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Fuzzy Logic based Diabetes Decision Support System

Salah-ud-din Khokhar*, Cheng-Chung Yang, Aaqib Inam***, Raeena Touqir****, M. Saleem Khan*******

**School of Intelligent Manufacturing and Control Engineering, Qilu Institute of Technology, Jinan, Shandong, 250200 China (sk16@qlit.edu.cn)*
***School of Intelligent Manufacturing and Control Engineering, Qilu Institute of Technology, Jinan, Shandong, 250200 China (younger@qlit.edu.cn)*
****School of Software Engineering, Xi'an Jiaotong University, Xi;an, Shaanxi, 710049 China (aaqib.inam@outlook.com)*
*****Department of Computer Science, G.C. University Lahore, Lahore, Punjab, 54000 Pakistan (raeena21@gmail.com)*
******Department of Computer Science, National College of Business Administration & Economics, Lahore, Punjab, Pakistan (mskgcu@yahoo.com)*

Abstract: In the medical field, where uncertainty and ambiguity are prevalent and patient numbers are continuously rising, there is a pressing need for an effective control system that can reduce vagueness and uncertainty for doctors while enhancing diagnostic accuracy. Medical tests play a crucial role for doctors in detecting diseases and determining their stages. In this research, the authors introduce a robust and efficient system proficient of handling various diabetic test inputs and delivering extremely reliable outputs for diagnosing health conditions and making decisions for treatment. Fuzzy logic has been selected for its simplicity in design and implementation, as well as its outstanding efficiency in handling uncertain and imprecise data. The fuzzy system uses data from medical test report as input parameters, and simulations are performed utilizing the MATLAB R2023b toolkit, with implementation completed in visual studio 2022 utilizing C# programming. The simulation outcomes closely match the designed values, with percentage errors falling within an adequate (< 9%) range, indicating the reliability of the model in improving diagnostic accuracy and treatment decision-making in diabetes management.

Keywords: Diabetes Control, Fuzzy Logic, Healthcare Sector, Percentage Error, Type-II Fuzzy Logic.

1. INTRODUCTION

Logic is a significant component in diverse scientific disciplines, precisely in the field of medical science. Fuzzy logic (FL), a kind of non-conventional logic, excels not only at recognizing ambiguity but also at controlling and measuring it in ways that surpass the capabilities of probabilistic logic. Instigating from the research of Lotfi A. Zadeh, FL is based on the concept of 'fuzzy sets' and is categorized by the absence of precise and clear limits. In place of binary false or true values, it operates with continuous values between the range of 0 and 1, which improves the representation of the knowledge. This flexibility permits FL to efficiently model human thought processes in scenarios that are incomplete, imprecise, and vague, making it essentially valuable in complex decision-making situations in the field of medical (Han et al., 2023; Mansour et al., 2023).

The procedure of FL can be broken down into three core phases: fuzzifier, defuzzifier, and inference engine. Fuzzifier and defuzzifier act as arbitrator procedures between the any FL system and the associated data to the phenomena being analyzed. In the fuzzifier phase, real arithmetical values are converted into linguistic values, permitting for a more instinctive representation of data. The inference engine then draws conclusions based on the defined rules in the rule-base, applying logical operations to the fuzzy inputs. Lastly, defuzzifier interprets these linguistic values back into arithmetical values, providing legitimate outputs that can be applied in decision-making procedures. This structured approach empowers FL systems to efficiently deal with ambiguity and uncertainty in diverse applications (Nadeem et al., 2024; Rehman et al., 2023).

Systems based on knowledge use inference structures that integrate FL to imitate capabilities of the human reasoning. This application of FL is predominantly beneficial in the field of medical, as it helps provide clear solutions to complex medical issues that are otherwise difficult to handle timely. Intelligent systems employing FL have transformed efficient and rapid diagnosis in the sector of healthcare, significantly assisting medical professionals in the treatment and prevention of diseases by efficiently evaluating criticality of the disease. With progression in the field of technology and medicine, the integration of Artificial Intelligence (AI) approaches in diagnostic procedures has become particularly crucial. These AI approaches produce enhanced outcomes swiftly, thereby improving the overall quality of patient care and facilitating timely interventions, even in the absence of doctors (Nguyen et al., 2023; Peng et al., 2020a).

FL approaches functional in medical analysis offer an effective technique for inexperienced professionals in the medical field, permitting them to diagnose diseases more accurately and swiftly. This technology is specifically beneficial for swiftly diagnosing common diseases in a safe and economical way.

FL stands out for its ability to cope uncertainty, providing rationally precise decisions that are extremely reliable for diverse circumstances. By employing approximate reasoning, FL guarantees stability, accuracy, consistency, and precision in outcomes. This is explicitly helpful for doctors or practitioners because it enhances the process of the disease diagnostic, assisting them to take accurate decisions regarding patient care and eventually improving the patient's health (Hadi et al., 2023; Zhao et al., 2024).

The procedure of decision-making in medical diagnoses is often challenging and complex due to the intrinsic uncertainty and ambiguity surrounding medical issues. This complexity stems from the fact that one symptom can specify several diseases, and one disease can manifest itself in various symptoms, complicating the duty of consultants. These days, medical practices become progressively intricate, the demand for FL approaches has increased expressively. AI approaches, primarily in the form of fuzzy systems, has emerged as a precious tool for the survival of any patient. These FL systems feign the procedure of human decision making utilizing the approximate reasoning and deliver precise solutions for complicated issues in the field of medical. The FL systems are particularly beneficial in the medical science field for addressing issues of imprecision, vagueness, and missing information of the inputs. Unlike orthodox mathematical procedures, FL systems suggest precise solutions by providing a rule-based problem-solving methodology. This procedure is crucial in the context of the medical field, where the requirement for precise and reliable decision-making is utmost (Inam et al., 2021; Demirak et al., 2022).

In the field of medical, where uncertainties and vagueness are predominant and patient numbers are on the rise, there is a serious requirement for an efficient control system. Such a system aims to decrease the uncertainties and vagueness tackled by medical practitioners, thereby improving the accuracy and quality of their diagnostic solutions. Medical tests play an essential role in this situation, as they are crucial for physicians or doctors not only in classifying diseases but also in defining their numerous phases. This emphasizes the significance of precise and reliable medical testing in the effective disease diagnosis, emphasizing the inevitability for systems that can support physicians or doctors in circumnavigating the difficulties of patient care (Gomes et al., 2024; Khokhar et al., 2023a).

