RESEARCH PAPER

An Intelligent Image Processing Framework for Automated Lung Cancer Detection, Segmentation, and Classification in Computed Tomography Images

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Received: 28th Feb, 2026; Revised: 6th March 2026; Accepted: 7th April, 2026; Available Online: 20th April, 2026

ABSTRACT
Lung cancer remains one of the leading causes of cancer-related mortality worldwide, primarily due to delayed diagnosis and inadequate identification of malignant pulmonary nodules. Computed Tomography (CT) imaging has emerged as a crucial diagnostic modality for early lung cancer detection; however, manual interpretation of CT scans is often time-consuming and susceptible to observer variability. This study proposes an intelligent image processing framework for automated lung cancer detection, segmentation, and classification in CT images. The proposed framework integrates image preprocessing, contrast enhancement, lung region extraction, adaptive tumor segmentation, feature extraction, and machine learning-based classification. Initially, noise reduction and histogram equalization techniques are applied to improve image quality. Subsequently, an adaptive thresholding and region-growing approach is utilized for accurate segmentation of suspicious nodules. Texture, shape, and intensity-based features are extracted from the segmented regions and employed for classification using a Support Vector Machine (SVM) classifier. Experimental evaluation conducted on publicly available lung CT datasets demonstrates improved segmentation accuracy, sensitivity, specificity, and classification performance compared with conventional methods. The results indicate that the proposed framework can effectively assist radiologists in early-stage lung cancer diagnosis, thereby enhancing clinical decision-making and reducing diagnostic errors.

Keywords: Lung Cancer, Computed Tomography, Medical Image Processing, Tumor Segmentation, Feature Extraction, etc..,

How to cite this article: Jalaldeen K, Ravikumaran P, Kumari P, Latha P, Ruba T, Pandimadevi M, Malathi M. An Intelligent Image Processing Framework for Automated Lung Cancer Detection, Segmentation, and Classification in Computed Tomography Images. Int J Drug Deliv Technol. 2026;16(64s):952-956. DOI: 10.25258/ijddt.16.64s.91
Source of support: Nil.
Conflict of interest: None

1. INTRODUCTION
Lung cancer is a significant global health challenge and is responsible for millions of deaths annually [1,2]. According to recent cancer statistics, lung cancer continues to exhibit high incidence and mortality rates, particularly among smokers and individuals exposed to environmental pollutants. Early detection substantially improves survival rates, making timely diagnosis a critical aspect of lung cancer management [4,5].

Computed Tomography (CT) imaging is widely employed for detecting pulmonary nodules and identifying abnormal tissue structures within the lungs [6]. Despite advancements in imaging technologies, manual interpretation of CT images remains challenging due to the large volume of image data and the subtle appearance of early-stage tumors. Consequently, automated computer-aided diagnosis (CAD) systems have gained considerable attention in medical image analysis [7,8].

Image processing techniques play a vital role in CAD systems by facilitating image enhancement, segmentation, feature extraction, and classification [9,10]. Recent studies have demonstrated the effectiveness of machine learning and artificial intelligence techniques in identifying lung abnormalities. However, many existing approaches suffer from limitations such as poor segmentation accuracy, sensitivity to image noise, and computational complexity [13,14].

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To address these challenges, this study presents an intelligent image processing framework that combines advanced preprocessing methods, adaptive segmentation algorithms, and machine learning-based classification techniques. The proposed framework aims to improve the accuracy and reliability of lung cancer detection and support clinical diagnosis [19,20].

2. MATERIALS AND METHODS

2.1 Dataset Acquisition

The study utilizes publicly available thoracic CT image datasets containing both normal and abnormal lung scans [3,12]. The dataset includes pulmonary nodules of varying sizes, shapes, and locations to ensure comprehensive evaluation of the proposed framework [13,19].

2.2 Framework Overview

The proposed framework for automated lung cancer detection in CT images consists of several sequential stages to improve diagnostic accuracy. Initially, CT images are collected from publicly available datasets [4,8]. Preprocessing techniques are then applied to enhance image quality and remove noise. After preprocessing, lung region extraction is performed to isolate the lung area from surrounding tissues. Tumor segmentation is subsequently carried out to identify suspicious nodules within the lung region[11].

Following segmentation, texture, shape, and intensity-based features are extracted from the detected nodules [7,18]. These features are used for classification using a Support Vector Machine (SVM) classifier to categorize the nodules as normal or cancerous [20]. Finally, the performance of the proposed framework is evaluated using metrics such as accuracy, sensitivity, specificity, precision, F1-score, and Dice Similarity Coefficient (DSC).

