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Predictive Modeling of Lung Infections Using Fuzzy Logic Systems

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Abstract

Lung infections continue to pose a serious challenge to global public health, often progressing into life-threatening respiratory illnesses if not diagnosed and managed in a timely manner. Conventional diagnostic techniques, although widely used, can sometimes fall short in providing early and accurate predictions due to the variability and uncertainty present in clinical data. This study introduces an intelligent prediction model based on fuzzy logic systems aimed at addressing these limitations. Fuzzy logic offers a unique capability to handle imprecise and ambiguous information, closely resembling the reasoning patterns of medical professionals. The proposed system integrates a range of clinical parameter including symptoms, vital signs, and other patient-specific data to evaluate the likelihood of lung infection. The model is designed to interpret overlapping and non-binary data inputs, producing reliable infection risk assessments. Using a curated dataset of anonymized patient records, the fuzzy logic system was trained and tested to measure its prediction accuracy. Results reveal that the model demonstrates strong performance in detecting potential lung infections at early stages, offering a promising supplementary tool for clinicians. By enhancing the speed and precision of infection prediction, this approach can lead to faster interventions, reduced hospitalization rates, and better overall healthcare outcomes. The study highlights the practical benefits of fuzzy logic in medical diagnostics and its potential for broader clinical applications.

Keywords: Accuracy, Fuzzy Logic, Lung Infection Levels, Memberships Functions, Precision, Recall.

Introduction

When a virus, bacteria, or fungus infiltrates your lungs and produces inflammation, it results in a lung infection. Mild to severe lung infections may necessitate medical attention. As the name suggests, a lung infection is an infection of one or both of your lungs. Lung infections come in a few common varieties. Pneumonia is among the most prevalent lung infections. Your lungs' tiny air sacs are impacted by pneumonia. Although viruses and fungi can also cause it, infectious bacteria are the most common cause. A lung infection can cause mild to severe symptoms. Your age, general health, and whether the infection is brought on by a virus, bacteria, or fungus are some of the variables that will determine this. Though they usually linger longer, the symptoms could resemble those of a cold or flu bacterium, but a virus or fungus may also be at blame. Soft computing is a collection of interconnected approaches that enable decision-making based on trustworthy information or the experience of experts. These days, the medical field makes extensive use of a variety of soft computing approaches, including neural networks, fuzzy logic, genetic algorithms, and hybrid systems. An algorithm for analyzing lung infections is described in this research. Developing the system architecture to determine the likely disease stage that a patient may have been the primary goal. The rule-based method is used to determine the disease's severity level. To calculate an infection level, the algorithm utilizes a Rule-base output that the user has entered. It is also possible to perform further hardware implementations (1).

Some related works in the field of fuzzy logic have been presented in this section. The Fuzzy Logic Techniques Survey has been detailed. There are many works in the literature that explain the design and implementation of a decision support system. A rule-based method is presented where the level of infection has been evaluated using the user input and output of Rule-base (2). A fuzzy logic-based deep learning (DL) approach to

