SJCS Scientific Journal of Computer Science
futuristech PT. Teknologi Futuristik Indonesia
Received: March 29, 2026; Revised: May 17, 2026; Accepted: June 19, 2026; Published: August 18, 2026; Current version: August 18, 2026. *e-ISSN: 3110-3170*
Digital Object Identifier 10.64539/sjcs.v2i2.2026.480

Article

Fuzzy-Based Model for Respiratory Disease Classification

Auwal Umar[1], Abdullahi Musa Yola[2], Musbahu Bala Ibrahim[3,*], Muawiyya Modibbo Musa[2,4], Habimana Jean Bosco[2], Haruna Kawuwa[4], Nura Muhammad Sani[5], Rutarindwa Jean Pierre[2]

[1] Department of Computer Science, Federal University of Kashere, Kashere 771103, Gombe, Nigeria; e-mail: auwalumar178@gmail.com (A. Umar).
[2] Department of Computer Science, Kigali Independent University, ULK, Kigali, Rwanda; e-mail: amyola@ulk.ac.rw (A. M. Yola), muawiyamodibbomusa@ulk.ac.rw (M. M. Musa), hjeanbosco@gmail.com (H. J. Bosco), ruta-rindwajeanpierre@ulk.ac.rw (R. J. Pierre).
[3] ICT Directorate, Federal University of Kashere, Kashere 771103, Gombe, Nigeria; e-mail: musbahubibrahim@gmail.com (M. B. Ibrahim).
[4] Department of Informatics Engineering, Universitas Dian Nuswantoro, Semarang, Indonesia; e-mail: haruna.kawuwa@gmail.com (H. Kawuwa).
[5] Department of Computer Science, Federal Polytechnic Kaltungo, Gombe, Nigeria; e-mail: nuramuhammad1059@gmail.com (N. M. Sani).
* Correspondence

The authors received no financial support for the research, authorship, and/or publication of this article.

Abstract: Respiratory diseases remain a major global health concern, highlighting the need for accurate and interpretable computer-aided diagnostic systems. This study proposes a Mamdani Fuzzy Inference System (FIS) for the classification of four respiratory disease categories: Chronic Obstructive Pulmonary Disease (COPD), Asthma, Infected, and Healthy Control (HC). The proposed model utilizes the original variables provided in the Exasens dataset, including dielectric permittivity measurements (Real Permittivity Minimum, Real Permittivity Average, Imaginary Permittivity Minimum, and Imaginary Permittivity Average) together with demographic attributes (Age, Gender, and Smoking Status). A stratified subset of 100 records was selected from the publicly available Exasens dataset and preprocessed using min–max normalization before fuzzification with triangular and trapezoidal membership functions. Expert-defined fuzzy IF–THEN rules were employed within a Mamdani inference framework, and centroid defuzzification was used to obtain the final disease classification. The proposed model was evaluated using stratified 10-fold cross-validation and achieved an overall classification accuracy of 93.00%, with a macro-average F1-score of 91.87%. The experimental results demonstrate that the proposed Mamdani FIS provides accurate, transparent, and interpretable respiratory disease classification while preserving methodological reproducibility. These findings indicate its potential as a decision support tool for respiratory disease diagnosis.

Keywords: Mamdani Fuzzy Inference System; Respiratory Disease Classification; Exasens Dataset; Dielectric Permittivity; Fuzzy Logic; Clinical Decision Support.

1. Introduction

Respiratory diseases continue to be a major public health problem globally, with a major impact on morbidity, mortality and in terms of healthcare systems [1]. Millions of people suffer from chronic respiratory diseases including asthma and chronic obstructive pulmonary disease (COPD), and these conditions continue to make a significant contribution to the global burden of disease, in addition to respiratory infections [2], [3]. The rising rate of respiratory diseases, including working environment pollution, smoking, urbanization, and ageing of the population, has led to the need for better diagnostic and disease management strategies. Early diagnosis is crucial for better outcomes for the patient, fewer complications, and timely clinical intervention.

The traditional diagnosis methods are clinical examination, laboratory examination, pulmonary function test, and medical imaging. While these techniques have important applications in respiratory healthcare, they may involve challenges related to diagnostic interpretation, uncertainty, and clinical decision-making under complex clinical conditions [4]. The application of conventional decision-making strategies based on predefined thresholds may not fully represent the continuous variations in symptoms, physiological measurements, and disease severity observed in clinical practice [5]. Accordingly, there is a desire to develop computational approaches that can assist healthcare practitioners in dealing with uncertain information in a more flexible and interpretable way [4], [6].

Advancements in AI have greatly aided in the diagnosis and classification of diseases. In the medical field, machine learning and deep learning technologies have been shown to be effective in various applications such as detection and classification of respiratory diseases [7]-[9]. Some of these methods use medical imaging information like chest X-rays and computed tomography (CT) scans. These are commonly used for high predictive performance, but can be implemented as black-box models with limited information on how they make their predictions. In addition, imaging-based methods might involve the need for a large number of annotated images, dedicated hardware and significant computing power, which can restrict their applicability in certain healthcare settings [10], [11].

Effective management of uncertainty is an important challenge in the diagnosis of respiratory diseases. The clinical decision-making process may often involve vague, incomplete, and overlapping information due to variations in patient conditions and clinical observations [12]. Such characteristics can be challenging to represent using conventional computational approaches based on crisp classification or fixed decision boundaries [13]. Therefore, computational approaches capable of handling uncertainty and providing interpretable reasoning mechanisms have attracted increasing attention in medical decision support systems [14].

Fuzzy logic has proved to be a valuable tool for tackling uncertainty in medical decision making. Fuzzy logic was introduced to model imprecise and uncertain information, which means that the variables are allowed to be in more than one class, with degrees of membership to each class. This ability allows fuzzy systems to better describe clinical observations and to model reasoning processes similar to human decision-making processes. The fuzzy logic approach has been used in healthcare applications with success in diagnosis of diseases risk assessment and treatment support and clinical decision support systems, due to its capability of dealing with uncertainty in an understandable way [5], [15]-[17].

Fuzzy systems and other computational intelligence techniques have been investigated in the health-care field in several studies. Previous studies have indicated that the fuzzy inference system, neuro-fuzzy model, and hybrid intelligent system can be used effectively in medical diagnosis and classification [18], [19]. These methods also have an important advantage over many black-box methods in that they give a transparent reason by means of a rule-based decision structure. Although the literature is rich with such research, however, not too much interpretable fuzzy support has been provided for respiratory disease classification, especially for an explicit treatment of uncertainty in the classification information.

While several machine learning and deep learning methods have been suggested for diagnosis of respiratory diseases, some models are black boxes with low interpretability. The alternative that is more transparent is the fuzzy inference system, which represents the knowledge of the expert with IF–THEN rules in a linguistic way. There are, however, few studies that directly consider the original dielectric permittivity measurements and demographic attributes in the Exasens dataset to be used as inputs to a Mamdani-type fuzzy inference system for the multi-class classification of respiratory diseases.

To fill this gap, the present study introduces a Mamdani fuzzy inference-based approach to classify respiratory diseases. The proposed framework is aimed at potentially supporting decision-making in respiratory disease classification by utilizing linguistic variables to express uncertainty and fuzzy reasoning mechanisms. The goal of the framework is to offer a classification output that is interpretable and can support healthcare practitioners in understanding the reasoning process behind the classification.

The proposed study involves the development of a Mamdani Fuzzy Inference System (FIS) using the original variables present in the Exasens dataset, including dielectric permittivity measurements (Real Permittivity Minimum, Real Permittivity Average, Imaginary Permittivity Minimum, and Imaginary Permittivity Average) and demographic attributes (Age, Gender, and Smoking Status) to classify four respiratory disease categories: Chronic Obstructive Pulmonary Disease (COPD), Asthma, Infected, and Healthy Control (HC). The proposed model uses triangular and trapezoidal membership functions and expert-informed fuzzy IF–THEN rules to create an interpretable classification system. It is evaluated using a stratified sample of Exasens data with standard performance measures, including accuracy, precision, recall, specificity, F1-score, confusion matrix, and ROC analysis.

