Received March 12, 2025, April 25, 2025, date of publication May 1, 2025.

Digital Object Identifier 10.21608/ijaici.2025.335358.1002

Review of lung cancer detection

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ABSTRACT Lung cancer continues to be the leading cause of cancer-related deaths worldwide, with nearly 2 million new cases and 1.76 million deaths each year. Late diagnosis plays a major role in poor outcomes, making early detection critical to improving survival rates. Advances in computer science, especially in data mining, machine learning, and artificial intelligence (AI), present new opportunities to transform lung cancer research by enabling more accurate and timely diagnoses. This study reviews a range of computational models used in lung cancer detection and diagnosis, with particular emphasis on image analysis and predictive analytics. Methods such as convolutional neural networks (CNNs), attention mechanisms, and transformers have been utilized to improve the accuracy of lung nodule segmentation, classification, and malignancy prediction. This work investigates the application of AI-driven models for evaluating extensive datasets derived from CT scans, along with enhancements in diagnostic consistency and accuracy relative to human radiologists. The discussion addresses the challenges of data integrity, model openness, and ethical considerations in integrating AI into therapeutic settings. This review provides an overview of the role of computer science in advancing lung cancer research, highlighting the possibilities for technological innovation. Interdisciplinary collaboration is essential for developing robust, intelligible, and scalable AI models that facilitate early diagnosis, enhance patient care, and seamlessly integrate into healthcare workflows.

INDEX TERMS Computed tomography, Deep learning, Lung nodule detection, Lung nodule segmentation

I. INTRODUCTION

Lung cancer arises in the lungs, which are the initial organs for respiration. It is the primary cause of cancer-related deaths worldwide. Lung cancer is categorized into two types: small-cell lung cancer (SCLC) and non-small cell lung cancer (NSCLC). Small cell lung cancer (SCLC) comprises little neoplastic cells observable by microscopy. Conversely, with SCLC, the cancer cells exhibit more proliferation. Typically, small cell lung cancer (SCLC) advances more rapidly than non-small cell lung cancer (NSCLC). NSCLC constitutes the predominant form of the disease. It occurs when atypical cells in the lungs proliferate uncontrollably, resulting in a tumor or cancer that originates in the lungs, the organs essential for respiration, which can disrupt normal lung function. Lung cancer is primarily attributed to smoking; however, it may also result from many environmental factors, including air pollution and exposure to radon gas. Tobacco consumption is the principal cause of lung cancer, responsible for more than 80% of all cases [1]. Prevalent dangers encompass exposure to air pollution, secondhand smoke, radon gas, and particular chemicals and substances found in certain occupational environments. The World Health Organization estimates that lung cancer will cause approximately 1.8 million deaths worldwide in 2020, representing nearly 18% of all cancer-related mortality, as illustrated in Figure 1 [2]. In 2019, 324,949 patients in Egypt received state-funded treatment for malignant neoplasms [3]. According to December 2020 estimates from the Global Cancer Observatory (GLOBOCAN), the most prevalent cancers in Egypt, with a 5-year prevalence across all age groups, include breast, lung, colorectal, prostate, stomach, liver, and cervical cancer, totaling 8,879,843 cases for all cancers, as depicted in Figure 2 [4].

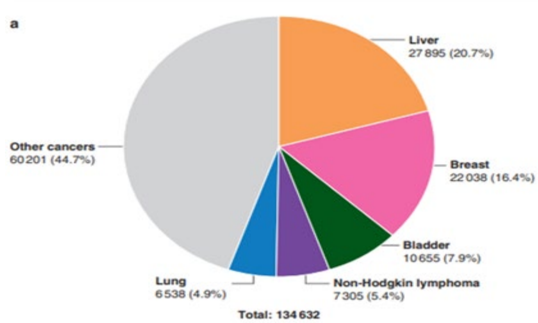

Figure 1: Statistics for cancers on the globe [2]

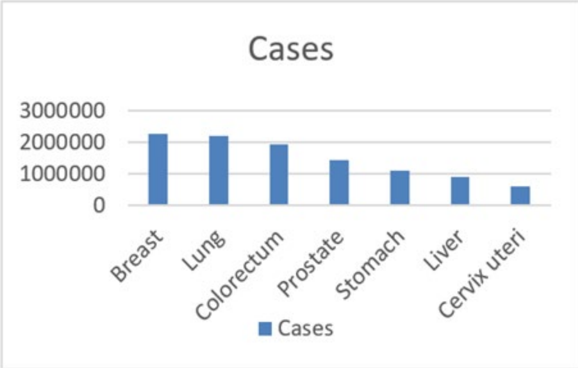

Figure 2: Statistics prevalent cancers in Egypt [4]

