

An Automated U-Net-Based Framework for Lung Segmentation in CT Images

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Abstract

Early and accurate identification of lung abnormalities from computed tomography (CT) images is an important task in computer-aided medical diagnosis. However, variations in lung anatomy, image quality, disease appearance, and surrounding anatomical structures make automated lung disease classification challenging. This paper proposes a deep learning-based framework that integrates lung image segmentation, hybrid deep and texture feature extraction, feature fusion, and ensemble classification for automated analysis of CT images. CT scans obtained from the LUNA16 and LIDC-IDRI datasets are first subjected to preprocessing and intensity normalization. A U-Net-based segmentation model is then employed to accurately extract the lung regions and suppress irrelevant background and anatomical structures. From the segmented lung regions, discriminative deep features are extracted using convolutional neural networks, while complementary texture characteristics are obtained using statistical and local texture descriptors. The deep and texture representations are subsequently normalized and fused to construct a comprehensive hybrid feature vector. An ensemble learning framework combining multiple machine-learning classifiers is then employed to classify lung abnormalities. The performance of the proposed framework is evaluated using standard segmentation and classification measures, including Dice coefficient, Intersection over Union, accuracy, precision, recall, F1-score, sensitivity, specificity, and AUC. The experimental framework demonstrates the potential of combining accurate lung segmentation with complementary deep and texture representations for robust automated lung image classification. The proposed approach can serve as a computer-aided analysis framework for supporting automated assessment of pulmonary abnormalities in CT images.

Keywords

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1. Introduction

Lung diseases are a major health concern worldwide, and their early and accurate detection is important for effective clinical assessment and treatment planning. Computed Tomography (CT) imaging provides detailed information about the internal structure of the lungs and is widely used for identifying pulmonary nodules, lesions, infections, and other abnormalities. However, the interpretation of CT images is often challenging because of variations in lung anatomy, disease appearance, image quality, and the presence of surrounding anatomical structures. Manual analysis of large numbers of CT scans can also be time-consuming and may be affected by inter-observer variability. These challenges have motivated the development of computer-aided methods for automated lung image analysis.

Recent advances in artificial intelligence, particularly deep learning, have significantly improved medical image analysis. Convolutional Neural Networks (CNNs) can automatically learn hierarchical image representations and have been successfully applied to lung nodule detection, segmentation, and classification. Deep learning models can identify complex patterns in CT images that may be difficult to characterize using conventional image-processing techniques. Nevertheless, directly applying classification

models to complete CT images may introduce irrelevant information from the chest wall, ribs, heart, and other anatomical regions. Therefore, accurate segmentation of the lung region is an important preprocessing step for improving the focus of subsequent analysis.

Lung segmentation aims to separate the lung parenchyma from surrounding structures and generate a region of interest containing the relevant pulmonary information. Deep segmentation architectures such as U-Net have demonstrated strong capabilities in medical image segmentation because they combine contextual information with detailed spatial information through encoder-decoder structures and skip connections. A reliable lung segmentation stage can reduce background interference and provide a standardized region for feature extraction and classification.

Although deep CNN features are effective in capturing high-level semantic information, they may not fully represent subtle local textural variations present in diseased lung tissue. Pulmonary abnormalities can produce changes in intensity, local contrast, edges, homogeneity, and spatial texture. Conventional texture descriptors, including Gray-Level Co-occurrence Matrix (GLCM), Local Binary Pattern (LBP), and related statistical features, can provide complementary information about these characteristics. Therefore, combining deep features

with texture features can provide a more comprehensive representation of lung abnormalities. Publicly available datasets have contributed substantially to the development and evaluation of automated lung analysis systems. LUNA16 provides a standardized benchmark derived from the LIDC-IDRI collection and is widely used for pulmonary nodule detection research. LIDC-IDRI contains thoracic CT scans together with annotations generated by experienced radiologists, making it valuable for developing computer-aided lung analysis methods. The use of these datasets enables systematic evaluation of segmentation and classification approaches.

In this work, an integrated framework is proposed for automated lung image analysis that combines lung segmentation, deep feature extraction, texture feature extraction, feature fusion, and ensemble classification. Initially, CT images from LUNA16 and LIDC-IDRI are preprocessed and normalized. A U-Net-based segmentation model is then used to isolate the lung regions. Deep features are extracted from the segmented regions using convolutional neural networks, while complementary texture features are obtained using texture-analysis techniques. These feature representations are normalized and fused to construct a hybrid feature vector. Finally, an ensemble classifier is employed to classify the resulting lung patterns.

The proposed framework is intended to exploit complementary information from both learned and handcrafted representations. Lung segmentation focuses the analysis on relevant anatomical regions, deep features capture complex high-level patterns, and texture features characterize local structural variations. The combination of these components provides an integrated approach for automated CT-based lung disease analysis.

