Mesopotamian Journal of Artificial Intelligence in Healthcare
Vol.2025, **pp**. 12–25
DOI: https://doi.org/10.58496/MJAIH/2025/002; ISSN: 3005-365X
https://mesopotamian.press/journals/index.php/MJAIH

Review Article

A Systematic Review of Artificial Intelligence's Function in the Diagnosis of Lung Cancer (2018–2024)

Rokan Hazim. Hamad [1,*]

[1] *Department of Biology, Ministry of Education, Director of Kirkuk Education, Kirkuk, Iraq.*

ARTICLE INFO

Article History

Received 18 Dec 2024
Revised 20 Jan 2025
Accepted 02 Feb 2025
Published 20 Feb 2025

Keywords

Lung cancer
Deep learning
Medical image analysis
Early detection
Pulmonary nodules

ABSTRACT

Lung cancer is a leading cause of cancer-related mortality, often diagnosed at advanced stages. This systematic review explores AI applications in lung cancer diagnosis, focusing on medical imaging, pathology, and genetic analysis. A systematic literature review methodology was employed, analyzing studies from databases such as PubMed, IEEE Xplore, and Scopus (2018–2024). Findings indicate that AI-powered diagnostic models, particularly deep learning techniques, outperform conventional methods in accuracy, sensitivity, and early detection capabilities. However, integration into clinical practice presents challenges, including data privacy concerns, model biases, and regulatory limitations. This review highlights the potential of AI in lung cancer screening and provides insights into future research directions.

1. INTRODUCTION

Lung cancer is a serious global health issue, causing millions of deaths annually, primarily due to late diagnosis [1]. In its early stages, symptoms often do not appear, preventing patients from seeking medical help in time [2]. By the time it is diagnosed, the cancer has usually progressed to an advanced stage with limited treatment options, significantly worsening the patient's condition. In contrast, early diagnosis greatly improves survival chances, highlighting the need for alternative methods for early lung cancer detection [3]. The stage at which lung cancer is diagnosed is the key determinant of treatment outcomes. Patients diagnosed in the early stages have a survival rate of over 50% for five years, whereas those in advanced stages have a survival rate of less than 5% [4]. In 2020, approximately 2.2 million lung cancer cases were recorded, with 1.8 million deaths attributed to the disease [5]. Nearly half of patients receive a diagnosis at the end of the disease, although less than 10% are asymptomatic upon diagnosis [6]. [7]. Despite improvements in current treatments, lung cancer remains the third most common cause of cancer-related deaths among women and the leading cause among men [5]. One promising technique for enhancing the diagnosis and treatment of lung cancer is artificial intelligence (AI). The technology has advanced dramatically since John McCarthy first used the term artificial intelligence (AI) in 1956, especially in the medical domain, where it has improved disease prognosis, diagnosis, and treatment approaches [8]. [9] [10]. In order to enable early detection and focused therapy, artificial intelligence (AI) systems are being created to scan millions of medical records and photos, including family history and cancer trends [11]. Patients with lung cancer have also been studied using AI approaches, with encouraging findings in terms of speeding up diagnosis and increasing survival rates [12][13]. AI's increasing importance in the medical arena is demonstrated by the rising body of research on its applications in the diagnosis of other diseases, including breast, brain, and chest cancer [14][15]. In cancer, artificial intelligence (AI) has become a game-changing tool that improves the precision of genetic analysis, pathology, and medical imaging. While several machine learning (ML) methods, including as Bayesian networks, Random Forest, and Support Vector Machines (SVM), have been investigated for the diagnosis of lung cancer, deep learning (DL) has proven to perform better, especially in the processing of medical images. DL models, like Convolutional Neural Networks (CNNs), are very good at identifying and categorising lung nodules because they can automatically extract hierarchical features from medical pictures without the need for human feature engineering.. Furthermore, DL-based systems have shown higher sensitivity and specificity in identifying malignant nodules compared

*Corresponding author. Email: rokanbio1998@gmail.com

to traditional ML methods. These advantages justify the focus on DL in this review, as it has become the leading AI approach for lung cancer diagnosis and prognosis. This review systematically examines the role of AI in lung cancer diagnosis, comparing its effectiveness with traditional diagnostic methods and evaluating its clinical applications and challenges.

2. METHODOLOGY

This study follows a Systematic Literature Review (SLR) methodology to ensure a structured, transparent, and reproducible process for analyzing AI applications in lung cancer diagnosis. The methodology adheres to standard SLR guidelines, covering the following aspects:

2.1 Research Objectives and Questions

The primary research objective of this review is: To analyze the role of artificial intelligence in lung cancer diagnosis, evaluating its effectiveness, challenges, and clinical integration.
Based on this, the study addresses the following research questions:

1. What are the most common AI methodologies used in lung cancer diagnosis?
2. How does AI compare to traditional diagnostic methods in terms of accuracy, sensitivity, and specificity?
3. What are the primary challenges and limitations associated with AI implementation in lung cancer screening?
4. What gaps exist in the current literature regarding AI applications in lung cancer diagnosis?

2.2 Search Strategy

To ensure comprehensive coverage of relevant studies, a structured search strategy was applied using the following criteria:

1. Databases Searched: PubMed, IEEE Xplore, Scopus, ScienceDirect, and Web of Science.
2. Keywords Used: "Lung cancer," "Artificial Intelligence," "Deep Learning," "Machine Learning," "Medical Imaging," "Pulmonary Nodules," "AI in Cancer Diagnosis."
3. Search Period: Studies published between 2018 and 2024 were included.
4. Language: Only peer-reviewed studies in English were considered.

2.3 Inclusion and Exclusion Criteria

TABLE I. A COMPARISON SUMMARIZES THE METHODOLOGIES AND FINDINGS OF THE REVIEWED STUDIES.

Criteria	Inclusion	Exclusion
Study Type	Peer-reviewed research papers, systematic reviews, and meta-analyses.	Abstracts, editorials, and non-peer-reviewed articles.
Focus Area	Studies focusing on AI in lung cancer diagnosis, including imaging, pathology, and genetics.	Studies on AI applications in other diseases or unrelated medical applications.
Methodology	Studies with clear AI models and performance metrics (accuracy, sensitivity, specificity).	Studies lacking performance metrics or detailed methodology.

2.4 Study Selection Process

The study selection was performed in three phases:

- Phase 1 (Initial Screening): Duplicate studies were removed, and articles were screened based on titles and abstracts.
- Phase 2 (Full-Text Review): Articles were reviewed based on inclusion/exclusion criteria, focusing on AI methodologies and their effectiveness.
- Phase 3 (Final Selection): The selected studies were analyzed in-depth, and relevant data were extracted.

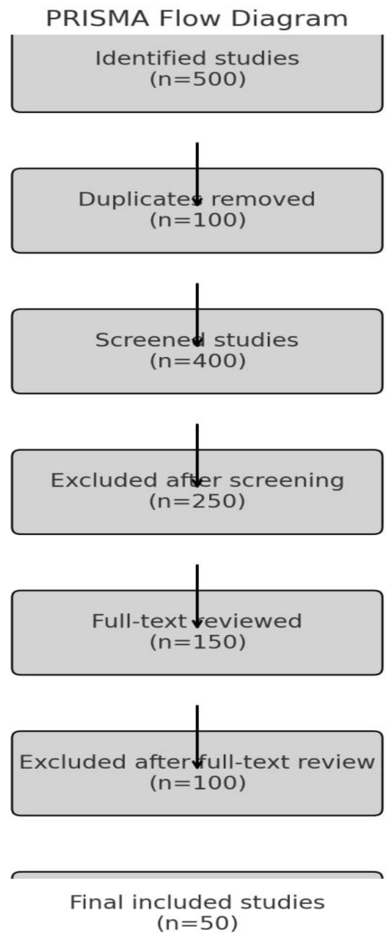

Fig. 1. A PRISMA flow diagram illustrates the selection process.

2.5 Data Extraction and Synthesis

Data extracted from the selected studies included:

- AI Methodology Used (Deep Learning, Machine Learning, Hybrid Approaches).
- Performance Metrics (Accuracy, Sensitivity, Specificity).
- Clinical Applications (Imaging, Pathology, Genetics).
- Challenges and Limitations Reported.

