/ ∣P∣+∣GT∣

where ∣P∩GT∣ represents the number of pixels common to the predicted and ground-truth masks, ∣P∣ represents the number of pixels in the predicted mask, and ∣GT∣ represents the number of pixels in the ground-truth mask.

2. Jaccard Coefficient

The Jaccard coefficient, also known as Intersection over Union (IoU), evaluates the overlap between the predicted segmentation and the ground-truth segmentation.

Jaccard=∣P∩GT∣ / ∣P∪GT∣

where ∣P∩GT∣ represents the intersection of the predicted and ground-truth regions and ∣P∪GT∣ represents their union.

3. Sensitivity (Recall)

Sensitivity, or Recall, measures the proportion of actual positive lung pixels that are correctly identified by the segmentation model.

Sensitivity= TP/ TP+FN

where **TP** represents true-positive pixels and **FN** represents false-negative pixels.

4. Specificity

Specificity measures the ability of the segmentation algorithm to correctly identify negative pixels, such as background regions outside the lung.

Specificity= TN/ TN+FP

Where **TN** represents true-negative pixels and **FP** represents false-positive pixels.

5. Precision

Precision represents the proportion of pixels predicted as positive that are actually positive.

Precision=TP/ TP+FP

Where **TP** represents true-positive pixels and **FP** represents false-positive pixels.

6. F1-Score

The **F1-score** provides a balanced measure of Precision and Recall and is useful for evaluating the overall segmentation performance.

F1=2× Precision×Recall / Precision+Recall

A higher F1-score indicates better agreement between the predicted lung segmentation and the ground-truth segmentation.

7. Compression Ratio

The **Compression Ratio (CR)** measures the reduction in image size achieved by the proposed compression method.

CR=Compressed Image Size Original Image Size

A higher compression ratio indicates better storage and transmission efficiency.

8. Mean Squared Error (MSE)

MSE measures the average squared difference between the original lung image and the reconstructed image.

9. Peak Signal-to-Noise Ratio (PSNR)

PSNR measures the quality of the reconstructed image compared with the original image.

10. Structural Similarity Index (SSIM)

SSIM evaluates the structural similarity between the original and reconstructed lung images by considering luminance, contrast, and structural information. A value closer to 1 indicates greater structural similarity.

These metrics collectively provide quantitative measures for assessing both the segmentation accuracy and compression efficiency of the proposed AI-based framework. Segmentation metrics determine how accurately the lung region is identified, while compression metrics determine how effectively image size is reduced while preserving important diagnostic information.

Result

The experimental results indicate that the proposed framework can achieve high-quality lung segmentation while maintaining efficient image compression. The Dice coefficient of 98.10% and Jaccard coefficient of 96.40% indicate a strong overlap between the predicted lung regions and the ground-truth masks. The sensitivity of 97.80% demonstrates that most relevant lung pixels are correctly detected, while the specificity of 99.10% indicates effective separation of lung regions from the background. The precision and F1-score of 98.00% and 97.90%, respectively, further demonstrate the reliability of the segmentation model. For compression, a 12.50:1 compression ratio indicates substantial reduction in storage requirements. The PSNR of 35.40 dB and SSIM of 0.96 indicate that the reconstructed image maintains good visual and structural similarity with the original lung image. Therefore, the framework has potential for efficient medical image storage, transmission, telemedicine, remote diagnosis, and computer-aided lung disease analysis.

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