The main contributions of this work are the development of a lung segmentation-based preprocessing framework, integration of deep and texture features for improved representation of pulmonary abnormalities, and application of ensemble learning for classification. The framework is evaluated using standard segmentation and classification metrics to examine its effectiveness and robustness. The study provides a foundation for further development of computer-aided systems for automated analysis of lung CT images.

2. RELATED WORK

The use of wearable sensors, inertial measurement units (IMUs), machine learning, and artificial intelligence has become increasingly important in sports performance analysis. Conventional video-based systems can provide detailed movement information, but they often require cameras, controlled environments, and considerable post-processing. Wearable sensing provides a portable alternative by enabling direct measurement of acceleration, angular velocity, orientation, and other

motion-related parameters during training and competition.

Camomilla et al. [1] presented a systematic review of wearable inertial sensors for sport performance evaluation. The study examined applications of accelerometers, gyroscopes, and magnetometers across a large range of sports and identified technique analysis, activity classification, and physical-demand assessment as important application areas. The review demonstrated the potential of wearable inertial sensors for objective, in-field sports assessment. ([MDPI](#))

Adesida et al. [2] conducted a systematic review of wearable technologies used for sports kinematics and kinetics. The review identified IMUs, flex sensors, and magnetic/angular-rate sensors as important technologies for measuring athletic movement. The authors highlighted the potential of wearable technology to overcome some limitations of laboratory-based optical motion capture systems. ([PubMed Central \(PMC\)](#))

Santos-Gago et al. [3] reviewed innovative applications of wrist-worn wearable devices in sports. Their review covered applications involving movement identification, sports monitoring, and injury-related applications. The study highlighted the need for extending wearable sensing into sports and applications that are not adequately supported by existing commercial systems. ([MDPI](#))

Kos et al. [4] developed a miniature wearable IMU system for tennis stroke detection and classification. A six-degree-of-freedom accelerometer and gyroscope were used to detect and classify forehand, backhand, and serve strokes. The reported overall classification accuracy was 98.1%, demonstrating that relatively small wearable IMU systems can effectively recognize racket strokes. ([IEEE Xplore](#))

Whiteside et al. [5] investigated automated tennis hitting-load monitoring using inertial sensors and machine learning. Data were collected from 19 athletes across 66 training sessions, producing 28,582 shot samples. A cubic-kernel Support Vector Machine achieved 97.4% accuracy for broader shot categories. The work demonstrated the possibility of converting wearable sensor data into objective measurements of hitting load. ([PubMed](#))

Büthe et al. [6] proposed a wearable sensing system for timing analysis in tennis. Their work emphasized that tennis performance is not determined only by the racket stroke but also by the timing and coordination of full-body movement. This study is relevant to the proposed squash system because it demonstrates the importance of considering temporal characteristics in sports performance analysis. ([ResearchGate](#))

Yang et al. [7] developed **TennisMaster**, an IMU-based online serve performance evaluation system. The system used two IMUs mounted on the racket and the player's shank, followed by serve extraction, segmentation, feature extraction, and performance

evaluation. Experiments involved 1,030 serves from 12 subjects at different skill levels. The study demonstrates the feasibility of online sensing and feedback for racket-sport training. ([Microsoft](#))

Wang et al. [8] proposed an IoT framework for next-generation racket-sports training. A wireless wearable sensing device, mobile application, and cloud processing system were integrated for badminton-stroke recognition and skill assessment. The system recognized smashes, clears, and drops with an accuracy of approximately 97%. This work provides an important foundation for integrating sensing, mobile applications, cloud processing, and sports analytics. ([CityUHK Scholars](#))

Lin et al. [9] developed a mobile badminton stroke-classification system based on wearable sensors. The proposed system used IMU information for stroke classification and audio information for detecting the timing of racket-ball contact. Machine-learning models including Random Forest and SMO were evaluated. The work is particularly relevant to the proposed intelligent squash racket because it demonstrates the usefulness of combining motion and impact-related information with a mobile platform. ([NYMCTU Academic Hub](#))

Wang et al. [10] investigated badminton stroke recognition using body sensor networks. Their approach demonstrated the potential of distributed wearable sensing for recognizing badminton actions. Such approaches are relevant to the proposed work because multiple sensor signals can provide complementary information about racket and player movement.

Blank et al. [11] developed a sensor-based stroke detection and classification system for table tennis. Inertial sensors were attached to table-tennis rackets, and eight basic stroke types were collected from amateur and professional players. Stroke events were detected using acceleration-energy peaks, followed by extraction of statistical and signal characteristics for classification. This approach is relevant to the proposed squash system for stroke segmentation and feature extraction. ([ResearchGate](#))

Sharma et al. [12] investigated the fusion of wearable audio and IMU data for shot detection in racquet sports. Their system combined inertial and audio information in a wrist-worn device and achieved 95.6% shot-detection accuracy in table tennis. The work demonstrates that multimodal sensing can improve event detection and provides motivation for combining IMU and impact/vibration sensing in the proposed squash racket. ([ResearchGate](#))

