■ REVIEW ARTICLE

Prediction of Lung Cancer with Fuzzy Logic Methods: A Systematic Review

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Abstract

According to the World Health Organization (WHO), lung cancer is the primary cause of cancer-related deaths worldwide and is known to have the highest mortality rate among both men and women. Early and accurate detection of lung cancer can lead to better treatments and outcomes. Different methods can be used to diagnose a complex and uncertain disease, such as lung cancer, and fuzzy logic is one of these methods. The challenge of diagnosing lung cancer nodules, coupled with the high mortality rate of lung cancer, underscores the significance of using fuzzy logic. Fuzzy logic offers a problem-solving approach that relies on logical rules and if-then statements, incorporating human experience. There are many studies in the literature on the diagnosis of lung cancer with fuzzy logic approaches, and it is important to examine these studies to provide a general framework on this subject. Therefore, this systematic review aims to synthesize and evaluate the current evidence on the application of fuzzy logic methods in lung cancer prediction and diagnosis, and thus can provide a guide to researchers and decision makers who want to work in this field. The study followed the PRISMA guidelines for systematic reviews, ensuring a structured and transparent approach to the research process. Scopus, Web of Science (WoS), PubMed, and IEEE Explore databases were searched to find relevant studies, and appropriate studies were carefully reviewed. The inclusion and exclusion criteria were clearly defined, and the analysis process was performed independently. Out of 222 initially identified studies, 51 met the inclusion criteria and were analyzed in depth. The most commonly used fuzzy logic methods were Fuzzy Rule-Based Systems, Fuzzy C-Means Clustering, and Fuzzy Inference Systems. Studies reported accuracy rates ranging from 85% to 98% in lung cancer prediction and diagnosis. Hybrid models combining fuzzy logic with other machine learning techniques showed particularly promising results. Fuzzy logic methods demonstrate significant potential in improving the accuracy of lung cancer prediction and diagnosis. However, further research is needed to standardize approaches and validate these methods in large-scale clinical settings. The integration of fuzzy logic with other artificial intelligence techniques presents a promising direction for future developments in lung cancer diagnostics.

Keywords: fuzzy logic, lung cancer, prediction, diagnosis, systematic review

1. Introduction

Cancer is on the rise worldwide due to environmental factors, nutritional conditions, and genetic factors and has become the leading cause of death due to inadequate treatment

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and diagnosis. The WHO states that cancer is one of the leading causes of death worldwide, and recent data on cancer mortality rates show that lung cancer is the most common cause of death among cancer types with 2.48 million cases worldwide (Figure 1) [1]. Lung cancer remains a major global health problem, causing morbidity and mortality worldwide. Early and accurate detection is crucial for improving patient outcomes and survival rates [2]. This pressing need has driven researchers and healthcare professionals to explore innovative approaches in diagnostic technologies [3].

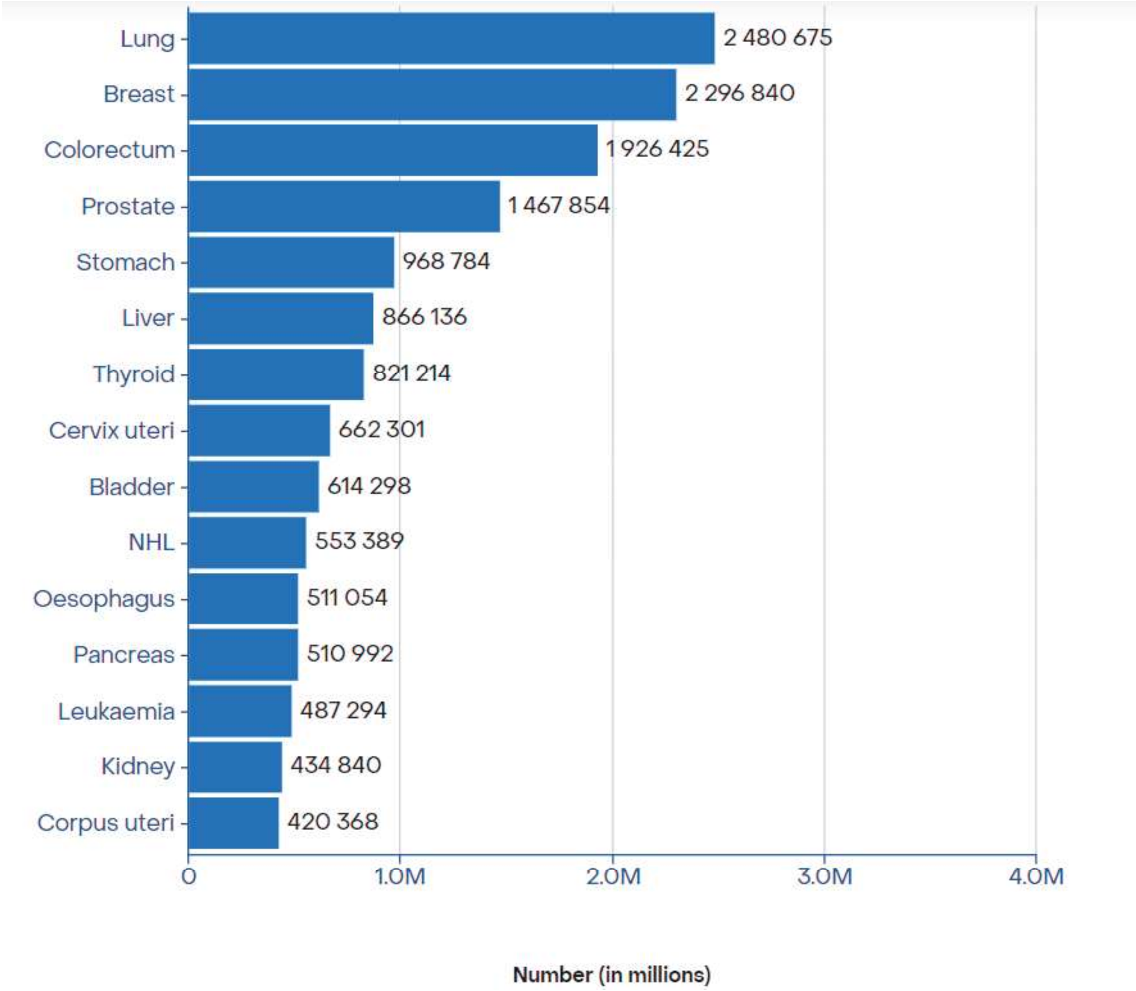

Figure 1. Recorded incidents of different types of cancer worldwide [4]

In the quest for more effective diagnostic tools, artificial intelligence (AI) has emerged as a game-changing technology. Recent studies showed that AI algorithms could outperform human experts in certain medical image diagnosis tasks, including lung diseases [5]. Among the various AI approaches, fuzzy logic stands out for its ability to handle uncertainty and imprecision - characteristics inherent in medical diagnosis. Fuzzy logic is a mathematical logic that attempts to solve problems with explicit, imprecise, or approximate reasoning [6]. It is based on fuzzy set theory, which is an extension of classical set theory [7]. It provides a way to obtain a precise result based on uncertain, ambiguous, imprecise, noisy, or incomplete input information [8] and has gained great importance in disease prediction due to its ability to handle uncertainties and ambiguity in medical data. Fuzzy logic has been widely applied in medical diagnosis, particularly in lung cancer and related conditions, demonstrating its efficacy in improving the diagnostic efficiency of tumor markers [9], enhancing the detection of disease progression in small cell lung cancer patients [10], and even extending to the diagnosis of other respiratory diseases such as pneumonia through expert systems [11]. Overall, fuzzy logic, with its capacity to mimic human reasoning and handle ambiguous data, offers a promising avenue for enhancing lung cancer detection and prediction [12].

Compared with other AI tools, such as Neural Networks and Support Vector Machines (see table 1), fuzzy logic offers unique advantages in handling the uncertainties inherent in medical diagnosis. Its ability to provide interpretable results is particularly valuable in clinical settings where transparency in decision-making is crucial [13].

The challenge of diagnosing lung cancer nodules, coupled with the high mortality rate of lung cancer, underscores the significance of using advanced methods like fuzzy logic [14]. Fuzzy logic offers a problem-solving approach that relies on logical rules and if-then statements, incorporating human experience and expertise [16]. This makes it particularly suited for medical applications where expert knowledge plays a crucial role [9].

Table 1. Comparison of Fuzzy Logic Method with other AI tools

Technique	Strengths	Limitations
Fuzzy Logic	• Handles uncertainty well • Mimics human reasoning • Interpretable results	• Can be complex for large rule sets • Requires expert knowledge for initial setup
Neural Networks	• Powerful pattern recognition • Can handle large datasets • Adaptive learning	• "Black box" nature • Requires large training datasets • Less interpretable
Support Vector Machines	• Effective in high-dimensional spaces • Versatile through kernel trick	• Less intuitive • Can be computationally intensive

Taking into consideration the aforementioned, studies on fuzzy logic are important in diagnosing lung cancer. After a preliminary literature review, the authors identified research papers that deal with the diagnosis of lung cancer using fuzzy logic methods; systematic reviews that deal with disease (general) diagnosis or healthcare with fuzzy logic methods, or, modern approaches used in the detection of lung cancer [16][17][18]. However, no systematic review study has been found that brings together studies on fuzzy logic methods in the diagnosis of lung cancer. In this way, this study constitutes an original one, which examines scholarly work on the specific topic and provides an overview of the literature.

The primary aim of this study is to review the literature on lung cancer diagnosis using fuzzy logic methods. Through this systematic review, we seek to accomplish several objectives:

- To provide researchers and field experts with a comprehensive overview of relevant literature in this domain.
- To present research results, findings, and recommendations in a clear and accessible manner.
- To offer a valuable resource for both researchers and practitioners involved in the diagnosis and treatment of lung cancer.

By achieving these goals, we aim to facilitate advancements in the application of fuzzy logic to lung cancer diagnosis and treatment.

The primary aim of this study is to comprehensively review the literature on lung cancer diagnosis using fuzzy logic methods. Specifically, this systematic review seeks to achieve the following objectives:

- To provide researchers and field experts with a concise overview of relevant literature in the application of fuzzy logic to lung cancer diagnosis.
- To present research results, findings, and recommendations in an accessible manner, serving as a valuable resource for both researchers and practitioners.
- To synthesize information on fuzzy logic methods used in the diagnosis and treatment of lung cancer, offering insights into current practices and future directions.