2.6 Findings and Discussion

The findings were categorized into three primary areas:

1. Medical Imaging: AI-based models improve nodule detection, classification, and segmentation.
2. Pathology: Deep learning enhances accuracy in cancer cell recognition.
3. Genetic Analysis: AI assists in mutation detection and treatment prediction.

While AI shows significant promise, challenges such as data limitations, model interpretability, and regulatory barriers remain. Future research should focus on addressing these limitations.

3. REVIEW

3.1 Artificial Intelligence

expanding ideas, methods, techniques, and useful systems to mimic, improve, and extend human intelligence is the goal of the expanding science of artificial intelligence (AI) (Figure 1). The four main components of the technical system of artificial intelligence are machine learning, natural language processing, image recognition, and human-computer interaction [15].Natural language processing combines linguistics, computer science, mathematics, and other disciplines to develop computer systems that can converse in natural language. Language translation, rule analysis, voice recognition, syntactic analysis, data extraction, and part-of-speech tagging, and information retrieval are some of its uses.. Image processing techniques include image acquisition, filtering, and modification, and feature extraction from images. Unlike traditional computers, AI-based image processing techniques enhance computational efficiency and reduce energy consumption at the chip level [16]. **Human-Computer Interaction (HCI) Technologies** leverage the results of natural language processing and image recognition to create an interactive experience. These technologies cover fields including augmented reality methods, computer graphics, and interactive user interface design. [16]. Machine learning encompasses a variety of approaches, the most notable of which include: **Supervised Learning:** Used for classification and regression tasks. **Unsupervised Learning:** Focuses on discovering patterns in unlabeled data. **Transfer Learning:** Leverages knowledge gained from one task to solve another. **Reinforcement Learning:** Based on learning through interaction with the environment to obtain rewards. **Ensemble Learning:** Combines the results of multiple models to achieve better performance. The algorithms representing these patterns include deep learning, artificial neural networks, decision trees [17][18][19], as well as optimization algorithms. All things considered, rule-based AI systems have demonstrated differing levels of clinical use in the management of lung cancer, including for disease prediction, personalized treatment recommendations, and detection [20]. [21]. these applications are illustrated in (Figure 2) and detailed in (Table 1).

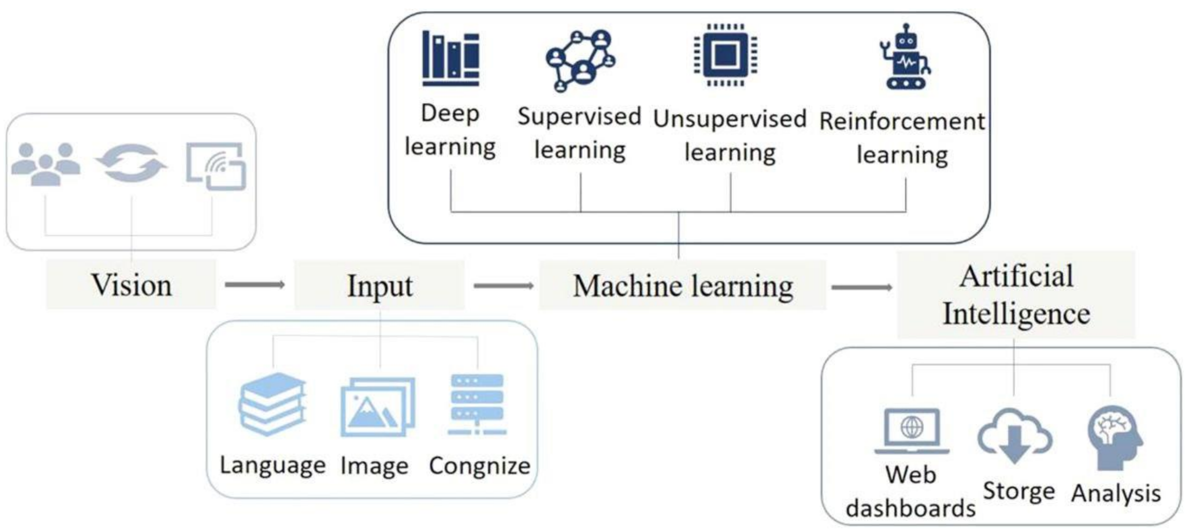

Fig. 2. The classification of AI.

TABLE II. THE DIFFERENT MODELS OF ARTIFICIAL INTELLIGENCE IN LUNG CANCER.

Clinical applications	Technology of AI	References
Diagnosis		
Imaging	3D DenseSharp network, CNN	[22] [23]
Pathology	DCNN, GAN, CGAN, SVM	[24] [25]
Laboratory indicators	Logistic regression, linear regression	[26] [27]

SVM stands for support vector machine; CDSS for compressed data storage system; DTA for decision tree analysis; XGBoost for extreme gradient boosting; CNN for convolutional network; DCNN for deep convolutional network; and GAN for generative adversarial networks.

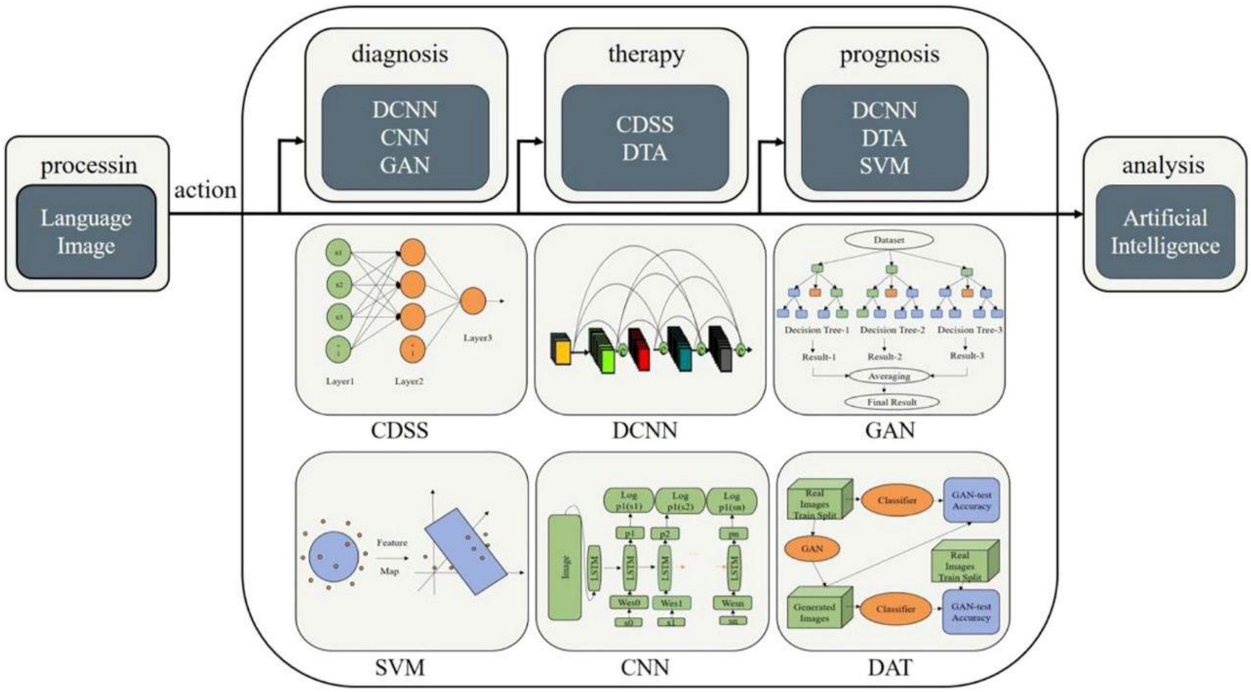

Fig. 3. The AI function diagram for lung cancer diagnosis, prognosis, and treatment. DTA, or decision tree analysis; DCNN, or deep convolutional network; CDSS, or compressed data storage system; GAN stands for generative adversarial networks; CNN for convolutional networks; and SVM for support vector machines.

