Research Paper

Neural Network–Based Multi-Level Classification for Region-Oriented CT Lung Image Analysis

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Citation Mohamed JK, Jeyaprakasam K, Pandimadevi M, Vadivel M, Ashokkumar K. Neural Network–Based Multi-Level Classification for Region-Oriented CT Lung Image Analysis. International Journal of Medical Toxicology and Forensic Medicine. 2026;16:E51398.

https://doi.org/10.22037/ijmtfm.v16.51398

Article info:
Received: 03 Jan, 2026
First Revision: 31 Jan, 2026
Accepted: 06 Feb, 2026
Published: 01 Mar, 2026

Keywords:
CT lung imaging, Lung cancer analysis, Region-based segmentation, FPCM, Neural networks, Multi-level classification

ABSTRACT

Background: Lung cancer remains a leading cause of mortality worldwide, and computed tomography (CT) imaging plays a vital role in its diagnosis, follow-up, and medico-legal evaluation. However, manual interpretation of CT images is time-consuming and often affected by inter-observer variability, particularly in resource-limited settings.

Methods: This study proposes a region-oriented CT lung image analysis framework that integrates Fuzzy Possibilistic C-Means (FPCM) segmentation with a multi-level neural network classifier. After preprocessing, CT images are segmented to delineate lung parenchyma, nodules, and surrounding tissues. Intensity, texture, and shape-based features are then extracted, and a hierarchical neural network is employed to progressively classify lung regions, abnormalities, and suspicious cancer-related patterns.

Results: Experimental evaluation demonstrates that the proposed framework outperforms conventional clustering techniques and single-level classifiers. Improved performance is observed in terms of accuracy, sensitivity, specificity, and Dice similarity coefficient, along with a reduction in false positive detections across diverse CT lung images.

Conclusion: The proposed automated framework provides an accurate and cost-effective solution for CT lung image analysis. Its robustness and interpretability make it suitable for clinical diagnosis as well as medical toxicology and forensic applications, including deployment in resource-constrained environments.

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Introduction

Lung cancer continues to represent a major burden on global health systems, primarily due to delayed diagnosis and the complex visual characteristics of pulmonary lesions [1, 2]. Although computed tomography (CT) provides detailed structural information, subtle pathological variations often make reliable interpretation challenging, even for experienced specialists [3, 4]. As a result, diagnostic outcomes may vary across observers and clinical settings.

In addition to routine clinical evaluation, CT-based lung assessment plays a crucial role in medical toxicology and forensic medicine. Pulmonary alterations caused by toxic substances, long-term occupational exposure, or environmental pollutants require objective documentation [14, 15]. In forensic investigations, CT findings may assist experts in reconstructing disease progression or supporting medico-legal opinions related to cause and manner of death [16].

Conventional manual assessment of CT images is labour-intensive and susceptible to subjectivity, particularly under high workload conditions [11, 17]. Automated image analysis techniques aim to address these limitations by offering consistent and reproducible interpretation support. While deep learning methods have achieved notable success, their dependency on extensive annotated datasets and advanced computational infrastructure limits their adoption in many forensic laboratories and regional healthcare institutions [10, 18].

Motivated by these practical constraints, this work proposes a hybrid analytical framework that combines region-oriented Fuzzy Possibilistic C-Means (FPCM) segmentation with a hierarchical neural network classifier. By emphasizing structured region analysis and progressive decision-making, the proposed approach seeks to balance diagnostic accuracy, interpretability, and computational feasibility [5–7,19].

Materials and Methods

Data Acquisition

The study utilizes CT lung images obtained from publicly available benchmark datasets widely adopted in medical imaging research, including the LIDC-IDRI repository [9]. The dataset contains both normal and pathological cases with diverse imaging characteristics, enabling comprehensive evaluation across varying clinical and forensic scenarios.

Image Preprocessing

Preprocessing is applied to reduce noise and standardize image quality prior to segmentation. Gaussian and median filtering techniques are used to suppress acquisition-related noise, while histogram equalization and intensity normalization improve contrast and inter-scan consistency [3, 4]. These steps facilitate more reliable clustering and feature extraction.