2. LITERATURE REVIEW

(Wardana et al., 2020) presented a FL system for the early diabetes diagnosis and fortitude of calorie necessities using the Mamdani model. The experiments were conducted in association with Jombang Regional Hospital and analyzed the outcomes of the FL system with those of general practitioner utilizing data from 50 inpatient medical records. This methodology purposes to enhance initial detection and controlling of diabetes through easily available diagnostic tools. (Ahmed et al., 2022) presented techniques for detecting chronic kidney disease (CKD) utilizing FL and ANFIS, aiming to enhance the precision of medical diagnostics. The development of these systems takes into account various factors, including height, weight, age, blood pressure, smoking status, glucose levels, and nephron function. The output variable specifies the precise stage of the chronic disease, which ranges from stage-1 to stage-5. MATLAB toolkit was employed to develop both the FL and ANFIS, providing a robust platform for analysis. Diabetes is a significant health concern due to its potential complications if not treated timely and accurately. (Gupta et al., 2022) explored FL systems used in diagnosing numerous diseases, mainly in those areas where there is an inadequate doctor-to-patient ratio. These FL systems serve as important tools that support aid physicians and specialists in their diagnostic and decision-making procedures. The study highlights diverse FL systems implemented in healthcare sector for decision-making and observes their effectiveness in disease diagnostic process, thereby emphasizing the potential of fuzzy logic to bridge gaps in healthcare access and improve patient outcomes.

(Salehi et al., 2022) implemented an ANFIS to simulate a specific method, utilizing experimental data for model training and evaluation. The inputs for the model included factors such as adsorption time, particle size, dose of adsorbent, temperature, adsorbent milling time and stirring rate. The response variable selected for the model was triglyceride (TG) removal. A Sobol sensitivity analysis revealed that the cinnamon dose had the most significant impact on TG removal (71%), followed by the adsorbent milling time or particle size (15%). This highlights the importance of these parameters in optimizing the process for effective triglyceride removal. (Malaysha et al., 2022) introduced machine learning (ML) procedures aimed at categorizing and determining LDL-C stages by leveraging fortes heuristic information and historical data of the medical record. This investigation employs different kinds of ML procedures, including Artificial Neural Networks (ANNs), Decision Trees, FL, Recurrent Neural Networks (RNNs), Support Vector Machines (SVMs), Logistic Regression, and a hybrid method that merges ANNs with FL to improve precision. Various properties of FL systems play an important part in streamlining the procedures of therapeutic management and medical diagnosis. (Sai Vyshnavi et al., 2022) designed an evaluation tool using FL to evaluate jeopardy of cardiac issues for any individual patient. Dissimilar from current applications of the FL that emphasis on precise issues of cardiology, this tool delivers a more comprehensive approach. It considers numerous parameters of the input, including cholesterol levels, blood sugar level, blood pressure, and other interrelated factors. The purposed FL tool then produced outputs as a risk assessment for issues related to cardiology based on the parameters of the input, providing a comprehensive assessment that can assist professionals in the healthcare sector in classifying patients at risk and applying precautionary measures.

(Faradisa et al., 2023) developed a model that automatically controls values of the body-mass-index and its classes using fuzzy system, confirming optimal nutritious status. To measure fat-percentage and body-mass-index, the authors proposed numerous sensors for the measurement of the weight and height of any individual, and a keypad for data collection of an individual such as gender, activity level, age, and name. The proposed system features a database that streamlines simple and real-time storage of the data, authorizing straight accessibility to output, consequently improving user experience and efficiency in monitoring nutritional health. (Pattun et al., 2023) proposed a novel approach that assimilates ML with FL procedures for predicting risk of the diabetes. In their research, three diverse ML procedures were trained using clinical data to classify patients into diverse categories of the diabetes. The outcomes confirmed promising precision, with the polynomial regression algorithm attaining a score of 0.947. Conspicuously, the SVR algorithm utilizing the radial basis function (rbf) kernel outperformed the others, attaining a score of 0.954, while the linear kernel scored 0.73. This combination of ML and FL improves the predictive abilities for risk assessment of the diabetes. (Othman and Zeki, 2023) introduced a FL system explicitly developed for the treatment of the hypertriglyceridemia. The findings validate the efficiency of the system in supporting pharmacists and physicians with treatment decisions. The findings specify that the fuzzy system offers a trustworthy management process, with its decision-making meticulously aligning with standard procedures across numerous situations of the hypertriglyceridemia treatment.

(Ciklacandir and Isler, 2023) designed an input-weighted fuzzy system utilizing MATLAB to assist clinical staff in prioritizing clinicians' equipment renewal requirements. The system assimilates four major criteria technical service features, hospital features, financial features, and device features integrating 20 sub-criteria based on the inputs of the user. The system's performance was verified across five hospitals, including 50 authority decisions. The outcomes validated that the proposed system reliably associated with the procurement priorities recognized by field experts. Moreover, an investigation of variance test revealed no statistically substantial difference between the simulation outcomes and the decisions of the experts, emphasizing the validity and reliability of the fuzzy system. (Khokhar et al., 2024) presented an efficient and robust fuzzy system developed to handle numerous inputs from lipid profiles, providing vastly reliable outcomes for diagnosing lipid profile conditions and providing different options for treatment decisions. Fuzzy systems can capture the inherent uncertainties of human knowledge by using linguistics variables. This model aims to decrease ambiguity and uncertainty for the professionals working in the healthcare sector while improving diagnostic precision. Moreover, fuzzy systems validate resilience against potential disruptions within the system.

3. METHODOLOGY

The Diabetes Decision Support System (DDSS) is designed as a rule-based model that leverages FL to improve the management of the diabetes. It operates by examining two vital parameters of the input: the diabetic values of the pre-prandial and the post-prandial. By assessing these inputs, the DDSS evaluates and produce output as patient's diabetic condition, offering crucial intuitions into their medical status. This methodology facilitates an extra nuanced and precise assessment of diabetic condition of the patient, as it reflects the complicated relationship between post-prandial and pre-prandial glucose levels. Consequently, the DDSS offers valuable information for professionals working in the healthcare sector that can monitor treatment decisions and improve patient health, eventually leading to more effective diabetes management fuzzy system (Noor et al., 2019).