The primary objective is currently to identify and predict cancer to initiate treatment promptly [5]. Screening and incidental findings represent the two primary approaches for identifying lung cancer. Like breast cancer screening, the main method for identifying lung cancer should involve screening [6]. Nonetheless, the majority of countries, including the UK, do not have a screening program, resulting in most cases being identified incidentally. Lung nodules are often identified incidentally during the evaluation of other organs. Nodules may be identified during a computerized tomography (CT) scan of the heart or liver. The primary challenge is the insufficient skills of radiologists in differentiating between benign and malignant nodules [7]. Patients should be referred to a pulmonologist for the administration of tests aimed at detecting malignant cells and excluding other medical conditions. Clinicians order a lung X-ray to identify signs of tumors, scarring, or fluid accumulation, as these may suggest the presence of a suspicious lump or nodule [8]. CT scans can identify even minor lung abnormalities that may be overlooked by X-rays. A biopsy can be performed using bronchoscopy, among other methods. The physician evaluates abnormal lung areas by introducing a lighted instrument through the patient's oesophagus and into the lungs. Mediastinoscopy is a procedure that acquires lymph node tissue samples by inserting surgical instruments through an incision at the base of the neck and behind the sternum. A needle biopsy is a procedure in which a physician inserts a needle into lung tissue via the chest wall, utilizing X-ray or CT imaging to identify abnormal cells. An alternative approach involves obtaining a biopsy sample from lymph nodes or other metastatic locations of the malignancy, including the liver [9]. The application of three-dimensional visualization diagnostics in lung cancer detection improves the capacity of radiologists and oncologists to comprehend the spatial distribution and characteristics of lung lesions. This facilitates accurate diagnosis, treatment planning, and continuous monitoring of lung cancer patients, potentially leading to enhanced patient outcomes over time [10]. The use of three-dimensional visualization diagnostics in lung cancer detection enables radiologists and oncologists to gain a thorough understanding of the spatial distribution and characteristics of lung lesions. This enables accurate diagnosis, treatment planning, and monitoring of lung cancer patients, leading to improved patient outcomes. This is accomplished by applying machine learning techniques to large datasets of healthcare images.

II. RELATED WORK

The early detection of lung cancer relies heavily on the identification, segmentation, and classification of lung nodules where great advancements have been seen with the use of Deep learning approaches. Over the past few years, several innovative strategies have emerged to pay attention to the performance of these tasks, built on more sophisticated neural network structures, attention models, and multi-scale feature extraction mechanisms. In this portion, the authors will mention some of the most advanced technologies that allow conducting lung nodule analysis in CT images.

In this review of the related literature, concepts of the key architectural developments and application of dataset goodness of fit which have progressed lung nodule analysis have been presented, forming a basis to appreciate the current standing of the field and its possible remaining challenges.

This review of the related literature presents concepts of the key architectural developments and application of dataset goodness of fit that have progressed lung nodule analysis, forming a basis for appreciating the field's current standing and possible remaining challenges.

Liu et al. [11] developed a data-driven method called the cascaded dual-pathway residual network (CDP-ResNet), where the ResNet architecture is modified with the goal of improving lung nodule segmentation in CT images. Thereafter, this model determines the probability associated with a voxel being a part of the nodule and demonstrates a 3D rendering of the nodule segmentation result. The lung image database consortium (LIDC) dataset providing 986 annotated nodules was the data-set that this method was applied on four times and evaluated by four radiologists. The results show that the effectiveness of the model CDP-ResNet is more than the assessment of four different radiologists. The Dice similarit coefficient (DSC) on the average between CDP-ResNet and each radiologist is 82.69 percent which is higher than the average variability between radiologists on the LIDC dataset which is 82.66 percent [11].

Liu et al. [12] implemented the context attention network CA-Net, which however is able to extract both context features and nodule and fuse them in the processes of benignity/malignancy." For the purpose of contextual feature(s) that may be associated with the nodule to be effective, an attention mechanism that incorporates nodule(s) is used as a cue. Furthermore, it is possible that the effects of contextual features on classification differ for different nodules. The data science bowl 2017 (DSB) is a dataset for lung cancer prediction worked for the purposes of test and evaluation. CA-Net is reported to have an accuracy of 83.79% [12].

Mei et al. [13] introduced the U-NET architecture to Mask R-CNN for the multi-class segmentation of nuclei in histopathology images for breast cancer detection. The RPN networks predict region proposals for image components that may contain the nodule of interest. The lung nodule analysis (LUNA) challenge is evaluated using the publicly available LUNA16 Dataset formed part of the ISBI 2016 competition. It is reported that Mask R-CNN gives a sensitivity of 88.1% [13].

Cai et al. [14] came up with a system that uses artificial intelligence in imaging for the lungs, naming it ALIAS which stands for Artificial Intelligence Lung Imaging Analysis System, which includes networks for the detection and segmentation of lung nodules. The three-dimensional cascade FPN of the rectified linear unit is applied for the identification of nodules. In the case of nodule based analysis, histograms of hounsfield units (Hus) and radionics features are being used in the extraction. These features enable the evaluation of the differences that malignant and benign nodules sized differently possess. The images used during the ALIAS were tested and evaluated on images acquired from collaborating institutes, based on the established Institutional review board protocols, and the particular material transfer agreements. This assessment covers a whole of 8540 pulmonary CT images obtained from 7716 patients. There were 138 malignant (positive) nodules and 91 benign (negative) nodules in the testing set, and the accuracy was therefore set at 83.8% [14].

In the study by Chen et al. [15], a slice-aware network (SANet) was deployed towards the detection of lung nodules. This network utilizes a combines a slice-grouped non-local (SGNL) module with U-net like structure ResBlock to produce the nodule candidate generation. The dataset PN9 was used to evaluate and validate the performance of SANet. PN9 consists of 40439 annotated thoracic nodules and 8798 CT scans of nodules.

