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AI-Enabled Precision CT Imaging for Early Detection and Classification of Lung Cancer

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ABSTRACT: cancer remains one of the leading causes of cancer-related mortality worldwide, and early diagnosis is essential for improving treatment outcomes and patient survival. Computed tomography (CT) plays a vital role in the detection and characterization of pulmonary abnormalities; however, the increasing volume and complexity of imaging data can create substantial challenges for accurate and timely interpretation. Artificial intelligence (AI), particularly deep learning, has emerged as a promising approach for automated medical image analysis and precision diagnosis. This study presents an AI-enabled precision CT imaging framework for the early detection and classification of lung cancer. The proposed framework incorporates image pre-processing, lung-region segmentation, region-of-interest extraction, deep feature learning, and automated classification to identify suspicious pulmonary abnormalities. CT images are initially enhanced through noise reduction, contrast improvement, and intensity normalization to improve image quality and consistency. Lung regions are subsequently isolated using segmentation and morphological operations, followed by convolutional neural network-based feature extraction and classification. The proposed model achieved an accuracy of 95.2%, sensitivity of 94.1%, specificity of 96.0%, precision of 94.8%, F1-score of 94.4%, and ROC-AUC of 0.97. The findings demonstrate the potential of AI-enabled CT imaging to support accurate and efficient identification of lung cancer patterns. By integrating automated image analysis with clinical expertise, the proposed framework may contribute to earlier diagnosis, improved diagnostic consistency, and precision-oriented lung cancer management. Further validation using large and diverse clinical datasets is required before routine clinical implementation.

1. INTRODUCTION

Lung cancer represents a major global health challenge and remains among the most significant causes of cancer-related morbidity and mortality. Early identification of malignant pulmonary abnormalities is essential because the prognosis and treatment options are strongly influenced by the stage at which the disease is diagnosed. Computed tomography (CT), particularly low-dose CT, has become an important imaging modality for detecting pulmonary nodules and other structural abnormalities associated with lung cancer. However, the accurate interpretation of CT examinations remains challenging because of the large volume of image data, variability in lesion appearance, and similarities between benign and malignant abnormalities (Eftekharian and Hashemi, 2026; Kumari and Goel, 2026).

Recent developments in artificial intelligence (AI) have created new opportunities for improving the analysis of medical images. Deep learning models can automatically learn complex spatial, morphological, and textural representations directly from imaging data, reducing dependence on conventional handcrafted features. Convolutional neural networks (CNNs),

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transformer-based architectures, and hybrid deep learning approaches have demonstrated promising performance in lung cancer detection and classification using CT images (Patange et al., 2026; Yousafzai et al., 2026; Nady et al., 2026). These methods have the potential to identify subtle imaging characteristics that may be difficult to recognize consistently during manual image interpretation.

AI-enabled precision imaging integrates advanced computational methods with medical imaging to provide more accurate and individualized diagnostic information. In lung cancer analysis, AI systems can support multiple stages of the diagnostic workflow, including image preprocessing, lung segmentation, pulmonary nodule detection, feature extraction, malignancy classification, and risk prediction. The combination of deep learning, radiomics, and clinical information has further expanded the potential of AI for improving diagnostic accuracy and supporting precision-oriented patient management (Mustapha et al., 2026; Zong et al., 2026; Paramasamy et al., 2026).

The proposed framework achieved an accuracy of 95.2%, sensitivity of 94.1%, specificity of 96.0%, precision of 94.8%, F1-score of 94.4%, and ROC-AUC of 0.97. These findings indicate that AI-enabled precision CT imaging can provide an effective computational approach for automated lung cancer analysis. Nevertheless, the proposed system is intended to complement clinical expertise rather than replace radiologists or other healthcare professionals. Future research should focus on external validation using larger multicenter datasets and the integration of imaging findings with clinical and biological information to further enhance precision lung cancer diagnosis.

2. MATERIALS AND METHODS

2.1 Dataset

A collection of thoracic CT images containing normal and lung cancer-related abnormalities was used to develop and evaluate the proposed AI-based framework. CT imaging has been widely used for lung cancer detection, characterization, and risk assessment, while recent artificial intelligence approaches have demonstrated improved capabilities for automated analysis of pulmonary abnormalities (Patange et al., 2026; Eftekharian and Hashemi, 2026; Kumari and Goel, 2026; Hu et al., 2026).