2. Literature review

2.1. Fuzzy Logic in Healthcare Applications

There are many uncertainties, incomplete information, and subjective clinical observations in healthcare decision making processes. There are differences in clinical signs and symptoms between patients with similar diseases, and between patients with different diseases. The complexity poses problems for traditional decision making, which uses hard coded thresholds and binary classifications. To overcome these drawbacks, fuzzy logic has been applied in medical applications since it can model uncertainty and represent imprecise information, which can be expressed as linguistic variables and degrees of membership [15], [16]. In contrast to classical logic systems, the clinical observations in fuzzy logic can also be a member of several classes along with degrees of membership. This property can be used to model human reasoning more naturally and to handle fuzzy information which is often found in medical contexts [5]. Therefore, fuzzy logic has been used in disease diagnosis, risk assessment, treatment planning, patient monitoring and clinical decision support system etc. Hence, the use of fuzzy logic in disease diagnosis, risk assessment, treatment planning, patient monitoring, and clinical decision support systems *etc*.

A number of studies have shown the effectiveness of fuzzy inference systems as an aid to decision-making in healthcare. Uncertainty and symptom variability are common in chronic diseases, making fuzzy-based approaches suitable for diagnosis and management of these diseases [15]. Hybrid systems using fuzzy logic and machine learning techniques to enhance learning have been studied elsewhere to enhance adaptation and yet retain interpretation [17], [18]. The methods try to strike a balance between predictive accuracy and interpretability of the decisions that still is crucial in health care applications. Besides the traditional fuzzy inference systems, researchers have explored other advanced fuzzy methods like fuzzy cognitive maps, and neuro-fuzzy systems. These methods go beyond that of fuzzy reasoning and can model complex relationships between variables and provide adaptive learning mechanisms [19]. Despite these advances, the interpretability is one of the prime benefits of fuzzy systems. The capacity to encode knowledge into easily comprehensible IF-THEN rules makes fuzzy logic very appealing for clinical applications where transparency of the decision making is critical.

Although earlier studies have demonstrated success, there are some problems that need to be overcome. The quality of membership function design and the extent of the rule construction is often a factor that affects the performance of fuzzy systems. In addition, some fuzzy models depend greatly on the rules that are set by the experts; if these are not carefully designed and validated, they may become subjective. However, fuzzy logic remains a valuable tool for dealing with uncertainties and enabling explainable decision-making in healthcare scenarios.

2.2. Computational Approaches for Respiratory Disease Classification

The expansion in the availability of healthcare data has provided motivation for computational methods in respiratory disease classification. With the growing availability of healthcare data, computational methods have been developed to classify respiratory disease. Due to their ability to detect complex patterns in medical data and assist in automated task classification, machine learning and deep learning techniques have gained widespread attention [7]-[9]. The techniques have been used in a range of respiratory health related challenges such as disease detection, risk prediction and clinical decision support. The existing studies are mostly linked to image classification for respiratory diseases such as chest X-rays and computed tomography (CT) images [7], [8]. The classification performance of CNNs and other deep learning architectures that automatically extract features from medical images has been good. The aforementioned methods have made great progress in computer-aided diagnosis, and have demonstrated a lot of promise in assisting healthcare practitioners.

While machine learning models and deep learning models have their benefits, they also come with some drawbacks. The most common problem reported is that the problem is not interpretable. Most highly successful models are black-box systems which are hard to interpret and understand why the classification results are obtained as such [10]. This restriction may lead to a decrease in trust and slow down the uptake of the intervention in healthcare settings where transparency is crucial to clinical decisions.

Another limitation is the dependence on large volumes of labelled data. Deep learning models usually need to have lots of training data and considerable computational power to perform well [11]. Furthermore, most image-based diagnostic systems require special equipment and imaging facilities that may not be readily available in every healthcare environment. These requirements can limit the applicability of such approaches, particularly in resource-constrained environments. The researchers also pointed out some issues of model generalization and robustness. In other words, models developed using certain data can be sub-optimal when used in a new population or in new clinical settings [20]. The impact of data quality, patient characteristics, and acquisition conditions on classification performance is not consistent, and can lead to lower reliability in real-world applications. These limitations have motivated continued interest in alternative ways of incorporating interpretability, transparency, and uncertainty management. In this case, fuzzy logic is a complementary framework which can be used to complement respiratory disease classification and can explicitly deal with uncertain and imprecise clinical information.

2.3. Research Gap and Study Motivation

While many advances are being made in computational healthcare, there are important challenges in the classification of respiratory disease. Existing machine learning and deep learning approaches have demonstrated strong predictive capabilities, but many of these methods provide limited interpretability and insufficient transparency regarding the reasoning behind classification decisions [10], [21]. In healthcare, this is especially relevant as doctors need to be able to decipher the computational recommendations to incorporate them into decision-making. One of the difficulties is dealing with uncertainty. Clinical information often is incomplete, imprecise or ambiguous, particularly in cases of symptom overlap between multiple respiratory diseases. Traditional classification methods aim for class separation and do not explicitly recognize the uncertainty of diagnostic information [22]. Therefore, it is important to have techniques that can deal with the uncertainty in the information, yet retain meaningful clinical interpretation.

Furthermore, most of the respiratory disease classification studies done so far are based on imaging data and advanced deep learning architectures [7]-[9]. These strategies have shown to be successful, but they need a lot of data, which requires a lot of computer power and special diagnostic equipment. These requirements could limit their usefulness in situations where access to sophisticated medical technologies is restricted.

The studies thus suggest the need for interpretable computational frameworks that can deal with uncertainty in the classification of respiratory diseases. Fuzzy logic has some properties which give it an edge in solving these problems, such as the rules are easy to be understood, vague clinical information can be model by fuzzy logic, and the decision making is explainable [5]. Based on these observations, the present study aims at proposing a Mamdani fuzzy inference based respiratory disease classification system. The approach proposed aims at offering a decision support tool that preserves the interpretability and uncertainty in the decision-making process, and yet keeps the reasoning process open and clear for the understanding of healthcare practitioners.

3. Methodology

The proposed framework uses Mamdani Fuzzy Inference System (FIS) for classification of respiratory diseases from the Exasens data set taken from the UCI Machine Learning Repository. The proposed approach is different from the conventional machine learning classifiers in that it captures the interactions between the input variables and disease classes in the form of interpretable fuzzy IF–THEN rules. The framework has five sequential steps as data acquisition and data preprocessing, fuzzification, fuzzy rule inference, aggregation, and defuzzification. All the methodology was executed in MATLAB Fuzzy Logic Toolbox with stratified 10-fold cross validation for model evaluation.

3.1. System Architecture

The proposed framework is based on a typical Mamdani fuzzy inference system composed of five components: input feature acquisition, fuzzification, rule evaluation, aggregation, and defuzzification as shown in Figure 1. The system is designed to process the dielectric permittivity data and demographic information from the Exasens data set to classify respiratory conditions in to four classes: COPD, Asthma, Infected, and Healthy Controls.

In the first stage, the selected dataset is acquired and pre-processed using normalization. The fuzzification process converts crisp input values into linguistic variables using triangular and trapezoidal membership functions. The fuzzy rule base is then used to determine the relationship between input feature patterns and disease classes through a series of IF–THEN rules. The activated rules are aggregated to produce a single fuzzy output for the DiseaseClass variable. Centroid defuzzification is then applied to obtain a single crisp output value. The resulting crisp value is interpreted using the output membership functions corresponding to COPD, Asthma, Infected, and Healthy Control to determine the predicted respiratory disease class.