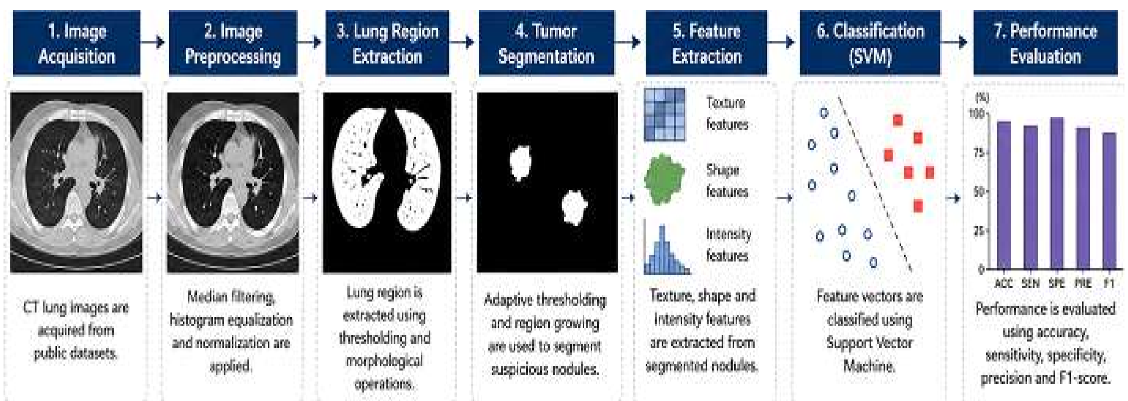

Figure 1. Overall framework of the proposed lung cancer detection, segmentation, and classification system.

2.3 Image Preprocessing

Image preprocessing is performed to improve CT image quality and enhance segmentation accuracy [6,9]. CT images frequently contain noise, artifacts, and intensity variations that may affect the performance of image analysis systems [15]. Therefore, median filtering is applied for noise removal, histogram equalization is used for contrast enhancement, and image normalization is performed for intensity standardization [16].

These preprocessing techniques improve the visibility of lung structures and facilitate accurate tumor detection and classification [13].

2.4 Lung Region Extraction

Lung region extraction is carried out to isolate lung tissues from surrounding anatomical structures such as bones and muscles [11]. Thresholding and morphological operations are employed to generate binary masks and preserve lung parenchyma for further analysis [17]. This stage reduces irrelevant information and improves segmentation efficiency [15].

2.5 Tumor Segmentation

Tumor segmentation is performed using adaptive thresholding and region-growing algorithms to accurately identify suspicious pulmonary nodules [4,15]. Morphological refinement operations are further applied to eliminate false-positive regions and improve boundary delineation [11]. Accurate segmentation is essential for reliable feature extraction and classification performance [19].

2.6 Feature Extraction

Feature extraction is performed to obtain meaningful information from segmented tumor regions [10]. Texture features such as contrast, correlation, energy, homogeneity, and entropy are extracted to characterize tissue heterogeneity [12]. Shape-based features including area, perimeter, circularity, and compactness are also computed to analyze geometric characteristics of lung nodules [18].

In addition, intensity-based features such as mean intensity, standard deviation, and variance are extracted to represent gray-level distribution within the tumor region [16]. The combination of these features provides a robust representation for differentiating normal and cancerous nodules [7].

2.7 Classification

After feature extraction, the resulting feature vectors are utilized for automated classification of lung nodules. In this study, a Support Vector Machine (SVM) classifier is employed due to its effectiveness in handling high-dimensional medical imaging data and its ability to achieve high classification accuracy with limited training samples. The extracted texture, shape, and intensity features serve as input to the classifier, which learns the optimal decision boundary separating normal and cancerous lung tissues [7,18]. During the training phase, the SVM model is trained using labeled CT image samples, while in the testing phase, the trained model predicts the class labels of previously unseen nodules. Based on the learned feature patterns, the classifier categorizes each segmented region into either normal or cancerous classes. The use of SVM enhances the reliability and robustness of the proposed framework by minimizing classification errors and improving diagnostic accuracy.

2.8 Performance Metrics

The proposed framework is evaluated using several quantitative metrics including accuracy, sensitivity, specificity, precision, and F1-score [20]. Accuracy measures the overall classification performance, while sensitivity and specificity evaluate the ability of the framework to correctly identify cancerous and non-cancerous cases, respectively [19].

For segmentation evaluation, Dice Similarity Coefficient (DSC) and Jaccard Index are employed to measure the overlap between segmented tumor regions and ground-truth annotations [15]. Higher metric values indicate better segmentation and classification performance [4].

