# Lung Cancer Detection in CT Images Using Deep Learning Techniques: A Survey Review

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## Abstract

INTRODUCTION: The Computed Tomography (CT) imaging-based Lung cancer detection is crucial for early diagnosis. This survey paper presents an overview of the techniques and advancements in CT-based lung cancer detection. It covers the fundamentals of CT imaging, including principles, types, and protocols.
OBJECTIVES: The paper explores image processing techniques for pre-processing, such as noise reduction, enhancement, and segmentation.
METHODS: Additionally, it discusses feature extraction methods, including shape, texture, and intensity-based features, as well as Deep Learning (DL) and Machine Learning (ML) methods for automated classification.
RESULTS: Computerised systems and their integration is examined with CT imaging along with performance evaluation metrics. The survey concludes by addressing challenges, limitations, and future directions. The imaging modalities and artificial intelligence techniques are used to improve lung cancer detection.
CONCLUSION: This comprehensive survey aims to provide a concise understanding of CT-based lung cancer detection for researchers and healthcare professionals.

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## 1. Introduction

One of the most prevalent and deadly forms of cancer worldwide is Lung cancer. It poses a significant public health challenge, accounting for substantial numerous deaths globally due to a cancer [1]. Early detection helps to provide a timely intervention and effective treatment strategies. The CT imaging has emerged as a vital tool in the lung cancer detection, offering detailed and cross-sectional images of the lungs with high resolution and accuracy [2, 3]. Over the years, advancements in CT technology and image analysis techniques have greatly improved the capabilities of lung cancer detection. CT imaging provides radiologists with the ability to visualize and characterize lung nodules, facilitating early diagnosis and subsequent treatment

planning. The ability to precisely identify and classify these nodules is paramount in determining their malignancy and guiding appropriate clinical decisions.

The process of lung cancer detection using CT imaging involves various stages, including image acquisition, pre-processing, classification and feature extraction. An Image pre-processing method used to minimise noise and enhance images, play a crucial role in improving the quality of CT images, thereby enhancing the detection of lung nodules [4]. Feature extraction methods extract quantitative measurements from the CT images, capturing relevant information about the shape, texture, and intensity characteristics of the nodules. These features serve as discriminative markers for distinguishing between benign and malignant nodules [5, 6]. Furthermore, ML and DL algorithms have shown remarkable potential in automating

the classification process and aiding radiologists in their decision-making. These algorithms can learn from a large volume of annotated CT images and develop robust models capable of accurately categorizing lung nodules based on their malignancy. This integration of artificial intelligence techniques with CT imaging has knowledge for best detection. However, despite the significant progress made in CT-based lung cancer detection, several challenges persist. The availability of annotated datasets is trained and validated, standardization of imaging protocols. Addressing these challenges and further advancing the field of CT-based lung cancer detection is essential for improving patient care, optimizing treatment strategies, and reducing the mortality rate associated with this devastating disease.

In this work, the comprehensive overview of lung cancer detection is presented using CT imaging. By exploring the advancements, challenges, and potential future directions, we hope to contribute to the collective knowledge and inspire further research and innovation in this critical area of medical imaging. The ultimate goal is to increase an efficiency, accuracy and effectiveness of lung cancer detection that leads to better patient outcomes effectively in global.

## 1.1. Medical image processing

CT imaging plays a pivotal role in modern medical diagnostics, providing detailed cross-sectional images of the human body. In medical field, CT images serve as a fundamental tool for identifying and characterizing lung nodules. However, before accurate analysis and interpretation can occur, CT images often undergo pre-processing techniques to enhance their quality and extract relevant features. Additionally, the application of classification algorithms aids in automated nodule classification, assisting radiologists in making accurate diagnoses and treatment decisions. The overall all ML and DL based image processing technique steps shown in Figure 1.
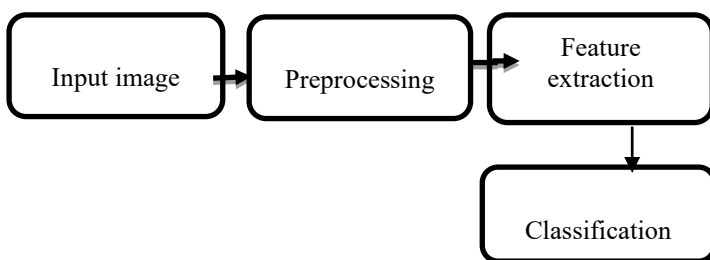