3.1.1. Input Features

This first phase of the proposed framework consists of the input features in Exasens dataset. This dataset consists of results from exhaled breath analysis, as well as demographic data such as age, gender, and smoking status. All numerical variables are normalized before they are fed into the fuzzy inference system to ensure a similar scale. The normalized values are then fuzzified into predefined linguistic terms using the corresponding membership functions. No additional clinical symptoms or surrogate variables are generated from the original Exasens variables.

3.1.2. Fuzzification

In the fuzzification stage, the normalized input values are converted to fuzzy linguistic variables according to the fuzzification functions (membership functions) that have been pre-defined. Triangular and trapezoidal membership functions are used to represent various degrees of a symptom, for example, Low, Medium, and High. Fuzzification is a way to assign multiple categories to a single input value, as opposed to assigning each value to a single one of the categories. This allows the model to simulate uncertainty and smooth fluctuations, typical in clinical symptoms.

3.1.3. Rule Evaluation

The fuzzy rule base constitutes the knowledge component of the proposed Mamdani Fuzzy Inference System (FIS). It is composed of a collection of rules, expressed in a

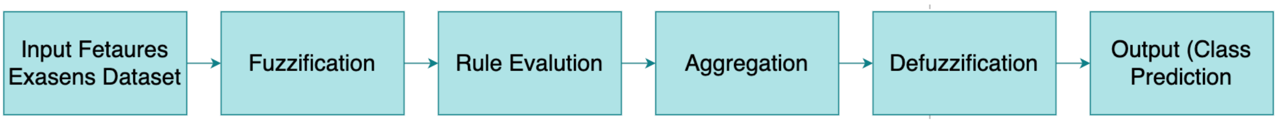

Figure 1. Proposed Fuzzy-Based Respiratory Disease Classification Framework.

Table 1. Summary of the Exasens Dataset Used in This Study.

Aspect	Description
Dataset Name	Exasens Dataset
Source	UCI Machine Learning Repository (Dataset ID: 523)
Dataset URL	https://archive.ics.uci.edu/dataset/523/exasens
Total Instances Used	100
Respiratory Classes	COPD (n=40), Healthy Controls (HC) (n=40), Asthma (n=10), Infected (n=10)
Input Features	Four dielectric permittivity measurements (real minimum, real average, imaginary minimum, imaginary average) and demographic attributes (Age, Gender, Smoking Status)
Missing Values	None (selected records).
Pre-processing	Normalization of numerical features to the range [0,1]
Class Distribution	Imbalanced (majority: COPD and HC; minority: Asthma and Infected)
Validation Method	10-fold stratified cross-validation

conditional format "IF-THEN," which define relationships between the set of input variables and the corresponding respiratory disease classes. The rules have been created using the original variables of the Exasens data set: Age, Gender, Smoking Status, Real Permittivity Minimum, Real Permittivity Average, Imaginary Permittivity Minimum, and Imaginary Permittivity Average. The fuzzy rules were formulated based on the linguistic characteristics of the input variables and expert-informed reasoning regarding the relationships between the selected Exasens features and the four respiratory disease classes. The rule base was reviewed for consistency, logical completeness, and interpretability during model development rather than being optimized against the classification accuracy of the evaluation data. These rules combine one or more input conditions using the "AND" logical operator and map the resulting conditions to one of the four respiratory disease classes: COPD, Asthma, Infected, or Healthy Control. The following represents some fuzzy rules which are:

- **Rule 1:** IF Age is Elderly AND Smoking Status is Current Smoker AND Real Permittivity Average is High AND Imaginary Permittivity Average is High THEN Disease is COPD.
- **Rule 2:** IF Age is Young AND Smoking Status is Non-Smoker AND Real Permittivity Average is Medium AND Imaginary Permittivity Average is Medium THEN Disease is Asthma.
- **Rule 3:** IF Age is Middle-aged AND Smoking Status is Former Smoker AND Real Permittivity Minimum is Medium AND Imaginary Permittivity Minimum is High THEN Disease is Infected.
- **Rule 4:** IF Age is Young AND Smoking Status is Non-Smoker AND Real Permittivity Minimum is Low AND Imaginary Permittivity Average is Low THEN Disease is Healthy Control.

The fuzzy rules are fired with the minimum (MIN) operator during the inference process and the output of the fired rules are aggregated with the maximum (MAX) operator. To obtain the final classification, the centroid defuzzification algorithm is used, making the Mamdani FIS interpretable for the classification of respiratory diseases.

3.1.4. Aggregation

The aggregation stage combines the fuzzy outputs of all activated rules into a single aggregated fuzzy output for the DiseaseClass variable. The maximum operator combines the contributions of multiple activated rules while retaining the strongest membership value at each point of the output universe. When multiple rules are activated simultaneously, their contributions are incorporated into the aggregated output before centroid defuzzification.

3.1.5. Defuzzification

In the last step, the aggregated fuzzy output of the DiseaseClass variable is converted into a single crisp numerical value using the centroid (center-of-gravity) defuzzification method. The resulting value represents the position of the inferred output within the normalized DiseaseClass output universe and should not be interpreted as a probability or rate of disease occurrence. The crisp output is then interpreted with respect to the four output membership functions representing COPD, Asthma, Infected, and Healthy Control to determine the predicted respiratory disease class.

3.2. Dataset Description and Pre-processing

3.2.1. Dataset Description

The proposed framework was evaluated using the Exasens dataset, a publicly available benchmark dataset hosted by the UCI Machine Learning Repository and originally introduced by [19]. The dataset is available at https://archive.ics.uci.edu/dataset/523/exasens (see Table 1). The complete dataset contains 399 patient records distributed across four respiratory disease categories: Chronic Obstructive Pulmonary Disease (COPD), Asthma, Infected, and Healthy Controls (HC). Although the complete Exasens dataset contains 399 patient records, a stratified random sample of 100 records was selected for this study to develop and evaluate the proposed Mamdani Fuzzy Inference System. Stratified random sampling was adopted to ensure that all four diagnostic classes were represented in the experimental dataset while maintaining a manageable dataset size for expert-driven fuzzy rule development. To enhance the reproducibility of the experimental procedure, the selected subset was generated using stratified random sampling with a fixed random seed and retained consistently throughout the preprocessing, fuzzy rule specification, model development, and performance evaluation stages. The selected subset consisted of 40 COPD cases, 40 Healthy Control cases, 10 Asthma cases, and 10 Infected cases.

The selected records include the original variables provided in the Exasens dataset, namely Real Permittivity Minimum, Real Permittivity Average, Imaginary Permittivity Minimum, Imaginary Permittivity Average, Age, Gender, and Smoking Status. These variables were used directly as inputs to the proposed Mamdani Fuzzy Inference System. No additional clinical symptoms or surrogate variables were generated, inferred, or mapped from the dataset. Consequently, the fuzzy inference system operates exclusively on the original Exasens measurements and demographic attributes, thereby ensuring methodological transparency and enabling reproducibility of the experimental procedure.

Before model development, all numerical variables were normalized to the interval [0,1] using the min–max normalization technique to eliminate differences in measurement scales and ensure compatibility with the fuzzy membership functions. The normalized numerical variables were subsequently fuzzified into the linguistic terms Low, Medium, and High using triangular and trapezoidal membership functions. The categorical variables Gender and Smoking Status were encoded according to the dataset specification before fuzzification.

3.2.2. Data Pre-processing

Prior to model training, the numerical attributes were normalized to the range [0,1] by applying Min–Max normalization method, as presented in Equation 1:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

to obtain equal scaling of all continuous variables. To make categorical variables (Gender and Smoking Status) numerical for fuzzification, these variables were coded according to the categories. The normalized variables obtained were then converted into fuzzy linguistic terms with triangular and trapezoidal membership functions.