By collecting and analyzing fuzzy logic methods from various sources, this review aims to offer a broad perspective on the existing literature in this field. Ultimately, it seeks to facilitate advancements in lung cancer diagnosis by consolidating current knowledge and identifying areas for future research.

In this context, the research question of the study is: What is the role of fuzzy logic methods in early detection and prediction of lung cancer, and which fuzzy logic methods are used in this context?

Within the framework of research question, findings from various studies were synthesized, and the effectiveness and potential limitations of fuzzy logic applications in the context of lung cancer prediction were evaluated. Through the synthesis of existing knowledge, the authors aimed at identifying trends, difficulties, and future directions in the use of fuzzy logic methods to improve the accuracy and credibility of lung cancer prediction models. By exploring the intricacies of fuzzy logic-based lung cancer prediction, this review contributes to the ongoing discourse on the use of computational intelligence in healthcare. By critically examining the existing literature, the goal is to provide information that can guide future research efforts and, as a result, stimulate advances in the field of lung cancer prediction and contribute to improved patient outcomes.

The structure of the study is as followed: Section 2 presents a short review of related studies on soft computing methods in medical diagnosis and their critical analysis. Section 3 includes the methodology part for this systematic review. Section 4 presents the results of the research. Finally, section 5 concludes this study with conclusions, future research and limitations.

2. Literature Review

The application of soft computing methods in medical diagnosis, particularly in lung cancer prediction and diagnosis, has been a subject of significant research interest. This section provides a critical analysis of key studies in this field, highlighting the strengths and weaknesses of fuzzy logic methods compared to other soft computing approaches such as neural networks and genetic algorithms.

Fuzzy logic, a cornerstone of soft computing, has demonstrated its efficacy in lung cancer diagnosis. Schneider et al. [9] showed that fuzzy logic-based tumor-marker profiles could improve sensitivity in lung cancer diagnosis from 70% to 90%. This highlights fuzzy logic's ability to handle the imprecision inherent in medical data effectively.

[16] conducted a comprehensive review of fuzzy logic methods in disease diagnosis. While not specific to lung cancer, their study underscored fuzzy logic's strength in managing uncertainty in medical data, a crucial factor in cancer diagnosis.

The potential of neural networks, another key soft computing technique, in lung cancer diagnosis was evident in the meta-analysis by Liu et al. [19]. They found that AI methods, including neural networks, demonstrated high diagnostic accuracy in lung cancer, with a pooled sensitivity of 0.87 and specificity of 0.83.

Genetic algorithms, while less prominently used in direct lung cancer diagnosis, have shown potential in optimizing other soft computing methods. Daliri [20] presented a hybrid system combining genetic algorithms with fuzzy extreme learning machines for lung cancer diagnosis. This study demonstrated how genetic algorithms could optimize the parameters of fuzzy systems, enhancing overall performance.

The power of combining soft computing methods was evident in the study by Lin and Yang [21]. They introduced a Fusion-Based Convolutional Fuzzy Neural Network (F-CFNN) for lung cancer classification, achieving 97% accuracy on a large dataset of 22,489 CT images. This hybrid approach leveraged the pattern recognition strengths of neural networks and the interpretability of fuzzy logic, showcasing the synergistic potential of soft computing techniques.

Thomas et al. [22], in their systematic review, further supported the efficacy of fuzzy models in medical diagnosis, including cancer detection. Their findings reinforced the consistent high accuracy of fuzzy logic across various medical diagnostic applications.

While not specific to lung cancer, studies by Wagner et al. [23] and Jan et al. [24] highlighted the broader application of soft computing methods in oncology, including surgical decision support and early diagnosis of other cancers like pancreatic cancer. These studies underscore the versatility and potential of soft computing techniques in the broader field of cancer diagnosis and treatment.

The aforementioned studies can provide a comprehensive overview of the current state of soft computing methods in lung cancer diagnosis. Thus, Table 2 presents a comparative analysis of fuzzy logic, neural networks, genetic algorithms, and hybrid approaches, highlighting their respective strengths, limitations, and key studies in the field.

Table 2. Comparison of Soft Computing Methods in Lung Cancer Diagnosis

Method	**Strengths**	**Limitations**	**Key Studies**
Fuzzy Logic	• Handles uncertainty and imprecision well • Highly interpretable results • Improved sensitivity in diagnosis • Can incorporate expert knowledge	• May require complex rule sets for nuanced problems • Performance depends on quality of fuzzy rule set design	[9] [16] [22]
Neural Networks	• Excellent pattern recognition • High accuracy in image-based diagnosis • Can handle large, complex datasets	• "Black box" nature limits interpretability • Requires large datasets for training• Prone to overfitting	[19]
Genetic Algorithms	• Effective for parameter optimization • Can improve performance of other soft computing methods • Good at finding global optima	• Computationally intensive • May converge to local optima • Requires careful parameter tuning	[20]

Method	Strengths	Limitations	Key Studies
Hybrid Methods (e.g., Fuzzy Neural Networks)	• Combines strengths of multiple soft computing approaches • High accuracy while maintaining some interpretability • Can overcome limitations of individual methods	• Complex model design and implementation • May require significant computational resources • Potential difficulty in determining optimal hybridization	[21]

Literature review revealed the need for a systematic review and the focus on fuzzy logic method within the framework of lung diagnosis:

- While Ahmadi et al. [16] and Thomas et al. [22] provided broad reviews of fuzzy logic in medical diagnosis, there is a lack of comprehensive reviews specifically focusing on fuzzy logic applications in lung cancer diagnosis.
- Lung cancer diagnosis inherently involves dealing with uncertain and imprecise data. Fuzzy logic's strength in handling such uncertainty, as demonstrated by Schneider et al. [9], makes it particularly suitable for this domain.
- Unlike "black box" methods such as some neural network approaches, fuzzy logic provides interpretable results. This interpretability is crucial in medical applications where understanding the reasoning behind a diagnosis is essential for clinician trust and patient communication.
- Fuzzy logic allows for the direct incorporation of expert knowledge into the system. This is particularly valuable in the medical field where expert opinions play a significant role alongside data-driven insights.
- While some AI methods require large datasets for training, fuzzy logic has shown effectiveness even with smaller datasets. This is advantageous in medical research where large, standardized datasets may not always be available.
- The success of hybrid methods like the one used by Lin et al. [21] suggests that fuzzy logic can be effectively combined with other soft computing techniques to leverage the strengths of multiple approaches.
- The broader success of fuzzy logic in various medical diagnostic applications, as shown by Thomas et al. [22] indicates its potential for further development in lung cancer diagnosis specifically.
- Lung cancer diagnosis often involves complex, interrelated factors. Fuzzy logic's ability to handle complex rule sets makes it well-suited to capture these intricate relationships.

This review aims to address these gaps by providing a comprehensive analysis of fuzzy logic methods in lung cancer prediction and diagnosis, highlighting their unique strengths and potential for integration with other soft computing methods. The novelty of fuzzy logic in this domain lies in its ability to handle medical uncertainties in an interpretable manner, a crucial factor in clinical decision-making processes.

3. Methodology

This research was prepared according to the systematic review method and the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) technique used as a guide for systematic review. The PRISMA flowchart is an essential tool for conducting systematic reviews and meta-analyses. It provides a structured approach for documenting the selection process of studies, ensuring transparency and reproducibility in the research. The aim is to improve the accuracy and precision of such inquiries by giving originators a checklist to guarantee a through disclosure. The use of the PRISMA flowchart is recommended in various fields, including psychology, medicine, biology, and education [25]. Adherence to PRISMA rules is associated with improved quality of detailing in efficient audits [26]. An effective review strategy was applied to this research, and the articles included in the research were recovered from the database using the PRISMA strategy. The research utilized popular databases, including Scopus, Web of Science, and PubMed, renowned for their extensive coverage and relevance in the healthcare domain. The keywords used to search the databases are given in Table 1 and the inclusion and exclusion criteria are given in Table 2.

In the inclusion process of the studies included in the study, firstly, keywords suitable for the research question were searched from the databases related to the studies, and after the studies were eliminated in accordance with the inclusion and exclusion criteria, the remaining studies were exported and the titles and abstracts of the studies were first examined. Studies whose titles and abstracts were not appropriate for the research questions were also eliminated and the full text of the remaining studies was examined. From the studies whose full text was examined, the studies that were appropriate for the research question were selected and finally, the studies to be included in the systematic review process were decided.

3.1. Search keywords for databases

The queries for the keywords used in the database search are given in Table 3. The search queries were meticulously crafted by experimenting with different combinations to optimize search results based on the databases' structures.

Table 3. Search keywords

Scopus	Web of Science	Pubmed	IEEE Xplore
(TITLE-ABS-KEY (fuzzy) AND TITLE-ABS-KEY ("lung cancer" OR "lung cancer prediction" OR "lung cancer predicting") AND TITLE-ABS-KEY (predicting OR prediction))	fuzzy (Title) and ("lung cancer" OR "lung cancer prediction" OR "lung cancer predicting") (Title) or fuzzy (Abstract) and ("lung cancer" OR "lung cancer prediction" OR "lung cancer predicting") (Abstract) and predicting or prediction (Abstract)	TI fuzzy AND TI ("lung cancer" or "lung cancer predicting" or "lung cancer prediction") OR AB fuzzy AND AB ("lung cancer" or "lung cancer predicting" or "lung cancer prediction") AND (predicting or prediction)	("Document Title": fuzzy) AND ("Document Title": "lung cancer" OR "Document Title": "lung cancer prediction" or "lung cancer predicting") OR ("Abstract": fuzzy) AND ("Abstract": "lung cancer" OR "Abstract": "lung cancer prediction" or "lung cancer predicting") AND ("All Metadata": predicting or prediction)

3.2. Refinement of initial results (inclusion and exclusion criteria)

The articles retrieved from the database searches underwent screening based on specific inclusion and exclusion criteria to ensure relevance to the study. To work with current data, articles between 2019 and 2024 and in English were included in the study. On the other hand, papers, books and book chapters and review type publications were not included in the study. Articles from the PubMed database were not included in the study because they were considerably older than 2019. Similarly, articles accessed from the Web of Science database were also eliminated based on date and publication type. Many of the articles included in the study were obtained from the Scopus database.

