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Application of overlapping areas of fuzzy triangles in a fuzzy MCDM model for lung disease classification

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Abstract

This research proposes an innovative fuzzy Multi Criteria Decision Making (MCDM) approach for classifying lung diseases based on the overlapping areas of fuzzy triangular numbers. Seven clinically relevant symptoms—cough, productive cough, shortness of breath, fever, chest pain, weight loss, and night sweats—are modeled as fuzzy triangular membership functions and weighted according to expert derived diagnostic significance. By calculating the area of overlap between a patient's fuzzy symptom vector and disease prototypes, the method generates a crisp similarity score through weighted aggregation, thereby handling the uncertainty inherent in medical data. The model was evaluated on a dataset of 15 common lung diseases, achieving an overall classification accuracy of approximately 87 % and correctly identifying pneumonia and tuberculosis as the most probable diagnoses with the highest crisp scores. The results demonstrate that incorporating fuzzy triangle overlap areas into an MCDM framework enhances both the objectivity and accuracy of lung disease classification, offering a transparent and interpretable tool for clinical decision support systems that can improve diagnostic performance in complex respiratory conditions.

Keywords: Clinical decision support system, Fuzzy Multi-Criteria Decision Making, Lung disease diagnosis, Overlapping area of fuzzy triangles, Triangular fuzzy numbers.

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1. Introduction

In recent years, the application of fuzzy set theory in medical decision-making has gained considerable attention due to its ability to handle uncertainty and vagueness inherent in clinical data [1, 2]. Specifically, the concept of overlapping areas in fuzzy triangular numbers provides a nuanced mechanism to quantify similarity between patient symptoms and disease profiles [3]. This study introduces an innovative approach by integrating the overlapping areas of fuzzy triangles into a Fuzzy Multi-Criteria Decision Making (MCDM) framework tailored for lung disease classification. This advanced method aims to improve diagnostic precision by effectively modeling the ambiguous boundaries of symptom expression, thus supporting clinicians in making more informed and accurate decisions in complex respiratory disease cases [4].

Lung diseases, including pneumonia, chronic obstructive pulmonary disease (COPD), lung cancer, and tuberculosis, represent major challenges in the global health system [5-7]. Accurate classification of these diseases is critical for effective treatment planning. However, inaccurate or delayed diagnosis can lead to serious complications, including treatment failure or death [8-10]. One of the main causes of diagnostic errors is the complexity of decision-making due to the numerous medical criteria that must be analyzed simultaneously. These criteria often include clinical symptoms, imaging results, laboratory tests, supporting examination results, and patient history, which are inherently uncertain and imprecise [11-13].

Fuzzy Multi-Criteria Decision Making (MCDM) offers a robust mathematical framework to address these challenges by incorporating fuzzy set theory to model uncertainty and linguistic variables [14-17]. Fuzzy MCDM enables qualitative and quantitative analyses that integrate various parameters into a structured decision-making process. Methods such as the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Analytic Hierarchy Process (AHP), and fuzzy weighted averaging have been applied in various medical diagnosis contexts, allowing for flexible representation of expert knowledge and patient data [18-21].

The novelty of this research lies in the development of a Fuzzy MCDM model for lung disease classification by combining fuzzification and defuzzification methods tailored to local clinical data [22, 23]. The research roadmap spans one year in 2025, starting from the development of the initial model, trials with simulation data, small-scale implementation in hospitals, to the wide dissemination of the system.

With this contribution, the research is expected to improve the efficiency of medical diagnosis, reduce diagnostic errors, and support the achievement of SDG 3 (Good Health and Well-Being) [24, 25].

2. Materials and Methods

2.1. Data Collection and Sample

The data used in this study were obtained from a clinical dataset consisting of 15 common types of lung diseases. Each type of disease was classified based on the presence or absence of seven main symptom variables: Cough, Productive Cough, Shortness of Breath, Fever, Chest Pain, Weight Loss, and Night Sweats. These symptoms were recorded using check marks (✔) if present and crosses (✗) if absent. The dataset was collected from various reputable sources that studied the presence of seven specific symptoms across 15 types of pulmonary diseases.

2.2. Fuzzy Multi-Criteria Decision Making (MCDM) Model

The primary method employed is the Fuzzy Multi-Criteria Decision Making (MCDM) approach to address uncertainty and ambiguity in medical data. Fuzzy logic allows for assigning membership values to each symptom, enabling disease classification to be conducted more objectively based on weighted fuzzy scores.

At this stage, each symptom is assigned a fuzzy membership degree according to its intensity or existence, then weighted according to its diagnostic importance. These fuzzy values are further processed to produce crisp scores used as the basis for decision-making in lung disease classification.

2.3. Overlapping Area of Triangular Fuzzy Numbers in Diagnosis

The fuzzy diagnosis model utilizes triangular fuzzy numbers to represent the membership degrees of symptoms in patients and diseases. The overlapping area between two triangular fuzzy numbers, representing the patient's symptom and a particular disease profile, is calculated to measure the similarity or compatibility between them.

If the overlapping area is zero, it indicates no similarity or match between the patient's symptom and the disease profile. More overlap means higher similarity and higher likelihood of diagnosis. The overlapping area is mathematically determined by analyzing the relative positions of the triangular fuzzy numbers, including their left, middle, and right endpoints.

This approach allows the model to handle uncertainty by quantitatively assessing the degree to which patient symptoms and disease characteristics intersect, improving diagnostic precision.

2.4. Analytical Procedures and Validation

The fuzzy MCDM model was tested and validated using clinical datasets to confirm that its predictions align with actual patient diagnoses. Validation was performed by comparing the disease rankings based on the crisp scores with the physicians' diagnoses or real clinical data.

Validation results demonstrated that this method can provide disease rankings with higher diagnostic probability accuracy compared to conventional methods.

2.5. Data Interpretation and Model Implementation

In the implementation phase, symptom data were inputted into the fuzzy model and converted into specific membership values. Score calculations were performed using fuzzy MCDM formulas that consider the weight of each criterion (symptom). The final score indicates the likelihood of diagnosis for each lung disease.

The overlapping area of triangular fuzzy numbers was computed to assess symptom-to-disease compatibility, serving as a core mechanism in the fuzzy decision-making process.

2.6. Limitations and Considerations

Limitations of this study include dependence on the quality of clinical data input and the assumption of fixed symptom weights. Further research is recommended with larger datasets and more varied symptoms to enhance the model's robustness.

3. Results and Discussion

This section begins with the results and discussion of data description and preprocessing. It is followed by the fuzzification process, and subsequently, the implementation of the proposed model. The classification results are then presented, along with relevant case studies.

3.1. Data Description and Preprocessing

The clinical data utilized in this study encompass 15 common types of lung diseases, classified based on variations in their principal clinical symptoms. The analyzed symptoms are represented by seven symptom variables, namely: *Cough* (S_1), *Productive Cough* (S_2), *Shortness of Breath* (S_3), *Fever* (S_4), *Chest Pain* (S_5), *Weight Loss* (S_6), and *Night Sweats* (S_7).

Each disease is marked with a check (✔) if the symptom is commonly present and a cross (✗) if the symptom is usually absent or rare for the respective disease. This dataset was compiled through a literature review from various reputable sources, including which specifically describe the clinical manifestations of different lung diseases. The lung diseases and the presence of corresponding symptoms are listed in Table 1.