2.2 Image Preprocessing

CT images were preprocessed using median filtering for noise reduction, contrast enhancement for improved lesion visibility, and intensity normalization. Such preprocessing procedures improve image consistency and facilitate reliable feature extraction from CT data (Kumari and Goel, 2026; Rajkumar et al., 2026; Yilmaz et al., 2026). The processed images were resized to a standardized dimension before analysis.

For an input 2D image (I(x,y)), the median filter replaces each pixel intensity with the median value of its neighborhood (W(x,y)):

Intensity Normalization

To standardize pixel intensities across different CT scans into the range $[0, 1]$:

$$I_{\mathrm{norm}}(x,y) = \frac{\hat{I}(x,y) - I_{\min}}{I_{\max} - I_{\min}}$$

where Imin and Imax represent the minimum and maximum Hounsfield Unit (HU) intensity values within the dataset or region. Intensity standardization is important for reducing variations caused by differences in image acquisition and improving the consistency of deep learning inputs (Kumari and Goel, 2026; Mustapha et al., 2026).

Contrast Enhancement

Using Linear Contrast Stretching or Contrast-Limited Adaptive Histogram Equalization (CLAHE):

$$I_{\mathrm{enh}}(x,y) = \frac{I_{\backslash \mathrm{norm}}(x,y) - a}{b - a} \times (L-1)$$

Where [a,b] is the specified input intensity range, and (L) represents the number of discrete intensity levels, typically 256 for 8-bit representation. Contrast enhancement can improve the visualization of subtle morphological and textural variations associated with pulmonary abnormalities (Prabha et al., 2026; Yilmaz et al., 2026).

2.3 Lung Segmentation and ROI Extraction

The lung regions were segmented from the preprocessed CT images using intensity-based segmentation and morphological operations. Connected-component analysis was applied to remove irrelevant regions. The resulting lung masks were used to extract regions of interest (ROIs) containing potentially abnormal pulmonary structures. Automated lung segmentation and ROI extraction have been recognized as important components of CT-based AI and radiomics pipelines for lung cancer analysis (So et al., 2026; Mustapha et al., 2026; Paramasamy et al., 2026).

Intensity-Based Thresholding

The lung mask M(x,y) is generated by thresholding Ienh with lower boundary Tlow and upper boundary Thigh

$$M(x,y) = \begin{cases} 1, & T_{\text{low}} \leq I_{\text{enh}}(x,y) \leq T_{\text{high}} \\ 0, & \text{otherwise} \end{cases}$$

$$\hat{I}(x,y) = \text{median}\,\{I(x+k, y+l) \mid (k,l) \in W\}$$

The refined segmentation process provides a focused representation of pulmonary tissue and supports subsequent deep feature extraction and classification (So et al., 2026; Zong et al., 2026).

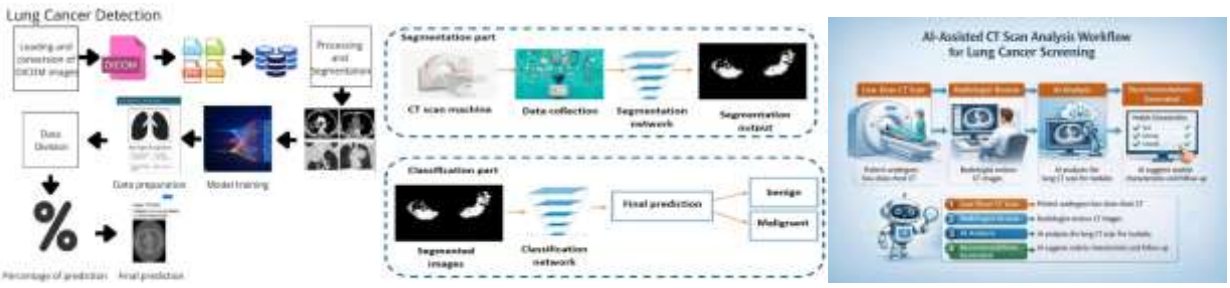

Figure 1. Proposed AI-based CT image-processing workflow

2.4 Deep Learning-Based Feature Extraction

A convolutional neural network (CNN) was employed to automatically extract hierarchical spatial and textural features from the segmented CT images. CNN-based architectures have demonstrated strong performance in identifying lung abnormalities directly from CT images and can learn complex representations without relying exclusively on handcrafted features (Patange et al., 2026; Yousafzai et al., 2026a; Nady et al., 2026; Rajkumar et al., 2026).