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differentiate between CXR images of patients with Covid-19 pneumonia not related to Covid-19 (3).
A high classification accuracy rate of up to 81% has been reported. A fuzzy rule based expert system is designed to alleviate blockage in the airways that carries air from the lungs by diagnosing asthma at initial stage (4). A systematic literature review and various categories of fuzzy logic application in an infectious disease has been carried out (5). A chapter has been presented where the application of fuzzy logic in medicine is described (6). To diagnose various lung diseases along with pneumonia, a fuzzy expert system which offers 93 percent accuracy has been designed (7). A study that utilizes the novel gray level Fuzzy Neural Network (GFNN) with fuzzy rules and its performance comparison with the Mamdani model Fuzzy Logic (FZ) algorithm to increase the detection accuracy of asthma is explained. This results in enhanced accuracy of 92.40 percent (8). Some more applications of Fuzzy logic are presented in different pulmonary infections (9-13). Application of fuzzy logic in pulmonary effusions has been presented (14). A computational method for the analysis of lung infection is demonstrated (15). Optimized fuzzy C-means (FCM) algorithm combined with MRI scan technique has been analysed in the diagnosis of tracheal foreign bodies in children (16). A novel technique has been analysed for the lung disease predictions like pneumonia and Covid-19 from the chest X-ray images of patients (17, 18). One of the studies demonstrated that combination of deep learning and image enhancement technique increases a high accuracy (19). In other studies, on COVID-19 patients, an interval type-2 fuzzy expert system has been used for prediction of ICU admission (20). While a real-time rule-based Fuzzy Logic classifier is used (21). Regress analysis has been done for classification of respiratory infections using fuzzy logic (22, 23). Some fuzzy logic applications are also demonstrated in other areas also (24, 25). A neural network based fuzzy logic approach has been also used for feature optimization in chest X-ray images (26, 27).
In one of the study an automated system has been proposed for the identification of multi lung diseases in X-Ray and CT scans (28). In other research machine learning models have been analyzed to predict obstructive and non-obstructive pulmonary diseases (29). Many more different techniques have been used for detection of respiratory diseases (30- 33).

Methodology

The proposed method aims to predict the likelihood of lung infections using a fuzzy logic system that handles the uncertainties and imprecision in medical data. The system uses three key clinical parameters cough, fever, and breathlessness to assess the probability of a lung infection. These symptoms often exhibit varying degrees of intensity, which can be challenging to quantify with traditional binary logic. Fuzzy logic function is proposed for a more flexible and human-like decision-making process, accounting for the gradual onset and progression of symptoms. Figure 1 shows flow of proposed method. Proposed methods will be useful for medical expert to verify the infection level.

Logic System

The approach adopted in developing Fuzzy Logic base lungs infection prediction System. Fuzzy logic is particularly useful for dealing with problems involving uncertainty or imprecision, such as medical diagnoses. When applied to lung infection analysis.

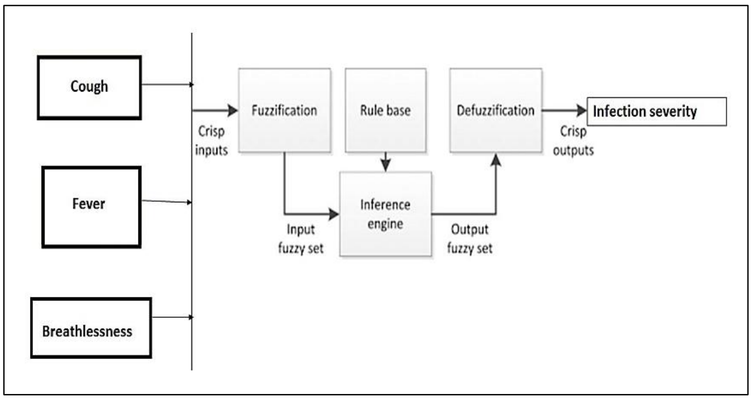

Figure 1: Block Diagram of Proposed Method of Predictive Modeling of Lung Infections Using Fuzzy

It can help assess symptoms, diagnostic indicators, and risk factors by modeling the inherent uncertainties in medical data. The framework comprises of three main components are shown in Figure 2 and are listed below,