The proposed fuzzy model is planned around four core procedures: fuzzification, defuzzification, rule selection, and inference engine. In the fuzzification stage, membership functions (MFs) and sections are designed for every parameter of the input and output. This phase is central for converting actual arithmetical values into FL values that the model can process. Following, the inference engine (IE) applied the min-max inference technique, utilizing a min-AND method to produce rules. The IE is the model's decision-making core, where the fuzzy rules are utilized to the fuzzified inputs. In the rule selection stage, the fuzzy model receives crisp inputs and, based on the predefined algorithmic rules, delivers singleton values for the designed output within the fuzzy model. This stage is essential for choosing the applicable rules based on the input. Lastly, the defuzzification phase translates the output of the IE back into actual values. This is attained utilizing the center-of-average (C.O.A) procedure, calculated by the formula Σ Si * Ri / Σ Ri, where Si represents the value of the output and Ri is the membership degree. This last phase is vital for interpreting the fuzzy results back into actual outputs.

4. DESIGN ALGORITHM

In this research, the DDSS is explicitly developed to evaluate two types of inputs: post-prandial diabetics and pre-prandial diabetics. These inputs are essential in evaluating the diabetic condition of any patient, which is the output of the proposed model. The architecture of this fuzzy model includes different main components for fuzzification, an IE, a defuzzifier, a rule base, as shown in the Fig. 1. The functionality of the fuzzifiers are translating the arithmetic inputs into FL values that can be processed by the fuzzy model. The rule base comprises the set of fuzzy rules that define how the inputs will be translated. The IE then applies fuzzy rules to the fuzzified inputs to make a decision about the diabetic condition of the patient. Lastly, the defuzzifier translates the output of the IE back into an actual output. This systematic approach allows for a nuanced and effective analysis of diabetic data (Khokhar et al., 2023b).

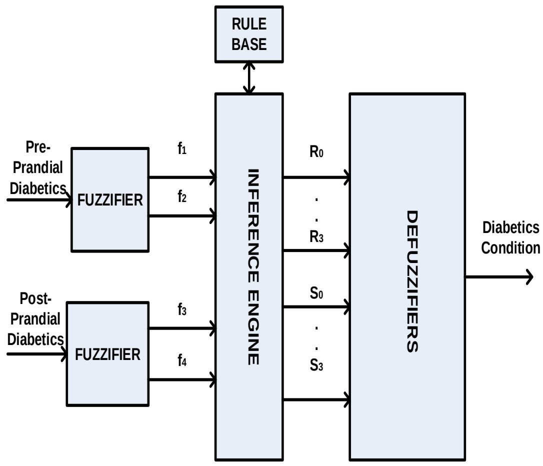

Fig. 1. System design of DDSS.

In the defined fuzzy model, which is designed to handle two precise parameters of the input, the MFs for "post-prandial diabetics" and "pre-prandial diabetics" are two basic components. The detail of these MFs is provided in the Table 1 and Table 2. These MFs are essential for translating the real-world, numerical values of pre-prandial and post-prandial diabetics into fuzzy values.

Table 1. Ranges and MFs of pre-prandial diabetic

Membership Function	Pre-Prandial Diabetics in mmol/L
Very Good	4.0 – 5.0
Good	4.0 – 6.0
Normal	5.0 – 7.0
High	6.0 – 8.0
Very High	7.0 – 8.0

Table 2. Ranges and MFs of post-prandial diabetic

Membership Function	Post-Prandial Diabetics in mmol/L
Excellent	7.0 – 7.5
Very Good	7.0 – 8.0
Good	7.5 – 8.5
Normal	8.0 – 9.0
Above Normal	8.5 – 9.5
High	9.0 – 10.0
Very High	9.5 – 10.0

In the given context, Fig. 2 and 3 provide graphical representations of the classification of MFs for the two input variables, "pre-prandial" and "post-prandial" respectively. These figures illustrate the specified five and seven MFs, along with their corresponding four and six sections for every input variable.

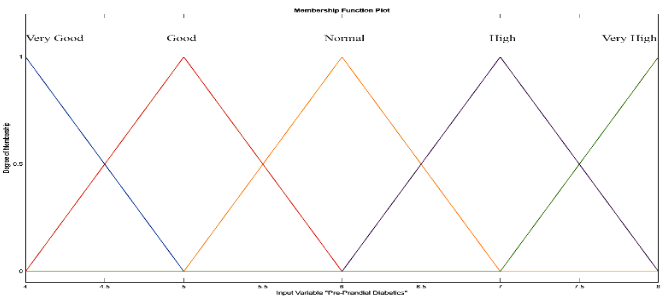

Fig. 2. MFs for pre-prandial diabetics.

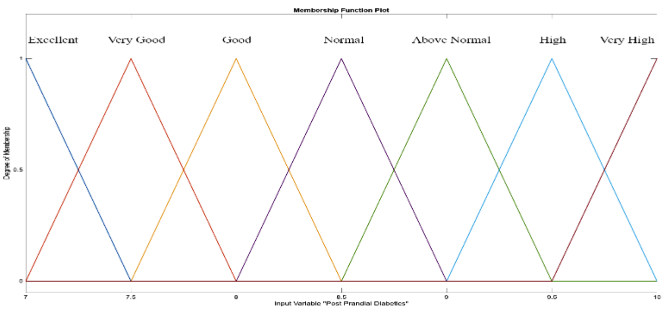

Fig. 3. MFs for post-prandial diabetics.

In the proposed DDSS, the output variable "diabetic condition" is characterized by six distinct MFs. These MFs are essential for translating the outcomes of the FL analysis. Table 3 likely details information about these MFs. Fig. 4 displays the plot of the MFs for the output parameter "diabetic condition." This plot is crucial as it visually represents how the DDSS interprets and categorizes the diabetic condition based on the FL analysis of the input data.

Table 3. MFs of diabetic condition

Diabetic Condition	Membership Function	Singleton Values
0 – 20	Critical	$S_0 = 0$
0 – 40	Worse	$S_1 = 0.2$
20 – 60	Above Normal	$S_2 = 0.4$
40 – 80	Normal	$S_3 = 0.6$
60 – 100	Good	$S_4 = 0.8$
80 – 100	Excellent	$S_5 = 1$

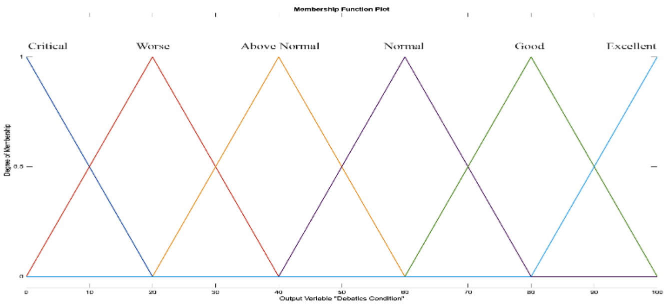

Fig. 4. MFs for diabetic condition.

