Knowledge Based Recommender System for Disease Diagnostic and Treatment Using Adaptive Fuzzy-Blocks

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Abstract

Identifying clinical pathways for disease diagnosis and treatment process recommendations are seriously decision-intensive tasks for health care practitioners. It requires them to rely on their expertise and experience to analyze various categories of health parameters from a health record to arrive at a decision in order to provide an accurate diagnosis and treatment recommendations to the end user (patient). Technological adaptation in the area of medical diagnosis using AI is dispensable; using expert systems to assist health care practitioners in decision-making is becoming increasingly popular. Our work architects a novel knowledge-based recommender system model, an expert system that can bring adaptability and transparency in usage, provide in-depth analysis of a patient's medical record, and prescribe diagnostic results and treatment process recommendations to them. The proposed system uses a set of parallel discrete fuzzy rule-based classifier systems, with each of them providing recommended sub-outcomes of discrete medical conditions. A novel knowledge-based combiner unit extracts significant relationships between the sub-outcomes of discrete fuzzy rule-based classifier systems to provide holistic outcomes and solutions for clinical decision support. The work establishes a model to address disease diagnosis and treatment recommendations for primary lung disease issues. In this paper, we provide some samples to demonstrate the usage of the system, and the results from the system show excellent correlation with expert assessments.

Keywords: Knowledge-based decision support system, Fuzzy rule-based classification, Parallel fuzzy systems architecture, Health care recommendation system, Disease diagnosis and treatment.

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1. Introduction

Recommendation systems are an inevitable tool for information filtering and knowledge extraction [1]. They are modeled to serve applications in diverse domains, including e-commerce, entertainment, social media, news, and more [2]. The impact of adhering to recommendations for decision support may have low-risk to high-risk effects on an application domain [3]. Healthcare recommender systems (HRS) are one such domain that needs to be modeled and designed to deliver minimal or zero error-tolerant recommendation information that is trustworthy, transparent, and reliable [4]. The recommendable item of interest in HRS happens to be medical information, which needs to be arrived at through a methodology that is scientifically proven or at least generally accepted [5]. There are many sub-domain classifications in the health care recommender domain. The wellness domain, health care services, food and nutrition information, physical exercise and sports, diagnosis, and treatment/medication are some sub-domains that are worth mentioning [6].

The recommender system elements, users, items, and context of recommendation system usage can vary for each sub-domain of the health care recommender system. In the case of food recommender systems, a sub domain of health recommender systems, end-users can be healthy people. Items can be referred to here as healthy food choices, and in the context of recommender system usage, it can prescribe appropriate nutrition intake to prevent diseases and promote healthy living [7]. Depending on the requirements of the application, several studies on health care recommender systems offer various strategies. Prominently suggested strategies are collaborative filtering, content-based, knowledge-based, and hybrid techniques, which are combinations of the aforementioned methods [8].

In the health condition diagnostics and treatment process health care recommender domain, the recommender element 'user' refers to a patient or healthy person, the recommender element 'item' refers to prescribed content for various diagnosed medical conditions or prescribed content of treatment processes is referred to features of the items [5].

Knowledge-based recommender systems are an ideal technique for developing medical diagnosis and treatment process recommendation systems [8],[9]. These systems gather and construct a knowledge base using information about items, including descriptions and attributes, leveraging the domain knowledge of experts. They explicitly capture user preferences and create user profiles tailored for the recommendation process. Based on item knowledge, the system generates recommendations by matching the user's profile with item attributes and characteristics gathered in the knowledge base. It applies filtering and ranking techniques based on the relevancy of mapping in the knowledge base. In this context, the patient's health record can be seen as explicit user input, which should be transformed into a patient profile to facilitate the mapping with the knowledge base, representing various diagnosis conditions (items) [10]. Rule-based systems are well-suited for representing the knowledge base due to their capacity to offer transparency in design [11].

Healthcare experts use their past experiences to recommend high-quality medical treatment to their patients. They need to analyze patient health information consisting of diagnostic data, their personal health data and other supporting information relating to health for decision-making [12],[13]. Because doctors are humans, missing criteria during the analysis of medical reports can result in an error of judgment in decision-making [14]. The need for decision-support systems is crucial for healthcare experts in helping them in accurately assess a patient's condition and provide precise treatment recommendations. They also help healthcare professionals follow established clinical guidelines and send alerts to prevent deviations from standard procedures [15],[16].

Although knowledge-based decision support systems offer numerous benefits, their integration into clinical settings is not without hurdles. It necessitates a close collaboration between healthcare professionals and system engineers to configure the system for practical clinical use. One of the most prevalent challenges lies in designing the system to seamlessly accommodate routine care, enabling the system to update settings in accordance with the latest evidence and guidelines [17],[18]. To overcome these barriers, it is crucial that the configuration of rules in knowledge-based systems be transparent, facilitating the identification of deviations and offering ease of reconfiguration [19]. Another pivotal design consideration is adaptability, where the system model must be sufficiently flexible to incorporate new criteria in a clinical setting with minimal or no intervention required from system engineers [20].

Our proposed work can be modeled as an expert guiding tool for the clinical treatment pathway adhering to proper guidelines and expert knowledge for the specific disease or medical condition under consideration. The proposed model addresses an individual's health condition, particularly when they are under specific medical observation. This innovative system, adopting the recommendation system model as an expert system aims to assist healthcare practitioners in comprehending the patient's personal health record, effectively representing their health status, and facilitating the proficient presentation of pertinent information. The information is presented in relation to the current health condition, along with associated score values and potential subsequent conditions, providing a more comprehensive analysis for decision support.

The proposed model uses discrete parallel fuzzy systems [21], referred to as "fuzzy blocks" which serve as fuzzy rule-based classifiers. These 'fuzzy blocks' possess the capacity to deliver diagnosis outcomes for sub-medical conditions. A novel rule-based combiner component combines the outputs of these discrete fuzzy systems, utilizing a knowledge base, thereby yielding holistic diagnosis for medical conditions and furnishing pertinent treatment recommendations. The model supports sequential decision processing with state maintenance capability, which is an ideal foil for directing the clinical pathway for diagnostic and treatment process recommendations. To facilitate these functions, a dedicated configuring unit, known as the 'fuzzy composer,' is employed. This component takes on a crucial role not only in configuring individual discrete fuzzy rule-based classifier systems but also in organizing them for the sequential process to comply with specific domain requirements within the realm of healthcare.

2. Background

Fuzzy logic systems work well for such decision-intensive tasks since they imitate the way of decision-making of expert humans [22]. Fuzzy rule-based systems can be designed for representing expert knowledge related to the application under purview. Here, the knowledge-based fuzzy sets, combined with fuzzy logic rules, are used to represent the relationship between input and output. This can closely resemble a trained human by mimicking the way of approach, perception, and cognition in decision-making for a given application domain [23]. Further fuzzy-based systems are effective in resolving conflicts of multiple criteria and provide better logical assessment of options as well as modeling the interactions and relationships existing between its variables [24],[25].

2.1 Fuzzy Based Systems in Medical Diagnostics

Works based fuzzy rule-based systems in the area of medical diagnostics have been available since 1986, and since then substantial papers have been published to date. Rustempasic and Can (2013) [26] proposed fuzzy C-mean clustering-based pattern recognition in order to identify Parkinson's illness. They analyzed the ambiguity of the problem and adopted fuzzy logic to address it. Hasan et al.'s (2010) [27] introduced a fuzzy-based expert system, an online diagnosis tool. Users in their system have the option of selecting between illnesses and symptoms. The technology might offer a pertinent likelihood of sickness by asking them questions about their symptoms. Later, a web-based application diagnostic system was presented by Samuel et al. (2013) [28], adopting fuzzy logic for diagnosing typhoid fever. Biyouki et al.'s (2015) [29] applied a fuzzy rule-based expert system in order to detect thyroid illness. They used a mamdani-based inference engine and a centroid approach-based defuzzification. Saikia and Dutta (2016) [30] applied fuzzy inference systems to predict dengue disease status. Behnam Malmir et al.'s (2017) [31], developed a medical decision support system based on a fuzzy rule-based inference system and used the Mamdani defuzzification process to diagnose risk level of kidney stones and kidney infections based on input symptoms. Singla, Jimmy, et al.'s (2020) [32] work addressed kidney disease and incorporated a scoring system for expressing the severity of symptoms to serve the fuzzification process retrieved from questioning the patients. Improta, Giovanni, et al.'s (2020) [33] presented a fuzzy inference system for decision support in monitoring renal function. The model uses the Mamdani-type FIS right from the analysis of the data and uses previous clinic knowledge of the subject.

