A Systematic Review of Multimodal Deep Learning for Medical Diagnosis (Lung Cancer)

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Abstract— **Lung cancer is one of the most serious and life-threatening diseases worldwide, causing numerous cancer-related deaths annually. Early stage disease detection is extremely important for improving treatment effectiveness and increasing patient survival rates. With the rapid growth of artificial intelligence, deep learning techniques have become widely used in medical imaging and computer-aided diagnostic systems (CADs). Recently, multimodal deep learning has gained significant attention because it combines different types of medical data, including CT scans, chest radiographs, histopathology images, and clinical information, to provide more accurate and reliable diagnostic results. By integrating multiple data sources, multimodal systems can capture richer features and improve disease detection, classification, and prognosis prediction compared with traditional single-modality approaches. This review presents a detailed analysis of recent multimodal deep learning methods developed for lung cancer diagnosis and survival prediction. Twenty research papers published between 2020 and 2026 were systematically examined based on imaging modalities, deep learning architectures, fusion strategies, datasets, and clinical applications. The review highlights commonly used datasets, such as LIDC-IDRI, TCIA, LC25000, and ChestX-ray14, while discussing the applications of convolutional neural networks, transformer-based models, explainable artificial intelligence, and hybrid learning frameworks. In addition, this study explores major challenges, including limited annotated datasets, computational complexity, interpretability issues, and multimodal data integration difficulties. Finally, future research opportunities, such as federated learning, self-supervised learning, vision-language models, and explainable multimodal AI, are discussed. This review aims to provide researchers and healthcare professionals with a clear understanding of recent developments and future possibilities of multimodal deep learning for lung cancer diagnosis.**

Keywords: Lung cancer diagnosis, multimodal deep learning, medical imaging, CT imaging, histopathology, explainable AI, deep learning, multimodal fusion.

I. INTRODUCTION

Lung cancer is one of the leading causes of cancer-related death worldwide and continues to pose a major public health challenge. Early detection and accurate diagnosis are essential for improving patient survival and treatment outcomes. Traditional diagnostic methods mainly depend on radiological imaging and physician expertise, which can be time-consuming and may result in diagnostic variability. Recent advancements in artificial intelligence (AI) and deep learning (DL) have significantly improved computer-aided diagnosis systems for medical imaging applications [1], [2].

Recent studies have demonstrated the effectiveness of multimodal deep learning in lung cancer diagnosis and prognosis. A multimodal framework, DeepMMSA, was introduced for non-small cell lung cancer survival analysis by integrating CT images and clinical data, showing improved prognostic performance compared with unimodal approaches [1]. Another multimodal AI framework combined convolutional neural networks (CNNs) and artificial neural networks (ANNs) using CT scans and patient clinical information to enhance diagnostic accuracy through multimodal feature fusion [2]. In addition, a multimodal representation learning framework was proposed for lung cancer survival prediction, highlighting the importance of combining imaging and clinical information for improved predictive performance [3].

Several researchers have focused on multimodal image fusion techniques to improve lung cancer classification. A multimodal medical image fusion framework was developed for non-small cell lung cancer classification by integrating multiple imaging modalities to improve feature extraction and classification accuracy [4]. A comprehensive review of multimodal deep learning frameworks for lung cancer detection discussed hybrid architectures, fusion strategies, and explainable AI methods, while identifying challenges such as computational complexity and data imbalance [5]. Furthermore, explainable artificial intelligence techniques have been extensively reviewed to improve the transparency and interpretability of deep learning-based lung cancer diagnosis systems [6].

Deep learning approaches have also been widely used for survival prediction and histopathological analysis in lung cancer. A deep learning-based framework that integrates biomarker interpretation and imaging features has been developed for lung cancer survival analysis and prognosis prediction [7]. Another weakly supervised learning framework used virtually stained histopathological tissue images for lung cancer diagnosis while reducing dependence on manual annotations [8]. Explainable deep learning methods using histopathological images and Grad-CAM visualization techniques have also been introduced to improve model interpretability and physician trust in non-small cell lung cancer diagnosis systems [10].

Chest radiography and computed tomography (CT)-based diagnostic systems have shown promising results in the early detection of lung cancer. A weakly supervised tumor localization framework using chest X-ray images was proposed for survival prediction and tumor detection in lung cancer screening applications [9]. Similarly, deep learning-based malignancy prediction models using chest radiographs have demonstrated the capability of CNN-based systems in detecting cancerous abnormalities [12]. Another deep learning framework achieved high sensitivity in pulmonary.