**Figure 1.** Overall processing steps

CT image pre-processing encompasses a range of techniques aimed at improving image quality and reducing noise artifacts. One of the most common pre-processing steps is noise reduction. CT images are prone to various types of noise, including Gaussian and salt-and-pepper noise, which can hinder the accurate detection of lung nodules. To address this, filters such as median, Gaussian, and bilateral filters are commonly employed. The median filter is effective in removing salt-and-pepper noise, while the Gaussian and bilateral filters smooth the image, reducing random variations in pixel intensities caused by noise. These filters preserve the edges of structures, ensuring that important nodule details are not lost during the pre-processing stage. In addition to noise reduction, CT image pre-processing may involve contrast enhancement techniques. Histogram equalization and contrast stretching are commonly utilized methods to improve the visual appearance of CT images, enhancing the visibility of structures with varying intensities. Histogram equalization redistributes the pixel intensities across the entire range, enhancing the contrast and details in the image. Contrast stretching stretches the intensity range to cover the full dynamic range of the display, enhancing the visibility of subtle variations in pixel intensities within the lung nodules. These techniques adjust the image's pixel intensity distribution, improving the overall clarity and aiding in the identification of lung nodules.

Once the pre-processing stage is complete, feature extraction techniques are employed to capture quantitative information from the CT images. The features are extracted. Shape-based features provide geometric measurements of the lung nodules, such as volume, surface area, and sphericity. These features capture the size and shape characteristics of the nodules, providing valuable information for their classification. Texture-based features characterize the spatial arrangement and variations in pixel intensities within the nodules. Common texture analysis techniques include gray-level, run-length matrix and Gabor filters [7]. These features capture the heterogeneity and textural patterns within the nodules, aiding in differentiating among malignant and benign nodules. Also, this feature includes mean, standard deviation, and histogram-based features to learn the image patterns deeply. The accuracy of DL or ML model purely depends on feature selection and extraction.

With the extracted features in hand, classification algorithms are employed for lung prediction. ML algorithms have been widely utilized in lung cancer classification. These algorithms are trained using a set of labelled CT images and their corresponding features, learning to differentiate between different nodule types based on the extracted characteristics. DL algorithms, particularly CNN, have shown remarkable performance that learnt hierarchical features directly from the raw CT images, allowing for end-to-end classification without the need for explicit feature extraction.

The integration of these filtering techniques, feature extraction methods, and classification algorithms has significantly advanced the field of CT-based lung cancer detection. These tools and techniques aid radiologists in making accurate diagnoses, reducing false positives and false negatives, and ultimately improving patient outcomes. In this paper, we will explore various pre-processing

techniques, including filters for noise reduction and contrast enhancement. It will delve into the details of each technique, discussing their underlying principles and their impact on CT image quality. Additionally, we will discuss feature extraction methods, encompassing shape-based, texture-based, and intensity-based features, highlighting their relevance in capturing essential characteristics of lung nodules. Furthermore, it will provide an in-depth analysis of classification algorithms commonly employed in lung cancer detection, ranging from traditional ML algorithms to cutting-edge deep learning approaches. We will discuss the limitations and advantages of every algorithm, emphasizing their role in automating nodule classification and supporting radiologists in their diagnostic process. Through this comprehensive exploration, it aims to provide a detailed understanding methods used in CT-based lung cancer detection and their significance in improving diagnostic accuracy and patient care.