3.2 The Importance of Artificial Intelligence in Lung Cancer Pathology

Currently, pathological biopsy is the gold standard for diagnosing lung cancer. However, the significant diversity of the disease's subtypes makes it challenging to achieve high diagnostic accuracy using manual reading alone [27]. This is where AI comes into play, as its ability to analyze abnormal structures in tissues or cells can significantly reduce false-negative rates. This contributes to the early detection of lung cancer, as well as improving the accuracy of its classification, thereby enhancing the effectiveness of diagnosis and treatment.

3.3 Lung Cancer Diagnosis

Applications of artificial intelligence in lung cancer diagnosis encompass several fields, including imaging, pathology, and genetics. Numerous image analyses are necessary for diagnosis in order to obtain multi-level quantitative features that help forecast histological types and differentiate benign from malignant tumors., and assessing the extent of invasion. This approach is a key support for clinical diagnosis [28].For example, Yu et al. [29] utilized machine learning techniques to analyze CT scan slices and lung cancer pathology images, focusing on pulmonary nodules and nuclear segmentation, along with digital pathology results. The findings demonstrated the tool's effectiveness in screening pulmonary nodules and nuclear examination. The diagnostic accuracy was similar to that of less experienced doctors. Additionally, the average scan time was reduced by 58%, improving efficiency and reducing the workload for physicians. The tool supported clinical decisions by providing accurate and reliable diagnoses.

3.4. Artificial Intelligence Applications in Lung Cancer Diagnosis

3.4.1. Early Differentiation of Lung Cancer through Imaging

Roughly 70% of patients with lung cancer receive a diagnosis at an intermediate or advanced stage, which impairs treatment efficacy and lowers survival rates. A key element in lowering the death rate from lung cancer is early screening. Whether benign or malignant, pulmonary nodules are early indicators of the disease, and their timely and precise discovery helps to improve diagnosis, enable early treatment, and boost survival rates .The position, size, and density of the nodule in relation to neighboring structures are usually evaluated by radiologists; however, these assessments are frequently subjective. "The American Lung Cancer Screening Program, for example, discovered that first CT scans failed to detect 8.9% of lung cancer patients. [30]. In a study by Zhang et al., the effectiveness of AI was contrasted with manual assessments of chest CT scans for 50 patients with benign pulmonary nodules and 60 patients with early-stage lung cancer. All diagnoses were verified by pathological tests. The findings demonstrated that AI's sensitivity in identifying lung cancer in its early stages outperformed human assessments. According to these results, using AI methods in healthcare settings can improve diagnosis speed and accuracy, which will benefit patient outcomes [30].Currently, CADe/CADx systems are widely used to reduce false positive rates in the detection of pulmonary nodules. The CADe system works by first identifying all suspected nodules, then classifying them as nodules or non-nodules, accurately and sensitively removing the latter. This system relies on deep learning techniques, using a standardized lung image database to analyze nodule morphology, density, and texture". However, studies show some variability in results, which may be attributed to differences in the nature of the nodules being examined. For instance, ground-glass nodules (GGNs) and nodules close to blood vessels are among the types most associated with higher false positive rates. Therefore, there is an urgent need to improve screening techniques to enhance detection accuracy. Convolutional Neural Networks (CNNs) are widely used in this field for examining pulmonary nodules. For example, Mahmood et al. [31] developed a system based on AlexNet, an advanced type of CNN that features an improved layer arrangement (as shown in Figure 3). This system demonstrates optimized parameters and functions compared to traditional systems, contributing to enhanced accuracy and efficiency in detecting pulmonary nodules.

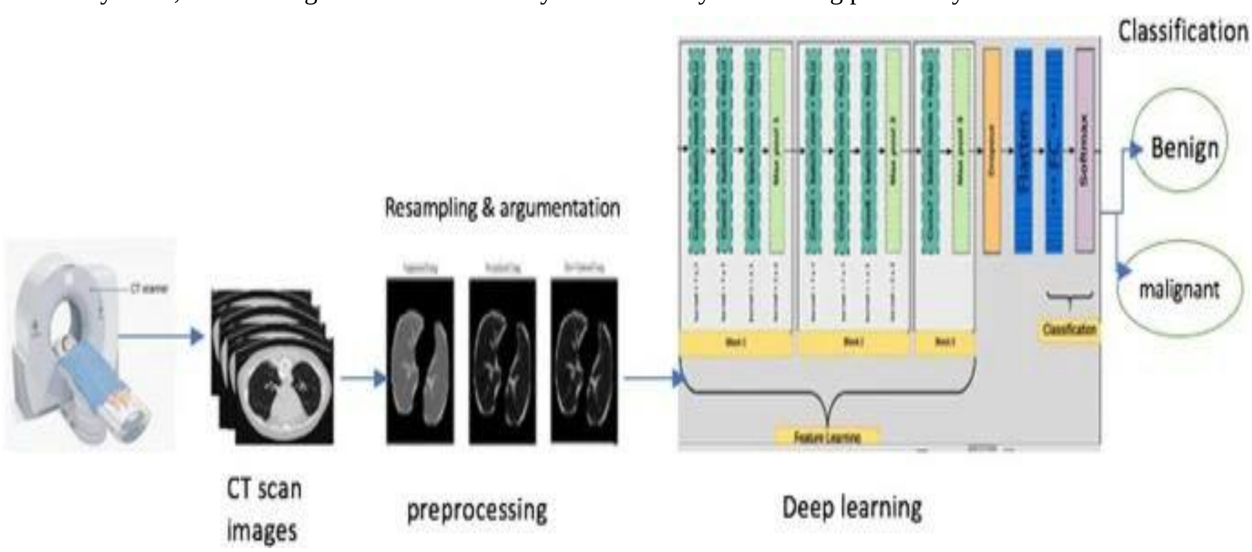

Fig. 4.:illustrates the proposed network structure based on the Alex Net architecture, with multiple enhancements to the layer arrangement, hyper parameters, and functions used to improve the network's performance in analyzing pulmonary nodules. To achieve a well-trained model, several **preprocessing steps were applied to the entire dataset, including: **Segmentation**: Dividing images into smaller parts to increase analysis accuracy. Normalization: Improves data consistency to reduce inter-sample variance. Zero-centering: Adjusts the data to be centered around zero to facilitate model training. After implementing these improvements, the proposed system achieves 98.7% accuracy, 98.6% sensitivity, and 98.9% specificity, which represents better performance compared to the original AlexNet architecture.

Numerous image analyses are Changes to the original AlexNet architecture covered customized improvements to the layer association and hyperparameters, as well as the use of optimization features designed to improve the version's sensitivity and accuracy in lung nodule evaluation. These changes immediately improved community performance by allowing the computer to generate results quickly and properly. These findings imply that tailored enhancements to neural networks that may be appropriate for the nature of the data and diagnostic needs can significantly increase the efficacy of lung nodule medical analysis. This study shows how artificial intelligence may significantly improve the quality and precision of scientific diagnoses [32]. To produce a lung region map, the lung scan image sequence was processed using a segmentation technique. This map was used to extract the lung image and identify the regions associated with pulmonary nodules. The process's primary steps were as follows: Nodule Region Image Creation: A customised image with just the pulmonary nodule regions was created using the extracted lung region image and nodule labelling data. Instruction Pulmonary Nodule Segmented: To precisely segment pulmonary nodules in the generated images, a Convolutional Neural Network (CNN) was employed to create a model. To find suspicious locations, suspected nodules were divided into segments and examined. Classification using 3D Neural Network: Following the identification of the suspicious nodules, the nodules were categorised using their 3D structural information using a 3D