4.1 Fuzzifier

The proposed model incorporates two fuzzy input parameters: pre-prandial diabetics and post-prandial diabetics. Each of these parameters is divided into distinct sections, with pre-prandial diabetics being categorized into four sections and post-prandial diabetics into six. For each input parameter, there are two linguistic values assigned. Specifically, pre-prandial diabetics is associated with linguistic values f_1 and f_2, while post-prandial diabetics corresponds to linguistic values f_3 and f_4. Table 4 likely provides detailed information about these linguistic values and how they are mapped using the MFs. This mapping is crucial for the fuzzification process, where real-world numerical data is converted into fuzzy values that can be processed by the FL system.

Table 4. Input variables mapping with sections for DDSS

Input Variables	Linguistic Variable Outputs	Section 1	Section 2	Section 3	Section 4	Section 5	Section 6
Pre-Prandial Diabetics	f_1	$f_1[1]$	$f_1[2]$	$f_1[3]$	$f_1[4]$		
	f_2	$f_1[2]$	$f_1[3]$	$f_1[4]$	$f_1[5]$		
Post-Prandial Diabetics	f_3	$f_2[1]$	$f_2[2]$	$f_2[3]$	$f_2[4]$	$f_2[5]$	$f_2[6]$
	f_4	$f_2[2]$	$f_2[3]$	$f_2[4]$	$f_2[5]$	$f_2[6]$	$f_2[7]$

In DDSS, each fuzzifier for the inputs is equipped with several components to process the input data accurately. These components include a multiplier, comparator, subtractor, multiplexer, divider, and an additional fuzzy set subtractor. The multiplier scales the input voltage to a crisp value. For pre-prandial diabetics, an input voltage of 0-5 volts is translated to a crisp value of 4.0-8.0, multiplied by 1. For post-prandial diabetics, the input voltage translates to a crisp value of 7.0-10.0, but is multiplied by 0.5. The comparator is used to define the section where the input variable value is placed. The subtractor is deployed to determine the changes in the crisp value from the preceding value in each section. The multiplexer selects the address of the reserved location and partial data from the four or six provided subtractors. It then multiplexes these four or six values because the DDSS is designed to pre-determine four sections for pre-prandial diabetics and six sections for post-prandial diabetics. The divider component separates the value of alteration for every designated section. For pre-prandial diabetics, it calculates the associated value in that section by dividing the change value by 1. For post-prandial diabetics, the process involves dividing the change value in each selected section by 0.5 to find the membership function input. An additional fuzzy subtractor is used to ascertain the active value by deducting the initial active value of the fuzzy set from 1 to obtain another value (Khokhar et al., 2023c; Inam et al., 2023). Figs. 5 and 6 illustrate the internal circuitry of these fuzzifiers, showcasing the various components involved in data input, processing, and output.

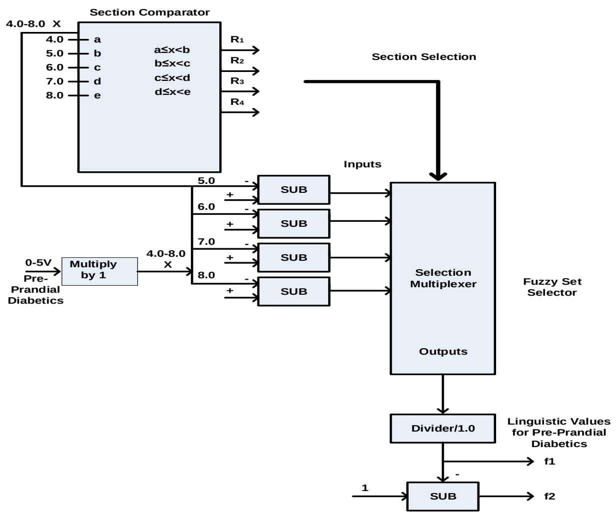

Fig. 5. Interior architecture of pre-prandial diabetics fuzzifier.

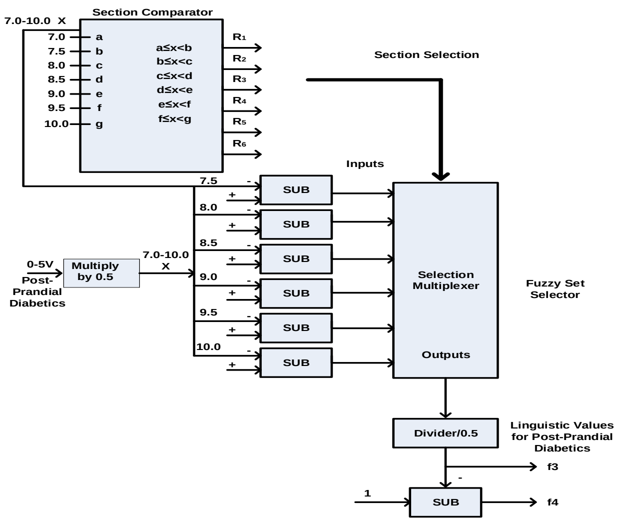

Fig. 6. Interior architecture of post-prandial diabetics fuzzifier.

4.2 Inference Engine for DDSS

The IE in the DDSS plays an essential part in the fuzzy model's decision-making process. The IE is equipped with four AND operators, which perform in a different way from conventional AND operators. In this situation, the AND operators are designed to choose the smallest value from the fuzzy inputs they accept. The fuzzifiers delivers four fuzzy values to IE. These fuzzy values derived from the preliminary raw data of post-prandial diabetics and pre-prandial diabetics. This procedure contains assessing the inputs based on the fuzzy rules and then defining the smallest value of these inputs. After the min-max assessment, the IE produces outputs, denoted as 'R'. The unique methodology of utilizing the smallest value selection by the AND operators, rather than conventional logical combination, permits for appropriate management of the fuzzy values. The min-max inference method employs a min-AND approach with four inputs, as illustrated in Fig. 7.

$$R_0 = f_1 \wedge f_3 = f_1[1] \wedge f_2[1]$$
$$R_1 = f_1 \wedge f_4 = f_1[1] \wedge f_2[2]$$
$$R_2 = f_2 \wedge f_3 = f_1[2] \wedge f_2[1]$$
$$R_3 = f_2 \wedge f_4 = f_1[2] \wedge f_2[2]$$

In this method, the symbol ^ is used to represent the min-AND operation between MF values. This approach results in obtaining the lowest values via the min-AND function.