- Knowledge based,
- Fuzzy inference system
- Defuzzification

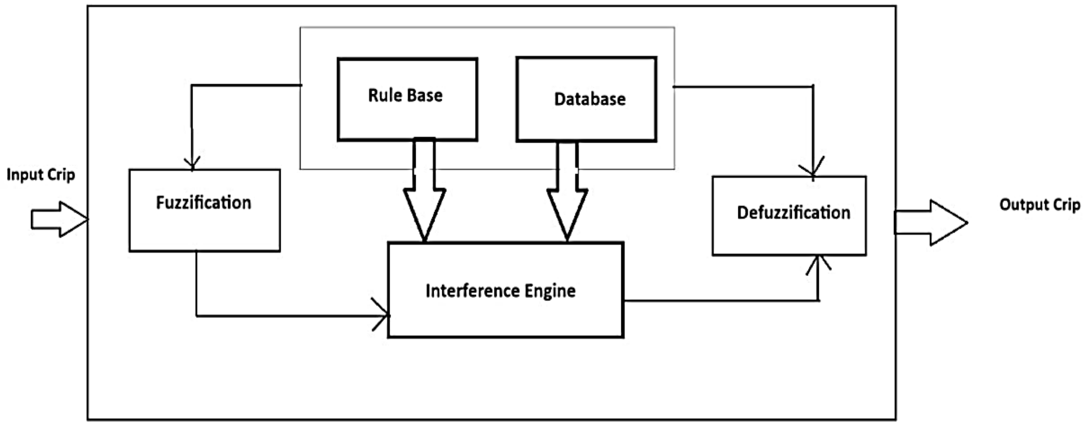

Figure 2: Fuzzy Logic Framework

The details of fuzzy logic explained in Figure 2 of each block are given below.

Rule Base: Based on linguistic data, it includes the set of guidelines and IF-THEN conditions that the experts have offered to control the decision-making mechanism. A number of efficient techniques for designing and fine-tuning fuzzy controllers are provided by recent advances in fuzzy theory. The majority of these advancements decrease the quantity of fuzzy rules.

Fuzzification: It is employed to transform inputs—that is, discrete numbers—into fuzzy sets. Crisp inputs are essentially the precise inputs—such as temperature, breathiness', cough, and application—that are measured by sensors and sent to the control system for processing.

Inference Engine: It chooses which rules should be fired based on the input field and calculates the degree to which the current fuzzy input matches each rule. The control actions are then created by combining the fired rules.

Defuzzification: It is employed to transform the fuzzy sets that the inference engine has produced into a precise value. To lower the error, the most appropriate defuzzification technique is applied in conjunction with a certain expert system.

Fuzzy Set Selection for Symptoms

Symptoms of lung infections, such as coughing, fever, shortness of breath, can be described using fuzzy sets because they vary in intensity and may not have crisp boundaries. As if considered Coughing Intensity can be classified into fuzzy sets like mild, moderate, and severe and more sub category. Fever Temperature could have fuzzy sets like low, moderate, and high, representing different ranges of body temperature. Shortness of Breath could be categorized as none, mild, moderate, and severe. Each fuzzy set has a membership function that defines the degree to which a particular observation temperature of belongs to a set.

In this paper each parameter is considered into six different conditions. Here Trapezoidal membership function is considered to represent the all-parameters relations.

Fuzzy Inference System for Lungs

A fuzzy inference system (FIS) designed to detect lung infections based on symptoms like cough, fever, and breathlessness, the goal is to classify the severity or likelihood of infection using these inputs. Fuzzy logic can handle the uncertainty and imprecision inherent in medical diagnosis, where symptoms vary in intensity. Structuring the fuzzy inference system for lung infection diagnosis different input is considered.

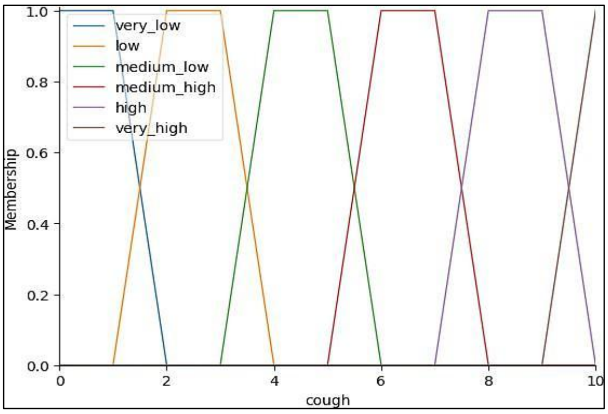

Figure 3: Input Membership Function for Cough Parameter Having Trapezoidal Membership Function

For defining Inputs cough, Fever, Breathless and output of infection are divided into six different conditions.