Convolutional Neural Network (CNN). Finding the nodules precisely and determining their degree of confidence were the objectives in order to determine whether the nodules were suspicious or real. This cutting-edge approach was effective in raising the possibility for diagnosis, boosting early medical intervention in cases of lung cancer, and improving detection accuracy and location identification. [32] . The dataset was zero-centered, segmented, normalized, and thoroughly pre-processed. Overall, the performance was good, with 98.7% accuracy, 98.6% sensitivity, and 98.9% specificity. Although 3D CNNs require a more sophisticated network and have a higher computing load than 2D CNNs, they are more successful at analyzing spatial information. The sensitivity is higher, which is more significant. Yang and associates [33]
addressed the difficulties presented by varying angles of view in a multi-view model by integrating features using a pressure stimulation unit. To administer pressure stimulation, they constructed a multi-view 3D CNN. 96.04% and 98.59%, respectively, were the classification accuracy and sensitivity for benign and malignant lung nodules.. "Compared to other approaches, the agreement rate with pathological diagnoses was greater, at 94.8%. Physicians benefited greatly from the model's ability to understand the spatial variation of lung nodules and resolve the problem of multi-view variance. Ma et al. [34] created an improved 3D regional CNN for identifying and categorizing ground-glass nodules (GGNs) by employing a feature-weighted aggregation algorithm to eliminate false images, a 3D target detection network to locate the lesions and assess their malignancy status, and a pre-trained 3D U-Net network to extract lung tissues.. The average detection accuracy was good, and the false alarm rate was low. The feature-weighted aggregation technique in this deep learning-based system could help doctors find, classify, and automatically find GGNs with high accuracy.
Using both synthetic intelligence and human physicians, Liu et al. [35] examined images of 262 sufferers with pulmonary GGNs. The findings proven that even as AI turned into more sensitive and had decrease leakage fees than physicians, it additionally had a higher chance of incorrect diagnoses. The examine made clear that to be able to boom diagnostic accuracy, docs and AI engineers need to work collectively greater closely. In the in the meantime, Wu et al. [36] hired AI to observe pictures of 175 lung nodule patients who had ordinary checkups. The findings of the take a look at established that the initial size of the nodules, the average computed tomography value, floor markers, and the chance of malignancy all had an impact on the nodules' boom. In order to come across nodule growth early and start therapy on time, the researchers cautioned physicians to take those factors into consideration while choosing follow-up schedules[37].

3.4.2 AI Recognition and Computed Tomography Imaging

AI-powered medical image analysis improves image processing and imaging efficiency while allowing primary hospitals to conduct remote consultations [38]. A dual-path network for nodule detection and Mask-CNN for image segmentation were used to evaluate 90 lung cancer patients in a study by Feng et al. [39]. The computed tomography (CT) imaging accuracy was 88.37%, with sensitivity and specificity of 82.91% and 87.43%, respectively, while the dual-path network showed an accuracy of 88.74% in identifying lung lesions. The system obtained 100% specificity, 98.12% sensitivity, and 97.94% accuracy for deep learning-based CT screening with serum markers [39]. However, utilizing a dataset of 3038 nodules with verified pathological markers and 14,735 ambiguous lesions, a Semi-Supervised Deep Learning (SDTL) framework was utilized to identify benign and malignant lung nodules. The findings demonstrated that SDTL performed better in terms of diagnosis, with semi-supervised learning increasing accuracy by 2.9% and migration learning boosting accuracy by 2%. It is anticipated that these useful categories would find significant use in clinical practice[40].Fang et al. [41] used AI to identify GGNs based on quantitative characteristics and CT imaging markers after analyzing CT scans of 224 nodules, including hypothesized and GGNs from 210 patients. Early pulmonary gland cancer subtypes were detected by the AI. By improving accuracy and early tumor detection, the combination of AI data and CT imaging indicators increased the efficacy of diagnosis.

3.4.3 AI and Pathological Diagnosis

Numerous studies have demonstrated that artificial intelligence may greatly increase diagnostic efficiency and decrease workloads by helping pathologists identify genetic alterations, make clinical judgements, and promptly diagnose different forms of lung cancer [42]. Wang et al. [43] conducted a study with 101 individuals who had received a lung cancer clinical diagnosis. evaluated 94 lung biopsy samples, 6 pleural effusion samples, and 1 ascites sample using an AI-based cellular disease diagnosis method and on-site quick assessment. The findings showed that while AI's diagnostic accuracy was equivalent to that of on-site fast evaluation, it was somewhat less accurate than pathologists'. The method is a useful tool for lung cancer diagnosis because it also decreased workload and increased efficiency. Chen and associates [44] examined 20 non-cancerous pleural fluid samples (as controls) and 110 pleural fluid samples for lung adenocarcinoma. They used both proven and suspected lung cancer cells to train a Yolo V4 model and various cell classifications to train an Inception V3 model. The trained Inception V3 model had an accuracy of 98%, whereas the Yolo V4 model had an average of 20% across all categories in identifying and labelling suspected and confirmed lung cancer cells in pleural effusion. Accuracy and efficiency were improved by the dispersion of cell clusters into individual cells. Thus, AI improved the detection of lung cancer and provided a powerful real-world example of deep learning application by accurately detecting and classifying lung adenocarcinoma cells in pleural fluid.

3.4.5 AI and Genetic Patterns

Geneticists and medical professionals can evaluate sequencing results with more accuracy when artificial intelligence is used to handle the vast and intricate amounts of data generated by genomic analyses. Nevertheless, there are presently few AI applications in this area, necessitating additional advancements. To find genes with high variability, Liu et al. [45] employed a KL-divergence-based gene selection method. They created a deep neural network using a focal loss function and then used k-fold cross-validation to choose the best model. The findings showed that the validation set's area under the curve (AUC) was 0.99, indicating a notable increase in the accuracy of lung cancer prediction. Furthermore, Wang et al. [46] predicted the results of EGFR-tyrosine kinase inhibitor-treated patients with EGFR mutations by extracting lung information from CT images using a fully automated AI system. 18,232 patients' pictures and EGFR gene sequences from nine cohorts in China and the US were gathered. Kaplan-Meier analysis showed that the fully automated AI systems outperformed the tumor-focused deep learning models, with AUCs ranging from 0.748 to 0.813 across the various cohorts. Patients with EGFR mutations who had a significant risk of developing resistance to tyrosine kinase inhibitors were detected by these systems' deep learning features (a total of 29). [47].

3.4.6 Staging of Lung Cancer

Accurately determining the stage of cancer helps doctors select appropriate treatments for patients[48].. Artificial intelligence (AI) primarily concentrates on lymph nodes and distant metastasis based on original tumor characteristics, even though radiologists can more accurately identify tumor stages by investigating local invasion and distant metastasis utilizing multimodal images. Additionally, AI is capable of differentiating between benign and malignant lymph node [49]. s. There is evidence that AI can help radiologists in their profession, even though they are still indispensable. In their evaluation of 96 patients with peripheral non-small cell lung cancer, Yang et al. [50] used the TNM approach to establish tumor staging. Prior to surgery, all patients had multi-detector CT imaging. To ascertain the T stage prior to surgery, the maximal lesion diameter was measured using two techniques: AI-based measurement and manual measurement by the doctor. The accuracy of the AI was 83.33%, compared to 67.71% for the doctor. While the two methods showed good consistency in detecting the problematic T stage, the results showed that AI performed better than the other methods in terms of accuracy, repeatability, and stability when determining the T stage from CT imaging.

3.5 Limitations and Critical Analysis of AI-Based Lung Cancer Diagnosis

Although the diagnosis of lung cancer has greatly improved thanks to artificial intelligence (AI), a careful analysis of earlier research reveals a number of issues that need to be resolved for successful clinical integration. For example, Yu et al. [29] showed how well machine learning methods work for examining CT scan slices and images of lung cancer pathology. Their model's efficacy, however, was heavily reliant on the dataset, which might have limited how broadly it could be applied to other populations. Similar to this, Zhang et al. [30] emphasised AI's potential for early lung cancer identification; however, their methodology lacked external validation on separate datasets, which raised questions regarding its dependability in practical applications. Furthermore, despite the widespread use of CADe/CADx systems, research shows inconsistent results in identifying certain nodule types, like ground-glass nodules (GGNs), because of their modest imaging appearance. This implies that in order to lower false positives and increase detection accuracy, more developments in deep learning architectures are required. In pathological diagnosis, Chen et al. [44] achieved good sensitivity and specificity by using YOLO V4 to identify lung cancer cells in pleural fluid samples. However, because of physical similarities, the model had trouble differentiating between benign and malignant cells, which could have resulted in misdiagnosis. A hybrid strategy that combines conventional feature extraction methods with deep learning may improve the precision of pathological diagnosis. In a similar vein, Wang et al. [46] created an AI system to forecast EGFR mutations and evaluate therapy outcomes. The study was constrained by the availability of high-quality genetic data, which affected the accuracy of predictions across a range of patient populations, even though it achieved a high AUC score (0.748–0.813). In order to solve this, clinical patient data combined with AI-driven genetic analysis could greatly increase clinical relevance and predictive accuracy..

