A Novel Deep Learning and Image Processing-based Model for Lung Cancer Detection

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Abstract: Lung cancer is among the most common causes of death in the world, and thus early and proper detection is necessary to enhance the survival rates. Conventional diagnostic methods are however usually hampered by late diagnosis, inconsistency in clinical interpretation and reliance on skilled radiologists. In order to address these issues, this systematic review investigates the combination of deep learning (DL) and image processing methods to identify lung cancer reliably and automatically. The authors of the study focus on such challenges as low-quality imaging, variability of data as well as on the lack of diagnostic efficiency and suggest to use advanced preprocessing and intelligent learning models. The systematic review methodology (according to PRISMA guidelines) was considered, which examined 137 peer-reviewed journal articles published in 2019-2026 and included in the Scopus database. Some of the methods used in the reviewed studies include Convolutional Neural Networks (CNNs), transfer learning models (ResNet, DenseNet, EfficientNet), hybrid architectures, and detection frameworks like YOLO, as well as preprocessing techniques, like CLAHE, filtering, and segmentation. The reported results are high in performance with an accuracy of up to 99.9, a recall of up to 100, a Dice Similarity Coefficient (DSC) of up to 99.1 and a mean Average Precision (mAP) of up to 0.894. These results affirm that DL and image processing can be used as an effective and scalable approach to detecting early lung cancer, and also pinpoint the issues and potential future research directions to apply to clinical practice.

Keywords: *Lung Cancer Detection, Deep Learning, Image Processing, CAD*
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1. Introduction

Cancer is defined as the formation of abnormal tissues that are undesirable, uncontrollable, and quickly spread throughout the body; if it is not properly treated from the beginning, it spreads and affects other organs as well (Muhammedetal.,2025). The application of current technology has made significant contributions to the health sector, particularly in the identification of lung cancer. It assists in the diagnosis and treatment of diseases by medical professionals (Zia et al., 2023). Lung cancer is one of the most lethal illnesses known to humanity because of the high number of fatalities it causes globally (Ponnada et al., 2019; Pesce et al., 2019; Hayat et al., 2024; Maksimoc et al., 2024). Researchers found 2.21 million incidences of lung cancer in 2020, with 1.8 million deaths attributable to the disease. With an estimated 1.80 million deaths worldwide in 2020, lung cancer ranks higher than all other malignancies, according to research released by the "World Health Organization (WHO)"(Jopek et al., 2024). According to the WHO, Figure 1 depicts the specifics of cancer-related extinction in 2020. Lung cancer is one of the illnesses where early-stage detection and disease management are vital for effective therapy (Ragab et al., 2022; Yang et al., 2020; Hu et al., 2022; Ozdeir et al., 2025., Kumar et al., 2026).

The likelihood of survival increases with early identification of lung cancer, as is the case with other malignancies (Park et al., 2025). The total patient survival rate is less than 20% after five years, and a considerable majority of those affected by lung cancer do not survive because early identification is delayed (Sadoon et al., 2024). In terms of patient survival, age is not an important prognostic factor. Its victims include both sexes. Lung cancer is more common in men than in women. The mortality rate from lung cancer is greater in males than in females, according to studies (Ahed et al., 2025; Tan et al., 2024; Aumente et al., 2025; Yang et al., 2023). Tobacco, secondhand smoking, infectious diseases, air pollution from ionizing radiation, and bad lifestyle choices all have a role in the alarming rise in lung cancer cases (Wang et al., 2025). The most important risk factor for lung cancer is a history of chronic obstructive pulmonary disease (COPD). The significant rise in the number of automobiles and unhealthy smoking practices also contribute significantly (Zhang et al., 2024). The mortality toll from lung cancer can be decreased by regulating tobacco smoking, because it is a major component driving this development. Fatigue, trouble breathing, and a persistent cough are some of the symptoms. Diagnosis might be challenging since, in addition to shared symptoms, individual symptoms can differ greatly. It can be asymptomatic, and a person could have cancer without any symptoms (Lu et al., 2021). Lack of symptoms in the early stages leads to a delayed diagnosis of lung cancer. One of the most important cornerstones of human civilization is maintaining one's health, hence modern approaches to medical issues are required(Das et al., 2024). The amount of information available in the form of lab tests, research papers, clinic reports, and other documents has increased due to advancements in the biomedical area.

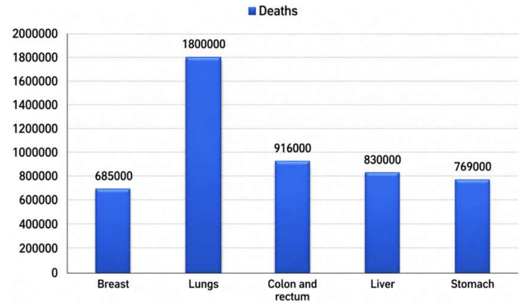


Figure 1: Extinction graph of cancer in 2020(Hu et al., 2022).

Over the past few years, the development of artificial intelligence (AI), specifically deep learning (DL) and image processing, has demonstrated tremendous potential in medical diagnosis (Seo et al., 2021; Seo et al., 2020; Djaroudid et al., 2024; Prasad et al., 2022). CNNs and other DL algorithms have shown impressive results in processing medical images, with automatic feature extraction and pattern detection(Javed et al., 2024). Such models have the capability of carrying out imaging massive data with high accuracy, and thus detecting abnormalities with speed and accuracy. Image processing methods also improve the quality of medical images by reducing noise, enhancing contrast, and highlighting key areas, thus helping to interpret and analyze them better (Ananthakrishnan et al., 2023).

