Proceedings of the 1st International Conference on Statistical Sciences and Data Analytics

# DEEP LEARNING AND TRANSFER LEARNING TECHNIQUES FOR LUNG CANCER DIAGNOSIS: A SYSTEMATIC REVIEW

**Maaruf Mohammed Lawal [1], Abdulrasheed Habib[1] and Abdulrashid Abdulrauf [2,]***

[1]Department of Computer Science, Ahmadu Bello University, Kaduna State
[2]Department of Computer Science, Federal Polytechnic Kaltungo, Gombe State

*Corresponding Author: abdulrashid.abdulrauf2022@nda.edu.ng

## ABSTRACT

Lung cancer is a leading cause of cancer-related deaths globally, and early detection through imaging remains critical to improving patient outcomes. Recent progress in deep learning and transfer learning has demonstrated significant potential in automating lung cancer detection and classification using imaging techniques such as CT and X-ray. However, challenges persist, including limited data availability, class imbalance, misclassification errors, poor generalizability across clinical settings, and lack of model interpretability. This systematic review analyzes 44 peer-reviewed studies using a structured keyword-based search across major databases to evaluate current advancements, identify gaps, and propose future directions in imaging-based deep learning applications for lung cancer. The review highlights trends such as the emergence of advanced architectures like 3D CNNs, the effective use of pre-trained models through transfer learning, and the growing adoption of explainable AI (XAI) to enhance clinical trust. Despite improvements in accuracy and robustness, models still struggle with detecting small nodules, achieving real-time performance, and ensuring generalizability. To understand the root cause of these problems, a deep knowledge/analysis of these root causes needs to be conducted. The findings underscore the need for more sophisticated, interpretable, and clinically applicable AI systems to enhance diagnostic precision and improve lung cancer patient outcomes.

**Keywords:** Cancer, Deep Learning, Diagnosis, Lung, Transfer Learning, Review

## 1. INTRODUCTION

Lung cancer remains the leading cause of cancer-related deaths globally, with a high incidence and mortality rate, especially in developed countries such as the United States (Siegel et al., 2022). According to GLOBOCAN, approximately 2.09 million new cases and 1.76 million deaths were recorded worldwide in 2018 alone, underscoring the pressing need for early and accurate diagnostic strategies (Bade & Cruz, 2020). Non-small cell lung carcinoma (NSCLC) accounts for approximately 85–88% of lung cancer cases, while small cell lung cancer (SCLC) represents around 12–15% (Stamatis et al., 2004). Due to the invasive nature and heterogeneity of lung cancer, early diagnosis and intervention significantly increase the 5-year survival rate (Chiang et al., 2008).

Various imaging techniques such as chest X-ray, low-dose computed tomography (LDCT), positron emission tomography (PET), magnetic resonance imaging (MRI), and computed tomography (CT) have been extensively explored for lung nodule detection over the past two decades (Journy et al., 2015). Among these, CT is considered the gold standard for lung cancer diagnosis but is limited by high false-

positive rates and exposure to harmful radiation (Journy et al., 2015). LDCT, while reducing radiation exposure, has been associated with a concentration of cancer-related deaths among screened populations (NLSTRT, 2011). More advanced imaging techniques such as 18F-fluorodeoxyglucose PET (18F-FDG PET) offer semi-quantitative analysis of tumor metabolism and have shown promise in NSCLC detection, although their clinical utility still requires further validation (Ippolito et al., 2013; (Park et al., 2015). Emerging modalities like magnetic induction tomography (MIT) are under development for early-stage cancer cell detection but currently lack validation in clinical settings (Griffiths, 2011).
To enhance the accuracy of diagnosis, computer-aided detection systems have been introduced, providing superior performance in identifying lung nodules compared to human radiologists (Brown et al., 2020). A typical CAD system encompasses four stages: image preprocessing, region of interest extraction, feature selection, and classification. Among these, the feature selection and classification stages are crucial in determining the system's diagnostic performance.

The advent of deep learning (DL) has significantly transformed CAD systems. Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated remarkable proficiency in detecting and classifying lung cancer from CT and X-ray images by automatically learning high-level features from vast datasets (Saleh et al., 2021; Rajpurkar et al., 2018). Research in this domain has primarily focused on developing new network architectures, customized loss functions, and advanced segmentation techniques to improve diagnostic performance (Mandal & Vipparthi, 2022; Alireza et al., 2022).
Transfer learning, a powerful subset of deep learning, has further enhanced diagnostic accuracy, especially when annotated medical data is limited. By repurposing models pre-trained on large-scale datasets like ImageNet, researchers can fine-tune these networks for lung cancer classification with relatively small medical datasets, leading to faster convergence and improved generalization (Zhang, 2023). Such methods have expedited the deployment of intelligent diagnostic tools in clinical workflows. This review seeks to examine the current state, emerging trends, and future research directions in lung cancer detection and classification using imaging-based deep learning techniques. Particular attention is given to challenges such as data imbalance, model generalizability, and the integration of multimodal data to improve diagnostic reliability and patient outcomes.

## 2. MATERIALS AND METHOD

This review adopts a systematic approach to explore and evaluate existing studies on the application of deep learning and transfer learning techniques in lung cancer detection and classification. The methodology encompasses clearly defined search strategies, relevant keywords, and the use of reputable academic databases to ensure comprehensive coverage of pertinent literature. The review process is guided by established systematic review protocols within the field of computer science, as outlined in previous scholarly works, serving as a structured foundation for the identification, organization, and critical analysis of selected studies.

### 2.1. Search Method

To ensure alignment with systematic literature review guidelines, this study conducted an extensive search across a wide range of reputable digital libraries and academic databases. These include BMC Medical Imaging, ScienceDirect, IEEE Xplore, IJCRT, IJEER, ISTP, Scientific Reports, IJIRCST, Springer Nature, arXiv, SAI, Frontiers, MDPI, IJEECS, Hindawi, JCBI, IJATEE, BMC Medicine, Springer, Ijain, IOP Conference Series: Materials Science and Engineering, and npj Digital Medicine. The primary focus of this review is to explore and synthesize research on the application of advanced deep learning and transfer learning techniques for the classification and detection of lung cancer. Detailed search strategies, including carefully selected keywords and database usage, were employed to ensure a comprehensive and systematic evaluation of relevant literature.