All things considered, even if AI has shown significant progress in the detection of lung cancer, issues with data heterogeneity, external validation, and practical application continue to be major worries. Optimising AI's use in clinical cancer will need addressing these constraints through multi-modal data integration, hybrid AI techniques, and more thorough validation studies..

3.6 Prognostic Prediction

In addition to producing exact prognostic forecasts that aid in the selection of suitable treatment approaches, artificial intelligence (AI) is essential for the early and accurate identification of people at risk for lung cancer. Miller et al. [51] achieved extremely accurate patient survival forecasts by combining metabolic data from tumour biopsies with a machine learning approach. Similarly, Wei et al. [52] employed an AI-supported diagnostic method to extract features from computed tomography (CT) images of 162 patients with ground-glass nodules (GGNs) associated with thyroid cancer. The study revealed that the pure GGN group exhibited superior recurrence-free survival and five-year survival rates post-surgery compared to the mixed GGN group. Furthermore, specific imaging characteristics, including microvascular patterns, nodule size, length, and diameter, were identified as independent risk factors for poor survival outcomes. Additionally, central nodule density and lymph node metastases were recognized as independent risk factors for poor recurrence-free survival. These findings underscore the efficacy of AI-assisted diagnostics in predicting the prognosis of GGN-type lung cancer and facilitating personalized treatment planning. Such studies also contribute to improving lung cancer prevention strategies. At present, AI's advantages are widely acknowledged in computer-aided design systems for lung cancer screening, which enhance the detection and segmentation of lesions. Many of these tools have undergone validation and are commercially available [53] (Figure 4).

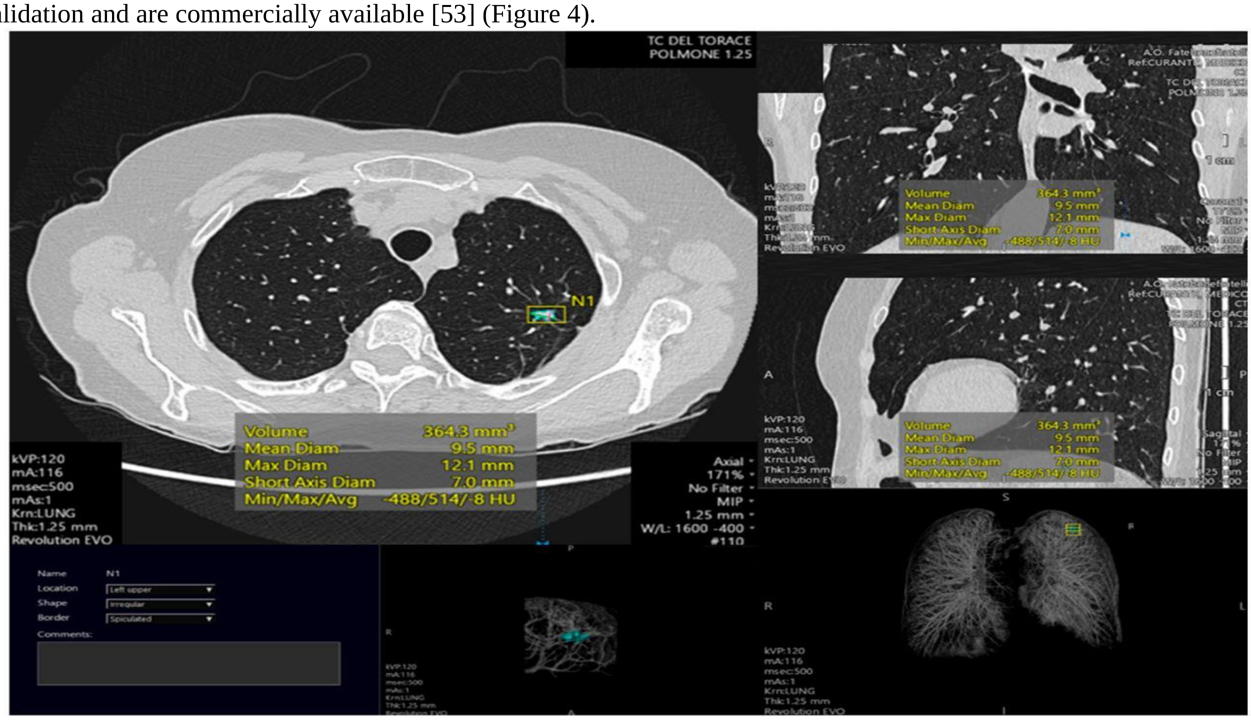

Fig. 5. AI function diagram for diagnosis, prognosis, and treatment of lung cancerCDSS, or compressed data storage system; DCNN, or deep convolutional network; DTA, or decision tree analysis; CNN stands for convolutional networks, SVM for support vector machines, and GAN for generative adversarial networks.

Lung structures suspected of being cancerous have been identified by automatic nodule identification. Specifically, the use of deep learning systems in lung research has shown great accuracy in radiogenomic analysis, risk stratification, nodule segmentation, and lesion detection and screening. These applications are essential to oncological imaging since they have also helped with prognostic prediction, treatment planning (including tumour size, shape, and lesion connections), and evaluating tumour response to treatment (see Figure 5).

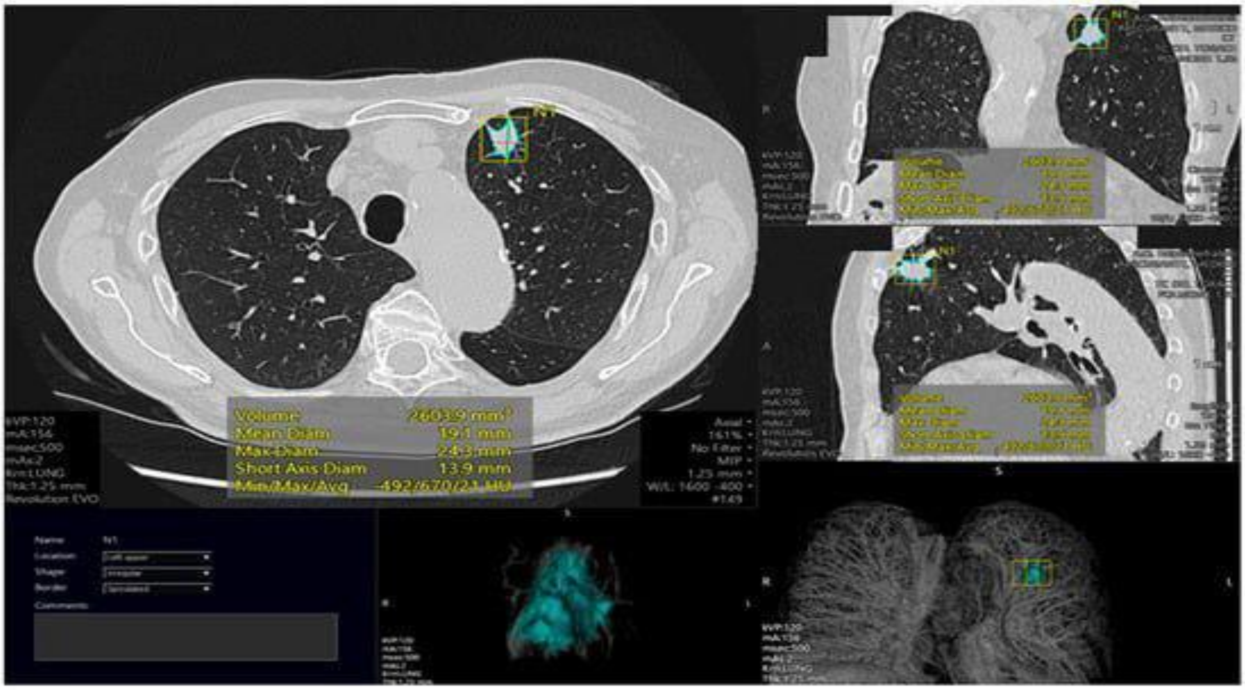

Fig. 6. Automated analysis of a pulmonary lesion in the left upper lobe. Calculating several lesion metrics, including volume (mm3), mean diameter (mm), maximum diameter (mm), short axis diameter (mm), and density (Hounsfield Units), is made possible by the automated study. In order to analyse the diagnosed lesion, a circle mark is made around the lung nodule. 3D reconstruction is also displayed [53].