DL with image processing has proven to be extremely promising in transforming the lung cancer detection. These systems are capable of analyzing images of lungs in a more detailed and systematic way by means of using sophisticated algorithms(Jain et al., 2024; Pawar et al., 2022; Shrivastava et al., 2025). They assist to determine suspicious areas, enhance visualisation, and assist in making better clinical decisions. These methods not only ease the burden of healthcare specialists but also improve diagnostic consistency and reliability. In addition, the technologies prove especially useful in the areas where the number of trained radiologists is low, which enhances the access to healthcare(Catalano et al., 2024).Our research is novel because it takes a holistic approach to the application of DL in diagnosing lung cancer and the objectives are as follows:

- Proposed a novel DL and image processing-based framework for lung cancer detection.
- Integrated advanced image pre-processing techniques (e.g., noise reduction, contrast enhancement, ROI extraction) to improve image quality.
- Utilized DL models (CNN-based architectures) for automatic feature extraction and classification.
- Combined pre-processing and DL to enhance diagnostic accuracy and robustness.
- Conducted a comprehensive systematic review (2019–2026) covering 137 research articles using PRISMA methodology.
- Identified key datasets, evaluation metrics, and state-of-the-art techniques used in lung cancer detection.

2. Literature Review

2.1 DL Models for Medical Image Classification

DL models have transformed the field of medical image classification by allowing the automatic, precise and scalable processing of intricate imaging data including “X-rays, CT scans, MRI, and histopathological images”(Li et al., 2018; Zhang et al., 2020; Balaha et al., 2025; Hussein et al., 2025). Such models, especially Convolutional Neural Networks (CNNs) are intended to learn feature representations at arbitrary levels directly on the raw image data, thus leaving out feature engineering (Tawfik et al., 2024; Kumar et al., 2025; Venkatesh et al., 2024). The original architectures such as AlexNet and VGGNet showed the capabilities of DL in the image recognition task, and the further development of the models such as ResNet, DenseNet, and EfficientNet has shown a lot of improvement, addressing the problems of vanishing gradients and computational efficiency (Xiao et al., 2021; Guo et al., 2019). These models in the medical field are trained with a large annotated dataset to discover patterns related to diseases, such as tumors, lesions, and abnormalities in organs(Sah et al., 2026; Deepak et al., 2025).

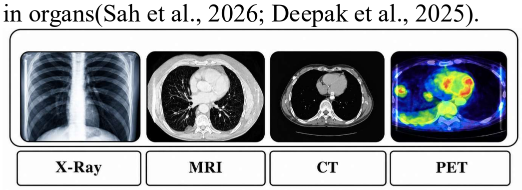


Figure2: Modalities in lung cancer detection—a visual exploration of imaging techniques (Kumar et al., 2025).

DL has become a paradigm shift in the field of medical image classification, allowing the automatic, error-free, and efficient diagnosis of diseases (Vishwanath et al., 2025; Rehman et al., 2026). Different research efforts have investigated state-of-the-art CNN designs, and hybrid designs to improve diagnostic results across different types of medical imaging. Buriboev et al. (2024) suggested a concatenated CNN with an image enhancement approach using fuzzy logic, with a better performance (98.9% accuracy) of pneumonia detection through the enhancement of image quality and feature detection. Equally, Arslan et al. (2025) presented a CNN-BiLSTM framework with a SDR-based signal acquisition and decomposition system with a 99.4% accuracy in recognizing respiratory patterns. Masud et al. (2021) created a DL model to classify lung and colon cancer histopathological images, obtaining an accuracy of 96.33% which indicates that AI can be used to diagnose cancer early. ResNet-50 and the YOLO-based ensemble-based model were used by Marcomini et al. (2024) to detect COVID-19 in chest X-rays with high classification and localization accuracy. Vandana et al. (2026) presented the MpoxSegNet model that was based on transfer learning and segmentation methods and obtained the highest accuracy of up to 99.47 in multi-class skin disease classification. A CNN-based leukemia detecting system was created by Ilyas et al. (2024) on blood smear images and obtained 99% accuracy by optimizing the preprocessing and feature extraction. Muthukrishnan et al. (2025) presented LMGCNN using multi-head attention to detect breast cancer, with the highest accuracy of 99.9% on a benchmark dataset.

Tai et al. (2024) put forth a lightweight self-attention-based framework integrated with Double-Condensing Attention Condensers for the purpose of skin cancer detection that is both efficient and accurate, achieving high AUC at a lower computational cost. Moitra et al. (2019) created a hybrid CNN-RNN architecture meant for the automated staging process of non-small cell lung cancer, which performs better than traditional machine learning methods. Aarthy et al. (2024) described an approach based on GCNN for classifying bone cancer that uses advanced preprocessing and segmentation techniques to enhance accuracy as well as the quality of features. Abinaya et al. (2022) proposed a model called DA-Deep CNN for detecting cervical cancer with an accuracy rate of 99.2% using augmented biopsy images; this was in the year 2022. Naseer et al. (2022) conducted comparative research on various architectures of CNN and found AlexNet with SGD optimizer to be the best performer (97.42% accuracy) in lung cancer detection. Munoz et al., (2024), created a system based on CNN for analyzing lung ultrasound that allows real-time identification of pulmonary features with great precision. Zahari et al., (2024), presented an uncertainty-aware DL framework enhanced by ensemble techniques and Monte Carlo dropout which improved robustness and achieved up to 95.9% accuracy. Yinusa et al., (2025), addressed adversarial robustness in medical imaging by proposing a defense pipeline that combines data sanitization and distillation while maintaining high accuracy even under label-flipping attacks. These studies jointly affirm the merits of DL models, enhanced pre-processing, hybrid architectures, and robustness strategies in advancing medical image classification systems.