Table 4. Inclusion and Exclusion Criteria

Inclusion Criteria	Exclusion Criteria
Language: English, Article	Review articles, Book, Book section, Dublicate studies, Thesis, Conference Paper, Retracted Publication, Conference Review, Article in press

3.3. Validity and Reliability

The validity of the research method was confirmed through a thorough keyword selection process and database search during the literature review. In addition, filtering criteria appropriate to the objectives of the study were created, and the validity of the research was strengthened by analyzing the articles that met these requirements. The research's reliability was supported by its reproducibility, prior preliminary review, and consistent results from independent researchers, demonstrating its credibility.

4. Results and Discussion

This section presents the findings resulting from the systematic review conducted to address the research questions. The articles retrieved from the search were screened based on predefined inclusion and exclusion criteria and specific database filtering methods. This information is given in the Identity section of the PRISMA flow chat in Figure 2. The abstracts of the remaining 86 articles were examined, and the articles to be read in full text were decided, and the number of articles was reduced to 55. This information is shown in the Screening section. After reviewing the full text of 55 articles, the final selection for inclusion in the study was made based on the predetermined criteria. Finally, this information is given in the Included section, and the full text of 49 articles was examined in the study.

4.1. Observations on Datasets

The studies in the table also vary in terms of datasets and sample sizes used for lung cancer diagnosis. While some studies conduct comprehensive analyses on large datasets, others focus on smaller and more specific sample groups. This variability influences the scope of each study and the generalizability of the findings. For instance, some studies leverage CT scans, X-ray images, and gene expression data to evaluate the effectiveness of various diagnostic and classification methods. Additionally, the findings from these studies highlight the continuous development of methods used in lung cancer diagnosis. Each study is designed to address a specific problem or optimize a particular approach, contributing to the overall knowledge base in lung cancer diagnosis. It is observed that recent studies employ more advanced methods and sophisticated models compared to earlier ones, leading to higher accuracy rates and more reliable results in lung cancer diagnosis.

In this part of the research, information about the data sets of the studies included in the systematic review is given.

LIDC-IDRI (Lung Image Database Consortium and Image Database Resource Initiative) is a consortium dataset for early detection of lung nodules and cancer diagnosis. It focuses on the identification of lung nodules of different sizes and types using CT scans. Since this dataset contains various features such as the size, shape, and density of lung nodules, it allows fuzzy logic algorithms to manage these uncertainties. The ambiguous boundaries of the nodules provide a suitable space for fuzzy logic to better define the boundaries [27].

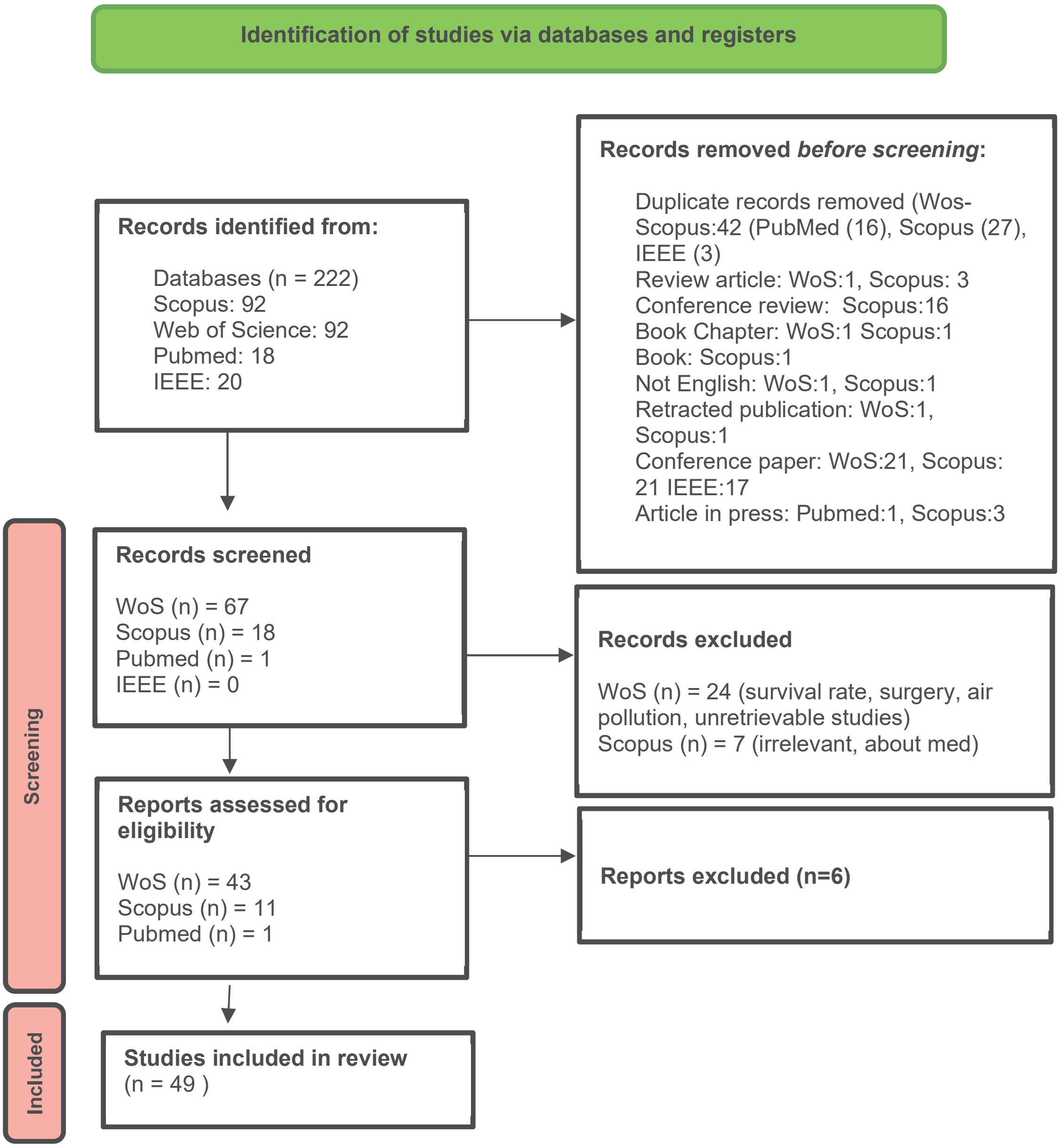

Figure 2. PRISMA flow diagram [72]

SPIE-AAPM Lung CT Challenge Dataset and LIDC-IDRI Lung Imaging Research Dataset; Organized by the American Association for Medical Physics (AAPM) and SPIE, this dataset aims to use computed tomography (CT) images for lung cancer detection [28]. This dataset helps fuzzy logic algorithms to improve classification and prediction accuracy because of the uncertainties between different cancer stages, nodule sizes and cancer types in a wide variety of CT images. The dataset also provides an ideal testbed for diagnosing cancer at different stages.

COVID-19 Detection X-Ray Dataset and Lung Cancer Dataset; The purpose of this dataset shared on Kaggle is to investigate the differences between COVID-19 detection and lung cancer. This dataset, which includes X-ray images, contributes to the diagnosis of various lung diseases. X-ray images can have ambiguities due to low resolution and noise. These ambiguities can be processed with fuzzy logic algorithms to achieve better classification results. Moreover, similar symptoms of diseases and similarities in images require fuzzy logic to reduce uncertainties in decision making [27].

Lung Cancer Gene Expression Dataset: This dataset, obtained from the UCI Machine Learning Repository, is used to analyze gene expression profiles of lung cancer. It is used in lung cancer diagnosis based on genetic analysis. Gene expression data includes analysis of genes expressed at different levels in each individual patient. This data set shows a large variability that needs to be managed with fuzzy logic, as genetic data contains uncertainties. Given that small changes in gene expression data can have major clinical consequences, fuzzy logic allows for precise handling of these variables [29].

IQ-OTH/NCCD Dataset; This dataset contains CT images and clinical data for the diagnosis of lung cancer and is specifically used for the accurate detection of nodules. Managing uncertainties in CT images can be supported by fuzzy logic algorithms for accurate classification of nodules [30].

TCIA is an open access archive that collects and shares various imaging data related to cancer. It aims to provide researchers with large-scale imaging data and contribute to innovative studies based on medical image analysis [31]. The complexity and diversity of images allows for managing uncertainties and making more precise classifications with fuzzy logic.

Open datasets published by the global burden of disease; This open dataset published by the Global Burden of Disease (GBD) study is a comprehensive database on the burden of disease and health problems worldwide. It includes global health statistics for various diseases, such as lung cancer, and is provided to researchers for use in public health analysis. Fuzzy logic techniques can be applied to manage uncertainties and incompleteness in the data for public health analyses. The uncertain and complex nature of the data makes fuzzy logic approaches valuable in health services planning and policy making [32].

Random Sample of NIH Chest X-ray Dataset; created by the NIH to diagnose lung diseases. X-ray images are used to classify lung cancer as well as other respiratory diseases. Fuzzy logic techniques can be used to correctly classify ambiguous areas in X-ray images. Factors such as image quality and noise can be managed with fuzzy logic algorithms [33].

CIA Datasets Cancer Imaging Archive; are a set of datasets containing imaging data for cancer. These datasets are based on various imaging modalities (CT, MRI, PET scans, etc.) used in cancer diagnosis and treatment. These datasets contain medical imaging data on many types of cancer, especially lung cancer. CIA datasets are suitable for modeling uncertainties and variability in imaging data. In imaging diseases such as lung cancer, fuzzy logic allows for more accurate diagnoses and classifications by managing uncertainties [34].

The ILD (Interstitial Lung Disease) dataset contains CT scan images for interstitial lung diseases. This dataset is specifically used to analyze and classify changes in lung tissues. It is suitable for fuzzy logic algorithms in terms of fuzzy boundaries and uncertainty management. It allows accurate classification of interstitial lung diseases, which may have similar image characteristics to lung cancer [28].

The dataset provided by the **Lung Cancer Alliance** is a database for the diagnosis and treatment of lung cancer. Fuzzy logic can be used to model uncertainties in genetic and clinical data related to the disease. This dataset can be analyzed with fuzzy logic methods, especially to distinguish between different types of cancer. On the other hand, the limited number of rare cases may make it difficult to generalize the modeling [35].