Recent review studies have highlighted the growing role of transformer architectures, hybrid neural networks, and large multimodal AI systems in lung cancer diagnosis and prognosis. Different deep learning paradigms, including CNNs, transformers, and hybrid architectures, have been extensively analyzed for medical image analysis applications [17], [18]. Comprehensive surveys on multimodal medical imaging have discussed various fusion strategies and multimodal architectures used in cancer detection systems [19]. In addition, large multimodal AI models and vision-language systems have shown strong potential for lung cancer screening, diagnosis, and treatment planning [20]. Despite significant progress, challenges such as limited annotated datasets, computational complexity, multimodal integration difficulties, and lack of interpretability remain in multimodal lung cancer diagnosis systems [5], [6], [19].

Therefore, this review provides a systematic overview of recent research focused on lung cancer diagnosis using multimodal deep learning approaches. This review aims to evaluate existing methodologies, widely used datasets, fusion techniques, deep learning models, and modern medical imaging technologies used in intelligent lung cancer diagnostic systems. In addition, this study discusses the current research challenges, limitations, and potential future directions to enhance the accuracy, robustness, interpretability, and real-world clinical implementation of multimodal DL-based lung cancer diagnosis systems.

Lung cancer diagnosis using multimodal deep learning can be formulated as a binary classification problem:

$$y_i \in \{0,1\}$$

where

$y_i = 1 \rightarrow$ patient has cardiovascular disease

$y_i = 0 \rightarrow$ patient does not have cardiovascular disease

The prediction function can be expressed as:

$$\hat{y} = f(x)$$

II. LITERATURE REVIEW

Wu et al. [1] proposed DeepMMSA, a multimodal deep learning framework for non-small cell lung cancer survival analysis using CT images and clinical information. The study showed that integrating heterogeneous medical data improved prognosis prediction and overall survival analysis performance.

Oncu et al. [2] developed a multimodal AI framework that combined convolutional and artificial neural networks for lung cancer diagnosis. Their framework integrates CT scans and clinical patient data to improve diagnostic accuracy and feature extraction.

Farooq et al. [3] introduced a multimodal representation-learning framework for lung cancer survival prediction. This study combined imaging and clinical information to enhance the prognostic analysis and predictive performance in healthcare applications.

Hassan et al. [4] proposed a multimodal medical image fusion framework for non-small cell lung cancer classification. The model integrates features from multiple imaging modalities to improve the accuracy of tumour classification.

$$F_{fusion} = \alpha F_1 + \beta F_2$$

Here:

- F_{fusion} represents the final fused features.
- F_1 are features from the first modality (e.g., CT scan).
- F_2 are features from the second modality (e.g., clinical data).
- α and β are weights that control the importance of each modality.

The review study in [5] analysed multimodal deep learning frameworks used in lung cancer detection systems. This study discusses multimodal fusion strategies, explainable AI methods, and hybrid deep learning architectures.

Koutoulakis et al. [6] reviewed the explainable deep learning techniques for lung cancer diagnosis. This study emphasises the importance of interpretability and transparency in AI-based healthcare systems.

Cui et al. [7] developed a deep learning-based framework integrating imaging features and biomarker information for lung cancer survival prediction. The model improves prognosis analysis and personalised treatment planning.

$$h(t|x) = h\theta(t)e^{\beta x}$$

Chen et al. [8] proposed a weakly supervised learning framework using virtual histopathological tissue images for lung cancer diagnosis. This approach reduced the dependence on detailed manual annotations while maintaining the classification performance.

Hermoza et al. [9] introduced a weakly supervised tumour localisation framework using chest X-ray images for survival prediction and tumour detection using chest X-ray images. Their model improved the lung cancer screening performance using radiographic data.

Civit-Masot et al. [10] explained deep learning model for non-small cell lung cancer diagnosis using histopathological images and Grad-CAM visualisation techniques to improve interpretability.

Cui et al. [11] developed a CT-based deep learning framework for pulmonary nodule screening. This study achieved high sensitivity in detecting lung nodules for early stage lung cancer diagnosis.

yi ∈ {0,1}

Horry et al. [12] developed a deep learning-based malignancy prediction model using chest radiographs. The CNN-based framework effectively identified abnormal lung patterns associated with cancer.

Mohandass et al. [13] proposed an optimized attention-based CNN integrated with DenseNet-201 transfer learning for CT-based lung cancer classification. The attention mechanism improved the feature extraction and classification performance.

$$Attention(Q,K,V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Hammad et al. [14] developed an automated lung cancer detection framework using genetic TPOT feature optimization with deep learning techniques. This study improved the optimisation efficiency and automated feature selection.

