AI in lung nodule detection and diagnosis

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Abstract

Lung nodule detection plays a crucial role in the early diagnosis and management of lung cancer, where accurate segmentation and classification can significantly improve patient outcomes. Recent advancements in artificial intelligence (AI) and deep learning have significantly enhanced the ability of medical imaging to automatically detect and classify lung nodules, overcoming the limitations of traditional diagnostic methods. This chapter explores advancements in AI techniques for lung nodule segmentation, classification, and detection. These models offer robust solutions by leveraging self-attention mechanisms, computational efficiency, and large-scale pre-training, improving accuracy and generalization across diverse datasets. While traditional machine learning algorithms have proven valuable, they demonstrate limitations in processing complex sample data. The recent advent of deep learning has transformed medical image analysis, facilitating significant advancements in this domain. This chapter delves into recent advancements in deep learning methodologies for segmenting, classifying, and detecting pulmonary nodules. Traditional machine learning techniques, such as Support Vector Machines (SVM) and K-Nearest Neighbors (KNN), exhibit certain limitations, prompting the adoption of more advanced approaches, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNN), and Generative Adversarial Networks (GAN). This chapter also explores the integration of ensemble models and cutting-edge techniques, highlighting the recent advancements in lung cancer diagnosis. Combining deep learning algorithms with various analytical methods has significantly enhanced the accuracy and effectiveness of pulmonary nodule analysis, surpassing traditional approaches, particularly in nodule classification. Despite the ongoing challenges, continuous technological progress is anticipated to improve further the application of deep learning in medical diagnostics, particularly for the early detection and diagnosis of lung cancer.

1. Introduction

Lung cancer remains one of the deadliest cancers globally and poses a significant threat to human health. In 2022, approximately 2.5 million new cases were diagnosed worldwide, with 1.8 million deaths according to the latest assessment by the International Agency for Research on

Cancer (IARC) of the World Health Organization (WHO) [1]. Early-stage lung cancer often presents with symptoms that are not easily noticeable, leading patients to miss the optimal treatment window. Early detection is essential, and CT scan screening is instrumental in identifying lesions prior to the onset of clinical symptoms, thereby significantly improving the likelihood of diagnosing lung cancer at an early stage. This emphasizes the persistent challenges in addressing lung cancer and underscores the significance of ongoing research and preventive strategies. Computer-aided diagnosis (CAD) systems have been developed to support the analysis of medical images by automating the identification of irregularities, such as in CT scans [2]. These systems play a crucial role in enhancing diagnostic precision and reducing the workload of radiologists. CAD systems can identify and analyze pulmonary nodules in lung cancer detection. With advancements in deep learning and artificial intelligence, these systems have become more accurate, faster, and more reliable, facilitating the early diagnosis of lung cancer.

In clinical practice, lung cancer detection begins with identifying pulmonary nodules, a key radiological sign for early diagnosis. Although various factors contribute to potential malignancy, nodule size (< 3 cm) is a critical indicator. These nodules typically appear as small, rounded opacities within the lung parenchyma on imaging [3], [4]. Lung nodules vary widely in shape, size, and type [5]. Pulmonary nodules can range in size from less than 0.2 cm up to approximately 0.3 cm and often appear spherical [6]. However, some nodules have intricated vascular attachments within areas of the lung that contain large blood vessels, making them difficult to detect. For instance, solid nodules (SNs) and sub-solid nodules (SSNs) exhibit densities only marginally higher than those of the surrounding lung parenchyma, further complicating their identification. Solid nodules (SNs), which are completely opaque on imaging, are the most prevalent type of SN. Conversely, subsolid nodules (SSNs) are identified by ground-glass opacity (GGO) and can be divided into part-solid and pure ground-glass nodules [6]. These SSNs have greater attenuation than the surrounding lung tissue but do not entirely obscure the underlying broncho-vascular structures.