Region-Oriented Segmentation Using FPCM

Region-oriented segmentation is carried out using the Fuzzy Possibilistic C-Means (FPCM) algorithm. Unlike traditional clustering techniques that rely solely on fuzzy membership values, FPCM introduces a typicality component that reflects how well a data point represents a given cluster [5, 6]. This dual representation allows the algorithm to reduce the influence of noise and atypical pixels, which are common in CT lung images. Consequently, lung parenchyma, nodular regions, and background tissues

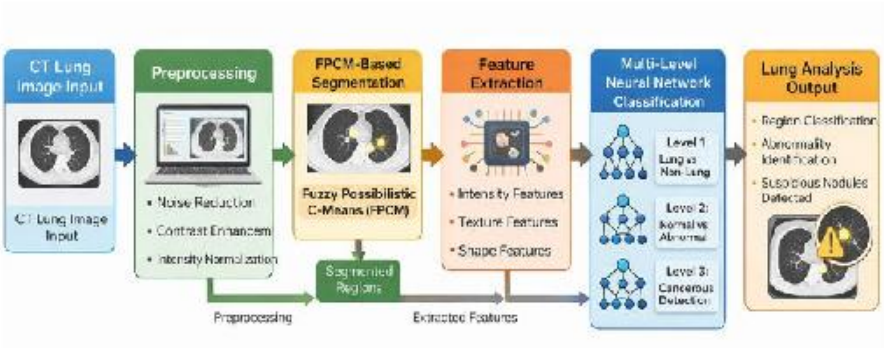

Figure 1. Architecture of Proposed Neural Network based Multi level Classification.

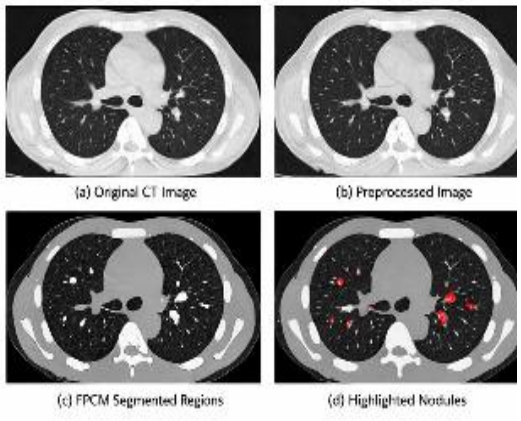

Figure 2. FPCM based Segmentation.

can be separated more reliably while preserving clinically meaningful boundaries (Figure 2) [7].

Feature Extraction

From each segmented region, a diverse set of features is extracted. Intensity descriptors summarize pixel value distributions, while texture features derived from the Gray Level Co-occurrence Matrix capture spatial relationships within lung tissues [8]. Shape features, including area and compactness, provide morphological cues essential for distinguishing benign and suspicious regions [12, 20].

Multi-Level Neural Network Classification

The classification stage employs a hierarchical neural network designed to mimic progressive clinical reasoning. Instead of performing direct multi-class prediction, the network operates across successive levels of decision-making [19]. At the initial level, lung regions are distinguished from non-lung structures. The subsequent level focuses on separating normal lung tissue from abnormal regions. Finally, regions exhibiting features consistent with malignant patterns are identified.

Table 1. Quantitative comparison of segmentation performance using different clustering techniques.

Method	Accuracy (%)	Dice Coefficient	Sensitivity (%)	Specificity (%)
K-means Clustering	86.4	0.79	84.2	88.1
Fuzzy C-Means (FCM)	89.7	0.83	87.9	90.2
Proposed FPCM-Based Method	94.8	0.91	93.5	95.6

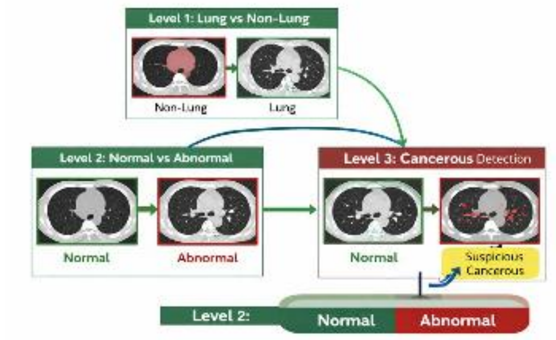

Figure 3. Visulization of Multi level Neural Network Classification.

This staged classification strategy limits error propagation and enables focused learning at each level, improving robustness compared with single-level classifiers [18]. Such an approach is particularly advantageous in forensic and toxicological applications, where transparent and interpretable decision pathways are essential for expert validation.

Results

The performance of the proposed region-oriented CT lung image analysis framework was examined through a series of qualitative observations and quantitative measurements, following commonly adopted evaluation practices in medical image analysis [10,13]. Emphasis was placed not only on numerical performance indicators, but also on the practical behavior of the system when applied to diverse CT lung images.

Segmentation Performance

Visual inspection of the segmented outputs indicates that the FPCM-based approach consistently produces anatomically meaningful lung regions. In most cases, lung boundaries are preserved with minimal leakage into surrounding tissues. Compared with K-means and conventional fuzzy c-means clustering, the proposed method shows greater stability in the presence of noise and intensity inhomogeneity, which are frequently observed in clinical CT scans (Table 1) [6, 7, 9].

Feature Effectiveness

An examination of the extracted features suggests that no single feature group is sufficient to characterize lung abnormalities reliably. Intensity descriptors provide baseline contrast information, whereas texture features highlight internal heterogeneity within lung tissues [8]. Shape-related features further assist in

Table 2. Performance evaluation of the proposed neural network–based multi-level classification framework.