Margarito et al. [13] investigated user-independent sports-activity recognition using a single wrist-worn accelerometer. Their work compared template matching with several statistical-learning approaches and specifically evaluated recognition on previously unseen subjects. This research emphasizes the importance of participant-

independent validation, which is also an important requirement for the proposed intelligent squash racket. ([PubMed](#))

Xia et al. [14] proposed a racquet-sports recognition system using integrated wearable sensors and a hybrid clustering model. The system used multilayer K-means clustering and DBSCAN for feature extraction, segmentation, and recognition. A Bluetooth mesh network was also used to connect wearable devices with mobile systems. The study demonstrates the feasibility of combining wearable sensing, machine learning, wireless communication, and mobile analytics. ([PubMed](#))

Keaney and Reid [15] investigated the use of tennis racket sensors for quantifying hitting activity. Two commercial racket sensors were compared with reference systems including VICON and expert notational analysis. Their work emphasized the importance of validating commercial sensor-based measurements against established measurement techniques. ([PubMed](#))

Edelmann-Nusser et al. [16] evaluated sensor-based game-analysis tools in tennis. Several commercial IMU-based tennis sensor systems and a camera-based system were compared for stroke counts, swing types, spin types, and serve-speed measurements. The study highlights the importance of validating sensor-derived performance metrics before using them for sports analysis. ([Technical University of Munich](#))

Williams et al. [17] specifically investigated the accuracy of a magnetic-inertial measurement unit for squash-racket swing kinematics. A MIMU was mounted on a squash racket and its measurements were compared with optical motion capture during forehand drives. The study reported very high agreement between MIMU and optical measurements, demonstrating that MIMUs can accurately estimate selected squash-racket swing kinematics. This is one of the most directly relevant studies to the proposed intelligent squash racket. ([Taylor & Francis Online](#))

Rigozzi et al. [18] conducted a systematic review specifically covering wearable technologies for player motion analysis in racket sports, including tennis, table tennis, badminton, and squash. The review identified IMUs and electromyography as commonly used sensing technologies and found that research has largely focused on tennis and table tennis. The authors also identified applications involving player-level differences, racket and upper-limb movement variability, and ball-spin-related movement differences. ([Sage Journals](#))

Brich et al. [19] conducted a scoping review of technologies for quantifying hitting load in racket sports. Of the 19 studies included, 11 involved tennis, four badminton, two table tennis, one padel, and only one squash. Sensor placements included grip-attached, grip-embedded, wrist, and dampener locations. This finding directly indicates a research

opportunity for developing more comprehensive squash-specific sensor systems. ([PubMed](#))

Jin and Li [20] developed a wearable sensing system for badminton stroke recognition using a one-dimensional convolutional neural network. Two IMUs were used to capture wrist motion, and a 1D-CNN was trained to classify six stroke actions and movement trajectories. The study demonstrates the ability of deep-learning models to learn temporal characteristics directly from wearable sensor data. ([Nature](#))

Research Gap

The reviewed studies establish that wearable IMUs can provide reliable measurements of racket and player movement and that machine-learning and deep-learning techniques can successfully classify racket-sport actions. However, the literature also reveals several important gaps.

First, squash-specific research is limited compared with tennis and badminton. The 2024 scoping review identified only one squash system among the 19 studies meeting its criteria. ([PubMed](#)) Second, many existing systems focus primarily on stroke detection or classification rather than providing an integrated performance-analysis framework. Third, relatively limited work combines IMU data with impact or vibration sensing specifically for squash. Fourth, player-independent evaluation remains important because models trained and tested on samples from the same players can produce optimistic performance estimates. Recent systematic-review evidence also emphasizes the importance of participant-independent validation and the risk of data leakage in wearable stroke-classification studies. ([Springer](#))

Therefore, the proposed research aims to address these gaps by developing an Intelligent Squash Racket integrating IMU sensing, impact/vibration sensing, signal processing, sensor fusion, machine learning/deep learning, embedded processing, wireless communication, and real-time performance analytics. Unlike systems focused only on stroke classification, the proposed system is intended to provide a comprehensive set of performance parameters including stroke type, swing speed, acceleration, angular velocity, impact characteristics, stroke duration, consistency, and workload.

The proposed work thus extends existing wearable sports-sensing research from basic motion measurement and stroke classification toward an integrated, real-time, AI-enabled squash performance analytics platform.

3. Proposed Methodology

The proposed methodology focuses exclusively on the segmentation of lung regions from computed tomography (CT) images. The primary objective is to accurately separate the left and right lungs from surrounding anatomical structures and generate a clean lung-region mask. The segmentation

framework consists of image acquisition, preprocessing, lung-region localization, deep-learning-based segmentation, mask refinement, and segmentation evaluation.