2.2 Image pre-processing and Enhancement Techniques

Image pre-processing and enhancement are essential elements of medical image processing, which considerably improve the quality of images obtained through various imaging techniques (Wubineh et al., 2024). Image enhancement is performed in order to remove noise from images, increase their contrast, and highlight only those areas that are important for clinical practice (Alqahtani et al., 2023; Vemula et al., 2024; Lu et al., 2021).

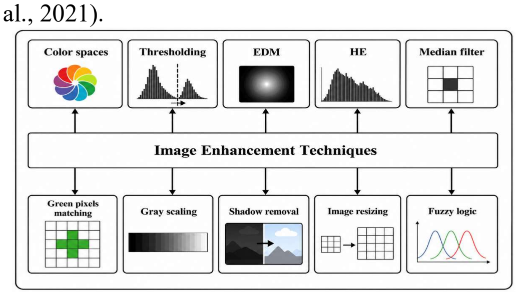
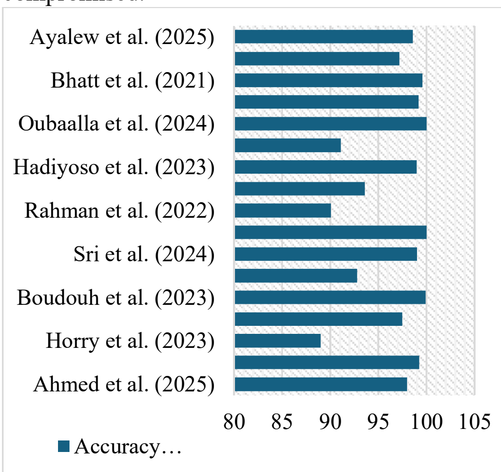
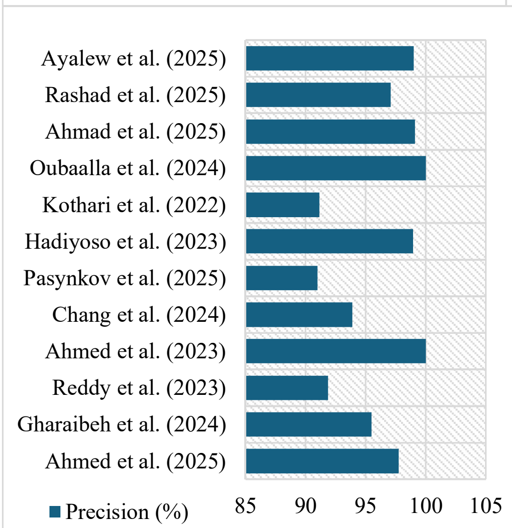
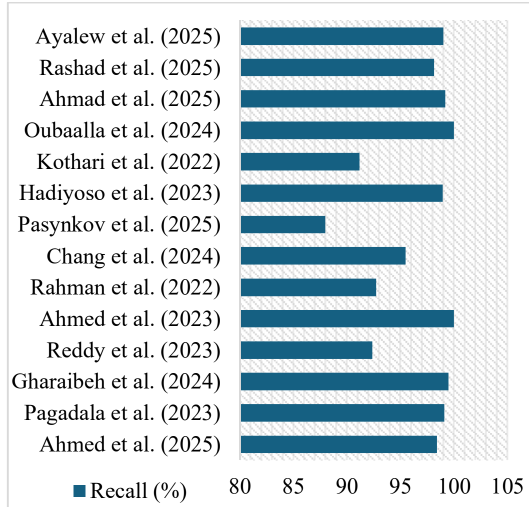


Figure3: Image pre-processing techniques (Lu et al., 2021).

As medical imaging datasets often suffer from variability, artifacts, and low contrast, pre-processing ensures consistency and reliability in diagnostic systems, ultimately supporting accurate and early disease detection (Abd et al., 2022; Gao et al., 2022; Nasrullah et al., 2019). There have been studies that have indicated how pre-processing techniques can be employed to enhance the performance of lung cancer image analysis. Ahmed et al. (2025) developed a DL model (YOLOv11) that integrates pre-processing algorithms, such as Contrast Limited Adaptive Histogram Equalization (CLAHE), lung segmentation, and region-of-interest (ROI) extraction to improve pneumonia detection accuracy and interpretability by using Grad-CAM visualizations. On the same note, Pagadala et al. (2023) employed histogram equalization and multidimensional filtering to improve the image of lung cancer, which facilitates a better performance of detecting lung cancer in terms of high sensitivity, specificity and accuracy. To minimize bias and enhance model generalization in datasets, Horry et al. (2023) proposed a complete pre-processing pipeline that included histogram equalization, rib suppression, and lung field segmentation. Gharaibehet al. (2024) used Butterworth filtering to eliminate noise without affecting image quality with the assistance of the next-level feature selection and extraction methods to improve the classification performance. Boudouh et al. (2023) used pre-processing techniques including ROI extraction, noise removal, and data augmentation to detect breast cancer with high accuracy using pretrained CNNs. Moreover, both Singh et al. (2024) and Song et al. (2025) noted that pre-processing is an essential factor when enhancing AI-based cancer detection systems when resources are scarce and the quality of imaging can be compromised.