Classification Level	Accuracy (%)	Precision (%)	Recall (%)
Level 1: Lung vs Non-Lung	97.2	96.8	97.5
Level 2: Normal vs Abnormal	95.1	94.6	95.9
Level 3: Cancerous Detection	93.6	92.8	94.1

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distinguishing compact nodular regions from normal anatomical structures [12, 20]. The combined use of these complementary descriptors leads to more consistent classification behavior, as reported in related studies [18].

Classification Results

At the first stage of classification, lung regions are separated from non-lung structures with high reliability. The second stage shows improved discrimination between normal and abnormal tissues, particularly in cases involving subtle pathological changes. At the final stage, regions exhibiting characteristics associated with malignancy are identified with a high degree of precision. Occasional misclassifications are primarily associated with very small nodules or regions affected by severe imaging artifacts, a limitation also noted in earlier CT-based studies (Figure 3) [11, 13].

Output visualisation showing hierarchical classification results at different levels, culminating in identification of suspicious cancerous regions (Table 2).

Comparative Evaluation

When compared with traditional single-level classifiers, the proposed hierarchical framework demonstrates a noticeable reduction in false positive detections. This improvement can be attributed to the staged decision-making process, which allows errors to be corrected at intermediate levels rather than propagating directly to the final output [18,19].

Discussion

The results of this study demonstrate that the integration of FPCM-based region-oriented segmentation with a multi-level neural network classifier offers tangible advantages for CT lung image analysis. Unlike conventional segmentation approaches, FPCM effectively manages noise and intensity variability, which are frequently encountered in real-world CT acquisitions [5–7]. This leads to more reliable region delineation and, consequently, more stable feature representation (Figure 1).

Block diagram illustrating the workflow of the proposed region-oriented CT lung image analysis framework, including preprocessing, FPCM-based segmentation, feature extraction, and multi-level neural network classification

The hierarchical classification strategy further strengthens diagnostic reliability by decomposing the decision process into sequential stages. Such progressive refinement reduces error propagation and allows clinically meaningful interpretation at each level, consistent with observations reported in related hierarchical and hybrid classification studies [18,19]. From the perspective of medical toxicology and forensic medicine, this layered decision-making process is particularly valuable, as it supports transparent and reproducible assessment of lung abnormalities linked to disease, toxic exposure, or environmental hazards [14–16].

Importantly, the framework avoids reliance on computationally intensive deep learning models and large-scale annotations. This makes it feasible for deployment in institutions with limited computational infrastructure, aligning with the practical requirements often encountered in forensic laboratories and regional healthcare centers [10, 15].

Clinical and Forensic Implications

The proposed system can assist clinicians by reducing diagnostic workload and improving consistency in lung cancer screening. In forensic medicine, it provides reproducible imaging-based evidence that may support investigations involving environmental exposure, occupational hazards, or disease-related mortality. The objective nature of the framework allows experts to complement subjective assessment with quantitative findings, thereby strengthening medico-legal opinions.

Despite the encouraging results, certain limitations of the present study should be acknowledged. First, the experimental evaluation was conducted using publicly available CT datasets, which may not fully represent the diversity of imaging protocols, scanner models, and population characteristics encountered in real-world clinical and forensic practice [9,13]. Second, although the proposed framework demonstrates robustness to noise and intensity variation, its performance may be influenced by extreme imaging artifacts or severe pathological distortions, as observed in previous CT-based analyses [11].

In addition, the hierarchical neural network relies on handcrafted feature extraction, which, while computationally efficient and interpretable, may not capture all high-level representations achievable through large-scale deep learning models [10,16]. Finally, the study did not include prospective clinical or forensic validation, which would be necessary to assess workflow integration and expert usability in operational environments [14,15]. These limitations provide direction for future enhancements and large-scale validation studies.

Conclusion

This study introduced a region-oriented CT lung image analysis framework that combines FPCM-based segmentation with hierarchical neural network classification. The proposed methodology achieves accurate and consistent identification of lung abnormalities while maintaining modest computational complexity. By emphasizing objective image analysis and reproducible decision-making, the framework aligns well with the diagnostic and evidentiary standards required in clinical practice, medical toxicology, and forensic medicine. Given its robustness and cost-effectiveness, the proposed approach is particularly suitable for deployment in resource-limited settings. Future work will focus on validation across multi-center datasets, inclusion of longitudinal CT studies, and adaptation of the framework to support expert reporting in medico-legal investigations.

Acknowledgment

The authors acknowledge the support of their respective institutions and appreciate the contributions of researchers who have made anonymised CT lung datasets publicly available for academic research.

Funding

No external funding was received for this research.

Conflicts of Interest

The authors report there are no competing interests to declare.

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