Bhandary et al. [15] proposed a multimodal deep learning framework that integrates chest X-ray and CT scan images for lung abnormality detection. Their system improved robustness and classification accuracy compared to single-modality approaches.

Masud et al. [16] developed a deep-learning-based classification framework for diagnosing lung and colon cancers using medical imaging data. This study demonstrated an effective automated cancer classification performance.

Patel et al. [17] reviewed various deep learning paradigms used in lung cancer diagnosis, including CNNs, transformers, and hybrid architectures. This study highlighted the advancements in medical image analysis systems.

The review study in [18] discussed artificial intelligence techniques and hybrid neural networks for lung cancer diagnosis and prognosis prediction. This study emphasises the importance of multimodal learning frameworks.

Yan Tian et al. [19] presented a comprehensive survey on deep learning approaches in multimodal medical imaging for cancer detection. This study analysed multimodal fusion strategies and medical imaging architectures.

$$F_m = g(F_1, F_2, \dots\dots., F_n)$$

Zhong et al. [20] reviewed large multimodal AI models and vision-language systems for lung cancer screening, diagnosis, and treatment planning. This study highlights the future potential of foundation models in intelligent healthcare systems.

Author(s) [Ref]	Year	Dataset Used (Name + Type)	Method / Algorithm Used	Description
Wu et al. [1]	2021	TCIA(CT images + clinical datasets)	DeepMMSA, Multimodal Deep Learning	Proposed an active learning multimodal framework combining CT

				imaging and clinical information for NSCLC survival analysis and prognosis prediction.
Oncu et al. [2]	2025	LIDC-IDRI + Clinical Records (CT + structured clinical data)	CNN + ANN Hybrid Mode	Demonstrated that hybrid framework integrating imaging and patient information to improve lung cancer diagnosis accuracy.
Farooq et al. [3]	2025	TCIA (Imaging + clinical dataset	Multimodal Representation Learning	Comparative analysis techniques to extract complementary information.
Hassan et al. [4]	2024	NSCLC Imaging Dataset (multimodal imaging dataset)	Multimodal Image Fusion Framewor r	Designed an image fusion approach to integrate multiple imaging modalities for improved tumor classification..
Review Study [5]	2026	Multiple Public Datasets	Hybrid Deep Learning Frameworks	Reviewed multimodal fusion techniques and AI methods for lung cancer detection.
Koutoulakis et al. [6]	2026	Multiple Medical Imaging Datasets	Deep Learning (XAI)	Examine the methods used in AI systems
				and discussed their importance in clinical decision support.
Cui et al. [7]	2020	Real-world Cancer Imaging Archive (TCIA) + Biomarker Dataset (medical imaging and biological marker data)	Deep Survival Analysis Mode	Demonstrated the Combined biomarker information and imaging features to improve survival prediction.
Chen et al. [8]	2024	Histopathology Dataset (Population health data)	Weakly Supervised Learning	Studied supervision for histopathological image analysis while reducing annotation requirements..
Hermoza et al. [9]	2024	Chest X-ray Dataset (Clinical structured dataset)	CNN, Feature Selection Algorithms	Proposed deep learning for survival prediction using chest radiographs.
Civit-Masot et al. [10]	2022	LC25000 (Histopathology image dataset) (Clinical datasets)	CNN + Grad-CAM Models	Reviewed DL algorithms histopathological image classification for improved interpretability
Cui et al. [11]	2020	LIDC-IDRI CT scan image dataset	CNN-based Pulmonary Nodule Detection	Proposed a CT-based screening framework for early detection