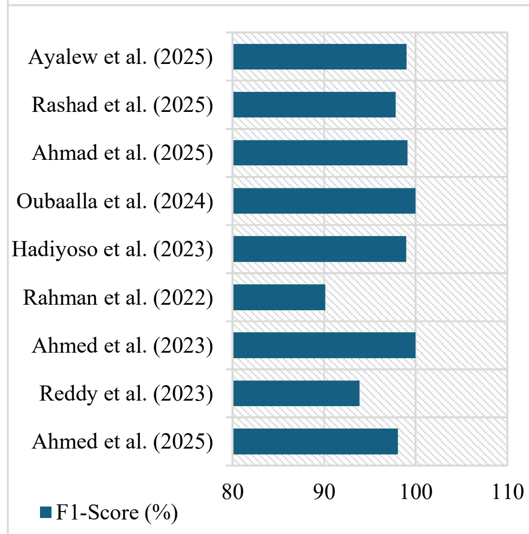


Figure 4: Comparison graph of accuracy, precision, recall, and F1-score based on image pre-processing methods

More research confirms the significance of pre-processing in improving diagnostic accuracy in various imaging modalities. Reddy et al. (2023) emphasized the application of pre-processing, segmentation, and feature extraction in CT images to detect early lung cancer, whereas Sri et al. (2024) used the fuzzy C-means segmentation and CNNs to obtain high classification accuracy. Ahmed et al. (2023) showed that the texture-dependent characteristic of an image can be better detected by employing the Gray Level Co-occurrence Matrix (GLCM), machine learning, and DL methods, leading to more effective detection. Rahman et al. (2022) used pre-processing methods in the analysis of microscopic biopsy images by transfer learning models, minimizing the role of human error and maximizing the classification results. Chang et al. (2024) suggested using a hybrid method that integrates handcrafted texture attributes with DL models to improve the pulmonary nodules classification. In ultrasound imaging, Pasynkov et al. (2025) aimed at ROI detection and contour extraction to increase the performance of lesion segmentation, and Hadiyoso et al. (2023) showed that CLAHE is a powerful method to improve the performance of the histopathological image classification. In addition, Kothari et al. (2022) and Oubaalla et al. (2024) emphasized the importance of pre-processing in tumor detection and classification with DL. Ahmad et al. (2025) enhanced CNN-based diagnosis by using data augmentation and noise removal methods, whereas Bhattacharjee et al. (2021) demonstrated that pre-processing plays a crucial role in the CAD systems to ensure accurate pulmonary nodules detection. Rashad et al. (2025) used image enhancement in skin lesions classification, and Ayalew et al. (2025) used pre-processing and augmentation in IoT-based breast cancer detection systems. In general, the summation of these studies indicates that effective pre-processing and enhancement strategies are important towards enhancing accuracy, generalization and clinical relevance of medical image analysis systems.

2.3 Feature Extraction and Segmentation Methods

The advancement of DL techniques has significantly transformed the field of medical image analysis, particularly in feature extraction and segmentation tasks(Ayalew et al., 2025; Malathi et al., 2023; Zhang et al., 2024; Zhao et al., 2024; Thanoon et al., 2026; Nicolas et al., 2026). Accurate identification of regions of interest and extraction of discriminative features are critical steps for improving early diagnosis, treatment planning, and clinical decision-making in diseases such as lung cancer(Mourdi et al., 2024; Tiwari et al., 2024; Carletti et al., 2025; Bishnoi et al., 2023). However, challenges such as low contrast images, heterogeneous lesion structures, limited annotated datasets, and variability across imaging modalities continue to hinder the performance of conventional methods(Aharonu et al., 2023; Mondal et al., 2021; Haque et al., 2025; Ozdemir et a., 2019; Usman et al., 2025).Numerous studies have been performed relating to issues associated with feature extraction and segmentation in the medical imaging domain (Sathiyamurthy et al., 2024; Kumar et al., 2024; Bhajgotar et al., 2022).

Table1: Comparison of previous study based on feature extraction and segmentation methods

Author (Year)	Data set	Methods Used	Segmentation Methods	Feature Extraction Methods	Results /Performance
Wang et al. (2021)	COVID-19 CT + non-COVID datasets	Transfer learning + 3D U-Net	Hybrid-encoder segmentation	Multi-lesion feature fusion with attention	DSC: 0.704, Accuracy: 99.4, F1-score: 70.7, recall: 68.2%
Xu et al. (2020)	1612 US images (255 patients)	Deep CNN (BRN)	Boundary-Restored Network	CNN-based automatic features	DSC: 83.45%, MCC: 0.833, accuracy: 98.52%, recall: 85.17%, precision: 88.07%,
Wu et al. (2025)	286 SPECT images	Adversarial DL framework	Multi-scale adversarial segmentation	Dilated convolutions, multi-scale modules	DSC: 66.7%, Precision: 72.2%, Recall: 61.9%
Wei et al. (2022)	SRS lung cancer dataset	MPF-Net work	Automated segmentation	Parallel fusion + nonlinear decomposition	DSC: 93.5
Ahmed et al. (2024)	SIPaKMeD dataset	SVM + PCA	CNN-based segmentation pipeline	Feature fusion (MobileNet, DenseNet, etc.)	Accuracy: 97%, precision: 96%, recall: 96%, F1-score: 96%
Venkatachalam et al. (2025)	Lung & colon histopathology dataset	Hybrid DL (Xception + ResNet)	Not emphasized	Deep hybrid feature extraction	Accuracy: 98.96%