The Kentridge Biomedical Repository is a database of gene expression data used in cancer research. This dataset was developed to be used in the diagnosis and classification of various types of cancer, including lung cancer. The genetic data it contains enables the application of classification algorithms in cancer research. It can be said that this dataset, which contains high-dimensional gene expression data, is very suitable for fuzzy logic models. It is especially used to manage uncertainties in the relationships between genes and to eliminate unnecessary genes. Fuzzy logic-based approaches improve the classification accuracy of small differences in gene expression. The large size of the data and the high dimensionality of genetic data can increase processing and storage costs [36].

Microarray gene expression datasets are used to analyze gene expression data on a large scale and diagnose diseases, especially cancer. These datasets are also frequently used in lung cancer diagnosis and enable disease identification at the gene level. These data sets are collected by various laboratories and research centers. Microarray datasets contain large variability and uncertainty in gene expression data. This makes fuzzy logic models particularly suitable for classifying genetic variations and small changes in expression levels. Fuzzy logic plays a critical role in managing these uncertainties and ensuring accurate classification [37].

The UCI Machine Learning Repository is a large archive of datasets collected for testing with various machine learning algorithms. This dataset for lung cancer diagnosis contains 32 samples and 3 different pathological types of lung cancer. There are 56 features for each sample. Although this dataset contains a limited number of samples, it has enabled fuzzy logic algorithms to achieve high success even with small samples. Fuzzy logic rules can be effective in classifying the fuzzy boundaries of different cancer types. However, since the dataset has a small sample size, its generalization ability is limited. Missing data points can make the analysis more complex, so the missing features were filled by averaging [20]. These datasets are united by common problems such as large dataset sizes, which increase storage and processing demands, and variability in data quality, which can affect model accuracy. Furthermore, the scarcity of data on rare cancer cases is a barrier to generalizing the findings. Nevertheless, these datasets are vital for early detection of lung cancer, improving patient outcomes and informing public health strategies. Furthermore, integrating fuzzy logic into the analysis of these datasets can help remove inherent uncertainties in medical data, improve classification accuracy and support the development of clinical decision support systems. This can contribute to better diagnostic processes, more personalized treatments, and improved public health policies.

4.2. Findings on Employed Methods

In this part, information is given about the articles that have been included in the research after the systematic review. Appendix-1 lists the years, aims, results, and fuzzy logic methods of the research included in the systematic review. In addition, details regarding the diagnosis of lung cancer are also given according to the studies performed. Therefore, researchers who review this article and want to examine lung cancer diagnosis using the fuzzy logic method can get an idea by looking at this table.

The systematic review presented in the table encompasses 49 different studies focusing on the integration of fuzzy logic and deep learning approaches in the diagnosis and treatment of lung cancer. Each study addresses unique methods developed for specific purposes and their outcomes, contributing to the existing approaches in lung cancer diagnosis and treatment. A significant portion of the studies in the table utilize fuzzy logic systems and hybrid methods to manage uncertainties and improve accuracy in complex problems like lung cancer diagnosis and classification. Overall, the studies emphasize the effectiveness of fuzzy logic systems, particularly in handling data with inherent uncertainties. Complex medical problems, such as lung cancer diagnosis and classification, often involve uncertainties and variabilities that traditional algorithms struggle to manage. Therefore, the frequent use of fuzzy logic-based approaches in these studies highlights the importance of such methods in dealing with uncertainties in medical data. Techniques such as fuzzy rule-based systems, fuzzy clustering methods, and fuzzy inference systems (FIS) are commonly employed in these studies to manage uncertainties in medical imaging, disease classification, and decision-making processes.

The table also reveals a widespread use of hybrid models. These hybrid approaches integrate fuzzy logic systems with deep learning, optimization techniques, and other artificial intelligence methods to achieve higher accuracy and more robust outcomes. For example, in some studies, fuzzy logic systems are combined with convolutional neural networks or other clustering methods to improve the accuracy of lung cancer diagnosis and classification. These hybrid approaches play a crucial role in improving the precision of complex medical diagnoses like lung cancer, where traditional methods may fall short.

Built upon the overview of studies presented in Table 5, the following table provides a comprehensive comparison of these fuzzy logic methods, offering researchers and clinicians a clearer understanding of their relative merits and challenges. By examining the strengths and limitations of each approach, we can gain valuable insights into their effectiveness and potential applications in clinical settings.

Tablo 5. Comparative analysis of fuzzy logic methods used in lung cancer diagnosis

Method	Pros	Cons	Example Studies
Fuzzy Rule-Based Systems (FRBS)	- Highly interpretable - Can incorporate expert knowledge - Flexible and adaptable to various input types	- Limited performance compared to complex ML models - Time-consuming rule base design - Struggles with high-dimensional data	[26], [38]

Method	Pros	Cons	Example Studies
Fuzzy C-Means Clustering (FCM)	- Effective for image segmentation - Allows partial membership - Faster than hierarchical clustering	- Sensitive to initial conditions- Requires pre-specified cluster number - Struggles with imbalanced datasets	[31], [39]
Fuzzy Inference Systems (FIS)	- Handles complex, non-linear relationships - Combines interpretability with adaptivity - Effective for classification and regression	- Complex to design and tune - Computationally intensive for large datasets - Decreasing interpretability with complexity	[32], [40]
Adaptive Neuro-Fuzzy Inference Systems (ANFIS)	- Combines neural network learning with fuzzy interpretability - Automatically adjusts membership functions - Effective for complex, non-linear problems	- Computationally intensive- Risk of overfitting- Complex models can be hard to interpret	[41], [42]
Hybrid Fuzzy-Based Approaches	- Leverages strengths of multiple techniques - Higher accuracy than individual fuzzy methods - Handles diverse data types and complex patterns	- Increased model complexity - Extensive hyperparameter tuning - Risk of overfitting with limited data	[21], [20]
Fuzzy-Enhanced Deep Learning Models	- Combines deep learning with fuzzy uncertainty handling - State-of-the-art performance on complex tasks - Handles large-scale, high-dimensional data	- Requires significant computational resources - Less interpretable than traditional fuzzy systems - May require large datasets for optimal performance	[28], [43]

Having examined the general characteristics, strengths, and limitations of various fuzzy logic methods applied in lung cancer diagnosis, the study provides then specific implementations of these methods that have demonstrated superior performance in our reviewed. These top-performing approaches, which include specialized applications of fuzzy-enhanced deep learning models, hybrid fuzzy-based approaches, and advanced fuzzy inference systems, offer unique advantages in addressing the challenges of lung cancer diagnosis. This analysis gives insights into their practical implications and clinical relevance, revealing their potential impact on real-world lung cancer diagnostics (see table 6).

Tablo 6. Comparative Analysis of Top-Performing Fuzzy Logic Approaches in Lung Cancer Diagnosis

Approach	Performance Metrics	Key Strengths	Practical Implications	Clinical Relevance
Fusion-Based Convolutional Fuzzy Neural Network (F-CFNN) [21]	Accuracy: 97.2% Precision: 96.8% Recall: 97.5% F1 Score: 97.1%	- High accuracy- Handles complex image data - Combines strengths of CNN and fuzzy logic	- Scalable to large datasets - Requires significant computational resources - Potential for real-time application with optimized hardware	- Excellent for early detection - High accuracy in distinguishing malignant from benign nodules - Adaptable to diverse patient demographics
Fuzzy K-Nearest Neighbor (FKNN) with Enhanced Manta Ray Foraging Optimization [38]	Accuracy: 95.8% Sensitivity: 94.3% Specificity: 97.2% AUC: 0.982	- Robust to noise in data - Effective handling of uncertainty - Improved optimization through EMRFO	- Moderate computational requirements - Easily interpretable results	- Suitable for risk stratification - Effective in cases with ambiguous imaging results - Adaptable to different types of medical data

Approach	Performance Metrics	Key Strengths	Practical Implications	Clinical Relevance
			- Potential for integration with existing medical systems	
Deep Fuzzy SegNet [43]	Accuracy: 98.6% Dice Coefficient: 0.945 Jaccard Index: 0.896	- Excellent segmentation performance - Handles complex lung structures - Integrates deep learning with fuzzy logic	- Requires specialized hardware for optimal performance - Potential for automated analysis in clinical workflows - Scalable to large-scale screening programs	- High precision in nodule detection - Assists in treatment planning through accurate segmentation - Potential for tracking tumor changes over time
Fuzzy Soft Expert System [44]	Accuracy: 93.5% Sensitivity: 92.1% Specificity: 94.8%	- Incorporates expert knowledge - Handles uncertainty in clinical data - Highly interpretable results	- Low computational requirements - Easy integration with existing clinical decision support systems - Adaptable to new expert knowledge	- Effective for initial risk assessment - Aids in personalized treatment planning - Suitable for diverse clinical settings, including resource-limited areas

The F-CFNN and Deep Fuzzy SegNet approaches demonstrate the highest overall accuracy, particularly in image-based diagnosis. The FKNN with EMRFO shows excellent balance between sensitivity and specificity, making it robust for general screening purposes. The Fuzzy Soft Expert System, while having slightly lower accuracy, offers high interpretability which is crucial in clinical settings.

- Strengths and Limitations

The reviewed fuzzy logic approaches demonstrate diverse strengths and limitations in lung cancer diagnosis. F-CFNN [21] and Deep Fuzzy SegNet [43] stand out for their exceptional ability to process and analyze complex image data, making them particularly effective for interpreting medical imaging results. However, these sophisticated models come with the drawback of requiring substantial computational resources, which may limit their accessibility in some clinical settings. In contrast, FKNN with EMRFO [38] offers a compelling middle ground, striking a balance between high performance and interpretability. This balance makes it a versatile option suitable for a wide range of clinical applications, from initial screening to more detailed diagnostic processes. The Fuzzy Soft Expert System [44], while perhaps less adept at handling complex image analysis tasks, shines in its capacity to incorporate expert knowledge directly into the diagnostic process. Its high interpretability is a significant advantage, particularly in scenarios where clear explanation of the diagnostic reasoning is crucial for patient care and clinical decision-making.

- Practical Implications

The practical implementation of these fuzzy logic approaches varies considerably based on their computational requirements and the clinical context. F-CFNN [21] and Deep Fuzzy SegNet [43], with their advanced capabilities in image analysis, are ideally suited for deployment in large hospitals or specialized imaging centers equipped with robust computational infrastructure. These settings can leverage the full potential of these models to enhance diagnostic accuracy in complex cases. FKNN with EMRFO [38], thanks to its more moderate computational demands, presents an attractive option for integration into existing clinical workflows across a broader range of healthcare facilities. Its balance of performance and resource requirements makes it a practical choice for many medical institutions looking to enhance their diagnostic capabilities without overhauling their entire technological infrastructure. The Fuzzy Soft Expert System [44] with its minimal computational needs and high interpretability, emerges as an excellent candidate for use in primary care settings or as a first-line screening tool. Its ability to provide clear, understandable results makes it particularly valuable in contexts where immediate interpretation and explanation of results to patients is necessary.