Fuzzy rule-based classifiers (FRBCs), a component of fuzzy logic-based decision support systems (DSS), solve classification problems in a wide range of application fields, particularly in the areas of risk assessment, pattern recognition, and medical diagnostics recommendations [34],[35]. The ability to represent classification results along with a clear explanation and measure of the associated uncertainty is highly appealing and is attracting a great deal of research interest [36].

Substantial work in the area of fuzzy rule based classifiers (FRBCs) has been proposed, with different types of classifier systems being proposed based on the domain under consideration [37]. Many related works based on fuzzy-based classifier systems have been developed for specific applications [38]. Building a fuzzy rule based classifiers requires developing a knowledge base consisting of rules and databases, and designing a mechanism to classify input data based on the knowledge base. Fuzzy classifiers have to be modeled based on consideration of the following parameters: number of variables; number of fuzzy sets; selection of fuzzy membership function; completeness of rules; inference engine type; defuzzification type [37]. Different algorithms are proposed for generating the best rules used to classify example data set effectively. Decomposition strategies address the classification problem, each strategy adopts a scoring technique called rule weight for computing the confidence level of classes, which is interpreted as discrimination and selection of a class [39],[40]. As an assessment criteria for any proposed classifier system, performance, interpretability, and differentiability would largely determine the evaluation of any proposed fuzzy classifier model [41].

Fuzzy logic systems for decision support might follow different architecture styles, such as a parallel architecture design style or a hierarchical approach consisting of combination of multiple fuzzy logic system modules. The hierarchical architecture has each fuzzy sub-module connected in cascaded mode, with the consequent part of one fuzzy sub-system becoming one of the inputs to the next system. The parallel architecture has each module parallel-fed with different antecedent parts. The output of each module is fed to a combiner unit, which would adopt a strategy to arrive at a holistic decision support outcome [36].

3. Proposed Work

Most of the previous works addressed diagnosing single diseases and used a single fuzzy rule-based system to adopt expert knowledge and recommend diagnostic outcomes for given input. The work adopting fuzzy models takes input medical diagnostic parameters as a whole and gets processed by a fuzzy inference unit. The output observed through defuzzification is the diagnostic result for the specific disease under consideration. Our proposed work subdivides the input into sub-medical conditions; hence, the need for complex single fuzzy unit modeling is avoided. Multiple fuzzy units addressing sub-medical conditions separately bring clarity and depth to the diagnosis. This section addresses the design and modeling of the proposed system, which is employed for lung function diagnosis and treatment recommendations.

3.1 Architecture

Fig. 1 represents the proposed architecture of the expert system to address health care recommendations for diagnostic and treatment processes. The proposed fuzzy logic inference system adopts a multi-stage processing model and incorporates a novel fuzzy composer segment, a configuration and data organizing segment, to configure parallel discrete fuzzy logic systems referred to as "fuzzy blocks". Each fuzzy block is a Fuzzy Rule Based Classifier System (FRBCS), a subsystem representing a discrete sub-medical condition. This parallel architecture strategy consisting of discrete fuzzy blocks provides discrete diagnostic solutions, which are combined in the "knowledge-based combiner segment" to provide holistic solutions for the given medical data prescribed for the medical test under consideration.

3.2 Modeling Adaptive Fuzzy Blocks

Each stage in the process utilizes expert knowledge to establish different segments of the proposed architecture, with each of these segments constituting essential elements of the fuzzy logic system. The system's output is a diagnosed medical condition and treatment process recommendations, along with an explanation and a measure of how certain the recommendations are. The proposed model operates in two distinct modes: 1. Configuration mode. 2. Execution mode.

In configuration mode, the fuzzy composer segment instantiates fuzzy blocks, which would address all potential criteria of the specific medical conditions under consideration associated with medical diagnostic and treatment procedures. The essential steps involve identifying and categorizing potential fuzzy blocks into three distinct types: primary blocks, support blocks, and auxiliary blocks, all pertinent to the targeted disease diagnostic procedure under consideration. Primary blocks constitute the fundamental part of initiating the process, which is indispensable for the complete diagnosis process. Support blocks, which come into play after the mandatory primary blocks or other support blocks, are recommended for subsequent diagnostic stages. Auxiliary blocks serve as supplementary elements, contributing additional information for the purposes of diagnosis and treatment. Configure the properties (diagnostic parameters) as per the guidelines and standards for each block. This process involves categorizing fuzzy sets, allotting linguistic labels, establishing ranges for each property, and assigning appropriate fuzzy membership functions to align with the nature of the data and the problem domain in hand. The rule base for each fuzzy block is set based on the training set and expert domain knowledge. There is a large possibility of rules that can be set theoretically, but only rules that make practical sense are used. Here, the consequent part for each rule is associated with a class label, which is defined in accordance with the intrinsic attributes of the problem domain and the underlying data distribution. The novel rule-based combiner segment is configured with intra-block relationship rules derived through the rule base based on experts' knowledge to propose holistic diagnosis and recommendations for treatment. The combiner segment consists of possible sets of rules that map various combinations of discrete fuzzy block outcomes.

In the execution mode, the fuzzy composer undertakes the task of not only validating incoming parameters but also allocating them to suitably configured fuzzy blocks. This involves the establishment of primary blocks and support blocks, which could potentially be necessary for the ensuing subsequent diagnostic processes. Every unit of the fuzzy block rule-based classifier operates on its respective input medical data during the diagnostic process. The activated rules within each fuzzy block, with their respective class labels and yielding activation scores as a consequent part are observed. Each fuzzy block's consequent part provides specific medical insights for each sub-medical condition. The novel rule-based combiner unit consolidates the decision outcomes of discrete fuzzy blocks and provides comprehensive decision outputs. The firing rules of the combiner segment represent the holistic recommendations.

The following segment of the section elaborates on the proposed model.

1. Tabulate all conceivable medical parameters essential for diagnosis and identify the fuzzy parameters for the disease under consideration. Let 'n' denote the overall count of parameters under consideration.

$$\mathrm{X} = \{ x_1, x_2, \ldots x_n \} \tag{1}$$

2. Configure all pertinent fuzzy blocks for the disease under consideration for the diagnostic process. Each individual fuzzy block functions as a Fuzzy Rule Based Classifier System (FRBCS), constituting a subsystem responsible for representing discrete sub-medical conditions. A mapping function Compf(X) is utilized to configure fuzzy blocks based on the input X used for a particular diagnostic system.

$$\mathrm{V} = \underset{config=1,2\ldots m}{\mathrm{Comp}f}(\mathrm{X})$$

$$\mathrm{V} = \left\{ \{x_{11}, x_{12}\ldots x_{1\mathrm{p}}\}^1, \{x_{21}, x_{22}\ldots x_{2\mathrm{q}}\}^2 \ldots \{x_{\mathrm{d}1}, x_{\mathrm{d}2}\ldots x_{\mathrm{dr}}\}^d \ldots \{x_{m1}, x_{m2}\ldots x_{\mathrm{ms}}\}^m \right\} \subseteq \mathrm{X}$$

$$\text{Let } \mathrm{v_d} = \{\mathrm{x_{d1}, x_{d2}, \ldots x_{dr}}\}$$

$$\mathrm{V} = \{\mathrm{v_1, v_2, \ldots v_d, \ldots v_m}\} \tag{2}$$

Let V denote the ensemble of 'm' fuzzy inference systems, with V_d representing the d^{th} fuzzy block. In this context, each individual fuzzy inference system is denoted as a 'fuzzy block,' strategically employed for diagnosing specific medical conditions. Collectively, these distinct fuzzy blocks collaborate to deliver a holistic medical diagnosis along with corresponding treatment recommendations. Through expert intervention, a configuration table is employed to establish the grouping of all conceivable input parameters for the establishment of fuzzy blocks, guided by diagnostic criteria. For each pertinent input parameter, the associated fuzzy linguistic variables, the corresponding range of values, an appropriate membership function, and the required accuracy for intervention are meticulously defined.