Cifci et al. (2022)	Lung CT images	U-Net + attention	SegChaNet	Dense multi-scale extraction	DSC: 95.94%, IOU: 84.8%, accuracy: 98.9%
Hosny et al. (2025)	Lung colon	Multi-modal DL	Multi-modal segmentation	Inception-ResNet + attention	Accuracy: 99.73%, precision: 100%, Recall: 99.73%, F1-score: 99.73%
Hui et al. (2024)	LIDC-IDRI dataset	EMC-UNet	Edge-aware 3D segmentation	Multi-scale + attention features	DSC: 87.95%, IoU: 78.5%, accuracy: 99.81%, recall: 87.54%
Fang et al. (2025)	Multi-modal datasets	Transfer learning (THTL)	Not focused	CNN-based feature similarity (EMD, cosine)	Improved domain selection
Farhan et al. (2023)	Multi-modal medical images	MCLSG framework	ROI-based (no explicit segmentation)	CNN + feature engineering	Accuracy ↑ 3.5%, severity ↑ 6.8%
Elhassan et al. (2025)	IQ-OTHNCCD lung cancer dataset	ResNet-101 + YOLOv8 + DCGAN	YOLOv8 detection/segmentation	CNN hierarchical features	Accuracy: 97.67%, IoU: 0.85, Precision: 96%, recall: 96.2%, F1-score: 96.1%
Ezhilraja et al. (2024)	LIDC, Chest CT dataset	VGG16	Implicit segmentation	Shape-based + CNN features	Accuracy: 91.64%, Precision: 96%, recall: 96%, F1-score: 96%
Xu et al. (2025)	LUNA16 dataset	FRMANet	Multi-scale attention segmentation	Feature reconstruction + attention	mAP: 0.894, F1: 0.923
Su et al. (2022)	Nano-CT images	GCPSO + CRNN	GCPSO segmentation	Gabor + BoVW + CRNN	Precision of 96.5%, accuracy of 99.35%, sensitivity of 97%, specificity of 99% and F1 score of 95.5%
Prasad et al. (2025)	DermNet dataset	GAN + Mask R-CNN + CNN	Mask R-CNN segmentation	GAN-enhanced CNN features	Accuracy of 95.65%, a recall of 97.09%, and an F1-score of 96.98%
V Asha et al. (2024)	LUNA16 (888 CT scans)	V-Net (3D CNN)	3D V-Net segmentation	Volumetric CNN features	mIOU: 98%, DSC: 99.1
Prakash et al. (2023)	Lung CT dataset	MRKM + ICNN	MRKM clustering segmentation	CNN + ATSO optimization	Accuracy: 96.5%, DSC: 94.5%, recall: 98%
Zhang et al. (2021)	56 CT patient scans	Mask R-CNN + Fast	CNN-based segmentation	CNN features	Accuracy: 92.85%

		er R-CNN			
Kaur et al. (2025)	ISIC 2020 dataset	N-DCNN	Deep segmentation model	CNN feature extraction	Accuracy: 93.40%, precision: 93.45, recall: 94.51%, F1-score: 93.98