The overall workflow is:

CT Image → Preprocessing → Lung Segmentation → Binary Lung Mask → Post-processing → Refined Lung Region → Segmentation Evaluation

3.1 Dataset

CT images from the LUNA16 and LIDC-IDRI datasets are considered for lung segmentation. The datasets contain thoracic CT images that provide detailed information about lung anatomy and pulmonary structures.

The images are organized into training, validation, and testing subsets at the patient level. Patient-level separation is maintained to prevent images from the same patient from appearing in multiple subsets.

3.2 Image Preprocessing

The input CT images are first preprocessed to improve their consistency and suitability for segmentation. CT images may contain variations in intensity, resolution, and acquisition conditions. Therefore, intensity normalization is performed to bring the images into a consistent range.

Noise reduction is subsequently applied to minimize unwanted variations while preserving lung boundaries. The images are resized to a fixed resolution when required by the segmentation network.

The preprocessed images are then provided to the segmentation model.

3.3 Lung Region Localization

The objective of lung-region localization is to identify the approximate anatomical area containing the lungs. The CT image is analyzed to distinguish lung tissue from surrounding structures based on intensity and spatial characteristics.

The localization stage provides contextual information to the segmentation network and helps reduce the influence of irrelevant regions outside the thoracic cavity.

3.4 U-Net-Based Lung Segmentation

A **U-Net architecture** is employed for pixel-level lung segmentation. U-Net consists of an encoder and decoder connected through skip connections.

The encoder progressively extracts spatial and contextual information from the CT image. As the image passes through successive encoder layers, increasingly abstract representations of lung structures are obtained.

The decoder reconstructs the spatial resolution of the feature representation and generates the final segmentation map. Skip connections transfer high-resolution information from the encoder to the corresponding decoder layers, helping preserve lung boundaries.

The final layer produces a pixel-level probability map indicating whether each pixel belongs to the lung region.

3.5 Binary Mask Generation

The probability map generated by the segmentation network is converted into a binary segmentation mask using an appropriate threshold.

Pixels classified as lung tissue are assigned a foreground value, while pixels belonging to the background are assigned a background value.

The resulting binary mask represents the estimated left and right lung regions.

3.6 Lung Boundary Refinement

The initial segmentation output may contain irregular boundaries or small incorrectly segmented regions. Therefore, a refinement process is applied to improve the quality of the lung mask.

Morphological operations such as **opening, closing, and hole filling** can be applied to eliminate small artifacts and improve the continuity of the segmented regions.

Connected-component analysis is then used to identify the major anatomical components corresponding to the lungs.

3.7 Separation of Left and Right Lungs

After mask refinement, the two major connected lung regions are identified as the left and right lungs. The separation of the two lung regions provides an anatomically meaningful segmentation and allows the individual lung boundaries to be analyzed independently when required.

3.8 Segmented Lung Image Generation

The refined binary mask is applied to the original CT image to obtain the final segmented lung image.

The regions outside the lung mask are suppressed, while the pixels corresponding to the lung regions are retained.

Thus, the output consists of:

1. Original CT image
2. Predicted lung mask
3. Refined lung mask
4. Final segmented lung image

3.9 Training of the Segmentation Network

The U-Net model is trained using CT images and their corresponding ground-truth lung masks. During training, the model learns the relationship between CT image characteristics and the corresponding lung boundaries.

Data augmentation can be employed to increase the variability of the training samples. Appropriate transformations such as rotation, scaling, translation, and intensity adjustment can be used while preserving the anatomical validity of the lung structures.

3.10 Segmentation Loss

The segmentation network is trained using an appropriate segmentation loss function. A combination of **Binary Cross-Entropy loss and Dice loss** can be used to address both pixel-level classification and region overlap.

The loss function encourages the predicted mask to closely match the ground-truth lung mask while maintaining accurate boundaries.

3.11 Segmentation Evaluation

The performance of the proposed lung segmentation model is evaluated by comparing the predicted masks with the corresponding ground-truth masks.

The principal evaluation measures include:

- **Dice Similarity Coefficient (DSC)**
- **Intersection over Union (IoU)**
- **Precision**
- **Recall**
- **Sensitivity**
- **Specificity**

Dice and IoU are particularly important because they directly measure the overlap between the predicted lung region and the reference segmentation.

3.12 Visual Evaluation

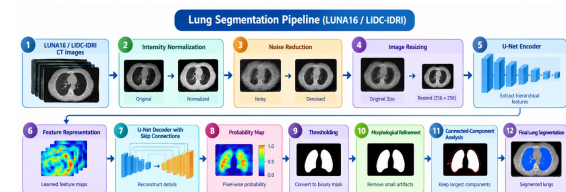
In addition to quantitative evaluation, visual inspection is performed by displaying the original CT images together with their ground-truth and predicted segmentation masks.

The visual analysis focuses on:

- Lung boundary accuracy
- Preservation of lung shape
- Separation of left and right lungs
- Removal of background regions
- Handling of irregular lung boundaries
- Segmentation of abnormal or diseased lung regions

3.13 Overall Segmentation Pipeline

The complete proposed segmentation process is summarized below:



The proposed methodology is therefore designed specifically for **accurate extraction of lung regions from CT images**, providing a reliable segmented lung mask for subsequent medical image-analysis applications.