## 2. Literature Survey

*Massion, et al.* [8] proposed a CAD method for coronary calcifications in helical X-ray CT images. The algorithm involves classifying heart slices, extracting the heart region, detecting candidate regions of coronary calcifications, and employing a neural network-based diagnostic rule to refine the diagnosis by excluding artifact regions. This method improves an accuracy and reliability of diagnosing coronary calcifications in mass screening for lung cancer. *Yongbum Lee et al.* [9] have developed a CAD technique to find lung nodules in CT images. Their approach introduces a template-matching model combined with genetic algorithm (GA). A GA is determined the target location and choose an appropriate template image for quick template matching. Also, the fuzzy logic is integrated with template matching to increase the classification capability of algorithm. The authors extracted 13 feature values to eliminate false-positive findings. The study involved 20 clinical cases and achieved a 72% detection rate with approximately 1.1 false positives per sectional image.

*Brown et al.* [10] introduced DL models for medical image processing. It proposed a novel approach that utilizes an image processing techniques to find shape and size of nodule. This method offers a promising solution for medical field. A segmentation-by-registration approach is presented by *Sluimer et al.* [11] for lung scans. Further, voxel classification is integrated to increase a segmentation accuracy of lung cancer detection. Compared to a user-interactive technique, the voxel classification approach shows higher accuracy.

*Diciotti et al.* [12] have presented a semiautomatic segmentation technique based on grey-level similarity. It applies fusion aggregation strategy to perform a volumetric analysis. The techniques validation on small nodule low-dose CT scans and in vivo lung nodules demonstrated promising results, including accurate outlining of nodule contours and a low RMS error. *Woo et al.* [13] aimed to obtain multimodal tumor images using CT images. A

registration method combined with fuzzy logic were employed. Clinical CT images were acquired to enhance anatomical localization of PET uptake. The study included 124I-FIAU-PET scans of mice with contrast-enhanced CT images and hepatocellular carcinoma taken three hours after contrast agent injection. *Sun et al.* [14] proposed lung segmentation in the presence of pathologies based on fully automated method. It has two steps namely robust active shape model (RASM) model attain an initial lung outline, and an optimal surface finding model for further adaptation. The evaluation achieved an average Dice coefficient of 0.867±0 than previous respectively. *Xu et al.* [15] provided a novel approach that incorporates a sparse constraint into a statistical iterative reconstruction model using a redundant dictionary. This dictionary can be adaptively defined as part of the reconstruction process. To minimize the objective function, they employed an alternating minimization scheme. To evaluate the effectiveness of their approach, they conducted experiments using low-dose X-ray images.

*Han et al.* [16] conducted a study highlighting the significance of CT imaging signs in diagnosing diseases. They established specific criteria for selecting CT scans and imaging signs to be included in their database. The researchers also developed software capable of annotating abnormal regions and designed an efficient storage system for CT images and annotation data. As part of their work, they introduced LISS, a publicly accessible database. These regions were further classified into CT images. The database provides ground truth annotations alongside the corresponding categories for each abnormal region. *Song et al.* [17] introduced a segmentation model consisting of four steps: pre-processing, seed point identification, lesion extraction, and overall classification. The approach achieves high lesion detection sensitivity (96.35%) without requiring human interaction or training datasets. Evaluation demonstrates comparable segmentation accuracy to manual segmentation. Comparisons with level set and skeleton graph cut methods show significant improvement in segmentation accuracy using TBGA.