Results of the analysis demonstrate that SANet reaches a precision and recall of 35.92% and 70.20%, which indicates that the accuracy stands at 87% [15].

Mkindu et al. [16] came up with a method for computer aided detection of CAD involving a 3D Vision transformer multi-scale (MSViT). One of the architecture possesses a Local-global transformer back block, the local transformer stage of this architecture first processes each scale patch separately and integrates when they get to the global transformer level in order to fuse multi-scale features. The proposed CAD scheme was validated using 888 CT images extracted from LUNA16 dataset, a publicly available database. Trained and tested using 3D-MSViT algorithm Achieved accuracy rate of 91.1% [16].

Zhang and Zhang [17] located a 3D selective kernel residual network SK-ResNet which is based on selective kernel network and three-dimensional residual network. A 3D RPN employing SK-ResNet has been proposed for lung nodule recognition and a multi-scale feature fusion network for nodule classification has been developed. The validity of the method has been performed and evaluated on LUNA16, publicly available dataset. For the SK-ResNet, the accuracy of 91.75% was attained [17].

Lavika and Satyansh [18] proposed a hybrid deep learning approach combining a modified YOLOv3 architecture with the Biogeography-Based Optimization (BBO) and Exponential Elitism (EE) optimizer for lung cancer detection. This model leverages the efficiency of YOLOv3 for real-time object detection, while the BBO/EE optimizer fine-tunes the model's hyperparameters to enhance detection accuracy and computational performance. The method was evaluated on the publicly available LUNA16 dataset, achieving an impressive detection accuracy and sensitivity of 93.5%, demonstrating its effectiveness in identifying and classifying lung nodules in CT scan images [18].

Z. UrRehman et al. [19] proposed an effective deep convolutional neural network (CNN) for lung nodule detection that integrates dual attention mechanisms to enhance feature extraction and improve the detection of small and subtle lung nodules. Their model leverages both spatial and channel-wise attention to refine feature maps, significantly boosting the accuracy of the network in detecting lung nodules in CT scan images. Evaluated on the LUNA16 dataset, the model achieved a sensitivity of 92.7% and a specificity of 89.5%, demonstrating its robustness in distinguishing between malignant and benign nodules [19].

Brocki and Chung [20] proposed an innovative approach that combines radiomics and tumor biomarkers with interpretable machine learning models for cancer diagnosis. Their model integrates advanced machine learning techniques to analyze radiomics data, improving both the accuracy and interpretability of cancer detection systems. By using tumor biomarkers in conjunction with radiomic features, the model showed promising results in enhancing detection performance across various cancer types. The method demonstrated its potential in clinical settings by improving the accuracy of diagnoses while maintaining model transparency, which is crucial for clinical decision-making. Their work highlights the importance of integrating domain-specific features for improved cancer detection and classification [20].

In addition, Brocki and Chung [21] introduced ConRad, an open-source framework designed to integrate radiomics and tumor biomarkers into machine learning models. The framework, available on GitHub, provides a versatile tool for researchers and clinicians, allowing for more personalized and accurate cancer diagnostic models. This tool has the potential to significantly advance research by enabling easy access to a robust platform for integrating clinical data and machine learning [21].

Xie et al. [22] introduced a novel approach to the challenging task of automated pulmonary nodule detection in CT images. The primary objective of their work is to assist the CT reading process by quickly identifying lung nodules. They proposed a two-stage methodology: first, nodule candidate detection, and then false positive reduction. Their detection framework is built on a modified version of Faster Region-based CNN (Faster R-CNN), which includes two region proposal networks and a deconvolutional layer for detecting nodule candidates. Three models were trained for different slice types to incorporate 3D lung information, with the results later fused. To reduce false positives, the authors developed a boosting 2D CNN architecture, sequentially training three models to handle increasingly complex mimics. Misclassified samples were retrained to enhance sensitivity. Evaluating their model on the LUNA16 dataset, they achieved a sensitivity of 86.42% for detecting nodule candidates and sensitivities of 73.40% and 74.40% at 1/8 and 1/4 false positives per scan, respectively, for false positive reduction [22].

Sun et al. [23] addressed the issue of low accuracy in traditional lung cancer detection methods, particularly in real-world diagnostic environments. To overcome this limitation, they proposed the use of the Swin Transformer model for both lung cancer classification and segmentation tasks. Their approach introduces a novel visual converter that produces hierarchical feature representations with linear computational complexity relative to the input image size. The LUNA16 and MSD datasets were used for segmentation tasks, comparing the Swin Transformer's performance with other models like Vision Transformer (ViT), ResNet-101, and Data-Efficient Image Transformers (DeiT-S). The results revealed that the pre-trained Swin-B model achieved a top-1 accuracy of 82.26% in classification tasks, outperforming ViT by 2.53%. In segmentation tasks, the Swin-S model showed a mean Intersection over Union (mIoU) of 47.93%, outperforming other methods and demonstrating the model's superior performance [23].

Agnes et al. [24] tackled the challenge of manually examining small nodules in CT scans, a time-consuming task hindered by the limitations of human vision. To address this, they introduced a deep learning-based computer-aided diagnosis (CAD) framework for faster and more accurate lung cancer diagnosis. The authors employed a dilated SegNet model for lung segmentation from chest CT images, alongside a custom CNN model with batch normalization to identify true nodules. The performance of the segmentation model was evaluated using the Dice coefficient, while sensitivity was used to assess the nodule classifier. The CNN model's discriminative power was further validated using principal component analysis. Experimental results showed that the dilated SegNet model achieved a Dice coefficient of 89.00 ± 23.00%, and the custom CNN model achieved a sensitivity of 94.80% for nodule classification. These models excelled in both lung segmentation and 2D nodule patch classification within the CAD system for CT-based lung cancer diagnosis [24].