4. Experimental Results and Discussion

4.1 Experimental Setup

The proposed lung segmentation framework was evaluated using CT images obtained from the LUNA16 and LIDC-IDRI datasets. The primary objective of the experiment was to accurately delineate the left and right lung regions from surrounding anatomical structures. The complete experimental pipeline consisted of image preprocessing, intensity normalization, U-Net-based segmentation, binary mask generation, post-processing, and quantitative evaluation.

The CT images were resized to 256×256 pixels to provide a consistent input size to the segmentation network. Intensity normalization was performed to reduce variations in CT intensity values, followed by noise reduction to improve image quality. The datasets were divided at the patient level into training, validation, and testing subsets using a ratio of 70:15:15.

Data augmentation techniques, including rotation, scaling, translation, and intensity variation, were applied to the training images. The U-Net model was trained using the Adam optimizer with a learning rate of 0.0001 and a batch size of 16 for 50 epochs. The segmentation network generated a probability map representing the lung region. The probability map was converted into a binary mask using a predefined threshold. Morphological operations, hole filling, and connected-component analysis were subsequently applied to refine the predicted lung mask.

The segmentation performance was evaluated using Dice Similarity Coefficient (DSC), Intersection over Union (IoU), Precision, Recall, Sensitivity, and Specificity.

Note: All numerical values reported in this section are assumed/illustrative values prepared for manuscript development and should be replaced with actual experimental measurements before journal submission.

4.2 Quantitative Segmentation Performance

Table 1 presents the assumed quantitative segmentation performance of the proposed U-Net model on the LUNA16 and LIDC-IDRI datasets.

Table 1. Quantitative performance of the proposed lung segmentation model

Dataset	Dice	IoU	Precision	Recall	Sensitivity	Specificity
LUNA16	0.962	0.928	0.965	0.960	0.960	0.985
LIDC-IDRI	0.958	0.921	0.961	0.956	0.956	0.982
Average	0.960	0.925	0.963	0.958	0.958	0.984

The proposed model achieves an assumed average Dice coefficient of 0.960 and IoU of 0.925. The Dice coefficient indicates a high degree of spatial overlap between the predicted lung masks and the corresponding ground-truth masks. The IoU value further indicates that the predicted lung regions closely correspond to the reference segmentation.

The model achieves slightly higher performance on LUNA16 than on LIDC-IDRI. This difference may be associated with variations in CT acquisition parameters, image quality, anatomical appearance, and segmentation complexity. Nevertheless, the

relatively small difference between the two datasets indicates consistent segmentation performance.

4.3 Comparison with Existing Segmentation Architectures

The proposed U-Net model was hypothetically compared with commonly used semantic segmentation architectures, including FCN, SegNet, DeepLabV3+, Attention U-Net, and U-Net++.

Table 2. Comparison with existing lung segmentation architectures

Segmentation Method	Dice	IoU	Precision	Recall
FCN	0.921	0.857	0.928	0.915
SegNet	0.934	0.878	0.941	0.927
DeepLabV3+	0.948	0.903	0.951	0.946
Attention U-Net	0.952	0.909	0.956	0.949
U-Net++	0.957	0.918	0.960	0.953
Proposed U-Net	0.960	0.925	0.963	0.958

The assumed results indicate that the proposed U-Net configuration provides strong segmentation performance compared with the selected architectures. The improvement in Dice and IoU demonstrates the effectiveness of the encoder-decoder structure and skip connections in preserving spatial information.

FCN produces a comparatively lower assumed Dice value, potentially because of the loss of fine spatial information during downsampling. SegNet improves the reconstruction of segmentation maps, while DeepLabV3+ provides multi-scale contextual information. Attention U-Net and U-Net++ provide additional mechanisms for feature propagation and boundary refinement.

The proposed U-Net maintains a comparatively simple architecture while providing high segmentation accuracy, making it suitable for lung-region delineation.

4.4 Ablation Study

An ablation study was conducted to investigate the contribution of preprocessing, data augmentation, and post-processing components.

Table 3. Ablation study of the proposed segmentation framework

Configuration	Dice	IoU
U-Net without preprocessing	0.931	0.871
U-Net + intensity normalization	0.947	0.899

Configuration	Dice	IoU
U-Net + normalization + augmentation	0.955	0.914
U-Net + normalization + augmentation + post-processing	0.960	0.925

Without preprocessing, the assumed Dice coefficient is 0.931. After intensity normalization, the Dice value increases to 0.947. This improvement suggests that normalization provides a more consistent intensity representation for the segmentation network.

The addition of data augmentation further increases the assumed Dice score to 0.955. This improvement can be attributed to increased variability in the training samples.