*Zhang et al.* [18] have proposed a texture-based image reconstruction model that integrates the edge-preserving regional noise smoothing paradigm with the Markov random field model. The MRF model incorporates image textures for noise smoothening. The feasibility of the framework is demonstrated through experiments using public data set images. *Setio et al.* [19] proposed a novel CAD system to extract multi-level feature from lung CT images using multi-view convolutional networks (ConvNets). The system combines three candidate detectors for different types of nodules and extracts 2-D patches from various planes. Multiple convolution layers used, and a fusion method combine their outputs for final classification. The method achieves high detection sensitivities on the public dataset and is evaluated on public datasets. *Dou et al.* [20] addressed the challenge of lung image processing. They developed a 3D-CNN model for volumetric. Additionally, a strategy to encode multilevel contextual information is introduced. The framework achieves maximum accuracy level in LUNA16 challenge.

*Jiang et al.* [21] developed modified residual layer-based CNN, for lung tumor detection and segmentation. Residual connections are employed to fuse networks in order to evaluate their effectiveness across various datasets and tumor types. This methodology was tested on different data sets. The training utilized the multiple datasets, validation was performed on the specific dataset, and the Kaggle dataset was used for testing purposes. *Xie et al.* [22] proposed a multi-scale DL model for malignant and benign lung cancers in CT image. The model decomposes images into nine fixed views and utilizes knowledge-based collaborative sub models to capture different characteristics. The sub models fine-tune pre-trained networks using three types of image patches. An adaptive weighting scheme is applied to jointly classify the nodules, and a penalty loss function is employed to reduce false negatives. Evaluation on the public dataset demonstrates superior performance compared to existing techniques, achieving an accuracy of 92. 3 % and precision rate of 96.2 %.

*Kumar et al.* [23] proposed a supervised convolutional neural network (CNN) to improve the processing in CT images. The CNN encodes modality-specific features and generates fusion maps that capture the important features. The results shows that the capability of CNN model for extracting multiple features in different image modalities in dataset images. The combination of CNN with feature selection technique leads to better performance of medical image processing. *Zheng et al.* [24] proposed a CNN-based approach that uses maximum intensity for lung nodule detection. The consideration of intensity with axial section slices improves the spatial information observation of the model for accurate nodule detection. By leveraging the morphological differences between nodules and vessels, their method achieves high sensitivity, with 92.7% of improved performance rate.

*Ozdemir et al.* [25] proposed a DL model for medical image processing. Their system, based on 3D CNN, and applied on Kaggle Data sets. By considering the discriminate features for segmentation, the performance of model is improved. *Masood et al.* [26] propose a modified recurrent neural network for automated image processing. Their system uses layer fusion technique with median intensity projection to accurately detect lung nodules. The system achieves promising detection performance on the public dataset, with a sensitivity of 89.2 % and classification accuracy of 96.80%, outperforming existing methods in nodule detection and classification. In their study, *Wang et al.* [27] devised a DL framework for COVID-19 classification using CT images, employing a weakly-supervised approach. This framework encompasses lung segmentation, a DL network for predicting COVID-19 probability, and lesion localization utilizing activation regions and unsupervised connected components. The algorithm achieved high performance with a very high-performance parameter value.

*Zhou et al.* [28] developed a modified CNN method for segmenting and quantifying COVID-19 affected regions on CT scans. Their method includes a CT scan simulator and a new DL algorithm that addresses the problem,

improving segmentation accuracy. *Liu et al.* [29] suggested enhancing lung nodule detection systems' generalization and robustness by incorporating adversarial synthetic and confrontational attack samples into the trained data. This approach utilizes projected gradient descent (PGD) to generate challenging examples for nodules and noise patterns that trigger over-confident mistakes. *Yao et al.* [30] presented a new approach for lung segmentation. The proposed approach test for analysing the lungs of COVID-19 affected patients for disease assessments. The strong patterns of lesions are identified using voxel-level anomaly modelling. For classification, a normalcy-recognizing network (NormNet) is applied. *Mei et al.* [31] introduced slice aware network for lung image processing. It involves the processing of image pixels with the awareness of region of interest. Experimental results on CT lung image dataset prove the effectiveness of slice aware network in terms of true positive and negative detection rates.