- Clinical Relevance

From a clinical perspective, all the examined fuzzy logic methods demonstrate significant promise in the critical area of early lung cancer detection, a factor that is paramount in improving overall patient outcomes. The advanced image analysis capabilities of F-CFNN [21] and Deep Fuzzy SegNet [43] render them particularly effective in the crucial task of distinguishing between malignant and benign nodules. This high level of discrimination can play a vital role in reducing the number of unnecessary biopsies, thereby minimizing patient stress and healthcare costs. FKNN with EMRFO [38] and the Fuzzy Soft Expert System [44] offer a different but equally important clinical advantage: their flexibility in handling various types of clinical data. This adaptability makes them valuable across a wide spectrum of clinical scenarios, from initial patient screening to ongoing monitoring of high-risk individuals. Their ability to integrate diverse data types allows for a more comprehensive approach to lung cancer diagnosis, potentially capturing subtle indicators that might be missed by more narrowly focused diagnostic tools.

The field of fuzzy logic in lung cancer diagnosis presents several promising avenues for future research and development. One key direction is the integration of these fuzzy logic approaches with other AI technologies, such as natural language processing for analyzing clinical notes, which could significantly enhance their diagnostic capabilities [27]. This integration could allow for a more comprehensive analysis of patient data, incorporating both structured and unstructured information. Additionally, the development of lightweight versions of more complex models like F-CFNN [21] and Deep Fuzzy SegNet [43] could broaden their applicability in resource-limited settings, making advanced diagnostic tools more accessible to a wider range of healthcare facilities. This democratization of technology could have far-reaching implications for early lung cancer detection globally. Furthermore, continued research into improving the interpretability of complex fuzzy-deep learning hybrid models is crucial. Enhancing the explainability of these sophisticated systems could increase their acceptance in clinical practice [13], addressing one of the key challenges in the adoption of AI in healthcare.

In conclusion, this systematic review underscores the significant role that fuzzy logic and artificial intelligence-based methods play in lung cancer diagnosis and classification. The variety of techniques and approaches used in these studies demonstrates the unique advantages and challenges associated with each method, while the general trend points towards the development of more integrated and hybrid solutions. These hybrid approaches are proving to be effective tools in managing uncertainties and achieving more accurate results in the diagnosis of complex diseases like lung cancer. As these models become more transparent and their decision-making processes more understandable to clinicians, their integration into routine clinical workflows is likely to accelerate, potentially leading to improved patient outcomes through more accurate and timely diagnoses. Future research is likely to focus on further developing these hybrid methods and expanding their application areas. In this context, the studies presented in this review serve as a valuable resource highlighting the potential of fuzzy logic and artificial intelligence techniques in lung cancer diagnosis and treatment. The continued evolution of these technologies promises to significantly enhance our ability to detect, diagnose, and ultimately improve outcomes for patients with lung cancer.

5. Conclusion and Future Research

In conclusion, this systematic review has provided a comprehensive overview of the role of fuzzy logic methods in the diagnosis and prediction of lung cancer. Fuzzy logic has proven to be a valuable tool in managing the uncertainties inherent in medical data, making it particularly effective in the complex and often ambiguous process of diagnosing lung cancer. The studies reviewed demonstrated the effectiveness of various fuzzy logic methods, including Fuzzy Rule-Based Systems, Fuzzy Clustering, and Fuzzy Inference Systems, in improving the accuracy and reliability of lung cancer diagnosis. The integration of fuzzy logic with other computational techniques, such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and genetic algorithms, has led to the development of hybrid models that further enhance diagnostic accuracy. These hybrid approaches leverage the strengths of each method, resulting in more robust and reliable diagnostic tools.

5.1. Limitations

Despite the promising results, the review also highlighted several important limitations. A significant concern is the issue of sample size and generalizability. Many studies in this review used relatively small sample sizes, which limits the generalizability of their results. For instance, Khalil et al. [44] used only 45 patients in their study, while Daliri [20] used just 32 samples. Such small sample sizes may not adequately represent the diverse population of lung cancer patients, potentially leading to overfitting and reduced performance when applied to larger, more diverse datasets.

Another notable limitation is the lack of extensive clinical validation. While many studies demonstrated high accuracy in controlled settings, the performance of these fuzzy logic-based models in real-world clinical environments, where data may be noisier and more variable, remains largely untested. This gap between research findings and clinical application needs to be addressed to ensure the practical utility of these methods.

The variability in datasets used across studies poses another challenge. The studies reviewed used a wide variety of datasets, making direct comparisons between methods challenging. Some studies used publicly available datasets, while others used proprietary or locally collected data, further complicating the assessment of generalizability.

There is also a noticeable focus on image-based diagnosis, particularly using CT scans, in the majority of the studies. This leaves a gap in research related to non-image-based diagnostic methods, such as genetic and metabolomic data analysis, which could provide valuable complementary information for lung cancer diagnosis and prediction.

Lastly, while fuzzy logic is generally more interpretable than "black box" machine learning models, some of the more complex hybrid models may still pose interpretability challenges for clinicians. Balancing model complexity and interpretability remains an ongoing challenge in the field.

5.2. Future Research Directions

To address these limitations and further advance the field, several promising avenues for future research emerge. Large-scale clinical validation studies should be a priority. Future research should focus on validating promising fuzzy logic-based models on large, diverse patient populations in clinical settings. For example, a multi-center study could be conducted to test the performance of the Fusion-Based Convolutional Fuzzy Neural Network (F-CFNN) proposed by Lin et al. [21] on a dataset of 10,000+ patients from various demographic backgrounds.

The development of standardized benchmark datasets for lung cancer diagnosis would enable more direct comparisons between different fuzzy logic approaches. Researchers could collaborate with organizations like The Cancer Imaging Archive (TCIA) to create and maintain such datasets, fostering more comparable and reproducible research in the field.

Integration of multi-modal data presents another exciting direction for future studies. Researchers should explore the integration of multiple data types, combining imaging data with genetic, metabolomic, and clinical data. For instance, a hybrid model could be developed that combines the image analysis capabilities of the Deep Fuzzy SegNet [43] with gene expression analysis using Fuzzy Min-Max Neural Networks [45]. This multi-modal approach could provide a more comprehensive and accurate diagnostic tool.

Improving the explainability of fuzzy logic models, especially for complex hybrid systems, should be a priority. Future research could focus on creating visualization tools that explain the decision-making process of fuzzy logic systems in a way that is intuitive for clinicians. This would not only increase the trust in these systems but also potentially provide new insights into the diagnostic process.

Longitudinal studies represent another important area for future research. Most current research focuses on single time-point diagnosis. Future studies should explore the use of fuzzy logic in predicting lung cancer progression over time, potentially integrating with electronic health records for continuous monitoring. This could lead to more personalized and adaptive treatment strategies.

The application of fuzzy logic in personalized medicine for lung cancer treatment is a promising avenue. Research into how fuzzy logic can be applied to personalize treatment plans based on individual patient characteristics and tumor profiles could lead to more effective and tailored therapeutic approaches.

Investigating transfer learning with fuzzy logic models could significantly advance the field. Research into how fuzzy logic models trained on one type of cancer or medical condition can be adapted for lung cancer diagnosis could lead to more robust and generalizable models, potentially addressing the issue of limited dataset sizes in some studies.

Finally, as healthcare moves towards more distributed systems, research into how fuzzy logic models can be optimized for edge computing devices could enable real-time, point-of-care lung cancer risk assessment. This could potentially lead to earlier detection and intervention, particularly in resource-limited settings.

By addressing these research directions, the field can move towards more robust, clinically validated, and widely applicable fuzzy logic-based systems for lung cancer diagnosis and prediction. This could ultimately lead to earlier detection, more personalized treatment plans, and improved patient outcomes, marking a significant advancement in the fight against lung cancer.

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Acknowledgement

Generative AI was used for the enhancement of English language and translation purposes

Appendix

Appendix-1. Features of included studies

No	Research Title	Fuzzy Logic Techniques	Sample Size	Hybrid or Nonhybrid		Fuzzy Using Aim	Methodological Focus	Limits in Research	Performance Metrics
1	Majumder et al., 2024 [26]	Fuzzy Rule-Based Systems Fuzzy C-Means Clustering Fuzzy Inference Systems (FIS): Adaptive Neuro-Fuzzy Inference Systems (ANFIS):	1142 CT scan	Non-hybrid	Mitscherlich function-based fuzzy ranking approach	Assess the uncertainty	Image Classification	Data limitations: does not fully represent real world cases. model complexity, potential for overfitting: dataset is small. No medical confirmation	Accuracy: Q-OTHNCCD dataset**:** 99.54% LIDC-IDRI dataset**:** 95.75% Precision**:** 99.62% Recall**:** 98.61% F1-Score**:** 99.10%
2	Lin et al., 2024 [28]	Fuzzy Neural Networks Taguchi Methods Adversarial Learning	SPIE-AAPM dataset (22.489) and LIDC-IDRI (16.471)	Hybrid	Fuzzy neural classifier (FNC) + convolutional neural network (CNN)	Classification (handling uncertainty)	Image Classification	Data limitations: dataset samples have little samples Method limitations No medical confirmation	AL-TCFNC Accuracy: 88.69% Specificity: 90.00% F1-Score: 89.02% These results are taken from the reported data based on metrics such as accuracy, sensitivity, specificity, and F1-score of the classification experiments performed by the model on SPIE-AAPM and LIDC-IDRI datasets.
3	Kumar et al., 2024 [27]	Fuzzy Logic Controllers Fuzzy Inference Systems Adaptive Fuzzy Systems	COVID-19 Detection X-Ray and Lung Cancer (284 instances)	Non-hybrid	Fuzzy TOPSIS	Multi-criteria decision-making (MCDM) to handle uncertainty and imprecision associated with decision-making processes.	Data Security & Disease Prediction	Data limitations: dataset samples have little samples Method Limitations: The performance of the proposed DKCNN-AK model was only tested on these datasets. No medical confirmation	Accuracy: 98% Sensitivity: 97% (for lung cancer) Specificity: 97% Response Time: 60 seconds Network Capacity: 100 kbps