3.3. Membership Functions

The membership functions, such as triangular and trapezoidal functions, were used because they are simple, efficient in terms of computation, and appropriate for modeling uncertainty in medical information. The proposed Mamdani Fuzzy Inference System (FIS) is effectively able to represent the gradual transitions between the respiratory disease classes when these functions convert crisp input values into fuzzy linguistic variables. The fuzzy model has been built from the seven initial variables of the Exasens data set: Age, Gender, Smoking Status, Real Permittivity Minimum, Real Permittivity Average, Imaginary Permittivity Minimum and Imaginary Permittivity Average. The continuous variables were expressed as Low, Medium and High and Age as Young, Middle-aged and Elderly. Categorical variables Gender and Smoking Status were expressed as their category.

As shown in Figure 2, overlapping membership functions allow a single input value to belong to multiple fuzzy sets with different degrees of membership, thereby improving the robustness and interpretability of the fuzzy inference process.

The Figure 2 illustrates the fuzzy membership functions defined for the seven input variables obtained from the Exasens dataset. Panel **(a)** shows the normalized age variable represented by three overlapping triangular membership functions: Young**,** Middle-aged, and Elderly. Panel **(b)** presents the binary Gender variable using two membership functions corresponding to Male and Female. Panel **(c)** depicts Smoking Status with three linguistic categories: Non-Smoker**,** Former Smoker, and Current Smoker**.** Panels (d)**-**(g) illustrate the membership functions for the dielectric permittivity measurements, namely Real Permittivity Minimum**,** Real Permittivity Average, Imaginary Permittivity Minimum, and Imaginary Permittivity Average, respectively. Each dielectric variable is partitioned into the linguistic terms Low**,** Medium**,** and High using overlapping triangular membership functions. The overlap between adjacent linguistic terms provides smooth transitions during fuzzification, allowing the Mamdani FIS to effectively handle uncertainty and variability in the respiratory measurements while preserving the interpretability of the classification process.

3.4. Fuzzy Rule Base

The fuzzy rule base was composed of a set of IF-THEN rules linking the various combinations of the levels

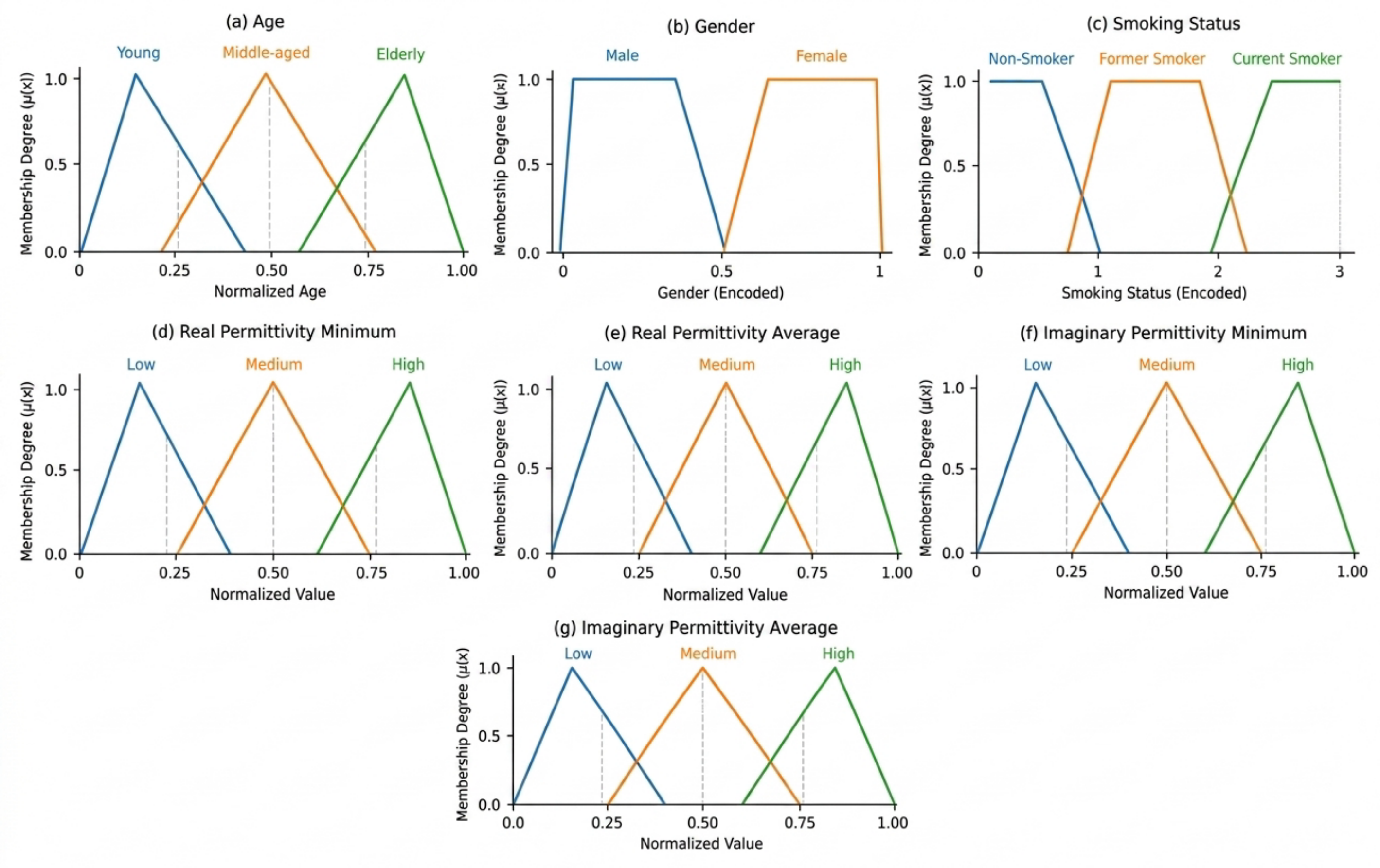

Figure 2. Input variable membership functions.

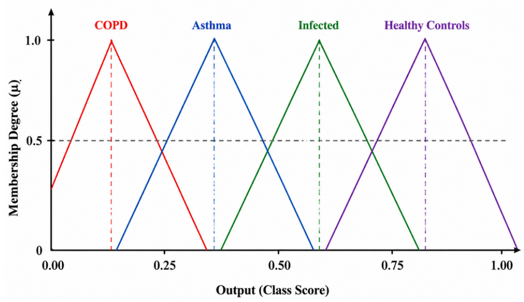

Figure 3. Output variable membership functions for the four respiratory classes.

of the input features with the four classes of respiration. The rules were formulated to be able to describe all important patterns present in the normalized Exasens features without losing the understanding of the rules in terms of linguistic reasoning.

3.5. Inference and Defuzzification

In the Mamdani inference mechanism, the minimum operator is used for rule activation and the maximum operator is used for aggregation. The activated rules produce an aggregated fuzzy output for the DiseaseClass variable. This aggregated fuzzy output is transformed into a single crisp value using centroid defuzzification. The Mamdani inference system represents the four respiratory disease classes—COPD, Asthma, Infected, and Healthy Control—as output membership functions, as shown in Figure 3. The output membership functions are defined over the normalized DiseaseClass range [0,1] and overlap to represent gradual transitions between the respiratory disease classes. The resulting crisp output value is interpreted with respect to these output membership functions to determine the corresponding predicted disease class.

3.6. Implementation Details

The proposed model was implemented using the MATLAB Fuzzy Logic Toolbox (MATLAB R2024a), which has tools for designing, simulation and analysis of Mamdani fuzzy inference systems. Implementation consisted of defining fuzzy membership functions for the features selected from Exasens, creating the fuzzy rule base, setting up the inference mechanism and testing the classification outputs.

Specifically, the implementation process involved:

a) Defining fuzzy input variables by triangular and trapezoidal membership function.
b) Building a set of IF-THEN rules to represent the relationships between input feature and the target respiratory disease classes.
c) Configuring the Mamdani inference system using the minimum operator for rule activation the maximum operator for aggregation, and centroid method for defuzzification.