Cough: This can be represented by different levels of intensity of cough. Conditions are for cough Very Low, Low, Medium Low, Medium, High, Very High (Severe). Using Trapezoidal membership function cough are represented in fuzzy interface system. As shown in Figure 3.

Fever: Typically measured in degrees, fever can be categorized into Very Low, Low, Medium Low, Medium, High, Very High (Severe). Using Trapezoidal membership function cough are represented in fuzzy interface system. As shown in Figure 4.

Breathlessness This symptom can vary in severity and can be defined as Very Low, Low, Medium Low, Medium, High, Very High (Severe). Using Trapezoidal member- ship function cough is represented in fuzzy interface system. As shown in Figure 5

Infection level (Output Variable): The output could represent the risk or severity of lung infection, with levels different level. Levels are defined as very Low, Low, Medium Low, Medium, High, Very High (Severe). Using Trapezoidal membership function cough are represented in fuzzy interface system. As shown in Figure 6 each of these variables will be represented by fuzzy sets using linguistic terms (e.g., low, medium, high), and membership functions will define the degree of truth of each condition.

Fuzzy Rule Base for Lungs Infection

The fuzzy rules are essential in linking the symptoms (inputs) to the lung infection diagnosis (output). Each rule will take the form of IF-THEN statements. Combination of all conditions has to be considered. The knowledge base was developed using clinical guidelines and literature on symptom severity for fever, cough, and breathlessness (5). Expert input was used to define fuzzy rules and membership functions for infection prediction. Here few rules are listed as an example.

Rule 1: IF Cough is very high AND Fever is High AND Breathlessness is very high, THEN Infection is very high.

Rule 2: IF Cough is medium AND Fever is Low AND Breathlessness is medium, THEN Infection is medium.

Rule 3: IF Cough is medium AND Fever is medium AND Breathlessness is medium, THEN Infection is medium.

These rules are based on the assumption that the combination of symptoms reflects the severity of the lung infection. Table 1 shows few rules related to mamdani interference system.

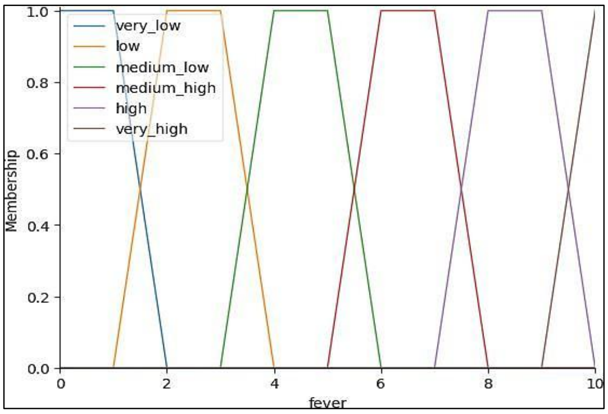

Figure 4: Input Membership Function for Cough Parameter Having Trapezoidal Membership Function

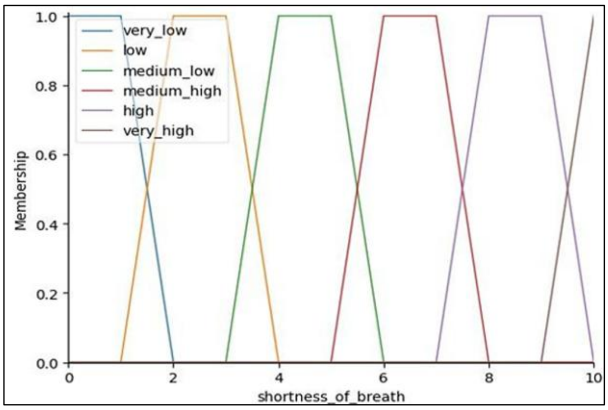

Figure 5: Input Membership Function for Breathlessness Parameter having Trapezoidal Membership Function