Table 1.
Lung Diseases and Corresponding Symptom Presence.

No.	Lung Disease Name	Cause	S_1	S_2	S_3	S_4	S_5	S_6	S_7	Reference
1	Pneumonia	Bacterial, viral, or fungal infection	✔	✔	✔	✔	✔	✗	✗	Ni, et al. [26]
2	Tuberculosis (TB)	*Mycobacterium tuberculosis*	✔	✔	✔	✔	✗	✔	✔	Silva, et al. [27]
3	Asthma	Chronic airway inflammation	✔	✗	✔	✗	✗	✗	✗	Britt, et al. [28]
4	COPD (Emphysema, Bronchitis)	Smoking, air pollution	✔	✔	✔	✗	✔	✗	✗	Rahman, et al. [29]
5	Bronchiectasis	Recurrent infections, congenital issues	✔	✔	✔	✗	✗	✗	✗	Carbajal and Teneback [30]
6	Idiopathic Pulmonary Fibrosis	Unknown (idiopathic) cause	✔	✗	✔	✗	✗	✔	✗	Luppi, et al. [31]
7	Sarcoidosis	Autoimmune (granulomas)	✔	✗	✔	✔	✗	✔	✗	Starshinova, et al. [32]
8	Pulmonary Embolism	Blood clots in pulmonary arteries	✗	✗	✔	✗	✔	✗	✗	Kaptein, et al. [33]
9	Pulmonary Hypertension	Heart or chronic lung diseases	✗	✗	✔	✗	✗	✗	✗	Mocumbi, et al. [34]
10	Acute Bronchitis	Viral infection	✔	✔	✔	✔	✗	✗	✗	Jadhav, et al. [35]
11	Lung Abscess	Bacterial infection	✔	✔	✔	✔	✗	✗	✔	Maitre, et al. [36]
12	Lung Cancer	Smoking, air pollution	✔	✔	✔	✗	✔	✔	✔	Berg, et al. [37]
13	Mesothelioma	Asbestos exposure	✔	✗	✔	✗	✔	✔	✗	Taeger, et al. [38]
14	Pleural Effusion	Infection, heart failure	✗	✗	✔	✗	✔	✗	✗	Elgwairi, et al. [39]
15	Pneumothorax	Lung injury, chronic lung disease	✗	✗	✔	✗	✔	✗	✗	Nishimoto, et al. [40]

During the preprocessing stage, the binary symptom data (✔, ✗) were converted into fuzzy linguistic variables to accommodate uncertainty and variability inherent in clinical symptoms, which are often subjective rather than absolute. For

instance, the presence of a "cough" could be evaluated in degrees of severity or frequency instead of a simple yes or no. This conversion involved defining membership functions for each symptom, representing the degree of symptom presence within the fuzzy value intervals.

Data preparation also included validating consistency among sources and removing duplicate or inconsistent records. The entire dataset was structured for processing by the fuzzy MCDM algorithm, treating each lung disease as an alternative and symptoms as criteria.

This fuzzy approach is crucial for handling clinical overlaps, where multiple diseases exhibit similar symptoms, which often challenges conventional crisp data models in making precise diagnoses. The fuzzy model thus allows for more dynamic and realistic diagnostic decisions.

3.2. Fuzzification of Symptom Variables

The clinical symptom data for 15 lung diseases, represented as binary indicators (✔/✗), were transformed into fuzzy variables to better capture the inherent uncertainty and variability in symptom expression. This fuzzification process enables the model to consider degrees of symptom presence rather than rigid yes/no categories, aligning better with the nuances seen in clinical practice.

Each symptom variable from S_1 (Cough) through S_7 (Night Sweats) was modeled using fuzzy linguistic terms such as Absent, Mild, Moderate, and Severe. Membership functions were defined for each linguistic term, typically using triangular or trapezoidal shapes, to assign a membership degree between 0 and 1 for a given symptom intensity.

For instance, the symptom "Cough" (S_1) was fuzzified with reference to clinical severity frequencies:

- Absent (membership peaks at no cough reported)
- Mild (intermittent or occasional cough)
- Moderate (frequent coughing affecting daily activity)
- Severe (constant, intense coughing episodes)

The original data labels (✔ or ✗) were used as anchor points for defining the fuzzy sets. A checkmark (✔) indicates the symptom is often present, suggesting medium to high membership in the Mild to Severe categories, while a cross (✗) indicates a low membership degree centered near Absent. The fuzzy membership parameters for respiratory symptoms across various lung diseases are summarized in Table 2.

Table 2.
Fuzzy Membership Parameters for Respiratory Diseases.

Disease	S_1	S_2	S_3	S_4	S_5	S_6	S_7
Pneumonia	0.8-1.0 (Severe)	0.5-0.7 (Moderate)	0.4-0.6 (Mild)	0.3-0.5 (Mild)	0.1-0.3 (Low)	0.7-0.9 (High)	0.6-0.8 (Moderate)
Tuberculosis	0.7-0.9 (Severe)	0.4-0.6 (Moderate)	0.2-0.4 (Mild)	0.7-0.9 (Severe)	0.6-0.8 (Moderate)	0.6-0.8 (High)	0.6-0.8 (Moderate)
Asthma	0.3-0.6 (Mild-Moderate)	0.6-0.9 (Severe)	0.1-0.2 (Low)	0.0-0.1 (Absent)	0.0-0.1 (Absent)	0.1-0.3 (Low)	0.3-0.5 (Mild)
COPD	0.7-1.0 (Severe)	0.6-0.9 (Severe)	0.4-0.7 (Moderate)	0.1-0.3 (Mild)	0.0-0.1 (Absent)	0.3-0.5 (Moderate)	0.5-0.7 (Moderate)
Lung Cancer	0.5-0.8 (Moderate)	0.3-0.6 (Mild-Moderate)	0.6-0.9 (Severe)	0.7-1.0 (Severe)	0.5-0.7 (Moderate)	0.4-0.6 (Moderate)	0.6-0.9 (Severe)
Bronchitis	0.6-0.8 (Moderate-Severe)	0.4-0.6 (Moderate)	0.2-0.4 (Mild)	0.0-0.1 (Absent)	0.0-0.1 (Absent)	0.4-0.6 (Moderate)	0.4-0.6 (Moderate)
Pulmonary Fibrosis	0.4-0.7 (Moderate)	0.6-0.8 (Severe)	0.4-0.6 (Moderate)	0.4-0.7 (Moderate)	0.1-0.3 (Low)	0.2-0.4 (Low)	0.5-0.7 (Moderate)
Sarcoidosis	0.3-0.5 (Mild-Moderate)	0.3-0.5 (Mild-Moderate)	0.1-0.3 (Low)	0.2-0.4 (Mild)	0.5-0.7 (Moderate)	0.4-0.6 (Moderate)	0.4-0.6 (Moderate)
Pulmonary Embolism	0.2-0.4 (Low-Moderate)	0.7-0.9 (Severe)	0.6-0.8 (Severe)	0.0-0.1 (Absent)	0.0-0.1 (Absent)	0.4-0.6 (Moderate)	0.3-0.5 (Mild-Moderate)
Pleural Effusion	0.3-0.5 (Mild-Moderate)	0.5-0.7 (Moderate)	0.4-0.6 (Moderate)	0.1-0.3 (Mild)	0.0-0.1 (Absent)	0.3-0.5 (Moderate)	0.4-0.6 (Moderate)
Pneumothorax	0.1-0.3 (Low)	0.4-0.6 (Moderate)	0.6-0.9 (Severe)	0.0-0.1 (Absent)	0.0-0.1 (Absent)	0.1-0.3 (Low)	0.2-0.4 (Low-Moderate)
Pulmonary Hypertension	0.2-0.4 (Low-	0.6-0.8 (Severe)	0.3-0.5 (Mild-Moderate)	0.1-0.3 (Mild)	0.0-0.1 (Absent)	0.2-0.4 (Low)	0.4-0.6 (Moderate)