		(Clinical dataset)		of pulmonary nodules.
Horry et al. [12]	2021	Chest X-ray Dataset (Medical datasets)	Deep Learning (CNN-based Classification)	Reviewed deep learning framework for identifying abnormal lung patterns from radiographs.
Mohandass et al. [13]	2024	LIDC-IDRI (CT image dataset)	Attention CNN + DenseNet-201	Proposed an attention-enhanced transfer learning framework for CT-based lung cancer classification.
Hammad et al. [14]	2024	Multiple Imaging Datasets	Genetic TPOT + Deep Learning	Proposed automated feature optimization techniques to improve classification performance.
Bhandary et al. [15]	2020	Chest X-ray + CT Dataset (Healthcare dataset)	Multimodal CNN Framework	Reviewed and Integrated multiple imaging modalities to improve robustness in lung abnormality detection.
Masud et al. [16]	2021	LC25000 (Medical image dataset)	Deep Learning Classification Framework	Developed an automated system for classifying lung and colon cancer using
				medical images.
Patel et al. [17]	2025	Multiple Lung Disease Datasets	CNN, Transformers, Hybrid Models	Systematic review recent deep learning paradigms and their applications in lung cancer diagnosis.
Review Study [18]	2025	Real-world Healthcare Dataset	Hybrid Neural Networks	Reviewed hybrid architectures and their role in prognosis prediction and diagnosis systems.
Yan Tian et al. [19]	2023	Multimodal Imaging Prediction Dataset	Fusion Strategies	Surveyed multimodal deep learning approaches in cancer detection.
Zhong et al. [20]	2025	Imaging + Clinical Dataset	Vision-Language Models	Investigated large AI models for diagnosis and treatment planning.

Table 2.1 -Table Representing Multimodal For LC

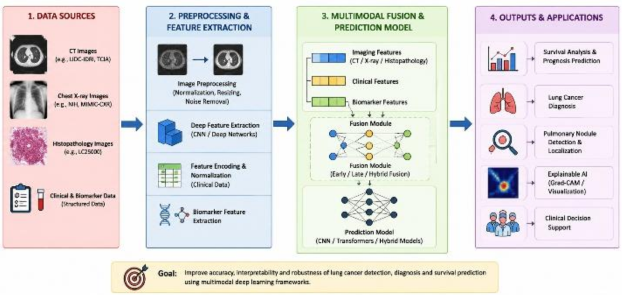

Figure 2.1 : LC Prediction Goals

III. METHODOLOGY

The literature search for this review was conducted using several major academic databases, including IEEE Xplore, Scopus, PubMed, ScienceDirect, SpringerLink, arXiv and Google Scholar. These databases were selected because they contain a large collection of peer-reviewed research papers related to artificial intelligence, deep learning, medical imaging, and healthcare applications. The search mainly focused on studies published between 2020 and 2026, as this period included recent developments in multimodal deep learning techniques for lung cancer diagnosis and prognosis prediction. A Boolean search strategy was adopted using combinations of keywords such as "lung cancer diagnosis," "multimodal deep learning," "medical imaging," "CT scan," "histopathology," "chest X-ray," "artificial intelligence," "deep learning," "CNN," "transformers," and "multimodal fusion." These keyword combinations were used to identify studies related to multimodal AI-based lung cancer diagnosis systems.

After the initial search process, approximately 90–100 research records were identified in the different databases. Duplicate articles and irrelevant studies were removed during the screening process, and 70+ studies were selected for a detailed evaluation. The inclusion criteria specified that selected papers should focus on lung cancer diagnosis, classification, prognosis prediction, or multimodal deep learning approaches. Furthermore, studies must provide experimental evaluation measures, such as accuracy, precision, recall, F1-score, AUC, and survival prediction metrics. Studies were excluded if they lacked experimental validation, addressed unrelated diseases, or did not clearly describe their methodologies and datasets. After applying these criteria, 20 studies were selected for the final literature synthesis and comparative analysis.

To ensure reliability and quality throughout the review process, a structured bias assessment was performed for each selected study. The assessment considered several factors, including dataset quality, transparency of multimodal architectures, feature fusion strategies, evaluation methods, and reporting of experimental findings. Studies using publicly available datasets, such as LIDC-IDRI, TCIA, LC25000, and ChestX-ray14, along with clearly defined evaluation protocols, were considered to have a lower bias. Finally, a systematic data extraction process was used to collect information on datasets, deep learning models, multimodal techniques, evaluation metrics, key findings, and research limitations. This methodology enabled a comprehensive comparative analysis of multimodal deep learning approaches used in lung cancer diagnosis systems.