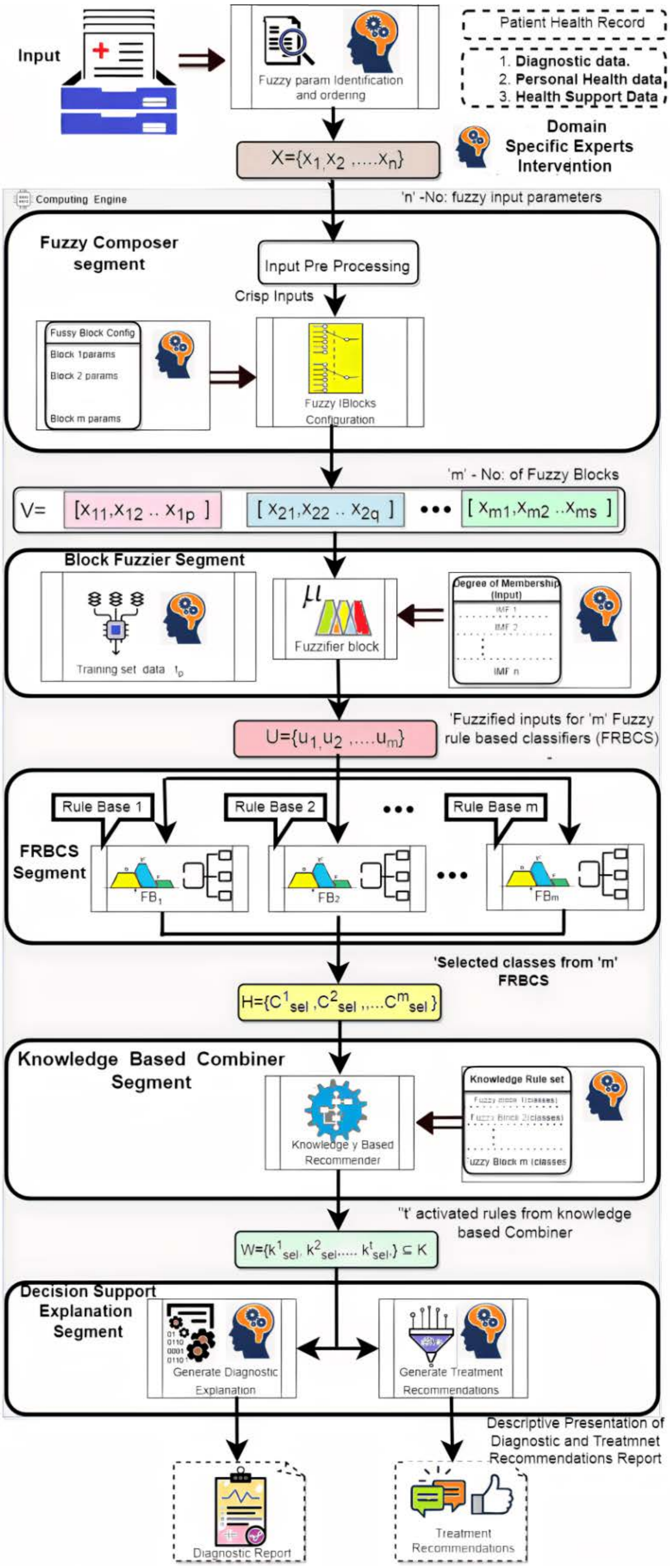

Fig. 1. Shows the architecture of adaptive fuzzy blocks based health care recommender system. (Source : The authors)

The configuration table also encompasses the specifications concerning the designation of fuzzy blocks as either primary, support, or auxiliary within the framework for establishing a sequential process for diagnosis and treatment computation.
3. Every fuzzy block encompasses a set of medical parameters that are relevant to its operation. These input parameters undergo preprocessing and are subsequently fed into the fuzzier input segment of the system as crisp values. Let u_d represent the fuzzified values of the input parameters of the d^{th} fuzzy block under consideration after the fuzzification process.

$$u_d = \underset{i=1,2\ldots r}{\mu\bar{A}}\,(x_i) \mid x_i \in X_i \text{ for all } i=1,\ldots r$$

The notation $\mu A(x_i)$ embodies the fuzzification process, establishing the connection between the crisp input value x_i and the fuzzy set **A**. The symbol μ stands for the membership function, capable of adopting either trapezoidal or triangular configurations. This function generates a fuzzified value that quantifies the degree of belongingness to the set. Conversely, $\bar{A}$ encompasses a collection of fuzzy sets, encompassing a range of fuzzy values associated with a particular crisp input value. Step functions are used for boolean set representations.
Let the fuzzification operation on a fuzzy block be Fuzz*f*(u) then

$$U = \underset{i=1,2\ldots m}{\mathrm{Fuzz}f}\,(u_i) \mid u_i \in U \text{ for all } i=1,\ldots m$$

$$U = \{u_1, u_2, \ldots u_d, \ldots u_m\} \mid u_d \in U \quad (3)$$

U is the collection of fuzzy block parameters after fuzzification operation performed on 'm' fuzzy blocks.

$$W_d = \{\omega_1, \omega_2, \ldots \omega_q, \ldots \omega_n\}$$

This expression represents a collection ($\mathbf{W_d}$) of activation strengths (**ω**) computed for each rule within the d^{th} fuzzy block. ω_q corresponds to the activation strength of a specific rule q within the block. The computed rule activation strength ω_q is associated with a class label $\boldsymbol{C_j}$ classified from a set of **k** classes. For a sample input $\mathbf{x_e}$, the class strength for each of the provided classes is computed for all the rules within the fuzzy block $\mathbf{u_d}$.

$$\text{Computing activation strength for } C_j = \sum_{R_q \in RB; C_j = C} \omega_j \mid C=1,2....,k$$

Classification for the fuzzy block $\mathbf{u_d}$ is carried out using the majority voting method. This means that the classes with the highest activation strengths are ordered and recommended as the final classification. The result is represented as C_{sel}^d, which signifies the selected classes for the $\mathbf{d^{th}}$ fuzzy block based on their activation strengths. Classes with an activation strength of zero are excluded from this selection.

$$C_{sel}^{d} = \arg \underset{i=1,2\ldots k}{\mathrm{sort}}\ \mathrm{class\_strength}f(C_i)$$

For each of the fuzzy blocks, the classes of respective fuzzy blocks with higher scores are arranged or ordered. Typically, the one with the highest score is selected to address discrete medical conditions of that block.

$$H = \underset{i=1,2\ldots m}{fuzzy\_classifier}\,(u_i) \mid u_i \in U \text{ for all } i=1,\ldots m$$

The resulting collection of selected classes ($\mathbf{C_{sel}}$) from each block becomes the consequent part of those respective blocks. These selected classes serve as a mapping to the respective diagnostic condition in the context of each block.

$$H = \left\{ C_{sel}^{1}, C_{sel}^{2}, \cdots C_{sel}^{d} \cdots C_{sel}^{m} \right\} \quad (4)$$

5. The outcomes of the consequent parts of all parallel discrete fuzzy blocks, each characterizing discrete medical conditions, are collectively cascaded to a novel combiner segment referred to as the knowledge-based recommender segment. This segment encompasses a set of rules that are formulated through the combination of class labels that result from diverse parallel discrete fuzzy blocks that have been configured. These rules express insights into the cumulative influence of various discrete medical conditions, resulting in the presentation of a comprehensive diagnostic and treatment recommendation outcome from a holistic standpoint.