Yuan et al. [25] proposed a novel method for early lung cancer diagnosis and timely treatment through the detection of malignant nodules in chest CT scans. Their method combines structured radiological data with unstructured CT patch data to distinguish between benign and malignant nodules. The multi-modal fusion multi-branch classification network they developed utilizes a multi-branch fusion-based effective attention mechanism for 3D CT patch data. It incorporates a 3D ECA-ResNet, inspired by ECA-Net, to dynamically adjust features. Tested on the LUNA16 and LIDC-IDRI datasets, the network achieved an accuracy of 94.89%, sensitivity of 94.91%, and F1-score of 94.65%, with a low false positive rate of 5.55% [25].

Hassan Mkindu et al. [26] introduced a computer-aided diagnosis (CAD) system for lung nodule prediction based on a 3D multi-scale vision transformer (3D-MSViT). The goal was to enhance the prediction efficiency of lung nodules from 3D CT images by improving multi-scale feature extraction. The 3D-MSViT architecture uses a local-global transformer block structure, where the local transformer stage processes each scale patch individually before merging multi-scale features at the global transformer level. Unlike traditional methods, this approach relies solely on the attention mechanism, reducing the network's parameters by eliminating the use of CNNs. Evaluating the model on the LUNA16 database, they achieved the highest sensitivity of 97.81% and competition performance metrics of 91.10%. While this method was highly effective, it is limited to a single image modality (CT images) and lacks a stage for false-positive reduction. The 3D-ViTNet architecture, which relies on a single-scale vision transformer encoder without CNNs, was also tested, showing that integrating 3D ResNet with the attention module significantly improved detection sensitivity. However, 3DViTNet's performance was slightly lower in terms of sensitivity compared to the 3D-MSViT model, which provided the best results [26].

Tan et al. [27] proposed a deep learning model for discriminating between tuberculosis (TB) lung nodules and early lung cancers in CT images. Their model leverages deep learning techniques to identify subtle differences between the two conditions, which can often be challenging for radiologists. The study showed promising results in improving the accuracy of lung cancer detection by distinguishing between TB-related nodules and early-stage lung cancers [27].

National Institute of Allergy and Infectious Diseases [28] provides an online TB portal for research and resources related to tuberculosis. This platform supports various scientific communities by offering valuable tools and datasets. It serves as a key resource for understanding TB-related diseases and provides data that can be integrated with other health research, including lung cancer detection studies [28].

Li et al. [29] introduced the concept of time-distance vision transformers for lung cancer diagnosis using longitudinal CT images. Their model leverages temporal information to track nodule growth and detect potential malignancies over time. By employing vision transformers, the model can analyze the sequential nature of CT scans, leading to improved accuracy in lung cancer detection and diagnosis [29].

Li [30] developed the code for the Time Distance Transformer, which can be accessed via GitHub. This open-source tool provides researchers with a framework for applying vision transformers to longitudinal CT data, enabling better modeling of temporal dependencies in lung cancer detection [30].

Lu et al. [31] proposed a deep learning model that uses chest radiographs to identify high-risk smokers for lung cancer screening, utilizing computed tomography (CT) scans. Their prediction model was developed and validated with clinical data, showing significant potential in identifying individuals at high risk for lung cancer, thus improving early detection rates. The model's effectiveness in identifying high-risk individuals for lung cancer screening has implications for targeted interventions and prevention strategies [31].

Jian et al. [32] proposed a dual-branch network, DBPNDNet, which uses 3D Convolutional Neural Networks (3D-CNN) for pulmonary nodule detection. Their approach, aimed at enhancing detection accuracy, utilizes two branches that independently process different scales of CT images, improving both sensitivity and specificity for lung cancer diagnosis. The model achieves promising results in detecting lung nodules, helping clinicians in the early diagnosis of lung cancer [32].

Zhao et al. [33] introduced an attentive and adaptive 3D CNN for automatic pulmonary nodule detection in CT images. Their model integrates attention mechanisms to focus on relevant features, significantly enhancing detection accuracy. Evaluated on a variety of CT scans, their method demonstrated improvements in the detection of small and subtle nodules compared to traditional CNN-based approaches[33].

Ahmadyar et al. [34] developed a hierarchical approach for pulmonary nodule identification by combining a YOLO model with a 3D neural network classifier. This framework efficiently detects and classifies lung nodules in CT images. The integration of YOLO for initial nodule localization followed by 3D CNN-based classification significantly improves the accuracy of nodule detection [34].

Ma et al. [35] introduced TICNet, a transformer-based network integrated with CNNs for pulmonary nodule detection. Their model, leveraging the strengths of transformers in handling long-range dependencies, showed enhanced performance over traditional CNNs for detecting lung nodules in CT scans. The fusion of convolutional and transformer-based architectures allowed for better handling of complex CT images [35].