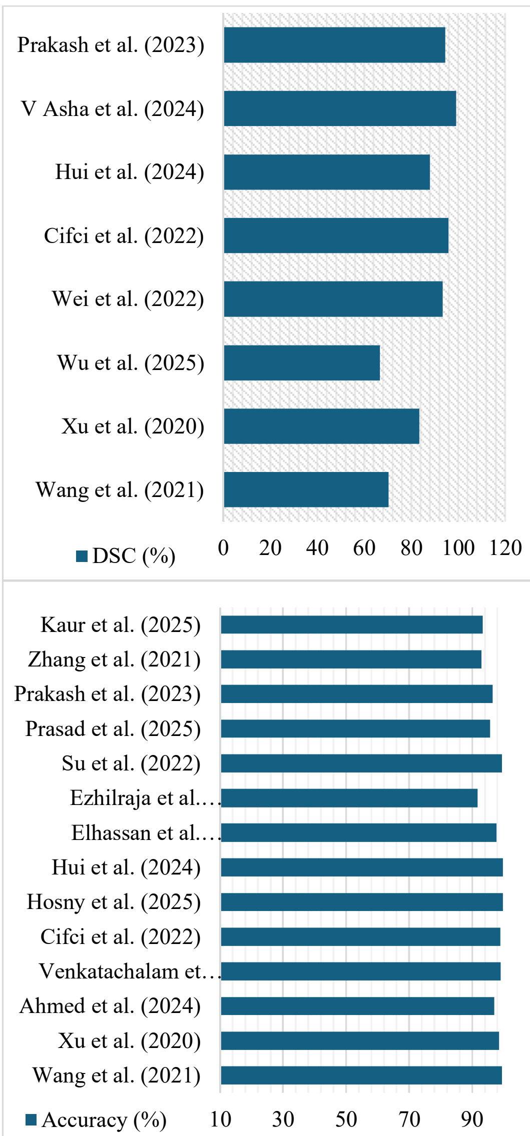


Figure5: Comparison graph of DSC and accuracy

3. Review Methodology

3.1 Overview

The systematic review involved in this study suggests lung cancer detection using DL and image processing tools, datasets, and open research challenges between 2019 and 2026. The purpose of the review is to summarize the latest progress in DL based lung cancer detection, test the most popular datasets, and find new gaps in the literature that influence the robustness of the model and its scalability as well as its application in the real world. "Preferred Reporting Items of Systematic Reviews and Meta-Analyses (PRISMA)" was used to guarantee the methodological transparency, reproducibility, and systematic reporting of identification, screening, the evaluation of eligibility, and inclusion procedures. The review process was divided into five steps, including planning, searching, screening, eligibility assessment, and synthesis. The main goal was to review the recent DL-based lung cancer detection methods. The following research questions are covered in the review:

I. What DL and image processing techniques have been applied for lung cancer detection (2019-2026)?

II. What datasets are commonly used for evaluating lung cancer detection?

III. What performance metrics and evaluation strategies are adopted in recent studies?

IV. What are the key technical challenges and open research issues in lung cancer detection using DL?

3.2 Review Stages

The review process was guided by predefined inclusion and exclusion criteria to ensure the selection of high-quality and relevant research articles. Following figure shows the adapted literature search criteria:

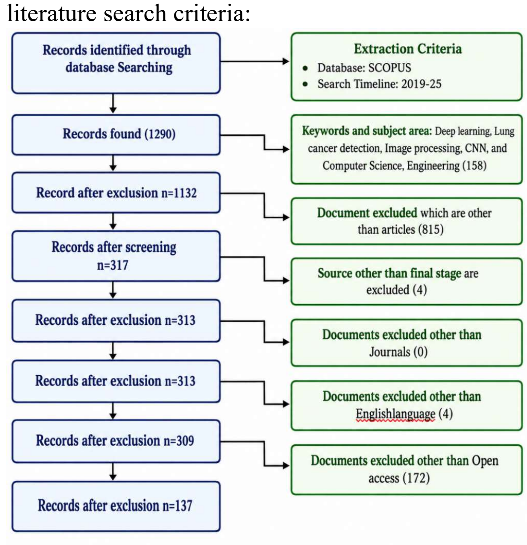


Figure 6: PRISMA Model for literature analysis

The first search generated 1396 records. After applying the year filter (2019–2026), 1290 records were retained. Subject area filtering (DL, Lung cancer detection, Image processing, CNN, Computer Science and Engineering) reduced it to 1132 records. The document type was restricted to peer-reviewed journal articles, resulting in 317 studies eligible for title screening. During the title screening process, 815 studies were irrelevant to lung cancer or did not have any ML/DL-based implementation and thus were excluded. A total of 309 full-text articles is assessed for eligibility, after the full-text review, 172 studies were excluded due to lack of experimental validation, lack of DL-specific implementation, or lack of performance analysis based on datasets. Finally, 137 studies that met all inclusion criteria have been included in this systematic review. Figure 6 shows a PRISMA-based description of filtering and screening, hence systematically reducing the number of studies from identification through to final inclusion. Selected studies were then analysed with respect to detection techniques used, datasets, performance evaluation metrics adopted, strategies for deployment considered as well as research limitations so as to synthesize current trends plus open challenges in lung cancer detection research. The screening and evaluation of eligibility criteria are done with predefined inclusion and exclusion criteria that are summarized in table 2. **Table 2: Inclusion and Exclusion Criteria**

Criterion	Inclusion	Exclusion	Justification
Keywords	DL, Lung cancer detection, Image processing, CNN	Studies unrelated to DL-based lung cancer detection	Ensures the selection of studies directly relevant to the core research domain and objectives.
Document Type	Peer-reviewed journal articles	Conference papers, book chapters, editorials	Ensures high-quality, well-reviewed, and reliable research contributions.
Source Type	Journals	Book series, books	Ensure academic rigour and reproducibility.
Timeframe	2019–2026	Published before 2019	Focus on recent DL advancements.
Language	English	Non-English	We include only English-language articles to ensure global accessibility, as well as due to time constraints in translating non-English publications.
Validation	Experimental evaluation using benchmark or real-world datasets	Theoretical-only studies without experimental validation	Ensures practical applicability and reliability of the proposed models through empirical evidence.
Data Availability	Papers with full text accessible	Abstracts only	Facilitates detailed analysis of methodologies and results.

4. Results

4.1 Study Characteristics

The proposed novel DL and image processing model for the detection of lung cancer shows a clear and gradual increasing trend in recent years.

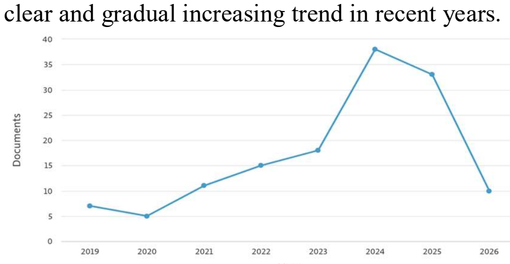


Figure 7: Document by year

The number of documents rose from 7 to 5 in the year of 2019-2020, and then increases steadily to 11 documents in 2021, 15 documents in 2022, and 18 documents in 2023, with a great jump to 38 documents in 2024, this suggests that DL with image pre-processing techniques in lung cancer detection are rapidly developing and is receiving huge attention. Despite the subsequent decline of number of documents to 33 and 10 in 2025 and 2026 respectively, the number of research has been steadily increased and these indicates that the proposed model plays an essential role for correct, timely and automatic lung cancer detection.