Let **K** be the set of rules representing the knowledge-based recommender segment, which can be denoted as:

$$K=\{k_1,k_2,\dots k_i,\dots k_m\}$$

For example, let's consider a specific rule k_i within this knowledge rule set. This rule can be represented as:

$$k_i = C_k^d \wedge C_l^f \wedge C_m^h$$

Here, C_k^d ,C_l^f, and C_m^h are labeled classes from the pool of the respective fuzzy block's consequent part. For instance, C_k^d represents the k^{th} class label from fuzzy block d, C_l^f represents the l^{th} class label from fuzzy block f, and C_m^h represents the m^{th} class from fuzzy block h. These rules are created through the combination of class labels from different blocks along with the range of activation scores.

$$W= \text{Rule\_Selection}f(H,K)$$

$$W = \left\{ k_{sel}^{1}, k_{sel}^{2}, \dots k_{sel,}^{n} \right\} \subseteq K \tag{5}$$

The rule selection function within the knowledge-based combiner segment determines a set of activated rules (W) based on the input obtained from the previous stage. The algorithm for rule selection is provided above. Given the input health record parameters to the system, as referenced in Equation 1, the mapping of the recommended output W comprises the set of activated rules retrieved from the knowledge-based decision support system described in Equation 5. The inference drawn from these activated rules from this segment, along with the consequent parts from each discrete fuzzy blocks from the previous stage, whether considered individually or in combination, provides holistic diagnostic information. This information aids in understanding the precise health issue and subsequently recommending a suitable treatment process.

6. The recommender explanation segment serves as the final stage of the proposed expert system, responsible for interpreting the activated rules generated by the combiner segment. Its objective is to deliver a comprehensive diagnostic report and treatment process recommendations through a clear and informative explanation. An effective recommender system explanation should possess qualities such as transparency, scrutability, trustworthiness, effectiveness, and persuasiveness. By embodying these qualities, it enhances the efficiency and user satisfaction of the system [36]. In the context of iterative diagnosis, when primary blocks are linked with support blocks, the recommender explanation becomes more consolidated and informative. Additionally, auxiliary blocks contribute supplementary information to the main blocks. The recommendation explanation aims to present decision support stemming from both the main block and the auxiliary block. This segment ensures that the clinical decision support is not only relevant but also aligned with the user's needs.

Algorithm : Rule Based Knowledge Retrieval Algorithm

Input : $K=\{k_1,k_2,...k_i,...k_m\}$; **K** is an array of combiner rules, 'n' refers to total set of rules representing knowledge based recommender segment .

$H=\left\{C_{sel}^{1}, C_{sel}^{2},\cdots C_{sel}^{d}\cdots C_{sel}^{m}\right\}$; H is an array 'm' refers to number of fuzzy blocks .The array composes of resultant collection of the consequent part of each fuzzy block would be selected classes (C_{sel}) from each block along with their activation score.

Output : **W**:Collection of fired rules from the knowledge rule base

```
procedure : Rule_Selection
initialize i←0
for i to length of K-1 do
    firedrules[i] ← TRUE
   for each rule in K do
     rule_arr[] ← parse(rule) /* Parse the rule */
     for each class_ label in rule_arr do
        if class_ label ∈ H then
           continue
       else
          firedrules[i] ← FALSE
           break
     end for
 end for
end for
for each flag in firedrules
  i←0
  if flag is TRUE then
    append W from K [i] /*with fired rules */
  end if
end for
end procedure
```

4. Materials and Methods

The evaluation of the proposed fuzzy expert system, configured to address basic lung disease diagnosis and treatment processes was carried out using a hospital database containing thoroughly examined health records by medical specialists. For the purpose of this assessment, a carefully chosen subset of 120 patient records has been chosen from the extensive hospital database originating from the Department of Pulmonology at the SRM Institute of Science and Technology. These patient records serve as a comprehensive and representative sample that will enable us to draw meaningful conclusions about the performance and applicability of our proposed approach. The prime focus of this evaluation lies in the meticulous examination of the classification efficiency of the configured fuzzy blocks. The objective is to ascertain the precision with which the provided health parameters are aligned with their corresponding classes within the fuzzy blocks. This evaluation brings insight into the proposed expert system's performance and its capacity to accurately associate input parameters with pertinent diagnostic outcomes.

4.1 Configuring the System

The proposed model is configured to address the basic lung function testing, diagnosis, and treatment processes. The model absorbs experts' knowledge at each stage to automate the process. The proposed model configures fuzzy blocks for the Pulmonary Function Test (PFT) , Breathlessness Test (BLT). Bronco Dilator Reversibility Test (BDR) to assess specific medical conditions to diagnose lung diseases like interstitial lung disease, chronic obstructive pulmonary disease (COPD), and asthma [42].

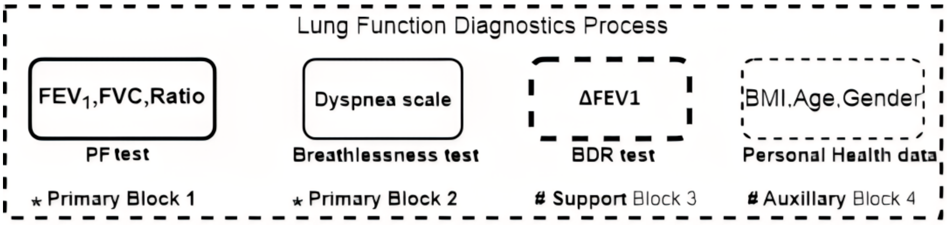

Fig. 2. Shows the fuzzy blocks configured for basic lung disease test process.
(Source : Experts' guidelines)

The fuzzy composer initializes the Pulmonary Function Test (PFT) and Breathlessness Test (BLT) as mandatory primary fuzzy blocks. Additionally, the PFT fuzzy block may recommend the Bronco Dilator Reversibility Test (BDR) as a support fuzzy block as a subsequent diagnostic step depending on the test's results. The Personal Health Data (PHD) constitutes an auxiliary fuzzy block, contributing supplementary information to enhance the predictability of diagnosis and treatment recommendations. **Fig. 2** shows the employed fuzzy blocks within the proposed system. Conforming to the ATS/ERS and Modified Medical Research Council (mMRC) guidelines, the medical parameters of each diagnostic block determine the ranges of FEV1 and FVC in the PFT block, as well as the dyspnea scale [43].

Measurable parameters are directly represented as crisp inputs, physicians examination of patient symptoms can be expressed in linguistic terms and associated with a range of score values from zero to a maximum range value [33]. The representation of patient symptoms, indicated by score values, utilizes either triangular or trapezoid distributions. **Fig. 3**, **Fig. 4**, and **Fig. 5** depict the fuzzy membership functions for the parameters of configured fuzzy blocks. In the appendix section, the following tables, from **Table 1** to **Table 9**, serve as illustrative examples of experimental setups, showcasing the step-by-step configuration process to be applied to each fuzzy block within the proposed model.

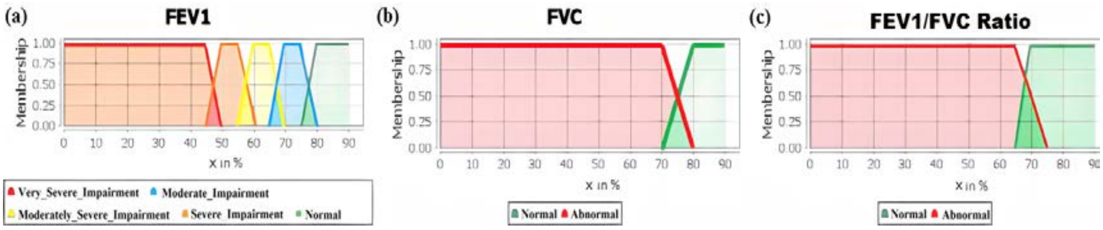

Fig. 3. Shows the fuzzy membership function for parameters of PFT block. (Source : Experts' guidelines)