*Chen et al.* [32] have introduced a 3D detection framework for nonsmall cell lung cancer (NSCLC) using 18F-FDG PET/CT images, guided by multimodality attention fusion. Their customized dual-path 3D CenterNet and multimodality attention module achieve improved sensitivity for NSCLC detection, outperforming previous methods. *Ahmed et al.* [33] presented an automated DL based system for lung cancer diagnosis, classification, and pulmonary segmentation. They evaluate various detection architectures and achieve reduced false positive rates and improved accuracy using a publicly available LIDC-IDRI dataset. *Li et al.* [34] have introduced a new DL framework based on gate consideration strategy for lung nodule segmentation. The gate attention mechanism used to extract all level of features with minimum complexity. Also, the parameter tuning is applied for low-cost computation.

## 3. Dataset Availability and Performance Measures

The dataset can be accessed and downloaded from the following website: https://www.kaggle.com/datasets/mohamedhanyyy/chest-ctscan-images. Kaggle, a renowned platform for data science and machine learning, hosts this dataset, providing a reliable source for researchers and practitioners. The dataset provides images in two commonly used formats, JPG and PNG, to ensure compatibility with various machine learning frameworks and tools. The dataset encompasses different cancers, along with a separate folder containing images of normal lung cells. When evaluating the performance of CT lung cancer image segmentation and classification models, several metrics can be used. Here are some commonly used performance metrics:

*Dice Coefficient (DSC):* The Dice coefficient calculates overlap between segmented outputs to ground truth to evaluate a performance of segmentation model. It can be computed as follows.

$$DSC = \frac{(2 \times Intersection)}{predicted\ Area + Ground\ Truth\ Area} \quad (1)$$

*Intersection over Union (IoU):* It is the ratio of the connection of the segmented and ground truth image. It quantifies the degree of overlap between the two masks and is commonly used for evaluating segmentation models.

$$IOU = \frac{Intersection}{Union} \quad (2)$$

*Sensitivity/Recall:* Sensitivity is the capability of the model to correctly spot the lung cancer images. It calculates the proportion of true positive cases that are properly detected out of all the actual positive cases.

$$Sensitivity = \frac{Correctly\ Predicted\ Cancer\ Cases}{(Correctly\ Predicted\ Cancer\ Cases + Incorrectly\ Predicted\ Cancer\ Cases)} \quad (3)$$

*Specificity:* Specificity measures the capability of the model to correctly spot negative cases (non-cancerous regions). It calculates the proportion of true negative cases that identified.

$$Specificity = \frac{Correctly\ Predicted\ non-Cancer\ Cases}{(Correctly\ Predicted\ non-Cancer\ Cases + Incorrectly\ Predicted\ non-Cancer\ Cases)} \quad (4)$$

*Accuracy:* Accuracy is a parameter that estimates the correctness of segmentation or classification model. It calculates the proportion of correctly classified cases (both positive and negative) out of the total number of samples.

$$Accuracy = \frac{(True\ Positives + True\ Negatives)}{Total\ Samples} \quad (5)$$

*Precision:* Precision quantifies the ratio of correctly predicted cancer cases out of all the predicted cancer cases. It can be computed as follows.

$$Precision = \frac{True\ Positives}{(True\ Positives + False\ Positives)} \quad (6)$$

*F1 Score:* It integrates precision and sensitivity into a single parameter. It can be computed as follows.

$$F1\ Score = \frac{2 \times (precision \times Sensitivity)}{(precision + Sensitivity)} \quad (7)$$

Table 1. Performance analysis of proposed models

| Methods | Accuracy (%) | Specificity (%) | Sensitivity (%) | F1score (%) |
|---|---|---|---|---|
| CNN | 96.96 | 98.78 | 96.23 | 99.5 |
| ResNet | 97.32 | 97.56 | 97.22 | 99 |
| VGG | 97.53 | 99.29 | 96.81 | 99 |
| U-Net | 98.34 | 96.12 | 99 | 98 |
| SegNet | 94.35 | 99.55 | 92.53 | 99 |
| Butterfly Net | 98.9 | 99.6 | 99.2 | 99.2 |