### 2.2. Search Keyword

To identify relevant literature in the domain of lung cancer detection and classification, a systematic keyword selection strategy was employed. This process involved formulating precise keyword queries aimed at retrieving studies that specifically addressed the application of deep learning and transfer learning techniques. The search strategy included the following combinations:

- Primary Topic Search:
  {Machine Learning} AND {lung cancer}
- Deep Learning Approaches:
  (deep AND learning) AND (image-based “lung cancer detection”)
- Transfer Learning Integration:
  (deep AND transfer AND learning) AND (image processing AND lung AND cancer AND classification)

These keyword queries were applied to the titles and abstracts of articles across the selected academic databases to ensure a thorough and targeted exploration of the literature. To further illustrate the scope and conceptual structure of the search strategy, a mind map was developed to visualize the interconnections among the selected keywords, reflecting the systematic methodology adopted for this review.

### 2.3. Screening of Relevant Papers

A total of 550 records were initially identified through comprehensive database searches and other relevant sources. After the removal of duplicates, 450 unique records remained for screening. During the title and abstract screening phase, 300 studies were excluded for being irrelevant to the research objectives. Subsequently, 150 full-text articles were assessed for eligibility based on predefined inclusion and exclusion criteria. To ensure the review captured only contemporary research, studies published before 2018 were excluded, thereby focusing on recent advancements in deep learning and machine learning applications for lung cancer detection and classification. The review was further limited to English-language, peer-reviewed publications to maintain linguistic consistency and scientific credibility, while non–peer-reviewed sources, such as preprints, conference abstracts, and grey literature, were excluded due to potential methodological limitations. Additional exclusions were made based on the relevance of study objectives, methodological rigor, completeness of data reporting, and overall quality. Ultimately, 44 studies published from 2018 and above that specifically addressed advanced deep learning and machine learning techniques for lung cancer detection and classification were included in the final qualitative synthesis. Given the heterogeneity of methodologies, datasets, and evaluation metrics among the included studies, this review adopted a qualitative synthesis approach rather than a quantitative meta-analysis. The selection process is summarized in Table 1, with a detailed flow of record identification and screening illustrated in Figure 1.

Table 1: Summary of Inclusion and Exclusion Criteria

| Criteria | Inclusion | Exclusion |
|---|---|---|
| **Publication Year** | Studies published from 2018 and above | Studies published before 2018 |
| **Study Focus** | Research addressing deep learning or machine learning methods for lung cancer | Studies focusing on other cancers or non-imaging-based approaches |

| | | |
|---|---|---|
| | detection and classification | |
| **Methodological Rigor** | Empirical studies with well-defined datasets, validated models, and performance metrics | Studies lacking methodological clarity or sufficient experimental validation |
| **Language** | English-language publications | Non-English studies |
| **Document Type** | Peer-reviewed journal articles and conference papers | Editorials, reviews, preprints, theses, and gray literature |
| **Data Source** | Studies using medical imaging datasets (e.g., CT, X-ray, PET) | Studies not involving medical imaging data |

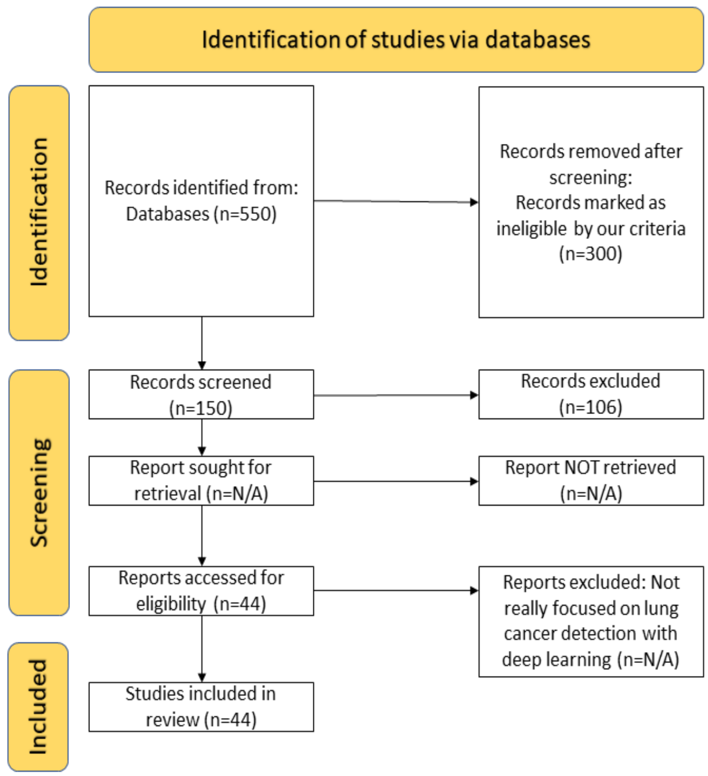


Figure 1. PRISMA Framework for our Literature Review (Malhotra, 2024).

### 2.4. Research Questions

Our review was guided by the following research questions:

1. What advancements have been made in utilizing deep learning techniques for the prediction and classification of lung cancer using imaging techniques?
2. How have transfer learning methods been employed to improve the identification and classification of lung cancer from medical images?
3. What research gaps and unresolved challenges remain in the field of imaging-based lung cancer classification?
4. What strategies and approaches have been proposed to address data imbalance and reduce misclassification errors in deep learning models for lung cancer detection?

## 3. RESULTS AND DISCUSSION

The systematic review provided valuable insights into the advancements in deep learning techniques for lung cancer prediction and classification using imaging methods. It also explored the application of transfer learning in enhancing model performance, identified persistent research gaps and challenges, and examined strategies proposed to address data imbalance and reduce misclassification errors in deep learning models. The findings are presented and discussed in the subsequent sections, organized according to the following four research questions:

### 3.1. Advancements in Deep Learning for Lung Cancer Prediction and Classification using Medical Imaging

Significant advancements have been made in utilizing deep learning techniques for the prediction and classification of lung cancer using imaging modalities, particularly CT scans. These advancements span across novel model architectures, integration with image processing and optimization techniques, improved handling of 3D volumetric data, and progress toward interpretability and clinical applicability.