Algorithm 1. Proposed Mamdani Fuzzy Respiratory Disease Classification Procedure.

Input: *Preprocessed Exasens dataset (Dielectric permittivity features, Age, Gender, Smoking Status)*
Output: *Predicted respiratory disease class*

Step 1: *Obtain the selected Exasens dataset containing the original input variables.*
Step 2: *Normalize the input features.*
Step 3: *Fuzzify the normalized input variables using triangular and trapezoidal membership functions.*
Step 4: *Evaluate the fuzzy IF-THEN rules using the Mamdani inference engine.*
Step 5: *Aggregate the activated rules into a fuzzy output for the DiseaseClass variable.*
Step 6: *Apply centroid defuzzification to obtain a single crisp output value.*
Step 7: *Interpret the crisp output using the output membership functions of COPD, Asthma, Infected, and Healthy Control.*
Step 8: *Assign the corresponding respiratory disease class as the predicted class.*

Table 2. Number of Samples for each class (total=100).

Class	Number of Samples
COPD	40
Healthy Control	40
Asthma	10
Infected	10
Total	**100**

d) Testing the model using the pre-processed Exasens dataset and analyzing the classification performance through MATLAB simulation and visualization tools.

The membership functions and fuzzy rules were established based on expert-informed linguistic definitions and were reviewed to ensure consistency with the selected Exasens input variables. Algorithm 1 outlines the step-by-step procedure of the proposed Mamdani fuzzy inference system for respiratory disease classification.

3.7. Experimental Setup

3.7.1. Experimental Environment

The proposed Mamdani Fuzzy Inference System (FIS) was designed and coded using MATLAB R2024a software equipped with the Fuzzy Logic Toolbox. The proposed Mamdani Fuzzy Inference System (FIS) has been designed based on MATLAB R2024a software and with the help of Fuzzy Logic Toolbox. Experiments were performed in a personal computer with Intel® Core™ i7 processor, 16 GB RAM and Windows 11 (64-bit) operating system. MATLAB is used to preprocess the data, implement the fuzzy rules, do the fuzzy inference, defuzzification and test the performance.

3.7.2. Experimental Dataset

Exasens datasets were used for the experiments, which are available from the UCI Machine Learning Repository [19]. A total of 399 patient records were available, of which a stratified random sample of 100 records was used to create the model and to validate and evaluate it. The sampling method used was designed to ensure that each category of respiratory diseases was represented, and at the same time keep the data set size reasonable for the purpose of fuzzy rule construction. Number of Samples for each class are shown in Table 2.

The fuzzy inference system was based only on the original Exasens variables which include Age, Gender, Smoking Status, Real Permittivity Minimum, Real Permittivity Average, Imaginary Permittivity Minimum and Imaginary Permittivity Average. No additional derived variables or clinical symptoms were added during the experiment.

3.8. Evaluation Metrics and Validation Approach

Standard multi-class classification metrics such as accuracy, precision, recall/sensitivity, specificity and F1-score were used to assess the performance of the proposed fuzzy classification framework. Such metrics are useful for a complete evaluation of the classification performance of the model across all respiratory disease classes.

a) Accuracy
Accuracy (ACC) represents the number of respiratory disease cases correctly classified overall in all four classes (COPD, Asthma, Infected, and Healthy Controls) by the proposed Mamdani fuzzy classification model. It gives a general idea of the ability of the model to classify the entire data set.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

where (TP), (TN), (FP), and (FN) represent the numbers of true positives, true negatives, false positives, and false negatives, respectively.

b) Precision
Precision is the percentage of cases correctly identified when the disease is a respiratory disease. For instance, it shows the number of samples that are predicted as COPD that are in fact COPD. The low false-positive rate corresponds to a high precision, and means that disease predictions are reliable.

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

where (TP) is the number of correctly classified positive instances and (FP) is the number of instances incorrectly assigned to that class.

c) Recall
Recall (also called sensitivity) is the proportion of the correct classification of all instances of each respiratory disease class. A high recall value means that the model is able to identify the majority of the patients in a disease category and will have few patients that it will fail to identify.

$$Recall = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{4}$$

where (FN) denotes the number of positive instances incorrectly classified as another class. A high specificity value indicates that healthy individuals or patients belonging to other respiratory disease classes are rarely misclassified as the target disease.

d) F1-Score
The F1-score provides a balanced evaluation of the classifier by combining precision and recall into a single performance measure. For the COPD cohort it is especially helpful to assess models trained using imbalanced data sets, like the COPD subset of Exasens, where cases of COPD and Healthy Controls are more common than Asthma and Infected cases.

$$F1 - score \ = \ 2 * \frac{precision * Recall}{precision + Recall} \tag{5}$$

A high F1-score indicates that the proposed fuzzy classification model achieves both high precision and high recall, reflecting balanced and reliable classification performance across all respiratory disease classes.

4. Results and Analysis

The proposed Mamdani fuzzy inference model was evaluated using a pre-processed subset of the Exasens dataset obtained from the UCI Machine Learning Repository. The dataset consists of 4 respiratory disease classes: COPD (Chronic Obstructive Pulmonary Disease), Asthma, Infected and Healthy Controls (HC). The chosen Exasens variables (Real Permittivity Minimum, Real Permittivity Average, Imaginary Permittivity Minimum, Imaginary Permittivity Average, Age, Gender and Smoking Status) were normalized and directly used as the input to the proposed Mamdani Fuzzy Inference System. No symptom mapping or feature transformation was performed.

The performance of the proposed model was assessed using 10-fold stratified cross-validation to provide a reliable estimate of its generalization capability while reducing the effects of the relatively small and imbalanced dataset. Evaluation of the classification performance was done by accuracy, sensitivity (recall), specificity, precision, F1-score, confusion matrix analysis and Receiver Operating Characteristic (ROC) curves. The experimental results indicate that the proposed fuzzy model successfully classified the four classes of respiratory diseases with 93.00% accuracy and 91.87% macro-average F1-score. The results suggest that the proposed model is capable of dealing with uncertainty and overlapping clinical features, and also can give an interpretable diagnostic decision using rule based fuzzy reasoning.

4.1. Performance Results

Despite the dataset limitations discussed earlier, the model achieved relatively balanced performance across the four respiratory disease classes, although the minority classes showed lower performance. Table 3 presents the performance of the proposed Mamdani fuzzy classification model. The model achieved an overall classification accuracy of 93.00% and a macro-average F1-score of 91.87%. COPD achieved a recall of 95.00%, precision of 92.68%, and F1-score of 93.83%, while Healthy Controls achieved a recall of 92.50%, precision of 94.87%, and F1-score of 93.67%. Asthma and Infected both achieved a recall and precision of 90.00%, resulting in an F1-score of 90.00% for each class.

The 10-fold stratified cross validation is used to calculate the confusion matrix heatmap which is shown in Figure 4 for the proposed Mamdani fuzzy classification model. The confusion matrix shows that 38 of 40 COPD cases, 9 of 10 Asthma cases, 9 of 10 Infected cases, and 37 of 40 Healthy Control cases were correctly classified. The remaining errors consisted of limited cross-class misclassifications, including COPD–Asthma, COPD–Healthy Control, Infected–Healthy Control, and Healthy Control–COPD classifications.

The one-vs-rest Receiver Operating Characteristic (ROC) curves of Mamdani fuzzy classification model presented in this study with 10-fold stratified cross-validation are shown in Figure 5. The ROC curves show the performance of the model in distinguishing the four classes of respiratory disorders, namely COPD, Asthma, Infected and Healthy Controls. The model discriminating between COPD and HC had an AUC of 0.992, whereas Asthma and Infected had an AUC of 0.936 and 0.934 respectively, with the latter having a higher similarity between classes. The overall performance of the proposed fuzzy model in the classification of the respiratory diseases is validated by the ROC analysis which indicates that the model discriminates the diseases very well in all categories.