Accurately measuring the diameter of a lung nodule is crucial for diagnosis because its size is strongly linked to its probability of being cancerous. The main guidelines for the risk associated with lung nodule measurement, including the Fleischner Society, German S3, and British Thoracic Society, all emphasize risk-based strategies but vary in their specific advice. The Fleischner guidelines focus on follow-up based on nodule size, with no regular monitoring of low-risk nodules smaller than 0.6 cm. The German S3 guidelines cover a wider range of patients and suggest CT monitoring for nodules up to 0.8 cm, with PET-CT or biopsy recommended for larger nodules. The

British Thoracic Society guidelines are distinct in using quantitative risk calculators, recommending CT monitoring for nodules under 0.8 cm and a more thorough evaluation for larger nodules with a malignancy risk of 10% or higher [7]. These guidelines aim to achieve a balance between the early detection of issues and avoiding unnecessary interventions. However, accurately measuring tiny nodules can be difficult, leading to potential errors in determining the nodule size. Nonetheless, the recent progress in imaging technology has enhanced the precision of these measurements.

Lung cancer treatment can be challenging, and approximately 70% of patients require radiation therapy, which can sometimes result in lung damage and reduce the effectiveness of the treatment. Radiologists frequently rely on CAD systems to enhance the accuracy of nodule identification and classification. These tools assist in minimizing errors, decreasing the likelihood of missed diagnoses, and providing a valuable second opinion when interpreting medical images [8]. Various studies showed that a CAD system can improve diagnostic accuracy by minimizing the differences between radiologist analyses [9]. Moreover, CAD systems offer data-driven decision approaches, such as biopsy recommendations [10], diagnostics checkups [9], and thoracotomies [8]. They aid in diagnostic evaluations, minimize unnecessary false-positive biopsies and thoracotomies, and differentiate between malignant and benign tumors [11].

The implementation of CAD systems in clinical settings has been demonstrated to enhance the accuracy of early detection of lung cancer. While CAD systems initially employed conventional methodologies, the integration of machine learning algorithms has led to enhanced precision. More recently, deep learning techniques have further augmented diagnostic accuracy.

2. CAD-based Pulmonary Lung Nodule Detection and Diagnosis

In recent years, advances in computer-aided diagnosis (CAD) systems have revolutionized several industries and significantly impacted the detection and diagnosis of lung cancer. Traditional methods of identifying lung nodules often rely on the skill of radiologists, are time-consuming, and can be subject to individual bias, which can affect the accuracy of diagnostic results. Typically, CAD-based systems involve several steps to detect and classify lung nodules. First, images are acquired from CT scans due to their high sensitivity and relatively low cost [12]. The images are then preprocessed to remove noise and artifacts [10], followed by extracting regions of interest (ROIs) to focus specifically on the lung area. Next, the lung region is segmented to separate it from the surrounding thoracic tissues, and potential nodules or lesions are identified. The system calculates the false positive (FP) rate by comparing the detected nodules with healthy tissue. Finally, the system extracts features, such as size, shape, and texture, to classify nodules as benign or malignant, as shown in Figure 1.

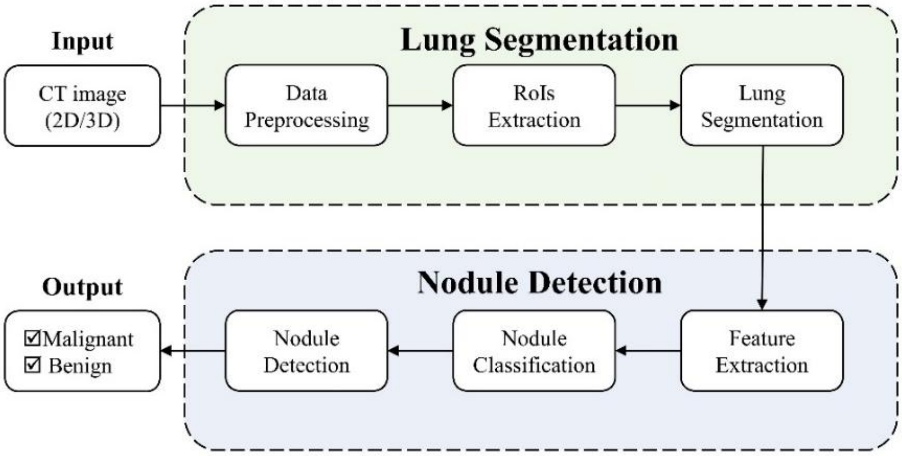

Figure 1. A general framework for CAD-based lung nodule detection system.