One key area of advancement is the development of novel deep learning architectures and models. For example, Asuntha and Srinivasan (2020) proposed a deep learning approach that combines handcrafted features such as Histogram of Oriented Gradients (HoG), wavelet transforms, Local Binary Patterns (LBP), Scale-Invariant Feature Transform (SIFT), and Zernike Moments with a Fuzzy Particle Swarm Optimization (FPSO)-based CNN, resulting in higher accuracy and lower computational complexity. Similarly, Sori et al. (2018) introduced a CNN architecture with a modified U-Net for segmentation and a multi-pathway CNN to capture contextual features for malignancy evaluation. Abd Al-Ameer et al. (2022) also demonstrated the effectiveness of deep CNNs trained on histopathological images. Shakeel et al. (2022) improved prediction accuracy using an ensemble classifier and a brightness-preserving preprocessing technique to address low-quality CT images.

Feature engineering and optimization techniques have also been integrated into deep learning pipelines. Asuntha and Srinivasan (2020) combined handcrafted features with CNNs, while Shakeel et al. (2020) employed a hybrid spiral optimization with an intelligent generalized rough set approach to optimize feature selection before ensemble classification. These techniques enhance the learning process by emphasizing the most relevant features, thus improving model performance.

Several studies have addressed specific challenges such as data imbalance and noise in imaging. Sori et al. (2018) introduced a retraining phase to mitigate label imbalance, while Shakeel et al. (2019) applied robust preprocessing methods like weighted mean histogram equalization to improve prediction accuracy in noisy images. Performance metrics reported across these studies consistently show high accuracy, precision, recall, and F1-scores. For instance, Shakeel et al. (2019) achieved a classification accuracy of 98.42%, and Yousef and Daraghmi (2025) reported an F1-score of 97.77% and an accuracy of 97.5% using a deep learning-based hybrid ensemble model.

Another major area of progress is the integration of explainable AI techniques. Wani et al. (2024) proposed "DeepXplainer," a hybrid approach combining CNNs with XGBoost and SHAP values to provide model interpretability. Dwivedi et al. (2023) developed an XAI-based framework for NSCLC subtype classification, enabling biomarker discovery and transparency in AI decisions. Efficiency and clinical deployment are also being prioritized. Wahab-Sait (2023) developed a lightweight deep learning framework for PET/CT image analysis using DenseNet-121, deep autoencoders for dimensionality reduction, and MobileNet V3-Small for classification. This approach demonstrated the feasibility of deploying resource-efficient models in clinical settings.

A notable shift is also observed toward 3D CNNs and volumetric analysis. Zhang et al. (2019) and Ardila et al. (2019) modified conventional 2D CNNs to analyze 3D CT images, leveraging full spatial information and eliminating the need for manual segmentation. Katase et al. (2022) and Yousef and Daraghmi (2025) further explored volumetric feature extraction, while Khademi et al. (2023) proposed a transformer-based model integrating spatial and temporal features from CT scans.

Advanced architectures have emerged as well. Shetty and Tunga (2022) introduced a Shepard CNN optimized by a novel algorithm (WSLnO), while Khademi et al. (2023) developed a hybrid CAET-Swin framework combining convolutional autoencoders and shifted window transformers. Other models, such as the Swin Transformer (Sun et al., 2023) and dilated SegNet (Yuan et al., 2023), have shown competitive results in segmentation and classification tasks. Segmentation techniques have been increasingly integrated with deep learning. For instance, Shetty and Tunga (2022) used deformable models in conjunction with CNNs. Aresta et al. (2019) introduced iW-Net for interactive segmentation using 3D convolutions. Tan et al. (2019) incorporated engineered texture features into their deep learning pipeline, thereby enhancing detection accuracy.

Interpretability remains a focal point for clinical integration. Brocki and Chung (2023) proposed "ConRad," which combines radiomics with deep learning using a concept bottleneck model to ensure transparency. Wani et al. (2024) also addressed explainability through SHAP-based visualization tools. These developments are vital for increasing clinicians' trust and adoption of AI tools.

Performance metrics across these advanced models indicate significant improvements in accuracy, sensitivity, specificity, and AUC. For example, Shetty and Tunga (2022) and Yuan et al. (2023) reported high accuracy and robustness, while Ardila et al. (2019) achieved state-of-the-art AUC scores in lung cancer screening, surpassing human radiologists in some scenarios.

Lastly, studies have shown promising results in terms of clinical workflow integration. Katase et al. (2022) demonstrated that using their CAD system as a second reader significantly enhanced radiologists' diagnostic capability. Primakov et al. (2022) developed an automated segmentation pipeline preferred by clinicians for its speed and reproducibility. Lu et al. (2020) and Tan et al. (2022) emphasized the practical use of deep learning with existing clinical data for improved screening eligibility and diagnostic decision-making.

### 3.2. Application of Transfer Learning in Enhancing Lung Cancer Detection and Classification from Medical Images

Transfer learning has emerged as a pivotal strategy for improving the performance of deep learning models in lung cancer detection and classification. By leveraging knowledge learned from large-scale, general-purpose image datasets and adapting it to medical imaging tasks, transfer learning effectively addresses one of the key challenges in this domain, the scarcity of annotated medical datasets. Rather than training networks from scratch, researchers repurpose pre-trained models, significantly reducing computational cost, training time, and data dependency while improving generalization.

To provide a clearer comparative framework, existing studies can be categorized based on three major dimensions:
(i) Type of pre-training dataset
(ii) Transfer strategy
(iii) Model type.

A. Based on Pre-training Dataset Type

Most studies rely on general-purpose datasets such as *ImageNet*, which contain millions of labeled natural images. Models pre-trained on ImageNet (e.g., VGG16, ResNet, InceptionV3, DenseNet) have shown remarkable capability in extracting discriminative low- and mid-level features transferable to CT and X-ray imaging tasks. For instance, Yousef and Daraghmi (2025) developed a hybrid ensemble using ResNet50, VGG19, DenseNet169, and InceptionV3, all pre-trained on ImageNet, to classify lung cancer from CT images. Their ensemble approach achieved notable improvements in both accuracy and F1-score, underscoring the adaptability of general-purpose features to medical contexts.