Effective computer-aided design (CAD) techniques have been developed and validated because to the availability of open-source picture datasets (see Figure 7).

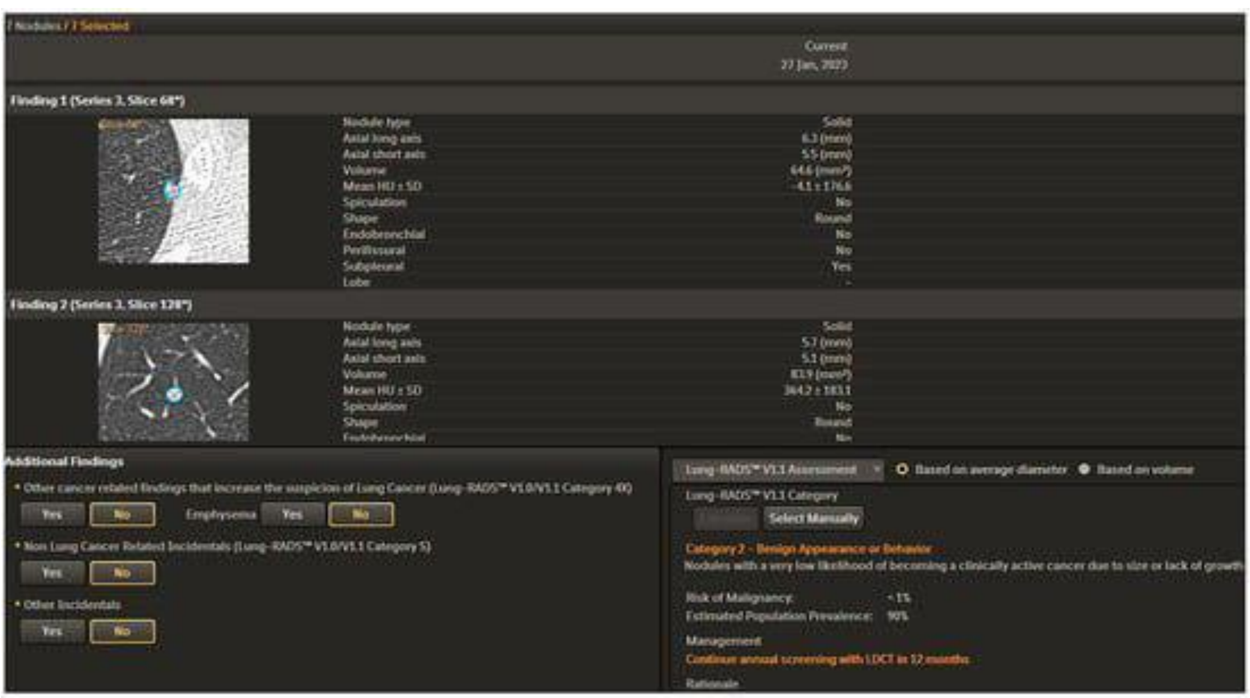

Fig. 7. The lower portion of the picture contains CAD analysis. Descriptions are given on the nodule type, size, volume, mean HU, form, side, and locatio. There is correlation with the LUNG-RADS classification. [53]

4. FINDINGS AND DISCUSSION

Artificial intelligence (AI) has demonstrated significant potential in improving lung cancer diagnosis, particularly in three primary domains: medical imaging, pathology, and genetic analysis. Various AI methodologies have been utilized, including deep learning (CNNs), traditional machine learning (SVM, XGBoost), and hybrid models that integrate multiple data sources. To systematically compare the performance of different AI techniques, the following table summarizes key studies reviewed in this paper.

TABLE III. COMPARISON OF AI-BASED STUDIES IN LUNG CANCER DIAGNOSIS A COMPARATIVE ANALYSIS OF THESE STUDIES REVEALS SEVERAL KEY TRENDS.

Key Findings	Specificity (%)	Sensitivity (%)	Accuracy (%)	Data Source	AI Method Used	Reference
Improved early-stage lung cancer detection	90.8	94.2	92.5	CT Scans (Public Dataset)	CNN (Deep Learning)	**[22]**
AI-enhanced radiomics improved classification of benign vs. malignant nodules	83.5	88.4	85.7	Multi-center CT Data	SVM + Radiomics	**[29]**
Enhanced AI-assisted cytology analysis	95.5	97.1	96.3	Pathology Slides	YOLO V4 (Deep Learning)	**[44]**
AI improved mutation detection and therapy prediction	88.1	90.2	89.4	Genomic Sequencing Data	Hybrid CNN-RNN	**[46]**
AI combined with clinical data outperformed imaging-only models	86.2	89.7	87.9	Multi-modal Imaging & Clinical Data	XGBoost	**[35]**

- Deep learning models (e.g., CNNs) consistently achieve the highest accuracy (>90%) in medical imaging analysis, making them highly effective in early lung cancer detection.
- Hybrid AI models that integrate imaging, genomic, and clinical data outperform single-modality approaches**,** suggesting that multi-source data fusion enhances diagnostic precision.
- Machine learning-based models (e.g., SVM, XGBoost) offer more interpretable decision-making but generally exhibit lower accuracy compared to CNN-based deep learning methods.
- AI applications in pathology demonstrate the highest sensitivity and specificity, indicating their reliability in identifying cancerous cells with minimal misclassification.

Despite the significant advancements AI has introduced in lung cancer diagnosis, several challenges and limitations hinder its full clinical adoption.

Data Scarcity and Quality: AI models rely heavily on large-scale, high-quality datasets for training. However, the availability of comprehensive medical datasets remains limited due to privacy concerns and institutional restrictions. Moreover, data heterogeneity—stemming from differences in imaging protocols, equipment, and patient demographics—can impact the generalizability of AI models across diverse populations [7,28,39]. Bias and Ethical Issues: The datasets used to train AI algorithms may contain biases. Disparities in diagnostic accuracy may result from a model's inability to appropriately represent under-represented groups if it is primarily trained on data from that population. Developing equitable AI applications requires ensuring dataset variety and putting bias-mitigation techniques into practice [20,26,30].

Interpretability and Trust in AI Systems: Most deep learning models operate as “black boxes,” making it difficult for clinicians to understand their decision-making processes. Concerns of accountability and trust in medical decision-making are brought up by this lack of interpretability. Clinicians' trust in AI-assisted diagnoses can be increased by attempting to improve AI explainability using strategies like saliency maps, attention mechanisms, and model-agnostic interpretation methods [10,42,47]. Implementation and Regulatory Obstacles: Before being used in clinical settings, AI-based diagnostic systems must adhere to stringent regulatory requirements. Getting regulatory agencies like the FDA or EMA to approve a product is a difficult and time-consuming process. Furthermore, resolving compatibility concerns with electronic health record (EHR) systems and guaranteeing physician training on AI-assisted diagnostics are necessary for a smooth integration of AI into current clinical workflows [21,43,48]. Computational and Resource Limitations: Real-time processing is difficult due to deep learning models' high memory and processing power requirements, particularly in healthcare settings with restricted resources. Accessibility in areas with limited resources is further limited by the high cost of AI deployment and maintenance [9,31,50]. For AI-based lung cancer diagnostic systems to be dependable, objective, interpretable, and therapeutically feasible, these issues must be resolved. Future studies should concentrate on removing these obstacles by increasing the diversity of datasets, improving the explainability of AI, and expediting the regulatory approval procedures.