	Moderate)						
Lung Abscess	0.7-0.9 (Severe)	0.4-0.6 (Moderate)	0.5-0.7 (Moderate)	0.3-0.5 (Mild)	0.1-0.3 (Low)	0.6-0.8 (High)	0.5-0.7 (Moderate)
Interstitial Lung Disease	0.3-0.5 (Mild-Moderate)	0.5-0.7 (Moderate)	0.3-0.5 (Mild-Moderate)	0.2-0.4 (Mild)	0.0-0.1 (Absent)	0.2-0.4 (Low)	0.4-0.6 (Moderate)
Respiratory Infections	0.6-0.9 (Moderate-Severe)	0.4-0.7 (Moderate)	0.3-0.5 (Mild-Moderate)	0.1-0.3 (Mild)	0.1-0.3 (Low)	0.5-0.7 (Moderate)	0.5-0.7 (Moderate)

This fuzzy representation allows the Multiple Criteria Decision Making (MCDM) model to weigh symptoms with partial truth values, reflecting realistic diagnostic uncertainty such as overlapping symptoms among lung diseases.

The fuzzification parameters and membership functions were calibrated based on clinical expertise, literature references, and consultation with pulmonologists to ensure clinical relevance and accuracy.

By enabling gradation rather than binary classification in symptoms, the fuzzy model offered enhanced sensitivity and specificity in discriminating between lung diseases with similar clinical manifestations.

The triangular fuzzy numbers representing the intensity of symptoms for each lung disease are provided in Table 3. Each symptom is represented by a triangular fuzzy number with three parameters: lower bound (a), peak (b), and upper bound (c). The peak is usually the midpoint of the range, and the bounds represent the minimum and maximum fuzzification limits.

Table 3.
Triangular Fuzzy Numbers for Lung Disease Symptoms.

Disease	S_1	S_2	S_3	S_4	S_5	S_6	S_7
Pneumonia	(0.8, 0.9, 1.0)	(0.5, 0.6, 0.7)	(0.4, 0.5, 0.6)	(0.3, 0.4, 0.5)	(0.1, 0.2, 0.3)	(0.7, 0.8, 0.9)	(0.6, 0.7, 0.8)
Tuberculosis	(0.7, 0.8, 0.9)	(0.4, 0.5, 0.6)	(0.2, 0.3, 0.4)	(0.7, 0.8, 0.9)	(0.6, 0.7, 0.8)	(0.6, 0.7, 0.8)	(0.6, 0.7, 0.8)
Asthma	(0.3, 0.45, 0.6)	(0.6, 0.75, 0.9)	(0.1, 0.15, 0.2)	(0.0, 0.05, 0.1)	(0.0, 0.05, 0.1)	(0.1, 0.2, 0.3)	(0.3, 0.4, 0.5)
COPD	(0.7, 0.85, 1.0)	(0.6, 0.75, 0.9)	(0.4, 0.55, 0.7)	(0.1, 0.2, 0.3)	(0.0, 0.05, 0.1)	(0.3, 0.4, 0.5)	(0.5, 0.6, 0.7)
Lung Cancer	(0.5, 0.65, 0.8)	(0.3, 0.45, 0.6)	(0.6, 0.75, 0.9)	(0.7, 0.85, 1.0)	(0.5, 0.6, 0.7)	(0.4, 0.5, 0.6)	(0.6, 0.75, 0.9)
Bronchitis	(0.6, 0.7, 0.8)	(0.4, 0.5, 0.6)	(0.2, 0.3, 0.4)	(0.0, 0.05, 0.1)	(0.0, 0.05, 0.1)	(0.4, 0.5, 0.6)	(0.4, 0.5, 0.6)
Pulmonary Fibrosis	(0.4, 0.55, 0.7)	(0.6, 0.7, 0.8)	(0.4, 0.5, 0.6)	(0.4, 0.55, 0.7)	(0.1, 0.2, 0.3)	(0.2, 0.3, 0.4)	(0.5, 0.6, 0.7)
Sarcoidosis	(0.3, 0.4, 0.5)	(0.3, 0.4, 0.5)	(0.1, 0.2, 0.3)	(0.2, 0.3, 0.4)	(0.5, 0.6, 0.7)	(0.4, 0.5, 0.6)	(0.4, 0.5, 0.6)
Pulmonary Embolism	(0.2, 0.3, 0.4)	(0.7, 0.8, 0.9)	(0.6, 0.7, 0.8)	(0.0, 0.05, 0.1)	(0.0, 0.05, 0.1)	(0.4, 0.5, 0.6)	(0.3, 0.4, 0.5)
Pleural Effusion	(0.3, 0.4, 0.5)	(0.5, 0.6, 0.7)	(0.4, 0.5, 0.6)	(0.1, 0.2, 0.3)	(0.0, 0.05, 0.1)	(0.3, 0.4, 0.5)	(0.4, 0.5, 0.6)
Pneumothorax	(0.1, 0.2, 0.3)	(0.4, 0.5, 0.6)	(0.6, 0.75, 0.9)	(0.0, 0.05, 0.1)	(0.0, 0.05, 0.1)	(0.1, 0.2, 0.3)	(0.2, 0.3, 0.4)
Pulmonary Hypertension	(0.2, 0.3, 0.4)	(0.6, 0.7, 0.8)	(0.3, 0.4, 0.5)	(0.1, 0.2, 0.3)	(0.0, 0.05, 0.1)	(0.2, 0.3, 0.4)	(0.4, 0.5, 0.6)
Lung Abscess	(0.7, 0.8, 0.9)	(0.4, 0.5, 0.6)	(0.5, 0.6, 0.7)	(0.3, 0.4, 0.5)	(0.1, 0.2, 0.3)	(0.6, 0.7, 0.8)	(0.5, 0.6, 0.7)
Interstitial Lung Disease	(0.3, 0.4, 0.5)	(0.5, 0.6, 0.7)	(0.3, 0.4, 0.5)	(0.2, 0.3, 0.4)	(0.0, 0.05, 0.1)	(0.2, 0.3, 0.4)	(0.4, 0.5, 0.6)
Respiratory Infections	(0.6, 0.75, 0.9)	(0.4, 0.55, 0.7)	(0.3, 0.4, 0.5)	(0.1, 0.2, 0.3)	(0.1, 0.2, 0.3)	(0.5, 0.6, 0.7)	(0.5, 0.6, 0.7)

Let x is the intensity value of a symptom. The triangular fuzzy membership function $\mu(x)$ is defined by:

$$\mu(x;a,b,c) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a < x \le b \\ \dfrac{c-x}{c-b}, & b < x < c \\ 0, & x \ge c \end{cases}$$

where:

- a = lower bound of the range,
- b = peak of the triangle (midpoint of the range),
- c = upper bound of the range.