Sweetline et al. [36] proposed a multi-crop CNN approach to address the challenge of accurately segmenting lung nodules. Their method uses multiple crop sizes to focus on different parts of the nodule, improving segmentation accuracy, particularly for smaller and irregular nodules. This approach showed improved performance compared to conventional segmentation methods [36].

Zhang et al. [37] introduced DS-MSFF-Net, a dual-path self-attention multi-scale feature fusion network for CT image segmentation. Their model uses self-attention mechanisms to capture long-range dependencies and multi-scale features, significantly improving the segmentation accuracy of lung nodules. The model was evaluated on standard datasets, showing better performance in terms of both segmentation accuracy and computational efficiency [37].

Suji et al. [38] explored the use of pretrained encoders for lung nodule segmentation, utilizing the LIDC-IDRI dataset. Their approach leverages transfer learning with pretrained models to enhance the accuracy of nodule segmentation, achieving promising results and reducing the training time required for deep learning models [38].

Asiya and Sugitha [39] focused on automatically segmenting and classifying lung nodules from CT images. They developed a deep learning-based framework that integrates segmentation and classification into a unified model, showing high sensitivity and specificity for classifying lung nodules, particularly in complex cases [39].

Tang et al. [40] introduced SM-RNet, a scale-aware multi-attention guided reverse network for pulmonary nodule segmentation. Their model utilizes attention mechanisms to guide the segmentation process, helping to improve performance in detecting both small and large nodules in CT images. The approach was evaluated on multiple datasets, demonstrating significant improvements in segmentation accuracy [40].

Cai et al. [41] proposed MDFN, a multi-level dynamic fusion network for lung nodule segmentation. Their model incorporates self-calibrated edge enhancement techniques to improve the detection of nodule boundaries, achieving high accuracy in both segmentation and classification tasks. This model shows promise in improving early diagnosis by enhancing the delineation of lung nodules [41].

Fu et al. [42] investigated the fusion of 3D lung CT data and serum biomarkers for diagnosing multiple pathological types of pulmonary nodules. Their approach combines imaging data with clinical biomarkers, improving the diagnostic performance of lung cancer models and aiding in the classification of benign and malignant nodules [42].

Zhan et al. [43] introduced an uncertainty-aware self-training framework with consistency regularization for multilabel classification of common CT signs in lung nodules. Their approach enhances model robustness and accuracy by incorporating uncertainty measures, making it more adaptable to real-world clinical environments [43].

Rahouma et al. [44] proposed an automated 3D CNN architecture designed for pulmonary nodule classification using a genetic algorithm. Their approach optimizes the CNN architecture for better accuracy and efficiency in detecting pulmonary nodules, achieving improved classification performance in lung cancer screening [44].

Lin et al. [45] developed a combined model that integrates deep learning, radiomics, and clinical data to classify lung nodules in chest CT scans. Their model improves classification accuracy by combining feature extraction from both image-based and clinical data, enhancing the performance of lung cancer diagnosis [45].

Singh [46] proposed a novel algorithm for pulmonary nodule classification using CNNs on CT scans. Their approach leverages CNN's feature extraction capabilities to classify lung nodules into malignant or benign categories, improving early detection and diagnosis of lung cancer [46].

Rana et al. [47] proposed a 3D visualization method for lung cancer detection aimed at assisting clinicians in the early diagnosis of lung cancer. Their method integrates the MobileNet model to enhance the efficiency of feature extraction by using depthwise separable convolutions, making it computationally efficient. A ray-casting volume rendering approach was used to create 3D pulmonary nodular models from CT scans. The method achieved a segmentation accuracy of 93.3% on the LIDC dataset, demonstrating its potential for enhancing early lung cancer detection through improved visualization of lung nodules in CT images [47].

Kadhim et al. [48] introduced a computer-aided diagnostic system for pulmonary nodule detection that evaluates the efficacy of various system types. They explored different machine learning approaches to enhance the performance of nodule detection on CT images. The study found that the proposed system significantly improved detection accuracy and was effective in identifying both benign and malignant lung nodules [48].

Bhatt et al. [49] used the YOLOv4 deep learning model for pulmonary nodule detection in CT images. Their approach achieved high sensitivity and specificity in detecting various types of nodules, outperforming traditional methods. The model's ability to quickly detect and classify lung nodules makes it suitable for real-time clinical applications [49].

De Mesquita et al. [50] proposed a novel method for lung nodule detection based on Boolean equations and a vector of filters technique. This method leverages advanced image processing techniques to enhance the detection of nodules in CT scans, improving the accuracy of automated detection systems [51].

Suzuki et al. [51] developed a modified 3D U-Net deep learning model for the automated detection of lung nodules in chest CT images. The model, validated on both the Lung Image Database Consortium and Japanese datasets, achieved high accuracy in detecting lung nodules, demonstrating its potential for clinical use [51].

Karrar et al. [52] presented an automated diagnostic system for detecting solitary and juxtapleural pulmonary nodules in CT images. Using machine learning techniques, their system achieved high detection rates, helping to improve early diagnosis and assist radiologists in clinical decision-making [52].

Bhaskar et al. [53] applied image enhancement techniques combined with deep learning models to improve the detection and classification of pulmonary lung nodules. Their approach demonstrated improved detection accuracy, particularly in complex cases where nodules have irregular shapes [53].