2.1. Datasets

High-quality datasets are essential for the training of deep learning models, as these models require substantial amounts of labeled data to identify lung nodules accurately. However, the creation of such datasets is complex and expensive. Despite these challenges, several research organizations have made their datasets publicly accessible to facilitate research on lung cancer detection. These datasets typically comprise CT scan images of the lungs annotated by radiologists with information regarding the size, location, and type of nodules. Open-source datasets are essential for advancing the development of CAD systems, which enhance the accuracy of detecting and classifying lung nodules by medical professionals. The availability of these datasets enables researchers to refine diagnostic tools, develop more effective training models, and ultimately contribute to earlier and more precise detection of lung cancer.

Table 1. Overview of different datasets for pulmonary lung nodule segmentation and detection.

Dataset	Number of Images	Image Size	Description	Annotation
LIDC-IDRI [5]	1,018	512 x 512	Pulmonary nodule Detection	✓
LUNA 16 [13]	888	512 x 512	Nodule Detection (Nodules > 3mm)	✓
NSCLC [14]	211	512 x 512	Non-Small Cell Lung Cancer	✓
ELCAP [15]	50	512 x 512	Early Lung Cancer Screening	✓
ANODE09 [16]	55	512 x 512	Nodule Detection (Various types)	✓
LNDb [17]	294	512 x 512	lung cancer detection	✓

The LIDC-IDRI [5] dataset consists of over 1,000 CT scan volumes from patients with lung cancer, with annotations for lung nodules provided by radiologists. It is widely used to develop and evaluate automatic nodule detection and classification algorithms. LUNA 16 [13] focuses on lung nodule detection and provides a large set of annotated CT scan slices from the LIDC-IDRI dataset. It is specifically designed for the LUNG 2016 Challenge and aims to assess the algorithm's performance in detecting pulmonary nodules. Non-Small Cell Lung Cancer (NSCLC) [14] dataset, often used for lung cancer research, includes clinical and imaging data and focus on identifying early-stage lung cancer and predicting treatment responses. The ELCAP [15] dataset is part of a long-term lung cancer screening program with chest CT scans and clinical data primarily used for early lung cancer detection. ANODE09 [16] was designed to evaluate automated nodule detection algorithms and includes CT scan slices annotated with nodule locations from the 2009 challenge. The Lung Nodule Database (LNDb) [17] provides CT scan images with annotated lung nodules, focusing on the early detection and classification of lung cancer. These datasets are invaluable resources for developing deep learning models and algorithms to improve early detection, diagnosis, and treatment planning for lung cancer.

2.2. Performance metrics

Performance metrics are essential for evaluating the effectiveness of deep learning algorithms for lung nodule segmentation and detection. These metrics help assess how well the model identifies and classifies lung nodules, which is crucial for diagnosing and treating lung cancer.

The most common performance metrics that assess the overall performance of deep learning models are listed in Table 2.

These metrics are critical in evaluating the effectiveness of lung nodule segmentation and classification models for medical imaging. Sensitivity, also known as the true positive rate (TP), measures the model's ability to correctly identify positive cases such as malignant nodules, making it essential to minimize missed diagnoses. The accuracy indicates the overall correctness of the model by calculating the proportion of true results (TP and TN) among the total number of cases. In segmentation tasks, the Dice Similarity Coefficient (DSC) and Intersection over Union (IoU) are widely used to assess the overlap between the predicted segmentation and the ground truth. The DSC emphasizes similarity by balancing FP and FN, whereas IoU measures the area of overlap relative to the total area covered by predicted and actual regions. The F1-score, which is the harmonic mean of precision and recall, offers a balanced measure that is particularly useful in cases of class imbalance

Table 2. Performance metrics for assessing lung nodule segmentation and classification.