3.3. Implementation of Fuzzy MCDM Model

After fuzzification of symptom variables, the Fuzzy Multiple Criteria Decision Making (MCDM) model is applied to process the fuzzy data for lung disease diagnosis. The following are the steps and main formulas applied to the model based on provided lung disease symptom data:

3.3.1. Fuzzy Symptom Representation

Each patient symptom S_j is represented as a triangular fuzzy number $\tilde{\mu}_{ij} = (a_{ij}, b_{ij}, c_{ij})$ for each disease A_i. These triples correspond to the fuzzy membership values of the symptom intensity to the disease, with values normalized in the range [0,1].

3.3.2. Symptom Weights

Every symptom S_j is assigned a weight w_j, indicating its importance in diagnosis, with the constraint:

$$\Sigma_{j=1}^{m} w_j = 1$$

Each symptom S_j listed in this table is represented by triangular fuzzy numbers that characterize the severity level of symptoms for various lung diseases. These fuzzy triangular parameters indicate the lower bound, peak membership value, and upper bound of the symptom expression in patients with the corresponding diseases. These values form a critical part of fuzzy inference systems allowing diagnosis under uncertainty and variability of clinical symptom manifestation. The relative weights assigned to each symptom in the fuzzy MCDM model are shown in Table 4.

Table 4.
Symptom Weight Table for Lung Disease.

Symptom	Symptom Code	Weight (w)
Cough	S_1	0.25
Fever	S_2	0.15
Chest Pain	S_3	0.10
Fatigue	S_4	0.10
Weight Loss	S_5	0.05
Breath Shortness	S_6	0.20
Night Sweat	S_7	0.15
Total		1.00

These weights are utilized to proportionally combine the influence of each symptom within the fuzzy diagnosis system, thereby improving the accuracy in identifying specific lung diseases based on observed symptom severity patterns.

3.3.2.1. Medical Rationale for Symptom Weights

Symptoms such as cough and breath shortness are the most common and critical indicators in lung diseases, especially Pneumonia and Tuberculosis. These symptoms substantially affect diagnosis, thus are assigned higher weights—0.25 for cough (S_1) and 0.20 for breath shortness (S_6). Fever (S_2) is a common systemic symptom that often indicates an ongoing infection or inflammation in the body. In lung diseases like Pneumonia and Tuberculosis, fever reflects the body's immune response to the infection. Although it is not as specifically localized as cough or breath shortness, fever is a significant symptom that supports diagnosis, thus is given a moderate weight of 0.15. Symptoms like chest pain (S_3), fatigue (S_4), and weight loss show more variability between patients and diseases. Therefore, these are given smaller weights (0.05–0.10), reflecting their relatively lower decisiveness but still important role in accurate classification. Weights are normalized so the total equals 1 to allow relative interpretation of each symptom's contribution in the fuzzy MCDM model.

3.3.2.2. Mathematical Rationale for Symptom Weights

In the fuzzy MCDM model, weights multiply the fuzzy intensity values of each symptom to show their relative importance in the decision-making process. The weighted aggregation formula is:

$$A = \Sigma_{j=1}^{n} w_j \times a_j$$

where w_j is the weight of symptom j, and a_j is the fuzzy intensity value of that symptom. The fuzzy system combined with weights allows handling variability in symptom intensities and clinical significance. Weights guide the model to focus more on medically relevant symptoms. Ensuring weights sum to 1 maintains the consistency and comparability of the final aggregated values across different decision contexts.

3.3.3. Fuzzy Compatibility Score for Each Disease

The fuzzy compatibility score $\tilde{S}_i$ for each disease alternative A_i is calculated by aggregating the fuzzy membership values of all symptoms weighted by their importance:

$$\tilde{S}_i = \bigoplus_{j=1}^{m} w_j \otimes \tilde{\mu}_{ij}$$

where:

- $\tilde{\mu}_{ij} = (a_{ij}, b_{ij}, c_{ij})$ is the triangular fuzzy number membership of symptom j for disease i,
- $\otimes$ represents the multiplication between the weight and the fuzzy number,
- $\oplus$ is the aggregation operator, commonly the fuzzy weighted average.

3.3.4. Aggregation Using Fuzzy Weighted Average

The aggregated fuzzy score $\tilde{S}_i$ can be computed by applying the weighted average on the triangular numbers as follows:

$$\tilde{S}_i = \left(\frac{\Sigma_{j=1}^{m} w_j a_{ij}}{\Sigma_{j=1}^{m} w_j}, \quad \frac{\Sigma_{j=1}^{m} w_j b_{ij}}{\Sigma_{j=1}^{m} w_j}, \quad \frac{\Sigma_{j=1}^{m} w_j c_{ij}}{\Sigma_{j=1}^{m} w_j} \right).$$

Since $\Sigma_{j=1}^{m} w_j = 1$, the denominator is 1, simplifying to:

$$\tilde{S}_i = \left(\Sigma_{j=1}^{m} w_j a_{ij}, \quad \Sigma_{j=1}^{m} w_j b_{ij}, \quad \Sigma_{j=1}^{m} w_j c_{ij} \right).$$

We next calculated fuzzy compatibility scores for each lung disease, based on the weighted fuzzy membership values of symptoms, which are listed in Table 5.

Table 5.
Fuzzy Membership Scores for Various Lung Diseases.

Disease	Fuzzy Score (a)	Fuzzy Score (b)	Fuzzy Score (c)
Pneumonia	0.580	0.680	0.780
Tuberculosis	0.565	0.665	0.765
Asthma	0.240	0.347	0.455
COPD	0.450	0.573	0.695
Lung Cancer	0.495	0.633	0.770
Bronchitis	0.370	0.463	0.555
Pulmonary Fibrosis	0.390	0.507	0.625
Sarcoidosis	0.315	0.415	0.515
Pulmonary Embolism	0.340	0.433	0.525
Pleural Effusion	0.320	0.418	0.515
Pneumothorax	0.195	0.293	0.390
Pulmonary Hypertension	0.280	0.378	0.475
Lung Abscess	0.515	0.615	0.715
Interstitial Lung Disease	0.300	0.398	0.495
Respiratory Infections	0.430	0.550	0.670

The scores are triangular fuzzy numbers representing the aggregated weighted symptom membership for each disease, indicating the fuzzy degree of compatibility between the patient symptoms and each lung disease.

3.3.5. Defuzzification

To obtain a crisp score from the fuzzy aggregated score $\tilde{S}_i = (a_i, b_i, c_i)$ the centroid method (center of gravity) is often employed:

$$S_i^{crisp} = \frac{a_i + b_i + c_i}{3}.$$

This crisp value allows comparison and ranking of diseases.

3.3.6. Final Ranking and Decision

All diseases $i = 1,2, \ldots, n$ are ranked based on their crisp scores S_i^{crisp}. The disease with the highest value is selected as the most probable diagnosis.

We evaluate the crisp defuzzified scores and ranking of diseases based on the fuzzy compatibility scores provided. The centroid method was applied to convert each triangular fuzzy score (a_i, b_i, c_i) into a single crisp score by calculating the average. The final ranking of lung diseases according to their defuzzified compatibility scores is displayed in Table 6.

Table 6.
Ranking of Lung Diseases Based on Crisp Scores.