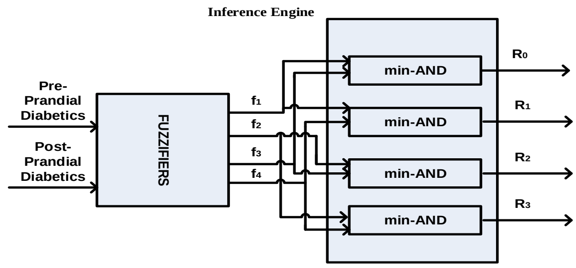

Fig. 7. Inference engine of DDSS.

4.3 Rule base for DDSS

The rule base in the DDSS acquires two distinct values labeled as pre-prandial diabetics and post-prandial diabetics. When the specifically crafted algorithm rules are applied to the model, they yield single values for the output functions. To determine the corresponding values S_0, S_1, S_2, and S_3, which relate to the divided sections, four fuzzy rules are essential for the two input variables. These mandatory rules are displayed in Table 5.

Table 5. Rules for DDSS

Rule No.	Pre-Prandial Diabetics	Post-Prandial Diabetics	Singleton Values	Diabetic Condition
1	Good	Above Normal	S_0	Normal
2	Good	High	S_1	Above Normal
3	Normal	Above Normal	S_2	Normal
4	Normal	High	S_3	Above Normal

The rule block accepts four crisp values of the input, distributes the treatise into the sections where every single section compels two fuzzy variables, fire the rules, and provides the crisp output. Fig. 8 shows the block diagram of rule base.

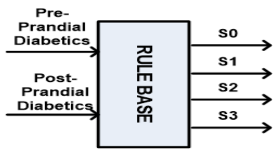

Fig. 8. Block diagram of rule base.

4.4 De-Fuzzifier

The DDSS is designed to assess the diabetic condition of a patient. It stands out for its adaptability and efficiency in conserving energy, time, and reducing the need for medical experts' involvement in diagnosing and managing the patient's diabetic health status. The system processes its inputs and, through defuzzification, produces distinct output values. In this setup, the defuzzifier handles eight inputs. The inference engine generates four output values, R_0, R_1, R_2, and R_3, while the rule base produces another set of four output values, S_0, S_1, S_2, and S_3. To calculate crisp output values, the system employs the C.O.A process, using the formula (Σ Si * Ri / Σ Ri), where i ranges from 0 to 3 (Sohaib et al., 2023). Fig. 9 shows the internal architecture of defuzzufier block.

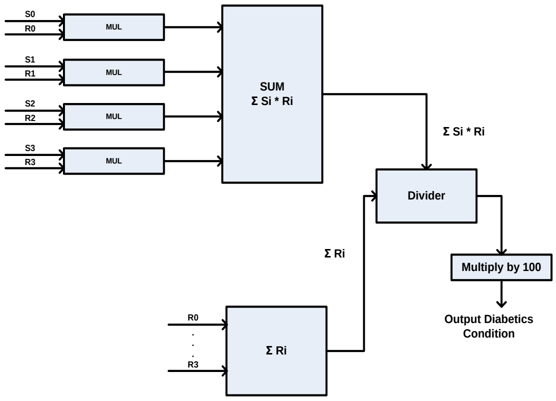

Fig. 9. Defuzzifier block for DDSS.

5. DESIGN VALUES CALCULATIONS

Design values for the DDSS are determined based on preset assumptions. In particular, the calculated design values for the DDSS are thoroughly explored. Assumptions were made for the two input variables, pre-prandial diabetics and post-prandial diabetics. Based on these assumptions, the diabetic condition of the patient was calculated.

Assumed Values:

1. Pre-Prandial Diabetics = 5.1 mmol/L
2. Post-Prandial Diabetics = 9.2 mmol/L

Calculation of f_1, f_2, f_3, and f_4 is given in Table 6.

Table 6. Evaluation of Fuzzy sets for DDSS

Input Values	Section Selection	Fussy Set Evaluation
5.1 Pre-Prandial Diabetics	5.0 <= x < 6.0 Section 1	f_1= (6.0 - 5.1) / 1.0 = 0.9 f_2 = 1- f_1 = 1 - 0.9 = 0.1
9.2 Post-Prandial Diabetics	9.0 <= x < 9.5 Section 4	f_3 = (9.5 - 9.2) / 0.5 = 0.6 f_4 = 1 - f_3=1 - 0.6 = 0.4

Rules are formulated as given below:

R_0= f_1 ^ f_3 = 0.9 ^ 0.6 = 0.6
R_1= f_1 ^ f_4 = 0.9 ^ 0.4 = 0.4
R_2= f_2 ^ f_3 = 0.1 ^ 0.6 = 0.1
R_3= f_2 ^ f_4 = 0.1 ^ 0.4 = 0.1

The assumed value for pre-prandial diabetics falls within section 2, which encompasses two linguistic values, f_1 and f_2, associated with the MFs labeled as "Good" and "Normal". Similarly, the assumed value for post-prandial diabetics is situated in section 5, featuring two linguistic values, f_3 and f_4, linked to MFs "Above Normal" and "High". The potential rules applicable to these chosen values have been previously detailed and are displayed in Table 7.

S_0 = 60 / 100 = 0.6
S_1 = 40 / 100 = 0.4
S_2 = 60 / 100 = 0.6
S_3 = 40 / 100 = 0.4

Now, calculate the S_i x R_i where i = 0 to 3

S_0 x R_0 = 0.6 x 0.6 = 0.36
S_1 x R_1 = 0.4 x 0.4 = 0.16
S_2 x R_2 = 0.6 x 0.1 = 0.06
S_3 x R_3 = 0.4 x 0.1 = 0.04

To find Σ S_i x R_i, sum up all the values of S_i x R_i, which equals 0.62. Then, calculate the sum of ΣR_i by aggregating all the values of R_i, resulting in a total of 1.2. The output value is determined using the formula (Σ S_i x R_i) / ΣR_i x 100. Consequently, the crisp value of the defuzzifier for the diabetic condition is 51.66.

6. RESULTS OF MATLAB SIMULATIONS

MATLAB simulations were carried out using the MATLAB R2023b toolbox. These simulations pertain to the DDSS. To compute the output, the rule viewer editor in MATLAB is employed to graphically display the fuzzy rules. Essentially, this represents the detailed approach to determining fuzzy output. The testing of the algorithm was verified through the rule-viewer, which allows for the observation of the fuzzy rules in relation to the crisp value. For this purpose, input values are assigned to the two input variables: pre-prandial diabetics at 5.1, and post-prandial diabetics at 9.2. The formula ΣS_i * R_i / ΣR_i is then used to calculate and generate crisp values for the output variable (Peng et al., 2020b), which in this case is the diabetics condition, quantified as 51.6, as illustrated in Fig. 10.