5. CONCLUSIONS AND RECOMMENDATIONS

Through genetic profiling, pathology analysis, and medical imaging, artificial intelligence has demonstrated impressive promise in improving the detection of lung cancer. Deep learning models (CNNs), hybrid AI approaches, and radiomics-based machine learning (ML) models are among the AI-based strategies that have shown excellent sensitivity and accuracy in identifying malignant nodules, enhancing early diagnosis, and supporting individualised treatment planning. Nevertheless, a number of significant obstacles still exist in spite of these developments, such as the lack of interpretability, restricted dataset diversity, regulatory obstacles, and computational limitations. To guarantee the broad clinical use of AI in oncology, these issues must be resolved.

◆ Recommendations

1. Improving Standardisation and Diversity of Data In order to increase dataset diversity and establish uniform benchmarks for AI model validation, multi-center partnerships ought to be promoted.
2. Creating XAI, or Explainable AI Future studies should concentrate on improving model transparency using interpretable AI methods such decision tree-based hybrid models, saliency maps, and attention processes.
3. Regulatory Compliance and Ethical AI Implementation Before being used in the real world, AI models must undergo thorough validation in accordance with FDA, EMA, and WHO standards to guarantee safety, equity, and dependability
4. .Improving AI Accessibility in Resource-Limited Settings Efforts should be made to optimize AI models for low-resource hospitals by developing lightweight, computationally efficient architectures.
5. Addressing Bias and Ethical Concerns AI training datasets should be balanced and representative of diverse populations to prevent biases that could lead to diagnostic disparities.

Funding
The authors had no institutional Funding or sponsor backing.

Conflicts Of Interest
The author's disclosure statement confirms the absence of any conflicts of interest.

Acknowledgment
The authors extend appreciation to the institution for their unwavering support and encouragement during this research.

References
[1] Z. Wang, L. Hu, J. Li, L. Wei, J. Zhang, and J. Zhou, "Magnitude, temporal trends and inequality in global burden of tracheal, bronchus and lung cancer: Findings from the Global Burden of Disease Study 2017," *BMJ Glob. Health*, vol. 5, e002788, 2020.
[2] J. E. Chaft, A. Rimner, W. Weder, C. G. Azzoli, M. G. Kris, and T. Cascone, "Evolution of systemic therapy for stages I–III non-metastatic non-small-cell lung cancer," *Nat. Rev. Clin. Oncol.*, vol. 18, pp. 547–557, 2021.
[3] A. Roointan, T. A. Mir, S. I. Wani, et al., "Early detection of lung cancer biomarkers through biosensor technology: A review," *J. Pharm. Biomed. Anal.*, vol. 164, pp. 93–103, 2019.
[4] C. Bardoni, L. Spaggiari, and L. Bertolaccini, "Artificial intelligence in lung cancer," *Ann. Transl. Med.*, vol. 12, no. 4, p. 79, Aug. 2024, doi: 10.21037/atm-22-2918.
[5] H. Sung, et al., "Global cancer statistics 2020: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries," *CA: Cancer J. Clin.*, vol. 71, no. 3, pp. 209–249, 2021.
[6] P. Sharma, et al., "Emerging trends in the novel drug delivery approaches for the treatment of lung cancer," *Chemico-biological interactions*, vol. 309, p. 108720, 2019.
[7] W. L. Bi, et al., "Artificial intelligence in cancer imaging: clinical challenges and applications," *CA: Cancer J. Clin.*, vol. 69, no. 2, pp. 127–157, 2019.

[8] M. P. Amisha, M. Pathania, and V. K. Rathaur, "Overview of artificial intelligence in medicine," *J. Family Med. Prim. Care*, vol. 8, pp. 2328–2331, 2019.

[9] M. Cellina, et al., "Artificial Intelligence in the Era of Precision Oncological Imaging," *Technol. Cancer Res. Treat.*, vol. 21, p. 15330338221141793, 2022.

[10] D. R. Baldwin, et al., "External validation of a convolutional neural network artificial intelligence tool to predict malignancy in pulmonary nodules," *Thorax*, vol. 75, pp. 306–312, 2020.

[11] W. Choi, et al., "Radiomics analysis of pulmonary nodules in low-dose CT for early detection of lung cancer," *Med. Phys.*, vol. 45, pp. 1537–1549, 2018.

[12] M. M. K. Krarup, et al., "Artificial intelligence for the characterization of pulmonary nodules, lung tumors and mediastinal nodes on PET/CT," *Semin. Nucl. Med.*, vol. 51, no. 2, 2021.

[13] L. Shi, et al., "CT-based radiomics for differentiating invasive adenocarcinomas from indolent lung adenocarcinomas appearing as ground-glass nodules: A systematic review," *Eur. J. Radiol.*, vol. 144, p. 109956, 2021.

[14] P. Dhiman, et al., "Reporting of prognostic clinical prediction models based on machine learning methods in oncology needs to be improved," *J. Clin. Epidemiol.*, vol. 138, pp. 60–72, 2021.

[15] D. A. Bluemke, et al., "Assessing radiology research on artificial intelligence: a brief guide for authors, reviewers, and readers—from the radiology editorial board," *Radiology*, vol. 294, no. 3, pp. 487–489, 2020.

[16] H. S. R. S. Rajaguru, "Analysis of decision tree and K-nearest neighbor algorithm in the classification of breast cancer," *Asian Pac. J. Cancer Prev.*, vol. 20, pp. 3777–3781, 2019.

[17] M. Sherafatian and F. Arjmand, "Decision tree-based classifiers for lung cancer diagnosis and subtyping using TCGA miRNA expression data," *Oncol. Lett.*, vol. 18, pp. 2125–2131, 2019.

[18] I. Aguirre-Allende, et al., "Early-rectal cancer treatment: a decision-tree making based on systematic review and meta-analysis," *Cir. Esp.*, vol. 99, pp. 89–107, 2020.

[19] M. M. Ghiasi and S. Zendehboudi, "Application of decision tree-based ensemble learning in the classification of breast cancer," *Comput. Biol. Med.*, vol. 128, p. 104089, 2021.

[20] A. Hosny, C. Parmar, J. Quackenbush, L. H. Schwartz, and H. Aerts, "Artificial intelligence in radiology," *Nat. Rev. Cancer*, vol. 18, pp. 500–510, 2018.

[21] H. Hricak, et al., "Medical imaging and nuclear medicine: a lancet oncology commission," *Lancet Oncol.*, vol. 22, pp. e136–e172, 2021.

[22] Y. Zhang, et al., "Lung nodule detectability of artificial intelligence-assisted CT image reading in lung cancer screening," *Curr. Med. Imaging*, vol. 18, pp. 327–334, 2022.

[23] H. Tang, H. Liu, and N. Sebe, "Unified generative adversarial networks for controllable image-to-image translation," *IEEE Trans. Image Process.*, vol. 29, pp. 1756–1769, 2020.

[24] S. Wang, R. Rong, D. M. Yang, J. Fujimoto, S. Yan, L. Cai, *et al.*, "Computational staining of pathology images to study the tumor microenvironment in lung cancer," *Cancer Res.*, vol. 80, pp. 2056–2066, 2020.

[25] X. Ren, Y. Zhang, Y. Lyu, B. Jin, H. Guo, J. Wu, *et al.*, "Lactate dehydrogenase and serum tumor markers for predicting metastatic status in geriatric patients with lung adenocarcinoma," *Cancer Biomark.*, vol. 26, pp. 139–150, 2019.

[26] M. M. K. Krarup, G. Krokos, M. Subesinghe, A. Nair, and B. M. Fischer, "Artificial intelligence for the characterization of pulmonary nodules, lung tumors and mediastinal nodes on PET/CT," *Semin. Nucl. Med.*, vol. 51, pp. 143–156, 2021.