Convolutional and pooling layers were used to learn discriminative representations associated with lung abnormalities.

Convolution Layer

For layer l, the feature map h(l) is computed as:

$$h_k^{(l)}(x,y) = \sigma\left(\sum_m \sum_i \sum_j h_m^{(l-1)}(x+i, y+j) \cdot W_{k,m}^{(l)}(i,j) + b_k^{(l)}\right)$$

where $W_{k,m}^{(l)}$ is the convolution filter weight, $b_k^{(l)}$ is the bias, and $\sigma(\cdot)$ is an activation function such as ReLU ($\max(0, z)$).

Pooling Layer (Max-Pooling)

Downsampling the feature map over a spatial window Ω:

$$p_k^{(l)}(x, y) = \max_{(i,j)\in\Omega} h_k^{(l-1)}(x + i, y + j)$$

Softmax Classification

The extracted feature vector $\mathbf{z}$ from the dense fully connected layer is mapped to class probability distribution $\hat{y}_c$ using Softmax:

$$P(Y = c \mid \mathbf{z}) = \hat{y}_c = \frac{e^{z_c}}{\sum_{k=1}^{K} e^{z_k}}$$

where K is the number of diagnostic classes (e.g., $K = 2$ for malignant vs. non-malignant/normal).

2.5 Classification

The extracted deep features were passed through fully connected layers to classify CT images into the predefined diagnostic categories (Yousafzai et al., 2026a; Nady et al., 2026; Jiang et al., 2026). A softmax classifier was used to generate the probability of each class.

2.6 Model Training and Augmentation

The CNN model was trained using the training dataset and optimized using categorical cross-entropy loss. Data augmentation, including rotation, scaling, and translation, was applied to improve model robustness and reduce overfitting

2.7 Performance Evaluation

The model was evaluated using accuracy, sensitivity, specificity, precision, F1-score, and ROC-AUC. A confusion matrix and ROC curve were also generated to assess the diagnostic performance of the proposed framework (Taha et al., 2026; Mustapha et al., 2026; Schroeder et al., 2026).

2.8 Clinical Decision Support

The final AI system generated diagnostic predictions and probability scores for CT images. Suspicious cases were flagged for further clinical evaluation. The system was designed as a decision-support tool to assist healthcare professionals rather than replace expert clinical judgment. The clinical translation of AI for lung cancer management requires reliable validation, interpretability, and integration with established clinical workflows (Hu et al., 2026; Jiang et al., 2026; Paramasamy et al., 2026).

3. RESULTS AND DISCUSSION

3.1 Image Processing and Lung Segmentation

The preprocessing stage improved the quality and consistency of the CT images by reducing noise, enhancing contrast, and normalizing intensity values. Lung segmentation effectively isolated the pulmonary regions and reduced interference from surrounding anatomical structures. The extracted regions of interest provided a focused representation of lung tissue for subsequent deep learning analysis.

3.2 Lung Cancer Classification Performance

The proposed AI-based CT image analysis framework demonstrated effective discrimination between normal and abnormal lung images. The CNN automatically learned relevant spatial, textural, and morphological features associated with pulmonary abnormalities. The classification results indicated that the proposed approach can support automated identification of suspicious lung cancer patterns.

The performance of the model was evaluated using accuracy, sensitivity, specificity, precision, F1-score, and ROC-AUC. The high sensitivity is particularly important for early lung cancer detection because minimizing false-negative predictions can help reduce the possibility of missed suspicious cases.