In contrast, a smaller group of studies explored medical-domain pre-training, where models are initialized using datasets like *ChestX-ray14* or *LIDC-IDRI*. These domain-specific pre-training approaches often enhance sensitivity to lung tissue characteristics. Tan et al. (2022), for instance, employed a modified VGG16 model initially trained on thoracic X-ray data, demonstrating higher precision in distinguishing lung cancer from latent tuberculosis.

B. Based on Transfer Strategy

Transfer learning can be operationalized through two major strategies:

1. Feature Extraction, where pre-trained weights are frozen and used to extract generic features for downstream classifiers.
2. Fine-Tuning, where pre-trained layers are partially or fully retrained on the target dataset to adapt to domain-specific characteristics.

Da Nóbrega et al. (2018) and Da-Nobrega et al. (2020) exemplified *feature extraction*-based transfer learning by utilizing CNNs (VGG16, VGG19, ResNet50, MobileNet, DenseNet201, Xception, and NASNet) to generate deep features that were subsequently classified using machine learning algorithms such as SVM, Naïve Bayes, MLP, KNN, and Random Forest. Their results demonstrated that features extracted from non-medical datasets can act as strong radiomic biomarkers for distinguishing malignant and benign nodules.

Conversely, Mukherjee et al. (2020) and Sun et al. (2023) adopted *fine-tuning* strategies to further optimize model weights for the lung cancer domain. Mukherjee et al. reported an increase in AUC from 0.82 to 0.85 in their fine-tuned LungNet model, while Sun et al. demonstrated that fine-tuned Swin Transformer models outperformed non-pretrained baselines across multiple medical imaging benchmarks.

C. Based on Model Type

Transfer learning has been applied across diverse architectures:

- CNN-based Models: Classical convolutional architectures (VGG, ResNet, Inception, DenseNet, and UNet variants) remain the most prevalent due to their effectiveness in feature extraction from CT and X-ray images. Studies by Bhatia et al. (2019), Abd Al-Ameer et al. (2022), and Wahab-Sait (2023) all exemplify CNN-based transfer learning approaches that yielded high classification performance with limited data.
- Transformer-based Models: Emerging studies have begun integrating transfer learning into Vision Transformer (ViT) and Swin Transformer architectures. Sun et al. (2023) showed that pre-trained Swin Transformers significantly improved feature representation in lung image classification tasks compared to CNN counterparts.
- Hybrid Models: Some researchers have combined CNN-based feature extractors with traditional ML classifiers or other deep learning components. Da Nóbrega et al. (2018; 2020)'s hybrid CNN–MLP/SVM approach exemplifies this trend, as does Yousef and Daraghmi (2025)'s ensemble of pre-trained CNNs that enhanced robustness and accuracy across multiple evaluation metrics.

### 3.3. Research Gaps and Unresolved Challenges in Imaging-Based Lung Cancer Classification

Despite significant progress in deep learning-based imaging for lung cancer classification, multiple challenges hinder optimal performance and widespread clinical integration. These unresolved issues are categorized below:

I. Accuracy and Diagnostic Performance

i. Achieving Near-Perfect Accuracy and Reducing Misclassifications

While some models report accuracies exceeding 97%, they still fall short of near-perfect precision. False positives and negatives can result in misdiagnoses and inappropriate treatment. Makaju et al. (2018) and Ardila et al. (2019) stress the importance of reducing such errors for safer clinical applications.

ii. Accurate Detection of Small and Complex Nodules

Detection of small (1–4 mm), non-solid, or irregular nodules remains a challenge due to subtle features. Aresta et al. (2019), Agnes and Anitha (2020), Yuan et al. (2023), and Tan et al. (2022) highlight difficulties in identifying these early indicators of lung cancer.

iii. Differentiation from Other Pulmonary Conditions

Distinguishing lung cancer from other thoracic diseases (e.g., tuberculosis) is particularly difficult in endemic regions. Tan et al. (2022) emphasized the need for improved differential diagnostic capabilities in such contexts.

II. Data Quality and Availability

i. Handling Noisy and Low-Quality Data

Image artifacts and noise during acquisition significantly impair model performance. Pawar et al. (2020) and Shakeel et al. (2022) noted the urgent need for robust models that function well with suboptimal data.

ii. Addressing Data Imbalance

An overrepresentation of healthy cases skews learning, impairing sensitivity to rare cancerous cases. Approaches such as SMOTE (Yu et al., 2019) and retraining (Sori et al., 2018) offer partial solutions but do not fully resolve the problem.

iii. Data Scarcity and Fragmentation

The availability of high-quality annotated medical imaging data is limited due to privacy issues and labeling costs. Han et al. (2019) and others note that while generative models (e.g., GANs) help, the data access issue remains a core barrier.

III. Model Deployment and Efficiency

i. Improving Computational Efficiency for Clinical Deployment

Deep learning models often demand high processing power, making real-time or resource-limited deployment difficult. Although lightweight models (Asuntha & Srinivasan, 2020; Wahab-Sait, 2023) exist, they often trade off accuracy for speed.

ii. Robustness to Data Variability and Imaging Protocols

Diverse imaging protocols and equipment across healthcare facilities reduce model generalizability. Singh and Gupta (2019), Katase et al. (2022), and Brocki and Chung (2023) advocate for external validation to enhance robustness.

IV. Explainability and Clinical Trust

i. Enhancing Model Interpretability and Trust

The "black-box" nature of deep neural networks poses a significant challenge for clinical adoption. Explainable AI (XAI) methods are still nascent. Wani et al. (2024), Dwivedi et al. (2023), and Brocki and Chung (2023) call for clinically interpretable models grounded in real-world decision support.

V. Advanced Data Representation and Generalization

i. Leveraging 3D and Temporal Information

Most systems rely on 2D slices or static 3D volumes, omitting valuable spatiotemporal progression of nodules. Integration of 3D CNNs and sequential imaging data has been recommended by Yousef and Daraghmi (2025), Khademi et al. (2023), Lu et al. (2020), and Ardila et al. (2019).

ii. Generalization to Other Cancer Types

Existing models are typically specialized for lung cancer. Cross-domain adaptability remains underexplored. Reddy et al. [49] suggest that methodologies could extend to other cancer types with appropriate adjustments.