Metric	**Description**	**Formula***
Sensitivity (SEN)	Measures real detected nodules	$\frac{TP}{TP+FN}$
Accuracy (ACC)	Overall correct nodule detection	$\frac{TP+TN}{TP+TN+FP+FN}$
Precision	Out of all the positive predictions	$\frac{TP}{TP+FP}$
Recall	Measures model ability to correctly identify correct nodule	$\frac{TP}{TP+FP+FN}$
F1-score	Balance between precision and recall	$2\times\frac{(precision\times recall)}{(precision+recall)}$
Intersection over union (IoU)	Overlap between predicted and real nodule	$\frac{TP}{TP+FP+FN}$
Dice similarity coefficient (DSC)	Predicted to real nodule area	$\frac{2\times TP}{(TP+FP)+(TP+FN)}$

***Note:** true positives (TP), true negatives (TN), false positives (FP), false negatives (FN)

Recall is used interchangeably with sensitivity, specifically focusing on the proportion of actual positives correctly identified, further emphasizing the model's ability to detect true cases. Collectively, these metrics provide a comprehensive evaluation framework for assessing and comparing the performance of AI models in precision diagnostics.

Overall, these performance metrics are crucial for assessing deep learning models in lung nodule detection, ensuring that they perform accurately and minimize risks to patients by reducing false positives and false negatives.

3. Deep learning for lung cancer detection

Recent advancements in artificial intelligence (AI) have significantly impacted healthcare, particularly the detection and diagnosis of lung cancer. Traditionally, the identification of pulmonary nodules as small lesions within the lungs, which may indicate early-stage cancer, relies extensively on manual analysis by radiologists. This conventional process is time-intensive, heavily dependent on individual expertise, and prone to subjective interpretation, potentially compromising diagnostic accuracy. AI has introduced novel approaches to overcome these limitations. Machine learning allows computational systems to analyze medical data and recognize meaningful patterns without explicit human instructions. Furthermore, the deep learning approach is widely applied in medical image analysis, including lung nodule detection. These algorithms demonstrate superior capability in accurately detecting, segmenting, and classifying pulmonary nodules from CT images, thus outperforming traditional diagnostic techniques. Consequently, deep learning-based methods enhance diagnostic precision, support clinical decision-making, facilitate timely medical interventions, and improve patient prognosis and survival rates.

3.1. Segmentation

Recent research efforts in lung nodule segmentation have predominantly utilized convolutional neural networks (CNNs) combined with specialized neural network architectures. Among these architectures, Fully Convolutional Networks (FCNs) [18], U-Net [19], and transformers [20] have emerged as effective approaches, demonstrating substantial improvements in segmentation accuracy. These segmentation models operate in two fundamental steps. In the initial step, CNN-based architectures apply a down-sampling operation to extract image features and reduce redundant or irrelevant information. After that, an up-sampling operation is employed to enhance the resolution and refine these image features, producing accurate, high-quality segmentation results. This two-step process ensures the precise delineation of lung nodules, thus supporting clinicians in accurate diagnosis and effective treatment planning.

Numerous studies on lung nodule segmentation have adapted existing deep learning models to enhance performance. Huang et al. [21] developed a system to detect and segment lung nodules. Initially, potential lung nodules were detected using Faster R-CNN and merged with similarly detected candidate nodules. After that, the false positive rate was reduced using a CNN, and the final nodule segmentation was performed using a customized FCN network. Their approach was tested using the LIDC-IDRI dataset. Tong et al. [22] used an improved U-Net model combined with residual blocks to better segment lung nodules. They first isolated the lung areas and cropped the images into 64 × 64 pixels to process the input data faster and with greater computational efficiency. Their model was validated on the LUNA16 dataset, which showed an enhanced segmentation performance. Usman et al. [23] used a dynamic approach and segmented the lung nodules using a two-stage method using a modified Deep Res-UNet. In the first stage, Deep Res-UNet was used to train and predict the axial axis of the CT images. The second stage focused on the new ROIs in the CT image and used the deep Res-UNet architecture for the coronal and sagittal axes to train the network. Zhao et al. [24] introduced a method involving a patch-based 3D U-Net and a contextual