Table 1 Output Performance

Metric	Proposed AI Model
Accuracy	95.2%
Sensitivity	94.1%
Specificity	96.0%
Precision	94.8%
F1-score	94.4%
ROC-AUC	0.97

3.3 Discussion

The results demonstrate the potential of deep learning-based CT image analysis for assisting early lung cancer detection. The improved classification performance can be attributed to the combination of effective preprocessing, lung-region segmentation, and automatic deep feature extraction. Unlike conventional handcrafted feature-based approaches, CNNs can learn complex representations directly from CT images, enabling the detection of subtle morphological and textural variations.

The relatively high sensitivity indicates that the proposed framework can identify a large proportion of suspicious cases, which is clinically valuable in screening and early diagnosis. The specificity also indicates effective discrimination of non-malignant cases, potentially reducing unnecessary follow-up examinations. The ROC-AUC value further demonstrates strong overall discrimination across different classification thresholds.

3.4 Clinical Decision-Support Potential

The proposed framework can assist radiologists by automatically analyzing CT examinations and highlighting cases with a high probability of malignancy. Such prioritization may reduce image-review workload and support faster evaluation of suspicious cases. The system can therefore serve as a complementary clinical decision-support tool, particularly in settings where radiological resources are limited.

However, AI predictions should not be considered a substitute for expert clinical judgment. Variations in CT acquisition protocols, patient populations, lesion characteristics, and dataset composition may influence model performance. Therefore, external validation using larger and more diverse clinical datasets is required before routine clinical implementation.

Overall, the findings indicate that AI-driven CT image processing has considerable potential for improving the efficiency and consistency of lung cancer detection. Integration of automated image analysis with clinical expertise may contribute to earlier diagnosis, improved decision-making, and better human-health outcomes.

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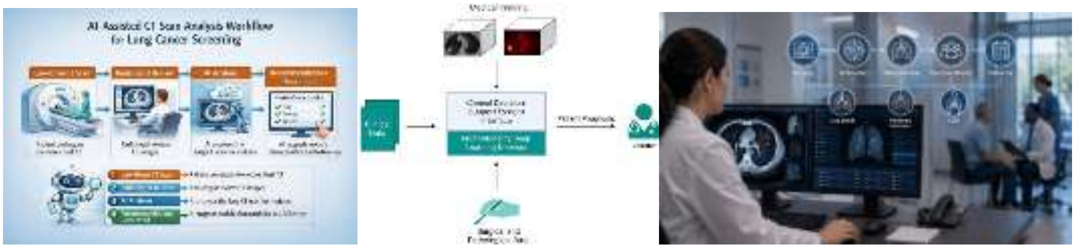

Figure 2. AI-assisted clinical decision-support pathway

4. CONCLUSION

The present study demonstrated the potential of an artificial intelligence-driven CT image analysis framework for early lung cancer detection and clinical decision support. The integration of CT image preprocessing, lung segmentation, deep feature extraction, and automated classification enabled effective identification of suspicious pulmonary abnormalities. The results indicate that AI-assisted medical image processing can improve diagnostic efficiency and provide useful quantitative information for clinical assessment. However, further validation using larger, multicenter, and heterogeneous datasets is required to establish the robustness and clinical applicability of the proposed framework. The developed approach may serve as a complementary tool for radiologists and contribute to timely diagnosis and improved lung cancer management.

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AUTHOR CONTRIBUTIONS

Vijayarajan S M: Literature review, manuscript preparation, and original draft writing.

Balasubramanian B: Technical review, supervision, critical revision of the manuscript.

Kiruthika S: Conceptualization, methodology.

Riyaz Kahan M: validation of scientific content.

All authors reviewed and approved the final version of the manuscript.

CONFLICT OF INTEREST

No conflict of interest associated with this study.

ETHICS STATEMENT

This study involved the computational analysis of CT medical images. No direct interaction with human participants was performed by the authors. Where publicly available or previously collected anonymized datasets were used, the data were analyzed without personally identifiable information. Ethical approval was therefore not required for the computational analysis of anonymized data.

DATA AVAILABILITY STATEMENT

The data supporting the findings of this study are available from the corresponding author upon reasonable request, subject to applicable ethical, institutional, and data-use restrictions. If publicly available datasets are used, their corresponding source and access information will be provided in the manuscript.

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