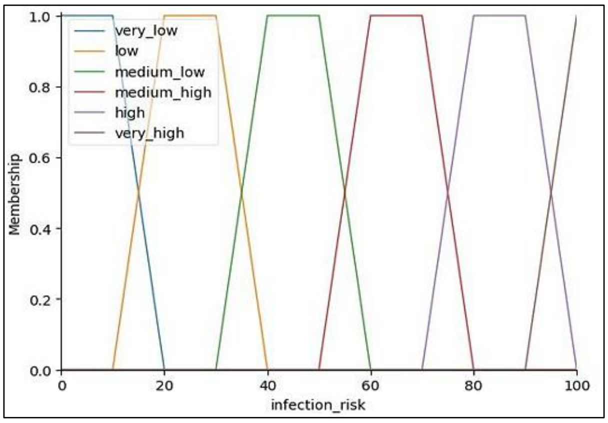

Figure 6: Output Membership Function for Infection Risk Parameter Having Trapezoidal Membership Function

Table 1: Fuzzy Inference Rule Table, Prediction of Lungs Infection

Cough	Fever	Breathlessness	Infection Severity
very low	very low	very low	very low
very low	low	low	very low
low	low medium	low	low
		high medium	
low	high medium		high medium
low medium	high medium	low medium	high medium

high medium	high medium	high medium	high
high	high	high medium	high
very high	high medium	very high	very high
very high	high high	very high	very high

Results and Discussion

In this paper, lungs infection prediction using fuzzy logic is proposed. fuzzy logic system is explained in previous section. Fuzzy logic system is developed using python platform. For validation different conditions are selected as different case study condition and quantitative analysis has been done. Table 2 shows 3 different conditions with membership function values.

Table 2: Details of Parameters and Predicted Level of Infection

Type	Cough Level	Fever	Breathlessness Level	Predicted Infection
Case study 1	4	3	3	Medium low infection
Case study 2	9	9	9	very high infection
Case study 3	2	2	1	Very low infection

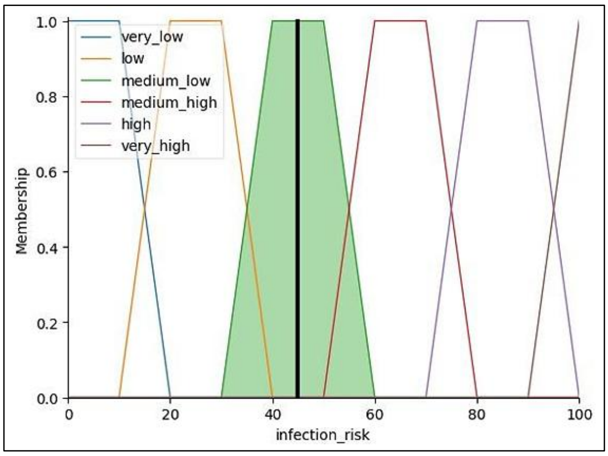

Figure 7: Result Shows Prediction of Infection is Medium Low by Shaded Area Using Membership Function (Case Study 1)

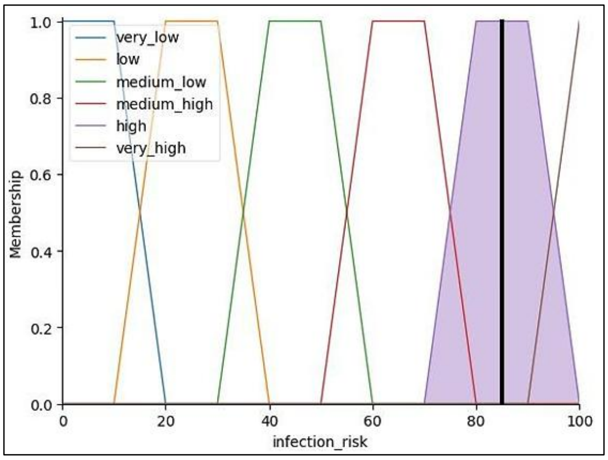

Figure 8: Result Shows Prediction of Infection High by Shaded Area Using Membership Function (Case Study 2)

Figure 7 shows output of case study 1, output variable infection risk level is high- lighted by shaded part in figure. When Input conditions are medium, infection is medium low. Figure 8 shows output of case study 2, output variable infection risk level is high- lighted by shaded part in figure. When input conditions are very high infection is also very high. Figure 9 shows output of case study 3, output variable infection risk level is highlighted by shaded part in the figure. When input conditions, infection is also very low.