Table 3. Performance Metrics of the Proposed Fuzzy Classification.

Class	Sensitivity (Recall) (%)	Specificity (%)	Precision (%)	F1-Score (%)
COPD	95.00	95.00	92.68	93.83
Asthma	90.00	98.89	90.00	90.00
Infected	90.00	98.89	90.00	90.00
Healthy Control	92.50	96.67	94.87	93.67
Overall	**93.00 (Accuracy)**	–	–	**91.87 (Macro Avg.)**

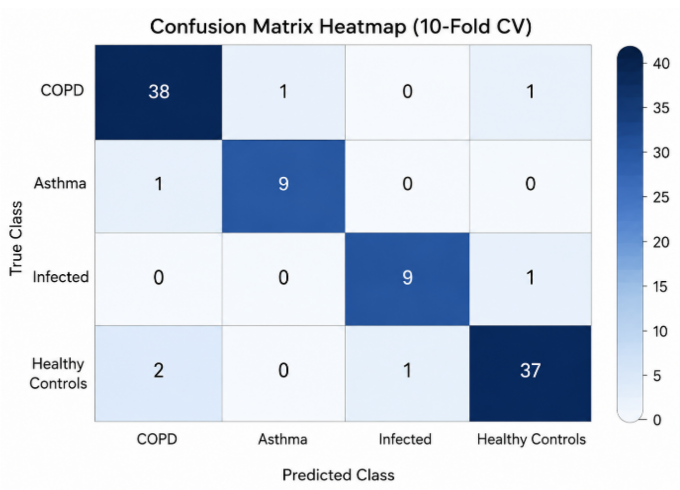

Figure 4. Confusion Matrix Heatmap.

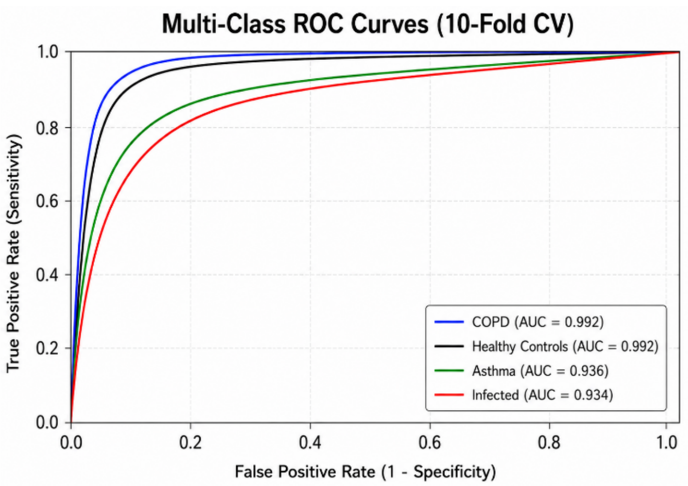

Figure 5. Multi-class ROC Curves.

4.2. Rule-Based Decision

The proposed Mamdani fuzzy classification model was visualised through MATLAB Rule Viewer as seen in Figure 6. The input values shown in Figure 6 are 0.72, 0.65, 0.88, 0.41, 0.50, 1, and 1 for Real Permittivity Minimum, Real Permittivity Average, Imaginary Permittivity Minimum, Imaginary Permittivity Average, Age, Gender, and Smoking Status, respectively. These inputs are then fuzzified in the respective linguistic membership functions to turn the different IF-THEN rules in the Mamdani inference engine.

The aggregated result of the activated rules is obtained using the maximum operator, and the final output is obtained through centroid defuzzification. For the example shown in Figure 6, the DiseaseClass output has a defuzzified center-of-gravity value of 0.87. This value represents the crisp output of the Mamdani FIS on the normalized DiseaseClass output universe. The value is interpreted using the four output membership functions corresponding to COPD, Asthma, Infected, and Healthy Control, resulting in the classification of the sample as COPD. The figure illustrates how the activated fuzzy rules contribute to the aggregated output and how the aggregated fuzzy output is converted into a crisp decision through centroid defuzzification.

4.3. Comparison with Relevant Exasens-Based Studies

To contextualize the performance of the proposed Mamdani Fuzzy Inference System (FIS), its results were compared with findings reported in previous studies that used the Exasens dataset. Table 4 summarizes selected Exasens-based studies employing machine learning approaches, together with the experimental settings and reported performance. These studies provide a useful reference for contextual comparison; however, they were conducted under different experimental conditions, including differences in sample size, class configuration, preprocessing procedures, feature selection, and validation protocols.

The proposed Mamdani FIS achieved an overall classification accuracy of 93.00% and a macro-average F1-score of 91.87% in the present experimental setting. These results are competitive with previously reported results on the Exasens dataset. However, direct performance comparisons should be interpreted with caution because the previous studies did not necessarily use the same subset, feature configuration, preprocessing procedure, or evaluation protocol as the present study.

For example, previous research using the Exasens dataset has investigated XGBoost for COPD and Healthy Control classification, while other studies have investigated SVM-based and Random Forest-based approaches for multiclass classification. The differences in experimental design make it inappropriate to conclude that the proposed Mamdani FIS definitively outperforms these methods solely on the basis of the reported accuracy values. Instead, the results indicate that the proposed approach provides competitive classification performance while offering an interpretable rule-based decision mechanism.

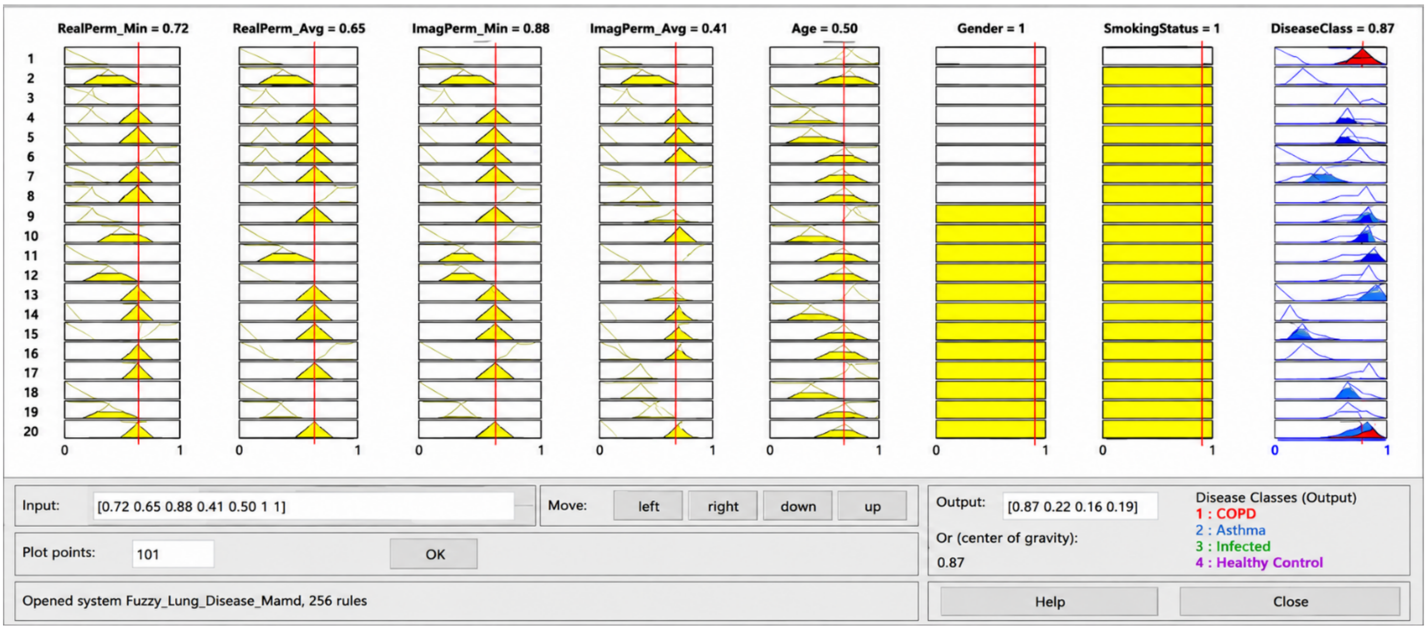

Figure 6. MATLAB Rule Viewer Showing the Inference Process of the Proposed Mamdani Fuzzy Classification Model.