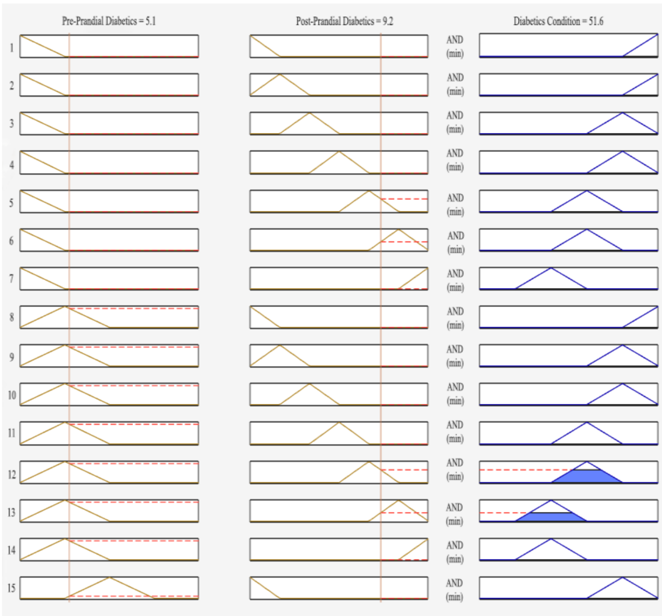

Fig. 10. Rule viewer of DDSS.

The surface viewer provides a comprehensive 3D graphical representation that effectively illustrates the relationship between input values and diabetic conditions, which is crucial for understanding how various factors influence diabetes management and patient outcomes. As demonstrated in Fig.

11, the analysis reveals that the diabetic condition remains relatively stable across most ranges of the MFs as the pre-prandial diabetic value increases. This stability suggests that, within certain thresholds, increments in pre-prandial glucose levels do not significantly alter the overall diabetic status, indicating a certain level of metabolic compensation or resilience in the body's response. In contrast, the diabetic condition exhibits notable variability when the post-prandial diabetic value increases, affecting all ranges of the MFs.

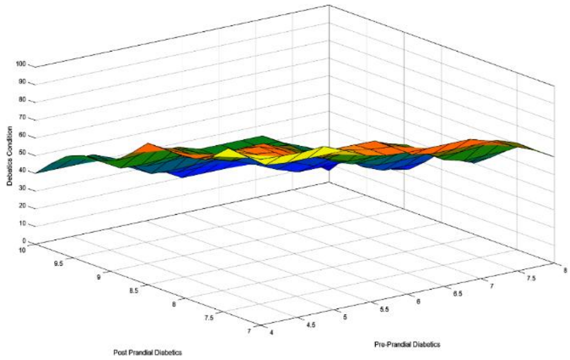

Fig. 11. 3D graph between pre-prandial diabetics, post-prandial diabetics, and diabetic condition.

7. IMPLEMENTATION

The DDSS structures an instinctive graphical user interface, developed using the C# programming language within the framework of the visual studio 2022. The GUI is designed to be user-friendly, enabling seamless interaction with the fuzzy logic backend and providing real-time data processing and visualization capabilities. This system efficiently signifies a FL technique, which improves system's competence to knob imprecision and uncertainty in the diabetes control. Specific classes have been precisely planned for the DDSS, with every class integrating methods that simplify an array of processes crucial for operative decision support system. These processes comprise selecting relevant sections, identifying MFs, performing fuzzification, generating the inference engine, formulating rules, defuzzifying outcomes, and providing output as diabetics condition. To certify the precision of the input values inside the DDSS, vigorous conditional statements and mechanisms of exception handling have been executed at the form level. This confirms that the inputs from the user are authenticated and any anomalies are handled appropriately, thus improving the usability and reliability of the proposed DDSS in medical environment (Peng and Noor) 2023). Fig. 12 shows the graphical user interface of the DDSS.

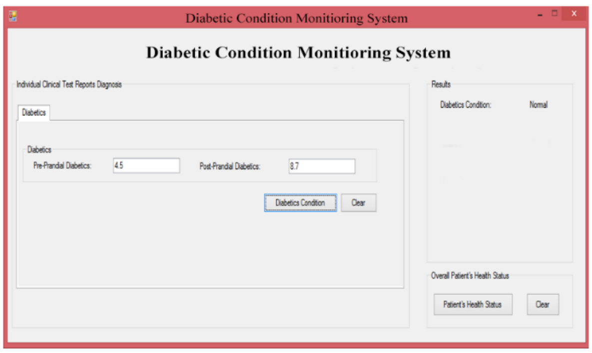

Fig. 12. Graphical user interface of DDSS.

8. OUTCOMES AND DISCUSSIONS

The simulation outcomes and the design algorithm are essentially consistent, presenting a high degree of similarity, and the percentage error generated by MATLAB software is in an adequate range. The outcomes specify that the proposed DDSS is efficient and operative. The proposed DDSS, efficaciously meets the objectives of observing the diabetic condition of any patient. It allows specialists to take exact measures to control the diabetics' condition of any patient, specifically in circumstances where the signs are critical or worse.

The dataset has been presented and used to regulate the proposed DDSS outcomes for every set of given values. An inclusive comparative analysis was conducted among the calculated design values and the simulated values produced by DDSS using different input values. To quantify the variance between these two sets of values, the percentage error was computed, offering a clear metric for assessment. This analysis is essential for assessing the precision and performance of the DDSS in predicting and handling diabetic conditions. Table 7 specifically presents the dataset used for the type-I DDSS, describing the input values and corresponding outcomes, which serves as a foundation for understanding the discrepancies observed and the overall efficacy of the type-I DDSS.

The proposed DDSS demonstrates high robustness in handling uncertainties and variations in input data. Fuzzy logic's inherent ability to manage imprecise and ambiguous data ensures that the system remains reliable even when input values deviate from expected ranges. A sensitivity analysis revealed that the system's outputs remain stable across a wide range of input values with percentage errors below 9% validating its robustness. This feature make the DDSS a reliable tool for diabetes diagnosis and management in real-world medical settings.