III. DISCUSSION

The application of deep learning in the interpretation of CT images has revolutionized the field of lung cancer detection. Through the use of sophisticated neural networks, the accuracy of lung nodule detection, segmentation, and classification has drastically improved. In this review, we analyzed several state-of-the-art approaches ranging from traditional Convolutional Neural Networks (CNNs) to more advanced Transformer-based architectures and Attention Mechanisms. Each of these models brings unique contributions to the task of lung nodule analysis, and their performance varies based on the techniques they utilize and the datasets they are trained on.

To facilitate a better understanding, the following diagram provides a high-level overview of the AI-assisted diagnostic process.

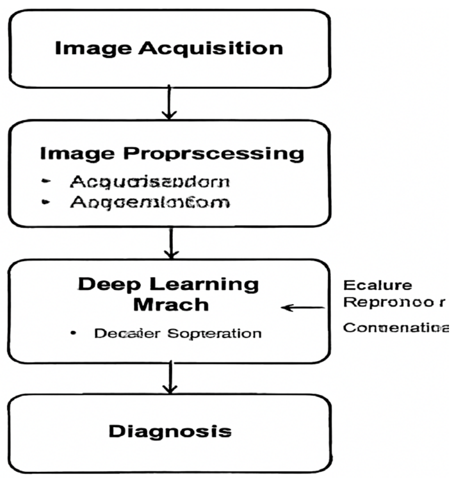

Figure 3:AI-Assisted Diagnosis Workflow

A. Key Contributions and Performance of Different Approaches

A comparison of various methodologies for lung cancer detection is presented in Table I, where different models like CDP-ResNet, CA-Net, Mask R-CNN, and ALIAS are evaluated. The table highlights their performance metrics, key contributions, and the advantages and limitations of each approach.

Furthermore, the computational complexity of the reviewed models is discussed in Table II, which compares the FLOPs, GPU memory usage, and other resource demands of each model. This table provides insight into the trade-offs between performance and computational efficiency for each architecture.

Additionally, Table III summarizes the different techniques for pulmonary nodule detection and diagnosis, showcasing how each model performs in terms of sensitivity and specificity. The table also outlines the main methods used, such as CNN, YOLOv4, and U-Net, and their performance across various nodule types and datasets.

B. *Challenges and Limitations*

While deep learning models have made remarkable strides, several challenges still need to be addressed for the broader adoption of AI systems in clinical settings:

1. Generalization to Real-World Data: A major limitation of current models is their dependence on curated datasets, like LUNA16 or LIDC, which may not fully represent real-world clinical data. In real-world clinical practice, CT scans vary in quality, and models trained on high-quality, curated data may struggle when faced with noisy, incomplete, or non-uniform data from diverse sources. The generalization of models to diverse patient populations, scanners, and medical settings remains a significant challenge that needs to be addressed to make AI systems reliable in real-world healthcare environments.
   Clinical Validation: To ensure that deep learning models perform well in clinical environments, they must be tested on real-world datasets from non-curated hospital CT scans. These scans often exhibit more variability than those from curated datasets, including different scanning protocols, patient demographics, and the presence of artifacts. Evaluating models on such datasets is crucial to assess their ability to generalize across the diverse, noisy, and incomplete data that is common in everyday clinical practice. Additionally, using data augmentation, domain adaptation, and transfer learning techniques could help improve the generalization of models, making them more suitable for clinical deployment.
2. Data Imbalance: Many lung cancer datasets suffer from class imbalance, with a disproportionate number of benign nodules compared to malignant ones. This imbalance can cause models to become biased toward detecting benign nodules, leading to false negatives, especially for rare or early-stage cancers. Approaches such as data augmentation, class weighting, or the use of more balanced datasets are essential to mitigate this issue and improve model performance.
3. Computational Complexity: Models like transformers, Mask R-CNN, and hybrid systems demand extensive computational resources. For example, models such as 3D-MSViT require high GPU memory (8–12 GB) and processing power, which can be prohibitive for deployment in low-resource settings or for real-time applications. While advancements in model optimization and hardware can address some of these issues, edge computing and model compression will be crucial for the adoption of these technologies in clinical practice.
4. Interpretability and Transparency: One of the major concerns with AI models is the lack of interpretability. Many deep learning models function as "black boxes," where the reasoning behind a model's decision is not easily understandable. In medical applications, this lack of transparency is a significant barrier to trust, as clinicians need to understand the rationale behind a diagnosis or recommendation. Developing explainable AI (XAI) solutions that provide insights into how decisions are made will be key to gaining clinician acceptance and integrating these systems into clinical workflows.

C. *Future Directions*

To overcome the current limitations and improve the clinical applicability of deep learning models for lung cancer detection, several areas need further exploration:

1. Federated Learning and Privacy-Preserving Models:
   The privacy concerns surrounding medical data can hinder the development of large, multi-institutional datasets. Federated learning, where models are trained on decentralized data across multiple hospitals without sharing patient information, can address these concerns while enabling the development of more generalized and robust models. This approach could significantly improve model performance and generalization.

2. Real-Time and Edge Computing Solutions: Many current models require significant computational power for both training and inference. To enable real-time detection of lung cancer in clinical settings, research should focus on optimizing models for edge computing, where the data processing happens on-site with minimal latency. This could make deep learning-based diagnostic tools more accessible in resource-limited environments, such as rural clinics or emergency rooms.