CNN for the automatic segmentation and classification of lung nodules. Initially, the 3D U-Net architecture was employed to segment lung nodules. Subsequently, generative adversarial networks (GANs) [25] were utilized to enhance the 3D U-Net, and a contextual CNN was applied to minimize the false-positive rate in lung nodule segmentation and improve the classification of nodules as benign or malignant. This approach yielded favorable outcomes for segmenting lung nodules.

Kumar et al. [26] employed V-Net [27] for their model focused on segmenting lung nodules. The architecture they proposed incorporated a 3D CNN model by utilizing only convolutional layers while excluding pooling layers. The model was tested on the LUNA16 dataset, and enhanced segmentation results were achieved. Pezzano et al. [28] introduced a lung nodule segmentation network that incorporated Multiple Convolutional Layer (MCL) blocks into the U-Net framework. Unlike end-to-end networks, the proposed architecture is divided into two distinct phases. Initially, the model was trained to generate preliminary results. After that, a morphological technique was applied for post-processing during the second phase, emphasizing the nodules along the lung edges. The architecture was trained and tested using the LIDC-IDRI database. Keetha et al. [29] introduced a U-Det architecture that efficiently utilizes by integrating U-Net with Bi-directional Feature Pyramid Network (Bi-FPN). The proposed network was trained and evaluated on the LUNA16 dataset, which resulted in enhanced segmentation masks.

Furthermore, the latest progress in lung nodule segmentation has introduced foundation models and transformers, thereby significantly advancing deep learning in medical image analysis. Models such as Vision Transformers (ViT) [30] and large pre-trained models such as Contrastive Language-Image Pretraining (CLIP) [31] are becoming increasingly popular in lung nodule detection. Their popularity stems from their capability to process intricate image features efficiently and manage large datasets, thereby surpassing the performance of traditional CNNs architectures. Transformers, initially developed for Natural Language Processing (NLP) applications, have demonstrated significant efficacy in the medical imaging domain, particularly in the segmentation of intricate structures such as lung nodules. These models capture long-range dependencies across various segments of an image, thereby enhancing their ability to comprehend context and interrelationships within the image. Transformers are capable of concentrating on pertinent regions of interest, thereby augmenting the segmentation accuracy by considering the entire image context rather than merely local patches. Similarly, foundation models, which are large-scale models pre-trained on extensive datasets and subsequently fine-tuned for specific tasks, are employed in lung nodule segmentation. These models are capable of learning from diverse medical image data and exhibit superior generalization, resulting in enhanced performance, even on smaller or heterogeneous datasets. Using such pre-trained models, researchers can leverage knowledge from other domains and adapt it to lung nodule segmentation with increased accuracy and efficiency.

In 2017, Vaswani et al. [20] introduced a transformer-based architecture that marked significant advancement, particularly owing to the implementation of self-attention mechanisms. Unlike conventional models that handle input data sequentially or concentrate on local features, transformers can capture long-range dependencies and relationships throughout the entire input sequence, which is essential for tasks such as medical imaging. The self-attention mechanism, a fundamental element of the transformer, functions by determining the relationships between various parts of the input through three primary matrices: query, key, and value. This enables the network to concentrate on the most pertinent features, allowing it to learn intricate patterns and enhance its performance in tasks such as image classification [32], segmentation [33], and detection.

By contrast, ViT modifies the transformer model by segmenting images into patches and handling them as a sequence. Utilizing self-attention, ViT adeptly captures both global and local image characteristics, which is especially advantageous in medical fields, such as detecting pulmonary nodules on CT scans. Recent research on pulmonary nodule segmentation and detection [34], [35] has shown that transformer-based models significantly enhance segmentation accuracy. The addition of transformer layers to the pulmonary nodule segmentation tasks improved accuracy. Similarly, Yang et al. [36] investigated the use of uncertainty-aware attention in UGMCS-Net, which further improved segmentation performance, particularly in complex nodule shapes and areas with low confidence.