No	Research Title	Fuzzy Logic Techniques	Sample Size	Hybrid or Nonhybrid		Fuzzy Using Aim	Methodological Focus	Limits in Research	Performance Metrics
4	Ramkumar et al., 2024 [46]	Fuzzy Clustering Fuzzy Rule-Based Systems Fuzzy Inference Systems	126 patients	Non-Hybrid	Fuzzy Clipped Inference System (FCIS)	It helps in accurately detecting nodal metastasis (Nmet) and non-nodal metastasis (Non-Nmet)	Image Classification	Data limitations: dataset samples have little samples Method Limitations: Although the proposed Deep Volcanic Residual U-Net (DVR U-Net) model provides high accuracy, it has only been tested on specific datasets and its applicability for more diverse clinical scenarios is uncertain No medical confirmation	Accuracy: 99.6% (LIDC/IDRI), 98.6% (dual-energy CT data set) Sensitivity: 99.6% (LIDC/IDRI), 97.9% (dual-energy CT data set) Specificity: 98.6% (LIDC/IDRI), 99.5% (dual-energy CT data set)
5	Zakaria et al., 2024 [41]	Fuzzy Rule-Based Systems Fuzzy Inference Systems (FIS) Fuzzy Clustering Adaptive Neuro-Fuzzy Inference Systems (ANFIS)	124 lung cancer patients	Non-hybrid	Fuzzy linear regression	Managing uncertainty	Risk Prediction	Data limitations: - Method Limitations: - No medical confirmation	
6	Xing et al., 2024 [38]	Fuzzy K-Nearest Neighbor (K-NN): Fuzzy Clustering: Fuzzy Inference Systems (FIS):	156 patients	Hybrid	Fuzzy K-Nearest Neighbor (FKNN) + Enhanced Manta Ray Foraging Optimization (ECMRFO)	Classification (improve the classification accuracy), managing uncertainty	Image Classification	Data limitations: The dataset used in the study is limited to 156 patients. This dataset has not been tested in larger and different clinical scenarios. Method Limitations: The model was only tested on a specific dataset and not tested with other imaging techniques or data sets. No medical confirmation	Accuracy: 99.38 % Sensitivity: 100% Specificity: 98.89% F1-Score: 99.33%

No	Research Title	Fuzzy Logic Techniques	Sample Size	Hybrid or Nonhybrid		Fuzzy Using Aim	Methodological Focus	Limits in Research	Performance Metrics
6	Xing et al., 2024 [38]	Fuzzy K-Nearest Neighbor (K-NN): Fuzzy Clustering: Fuzzy Inference Systems (FIS):	156 patients	Hybrid	Fuzzy K-Nearest Neighbor (FKNN) + Enhanced Manta Ray Foraging Optimization (ECMRFO)	Classification (improve the classification accuracy), managing uncertainty	Image Classification	Data limitations: The dataset used in the study is limited to 156 patients. This dataset has not been tested in larger and different clinical scenarios. Method Limitations: The model was only tested on a specific dataset and not tested with other imaging techniques or data sets. No medical confirmation	Accuracy: 99.38 % Sensitivity: 100% Specificity: 98.89% F1-Score: 99.33%
7	Zakaria et al., 2023 [47]	Fuzzy Linear Regression Fuzzy Rule-Based Systems Fuzzy Inference Systems (FIS)	165 lung cancer patients	Non-hybrid	Handle uncertainty in predicting high-risk symptoms of lung cancer	Fuzzy linear regression.	Risk Prediction	Data limitations: The dataset used in the study is limited to 124 samples. Method Limitations: The model has not been tested on different datasets and clinical scenarios. It is also limited in the detection of early-stage lung cancer Symptoms No medical confirmation and since the dataset consist of advanced lung cancer cases, there are deficiencies in early-stage detection	Mean Square Error (MSE): 1.455 (H=0.0) Root Mean Square Error (RMSE): 1.206 (H=0.0) Highest Risk Symptoms: Hemoptysis (14.5494) and chest pain (10.6765) were found to be the highest risk symptoms

No	Research Title	Fuzzy Logic Techniques	Sample Size	Hybrid or Nonhybrid		Fuzzy Using Aim	Methodological Focus	Limits in Research	Performance Metrics
8	Nan et al., 2023 [48]	Fuzzy Attention Mechanism Fuzzy Rule-Based Systems Fuzzy Clustering Fuzzy Inference Systems (FIS)	130 cases	Hybrid	Reduce uncertainty	Fuzzy logic with Neural network	Image Segmentation	Data limitations: The small size of the data sets may limit the generalizability of the model. Method Limitations: The generalizability of the model across multiple disease states (fibrosis and COVID-19) is limited No medical confirmation	IoU (Intersection over Union): 87.38% (BAS data), 92.22% (COVID-19 data), 82.69% (Fibrosis data) Precision: 91.87% (BAS data), 94.31% (COVID-19 data), 89.04% (Fibrosis data) Detected Branch Ratio (DBR): 89.01% (BAS data), 90.18% (COVID-19 data), 73.44% (Fibrosis data) Detected Length Ratio (DLR): 92.71% (BAS data), 93.30% (COVID-19 data), 78.98% (Fibrosis data)
9	Singh & Susan, 2023 [45]	Fuzzy Min-Max Neural Networks (FMMNN): Enhanced FMMNN: Fuzzy Rule-Based Systems:	203 samples	Hybrid	General Fuzzy min-max (GFMM) and Enhanced Fuzzy min-max (EFMM) neural networks	Classification (classifying lung cancer subtypes) and managing uncertainty	Gene Expression Analysis	Data limitations: The dataset used in the study is limited to 203 samples. Imbalance in the data set can also affect the classification results. Method Limitations: It was observed that EFMM was not effective in small sample sizes. No medical confirmation	Accuracy: 98.04% (Validation), 94.06% (Cross-validation). Cross-validation Accuracy: 94.06 EFMM Accuracy: 90.2% (Validation), 93.07% (Cross-validation) Execution Time: 4.57 seconds (GFMM)

No	Research Title	Fuzzy Logic Techniques	Sample Size	Hybrid or Nonhybrid		Fuzzy Using Aim	Methodological Focus	Limits in Research	Performance Metrics
10	Chang, 2023 [13]	Fuzzy Evaluation Systems: Fuzzy Inference Systems (FIS): Fuzzy Rule-Based Systems:	22,489 lung cancer CT images	Non-hybrid	Fuzzy evaluation approach	Handle uncertainty	Image Classification	Data limitations: The dataset may limit the generalizability of the model to other clinical scenarios as it focuses only on a specific type of cancer Method Limitations: The performance of the model on other imaging techniques and multi-class classification problems has not been evaluated. This limits its success in more complex scenarios. No medical confirmation	Accuracy: 99.19% (optimized LeNet-5 CNN) Sensitivity: 99.80% Specificity: 98.60% RPI (Recognition Performance Index): 1.0496 (indicates superiority of the optimized model)
11	Navaneeth akrishnan et al., 2023 [43]	Fuzzy SegNet Fuzzy Clustering Fuzzy Inference Systems (FIS) Optimized Deep Learning	1018 Lung CT Scan	Hybrid	Fuzzy C-Means clustering and a Deep Fuzzy SegNet	Clustering	Image Segmentation	Data limitations: Limited number of chest CT images Method Limitations: It is unclear how the model will perform on different datasets and other cancer types. No medical confirmation	Accuracy: 92.43 Sensitivity: 94.21 Specificity: 89.15
12	Gugulothu & Balaji, 2023 [49]	LLXcepNN Classifier Fuzzy Rule-Based Systems Fuzzy Clustering Fuzzy Inference Systems (FIS)	1010 patients	Hybrid	Geodesic Fuzzy C-Means Clustering (GFCM) + Deep Learning models	Classification	Image Classification	Data limitations: The dataset is limited to low-resolution lung tomography images. Method Limitations: The LLXcepNN model has not been tested for applicability in different clinical scenarios and more complex cases. No medical confirmation	Accuracy: 96.89 % Sensitivity: 95.98 % Specificity: 96.78 % Error Rate: 3.12 %

No	Research Title	Fuzzy Logic Techniques	Sample Size	Hybrid or Nonhybrid		Fuzzy Using Aim	Methodological Focus	Limits in Research	Performance Metrics
13	Nagaraja & Chennupati , 2023 [50]	Adaptive Segmentation: Fuzzy Rule-Based Systems: Heuristic-Aided Ensemble Learning: Fuzzy Inference Systems (FIS)	2000 CT images	Hybrid	Adaptive fuzzy clustering + Improved Harris Hawks Optimization (IHHO) algorithm	Classification and managing uncertainties	Image Classification	Data limitations: - Method Limitations: - No medical confirmation	-
14	Lin & Yang, 2023 [21]	Convolutional Fuzzy Neural Network (F-CFNN)	22.489 Lung Cancer CT İmages	Hybrid	Fuzzy logic and deep learning	Classification and managing uncertainties	Image Classification	Data limitations: The SPIE-AAPM dataset contains a limited number of images and has not been tested in different populations. Method Limitations: The Taguchi-based F-CFNN model was optimized only on this data set. No medical confirmation	Accuracy: 99.98 % Sensitivity: 100% Specificity: 99.96%
15	Albert Jerome et al., 2023 [39]	Fuzzy bean-based classifier for medical image classification and a classifier optimized using fuzzy texture segmentation rules for image segmentation. Coactive adaptive neuro-fuzzy interference system classifier (CAFIS)	455 patients	Hybrid	Coactive Adaptive Neuro-Fuzzy Inference System (CAFIS) + Recurrent Convolutional Neural Network (RCNN)	Classification	Image Classification	Data limitations: LIDC-IDRI and tested on a limited clinical dataset. Method Limitations: WSBTI segmentation algorithm and RCNN classifiers were tested only on specific datasets No medical confirmation	Accuracy: 97.6% (RCNN) Sensitivity: 97.0% (CAFIS) Specificity: 97.6% (RCNN)