### 3.4. What Strategies and Approaches have been Proposed to Address Data Imbalance and Reduce Misclassification Errors in Deep Learning Models for Lung Cancer Detection?

Several strategies and approaches have been proposed in the literature to effectively address data imbalance and reduce misclassification errors in deep learning models for lung cancer detection. These methods aim to enhance model performance, increase reliability, and ensure more accurate diagnosis, especially when working with imbalanced and limited datasets.

To address data imbalance, researchers have implemented various techniques. Sori et al. (2018) introduced a retraining phase in their convolutional neural network (CNN) architecture to mitigate label imbalance. Yu et al. (2019) applied the Synthetic Minority Over-sampling Technique (SMOTE) to oversample the minority class, particularly in the prediction of the pathologic stage of non-small cell lung cancer (NSCLC). Data augmentation has also emerged as a crucial method. Han et al. (2019) proposed a 3D Multi-Conditional Generative Adversarial Network (MCGAN) to generate realistic synthetic lung nodules, thereby improving the performance of 3D CNN-based detection systems. Similarly, Shetty and Tunga (2022) applied augmentation to segmented regions to balance class distributions and enhance classification accuracy.

In terms of reducing misclassification errors and improving the accuracy and reliability of classification models, several approaches have been explored. One major strategy involves the development of advanced deep learning architectures. These include the FPSO-CNN (Asuntha & Srinivasan, 2020), multi-pathway CNNs (Sori et al., 2018), and 3D CNNs (Zhang et al., 2019; Katase et al., 2022). Additionally, more recent architectures like hybrid transformer-based models (Khademi et al., 2023), Swin Transformers (Sun et al., 2023), and CNNs with batch normalization (Agnes & Anitha, 2020; Yuan et al., 2023; Tan et al., 2022) have shown improvements in feature learning and classification accuracy.

Transfer learning is another effective approach, particularly in cases with limited training data. Models pre-trained on large datasets are fine-tuned for lung cancer detection tasks, leading to better generalization and reduced training time (Da Nóbrega et al., 2018; Mukherjee et al., 2020; Tan et al., 2022; Yousef & Daraghmi, 2025).

Ensemble learning methods have been widely adopted to reduce classification errors. Bhatia et al. (2019) combined Random Forest and XGBoost classifiers after feature extraction using UNet and ResNet. Faisal et al. (2018) evaluated multiple ensemble methods and found that Gradient-Boosted Trees and majority voting strategies outperformed single classifiers. Yousef and Daraghmi (2025) implemented an ensemble approach by averaging predictions from five top-performing deep learning models, which led to improved detection reliability.

Robust preprocessing and segmentation techniques also play a vital role in reducing misclassification. These include grayscale conversion, noise reduction, binarization, and segmentation (Wasudeo et al., 2018), as well as advanced techniques like autoencoders for denoising, OTSU thresholding (Pawar et al., 2020), and marker-controlled watershed segmentation (Bharathy et al., 2022; Tripathi et al., 2019). Shetty and Tunga (2022) introduced Bayesian fuzzy clustering and deformable models for accurate region segmentation. Additionally, dilated SegNet and automatic volumetric pipelines have improved the precision of nodule detection (Agnes & Anitha, 2020; Primakov et al., 2022).

Another critical area is feature extraction and selection. Researchers have employed handcrafted feature methods such as Histogram of Oriented Gradients (HoG), wavelets, Local Binary Patterns (LBP), SIFT, and Zernike Moments (Asuntha & Srinivasan, 2020; Singh & Gupta, 2019; Rehman et al., 2021). Deep features extracted from CNN layers are often combined with statistical and spatial features (Khademi et al., 2023; Yuan et al., 2023). Feature selection techniques like Fast Correlation-Based Filter (FCBF) and hybrid spiral optimization with intelligent generalized rough sets help eliminate redundant information and retain the most discriminative features (Xie et al., 2021; Shakeel et al., 2022).

Optimization algorithms are employed to fine-tune hyperparameters and reduce training time. Notable examples include Adam (Wahab-Sait, 2023), Fuzzy Particle Swarm Optimization (Asuntha & Srinivasan, 2020), and WSLnO (Shetty & Tunga, 2022), which enhance convergence and generalization capabilities.

Moreover, multi-modal data fusion has been proposed as a powerful strategy, where structured radiological data are integrated with 3D CT patch data to provide a holistic view for better classification (Yuan et al., 2023). Combining clinical data with imaging data has also been found to enhance risk prediction accuracy (Lu et al., 2020). In addition, the use of prior CT volumes allows for temporal analysis of disease progression, thereby aiding in early detection and reducing false negatives and positives (Ardila et al., 2019). Hybrid approaches that combine deep learning with traditional machine learning techniques or image processing algorithms have been successful (Bhatia et al., 2019; Wasudeo et al., 2018; Pawar et al., 2020). Similarly, multi-stage classification frameworks that sequentially apply image enhancement, segmentation, and classification (Bharathy et al., 2022; Alam et al., 2018) further contribute to reducing misclassification.

### 3.5. What are the limitations in current research methods?

Despite the substantial progress in deep learning and transfer learning approaches for lung cancer prediction and classification, several limitations persist in current research methodologies. A major limitation is data-related challenges, including scarcity, imbalance, and poor quality of medical imaging data. Many studies, such as those by Han et al. (2019) and Yu et al. (2019), have highlighted that the limited availability of high-quality, annotated datasets restricts model generalization and scalability. Data imbalance, where non-cancerous samples outnumber malignant ones, often leads to biased learning and reduced sensitivity to minority classes, despite the use of techniques like SMOTE or retraining (Sori et al., 2018; Yu et al., 2019). Additionally, noisy or low-resolution CT images can degrade model accuracy, as observed in the works of Shakeel et al. (2022) and Pawar et al. (2020), who emphasized the need for robust preprocessing and enhancement techniques.

Another key limitation lies in the lack of standardization and reproducibility across studies. Variations in dataset size, preprocessing pipelines, and evaluation metrics make cross-comparison difficult and hinder the establishment of universal benchmarks (Singh & Gupta, 2019; Katase et al., 2022). Furthermore, most studies are trained and tested on a single dataset, raising concerns about external validity and model generalizability when applied to data from different institutions or imaging devices (Brocki & Chung, 2023; Wahab-Sait, 2023). This limits the clinical readiness of many proposed frameworks, which often perform well under controlled experimental settings but fail in real-world clinical environments.