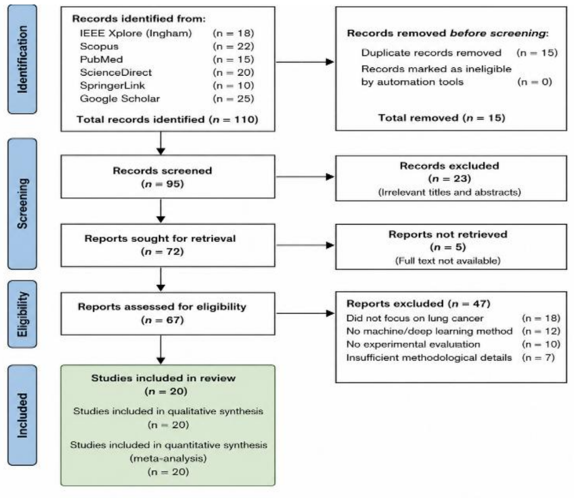

Figure 3.1: PRISMA Diagram

IV. RESEARCH GAP & FUTURE ROADMAP

A. Research Gaps Identified

Despite the considerable progress multimodal deep learning for lung cancer diagnosis, several important research gaps remain. Wu et al. [1], Oncu et al. [2], and Farooq et al. [3] proposed multimodal frameworks integrating imaging and clinical information for diagnosis and survival prediction. However, these studies mainly focused on improving prediction accuracy and prognosis performance while giving limited attention to explainability and real-time clinical implementation. In addition, many frameworks rely on individual architectures rather than integrating multiple complementary techniques into a unified system.

Another major research gap is associated with dataset limitations and class imbalance issues. Hassan et al. [4], the review study [5], and Cui et al. [7] highlighted challenges related to limited benchmark datasets and restricted patient diversity. Public datasets, such as TCIA and LIDC-IDRI, often contain small sample sizes and imbalanced class distributions. These limitations may lead to overfitting and reduced generalisation when models are applied to real-world healthcare environments.

A further challenge identified in the literature is the limited interpretability of the complex deep learning architectures. Koutoulakis et al. [6] and Civit-Masot et al. [10] emphasised that many AI systems still operate as black box models. Although explainable AI methods, such as Grad-CAM, improve visualisation and transparency, clinicians often find it difficult to understand the reasoning behind model predictions.

This lack of interpretability reduces physician trust and limits the adoption of AI-assisted diagnostic systems in clinical practice.

Another critical gap is the integration of multimodal AI systems with real-world healthcare infrastructure. Patel et al. [17], Yan Tian et al. [19], and Zhong et al. [20] reported challenges related to multimodal feature integration, computational complexity, scalability, and privacy concerns. Although several diagnostic models have demonstrated high performance in experimental settings, only a limited number have been deployed in practical healthcare environments because of interoperability and data security issues.

B. Future Research Roadmap

Future research on multimodal deep learning for lung cancer diagnosis should focus on addressing the identified limitations and improving real-world clinical applicability. One important direction is the development of large-scale healthcare datasets that integrate CT scans, chest X-rays, histopathology images, biomarkers, and electronic health records. Large and diverse datasets may improve model generalisation and reduce overfitting problems, as identified in studies such as [4] and [7].

Another promising research area involves the integration of multimodal AI systems with wearable devices and Internet of Medical Things (IoMT) technologies. Real-time patient monitoring systems may provide additional clinical information that can improve the accuracy of diagnosis and prognosis prediction. Future frameworks may combine imaging data with physiological signals and patient history for a comprehensive disease assessment.

Finally, emerging technologies such as federated learning, explainable AI, and privacy-preserving machine learning should be explored to improve the collaborative healthcare analytics. These approaches can support model training across multiple healthcare institutions without sharing sensitive patient data. Integrating privacy-preserving AI with multimodal lung cancer diagnosis systems may improve performance while ensuring patient confidentiality and scalable healthcare.

V. CONCLUSION

Lung cancer remains one of the leading causes of cancer-related deaths worldwide, making early diagnosis and accurate detection essential for improving patient survival and treatment outcomes. This review presents a systematic analysis of multimodal deep learning approaches used for lung cancer diagnosis, classification, prognosis prediction, and survival analysis. The reviewed studies demonstrated that deep learning techniques, such as convolutional neural networks, attention-based architectures, hybrid neural networks, and multimodal fusion methods, have been widely used for analysing CT scans, chest X-ray images, histopathological images, and clinical information. Furthermore, multimodal frameworks that integrate heterogeneous medical data have shown better predictive performance and diagnostic accuracy than traditional single-modality systems [1], [4].

Future research should focus on developing scalable, interpretable, and clinically applicable multimodal deep learning systems capable of handling large-scale healthcare datasets. The integration of explainable artificial intelligence, federated learning, privacy-preserving techniques, and large multimodal AI models may further improve the reliability and practical implementation of intelligent lung cancer diagnosis systems. By addressing current challenges and incorporating emerging technologies, multimodal deep learning has the potential to significantly improve early detection, personalised treatment planning, and future healthcare delivery systems [19], [20].

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