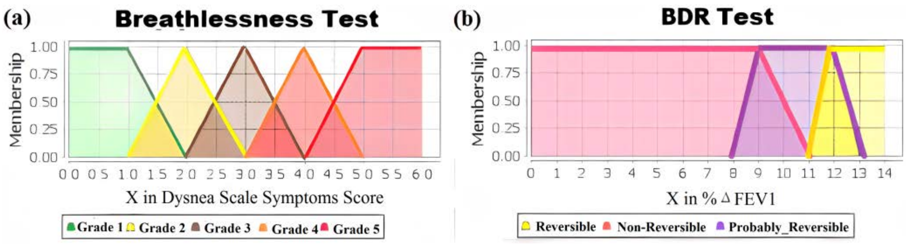

Fig. 4. Shows the fuzzy membership function for parameters of Breathlessness Test block and BDR block. (Source : Experts' guidelines)

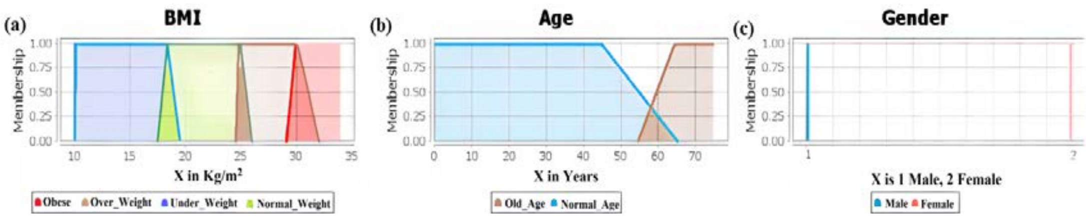

Fig. 5. Shows the fuzzy membership function for parameters of PHD block. (Source : Experts' guidelines)

5. Results and Discussion

Among the comprehensive dataset of 120 records, each meticulously documented with diagnostic and treatment recommendations by expert medical practitioners, an initial execution of the system yielded a notable outcome. Specifically, 112 records were found to be in line with both diagnostic and treatment directives as compared to the expert-assigned outcomes. Eight health records diverged from the expert's opinion, with four of them deviating at diagnostic stage itself and further four of them at subsequent combiner stage. 45 health records indicative of normal lung health were accurately classified throughout the diagnostic and treatment phases. For the subset of health records diagnosed with Chronic Obstructive Pulmonary Disease (COPD), encompassing 35 cases, the system demonstrated a strong performance. A total of 33 cases were correctly classified, while two cases were deemed as Mixed disease in their classification. The system's evaluation extended to 15 cases of asthma, achieving accuracy in 13 instances and noting a minor variance in two cases. Additionally, the system effectively identified 25 records associated with restrictive lung disease. In the combiner block, four records exhibited divergence, primarily attributed to the missing of specific criteria within the rule base. **Fig. 6** illustrates a visual representation of the dataset distribution for the examined parameters of FEV1, FVC, and FEV1/FVC ratio derived from the pulmonary function test and **Fig. 7** represents the numbers for the examined parameters of breathlessness test and bronco dilator reversibility test. This graphical depiction provides a distribution patterns and relationships within the dataset, aiding for analysis and interpretations of respective respiratory health indicators.

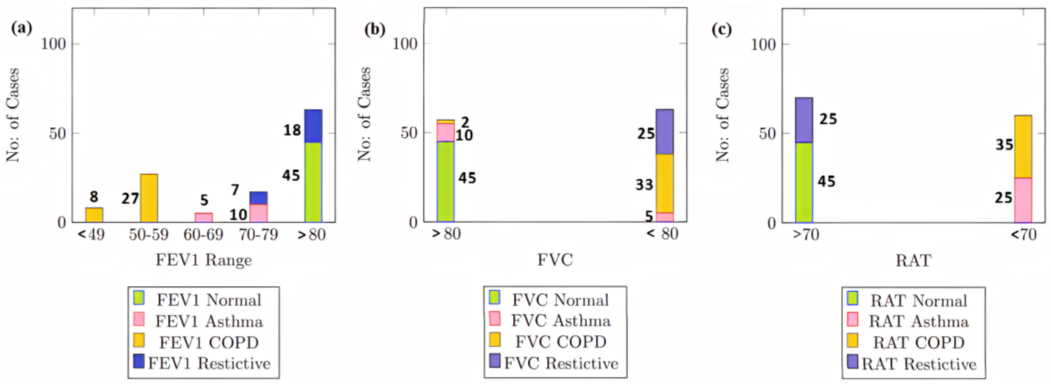

Fig. 6. Presents a visual representation of the dataset distribution of the examined pulmonary function test.(Source : Hospital database)

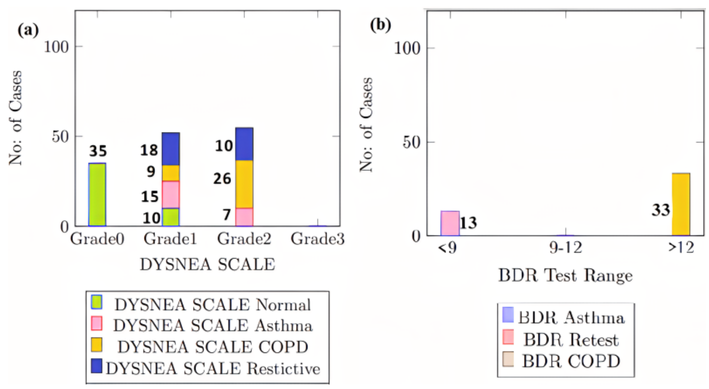

Fig. 7. Presents a visual representation of the dataset distribution of the examined Breathlessness Test and Bronco dilator Reversibility test. (Source : Hospital database)

5.1 Evaluating the Model

The assessment of proposed knowledge based recommender system can be observed in two ways [44].

1. Assessing the Accuracy of the Inference Mechanism: This involves examining how accurately the system's inference mechanism operates.
2. The completeness and structure of the knowledge base: This assessment focuses on the comprehensiveness and organization of the knowledge base. It ensures that the knowledge base contains all the necessary information and that the structure of this knowledge aligns with the requirements of the system.

We measure the performance of the system through precision, recall, and the F1 score [45] for each class of each block to check the correctness of the inference mechanism and identify any deviations. These metrics helps identifying specific issues, such as potential misalignment in defining the ranges of fuzzy sets or addressing cases where overlapping rules may be encountered.

For each class of a fuzzy block and collection of data set instances predicted for the class, determine the following:

True Positives (TP): The number of instances where the system identified true class and the expert predicted class match.

False Positives (FP): The number of instances where the expert predicted class is positive but the system identified true class is negative.

False Negatives (FN): The number of instances where the expert predicted class is negative but the system identified true class is positive.

Precision : Precision is measured for each class of the fuzzy block to assess the accuracy of classifying instances into a specific class. It is calculated as the ratio of true positives (instances correctly classified as belonging to the class in question) to the total instances predicted as that class, which includes both true positives and false positives.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}}$$

Recall : Recall is measured for each class of the fuzzy block to assess the system's ability to correctly classify all actual instances of a specific class. It is calculated as the ratio of true positives (instances correctly classified as belonging to the class) to the total instances that genuinely belong to that class, including true positives and false negatives

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

F1 score : The F1 score provides the harmonic mean of precision and recall. It combines precision and recall into a single metric that balances both aspects of classification performance.

$$\text{F1score} = \frac{2 ? \text{ Precision } ? \text{ Recall}}{\text{Precision - Recall}}$$

We calculate macro-averaged precision, recall, and F1 score to evaluate the overall performance of the fuzzy block across test dataset instances. For example, to compute macro-averaged precision, we calculate precision values individually for each class and then determine the mean of these precision values. Similarly macro-averaged recall and macro-averaged F1 score are computed.

$$\text{Precision}_{macroaverage} = \frac{1}{n}\sum_{i=1}^{n} \text{Precision}_i \quad ; \quad \text{Recall}_{aggregate} = \frac{1}{n}\sum_{i=1}^{n} \text{Recall}_i ;$$

$$\text{F1Score}_{macroaverage} = \frac{1}{n}\sum_{i=1}^{n} \text{F1Score}_i$$ 'n' represents number of classes in the block.