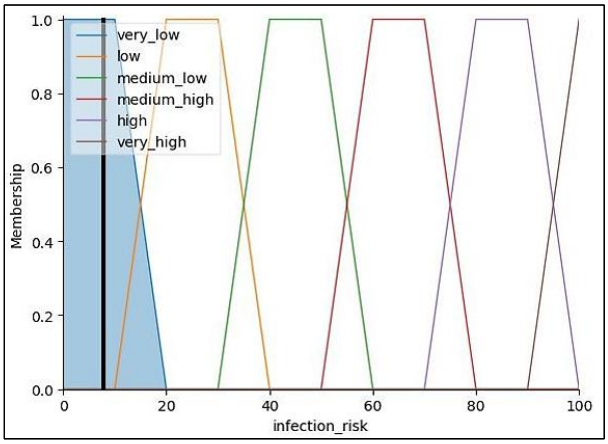

Figure 9: Result Shows Prediction of Infection is Very Low by Shaded Area Using Membership Function (Case study 3)

Quantitative Analysis

The results are valid by considering various conditions in the above sections. The metric-based evaluation is explained in this section. Metrics such as accuracy, recall, accurate and F-score. Four primary level characteristics are as follows, based on the above four characteristics, accuracy, which measure the ratio of the total number of correct prediction equations [1]. Similarly, recall measures the number of correct classifications penalized by the number of recall missed entries and is represented by the equation [2]. Likewise, the precision is a measure of the number of correct classifications penalize by the number of incorrect classifications, as given by equation [3].

$$Accurancy = \frac{T_p + T_N}{T_p + T_N + F_p + F_N} \quad [1]$$

$$recall = \frac{T_p}{T_p + F_N} \quad [2]$$

$$precision = \frac{T_p}{T_p + Fp} \quad [3]$$

$$F_{score} = \frac{2(prescision * recall)}{(prescision + recall} \quad [4]$$

F-score reflects the effect of accuracy and recall, there is no such solution that combines the effect of accuracy, accuracy, and recalls in the same function as is given in the equation [4]. Following Table 3 shows the result of proposed model for detection of lungs infection. It indicates proposed method works better than existing methods. Here, it is compared with linear regression (34) and changes in membership function. In the table best values are highlighted by bold number.

Table 3: Comparison of Proposed Method with Existing Method

Parameter	Trapezoidal Membership Function	Triangular Membership Function	Linear Regression (34)
Accuracy	94	74	90
Precision	92	70	82
Recall	94	76	93
F-Score	92	70	92

Conclusion

In this paper, proposed method predicts the lung infection level using a fuzzy logic system. An inventive and expert method of diagnosing lung infections based on fever, breathlessness, and coughing is provided by the use of fuzzy logic in the creation of such an automated system. Fuzzy logic is thought to be a reliable and affordable way to treat lung conditions when used in diagnostic system design. This work formalizes reasoning using rule-based systems and uses medical things as fuzzy sets. Developing a fuzzy base system to support the medical system is the goal. The proposed work is tested using lungs prediction dataset. Proposed method works better than existing method, proved using metric measures like accuracy, precision and recall. It is also verified by considering different conditions of infection level. It is proved that proposed method works better than existing methods.

Abbreviations

FN: False Negative, Fp: False Positive, Tp: True positive, TN: True negative.

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Author Contributions

All authors are contributed equally.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the content of this article.

Ethics Approval

Not Applicable.

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