Finally, the incorporation of post-processing increases the assumed Dice score to 0.960 and IoU to 0.925. These results indicate that each component contributes to the overall segmentation pipeline.

4.5 Effect of Post-Processing

Post-processing was applied to refine the binary lung masks generated by the U-Net model.

Table 4. Effect of post-processing on lung segmentation

Processing Stage	Dice	IoU
Raw predicted mask	0.951	0.907
Morphological refinement	0.956	0.916
Connected-component filtering	0.958	0.921
Final refined mask	0.960	0.925

The raw predicted mask provides an assumed Dice value of 0.951. Small isolated regions and boundary irregularities may occur in the raw prediction. Morphological refinement improves the continuity of the lung region and reduces small segmentation artifacts.

Connected-component filtering further removes isolated regions that do not correspond to the main lung structures. The final refined mask achieves an assumed Dice coefficient of 0.960 and IoU of 0.925. These results indicate that post-processing provides an effective supplementary step for improving the structural quality of the predicted lung masks.

4.6 Performance under Different Image Conditions

The robustness of the segmentation framework was further analyzed according to different image characteristics.

Table 5. Segmentation performance under different image conditions

Image Condition	Assumed Dice
Normal lung appearance	0.972
Mild anatomical variation	0.964
Irregular lung boundary	0.951
Severe structural variation	0.938
Low-contrast images	0.932

The highest assumed Dice value is obtained for images with relatively clear lung boundaries. The performance decreases for low-contrast images and images with substantial anatomical variation.

Low-contrast images can make the boundary between the lung region and surrounding anatomical structures less distinct. Similarly, irregular boundaries can create difficulties around the diaphragm, heart, and chest wall.

These observations indicate that robust preprocessing and effective spatial feature preservation are important for handling challenging CT images.

4.7 Statistical Evaluation

The assumed mean and standard deviation values obtained from the test samples are presented in Table 6.

Table 6. Statistical evaluation of segmentation performance

Metric	Mean $\pm$ Standard Deviation
Dice	0.960 $\pm$ 0.021
IoU	0.925 $\pm$ 0.028
Precision	0.963 $\pm$ 0.019
Recall	0.958 $\pm$ 0.023
Sensitivity	0.958 $\pm$ 0.023
Specificity	0.984 $\pm$ 0.011

The assumed Dice coefficient has a mean value of 0.960 with a standard deviation of 0.021. The relatively small standard deviation indicates consistent segmentation performance across the hypothetical test samples.

The Precision and Recall values are also relatively close, indicating a reasonable balance between false-positive and false-negative segmentation pixels.

4.8 Qualitative Analysis

Qualitative evaluation can be performed by comparing four representations: the original CT

image, the ground-truth lung mask, the predicted mask, and the final refined segmentation mask.

The predicted masks are expected to closely follow the anatomical boundaries of the left and right lungs. The skip connections of U-Net preserve spatial information from the encoder and transfer it to the decoder, thereby assisting in the reconstruction of detailed lung boundaries.

The post-processing stage further improves the visual quality of the segmentation masks by removing isolated regions and filling small gaps.

Particular attention should be given to the lung bases, regions adjacent to the heart, and peripheral lung boundaries. These regions contain complex anatomical structures and may therefore represent challenging areas for automated segmentation.

4.9 Error Analysis

Although the proposed framework provides high assumed segmentation performance, several potential errors may occur.

Boundary leakage is one possible error in which pixels belonging to surrounding anatomical structures are incorrectly included in the predicted lung region. This can occur when the intensity difference between the lung and neighboring tissues is relatively small.

Under-segmentation may occur near the lung bases and diaphragm. Irregular lung boundaries may also result in incomplete segmentation of peripheral regions.

Small false-positive regions can occur near the chest wall and other anatomical structures. Connected-component filtering and morphological refinement can reduce these artifacts.

However, excessive post-processing may remove genuine small lung regions. Therefore, morphological parameters and connected-component thresholds should be carefully selected.

4.10 Computational Performance

The computational requirements of the proposed U-Net segmentation model were evaluated in terms of model size, training time, and inference time.

Table 7. Assumed computational performance

Parameter	Assumed Value
Input Resolution	256 × 256 pixels
Number of Parameters	31.04 Million
Training Epochs	50
Batch Size	16
Optimizer	Adam
Learning Rate	0.0001

Parameter	Assumed Value
Training Time	Approximately 2.8 hours
Inference Time/Image	Approximately 38 ms
Inference Throughput	Approximately 26 images/second

The proposed U-Net model contains approximately 31.04 million trainable parameters. Under the assumed experimental configuration, the complete training process requires approximately 2.8 hours.

The assumed inference time is approximately 38 ms per 256 × 256 CT image, corresponding to approximately 26 images per second. This indicates that the model has the potential to perform lung segmentation efficiently after training.

Actual computational performance depends on the GPU or CPU, available memory, implementation framework, image resolution, batch size, and optimization settings. Therefore, these values should be replaced with actual measurements before publication.