Average Precision is a classification metric used to gauge the model's ability to accurately rank the top-N classes from a set of chosen classes. In multi-class classification, it is utilized to assess how well a model ranks the true class within a list of possible classes for each instance. It plays a crucial role in calculating Top-N recommendation, a metric that quantifies the proportion of instances where the true classes align with the top-N recommended classes in a specific order. For example, if N is set to 1 (Top-1), it measures the correctness of the model's first choice. If N is set to 3 (Top-3), it measures the correctness of the model's top 3 choices. A higher Top-N accuracy indicates a better model, as it indicates the model's ability to rank the correct classes among the top choices in order.

Average Precision (AP): For each sample data instance, AP (Average Precision) is a measure of the quality of recommendations based on the selected classes ordered by activation strength. It evaluates whether relevant classes (correct recommendations) are ranked in the correct order within the list.

$$\text{AP} = \frac{\sum_{i=0}^{N} (\text{Pr}ecision@i * \text{Rel}(i))}{\text{N}}$$

For top N selected classes based on activation strength representing recommendations of fuzzy block. Precision @ i is computing the precision at i^{th} position in the ranked list is given by

$$Precision@i = \frac{\text{Number of relevent activated classes @ Top } i \text{ position}}{i}$$

Rel(i) is a binary indicator function that equals 1 if the class at position "i" is relevant and 0 otherwise. N is the total number of classes in the ground truth list.

Mean Average Precision (MAP): It is a comprehensive metric that sheds light on the overall performance of a fuzzy block in terms of the relevance of its inference mechanism. It evaluates the correctness of the top-N recommendations across entire data set instances, providing a crucial assessment of the system's recommendation capability.

$$MAP = \frac{1}{n} \sum_{i=0}^{n} AP_i$$

'n' is the number of instances of test data set related to the category.

In the PFT fuzzy block, initially configured with 15 distinct rule sets, each rule is allotted to a specific class for the inference mechanism. When the data set was processed in the block, 11 distinct classes were correctly activated and 2 classes were wrongly activated. Notably, among the test dataset health records, four instances exhibited deviations from expert expectations due to false-positive responses within two distinct classes, specifically C8 and C10. Among the three misfiring classes, the breakdown of performance metrics is as follows: Class C3 correctly classified 6 instances out of the total 7 test data mapped to it, leading to a class precision of 0.86. Class C5 achieved a 0.60 precision rate, with 2 misclassifications among the 5 instances classified. Class C6 demonstrated a 0.66 precision rate, encountering 1 failure out of 3 classified instances. The classes C8 and C10 exhibited 0 recall and F1score values as the result of wrong activations. Experts assessed two COPD cases, but the system erroneously activated class C8, categorizing them as mixed diseases. As a result, experts recommended the addition of further criteria for class C8 labeled as mixed, and this was subsequently incorporated into the system. Similarly, the system erroneously classified two instances from the dataset as mildly obstructive, with an incorrect activation of class C10, while experts had identified them as cases of asthma. The remaining classes showcased a success rate of 1. The macro-averaged precision of classes in the PFT fuzzy block is calculated to be 0.93. **Fig. 8** represents the performance metrics of the PFT fuzzy block in terms of precision, recall, and F1score. Other clinical parameter blocks, namely the breathlessness test block and the bronchodilator reversibility test block, are less complex in functional aspects and have a 100% success rate in classification. Similarly, the personal health data block, containing observable patient-specific data like age, gender, and BMI, also achieved a 100% success rate in its classifications.

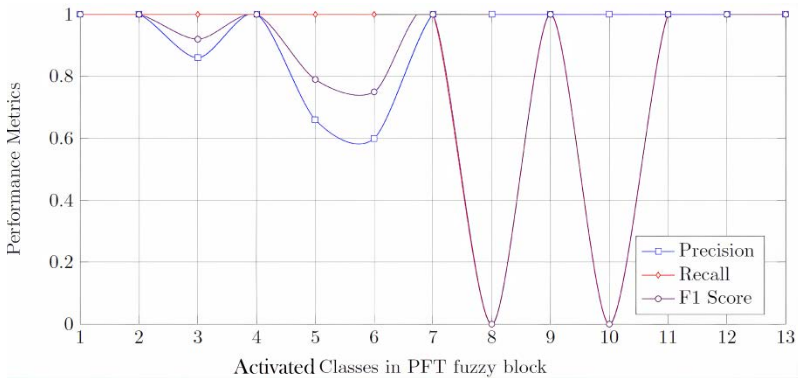

Fig. 8. Presents precision, recall and F1 score for each activated class of PFT fuzzy block for the given data set. (Source : Experts' evaluation)

We calculate the Average Precision (AP) for each instance in the dataset concerning the selected and ranked classes within the fuzzy block. This evaluation helps in assessing the top-N relevant diagnostic result recommendations offered by the fuzzy block. It can also assist in refining the structure of the knowledge base by adjusting fuzzy sets or formulating new rules to account for any missing diagnostic outcome criteria. Specifically, for the Pulmonary Function Test (PFT) block, we categorize the dataset into normal, obstructive, and restrictive outcomes. Our evaluation focuses on the precision of the top 2 recommendations within each of these three categories, and we subsequently calculate the mean precision across these categories. Calculating the mean of the average precision within each category offers valuable insights into the model's ability to provide accurate recommendations. In the dataset examined for obstructive conditions, four instances exhibited deviations from expert assessments. In these instances, the correct class was ranked second in the list based on the highest activation scores, leading to a reduced Average Precision (AP) and a resulting Mean Average Precision of 0.93. On the other hand, the other categories achieved a clean score of 1, indicating an accurate diagnosis. **Fig. 9** illustrates the system's performance in terms of MAP scores for lung conditions categorized as normal, obstructive, or restrictive in the PFT fuzzy block.

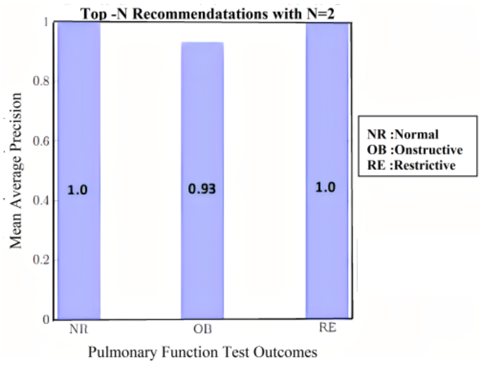

Fig. 9. Presents measure of Mean Average Precision for examined pulmonary function test outcomes.(Source : Experts' evaluation).

The rule bases within the combiner block are constructed from the combination of consequent parts derived from each connected fuzzy block. The creation of rules within the combiner rule base involves generating permutations and combinations of potential consequent parts originating from various fuzzy blocks. Drawing from expert knowledge and scrutinized health records, a total of 130 distinct rule sets were meticulously formulated to facilitate the combiner block's inference mechanism. Four instances of deviating records were identified, primarily attributed to missing criteria that resulted in erroneous judgments. Involving a total of 41 firing rules, the system achieved an impressive average class accuracy of 96%. Deviations in treatment recommendations within these records were traced back to patients presenting with additional health concerns. The resolution of these discrepancies hinges on the effective integration of those missing criteria. This could be effectively addressed through the introduction of an auxiliary block, which could provide valuable insights and alternative treatment options, aligning the expertise of actual physician experts. In the appendix section, **Table 10** and **Table 11** display selected records of patients for which the outcomes of discrete fuzzy blocks provide diagnostic results and a holistic diagnostic report with treatment recommendations realized by the fuzzy expert system.

5.2 Discussion

The strategy for implementation of the proposed model should be carried out incrementally. The initial setup of the system should involve configuring it with a defined set of primary criteria to yield coarse-grained options for clinical pathways as recommendations. This coarse-grained approach, broad in nature for providing decision support, provides an array of options that serve as valuable suggestions for decision support. Any disparities observed in the outcome recommendations can often be attributed to the absence of certain criteria within the system. By progressively integrating additional criteria for decision support and aligning them with an updated training set, the system can generate finer-grained recommendations. These refined suggestions are more precise, accurate, and intricately detailed. It's useful to conceptualize each criterion as a distinct fuzzy block within the proposed model.