Moreover, hybrid models such as the Swin Transformer have been developed to effectively handle high-resolution medical images through a hierarchical framework. This architecture allows the model to analyze images at multiple scales, capturing intricate features across different levels. For instance, Liu et al. [37] incorporated 3D coordinate attention and edge enhancement to achieve a high Dice coefficient by improving edge detection in pulmonary nodule segmentation. Similarly, Wang et al. [38] employed attention-gating and multi-task learning, which enhanced both segmentation and classification accuracy. These advanced transformer-based models, particularly ViT and its variants, have demonstrated significant potential for improving early lung cancer detection and diagnosis accuracy, sensitivity, and efficiency. Hybrid deep learning approaches integrate various neural network types into a single framework to address complex challenges such as segmentation, classification, and detection of pulmonary nodules. By harnessing the distinct advantages of different models, such as CNNs, RNNs, GANs, and attention mechanisms, these hybrid approaches strive to enhance overall performance, stability, and robustness. These models offer a significant benefit by overcoming the shortcomings of individual networks, enhancing feature extraction accuracy, minimizing the false positive rate, and improving computational efficiency.

Overall, these studies demonstrate how AI-driven methods can be customized to significantly improve the accuracy and reliability of lung nodule segmentation, thereby supporting better diagnosis and patient care.

3.2. Classification

Following the segmentation of the lung nodules, wherein the anatomical boundaries of the lesion are precisely delineated from the surrounding pulmonary structures, the subsequent phase in the diagnostic pipeline is classification. This stage aims to ascertain the likelihood of malignancy and is critical for clinical decision-making as it informs the urgency and type of further diagnostic procedures or interventions. Following acquiring ROIs, they were subjected to preprocessing procedures, including normalization and resampling, to ensure consistent input dimensions appropriate for the classification model. The preprocessed nodule data were then input into deep learning architectures designed to extract and analyze the relevant features for malignancy prediction.

Advanced classification models, including two-dimensional and three-dimensional CNNs, ViTs, and hybrid frameworks, can learn hierarchical and discriminative representations directly from the segmented nodule volume. These models capture complex morphological and textural features such as size, spiculation, lobulation, internal heterogeneity, and margin sharpness, indicative of benign or malignant pathology. In certain implementations, radiomic features derived from segmented lesions are integrated with deep-learning outputs to enhance model interpretability and robustness. Additionally, multimodal approaches can incorporate clinical metadata (e.g., age, gender, smoking history) alongside imaging features to improve classification performance. The output is typically a malignancy probability score or categorical classification that can be aligned with clinical risk stratification systems. Overall, the classification stage, built upon accurate segmentation, provides a critical step toward automated, reproducible, and clinically relevant lung cancer assessments using deep learning models.

Wu et al. [39] developed a deep learning model to classify lung nodules, a critical step in accurately diagnosing lung cancer. The model was constructed using a deep residual network, which enhances learning by effectively managing complex data. The researchers employed transfer learning by adapting a pretrained model to a new task. They used a 50-layer ResNet architecture and fine-tuned it to classify lung nodules. Principal Component Analysis (PCA) was also applied to simplify the data and reduce the parameters, increasing the model speed and accuracy. Tran et al. [40] proposed the LdcNet model to improve the accuracy of pulmonary nodule classification. They employed a 15-layer 2D CNN and applied focal loss to distinguish between nodules and non-nodules in pulmonary candidates.

Table 3 Applications of pulmonary nodule segmentation, detection, and classification using different AI models.