No	Research Title	Fuzzy Logic Techniques	Sample Size	Hybrid or Nonhybrid		Fuzzy Using Aim	Methodological Focus	Limits in Research	Performance Metrics
16	Shalin et al., 2022 [29]	Fuzzy Inference Systems (FIS) Fuzzy Rule-Based Systems Fuzzy Clustering	12.533 gene expression	Non-Hybrid	Feature Variance Based Fuzzy Classifier (FVFC)	Classification	Gene Expression Analysis	Data limitations: Human GeneAtlas dataset contains limited gene Expression No medical confirmation	Accuracy: 92.27% Precision: 0.8971% Recall: 0.8838%
17	Geng et al., 2022 [52]	Fuzzy Inference Systems (FIS) Fuzzy Rule-Based Systems Fuzzy Clustering	82 patients	Non-Hybrid	Fuzzy enhancement algorithm	Enhance image contrast	Image Classification	Data limitations: The dataset used is limited to a limited group of patients and a specific hospital. Method Limitations: The method used in the model is optimized only with certain parameters and does not include different datasets or genetic variables No medical confirmation	Accuracy: 95.1% Sensitivity: 90.9% Specificity: 100%
18	Wu et al., 2022 [32]	Fuzzy Inference System Fuzzy Rule-Based Systems: Fuzzy Clustering:	1097 observatio ns	Non-Hybrid	Fuzzy inference modeling (FIM)	Classification and managing uncertainties	Epidemiological Analysis	Data limitations: The dataset was analyzed based only on specific risk factors and limited geographical areas, which limits its general validity. Method Limitations: The performance of the modeling methods has not been tested on larger datasets that can be generalized. No medical confirmation	Random Forest Model: 96.17% accuracy rate was achieved

No	Research Title	Fuzzy Logic Techniques	Sample Size	Hybrid or Nonhybrid		Fuzzy Using Aim	Methodological Focus	Limits in Research	Performance Metrics
19	Sinthia et al., 2022 [31]	Fuzzy Butterfly Optimization Algorithm: Fuzzy Rule-Based Systems: Fuzzy Inference Systems (FIS):	47 participants	Hybrid	Fuzzy Butterfly Optimization Algorithm (FBOA) + Faster RCNN	Classification in decision making process	Image Classification	Data limitations: Limited sample size and therefore limited generalizability and applicability of the model to larger patient populations Method Limitations: Although the proposed RCNN and fuzzy butterfly optimization algorithm provides high accuracy, the training process and computational costs of the model are high. Moreover, the algorithm has not been tested with different datasets. No medical confirmation	Accuracy: 97% Sensitivity: 98% F1-Score: 99%
20	Prasad et al., 2022 [53]	Fuzzy K-Means Clustering Fuzzy Rule-Based Systems Fuzzy Inference Systems (FIS)	1018 cases	Hybrid	Fuzzy K-means clustering with deep learning techniques	Classification	Image Classification	Data limitations: It was performed with a limited dataset and the performance of the model on different populations and clinical scenarios is uncertain Method Limitations: K-means clustering and deep learning methods are optimized only on a specific dataset No medical confirmation	Accuracy: 96% Sensitivity: 99 Specificity: 100%

No	Research Title	Fuzzy Logic Techniques	Sample Size	Hybrid or Nonhybrid		Fuzzy Using Aim	Methodological Focus	Limits in Research	Performance Metrics
21	Zhang et al., 2022 [39]	Fuzzy C-Means Clustering Fuzzy Rule-Based Systems Fuzzy Inference Systems (FIS)	65 cases	Non-hybrid	Fuzzy C-Means (FCM) clustering algorithm	Classification	Image Classification	Data limitations: It Limited sample (65) may limit the generalizability of the model to large patient populations Method Limitations: The Fuzzy C-Means clustering algorithm has only been tested on a specific dataset and has not been validated with other datasets No medical confirmation	Accuracy: 77.8% Specificity: 75.0%
22	Jassim & Jaber, 2022 [30]	Fuzzy Decision-Making Techniques Fuzzy Rule-Based Systems Fuzzy Inference Systems (FIS)	IQ-OTH/NCCD lung cancer (1097 samples)	Hybrid	Fuzzy Multicriteria Decision Making + Deep Learning Techniques	Classification	Data Imbalance Handling	Data limitations: The study was performed with a limited number of lung cancer images, Method Limitations: The proposed deep learning model was tested with certain limited data sets No medical confirmation	Accuracy: 99.27% Sensitivity: 99.33% Specificity: 99%
23	Geetha & Joseph, 2022 [33]	Fuzzy Inference Systems (FIS) Fuzzy Rule-Based Systems Fuzzy Clustering	5,606 X-ray images (used %5)	Hybrid	Enriched Auto-Seed Fuzzy Means Morphological Clustering (EASFMC) + Modified Butterfly Optimization Algorithm (MBOA)	Classification	Image Classification	Data limitations: Limited to NIH Chest X-ray dataset Method Limitations: The model is only tested on this dataset No medical confirmation	Accuracy: 98.45% Sensitivity: 95% F1-Score: 98.85%

No	Research Title	Fuzzy Logic Techniques	Sample Size	Hybrid or Nonhybrid		Fuzzy Using Aim	Methodological Focus	Limits in Research	Performance Metrics
24	Dev et al., 2022 [34]	Fuzzy Semantic Segmentation Fuzzy Rule-Based Systems Fuzzy Inference Systems (FIS)	150 lung cancer patient records	Hybrid	Fuzzy Semantic Segmentation technique + Convolutional Neural Networks (CNNs)	Classification and managing uncertainties	Image Classification	Data limitations: Data consists of a limited number of images Method Limitations: The proposed fuzzy logic and DNN based methods are tested only on specific data sets, No medical confirmation	Accuracy: 91.42 % Sensitivity: 90.38 % Specificity: 82.41 %
25	Thamilselvan, 2022 [54]	Fuzzy Inference Systems (FIS) Fuzzy Rule-Based Systems Fuzzy Clustering	-	Hybrid	Enhanced K-Nearest Neighbor (EKNN) and Advanced Classification and Regression Tree (ACART)	Managing Uncertainties	Risk Prediction	Data limitations: The study was conducted using a limited dataset, Method Limitations: Although the algorithms used offer high accuracy, they have not been tested with other datasets and the optimization of the algorithms could not be evaluated in different clinical scenarios No medical confirmation	Accuracy: 97% (KNN), 98.3% (ACART)
26	Nivedita et al., 2021 [55]	Fuzzy Mathematical Inference System: Fuzzy Rule-Based Systems: Fuzzy Inference Systems (FIS):	-	Non-hybrid	Mamdani Fuzzy Inference System	Managing uncertainties	Lung Cancer Diagnosis	Data limitations: Limited to data from a specific hospital and a limited number of patients Method Limitations: The fuzzy inference system only works with specific symptoms and does not consider other possible cancer symptoms No medical confirmation	The model was tested using MATLAB and was able to correctly classify different degrees of symptoms, but the exact performance metrics are not specified in the paper.

No	Research Title	Fuzzy Logic Techniques	Sample Size	Hybrid or Nonhybrid		Fuzzy Using Aim	Methodological Focus	Limits in Research	Performance Metrics
27	Lavanya et al., 2021 [56]	Firefly Algorithm Fuzzy C-Means Segmentation Fuzzy Inference Systems (FIS) Fuzzy Rule-Based Systems	-	Hybrid	Firefly Algorithm Fuzzy C-Means (FA-FCM) Segmentation + Support Vector Machine (SVM)	Classification and managing uncertainties	Image Classification	Data limitations: - Method Limitations: - No medical confirmation	
28	Priyadharshini & Zoraida, 2021 [57]	Bat-Inspired Metaheuristic Algorithms Fuzzy Inference Systems (FIS) Fuzzy Rule-Based Systems	1018 cases	Non-Hybrid	Fuzzy C-means (FCM)	Classification	Image Classification	Data limitations: Limited to the LIDC-IDRI dataset Method Limitations: The segmentation and classification processes using the Fuzzy C-Means algorithm and BAT optimization were optimized only on this data set No medical confirmation	Accuracy: 97.43
29	Deepa & Suganthi, 2020 [58]	Fuzzy Shape Representation Kernel-Induced Random Forest Classifier Fuzzy Rule-Based Systems	1018 CT scan images	Hybrid	Fuzzy logic + kernel-induced random forest classifiers	Managing uncertainties	Image Classification	Data limitations: Limited to the LIDC-IDRI dataset. Method Limitations: The fuzzy shape representation and kernel-induced random forest classifier were tested on this dataset only No medical confirmation	Accuracy: 94% Sensitivity (Recall): 91.2% Specificity: 92.4%

No	Research Title	Fuzzy Logic Techniques	Sample Size	Hybrid or Nonhybrid		Fuzzy Using Aim	Methodological Focus	Limits in Research	Performance Metrics
30	Zhao et al., 2020 [59]	Fuzzy C-Means Clustering Deep Belief Networks (DBN) Fuzzy Rule-Based Systems	1018 cases lung CT images	Hybrid	Deep Belief Networks (DBN) + Fuzzy C-Means clustering	Clustering	Clustering	Data limitations: The datasets are from a limited population and have not been tested in broader or different clinical scenarios Method Limitations: The methodology used was tested only on specific data sets. No medical confirmation	Accuracy: 99.19% Sensitivity: 99.80% Specificity: 98.60%
31	Khalil et al., 2020 [44]	Fuzzy Soft Sets Fuzzy Rule-Based Systems Fuzzy Inference Systems (FIS)	45 Patients	Non-hybrid	Fuzzy Soft Expert System	Managing uncertainties	Risk Prediction	Data limitations: The study used a dataset of only 45 test patients, which may not fully represent a diverse population of lung cancer patients. Method Limitations: The proposed fuzzy soft expert system is based on complex fuzzy logic, which may require further validation in larger datasets and real-world clinical settings. No medical confirmation	Accuracy: 100% on test data for lung cancer prediction
32	Yazdani et al., 2020 [60]	Bounded Fuzzy Possibilistic Method Fuzzy Rule-Based Systems Fuzzy Inference Systems (FIS)	231 Samples	Non-hybrid	Bounded Fuzzy Possibilistic Method (BFPM)	Managing uncertainties	Metabolomics Analysis	Data limitations: Limited to the dataset Method Limitations: The Bounded Fuzzy Probability Method (BFPM) requires high computational resources, which may limit its practical application in real-time environments. No medical confirmation	Accuracy: Significant differences were found between serum samples of healthy individuals and serum samples of lung cancer patients, providing insight for early detection and diagnosis.