It is important to note that, within a given fuzzy block, the configuration of rule sets is tailored to the relevant domain knowledge of experts and validated sample datasets. Tuning a fuzzy rule-based classifier is typically an iterative process, and it's crucial to strike a balance between over-fitting and under-fitting. The development process hinges on the assessment of the fitness value, which is derived from measuring the class strength within the training dataset. This evaluation subsequently contributes to the enhancement of overall accuracy. Modifying the configuration of a fuzzy block can be accomplished by refining the fuzzification process, achieved through the adjustment of the fuzzy range intervals of parameters. If required, a method of generating new rules can be employed to accommodate instances that have not been encountered before. This rule generation technique is implemented to ensure that these previously unseen instances align with the established fitness value threshold.

One of the challenges associated with the proposed model is its dependence on expert input, which raises the following concerns: the input may be partial, inconsistent, or biased, and it can be influenced by personal preferences that may deviate from accepted norms. Future work involves the integration of an evidence-based framework by incorporating examined health records to construct a knowledge-based structure and inference mechanism.

6. Conclusion

The proposed work devises a model for knowledge-based recommender systems based on fuzzy rule-based inference systems. The experimental results indicate a high degree of compliance between the expert physicians' diagnostics and treatment recommendations and the configured recommender system. The model could be developed as a reliable tool mimicking an expert physician's expertise. The main advantage of the proposed model is its adaptability, as it provides an easy way of configuring new criteria by adding new fuzzy blocks and also provides the facility to fine tune the existing system configurations to achieve the best results. Similarly, the proposed model can be configured for other diseases and treatments too. The model is generic in nature to provide decision support to address any other domain problems that fit into a similar scheme of things. Although the recommendations provided by the proposed model for decision support provided expected results and complied with the expert physician's analysis for the given basic lung disease under consideration, future work would involve configuring the system for complex diagnostics, which can involve multiple-class selections from a fuzzy block with scores of class activation strength playing a vital role in rule formation. It requires extensive expert support and a sufficient sample data set in the form of well-analyzed health records to model the system.

Appendix

Table 1. Shows parameters, linguistic label and interval values for PFT(Pulmonary Function Test) block. (Source : mMRC guidelines)

Parameters		**Param1**	**Param2**	**Param3**	**Param4**	**Param5**
FEV_1	Linguistic	Very severe impairment (VS)	Severe impairment (SI)	Moderately severe impairment(MS)	Moderate impairment(MI)	Normal(N)
	mMRC Range	< 49%	50% -59%	60% -69%	70% -79%	> 80%
	Fuzzy Interval	(0,1) (40,1) (49,0)	(45, 0) (50,1) (65,1) (69,0)	(55, 0) (60,1) (65,1) (69,0)	(65, 0) (70,1) (75,1) (80,0)	(75, 0) (80,1) (95,1)
FVC	Linguistic	FVC Abnormal(AN)	FVC Normal(NR)			
	mMRC Range	< 80%	>80%			
	Fuzzy Interval	(0, 1) (70,1) (90,0)	(70,0) (80,1) (90,1)			
RAT	Linguistic	Ratio Abnormal(AN)	Ratio Normal(NR)			
	mMRC Range	< 70%	>70%			
	Fuzzy Interval	(0, 1) (65, 1) (75,0)	(65,0) (70,1)(90,1)			

Table 2. Shows rule base for PFT Block. (Source : Experts' guidelines)

Rule #	Fuzzy Rule	Class Label	Diagnostic Description
#1	**If** *RAT* is normal **and** *FVC* is normal **and** FEV_1 is normal	C1	No Issues
#2	**If** FEV_1 is severe **or** very severe **and** *RAT* is abnormal **and** *FVC* is abnormal	C2	Obstructive lung disease, likelihood of COPD with mixed features.
#3	**If** FEV_1 is severe **or** very severe **and** *RAT* is abnormal	C3	Obstructive lung disease ,There is a possibility of COPD or asthma .
#4	**IF** FEV_1 **is** moderate **or** moderately severe **and** *RAT* is abnormal **and** *FVC* **is** normal.	C4	Obstructive lung disease ,there is a likelihood of asthma.
#5	**if** FEV_1 is moderately severe **and** ***FVC* is** abnormal **and** *RAT* **is** abnormal.	C5	Mixed abnormality
#6	**If** *FVC* is abnormal **and** *RAT* is normal	**C6**	Restrictive lung disease with moderate impairment
#7	**If** FEV_1 is moderate **or** moderately severe **and** *RAT* is abnormal	**C7**	Mild obstructive lung disease , other than asthma or COPD
#8	**If** FEV_1 is moderate **or** moderately severe **and** *FVC* is normal	**C7**	Mild obstructive lung disease , other than asthma or COPD

***** *Only minimal rules used for initial configuration.*

Table 3. Shows parameters, linguistic label and interval values for Breathlessness Test block. (Source : mMRC guidelines)

Parameters		Param1	Param2	Param3	Param4	Param5
Dyspnea Scale	Linguistic	Grade0	Grade1	Grade2	Grade3	Grade4
	Symptoms score Range	0-2	1-3	243	3-5	4-5
	Fuzzy Interval	(0, 1)(1,1)(2,0))	(1,0)(2,1)(3,0)	(2,0)(3,1)(4,0)	(3,0)(4,1)(5,0)	(4,0)(5,1)(6,1)

Table 4. Shows rule base for Breathlessness Test Block. (Source : Experts' guidelines)

Rule #	Fuzzy Rule	Class Label	Diagnostic Description
#1	**If** *Dyspnea Scale* is Grade 0	C1	Grade0-"I only get breathless with strenuous exercise
#2	**If** *Dyspnea Scale* is Grade 1	C2	Grade1-"I get short of breath when hurrying on the level or up a slight hill"
#3	**If** *Dyspnea Scale* is Grade2	C3	Grade2-"I walk slower than people of the same age on the level because of

			breathlessness or have to stop for breath when walking at my own pace on the level"
#4	**If** *Dyspnea Scale* is Grade 3	C4	Grade3-"I stop for breath after walking 100 yards or after a few minutes on the level"
#5	**If** *Dyspnea Scale* is Grade 4	C5	Grade4-" I am too breathless to leave the house"

Table 5. Shows parameters, linguistic label and interval values for BDR block. (Source : mMRC guidelines)

Parameters		**Param**1	**Param2**	**Param3**
ΔFEV	Linguistic	Non reversible (NRV)	Probably reversible (PRV)	Reversible (RV)
	mMRC Range	< 9%	9% -12%	> 12%
	Fuzzy Interval	(0, 1) (7, 1) (9,0)	(7,0) (9,1) (12,1)(13,0)	(11,0) (12,1) (14,1)

Table 6. Shows Rule Base for BDR Block. (Source : Experts' guidelines)

Rule #	**Fuzzy Rule**	**Class Label**	**Diagnostic Description**
#1	**If** ΔFEV is Non-reversible	C1	Identified COPD
#2	**If** ΔFEV is probably reversible	C2	Take Re-Test
#3	**If** ΔFEV is reversible	C3	Identified Asthma

Table 7. Shows parameters, linguistic label and interval values for PHD (Personal Health Data) block. (Source : mMRC guidelines, expert guidelines)

Parameters		**Param**1	**Param2**	**Param3**	**Param4**
BMI	Linguistic	Under weight(UW)	Normal weight(NW)	Over weight(OW)	Obese(OB)
	mMRC Range	>18.5	18.5-25	25-30	< 30
	Fuzzy Interval	(0, 1) (18.5, 1) (19.5,0)	(17.5,0) (18.5,1)(25,1)(26,0)	(24.5,0) (25,1)(30,1)(32,0)	(29,0) (30,1)(34,1)
Age	Linguistic	Normal Age(NA)	Old Age(OA)		
	Range	>65 years	< 65 years		
	Fuzzy Interval	(0, 1)(45, 1) (65,0)	(55,0) (65,1)(75,1)		
	Linguistic	Male(M)	Female(F)		
	Range	1	2		