Task	**Author**	**Method**	**PN***	**Performance (%)**
Segmentation	Huang et al. [21]	2D FCN	< 3 mm	DCS = 79.3
	Tong et al. [22]	2D UNet	5-10 mm	DCS = 73.6
	Usman et al. [23]	2D Res-UNet	< 3 mm	DSC = 87.55
	Kumar et al. [26]	3D CNN	> 3 mm	DSC = 96.15
	Pezzano et al. [28]	3D UNet	< 3 mm	DSC = 86.10
	Keetha et al. [29]	3D UNet	> 3 mm	DSC = 82.82
	Yang et al. [36]	3D UNet	3-30 mm	DSC = 87.65
	Liu et al. [37]	3D VNet	> 3 mm	DSC = 87.50
Classification & Detection	Wang et al. [38]	3D nnUNet	3-30 mm	ACC = 92.30
	Wu et al. [39]	DRN	3 - 30 mm	ACC = 98.23
	Tran et al. [40]	2D DCNN	> 3 mm	ACC = 97.20
	Savitha et al. [41]	2D DCNN	< 3 mm	ACC = 89.48
	Pinheiro et al. [42]	2D UNet	< 3 mm	ACC = 93.71
	Dodia et al. [44]	3D VNet	< 3 mm	ACC = 98.21
	Lei et al. [45]	3D UNet	< 3 mm	ACC = 94.44
	Amini et al. [46]	FIG	< 3 mm	ACC = 77.54
	Gupta et al. [47]	SVM	< 3 mm	ACC = 96.00
	Zhai et al. [48]	2D CNN	< 5 mm	ACC = 95.59

***Note:** pulmonary nodule (PN)

Savitha et al. [41] employed a deep convolutional neural network (DCNN) in conjunction with conditional random fields (CRF) to minimize the false positive rate. Pinheiro et al. [42] combined swarm intelligence algorithms with CNNs to enhance accuracy and decrease training time. Similarly, Wang et al. [43] enhanced the precision of multi-class nodule detection by employing 3D texture and edge feature extraction techniques. Dodia et al. [44] combined V-Net and SqueezeNet, improving accuracy and successfully reducing the false positives rate. These advancements highlight the diverse range of innovations designed to achieve high classification accuracy while minimizing false positives and enhancing clinical decision-making capabilities. Lei et al. [45] applied SAM and a high-level feature enhancement scheme HESAM methods for shape and edge analysis, focusing on reducing false positives in lung nodule classification. Amini et al. [46] incorporated fuzzy information and texture features, contributing to improved accuracy, though with a slight trade-off in sensitivity. Similarly, Gupta et al. [47] explored the effectiveness of support vector machine (SVM) models for improving lung nodule detection. Zhai et al. [48] employed a Multi-task CNN, focusing on enhancing classification performance and reducing false positives. Sivakumar et al. [49] demonstrated the potential of optimization algorithms to achieve high performance in lung nodule classification. These studies highlight ongoing advancements in managing the complexities of differentiating between benign and malignant nodules, particularly in balancing sensitivity with false-positive control.

4. Conclusion

The integration of AI models into lung cancer detection represents a significant advancement in the field of medical diagnostics. Through deep learning algorithms, ensemble models, and cutting-edge techniques, AI has dramatically improved the accuracy and efficiency of lung nodule segmentation, detection, and classification, particularly in differentiating between benign and malignant nodules. AI-based models, which incorporate various approaches such as CNNs, ViTs, and other state-of-the-art hybrid architectures, have demonstrated superior performance over traditional methods, making them essential tools for early lung cancer diagnosis and treatment planning. Despite the progress made, challenges remain, particularly regarding data quality, model interpretability, and the need for large-scale, annotated datasets. The dependence on large, annotated datasets limits the scalability and clinical applicability of these models, and the "black box" nature of deep learning models raises concerns about transparency in medical decision-making. To address these limitations, future research should improve model interpretability through explainable AI (XAI) methods and overcome data constraints with techniques such as GAN-based data augmentation. Moreover, incorporating multimodal data, including clinical and genomic information, into CAD systems and developing hybrid models that integrate deep learning with traditional machine learning could substantially enhance diagnostic accuracy and clinical applicability. By addressing these challenges, deep learning has the potential to further revolutionize early lung cancer detection, improving patient outcomes. This chapter aims to provide valuable insights to guide future research in this rapidly advancing field.

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