3. Multimodal Data Integration: Incorporating multimodal data—such as combining CT images with clinical information (e.g., age, smoking history, genetic data)—can improve the model's diagnostic accuracy. Integrating diverse data sources allows for a more comprehensive understanding of the patient's condition, potentially leading to earlier detection and more personalized treatment plans.

4. Diversity in Datasets: There is a clear need for more diverse and representative datasets that capture variations in imaging conditions, patient demographics, and scanner types. Models trained on such diverse data are more likely to generalize well in real-world settings. Collaborative efforts between healthcare providers worldwide to build larger and more diverse datasets will be instrumental in addressing this issue.

Table I Comparison of Different Methodology

Method	Architecture	Dataset	Performance Metrics	Key Contributions	Advantages	Limitations	Complexity
Liu et al. [11]	CDP-ResNet (Cascaded Dual-Pathway ResNet)	LIDC (986 annotated nodules)	DSC: 82.69%	Superior segmentation accuracy; 3D visualization	High segmentation accuracy, 3D views	No classification module	High
Liu et al. [12]	CA-Net (Context Attention Network)	DSB 2017 (Cancer prediction)	Accuracy: 83.79%	Attention-enhanced context integration	Effective contextual feature capture	Lacks segmentation/detection	Medium
Mei et al. [13]	Mask R-CNN + ResNet-50 + FPN	LUNA16 (ISBI 2016 Challenge)	Sensitivity: 88.1%	Multi-scale feature learning	Strong detection performance	High computational burden	High
Cai et al. [14]	ALIAS (AI Lung Imaging Analysis System)	Collaborative (7,716 patients)	Accuracy: 83.8%	Joint segmentation & detection on large dataset	Diverse data improves generalization	Limited segmentation metrics	Medium
Chen et al. [15]	SANet (Slice-Aware Net with SGNL)	PN9 (40,439 annotated nodules)	Prec: 35.92%, Rec: 70.20%, Acc: 87%	U-Net-based; optimized candidate generation	Effective candidate detection pipeline	Low precision on difficult cases	Medium-High

Table II Computational Complexity of Reviewed Models for Lung Cancer Detection

Model	Architecture	FLOPs (Estimate)	GPU Memory Usage	Notes
CDP-ResNet	Cascaded Dual-Pathway ResNet	~20–40 GFLOPs	High (6–10 GB)	Dual pathways and 3D convolutions increase cost significantly.
CA-Net	Context Attention Network	~10–15 GFLOPs	Moderate (4–6 GB)	Attention modules increase cost but model remains relatively

				efficient.
Mask R-CNN + FPN	ResNet-50 + Feature Pyramid Network	~40–60 GFLOPs	High (8–12 GB)	Region proposal networks + multi-scale features are compute intensive.
ALIAS	Hybrid Deep Learning System	~15–25 GFLOPs	Moderate (~6 GB)	Complexity depends on segmentation and detection branches.
SANet	Slice-Aware Network + SGNL module	~25–30 GFLOPs	High (7–10 GB)	Multi-view slice processing and graph-based features increase cost.

Table III Computational Pulmonary Nodule Detection Table

Task	Type	Technique	Validation/Test Method	Nodules Types	Main Method	Model Performance
Pulmonary nodule detection and diagnosis with CAD	2D and 3D	CNN; SAE	Performance varies based on dataset used	Multiple appearances and shapes (size < 10mm)	Performance comparison of CAD methods	Accuracy, Sensitivity
YOLOv4 model for nodule detection	2D	YOLOv4	Sensitivity with FP/scan: 81%	Various nodule types	YOLOv4 model	Sensitivity with FP/scan: 81%
Nodule detection using 16 filters and Boolean logic	3D	CNN	10-fold cross-validation	Nodules larger than 3mm	16 filters and Boolean logic	Sensitivity: 92.75%, 8 false positives
Automated nodule detection with 3D U-Net	3D	CNN; 3D U-Net	10-fold cross-validation	Nodules > 5mm	Automated nodule detection with 3D U-Net	Internal CPM: 94.7%, External CPM: 83.3%
Segmentation and classification with SVM, DCNN	2D and 3D	SVM, DCNN	10-fold cross-validation	Solitary, juxta-pleural	Segmentation, SVM, DCNN	SVM: 91.4%, DCNN: 95%
U-Net for segmentation, CNN for classification	3D	U-Net, CNN	80:20 train-test split	Cancerous or non-cancerous	U-Net for segmentation, CNN for classification	Sensitivity: 0.75 (before), 0.65 (after classification)
Multi-task dual-branch 3D CNN with attention fusion	3D	Dual-branch 3D CNN	5-fold cross-validation	Lung parenchyma and chest wall nodules	Multi-task dual-branch 3D CNN with attention fusion	Sensitivity: 91.33%, 0.125 to 8 FPs/scan
Adaptive 3D CNN for lung cancer detection	3D	3D CNN	10-fold cross-validation	Types, shapes, sizes: 3-30mm	Adaptive 3D CNN	Sensitivity: 0.947, FP/s: 0.14
Hierarchical YOLOv5s	2D and 3D	YOLOv5s, 3D CNN	Evaluated on LUNA16	Pulmonary nodules	Hierarchical YOLOv5s, 3D	Sensitivity: 97.8%,