Table 7. Different scenarios of type-I DDSS

Sr. No.	Input Values		Output Values		
	Pre-Prandial Diabetics	Post-Prandial Diabetics	Designed Value	Simulated Value	Percentage Error
1.	4.5	8.7	64.44	70	7.942
2.	5	9	60	60	0
3.	5.6	8.9	60	60	0
4.	4.9	8.1	76.66	75.2	1.941
5.	4.8	8.9	62.86	64.8	2.994
6.	5.7	9.3	48.75	48.4	0.723
7.	4.6	8.3	64.4	68.4	5.789
8.	5.5	8.6	60	60	0
9.	5.1	9.2	51.66	51.6	0.116
10.	4.2	9.4	60	55.2	8.696

The deployment of the proposed FL based DDSS in healthcare settings raises important ethical considerations, including bias, data privacy, informed consent, and accountability. To address these concerns, authors recommend implementing robust data security measures, ensuring the use of diverse and representative datasets, and maintaining transparency in the system's decision-making process. Additionally, healthcare professionals should be trained to utilize the FL based DDSS as a supportive tool, with clear accountability mechanisms. These steps will ensure that the DDSS is implemented responsibly and align with ethical standards in healthcare.

The authors also simulated and implemented the proposed system using the type-II DDSS, and its accuracy was almost identical to that of the type-I DDSS for ten different scenarios. Fig. 13 shows the relative errors (%) comparison of the simulation results with respect to the designed output value. It is clear that the maximum relative error (%) of the DDSS is ~ 8% but still, it is in the range of commercially available component tolerances. The average relative error of all the scenarios implemented in the proposed DDSS is ~ 0.525% in type-1 DDSS and ~ 0.758% in type-II DDSS which indicates the accuracy of the proposed fuzzy model in the real-time scenario.

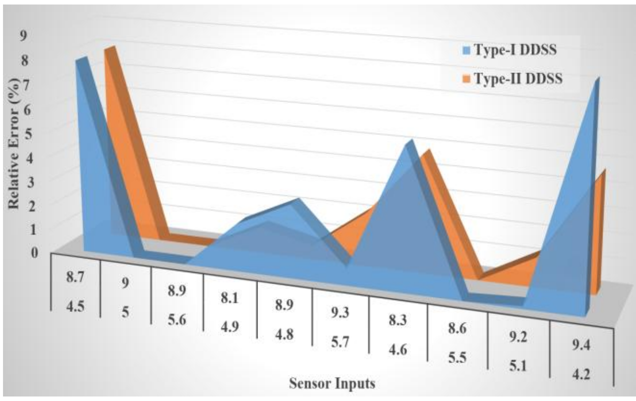

Fig. 13. Relative error comparison of type-I and type II DDSS.

Table 8 compares mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean square error (RMSE) for the type-I and type-II DDSS. Undoubtedly the proposed type-II DDSS performs better than type-I DDSS but there is not much difference between type-I and type-II DDSS which will not affect the accuracy and stability of the proposed DDSS. The proposed system can be used as a fuzzy system modelling tool in any industry.

Table 8. Comparison of different types of DDSS

Model Type	RMSE	MAE	MAPE
Type-I DDSS	2.756	1.813	2.820
Type-II DDSS	2.262	1.441	2.255

The accuracy of the results demonstrates the synergy of the processing system utilizing the simplified design model of the FL system. A comparison of the proposed DDSS with numerous FL systems accessible in the literature is shown in Table 9. The table explains the difference of the percentage error which is related to the performance metrics of the DDSS in association with other published fuzzy systems. Conspicuously, the studies referenced in Refs. (Peng et al., 2020a; Khokhar et al., 2023a; Noor et al., 2019; Khokhar et al., 2024) validate that the authors established their systems using two, three, and four input sensors which are closely related to the proposed DDSS. In comparison, the DDSS integrates a more inclusive methodology, using input variables, which expressively improves the performance of the DDSS. The outcomes evidently specify that the DDSS outperforms these other fuzzy systems, showing its higher capability in efficiently handling and observing diabetic conditions of any patient. This comparison emphasizes the improvements made by the proposed DDSS in the jurisdiction of FL applications for diabetes observation.

Table 9. Comparison of various models

	No. of Input Sensors	Designed Value	Percentage Error
Peng et al (2020a)	2	35.32	3.52
Khokhar et al (2023a)	3	56.06	1.2
Khokhar et al (2024)	2	37.53	4.3
Noor et al (2019)	4	37.5	1.8
This Work	2	58	**0.116**

A comparative analysis have conducted between the proposed FL based DDSS, and artificial intelligence based methods (decision trees and neural networks). The FL based DDSS achieves comparable accuracy to machine learning models while offering greater interpretability and robustness in handling uncertain or incomplete data. However, machine learning models may outperform FL in scenarios with large, well-labeled dataset. The outcomes presented in Table 10, provide a broader perspective on the strengths and limitations of the FL approach.

Table 10. Comparison with AI methods

References	Model	Percentage Error
Yadav A. et al (2023)	Guassian Process Regression + Bayesian Approach	0.15
Phyo P.P and Jeenanunta C. (2021)	Regression Tree + Deep Belief Network	3.25
Cruz J.C. et al (2023)	Decision Trees	0.69
Aydin N. et al (2022)	ANN + Decision Trees	9.08
This Work	Mamdani Model	**0.116**

To assess the long-term impact of the DDSS on patient outcomes, authors propose conducting longitudinal studies that span several years. These studies will evaluate key outcomes measures, such as glycemic control, complication rates, and quality of life, in diverse patient populations. By comparing outcomes between patients using the DDSS and those outcomes between patients using the DDSS and those receiving standard care, authors aim to provide robust evidence of the system's effectiveness in improving diabetes management over time. Addressing challenges such as data collection, patient retention, and ethical considerations will be critical to the success of these studies.

Inaccurate, incomplete, or inconsistent data can lead to erroneous outputs from the DDSS. Factors such as missing patient records, erroneous entries, or sensor inaccuracies can significantly affect performance. Implementing rigorous data collection protocols and ensuring regular updates to patient records can improve data quality. Utilizing real-time monitoring technologies, such as continuous glucose monitors, can also enhance data accuracy and completeness.

The FL model is built on certain assumptions about the relationships between variables. If these assumptions do not accurately reflect real-world complexities rigorous data collection protocols and ensuring regular updates to patient records can improve data quality. Utilizing real-time monitoring technologies, such as continuous glucose monitors, can also enhance data accuracy and completeness.

The inherent limitations of the FL method, including difficulties in capturing non-linear relationships and the subjective nature of fuzzy rules, can also contribute to errors. Regular validation of the DDSS against real-world outcomes can help identify discrepancies and refine the model. Engaging clinical experts in the review process can provide insights into adjusting assumptions and enhancing rule sets.