Table 4. Comparison with Relevant Exasens-Based Studies.

Study	Dataset / Task	Method	Reported Accuracy (%)	Experimental Setting
Zarrin *et al*. [23]	Exasens, COPD vs. HC; 80 samples	XGBoost	91.25	5-fold cross-validation
Zarrin *et al*. [24]	Exasens, binary (COPD vs. HC); 80 samples	ANN + memristive neuromorphic chip	89.00	5-fold cross-validation
Handayani, and Tjahjadi [25]	Exasens, four-class; 399 samples	SVM	52.63	Multiclass classification
Handayani, and Tjahjadi [25]	Exasens, four-class; 399 samples	PSO-SVM	56.40	Multiclass classification
Singh *et al*. [26]	Exasens, four-class; 399 samples	PSO-RF	99.05	10-fold cross-validation; SMOTE + EM imputation
This study	**Exasens, four-class; 100 samples**	**Mamdani FIS**	**93.00**	**10-fold cross-validation**

5. Discussion

The results show that the Mamdani Fuzzy Inference System (FIS) proposed in this work proves to be effective to classify respiratory diseases on the basis of the original variables given in the Exasens data set. Overall classification accuracy and macro-average F1-score were 93.00% and 91.87% respectively, suggesting that fuzzy logic can be used to model the nonlinear relationships between dielectric permittivity measurements, demographic attributes and respiratory disease classes. In addition, the rule-based approach of the proposed Mamdani FIS offers a transparent and interpretable decision-making process, which is a promising approach for supporting clinical decisions in the classification of respiratory diseases.

5.1. Interpretation of Key Findings

The performance measures and the confusion matrix indicate that the proposed model had the highest classification performance for COPD and Healthy Control classes, and comparatively lower performance for the Asthma and Infected classes. The difference is expected as the smaller number of samples in the selected set in the latter classes and the similarity of their dielectric permittivity characteristics make them harder to distinguish. Despite the relatively lower performance observed for Asthma and Infected classes, the overall results indicate that the proposed fuzzy rule base was able to capture useful relationships between the Exasens variables and the respiratory disease classes under the experimental conditions of this study. However, the relatively small number of samples in the minority classes limits the extent to which these findings can be generalized to broader patient populations.

The triangular and trapezoidal membership functions enabled "soft" transitions between linguistic categories, which enabled the model to represent the gradual variation that occurs in the dielectric permittivity measurements and demographic characteristics. All four disease classes present high AUC value which further confirms the good discriminative ability of the proposed Mamdani FIS.

5.2 Strengths, Limitations, and Clinical Implications

One of the advantages of the proposed model is its interpretability. The Mamdani Fuzzy Inference System is different from many machine learning and deep learning models in that it captures knowledge as explicit IF–THEN rules and makes it possible for the healthcare professional to understand and validate the reasoning for each classification. This transparency has a positive effect on the confidence in the diagnostic process, and therefore facilitates the use of the model as a potential decision support tool. Moreover, the proposed method directly makes use of the Exasens dataset which contains both dielectric permittivity measurements and demographic data, without requiring complex feature extraction or medical imaging.

Although the results were encouraging, there are some limitations which are noted. First, the study was based on a selected subsample of the Exasens data, which may restrict the validity of the findings. Secondly, fuzzy rule base and membership functions were built based on the expert knowledge, which added some subjectivity to the model design. Future research should test the proposed method with larger and more varied datasets of respiratory disease and to explore automatic techniques for membership function tuning and fuzzy rule generation.

The proposed Mamdani FIS achieved competitive classification performance relative to results reported in previous Exasens-based studies. However, these comparisons should not be interpreted as direct evidence that the proposed model outperforms conventional machine learning methods because the studies used different datasets, sample sizes, feature configurations, preprocessing procedures, and validation protocols. The main advantage of the proposed approach is its explicit rule-based representation, which provides an interpretable reasoning mechanism in addition to its classification performance. The proposed approach may serve as a potential decision-support framework for respiratory disease classification because of its combination of classification performance and rule-based interpretability. However, further validation using larger, independent, and clinically representative datasets is required before its use in real-world clinical practice can be considered.

6. Conclusion

This study presented a Mamdani Fuzzy Inference System (FIS) for the classification of four respiratory disease categories Chronic Obstructive Pulmonary Disease (COPD), Asthma, Infected, and Healthy Control using the original dielectric permittivity measurements and demographic attributes provided in the Exasens dataset. The proposed model uses triangular and trapezoidal membership functions along with fuzzy IF–THEN rules to classify in an interpretable and transparent way. The experimental results obtained from the stratified subset of the Exasens dataset showed that the proposed approach achieved an overall classification accuracy of 93.00% and a macro-average F1-score of 91.87% under the adopted experimental setting. The findings indicate that the Mamdani FIS provides a potentially useful and interpretable framework for respiratory disease classification. Nevertheless, the results should be interpreted in light of the limited sample size and the differences between the present experimental setting and those reported in previous studies.

7. Future Research Directions

Future work could be directed towards testing the proposed Mamdani Fuzzy Inference System with the full Exasens data set and with more large and diverse clinical data sets to evaluate its robustness and generalizability further. The fuzzy rule base can also be extended to incorporate additional respiratory diseases and common comorbidities. Additionally, adapting the fuzzy logic type-2 approach could more accurately address greater uncertainty and combining with Internet of Things (IoT) applications in healthcare could provide more real-time patient monitoring and decision support. Finally, hybrid approaches can be developed by integrating fuzzy inference with machine learning or deep learning methods, which still maintain interpretability, and further improve the classification performance and its clinical applications.

8. Declarations

8.1. Author Contributions

Auwal Umar: Methodology, Software, Validation, Formal analysis; **Abdullahi Musa Yola:** Conceptualization, Methodology, Formal analysis, Investigation, Writing – Original Draft; **Musbahu Bala Ibrahim:** Software, Methodology, Formal analysis, Visualization, Writing – Original Draft, Writing – Review & Editing; **Muawiyya Modibbo Musa:** Investigation, Data Curation, Resources; **Habimana Jean Bosco:** Investigation, Validation, Writing – Review & Editing; **Haruna Kawuwa:** Supervision, Methodology, Writing – Review & Editing; **Nura Muhammad Sani:** Validation, Investigation, Writing – Review & Editing; **Rutarindwa Jean Pierre:** Supervision, Project administration, Writing – Review & Editing.

8.2. Institutional Review Board Statement

Not applicable.

8.3. Informed Consent Statement

Not applicable.

8.4. Data Availability Statement

The data presented in this study are available upon reasonable request from the corresponding author (Musbahu Bala Ibrahim, musbahubibrahim@gmail.com). The data used in this study is the publicly avaialble Exasens dataset from the UCI Machine Learning Repository.

8.5. Acknowledgment

The authors would like to express their sincere gratitude to the Editor and the anonymous reviewers for their insightful comments and constructive suggestions, which greatly improved this manuscript. The authors also acknowledge the support provided by their respective institutions throughout the course of this research. Appreciation is extended to the UCI Machine Learning Repository and the developers of the Exasens dataset for providing the data used in this study.

8.6. Conflicts of Interest

The author declares no conflicts of interest.

9. References

[1] J. Oh *et al,*. "Global, regional, and national burden of chronic respiratory diseases and impact of the COVID-19 pandemic, 1990-2023: a Global Burden of Disease study," *Nature Medicine*, vol. 32, no. 1, pp. 197-223, 2026. https://doi.org/10.1038/s41591-025-04077-9.