In terms of model architecture, while numerous advanced networks such as CNNs, 3D CNNs, and transformers (Khademi et al., 2023; Sun et al., 2023) have achieved impressive accuracy, they often operate as black-box systems, offering limited interpretability. The lack of explainability poses a significant barrier to clinical adoption, as radiologists and clinicians require transparency in AI-driven decision-making (Wani et al., 2024; Dwivedi et al., 2023). Although explainable AI (XAI) models have emerged, their integration into diagnostic workflows remains limited and mostly at the experimental stage.

Additionally, the computational complexity of deep learning models presents practical constraints. Many state-of-the-art architectures, such as 3D CNNs and hybrid transformer frameworks, require high-end GPUs and extensive training time, making deployment challenging in low-resource clinical settings

(Asuntha & Srinivasan, 2020; Wahab-Sait, 2023). Lightweight models attempt to address this issue but often compromise predictive accuracy. Another limitation concerns overfitting and inadequate model regularization, which arise due to small dataset sizes and extensive model depth, leading to inflated accuracy during testing on familiar data but poor performance on unseen samples (Tan et al., 2022; Mukherjee et al., 2020).

Finally, while multimodal and hybrid frameworks combining imaging, radiomics, and clinical data have shown potential (Lu et al., 2020; Yuan et al., 2023), such integrations are still in their infancy and often lack standardized data fusion techniques. The absence of consistent evaluation frameworks and open-access benchmarks further complicates objective assessment. Overall, despite remarkable progress, current methodologies still face limitations related to data insufficiency, generalizability, interpretability, computational efficiency, and clinical validation, highlighting the need for robust, explainable, and scalable models to achieve real-world clinical applicability in lung cancer diagnosis.

### 3.6. Future Work and Research Directions

Future research on transfer learning for lung cancer detection should focus on developing domain-specific pre-trained models using large medical imaging datasets, exploring self-supervised and few-shot approaches to overcome data scarcity, and leveraging emerging architectures such as Vision Transformers and multimodal frameworks that integrate imaging with clinical or genomic data. Emphasis should also be placed on adaptive fine-tuning strategies, incorporating explainable AI methods to enhance clinical interpretability, and adopting federated learning frameworks to ensure privacy-preserving collaboration across institutions. Finally, establishing standardized benchmarks, datasets, and evaluation protocols will be essential to improve reproducibility, comparability, and the clinical translation of transfer learning models in lung cancer diagnosis.

## 4. CONCLUSION

This systematic review, analyzing 44 relevant studies identified through a comprehensive search across numerous academic databases, examines the current state, emerging trends, and future directions of imaging-based deep learning for lung cancer detection and classification. Significant advancements have been made, including the development of novel deep learning architectures and the integration of image processing and optimization techniques, moving towards more sophisticated 3D and volumetric analysis while also incorporating explainable AI (XAI) to enhance clinical trust. Transfer learning has proven particularly valuable, leveraging pre-trained models from large datasets to improve performance on limited medical images and facilitating the development of hybrid models. Despite this progress, critical challenges remain, such as the need to achieve near-perfect diagnostic accuracy, effectively handle noisy and imbalanced data, improve model generalizability across diverse clinical settings, reduce computational complexity for real-time deployment, and further enhance the interpretability of complex models, especially for accurately characterizing small and complex nodules. Researchers are addressing these gaps through various strategies, including advanced data augmentation techniques like GANs, the continued development of sophisticated architectures, the use of ensemble methods, robust preprocessing, advanced feature engineering, optimization algorithms, and the fusion of multi-modal data, underscoring a dynamic and multifaceted effort to develop more robust, accurate, and clinically applicable AI systems for improving lung cancer diagnosis and patient outcomes.

**References**


Abd Al-Ameer, A. A., Hussien, G. A., & Al Ameri, H. A. (2022). Lung cancer detection using image processing and deep learning. Indonesian Journal of Electrical Engineering and Computer Science, 28(2), 987–993.

Agnes, S. A., & Anitha, J. (2020). Appraisal of deep-learning techniques on computer-aided lung cancer diagnosis with computed tomography screening. Journal of Medical Physics, 45(2), 98–106.

Alam, J., Alam, S., & Hossan, A. (2018). Multi-stage lung cancer detection and prediction using multi-class svm classifie. In 2018 International Conference on Computer, Communication, Chemical, Material and Electronic Engineering (IC4ME2) (pp. 1–4). Rajshahi, Bangladesh: IEEE.

Alireza, H., Cheikh, M. S., Annika, K., & Jari, V. (2022). Deep learning for forest inventory and planning: A critical review on the remote sensing approaches so far and prospects for further applications. Forestry, 95(4), 451–465.

Ardila, D., Kiraly, A. P., Bharadwaj, S., Choi, B., Reicher, J. J., Peng, L., ... & Shetty, S. (2019). End-to-end lung cancer screening with three-dimensional deep learning on low-dose chest computed tomography. Nature Medicine, 25(6), 954–961.

Aresta, G., Jacobs, C., Araújo, T., Cunha, A., Ramos, I., van Ginneken, B., & Campilho, A. (2019). iW-Net: An automatic and minimalistic interactive lung nodule segmentation deep network. Scientific Reports, 9(1), 11591.

Asuntha, A., & Srinivasan, A. (2020). Deep learning for lung cancer detection and classification. Multimedia Tools and Applications, 79(11-12), 7731–7762.

Bade, B. C., & Cruz, C. S. (2020). Lung cancer 2020: Epidemiology, etiology, and prevention. Clinics in Chest Medicine, 41(1), 1–24.

Bhatia, S., Sinha, Y., & Goel, L. (2019). Lung cancer detection: A deep learning approach. In Soft computing for problem solving: Advances in intelligent systems and computing (pp. 237–249). Springer, Singapore.

Bharathy, S., Pavithra, R., & Akshaya, B. (2022). Lung cancer detection using machine learning. In 2022 International Conference on Applied Artificial Intelligence and Computing (ICAAIC) (pp. 1198–1203). Salem, India: IEEE.