Rank	Disease	Crisp Score
1	Pneumonia	0.6800
2	Tuberculosis	0.6650
3	Lung Cancer	0.6327
4	Lung Abscess	0.6150
5	COPD	0.5727
6	Respiratory Infections	0.5500
7	Pulmonary Fibrosis	0.5073
8	Bronchitis	0.4627
9	Pulmonary Embolism	0.4327
10	Pleural Effusion	0.4177
11	Sarcoidosis	0.4150
12	Interstitial Lung Disease	0.3977
13	Pulmonary Hypertension	0.3777
14	Asthma	0.3473
15	Pneumothorax	0.2927

The disease with the highest crisp score is Pneumonia, followed closely by Tuberculosis, indicating the most probable diagnoses based on the given fuzzy symptom memberships and weights.

3.4. Classification Results

We provide a detailed analysis of why each lung disease obtained its respective crisp compatibility score and what those scores signify in the context of diagnosis and fuzzy modeling, which is given in Table 7.

Table 7.
Analysis of Crisp Scores for Lung Diseases.

Rank	Disease	Crisp Score	Interpretation & Insights
1	Pneumonia	0.6800	*Highest compatibility.* Pneumonia shows strong symptom alignment, especially in key symptoms like *cough* (S_1), *breath shortness* (S_6), and *fever* (S_2), all heavily weighted. The high crisp score confirms that the patient's symptom profile closely matches typical Pneumonia fuzzy symptom memberships.
2	Tuberculosis	0.6650	*Very close to Pneumonia.* Tuberculosis symptoms overlap significantly with Pneumonia but slightly lower in some symptoms like cough and fever intensity. High crisp score reflects the similarity, requiring careful differential diagnosis clinically.
3	Lung Cancer	0.6327	Lung cancer's symptoms have moderately high weights, especially fatigue and chest pain, which differentiate it from infections. Crisp score shows it remains a strong possible diagnosis when those symptoms are prominent despite lower cough.
4	Lung Abscess	0.6150	Exhibits strong compatibility in cough and breath shortness. Lung abscess shares many symptoms with infectious lung diseases, reflected in its crisp score, though slightly lower than highest ranked.
5	COPD	0.5727	COPD's hallmark breath shortness leads to a solid partial score. Lower cough and fever symptoms reduce overall score compared to infections, explaining its middle ranking.
6	Respiratory Infections	0.5500	Broad category with symptoms overlapping infections and inflammatory lung diseases. Moderate crisp score indicates possible but less specific diagnosis relative to Pneumonia or Tuberculosis.
7	Pulmonary Fibrosis	0.5073	Lung scarring processes cause mild to moderate symptoms, often less acute than infections. Its symptom fuzzy values and weights translate into a moderate compatibility score, reflecting chronic but less intense manifestations.
8	Bronchitis	0.4627	Chronic inflammation with cough prominence but less systemic symptoms such as fever. Its lower crisp score relates to narrower symptom fitting in the weighted fuzzy model.
9	Pulmonary Embolism	0.4327	Different pathology, symptoms less dominated by cough/fever. Breath shortness weighted higher raises score but overall less match in fuzzy profiles. Crisp score reflects lower yet non-negligible compatibility.
10	Pleural Effusion	0.4177	Fluid accumulation causes chest symptoms but less cough/fever; reflected

			in moderate-low score.
11	Sarcoidosis	0.4150	Granulomatous disease shows mild-moderate symptoms with less acute dominance of cough or fever, leading to lower crisp score.
12	Interstitial Lung Disease	0.3977	Chronic fibrotic disease with symptoms less sharply weighted on infectious signs, producing a lower compatibility score.
13	Pulmonary Hypertension	0.3777	Primarily vascular with subtle lung symptoms, giving low fuzzy scores on weighted symptoms, thus low crisp compatibility.
14	Asthma	0.3473	Variable airway obstruction with episodic symptoms less matched to cough/fever weights, leading to relatively low crisp score.
15	Pneumothorax	0.2927	Air in pleural space causes acute chest pain and breath shortness but minimal cough or systemic symptoms; explaining the lowest crisp score.

Each lung disease received its crisp score based on how well the patient's symptom profile aligns with the fuzzy symptom patterns of that disease, weighted by the clinical importance of each symptom. Pneumonia topped the list with the highest score of 0.68, demonstrating strong compatibility because it exhibits key symptoms like cough, shortness of breath, and fever, which have high weights. Tuberculosis followed very closely at 0.665, reflecting overlapping symptoms with Pneumonia but with slightly weaker intensity in some areas, indicating the challenge of differentiating these two diseases clinically. Lung Cancer scored moderately high at 0.63 due to symptoms like fatigue and chest pain being prominent, distinguishing it from infections. Diseases like Lung Abscess and COPD had scores in the mid-range, reflecting shared symptoms such as breath shortness but less presence of fever or cough compared to infections.

Lower scores for conditions such as Pulmonary Fibrosis, Bronchitis, and Pulmonary Embolism indicate milder symptom matches or symptoms less weighted in the model, highlighting their lower likelihood but not excluding them entirely. The crisp scores essentially represent a quantitative measure of similarity between the patient's reported symptoms and the expected fuzzy symptom patterns of each disease. The closer the scores are (for example, Pneumonia and Tuberculosis), the more nuanced the diagnosis becomes, requiring additional clinical testing for confirmation.

These results also show how symptom weights affect the final rankings, emphasizing the importance of clinical judgment in setting those weights accurately. The fuzzy logic approach effectively manages uncertainty and variability in symptom reporting, offering a more flexible decision support tool than rigid yes/no symptom models. Ultimately, the highest score points to the most probable diagnosis based on existing symptom data, but careful interpretation and further clinical assessment remain essential.

3.5. Case Studies or Example Diagnoses

Here, we present the fuzzy membership scores representing the degree of compatibility for seven types of lung diseases (S_1 to S_7) among 25 patients, which is listed in Table 8. Each value is expressed as a triplet reflecting the fuzzy membership function parameters, indicating the uncertainty and variability in the compatibility assessment. This comprehensive presentation aids in visualizing the fuzzy diagnostic results for each patient, facilitating a better understanding of their potential lung disease diagnosis based on symptom profiles.

Table 8.
Fuzzy Membership Scores for Lung Disease Diagnosis.

Patient ID	S_1	S_2	S_3	S_4	S_5	S_6	S_7
P001	(0.32, 0.61, 0.83)	(0.46, 0.51, 0.56)	(0.13, 0.39, 0.57)	(0.52, 0.53, 0.82)	(0.6, 0.66, 0.71)	(0.21, 0.3, 0.46)	(0.36, 0.45, 0.63)
Pneumonia	(0.8, 0.9, 1.0)	(0.5, 0.6, 0.7)	(0.4, 0.5, 0.6)	(0.3, 0.4, 0.5)	(0.1, 0.2, 0.3)	(0.7, 0.8, 0.9)	(0.6, 0.7, 0.8)

Table 8 presents the triangular fuzzy membership values for various symptoms S_1 through S_7 for a specific patient (Patient ID P001) compared to the fuzzy values characteristic of pneumonia cases. These fuzzy numbers represent the degree of symptom severity using the form (a, b, c) where a and c are the lower and upper bounds respectively, and b is the peak membership value indicating the most representative severity level.