The performance of different models for lung images processing given in table 1. CNN achieves an accuracy of 96.96%, demonstrating a remarkable ability to correctly identify both present (96.23% sensitivity) and absent (98.78% specificity) elements. Its exceptional F1 score of 99.5 underscores a harmonious blend of precision and recall. ResNet follows suit, boasting a solid accuracy of 97.32%, effectively distinguishing positive instances (97.22% sensitivity) and negative instances (97.56% specificity), yielding an impressive F1 score of 99. VGG maintains its stride with an accuracy of 97.53%, adept at identifying negatives (99.29% specificity) and positives (96.81% sensitivity), reflected in its F1 score of 99.

Meanwhile, U-Net secures a high accuracy of 98.34%, excelling in capturing positives (99% sensitivity) and showing a slight trade-off with negatives (96.12% specificity), resulting in an F1 score of 98. Despite a slightly lower accuracy of 94.35%, SegNet excels in recognizing negatives (99.55% specificity) while facing some challenges in sensitivity (92.53%), maintaining a strong F1 score of 99. At the forefront, ButterflyNet showcases exceptional performance, achieving an accuracy of 98.9%, marked by superior sensitivity (99.2%) and specificity (99.6%), culminating in an outstanding F1 score of 99.2. The performance of model graphically shown in Figure 2.
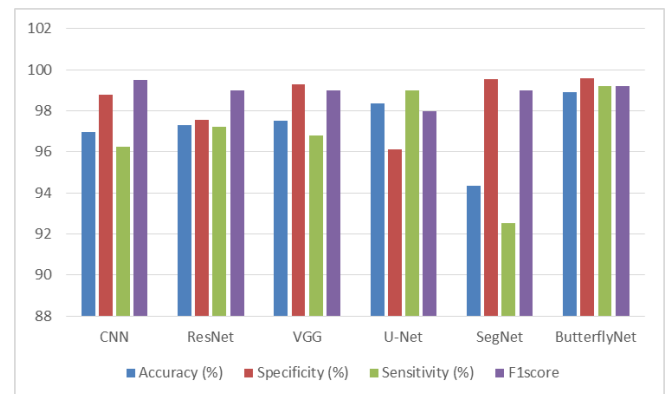
**Figure 2**. Different architecture chart model

# 4. Conclusion

In conclusion, this survey paper has provided a comprehensive overview of the advancements and techniques in lung cancer detection using CT imaging. CT imaging has proven to be a valuable tool in the early diagnosis of lung cancer, enabling timely intervention and improved patient outcomes. Through the exploration of various image processing techniques, including noise reduction, enhancement, and segmentation, the quality of CT images can be improved, facilitating accurate identification and characterization of lung nodules. Moreover, the integration of ML and DL algorithms has shown promising results in automated classification, aiding radiologists in distinguishing severity stages. The incorporation of CAD systems has enhanced the capabilities of CT imaging by providing additional decision support to radiologists. By utilizing performance evaluation metrics, the accuracy and efficiency of CAD systems can be assessed, leading to more reliable and consistent results. However, several challenges and limitations remain in image processing approaches. The availability of large, annotated datasets, standardization of imaging protocols, and the incidence of false-positive or false-negative results pose on-going concerns. Addressing these challenges and exploring future research directions, such as the integration of other imaging modalities and the utilization of artificial intelligence techniques, will further advance the field of lung cancer detection. Ultimately, the knowledge gained from this survey paper can inform researchers, clinicians, and healthcare professionals about the current state-of-the-art in CT-based lung cancer detection. By staying abreast of the advancements, understanding the challenges, and exploring future possibilities, we can collectively work towards improving the accuracy, efficiency, and effectiveness of lung cancer detection, ultimately leading to improved patient care and outcomes.

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