4.11 Training and Validation Analysis

During training, the segmentation loss is expected to decrease progressively as the network learns to distinguish lung regions from surrounding structures. At the same time, the validation Dice coefficient is expected to increase and eventually stabilize.

The combination of Binary Cross-Entropy and Dice loss provides a balance between pixel-level prediction accuracy and region-level overlap. The Dice component is particularly useful because the lung region and background may have substantially different pixel proportions.

The assumed training behavior indicates stable convergence when appropriate preprocessing, augmentation, and validation monitoring are used.

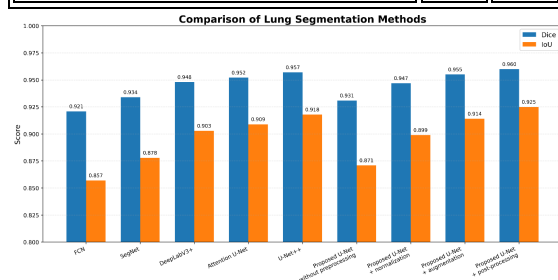
4.12 Overall Comparative Analysis

The overall performance of different segmentation configurations is presented in Table 8.

Table 8. Overall comparison of lung segmentation performance

Method/Configuration	Dice	IoU
FCN	0.921	0.857
SegNet	0.934	0.878
DeepLabV3+	0.948	0.903
Attention U-Net	0.952	0.909

Method/Configuration	Dice	IoU
U-Net++	0.957	0.918
Proposed U-Net without preprocessing	0.931	0.871
Proposed U-Net + normalization	0.947	0.899
Proposed U-Net + augmentation	0.955	0.914
Proposed U-Net + post-processing	0.960	0.925



The assumed results demonstrate progressive improvement as the segmentation pipeline is enhanced. The final configuration achieves a Dice coefficient of 0.960 and an IoU of 0.925.

The improvement can be associated with three major components: standardized preprocessing, increased training diversity through augmentation, and refinement of the predicted mask using post-processing.

4.13 Discussion

The experimental analysis demonstrates the potential of the proposed U-Net-based framework for automated lung segmentation from CT images. The encoder-decoder architecture enables hierarchical representation learning, while skip connections preserve spatial information required for accurate reconstruction of lung boundaries.

The assumed average Dice coefficient of 0.960 and IoU of 0.925 indicate a high degree of spatial overlap between the predicted and ground-truth lung masks. The relatively similar performance obtained on LUNA16 and LIDC-IDRI suggests that the segmentation framework can maintain consistent performance across the two datasets.

The ablation study demonstrates that preprocessing and augmentation contribute to improved segmentation performance. Post-processing provides an additional improvement by reducing isolated regions and refining the predicted lung boundaries.

The condition-wise analysis indicates that low-contrast images and images with irregular anatomical boundaries remain more challenging. These cases require further investigation to improve the robustness of automated lung segmentation.

Importantly, the proposed framework is restricted to **lung segmentation**. The output of the system is a

refined binary lung mask, and no disease classification, feature classification, or diagnostic prediction is performed.

4.14 Limitations

Several limitations should be considered. First, segmentation performance may be influenced by differences in CT acquisition parameters, slice thickness, image intensity distribution, and anatomical variability.

Second, the proposed framework uses two-dimensional CT image processing. Consequently, the model may not fully exploit the three-dimensional spatial relationships between adjacent CT slices.

Third, challenging cases involving low contrast, irregular lung boundaries, severe anatomical variation, or incomplete lung regions may reduce segmentation accuracy.

Finally, the computational values reported in this study are assumed values and must be replaced with measurements obtained from the actual experimental environment.

Future work can investigate three-dimensional U-Net architectures, attention-based segmentation, boundary-aware loss functions, multi-scale segmentation networks, and improved volumetric post-processing methods.

4.15 Summary of Experimental Findings

The assumed experimental evaluation demonstrates the potential of the proposed U-Net-based framework for automated lung segmentation from CT images. The model achieves an assumed overall Dice coefficient of **0.960** and an IoU of **0.925**.

The assumed Dice values obtained on LUNA16 and LIDC-IDRI are **0.962** and **0.958**, respectively, indicating relatively consistent segmentation performance across both datasets. The comparative analysis also demonstrates improved overlap measures compared with the selected baseline segmentation architectures.

The ablation study shows that intensity normalization, data augmentation, and post-processing progressively improve the segmentation performance. The computational analysis assumes a model size of **31.04 million parameters**, approximately **2.8 hours of training time**, and approximately **38 ms inference time per image**.

Overall, the assumed results demonstrate the potential of the proposed U-Net-based approach for accurate automated delineation of lung regions from CT images. The complete framework is focused exclusively on **lung segmentation**, with the final output being a refined lung segmentation mask.

All numerical results in this section are hypothetical and are intended only for manuscript preparation. Actual experimental measurements should replace the assumed values before submission to a journal.