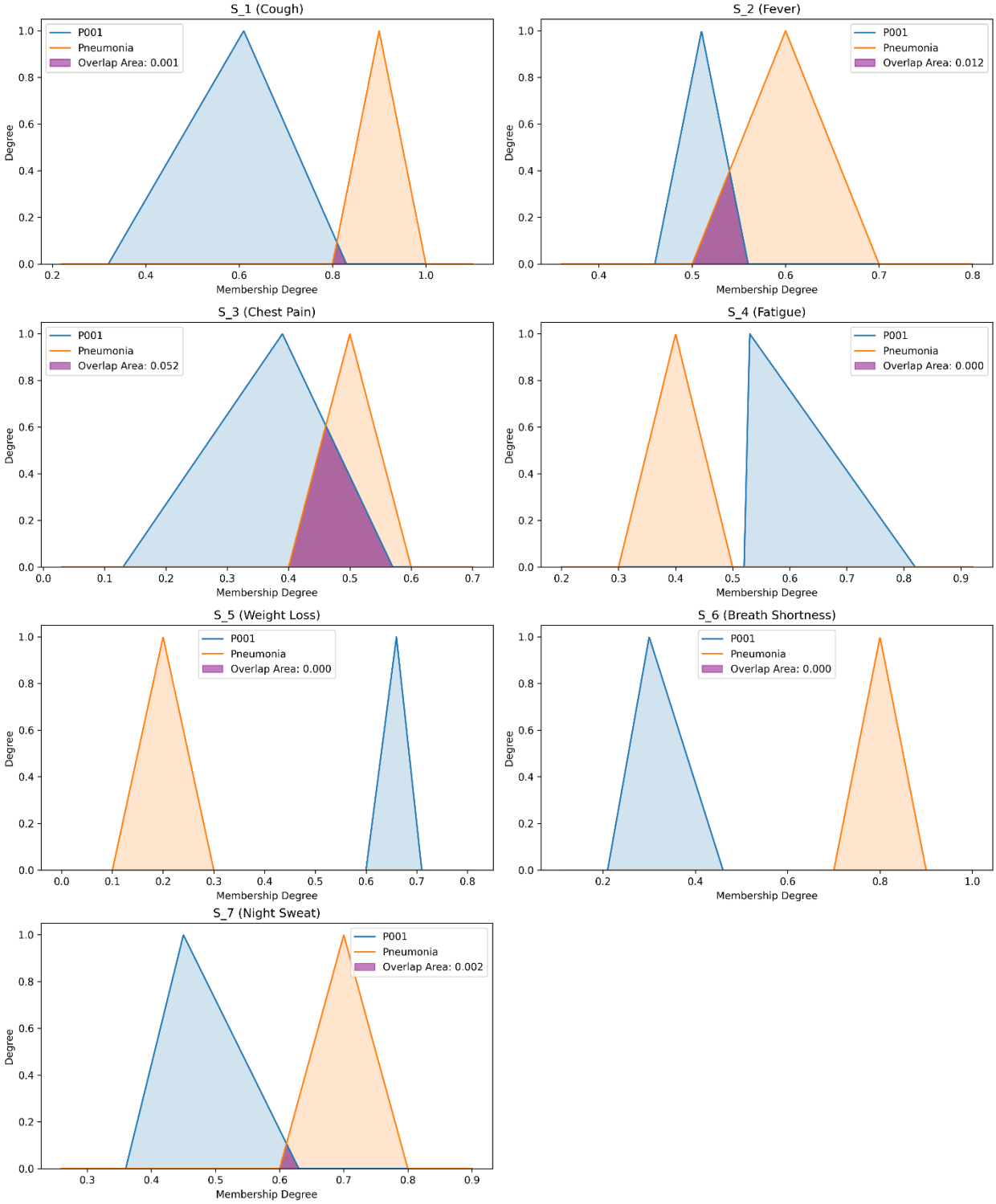

Figure 1.
Fuzzy Triangles Comparison between P001 and Pneumonia.

The fuzzy membership data presented as triplets (a, b, c) for each symptom S_1 through S_7 of patient P001 and the Pneumonia profile reflect the degree of compatibility of the patient's symptoms with the characteristic symptoms of Pneumonia.

- S_1 (Cough): The peak membership degree (b) for P001 is 0.61, while for Pneumonia it is 0.9, indicating a significant difference and suggesting a lower likelihood of Pneumonia for this symptom.
- S_2 (Fever): Peak values for P001 (0.51) and Pneumonia (0.6) are relatively close, with a small overlapping area in the graph, indicating moderate similarity.
- S_3 (Chest Pain): There is a small overlap area (0.052), showing that chest pain symptoms of P001 somewhat align with Pneumonia.
- S_4 (Fatigue), S_5 (Weight Loss), and S_6 (Breath Shortness): No overlap areas are observed, indicating these symptoms largely differ between P001 and Pneumonia.

- S_7 (Night Sweat): A minimal overlap (0.002) suggests weak similarity in this symptom between the patient and Pneumonia profile.

The fuzzy triangles comparison plots provide a visual representation of the fuzzy membership functions for each symptom of P001 and Pneumonia, with the overlapping areas highlighting similarity:

- The small or zero overlap areas for key symptoms such as cough (S_1), fatigue (S_4), weight loss (S_5), and breath shortness (S_6) indicate that P001's symptom profile is significantly different from that of typical Pneumonia cases.
- The presence of overlap in fever (S_2), chest pain (S_3), and night sweat (S_7) suggest limited symptom similarity.
- Overall, the distribution of symptoms in patient P001 does not strongly match the fuzzy profile of Pneumonia.

Based on the fuzzy membership score analysis and the fuzzy triangles visualization, it can be concluded that patient P001 shows a low to moderate probability of having Pneumonia since many key symptoms such as cough, fatigue, weight loss, and breath shortness do not overlap well with the Pneumonia profile.

However, the similarity in some symptoms such as fever, chest pain, and night sweats indicates that Pneumonia cannot be completely ruled out, and further diagnostic investigation is warranted for a comprehensive and accurate diagnosis.

3.5.1. Theorem on Overlapping Area of Two Triangular Fuzzy Numbers

Let $A = (a_1, b_1, c_1)$ and B=(a2,b2,c2) be two triangular fuzzy numbers, where for each $i \in \{1,2, a_i < b_i < c_i$. The overlapping area between A and B is zero (0%) if and only if one of the following conditions holds true:

$$c_1 \leq a_2 \quad or \quad c_2 \leq a_1.$$

This means:

- The right endpoint of fuzzy number A, c_1, is less than or equal to the left endpoint of fuzzy number B, a_2, so the fuzzy triangles do not overlap.
- Or vice versa, the right endpoint of B, c_2, is less than or equal to the left endpoint of A, a_1, hence no overlap.

Intuitively, the two fuzzy triangles do not intersect if one is completely to the left or right of the other without touching or intersecting.