Table 3: Literature Review of Lung Cancer Detection Methods

Autho	Dataset	Prepro	Model /	Perfor

r (Year)	Used	cessing Techniques	Method	mance Results
Wang et al., (2022)	PCamKaggle	Normalization, WSI processing	CNN-GRU Hybrid	Accuracy 86.21%, precision 85.50%, sensitivity 85.60%, specificity 84.71%, F1-score 88%, while AUC 0.89
Reddy et al., (2025)	Drug dataset (1.048 M moleculs es)	Data encoding	Graph Attention Network	Accuracy: 89.55, precision: 90.5, recall: 88.1, F1-score: 89.2
Zhang et al., (2025)	UOH & OTMC CT datasets	Slice selection (PM + PSM)	ILD-Slider (3D Adapter)	Accuracy: 79.6%, recall: 73, precision: 75, F1-score: 74
Wang et al., (2026)	LIDC-IDRI	Normalization	LungDetectNet (MedYOLO-based)	Mean Average Precision (MAP) of 0.793, with a precision of 0.896 and a recall of 0.664, precision: 76.3
Shatnawiet al., (2025)	Multi-class CT dataset	Image enhancement	EfficientNetB0	Accuracy: 97.9, precision: 99.5, recall: 99.2, F1-score: 99.6
Musthafaet al., (2024)	IQ-OTHNCCD	Resizing, Normalization, Gaussian blur, SMOTE	CNN	Accuracy: 99.64, recall: 99, precision: 96.7, F1-score: 98.36
Islam et al., (2023)	COVID + Lung cancer datasets	Image normalization	DCNN-GRU + XAI	Accuracy: 99.30, recall: 99, Precision: 99, f1-score: 99
Salam et al., (2026)	LIDC-IDRI, LUNA16, TCIA	Normalization, Augmentation	DualSet ViT-PSO-SVM	Accuracy: 96.75, recall: 96.20, precision: 95.5, F1-score: 95.85
Hamidi and Ahmadi (2026)	CT Scan dataset	Preprocessing + augmentation	YOLOv5 + ResNet101	Precision: 83.72, recall: 97.72, DSC: 90.09, F1-score: 90, IoU: 82.24
Ramk	Camely	Otsu +	ImDeTra	Accura

umaret al., (2024)	on16/17	clustering	C-BCNet-MIL	cy: 95.9, precision: 98, recall: 92.9, F1-score: 90, DSC: 90
Ibrahimet al., (2021)	X-ray + CT dataset	Image fusion	VGG19 + CNN	98.05 % accuracy (ACC), 98.05 % recall, 98.43 % precision, F1 score, 97.7% MCC, and 99.66 % AUC
Sahu et al., (2022)	1359 CT images	Preprocessing + augmentation	Stacked AlexNet-19	Accuracy, recall, and specificity value of 93.67 %, 0.93, and 0.97 respectively
Siddiquiet al., (2026)	HAM10000, ISIC	SMOTE (latent space)	CANNSkin	94.27 % accuracy, 93.95 % precision, 94.09 % recall, and 99.02 % F1-score
Joseph et al., (2025)	CT scan dataset	Resizing, normalization, GAN augmentation	GA-AGN	Accuracy: 93.8, recall: 94.8, precision: 94.4
Songet al., (2023)	Early Lung Cancer dataset	Preprocessing	3D CNN-CapsNet	Accuracy rate is 95.19 %, the recall is 92.31 %, the specificity is 98.08 %, and the F1-score is 0.95
Safdar et al., (2023)	Medical imaging dataset	Oversampling	End-to-End CNN	Accuracy: 83, recall: 68.66, F1-score: 80