Brocki, L., & Chung, N. C. (2023). Integration of radiomics and tumor biomarkers in interpretable machine learning models. Cancers, 15(9), 2459.

Brown, M. S., Lo, P., Goldin, J. G., Barnoy, E., Kim, G. H., Mcnitt-Gray, M. F., & Aberle, D. R. (2020). Toward clinically usable CAD for lung cancer screening with computed tomography. European Radiology, 30(3), 1822.

Chiang, T. A., Chen, P. C., Wu, P. F., Wang, T. S., Chang, P. Y., Ko, A. J., Huang, M. T., & Ko, Y. C. (2008). Important prognostic factors for the long-term survival of lung cancer subjects in Taiwan. BMC Cancer, 8(1), 324.

Da Nóbrega, R. V. M., Peixoto, S. A., da Silva, S. P. P., & Rebouças Filho, P. P. (2018). Lung nodule classification via deep transfer learning in CT lung images. In 2018 IEEE 31st International Symposium on Computer-Based Medical Systems (CBMS) (pp. 244–249). Karlstad, Sweden: IEEE.

Da-Nobrega, R. V. M., Reboucas Filho, P. P., Rodrigues, M. B., Da Silva, S. P., Dourado Júnior, C. M., & de Albuquerque, V. H. C. (2020). RETRACTED ARTICLE: Lung nodule malignancy classification in chest computed tomography images using transfer learning and convolutional neural networks. Neural Computing and Applications, 32(15), 11065–11082.

Dwivedi, K., Rajpal, A., Rajpal, S., Agarwal, M., Kumar, V., & Kumar, N. (2023). An explainable AI-driven biomarker discovery framework for non-small cell lung cancer classification. Computers in Biology and Medicine, 153, 106544.

Faisal, M. I., Bashir, S., Khan, Z. S., & Khan, F. H. (2018). An evaluation of machine learning classifiers and ensembles for early stage prediction of lung cancer. In 2018 3rd International Conference on Emerging Trends in Engineering, Sciences and Technology (ICEEST) (pp. 1–4). Karachi, Pakistan: IEEE.

Griffiths, H. (2011). Magnetic induction tomography. Measurement Science and Technology, 12(7), 1126–1131.

Gould, M. K., Huang, B. Z., Tammemagi, M. C., Kinar, Y., & Shiff, R. (2021). Machine learning for early lung cancer identification using routine clinical and laboratory data. American Journal of Respiratory and Critical Care Medicine, 204(4), 445–453.

Han, C., Kitamura, Y., Kudo, A., Ichinose, A., Rundo, L., Furukawa, Y., ... & Nakayama, H. (2019). Synthesizing diverse lung nodules wherever massively: 3D multi-conditional GAN-based CT image augmentation for object detection. In 2019 International Conference on 3D Vision (3DV) (pp. 729–737). Quebec City, QC, Canada: IEEE.

Huang, C. H., Zeng, C., Wang, Y. C., Peng, H. Y., Lin, C. S., Chang, C. J., & Yang, H. Y. (2018). A study of diagnostic accuracy using a chemical sensor array and a machine learning technique to detect lung cancer. Sensors, 18(9), 2845.

Ippolito, D., Capraro, C., Guerra, L., De Ponti, E., Messa, C., & Sironi, S. (2013). Feasibility of perfusion CT technique integrated into conventional $^18$FDG/PET-CT studies in lung cancer patients: Clinical staging and functional information in a single study. Journal of Nuclear Medicine and Molecular Imaging, 40(3), 156–165.

Journy, N., Rehel, J. L., Pointe, H. D., Lee, C., Brisse, H., Chateil, J. F., Caer-Lorho, S., Laurier, D., & Bernier, M. O. (2015). Are the studies on cancer risk from CT scans biased by indication? Elements of answer from a large-scale cohort study in France. British Journal of Cancer, 112(10), 1841–1842.

Katase, S., Ichinose, A., Hayashi, M., Watanabe, M., Chin, K., Takeshita, Y., ... & Yokoyama, K. (2022). Development and performance evaluation of a deep learning lung nodule detection system. BMC Medical Imaging, 22(1), 203.

Khademi, S., Heidarian, S., Afshar, P., Naderkhani, F., Oikonomou, A., Plataniotis, K. N., & Mohammadi, A. (2023). Spatio-temporal hybrid fusion of cae and swin transformers for lung cancer malignancy prediction. In ICASSP 2023—2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) (pp. 1–5). Rhodes Island, Greece: IEEE.

Lu, M. T., Raghu, V. K., Mayrhofer, T., Aerts, H. J., & Hoffmann, U. (2020). Deep learning using chest radiographs to identify high-risk smokers for lung cancer screening computed tomography: Development and validation of a prediction model. Annals of Internal Medicine, 173(9), 704–713.

Makaju, S., Prasad, P. W. C., Alsadoon, A., Singh, A. K., & Elchouemi, A. (2018). Lung cancer detection using CT scan images. Procedia Computer Science, 125, 107–114.

Malhotra, P. (2024). The rise of passive investing: A systematic literature review applying PRISMA framework. Journal of Capital Markets Studies, 8(1), 95–125.

Mandal, M., & Vipparthi, S. K. (2022). An empirical review of deep learning frameworks for change detection: Model design, experimental frameworks, challenges and research needs. IEEE Transactions on Intelligent Transportation Systems, 23(7), 6101–6122.

Mukherjee, P., Zhou, M., Lee, E., Schicht, A., Balagurunathan, Y., Napel, S., ... & Gevaert, O. (2020). A shallow convolutional neural network predicts prognosis of lung cancer patients in multi-institutional computed tomography image datasets. Nature Machine Intelligence, 2(5), 274–282.

Nasser, I. M., & Abu-Naser, S. S. (2019). Lung cancer detection using artificial neural network. International Journal of Engineering and Information Systems, 3(3), 17–23.

National Lung Screening Trial Research Team. (2011). Reduced lung-cancer mortality with low-dose computed tomographic screening. New England Journal of Medicine, 365(5), 395–409.