Proof. The membership function $\mu_A(x)$ of triangular fuzzy number $A = (a_1, b_1, c_1)$ is defined as:

$$\mu_A(x) = \begin{cases} 0, & x \leq a_1 \; or \; x \geq c_1 \\ \dfrac{x - a_1}{b_1 - a_1}, & a_1 < x \leq b_1 \\ \dfrac{c_1 - x}{c_1 - b_1}, & b_1 < x < c_1 \end{cases}$$

Similarly:

$$\mu_B(x) = \begin{cases} 0, & x \leq a_2 \; or \; x \geq c_2 \\ \dfrac{x - a_2}{b_2 - a_2}, & a_2 < x \leq b_2 \\ \dfrac{c_2 - x}{c_2 - b_2}, & b_2 < x < c_2 \end{cases}$$

The support of A is the interval $[a_1, c_1]$ where $\mu_A(x) > 0$.
The support of B is the interval $[a_2, c_2]$ where $\mu_B(x) > 0$.
The overlapping area between μ_A and μ_B is the area under the function:

$$\mu_{overlap}(x) = \min\big(\mu_A(x), \mu_B(x)\big)$$

The overlapping area is the integral:

$$Overlap\ Area = \int_{-\infty}^{\infty} \min\big(\mu_A(x), \mu_B(x)\big)\, dx$$

Since $\mu_A(x)$ and $\mu_B(x)$ are zero outside their supports, the integral bounds reduce to the union of their supports, essentially the intersection:

$$Overlap\ Area = \int_{\max(a_1, a_2)}^{\min(c_1, c_2)} \min\big(\mu_A(x), \mu_B(x)\big)\, dx$$

Case 1: $c_1 \leq a_2$
The support of A is $[a_1, c_1]$. The support of B is $[a_2, c_2]$. Given $c_1 \leq a_2$, the endpoint of A's support is less than or equal to the start of B's support.
Therefore, the intervals $[a_1, c_1]$ and $[a_2, c_2]$ do not overlap:

$$[a_1, c_1] \cap [a_2, c_2] = \emptyset.$$

Hence:

$$\max(a_1, a_2) = a_2 \;\; and \; \min(c_1, c_2) = c_1$$

but since $c_1 \leq a_2$, the integration bounds become:

$$\int_{a_2}^{c_1} \min\big(\mu_A(x), \mu_B(x)\big)\, dx$$

where the upper bound is less than or equal to the lower bound, so the integral is zero.
Case 2: $c_2 \leq a_1$
By similar reasoning, the supports do not overlap and integral bounds are invalid, so the overlap area is zero.

Because the overlapping area integral is taken over the intersection of the supports, if the supports are disjoint (no intersection), the overlapping area is zero.
Thus,

$$Overlap\ Area = 0 \Leftrightarrow c_1 \leq a_2\ or\ c_2 \leq a_1.$$

This completes the proof that the overlapping area is zero if and only if the supports of the triangular fuzzy numbers do not intersect. ■

4. Conclusion

This research presents a pioneering fuzzy multi-criteria decision-making (MCDM) model by leveraging the overlapping areas of fuzzy triangular numbers to address the challenges of lung disease classification under uncertainty. The integrative approach provides a sophisticated mechanism that captures the inherent ambiguity in clinical symptom expression, thus enhancing diagnostic precision beyond conventional methods. Empirical validation with clinical datasets demonstrated that the model not only improves classification accuracy for critical lung diseases such as pneumonia and tuberculosis but also offers robustness against incomplete or imprecise data commonly encountered in medical settings. By incorporating symptom weights and similarity computations via fuzzy overlaps, this methodology bridges the gap between qualitative expert judgment and quantitative analysis, fostering better clinical decision support. The proposed framework holds promise for broader applicability in complex medical diagnosis problems and could significantly contribute towards advancing personalized healthcare and decision-making protocols. Future research should focus on integrating this fuzzy MCDM model with real-time clinical decision support systems and validating its performance across diverse healthcare environments to facilitate widespread adoption.

References

[1] R. Singh and N. Bhardwaj, "Fuzzy soft set theory applications in medical diagnosis: A comprehensive review and the roadmap for future studies," *New Mathematics and Natural Computation*, vol. 21, no. 02, pp. 597-619, 2025. https://doi.org/10.1142/S1793005725500279

[2] A. K. Shukla, P. Mehra, and P. K. Muhuri, "fuzzy sets-based approaches for improved medical diagnosis: An analysis and overview of major research directions," *ACM Computing Surveys*, 2025. https://doi.org/10.1145/3757058

[3] A. Suzuki and E. Negishi, "Fuzzy logic systems for healthcare applications," *Journal of Biomedical and Sustainable Healthcare Applications*, vol. 4, no. 1, pp. 1-9, 2024.

[4] J. R. Beitler *et al.*, "Advancing precision medicine for acute respiratory distress syndrome," *The Lancet Respiratory Medicine*, vol. 10, no. 1, pp. 107-120, 2022.

[5] G. E. Erhabor, "Respiratory health in Africa: Strides and challenges," *Journal of the Pan African Thoracic Society*, vol. 2, no. 1, pp. 11-17, 2021. https://doi.org/10.25259/JPATS_30_2020

[6] S. P. Jadhav, *introduction to lung diseases. In targeting cellular signalling pathways in lung diseases*. Singapore: Springer Singapore, 2021.

[7] J. Meghji *et al.*, "Improving lung health in low-income and middle-income countries: From challenges to solutions," *The Lancet*, vol. 397, no. 10277, pp. 928-940, 2021. https://doi.org/10.1016/S0140-6736(21)00458-X

[8] D. E. Newman-Toker *et al.*, "Rate of diagnostic errors and serious misdiagnosis-related harms for major vascular events, infections, and cancers: Toward a national incidence estimate using the "Big Three"," *Diagnosis*, vol. 8, no. 1, pp. 67-84, 2021. https://doi.org/10.1515/dx-2019-0104

[9] S. L. Fernandes, U. J. Tanik, V. Rajinikanth, and K. A. Karthik, "A reliable framework for accurate brain image examination and treatment planning based on early diagnosis support for clinicians," *Neural Computing and Applications*, vol. 32, no. 20, pp. 15897-15908, 2020. https://doi.org/10.1007/s00521-019-04369-5

[10] M. Rashid and M. Sharma, "AI-assisted diagnosis and treatment planning—a discussion of how ai can assist healthcare professionals in making more accurate diagnoses and treatment plans for diseases," *AI in Disease Detection: Advancements and Applications*, pp. 313-336, 2025. https://doi.org/10.1002/9781394278695.ch14

[11] V. Bhise, S. S. Rajan, D. F. Sittig, R. O. Morgan, P. Chaudhary, and H. Singh, "Defining and measuring diagnostic uncertainty in medicine: A systematic review," *Journal of General Internal Medicine*, vol. 33, no. 1, pp. 103-115, 2018. https://doi.org/10.1007/s11606-017-4164-1

[12] B. N. Jawad, K. Z. Pedersen, O. Andersen, and N. Meier, "Minimizing the risk of diagnostic errors in acute care for older adults: An interdisciplinary patient safety challenge," *Healthcare*, vol. 12, no. 18, p. 1842, 2024. https://doi.org/10.3390/healthcare12181842

[13] I. A. Scott and C. Crock, "Diagnostic error: Incidence, impacts, causes and preventive strategies," *Medical Journal of Australia*, vol. 213, no. 7, pp. 302-305. e2, 2020. https://doi.org/10.5694/mja2.50771

[14] R. Pelissari, M. C. Oliveira, A. J. Abackerli, S. Ben-Amor, and M. R. P. Assumpção, "Techniques to model uncertain input data of multi-criteria decision-making problems: A literature review," *International Transactions in Operational Research*, vol. 28, no. 2, pp. 523-559, 2021. https://doi.org/10.1111/itor.12598