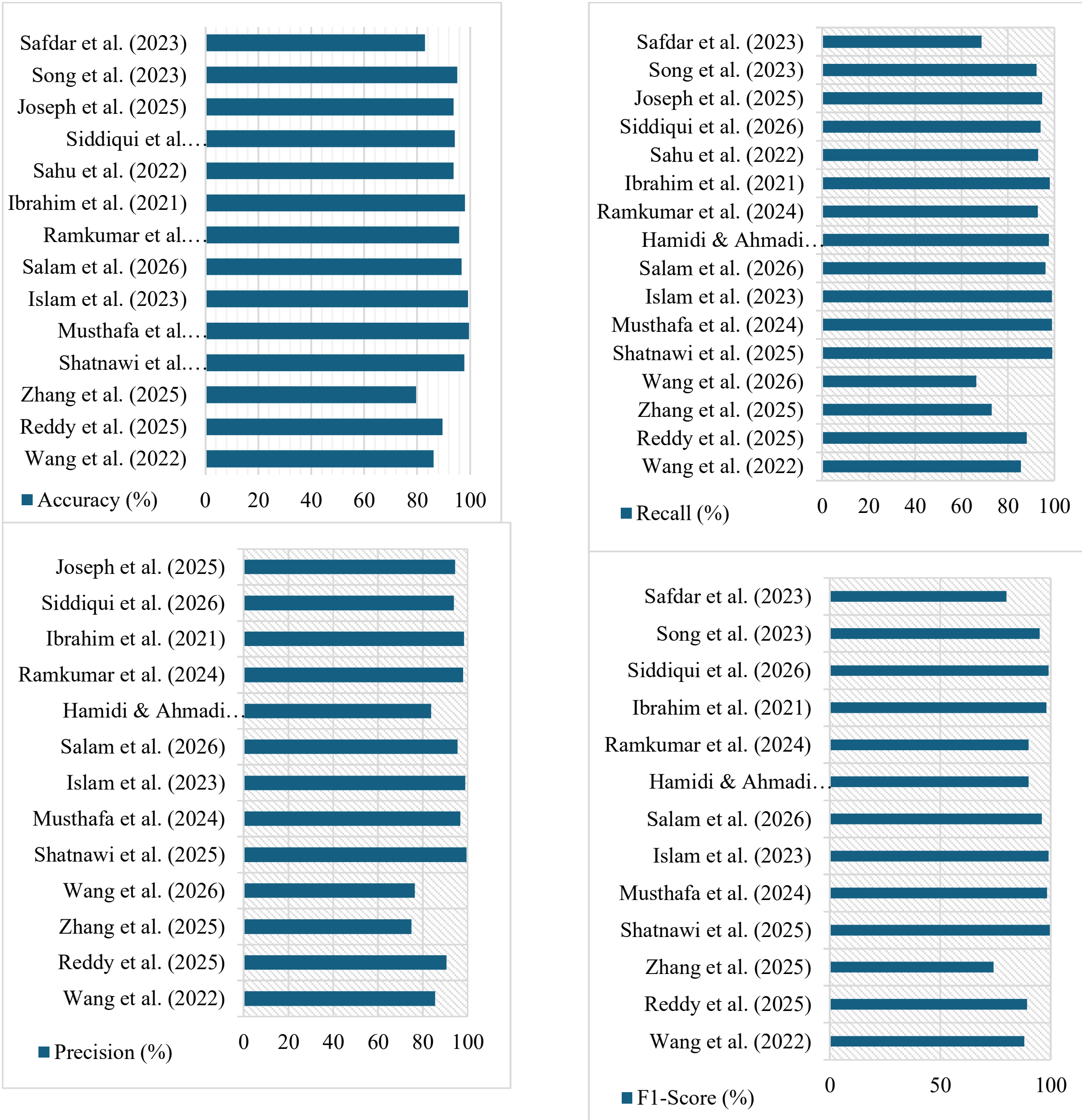


Figure8: Comparison graph of accuracy, precision, recall, and F1-score based on lung cancer detection methods

5. Discussion

Lung cancer detection has emerged as a prime research area owing to the disease's high mortality rate and the potential for improved survival outcomes through early diagnosis. The fast development of AI technology, especially DL and image processing techniques, has enabled considerable progress towards achieving an automatic and accurate diagnosis system. Various models that include CNNs, combined neural networks such as “CNN-RNN, CNN-BiLSTM, and image transfer learning models like ResNet, DenseNet, and EfficientNet”, along with object detection models like YOLO and Vision Transformer (ViT), have been used successfully to accurately classify and detect lesions on lungs.

Image processing techniques that include CLAHE, histogram equalization, filtering, segmentation, and region-of-interest detection have been largely used for improving images.

In conclusion, this research finds that the advanced techniques employed perform well across different data sets and imaging modalities. A maximum accuracy of 99.9%, a recall rate of 99-100% and F1-score of more than 99% was obtained through classification, while in the case of segmentation techniques, maximum Dice Similarity Coefficient (DSC) was 0.991 in locating tumor. The object detection-based methods such as YOLO-based methods attained mAP values up to 0.894 in robust detection of tumor. The aforementioned strengths of these approaches, however, do not remove some fundamental challenges in image classification, such as data imbalance, lack of large labeled datasets, variation of imaging conditions, and opacity of DL techniques, and thus limit its generalizability and clinical translation. In the future, effort needs to be made to make DL models explainable, light weighted and generalizable with common standard testing protocol and real-world verification.

6. Conclusion

In summary, DL and image processing algorithms are investigated in the context of lung cancer detection, and the study confirms the value of these techniques for augmenting diagnostic accuracy and speed. The systematic review, performed across 137 studies (2019-2026), concludes that new approaches such as CNNs, hybrid models, transfer learning and YOLO-based models can exhibit good results for detecting lung cancer. It's noted that, in the context of classification, results achieved values of 99.9% for accuracy, 99-100% for recall and greater than 99% for F1-score which indicates that the model can be considered effective. The methods used for segmentation reported DSC values up to 99.1% and detection models obtained mAP up to 0.894. In addition, pre-processing methods like CLAHE, filtering and ROI extraction can further improve the outcomes.

However, the presence of these high-performance results is accompanied by several problems that include unbalanced data sets, a shortage of labeled data, non-interpretability of the model, and large computational requirements. Such problems prevent the use of these models in practical applications. Future studies are expected to concentrate on creating interpretable, compact, and transferable models, among other things. In summary, the application of DL and image processing technologies offers a highly effective way of detecting lung cancer at an early stage, thus resulting in reduced mortality rates.

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