Task	Type	Technique	Validation/Test Method	Nodules Types	Main Method	Model Performance
and 3D CNN					CNN	confidence: 0.3
Transformer-based TiCNet for lung cancer detection	3D	Transformer, CNN	10-fold cross validation	Benign and malignant	Transformer, attention, multi-scale fusion	Sensitivity: 93%, <11 FP/scan, CPM: 90.73%
Multi-crop CNN with boundary refinement	2D	Multi-crop CNN	5-fold cross validation	Various nodule types	Multi-crop CNN, boundary refinement	DSC: LUNA16: 0.978, LIDC: 0.982
Self-attention multi-scale feature fusion network	3D	DS-MSFF-Net	10-fold cross validation	Benign and malignant	Self-attention multi-scale feature fusion network	LIDC-IDRI: 85.39%, LiTS2017 liver: 95.79%, LiTS2017 tumor: 91.75%
Pretrained encoders for lung nodule segmentation	2D	UNet, FPN, PSPNet	5-fold cross validation	Various nodule types	Pretrained encoders: ResNet	LUNA16: 0.978, Sensitivity: 97.6%
Custom-VGG16 model for nodule classification	2D	Custom-VGG16	10-fold cross validation	Benign and malignant	Custom-VGG16 with preprocessing	LIDC: 0.982, Sensitivity: 98%

IV. CONCLUSION

In conclusion, this review provides a comprehensive synthesis of deep learning advancements in lung cancer detection, highlighting a broad spectrum of model architectures and benchmark datasets. Techniques such as convolutional neural networks, residual networks, attention mechanisms, and transformer-based models have significantly enhanced the performance of lung nodule detection, segmentation, and classification, particularly in CT imaging. The use of large, annotated datasets like LIDC-IDRI, LUNA16, and DSB 2017 has further contributed to improvements in accuracy and consistency across various tasks in medical image analysis.

Despite these advancements, several challenges persist. Current models often demand substantial computational resources and may exhibit limited generalizability across diverse populations. Furthermore, many deep learning systems are not yet fully aligned with clinical workflows, facing issues related to interpretability and practical integration in healthcare environments. Addressing these limitations is essential for successful real-world adoption.

Future research should prioritize the development of lightweight and efficient models capable of integrating multi-scale features and contextual cues while maintaining high performance. Incorporating clinical knowledge into the design and evaluation of these models can enhance their reliability and clinical relevance. Additionally, the exploration of explainable AI techniques and federated learning frameworks may improve model transparency and cross-institutional adaptability. These research directions are expected to play a crucial role in advancing the deployment of deep learning models in clinical settings, ultimately facilitating earlier detection and more effective treatment of lung cancer.

V. Findings and Recommendations

Based on the comprehensive review of existing lung cancer detection techniques, the following findings and recommendations are presented to guide future research and practical implementations:

D. Findings

The review of existing lung cancer detection techniques has provided valuable insights into the strengths and limitations of various approaches. By analyzing the current state-of-the-art methods, we can identify key trends and areas that need further development. The following findings highlight the most significant observations from the literature, particularly in the application of deep learning, the challenges associated with traditional machine learning models, and the critical importance of data preprocessing and evaluation metrics. These findings will guide future research efforts and the practical implementation of lung cancer detection systems in clinical settings.

1. Deep Learning Dominance: Convolutional Neural Networks (CNNs) and transfer learning have shown consistently high accuracy in lung cancer detection, especially when trained on large datasets.

2. Traditional Machine Learning Limitations: Classical models such as SVM and KNN are still used but often fall short in performance compared to deep learning approaches, particularly in complex or noisy medical images.

3. Data Imbalance and Preprocessing: Most studies highlight the importance of preprocessing (e.g., image normalization, augmentation) and address data imbalance using techniques like SMOTE or class weighting.

4. Evaluation Metrics: Accuracy remains the most reported metric; however, sensitivity and specificity are more clinically relevant and should be emphasized.

E. Recommendations

Based on the findings from the comprehensive review, several key recommendations are made to guide future advancements in lung cancer detection techniques. These suggestions aim to address the current challenges, enhance model performance, and ensure the practical applicability of the methods in clinical environments. The following recommendations outline important steps for researchers and practitioners to improve the accuracy, reliability, and interpretability of lung cancer detection models.

1. Use of Recent Datasets: Researchers should prioritize publicly available, high-resolution, and annotated datasets such as LUNA16, LIDC-IDRI, and more recent Kaggle competitions.

2. Standardized Benchmarks: It's important to evaluate models on standardized benchmarks with consistent metrics and experimental setups for fair comparison.

3. Explainable AI (XAI): Incorporating interpretability tools (e.g., Grad-CAM, LIME) is recommended to improve trust in clinical applications.

4. Hybrid and Ensemble Approaches: Combining CNNs with attention mechanisms or ensemble learning has shown promise and should be further explored.

5. Reproducibility and Open Access: Future studies should publish code, model parameters, and training details to enhance reproducibility and collaboration.

ACKNOWLEDGMENT

The authors would like to thank the Department of Computer Science at Benha University for their support and guidance. No external funding was received for this research..

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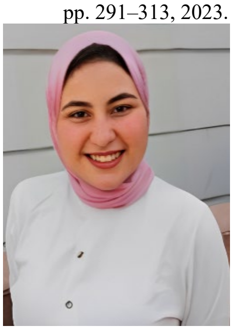

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