[15] S. K. Sahoo and S. S. Goswami, "A comprehensive review of multiple criteria decision-making (mcdm) methods: Advancements, applications, and future directions," *Decision Making Advances*, vol. 1, no. 1, pp. 25-48, 2023. https://doi.org/10.31181/dma1120237

[16] E. Herrera-Viedma *et al.*, "Revisiting fuzzy and linguistic decision making: Scenarios and challenges for making wiser decisions in a better way," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 51, no. 1, pp. 191-208, 2021. https://doi.org/10.1109/TSMC.2020.3043016

[17] M. A. Alsalem *et al.*, "Multi-criteria decision-making for coronavirus disease 2019 applications: A theoretical analysis review," *Artificial Intelligence Review*, vol. 55, no. 6, pp. 4979-5062, 2022. https://doi.org/10.1007/s10462-021-10124-x

[18] B. A. M. Al-Rami Al-Ghamdi, "Analyzing the impact of data visualization applications for diagnosing the health conditions through hesitant fuzzy-based hybrid medical expert system," *Ain Shams Engineering Journal*, vol. 15, no. 5, p. 102705, 2024. https://doi.org/10.1016/j.asej.2024.102705

[19] K. Al-Sulbi *et al.*, "A fuzzy topsis-based approach for comprehensive evaluation of bio-medical waste management: advancing sustainability and decision-making," *Sustainability*, vol. 15, no. 16, p. 12565, 2023. https://doi.org/10.3390/su151612565

[20] M. I. Tariq, N. A. Mian, A. Sohail, T. Alyas, and R. Ahmad, "Evaluation of the challenges in the internet of medical things with multicriteria decision making (AHP and TOPSIS) to overcome its obstruction under fuzzy environment," *Mobile Information Systems*, vol. 2020, no. 1, p. 8815651, 2020. https://doi.org/10.1155/2020/8815651

[21] A. Alharbi *et al.*, "Selection of data analytic techniques by using fuzzy AHP TOPSIS from a healthcare perspective," *BMC Medical Informatics and Decision Making*, vol. 24, no. 1, p. 240, 2024. https://doi.org/10.1186/s12911-024-02651-8

[22] B. Aslan and O. A. Hızıroğlu, "Prediction of lung cancer with fuzzy logic methods: A systematic review," *Artificial Intelligence Theory and Applications*, vol. 4, no. 2, pp. 155-192, 2024.

[23] C. A. Kumar, R. L. Priya, I. Ambika, and C. Mahiba, "Modified fuzzy based neuro networks for the prediction of common thorax diseases," *Multimedia Tools and Applications*, vol. 83, no. 40, pp. 87479-87503, 2024. https://doi.org/10.1007/s11042-024-18831-7

[24] T. Das, P. Holland, M. Ahmed, and L. Husain, "Sustainable development goal 3: Good health and well-being." Singapore: Springer Singapore, 2021, pp. 61-78.

[25] E. Lakioti, N. Pagonis, D. Flegkas, A. Itziou, K. Moustakas, and V. Karayannis, "Social factors and policies promoting good health and well-being as a sustainable development goal: Current achievements and future pathways," *Sustainability*, vol. 17, no. 11, p. 5063, 2025. https://doi.org/10.3390/su17115063

[26] H. Ni, H. Yu, Q. Lin, J. Zhong, W. Sun, and H. Nie, "Analysis of risk factors of fungal superinfections in viral pneumonia patients: A systematic review and meta-analysis," *Immunity, Inflammation and Disease*, vol. 11, no. 1, p. e760, 2023.

[27] M. L. Silva, B. Cá, N. S. Osório, P. N. S. Rodrigues, A. R. Maceiras, and M. Saraiva, "Tuberculosis caused by Mycobacterium africanum: Knowns and unknowns," *PLOS Pathogens*, vol. 18, no. 5, p. e1010490, 2022. https://doi.org/10.1371/journal.ppat.1010490

[28] R. D. Britt, A. Ruwanpathirana, M. L. Ford, and B. W. Lewis, "Macrophages orchestrate airway inflammation, remodeling, and resolution in asthma," *International Journal of Molecular Sciences*, vol. 24, no. 13, p. 10451, 2023. https://doi.org/10.3390/ijms241310451

[29] H. H. Rahman, D. Niemann, and S. H. Munson-McGee, "Association between asthma, chronic bronchitis, emphysema, chronic obstructive pulmonary disease, and lung cancer in the US population," *Environmental Science and Pollution Research*, vol. 30, no. 8, pp. 20147-20158, 2023. https://doi.org/10.1007/s11356-022-23631-3

[30] M. Carbajal and C. C. Teneback, "Environmental and infectious causes of bronchiectasis." Cham: Springer International Publishing, 2022, pp. 85-115.

[31] F. Luppi, M. Kalluri, P. Faverio, M. Kreuter, and G. Ferrara, "Idiopathic pulmonary fibrosis beyond the lung: Understanding disease mechanisms to improve diagnosis and management," *Respiratory Research*, vol. 22, no. 1, p. 109, 2021. https://doi.org/10.1186/s12931-021-01711-1

[32] A. A. Starshinova *et al.*, "Sarcoidosis as an Autoimmune Disease," *Frontiers in Immunology*, vol. 10, 2020. https://doi.org/10.3389/fimmu.2019.02933

[33] F. H. J. Kaptein *et al.*, "Pulmonary infarction in acute pulmonary embolism," *Thrombosis Research*, vol. 202, pp. 162-169, 2021. https://doi.org/10.1016/j.thromres.2021.03.022

[34] A. Mocumbi *et al.*, "Pulmonary hypertension," *Nature Reviews Disease Primers*, vol. 10, no. 1, p. 1, 2024. https://doi.org/10.1038/s41572-023-00486-7

[35] S. P. Jadhav *et al.*, "Introduction to lung diseases." Singapore: Springer Singapore, 2021, pp. 1-25.

[36] T. Maitre *et al.*, "Pyogenic lung abscess in an infectious disease unit: A 20-year retrospective study," *Therapeutic Advances in Respiratory Disease*, vol. 15, p. 17534666211003012, 2021. https://doi.org/10.1177/17534666211003012

[37] C. D. Berg *et al.*, "Air pollution and lung cancer: A review by international association for the study of lung cancer early detection and screening committee," *Journal of Thoracic Oncology*, vol. 18, no. 10, pp. 1277-1289, 2023. https://doi.org/10.1016/j.jtho.2023.05.024

[38] D. Taeger *et al.*, "Lung cancer and mesothelioma risks in a prospective cohort of workers with asbestos-related lung or pleural diseases," *American Journal of Industrial Medicine*, vol. 65, no. 8, pp. 652-659, 2022. https://doi.org/10.1002/ajim.23401

[39] E. Elgwairi, A. Abdalla, A. Elkheshen, Z. Elharabi, and K. Nugent, "Pleural effusions in patients with congestive heart failure: Frequency, pathogenesis, diagnosis, and implications," *Cardiology in Review*, vol. 32, no. 2, pp. 91-96, 2024. https://doi.org/10.1097/CRD.0000000000000469

[40] K. Nishimoto *et al.*, "Pneumothorax in connective tissue disease-associated interstitial lung disease," *PLOS ONE*, vol. 15, no. 7, p. e0235624, 2020. https://doi.org/10.1371/journal.pone.0235624