Radhika, P. R., Rakhi, A. S., & Veena, G. (2019). A comparative study of lung cancer detection using machine learning algorithms. In 2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT). Coimbatore, India: IEEE.

Rajpurkar, P., Irvin, J., Ball, R. L., Zhu, K., Yang, B., Mehta, H., ... & Lungren, M. P. (2018). Deep learning for chest radiograph diagnosis: A retrospective comparison of the chexnext algorithm to practicing radiologists. PLOS Medicine, 15(11), Article e1002686.

Park, S. Y., Cho, A., Yu, W., Lee, C. H., Lee, J. M., Kim, D. J., & Chung, K. P. (2015). Prognostic value of total lesion glycolysis by F-18-FDG PET/CT in surgically resected stage IA non-small cell lung cancer. Journal of Nuclear Medicine, 56(1), 45–49.

Pawar, V. J., Kharat, K. D., Pardeshi, S. R., & Pathak, P. D. (2020). Lung cancer detection system using image processing and machine learning techniques. International Journal of Advanced Trends in Computer Science and Engineering, 9(4), 5956–5963.

Primakov, S. P., Ibrahim, A., van Timmeren, J. E., Wu, G., Keek, S. A., Beuque, M., ... & Lambin, P. (2022). Automated detection and segmentation of non-small cell lung cancer computed tomography images. Nature Communications, 13(1), 3423.

Reddy, U., Reddy, B., & Reddy, B. (2019). Recognition of lung cancer using machine learning mechanisms with fuzzy neural networks. Traitement du Signal, 36(1), 87–91.

Rehman, A., Kashif, M., Abunadi, I., & Ayesha, N. (2021). Lung cancer detection and classification from chest CT scans using machine learning techniques. In 2021 1st International Conference on Artificial Intelligence and Data Analytics (CAIDA) (pp. 101–104). Riyadh, Saudi Arabia: IEEE.

Saleh, A. Y., Chin, C. K., Penshie, V., & Al-Absi, H. R. H. (2021). Lung cancer medical images classification using hybrid cnn-svm. International Journal of Advances in Intelligent Informatics, 7(2), 151.

Shakeel, P. M., Burhanuddin, M. A., & Desa, M. I. (2022). Automatic lung cancer detection from CT image using improved deep neural network and ensemble classifier. Neural Computing and Applications, 34(13), 1–14.

Shakeel, P. M., Burhanuddin, M. A., & Desa, M. I. (2019). Lung cancer detection from CT image using improved profuse clustering and deep learning instantaneously trained neural networks. Measurement, 145, 702–712.

Shetty, M. V., & Tunga, S. (2022). Optimized deformable model-based segmentation and deep learning for lung cancer classification. The Journal of Medical Investigation, 69(3.4), 244–255.

Siegel, R., Miller, K., Fuchs, H., & Jemal, A. (2022). Cancer statistics. A Cancer Journal for Clinicians, 72, 7–33.

Singh, G. A. P., & Gupta, P. K. (2019). Performance analysis of various machine learning-based approaches for detection and classification of lung cancer in humans. Neural Computing and Applications, 31(12), 6863–6877.

Sori, W. J., Feng, J., & Liu, S. (2018). Multi-path convolutional neural network for lung cancer. Multidimensional Systems and Signal Processing, 30(4), 1749–1768.

Stamatis, G., Eberhard, W., & Pöttgen, C. (2004). Surgery after multimodality treatment for non-small-cell lung cancer. Lung Cancer, 45, S107–S112.

Sun, R., Pang, Y., & Li, W. (2023). Efficient lung cancer image classification and segmentation algorithm based on an improved swin transformer. Electronics, 12(4), 1024.

Tan, J., Huo, Y., Liang, Z., & Li, L. (2019). Expert knowledge-infused deep learning for automatic lung nodule detection. Journal of X-ray Science and Technology, 27(1), 17–35.

Tan, H., Bates, J. H., & Matthew-Kinsey, C. (2022). Discriminating TB lung nodules from early lung cancers using deep learning. BMC Medical Informatics and Decision Making, 22(1), 161.

(2023). The transferability of transfer learning model based on imagenet for medical image classification tasks. Applied and Computational Engineering, 18(1), 143–151.

Tripathi, P., Tyagi, S., & Nath, M. (2019). A comparative analysis of segmentation techniques for lung cancer detection. Pattern Recognition and Image Analysis, 29(2), 167–173.

Wahab-Sait, A. R. (2023). Lung cancer detection model using deep learning technique. Applied Sciences, 13(22), 12510.

Wang, L. (2022). Deep learning techniques to diagnose lung.

Wani, N. A., Kumar, R., & Bedi, J. (2024). DeepXplainer: An interpretable deep learning based approach for lung cancer detection using explainable artificial intelligence. Computer Methods and Programs in Biomedicine, 243, 107879.

Wasudeo, R., Himali, D., Yamini, M., Anjali, K., & Satyajeet, J. (2018). Lung cancer detection using image processing and machine learning healthCare. In 2018 International Conference on Current Trends towards Converging Technologies (ICCTCT). Coimbatore, India: IEEE.

Xie, Y., Meng, W. Y., Li, R. Z., Wang, Y. W., Qian, X., Chan, C., ... & Leung, E. L. H. (2021). Early lung cancer diagnostic biomarker discovery by machine learning methods. Translational Oncology, 14(1), 100907.

Yousef, R., & Daraghmi, E. Y. (2025). Hybrid model detection and classification of lung cancer. IAES International Journal of Artificial Intelligence, 14(2), 1496–1506.

Yu, L., Tao, G., Zhu, L., Wang, G., Li, Z., Ye, J., & Chen, Q. (2019). Prediction of pathologic stage in non-small cell lung cancer using machine learning algorithm based on CT image feature analysis. BMC Cancer, 19(1), 1–12.

Yuan, H., Wu, Y., & Dai, M. (2023). Multi-modal feature fusion-based multi-branch classification network for pulmonary nodule malignancy suspiciousness diagnosis. Journal of Digital Imaging, 36(2), 617–626.

Zhang, Q., Wang, H., Yoon, S. W., Won, D., & Srihari, K. (2019). Lung nodule diagnosis on 3D computed tomography images using deep convolutional neural networks. Procedia Manufacturing, 39, 363–370.