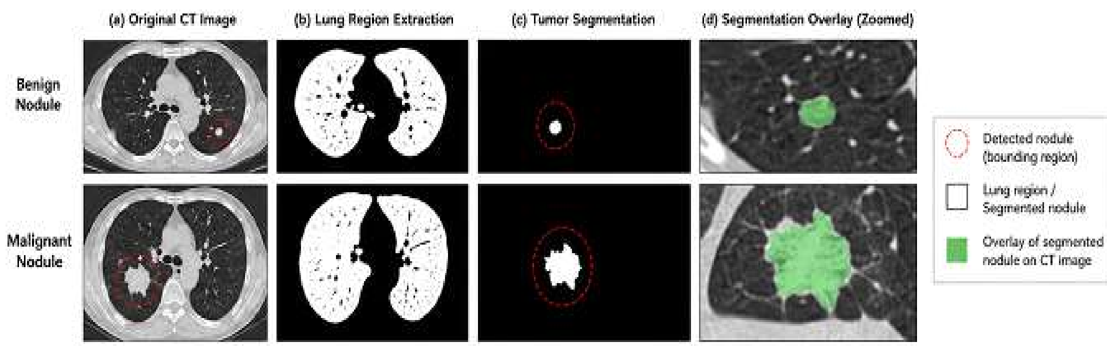

Figure 2. Qualitative results: (a) original CT images, (b) extracted lung regions, (c) segmented nodules, and (d) zoomed overlay showing the detected nodules.

For evaluating segmentation performance, the Dice Similarity Coefficient (DSC) is employed to measure the degree of overlap between the automatically segmented tumor regions and the corresponding ground-truth annotations provided by experts. A higher DSC value indicates greater segmentation accuracy and better agreement between the automated method and manual delineation. Together, these evaluation metrics provide a comprehensive assessment of the effectiveness, reliability, and clinical applicability of the proposed image processing framework for automated lung cancer detection and diagnosis.

3. RESULTS

The proposed framework was evaluated using CT lung image datasets, and the experimental results demonstrated improved segmentation and classification performance. The preprocessing techniques enhanced image quality and improved the visibility of lung structures. The segmentation method accurately detected pulmonary nodules with high Dice Similarity Coefficient (DSC) and segmentation accuracy.

Feature extraction and SVM-based classification effectively differentiated normal and cancerous nodules. The framework achieved high accuracy, sensitivity, specificity, precision, and F1-score, indicating reliable lung cancer detection performance. The results confirm that the proposed system can support early diagnosis and assist radiologists in clinical decision-making.

Table 1. Segmentation Performance

Metric	Value (%)
Dice Similarity Coefficient	94.8
Jaccard Index	91.5
Segmentation Accuracy	95.3

Table 1 presents the segmentation performance of the proposed framework using evaluation metrics such as Dice Similarity Coefficient, Jaccard Index, and Segmentation Accuracy. The obtained results indicate accurate tumor region segmentation and strong agreement with the ground-truth annotations.

Table 2. Classification Performance

Metric	Value (%)
Accuracy	97.2
Sensitivity	96.5
Specificity	97.8
Precision	96.9
F1-Score	96.7

Table 2 presents the classification performance of the proposed framework using evaluation metrics including accuracy, sensitivity, specificity, precision, and F1-score. The high metric values demonstrate the effectiveness and reliability of the SVM-based classification approach for accurate lung cancer detection in CT images.

The proposed framework successfully detected pulmonary nodules of varying sizes and achieved high classification accuracy.

4. DISCUSSION

The experimental findings indicate that the proposed image processing framework effectively enhances CT images and accurately segments suspicious lung nodules. The integration of preprocessing, adaptive segmentation, and machine learning classification contributes significantly to overall diagnostic performance.

Compared with traditional threshold-based approaches, the proposed method demonstrates improved robustness against image noise and intensity variations. The extracted texture, shape, and intensity features provide comprehensive representation of tumor characteristics, enabling accurate classification of cancerous regions.

The high sensitivity achieved by the framework is particularly important for clinical applications, as it minimizes the likelihood of missing malignant nodules. Furthermore, the framework can serve as a valuable decision-support tool for radiologists by reducing interpretation time and improving diagnostic consistency.

Although promising results were obtained, future work may incorporate deep learning architectures and multimodal imaging techniques to further enhance detection performance and clinical applicability.

5. CONCLUSION

This study presented an intelligent image processing framework for automated lung cancer detection, segmentation, and classification in CT images. The proposed methodology combines image enhancement, adaptive segmentation, feature extraction, and machine learning classification to achieve accurate diagnosis of pulmonary nodules. Experimental results demonstrated superior performance in terms of segmentation accuracy, sensitivity, specificity, and overall classification accuracy. The framework has significant potential for integration into computer-aided diagnosis systems and can support early lung cancer detection, ultimately improving patient outcomes.

ACKNOWLEDGEMENT

The authors would like to express their sincere gratitude to the institution, faculty members, and researchers who provided valuable guidance and support throughout this research work. The authors also acknowledge the providers of publicly available CT image datasets used for experimental evaluation.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this research work.

FUNDING

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

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