[27] N. N. Bian, X. Y. Shi, H. Y. Qi, X. Hu, Y. Ge, G. Y. An, *et al.*, "The relationship of plasma fibrinogen with clinicopathological stages and tumor markers in patients with non-small cell lung cancer," *Medicine (Baltimore)*, vol. 98, p. e16764, 2019.

[28] D. Ardila, A. P. Kiraly, S. Bharadwaj, B. Choi, J. J. Reicher, L. Peng, *et al.*, "End-to-end lung cancer screening with three-dimensional deep learning on low-dose chest computed tomography," *Nat. Med.*, vol. 25, pp. 954–961, 2019.

[29] H. Yu, Q. Zhang, and L. T. Yang, "An edge-cloud-aided private high-order fuzzy C-means clustering algorithm in smart healthcare," *IEEE/ACM Trans. Comput. Biol. Bioinform.*, 2023.

[30] Z. Zhigai, S. Xuanqi, and L. Liandi, "Analysis of the value of AI recognition technology in early lung cancer diagnosis," *Chin. Pract. Med.*, vol. 15, pp. 58–60, 2020, doi: 10.14163/j.cnki.11-5547/r.2020.22.023.

[31] S. A. Mahmood and H. A. Ahmed, "An improved CNN-based architecture for automatic lung nodule classification," *Med. Biol. Eng. Comput.*, vol. 60, no. 7, pp. 1977–1986, 2022.

[32] M. Rabbani, *et al.*, "Role of artificial intelligence in the care of patients with nonsmall cell lung cancer," *Eur. J. Clin. Invest.*, vol. 48, no. 4, p. e12901, 2018.

[33] Y. Yang, *et al.*, "Research on classification of benign and malignant lung nodules based on three-dimensional multi-view squeeze-and-excitation convolutional neural network," *J. Biomed. Eng.*, vol. 39, no. 3, pp. 452–461, 2022.

[34] H. Ma, *et al.*, "Automatic pulmonary ground-glass opacity nodules detection and classification based on 3D neural network," *Med. Phys.*, vol. 49, no. 4, pp. 2555–2569, 2022.

[35] M. Liu and X. Zhang, "Study on the value of artificial intelligence for early lung cancer screening," *Health Vision*, vol. 10, p. 004, 2021.

[36] J. C. Wu, T. Li, X. D. Li, Y. Zhuo, Y. J. Zhang, and J. Y. Liu, "Study on the factors influencing the prediction of lung nodule growth based on artificial intelligence follow-up," *Chin. Gen. Med.*, vol. 25, pp. 2115–2120, 2022.

[37] Y. Guo, R. B. Li, S. H. Liu, L. J. Wei, and F. S. Cui, "Research on lung cancer image assisted diagnosis application based on machine learning," *China Med. Equip.*, vol. 18, pp. 124–128, 2021.

[38] M. Mei, "Application of artificial intelligence technology in medical imaging," *Fam. Med.*, vol. 2, pp. 78, 2019, doi: CNKI:SUN:YYJT.0.2019-02-087.

[39] J. Feng and J. Jiang, "Deep learning-based chest CT image features in diagnosis of lung cancer," *Comput. Math. Methods Med.*, vol. 2022, pp. 1–7, 2022, doi: 10.1155/2022/4153211.

[40] F. Shi, B. Chen, Q. Cao, Y. Wei, Q. Zhou, R. Zhang, *et al.*, "Semi-supervised deep transfer learning for benign-malignant diagnosis of pulmonary nodules in chest CT images," *IEEE Trans. Med. Imaging*, vol. 41, pp. 771–781, 2022, doi: 10.1109/TMI.2021.3123572.

[41] W. Fang, G. Zhang, Y. Yu, H. Chen, and H. Liu, "Identification of pathological subtypes of early lung adenocarcinoma based on artificial intelligence parameters and CT signatures," *Biosci. Rep.*, vol. 42, pp. 1–28, 2022, doi: 10.1042/BSR20212416.

[42] H. Yu, L. T. Yang, Q. Zhang, D. Armstrong, and M. J. Deen, "Convolutional neural networks for medical image analysis: State-of-the-art, comparisons, improvement and perspectives," *Neurocomputing*, vol. 444, pp. 92–110, 2021. doi: 10.1016/j.neucom.2020.04.157.

[43] S. Wang, H. Yu, Y. Gan, Z. Wu, E. Li, X. Li, *et al.*, "Mine whole-lung information by artificial intelligence for predicting EGFR genotype and targeted treatment response in lung cancer: a multicohort study," *Lancet Digit. Health.*, vol. 4, pp. e309–e319, 2022, doi: 10.1016/S2589-7500(22)00024-3.

[44] Y. Y. Chen, W. Z. Kong, H. Q. Wu, and J. L. Ji, "A deep learning-based artificial intelligence-assisted diagnosis of lung cancer pleural fluid exfoliation cytology," *Chin. Clin. Med.*, vol. 29, pp. 396–400, 2022. doi: 10.12025/j.issn.1008-6358.2022.20220658.

[45] S. Liu and W. Yao, "Prediction of lung cancer using gene expression and deep learning with KL divergence gene selection," *BMC Bioinform.*, vol. 23, p. 175, 2022. doi: 10.1186/s12859-022-04689-9.

[46] S. Wang, H. Yu, Y. Gan, Z. Wu, E. Li, X. Li, *et al.*, "Mine whole-lung information by artificial intelligence for predicting EGFR genotype and targeted treatment response in lung cancer: A multicohort study," *Lancet Digit. Health*, vol. 4, pp. e309–e319, 2022. doi: 10.1016/S2589-7500(22)00024-3.

[47] Q. Li, Y. Liu, Y. W. Zhang, and Z. X. Ye, “Research progress of artificial intelligence in lung tumor imaging diagnosis,” *Chin. Cancer Clin.*, vol. 47, pp. 55–59, 2020. doi: 10.3969/j.issn.1000-8179.2020.02.987.

[48] J. R. Ferreira-Junior, M. Koenigkam-Santos, A. P. Magalhães Tenório, M. C. Faleiros, F. E. Garcia Cipriano, A. T. Fabro, et al., “CT-based radiomics for prediction of histologic subtype and metastatic disease in primary malignant lung neoplasms,” *Int. J. Comput. Assist. Radiol. Surg.*, vol. 15, pp. 163–172, 2020. doi: 10.1007/s11548-019-02093-y.

[49] D. Moitra and R. K. Mandal, “Automated AJCC (7th edition) staging of non-small cell lung cancer (NSCLC) using deep convolutional neural networks (CNN) and recurrent neural networks (RNN),” *Health Inf. Sci. Syst.*, vol. 7, p. 14, 2019. doi: 10.1007/s13755-019-0077-1.

[50] L. L. Yang, F. Wang, Z. R. Wang, Y. B. Yang, R. S. Ha, and M. Zhang, “A controlled study of imaging T-staging and pathological T-staging of non-small cell lung cancer based on artificial intelligence,” *Ningxia Med. J.* (in Chinese), vol. 43, pp. 782–784, 2021. doi: 10.13621/j.1001-5949.2021.09.0782.

[51] H. A. Miller, V. H. van Berkel, and H. B. Frieboes, “Pooled machine learning analysis of tumor core biopsy metabolomic data for lung cancer survival prediction and biomarker identification,” *Metabolomics*, vol. 18, p. 57, 2022. doi: 10.1007/s11306-022-01918-3.

[52] N. Wei, R. J. Lin, M. J. Ma, C. Chen, and B. Han, “Relationship between imaging microfeatures of artificial intelligence-aided diagnostic system and prognosis of ground glass nodule-like lung cancer,” *Cancer Control Res.* (in Chinese), vol. 48, pp. 877–882, 2021. doi: 10.3971/j.issn.1000-8578.2021.21.0255.

[53] M. Cellina, L. M. Cacioppa, M. Cè, V. Chiarpenello, M. Costa, Z. Vincenzo, D. Pais, M. V. Bausano, N. Rossini, A. Bruno, et al., “Artificial Intelligence in Lung Cancer Screening: The Future Is Now,” *Cancers*, vol. 15, p. 4344, 2023.