Gender	Fuzzy Interval	(1, 1)	(2,1)		

Table 8. Shows Rule Base for PHD Block. (Source : Experts' guidelines)

Rule #	Fuzzy Rule	Class Label	Diagnostic Description
#1	**If** *age* is normal age **and** *BMI is* normal **and** *gender* is male or female	C1	Predictability of result 100 %
#2	**If** age is old age **and** *BMI is normal* **and** *gender* is male	C2	Predictability of result 95 %
#3	**If** *age* is old age **and** *BMI is* obese **and** *gender* is male or female	C3	Predictability of result 90 %
#4	**If** *age* is normal age **and** *BMI* is overweight **and** *gender* is male	C1	Predictability of result 100 %
#5	**If** *age* is normal age **and** *BMI* is overweight **and** *gender* is female	C2	Predictability of result 95 %
#6	**If** age is old age **and** *BMI is normal* **and** *gender* is *f*emale	**C3**	Predictability of result 90 %

** Only minimal rules used for initial configuration..*

Table 9. Shows rule base for Combiner Block. (Source : Experts' guidelines)

Rule #	Fuzzy Rule	Class Label	Diagnostic Description
#1	**If** B1.C1 **and** B2.C1	K1	No Issues
#2	**If** B1.C1 **and** B2.C2	K1	No Issues
#3	**If** B1.C2 **and** B2.C2	K2	Obstructive lung disease, likelihood of COPD with mixed features, with Grade 1 dyspnea scale take BDR test
#4	**If** B1.C3 **and** B2.C2	K3	Obstructive lung disease ,There is a possibility of COPD or asthma , with Grade 1 dyspnea scale take BDR test
#5	**If** B1.C4 **and** B2.C2	K4	Obstructive lung disease, there is a likelihood of asthma, with Grade 1 dyspnea scale take BDR test
#6	**If** B1.C5 **and** B2.C2	**K5**	Mixed abnormality, with Grade 1 dyspnea scale
#7	**If** B1.C6 **and** B2.C2	**K6**	Restrictive lung disease with moderate impairment, with Grade 1 dyspnea scale
#8	**If** B1.C7 **and** B2.C2	**K7**	Obstructive lung disease, other than asthma or COPD, with Grade 1 dyspnea scale,take BDR test
#9	**if** K2 **or** K3 and B3.C1	**M1**	Indentified COPD with Grade 1 dyspnea scale
#10	**if** K2 **or** K3 and B3.C2	**M2**	Probably reversible with Grade 1 dyspnea scale

#11	**If** K4 and B3.C3	**M3**	Indentified Asthma with Grade 1 dyspnea scale
#12	**If** K1	M4	Normal result
#13	**If** K5	M5	Mixed abnormality with Grade 1 dyspnea scale.
#14	**If** K6	M6	Restrictive lung disease with moderate impairment and Grade 1 dyspnea scale.
#15	**If** K7	M7	Mild obstructive lung disease possibly other than asthma / COPD and Grade 1 dyspnea scale.
#16	**if** M1 and B4.C1	**O1**	Indentified COPD with Grade 1 dyspnea scale, result predictability 100%. Recommend treatment process TP1.
#17	**if** M2 and B4.C1	**O2**	Probably reversible with Grade 1 dyspnea scalewith Grade 1 dyspnea scale, result predictability 95% Recommend treatment process TP2.
#18	**if** M3 and B4.C1	**O3**	Indentified Asthma with Grade 1 dyspnea scale scale, result predictability 100% Recommend treatment process TP3.
#19	**if** M4 and B4.C1	**O4**	Normal result. result predictability 100%. Recommend treatment process TP4
#20	**if** M5 and B4.C1	**O5**	Mixed abnormality with Grade 1 dyspnea scale. result predictability 100%. Recommend treatment process TP5.
#21	**if** M6 and B4.C1	**O6**	Restrictive lung disease with moderate impairment and Grade 1 dyspnea scale. result predictability 100%. Recommend treatment process TP6.
#22	**if** M7 and B4.C1	**O7**	Mild obstructive lung disease with Grade 1 dyspnea scale. result predictability 100% Recommend treatment process TP7.
#23	**if** M7 and B4.C2	**O4**	Normal result. result predictability 100%. Recommend treatment process TP4

*** *Only minimal rules used for initial configuration.***

Table 10. A sample representation of tests performed with developed fuzzy recommender system. (Source : System evaluation)

#	**PFT Block (B1)**			**BGR Block (B2)**	**BDR Block(B3)**	**Personal Health Data Block (B4)**			**B1**	**B2**	**B3**	**B4**	**Combiner (Fired Rules)**
P	FEV_1	FVC	Ratio	Dyspnea Scale	Δ FEV1	BMI	Age	Gen	C^{sel}	C^{sel}	C^{sel}	C^{sel}	$K^{sel}M^{sel}$, O^{sel}
#P 1	56%	67%	83%	2.5	-	18.8	36	1	C6	C2	-	C1	K6, M1, O6
	MS	AN	NR	Grade2	-	NW	NA	M					
	68%	84%	81%	2	-	22	43	2					

#P 2	MI	NR	AN	Grade1	-	NW	NA	F	C7	C2	-	C1	K7, M7, O7
#P 3	45%	69%	65%	2.5	5%	20	38	1	C2	C2	C1	C1	K2, M1, O1
	VS	AN	AN	Grade1	NRV	NW	NA	M					
#P 4	62%	93%	67%	2	11%	19	43	1	C4	C2	C3	C1	K4, M3, O3
	SM	NR	AN	Grade2	RV	NW	NA	M					
#P 5	53%	82%	65%	2.5	6%	20.4	31	1	C3	C2	C1	C1	K3, M1, O1
	SI	NR	AN	Grade2	NRV	NW	NA	M					
#P 6	86%	90%	96%	1.5	--	22	38	2	C1	C2	-	C1	K1, M4, O4
	NR	NR	NR	Grade1	-	NW	NA	F					
#P 7	68%	82%	83%	2	-	17	75	1	C7	C2	-	C3	K7, M7, O4
	MS	NR	NR	Grade2	-	UW	OA	M					
#P 8	49%	74%	66%	2.5	-	21	53	1	C5	C2	-	C1	K5,M5,O 5
	SI	AN	AN	Grade2	-	NW		M					
#P 9	72%	68%	105%	**2**	**--**	24.5	45	1	**C6**	**C2**	**-**	**C1**	K6, M6, O6
	MI	AN	NR	Grade2	**-**	**NW**	**NA**	M					
#P 10	78%	90%	86%	2.5	-	19	39	2	C1	C2	-	C1	K1, M4, O4
	NR	NR	NR	Grade2	-	NW	NA	F					

Table 11. Shows the diagnostics and treatment description for Table 15 results. (Source : Experts' evaluation)

P#	Diagnostics and Treatment Description	Experts Compliance
#P1	Restrictive lung disease with moderate impairment and Grade 1 dyspnea scale. result predictability 100% ; TP6	Yes
# P2	Mild obstructive lung disease with Grade 1 dyspnea scale. result predictability 100%. Recommend treatment process TP7.	Yes
#P3	Indentified COPD with Grade 1 dyspnea scale, result predictability 100%. Recommend treatment process TP1.	Yes, Further evaluation to check for Mixed
#P4	Indentified Asthma with Grade 1 dyspnea scale scale, result predictability 100% Recommend treatment process TP3.	Yes
#P5	Indentified COPD with Grade 1 dyspnea scale, result predictability 100%. Recommend treatment process TP1	Yes
#P6	Normal result. result predictability 100%. Recommend treatment process TP4	Yes
#P7	Normal result. result predictability 100%. Recommend treatment process TP4	Yes, Due to age factor results are

		mapped to normal
#P8	Indentified Asthma with Grade 1 dyspnea scale scale, result predictability 100%. Recommend treatment process TP3.	Yes
#P9	Restrictive lung disease with moderate impairment and Grade 1 dyspnea scale. result predictability 100%. Recommend treatment process TP6.	Yes
#P10	Normal result. result predictability 100%. Recommend treatment process TP4	Yes

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