[2] K. M. Abubeker and S. Baskar, "B2-Net: an artificial intelligence powered machine learning framework for the classification of pneumonia in chest x-ray images," *Machine Learning: Science and Technology*, vol. 4, no. 1, p. 015036, Apr. 2023. https://doi.org/10.1088/2632-2153/acc30f.

[3] T. Samavat, M. Nazari, M. Ghalehnoie, M. A. Nasab, M. Zand, P. Sanjeevikumar, and B. Khan, "A Comparative Analysis of the Mamdani and Sugeno Fuzzy Inference Systems for MPPT of an Islanded PV System," *International Journal of Energy Research*, vol. 2023, Art. no. 7676113, 2023. https://doi.org/10.1155/2023/7676113.

[4] I. Chouvarda, E. Perantoni, and P. Steiropoulos, "Respiratory decision support systems," in *Wearable Sensing and Intelligent Data Analysis for Respiratory Management*, 2022, pp. 299–322. https://doi.org/10.1016/B978-0-12-823447-1.00008-7.

[5] L. A. Zadeh, "Fuzzy sets," *Information and Control*, vol. 8, no. 3, pp. 338–353, 1965. https://doi.org/10.1016/S0019-9958(65)90241-X.

[6] L. Daines *et al.*, "Use and acceptability of an asthma diagnosis clinical decision support system for primary care clinicians: an observational mixed methods study," *npj Primary Care Respiratory Medicine*, vol. 34, 2024. https://doi.org/10.1038/s41533-024-00401-x.

[7] A. Dounis and A. Stefopoulos, "Intelligent Medical Diagnosis Reasoning Using Composite Fuzzy Relation, Aggregation Operators and Similarity Measure of q-Rung Orthopair Fuzzy Sets," *Applied Sciences.*, vol. 13, no. 23, p. 12553, 2023. https://doi.org/10.3390/app132312553.

[8] Z. Attarilar, H. Vahedi, T. Samad-Soltani, R. N. Alipoor, and A. Jafarizadeh, "Application of fuzzy logic and systems in COVID-19 pandemics: a comprehensive review," *Discover Artificial Intelligence.*, vol. 5, no. 1, Art. no. 351, 2025. https://doi.org/10.1007/s44163-025-00543-y.

[9] S. Bharati, P. Podder, and M. R. H. Mondal, "Hybrid deep learning for detecting lung diseases from X-ray images," *Informatics in Medicine Unlocked*, vol. 19, Art. no. 100317, 2020. https://doi.org/10.1016/j.imu.2020.100391.

[10] M. E. H. Chowdhury *et al.*, "Can AI help in screening Viral and COVID-19 pneumonia?," *arXiv preprint arXiv:2003.13145*, 2020. https://doi.org/10.48550/arXiv.2003.13145.

[11] G. Huang, X. Wei, H. Tang, F. Bai, X. Lin, and D. Xue, "A systematic review and meta-analysis of diagnostic performance and physicians' perceptions of artificial intelligence (AI)-assisted CT diagnostic technology for the classification of pulmonary nodules," *Journal of Thoracic. Disease.*, vol. 13, no. 8, pp. 4797-4811, 2021. https://doi.org/10.21037/jtd-21-810.

[12] Y. Zheng, Z. Xu, T. Wu, and Z. Yi, “A systematic survey of fuzzy deep learning for uncertain medical data,” *Artif. Intell. Rev.*, vol. 57, Art. no. 230, 2024. https://doi.org/10.1007/s10462-024-10871-7.

[13] Q. Xu *et al.*, “ Interpretability of Clinical Decision Support Systems Based on Artificial Intelligence from Technological and Medical Perspective: A Systematic Review,” *Journal of Healthcare Engineering*, 2023. https://doi.org/10.1155/2023/9919269.

[14] S. Leelavathy, J. Ramprasath, I. M. Mary, R. Nagendran, and R. N. D. Kumar, “Harnessing fuzzy logic framework to quantify diagnostic uncertainty in medical decision support,” *Fuzzy Information and Engineering*, vol. 17, no. 4, pp. 425–445, 2025. https://doi.org/10.26599/FIE.2025.9270070.

[15] K. Jyoti, S. Sushma, S. Yadav, P. Kumar, R. B. Pachori, and S. Mukherjee, “Automatic diagnosis of COVID-19 with MCA-inspired TQWT-based classification of chest X-ray images,” *Computers in Biology and Medicine*, vol. 152, Art. no. 106331, 2023. https://doi.org/10.1016/j.compbiomed.2022.106331.

[16] S. Kumar, M. Patel, B. B. Jayasingh, M. Kumar, Z. Balasm, and S. Bansal, “Fuzzy Logic Driven Intelligent System for Uncertainty Aware Decision Support Using Heterogeneous Data,” *Journal of Machine and Computing*, vol. 5, no. 4, pp. 2672–2687, 2025. https://doi.org/10.53759/7669/jmc202505205.

[17] T. Mehta and N. Mehendale, “Classification of X-ray images into COVID-19, pneumonia, and TB using cGAN and fine-tuned deep transfer learning models,” *Research on Biomedical Engineering*, vol. 37, no. 4, pp. 803–813, 2021. https://doi.org/10.1007/s42600-021-00174-z.

[18] M. K. Sharma, N. Dhiman, V. N. Mishra, L. N. Mishra, A. Dhaka, and D. Koundal, “Post-symptomatic detection of COVID-2019 grade based mediative fuzzy projection,” *Computers and Electrical Engineering*, vol. 101, Art. no. 108028, Jul. 2022. https://doi.org/10.1016/j.compeleceng.2022.108028.

[19] Exasens, “UCI Machine Learning Repository,” 2020. [Online]. Available: https://doi.org/10.24432/C5M03M.

[20] G. Selvachandran, S. G. Quek, L. T. H. Lan, L. H. Son, N. L. Giang, and W. Ding, “A new design of Mamdani complex fuzzy inference system for multiattribute decision making problems,” *IEEE Transactions on Fuzzy Systems*, vol. 29, no. 4, pp. 716-730, Apr. 2021. https://doi.org/10.1109/TFUZZ.2019.2961350.

[21] 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, Jan. 2024. https://doi.org/10.53759/0088/JBSHA20240401.

[22] I. Moatadid, A. Idri, and I. Abnane, “Enhancing medical classification with fuzzy logic-based missing data imputation technique,” *International Journal of Data Science and Analytics*, vol. 20, no. 8, pp. 7281–7303, 2025. https://doi.org/10.1007/s41060-025-00867-z.

[23] P. S. Zarrin, N. Roeckendorf, and C. Wenger, “In-Vitro Classification of Saliva Samples of COPD Patients and Healthy Controls Using Machine Learning Tools,” *IEEE Access*, vol. 8, pp. 168053 – 168060, 2020. https://doi.org/10.1109/ACCESS.2020.3023971.

[24] P. S. Zarrin, F. Zahari, M. K. Mahadevaiah, E. Perez, H. Kohlstedt, and C. Wenger, “Neuromorphic on-chip recognition of saliva samples of COPD and healthy controls using memristive devices,” *Scientific Reports*, vol. 10, art. No. 19742, 2020 . https://doi.org/10.1038/s41598-020-76823-7.

[25] R. N. Handayani, and D. Tjahjadi, “Optimasi Support Vector Machine Menggunakan Particle Swarm Optimization untuk Klasifikasi Multiclass Dataset” *Jurnal Responsif: Riset Sains dan Informatika*, vol. 5, no. 1, 2023. https://doi.org/10.51977/jti.v5i1.1069.

[26] A. Singh, N. Prakash; A. Jain, “Particle Swarm Optimization-Based Random Forest Framework for the Classification of Chronic Diseases,” *IEEE Access*, vol. 11, pp. 133931 – 133946, 2023. https://doi.org/10.1109/ACCESS.2023.3335314.