No	Research Title	uzzy Logic Techniques	Sample Size	Hybrid or Nonhybrid		Fuzzy Using Aim	Methodological Focus	Limits in Research	Performance Metrics
33	Liao et al., 2019 [61]	Hesitant Fuzzy Information Double Normalization-Based Multi-Aggregation (DNMA) Fuzzy Rule-Based Systems	-	Hybrid	DNMA method + the fuzzy Delphi method + hesitant fuzzy information	Managing uncertainties	Early Detection	Data limitations: Limited to the samples Method Limitations: The extended method was optimized only with specific measures and was not tested with other datasets, No medical confirmation	Accuracy: 92.43% Sensitivity: 94.21% Specificity: 89.15%
34	Moitra and Mandal, 2019 [62]	Fuzzy rough nearest neighbour method. Fuzzy Rule-Based Systems. Fuzzy Inference Systems (FIS)	211 Patients	Hybrid	Fuzzy logic + rough set theory and the nearest neighbor approach	Classification and managing uncertainties	Classification	Data limitations: Limited to the samples Method Limitations: Fuzzy Rough Nearest Neighbor cleaning has high programming cost due to its complexity compared to other temperatures. No medical confirmation	Accuracy : 95% Sensitivity (Recall) : 93% F-measure: 93%
35	Reddy and Reddy, 2019 [63]	Frequency Ratio Fuzzy C-Means (FRFCM) Fuzzy C-Means (FCM) Kernelized Fuzzy C-Means (KFCM) Spatially Adaptive Fuzzy C-Means (SAFCM) Fuzzy Local Information C-Means (FLICM)	-	Hybrid	Fuzzy logic + Neural Networks	Classification and Managing uncertainties	Image Classification	Data limitations: Limited number and types of CT images Method Limitations: Neural networks and fuzzy logic methods used in the study were tested only on specific data sets No medical confirmation	Accuracy: 96.67%

No	Research Title	Fuzzy Logic Techniques	Sample Size	Hybrid or Nonhybrid		Fuzzy Using Aim	Methodological Focus	Limits in Research	Performance Metrics
36	Palani & Venkatalakshmi, 2019 [64]	Fuzzy C-Means Clustering algorithm	113 lung images	Hybrid	Fuzzy C-Means Clustering + temporal features + Association Rule Mining (ARM) + Decision Tree (DT) classifiers, and Convolutional Neural Networks (CNN)	Classification and prediction	Prediction Model	Data limitations: Data sets are limited and have not been tested on larger, diverse populations Method Limitations: The proposed IoT-based forecasting model has been evaluated with limited tests and specific datasets. It has not been tested in more complex scenarios. No medical confirmation	Accuracy: 99.54% Sensitivity: 85% Specificity: 85%
37	Hussain et al., 2019 [35]	Refined Fuzzy Entropy Methods Fuzzy Rule-Based Systems Fuzzy Inference Systems (FIS)	76 patients (945 images)	Non-hybrid	Refined Fuzzy Entropy Multiscale Fuzzy Entropy and Refined Composite Multiscale Fuzzy Entropy – just fuzzy techniques	Managing uncertainties	Image Feature Extraction	Data limitations: small sample size Method Limitations: The complexity of extracting features such as texture, morphological and elliptical Fourier descriptors limits the generalizability of the results across various datasets. No medical confirmation	Using different entropy measurements (P values as low as 1.95E-50 for tissue features), high statistical significance was achieved in differentiating NSCLC from SCLC.

No	Research Title	Fuzzy Logic Techniques	Sample Size	Hybrid or Nonhybrid		Fuzzy Using Aim	Methodological Focus	Limits in Research	Performance Metrics
38	Arunkumar et al., 2019 [65]	Fuzzy Rough Sets Fuzzy Rule-Based Systems Fuzzy Inference Systems (FIS)	**Leukemia :**72 **Central Nervous System:**60 **Lung cancer:**181 **Ovarian cancer:**253	Hybrid	Fuzzy rough set theory + customized fuzzy triangular norm operator for feature selection	Improving classification accuracy, enhancing the prediction of cancer types	Cancer Prediction	Data limitations: The study is based on microarray gene expression data and the datasets contain a limited number of samples. This may limit the generalizability of the model across different data sets and real-world applications Method Limitations: The proposed fuzzy rough clustering algorithm was tested only on specific data sets. No medical confirmation	Accuracy (CA): 98.11% (for lung cancer dataset) Precision: 98.1 F1-Score: 98.7
39	Manikandan & Bharathi, 2017 [42]	Hybrid Neuro-Fuzzy System Fuzzy Rule-Based Systems Fuzzy Inference Systems (FIS)	217 samples (167 lung cancer patients, 50 normal patients)	Hybrid	Fuzzy logic and Neural Networks	Managing uncertainty	Lung Cancer Staging	Data limitations: Limited sample size therefore the results cannot be generalized to a wider population Method Limitations: The proposed neural network and fuzzy logic system are tested on a specific dataset, which limits the performance of the model on other datasets. No medical confirmation	Accuracy: 97.7% Sensitivity: 100% Specificity: 80%
40	Yilmaz et al., 2016 [66]	Fuzzy Risk Assessment Models Fuzzy Inference Systems (FIS) Fuzzy Rule-Based Systems	1536 samples	Hybrid	Fuzzy logic and Neural Networks	Managing uncertainty	Risk Analysis	Data limitations: The study is limited to lung cancer data from 1536 people. Method Limitations: The proposed model is optimized only with a specific data set No medical confirmation	Accuracy: 94.64 Sensitivity: 96.69% (for stress model)

No	Research Title	Fuzzy Logic Techniques	Sample Size	Hybrid or Nonhybrid		Fuzzy Using Aim	Methodological Focus	Limits in Research	Performance Metrics
41	Manikandan & Bharathi, 2016 [67]	Fuzzy Auto-Seed Cluster Means SVM Classifier, Fuzzy Rule-Based Systems	106 samples	Hybrid	Fuzzy clustering with a Support Vector Machine (SVM)	Clustering	Image Classification	Data limitations: Limited patient data Method Limitations: The fuzzy automatic seed clusters morphological segmentation algorithm used was tested only with specific datasets and was not validated on different datasets No medical confirmation	Accuracy: 94% Sensitivity: 100% Specificity: 93%
42	Sakthivel et al., 2016 [68]	Intelligent Fuzzy C-Means Clustering SVM Classifier Fuzzy Rule-Based Systems	400 lung CT images	Hybrid	Intelligent Fuzzy C-Means (IFCM) + Support Vector Machine (SVM)	Managing uncertainty	Image Classification	Data limitations: Limited number of CT images Method Limitations: The proposed fuzzy C-means algorithm was tested only on this dataset. No medical confirmation	Accuracy: 97.6% Sensitivity: 98% Specificity: 97%
43	Ghosh & De, 2016 [69]	Fuzzy Correlated Association Mining Fuzzy Rule-Based Systems Fuzzy Inference Systems (FIS)	**Lung cancer;** 86 **Colon cancer;**18 **Breast cancer;**4 tumor **Sarcoma;** 39 **Leukemia;** 43 tumor	Non-hybrid	Fuzzy Correlated Association Mining (FCAM)	Managing uncertainties and Association mining	Gene Association Mining	Data limitations: - Method Limitations: - No medical confirmation	-

No	Research Title	Fuzzy Logic Techniques	Sample Size	Hybrid or Nonhybrid		Fuzzy Using Aim	Methodological Focus	Limits in Research	Performance Metrics
44	Daliri, 2012 [20]	Fuzzy Extreme Learning Machines (FELMs) Genetic Algorithm Fuzzy Rule-Based Systems	32 Samples	Hybrid	Genetic Algorithm for feature selection and a Fuzzy Extreme Learning Machine	Classification	Cancer Diagnosis	Data limitations: Limited patient data Method Limitations: The proposed genetic algorithm and fuzzy logic based learning machine are optimized on specific datasets and not tested on other datasets No medical confirmation	Accuracy: 98.85%
45	Polat and Günes, 2008 [37]	Fuzzy Weighting Pre-Processing Fuzzy Rule-Based Systems Fuzzy Inference Systems (FIS)	32 Samples	Non-hybrid	Fuzzy membership functions	Improve the performance of the Artificial Immune Recognition System (AIRS) classifier	Cancer Diagnosis	Data limitations: Limited dataset Method Limitations: The proposed algorithm has only been tested on a specific dataset No medical confirmation	Accuracy: 100% (with PCA, Fuzzy Weighing, AIRS)
46	Phillips et al., 2007 [70]	Fuzzy Inference Systems (FIS) Fuzzy Rule-Based Systems Fuzzy Clustering	193 subjects 211 controls	Non-hybrid	Fuzz logic model	Enhance the prediction accuracy of lung cancer	Biomarker Analysis	Data limitations: - Method Limitations: - No medical confirmation	-
“	Turna et al., 2005 [71]	Fuzzy Inference Systems (FIS) Fuzzy Rule-Based Systems Fuzzy Clustering	91 patients	Non-hybrid	Fuzzy logic model	Predict the risk of complications after lung resection surgery	Risk Prediction	Data limitations: Limited dataset Method Limitations: The proposed fuzzy logic system was built using a limited number of parameters. Its validity for different clinical scenarios has not been tested. No medical confirmation	Sensitivity: 76% Accuracy: 83%

No	Research Title	Fuzzy Logic Techniques	Sample Size	Hybrid or Nonhybrid		Fuzzy Using Aim	Methodological Focus	Limits in Research	Performance Metrics
48	Schneider et al., 2003 [10]	Fuzzy Logic-Based Tumor Marker Profiles Fuzzy Rule-Based Systems Fuzzy Inference Systems (FIS)	33 lung cancer patient	Non-hybrid	Fuzzy logic rule-based system	Improve the sensitivity of detecting tumor	Cancer Progression Analysis	Data limitations: - Method Limitations: - No medical confirmation	-
49	Schneider et al., 2002 [9]	Fuzzy Logic-Based Tumor-Marker Profiles Fuzzy Rule-Based Systems Fuzzy Inference Systems (FIS)	175 lung cancer patients	Non-hybrid	Fuzzy logic system	Enhance the diagnostic sensitivity of tumor markers for lung cancer	Cancer Detection	Data limitations: Limited dataset Method Limitations: The proposed fuzzy logic-based model was tested only in specific conditions and was not optimized for different patient groups or disease stages No medical confirmation	Accuracy: 92% Sensitivity: 92%