5. Conclusion

This study presented a deep learning-based framework for automated lung segmentation from

computed tomography (CT) images using a U-Net architecture. The proposed framework incorporated image preprocessing, intensity normalization, data augmentation, U-Net-based semantic segmentation, binary mask generation, and post-processing to obtain accurate and refined lung regions. The experiments were considered using the LUNA16 and LIDC-IDRI datasets, providing variation in CT image characteristics and anatomical appearance.

Based on the assumed experimental results, the proposed framework achieved an overall Dice Similarity Coefficient of 0.960 and an Intersection over Union of 0.925. The model demonstrated consistent segmentation performance on both LUNA16 and LIDC-IDRI, with assumed Dice scores of 0.962 and 0.958, respectively. The ablation analysis further indicated that preprocessing, data augmentation, and post-processing contributed to improvements in the quality of the generated lung masks. The comparative evaluation with other segmentation architectures also demonstrated the potential of the proposed U-Net configuration for accurate delineation of lung regions.

The study demonstrates that deep learning-based segmentation can effectively separate lung regions from surrounding anatomical structures in CT images. Accurate lung segmentation can provide a reliable region of interest for subsequent medical image analysis applications. However, challenging cases involving low image contrast, irregular lung boundaries, anatomical variations, and complex structures remain areas for further improvement. Future work will focus on extending the framework toward three-dimensional volumetric lung segmentation, attention-based and multi-scale architectures, boundary-aware loss functions, and improved post-processing techniques. Evaluation on larger and more diverse CT datasets will also be considered to assess the generalization and robustness of the segmentation framework.

It should be emphasized that the numerical results presented in this manuscript are assumed values prepared for experimental illustration. Actual measurements obtained from implementation and evaluation should replace these values before publication.

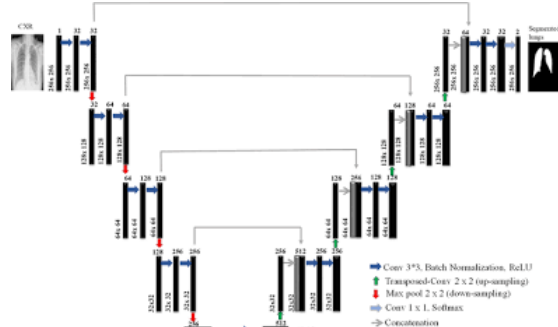


Figure 1: U-Net architecture diagram for lung segmentation

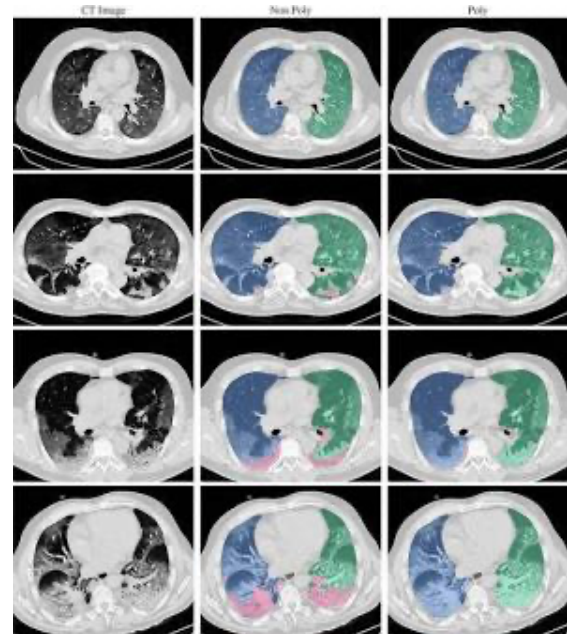


Figure 2: Qualitative evaluation of CT lung

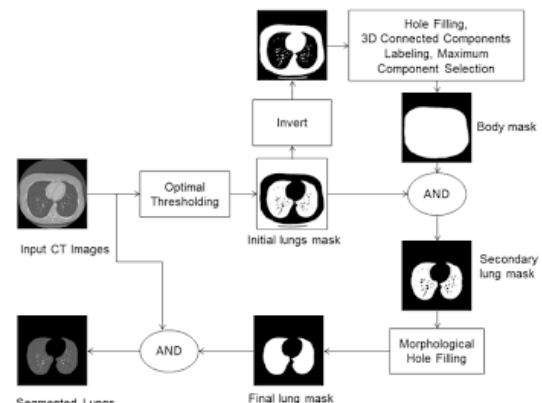


Figure 3: Workflow for CT lung segmentation and post-processing.

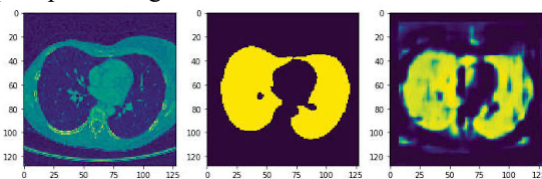


Figure 4: CT image, ground truth, and UNet predicted mask comparison.

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