9. CONCLUSIONS

The DDSS utilizing FL has been proposed, efficiently simulated, and implemented, designing a substantial improvement in diabetes controlling technology. This study validates the prospective of trailblazing technology to improve the diagnosis of diabetic conditions of any patient through a refined FL system. By leveraging the principles of FL, the proposed DDSS can manage the intrinsic complexities and uncertainties allied with diabetes, permitting for extra nuanced assessments of a patient's health status.

In line with predefined rules and methods, the fuzzy system is proficient at accurately and efficiently observing numerous features of the patient’s diabetic condition, including dietary intake, blood glucose levels, and physical activity. This proficiency permits healthcare providers to increase an inclusive considerate of every patient's unique condition, enabling personalized treatment strategies tailored to individual requirements.

Furthermore, the proposed DDSS presents a straightforward, effective, and precise solution for both practitioners and patients. For patients, it streamlines the procedure of following their health status, authorizing them to take a vigorous part in dealing with their diabetes. For healthcare practitioners, the DDSS improves decision-making procedures, providing most suitable understandings that can lead to superior patient care.

In future, the proposed DDSS could emphasis on creating it more generalized and versatile. By integrating further clinical tests, the proposed system can be extended to offer an extra inclusive evaluation of the health status of the patient. This sophisticated fuzzy system would use micro-controller technology based on field-programmable gate arrays (FPGAs), empowering further vibrant and receptive health monitoring abilities.

While the simulation results demonstrate the effectiveness of the proposed DDSS, future work will focus on validating the system through real-world testing and clinical trials. This will involve collaborating with healthcare institutions to test the system with real patient data and evaluate its performance in actual medical settings. Special attention will be given to ensuring data privacy and ethical compliance, as well as adapting the system to handle the complexities of real-world data. Testing with diverse patient populations will further validate the system's generalizability and reliability, paving the way for its integration into routine medical practice.

The proposed DDSS is currently designed for Type 2 diabetes, focusing on pre-prandial and post-prandial glucose levels as key input parameters. However, the system’s modular architecture allows for future adaptation to Type 1 diabetes by incorporating additional parameters, such as insulin dosage and carbohydrate challenges of Type 1 diabetes management. Demonstrating the system’s generalizability across different diabetic conditions will enhance its utility and broaden its applicability in clinical practice. The modular design of the DDSS allows for easy adaptation to different diabetic conditions, making it a versatile tool for healthcare professionals.

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REFERENCES

Ahmed, T.I., Bhola, J., Shabaz, M., Singla, J., Rakhra, M., More, S. and Samori, I.A. (2022). Fuzzy logic-based systems for the diagnosis of chronic kidney disease. *BioMed Research International*, pp. 1-15.

Aydin, N., Sahin, N,. Deveci, M. and Pamucar, D. (2022). Prediction of financial distress of companies with artificial neural networks and decision trees models. *Machine Learning with Applications*, 10, 100432.

Ciklacandir, S. and Isler, Y. (2023). Priority assessment of procuring medical equipment in Turkish hospitals using input-weighted fuzzy logic architecture. *Expert Systems with Applications*, 213, p.119195.

Demirak, S., Meryem, S. and Canpolat, E. (2022). Plant-based bioinsecticides for mosquito control: Impact on insecticide resistance and disease transmission. *Insects*, 13(2), p. 162.

Faradisa, I.S., Muhammad, R.P. and Girindraswari, D.A. (2023). A design of body mass index (BMI) and body fat percentage device using fuzzy logic. *Indonesian Journal of Electronics, Electromedical Engineering, and Medical Informatics*, 4(2), 94-106.

Gomes A. D. O. and Basilio, J. C. (2024). A fuzzy inference model to identify the current industry maturity stage in the transformation process to industry 4.0. *IEEE Trans. Automat. Sci. Eng.*, 21(2), 1607 1622.

Gupta, N., Singh, H. and Singla, J. (2022). Fuzzy logic-based systems for medical diagnosis–A review. *In 2022 3rd International Conference on Electronics and Sustainable Communication Systems (ICESC)*, 1058-1062. IEEE.

Hadi, M.H., Ker, P.J., Lee, H.J., Leong, Y.S., Thiviyanathan, V.A., Hannan, M.A., Jamaludin, M.Z. and Mahdi, M.A. (2023). Measuring color index of transformer oil–enabling single-wavelength spectroscopy with artificial neural network-fuzzy logic model. *IEEE Transactions on Automation Science and Engineering*, *21*(2), 1358-1368.

Han, M., Guo, G., Lam, H.-K., Han, B., and Wang, Z. (2023). Event-triggered positive filter design for positive polynomial fuzzy systems via premise integration and membership-function-dependent methods. *IEEE Trans. Fuzzy Syst.*, 31(11), 3799–3811.

Inam, A., Sarwar, A., Atta, A., Naaseer, I., Siddiqui, S.Y. and Khan, M.A. (2021). Detection of COVID-19 Enhanced by a Deep Extreme Learning Machine. *Intelligent Automation & Soft Computing*, *27*(3), 701-712.

Inam, A., Li, Z., Zafar, Z. and Imran, M. (2023). Energy Efficient and Intelligent Mosquito Repellent Fuzzy Control System. *Computers, Materials & Continua*, *77*(1), 699-715.

J. C. Cruz, D. Q. Oliveira, F. L. Albuquerque Neto and L. T. d. A. do Monte, (2023). Analysis of a wind speed prediction model based on decision trees, *2023 Workshop on Communication Networks and Power Systems (WCNPS)*, pp. 1-7. IEEE.

Khokhar, S.U.D., Peng, Q. and Noor, M.Y. (2023a). 2 in 1 humidifier+air purifier fuzzy control system. *Journal of Uncertain Systems*, *16*(02), p.2250015.

Khokhar S.U.D, (2023b). Use of augmented output membership functions to improve control accuracy of second-order fuzzy system, *Engineering Applications of Artificial Intelligence*, 126 Part A, p. 106711.

Khokhar, S.U.D. and Peng, Q. (2023c). Utilizing enhanced membership functions to improve the accuracy of a multi-inputs and single-output fuzzy system. *Applied Intelligence*, *53*(7), 7818-7832.

Khokhar, S.U.D., Nadeem, A., Rizvi, A.A., Tanveer, M., Inam, A., Touqir, R. and Khan, M.S. (2024). Fuzzy logic based Lipid profile control system. In *International Conference on Intelligent and Fuzzy Systems,* 444-455. Cham: Springer Nature Switzerland.

Malaysha, S., Awad, M. and Hadrob, R. (2022). Classification and prediction of low-density lipoprotein cholesterol LDL-C in The palestinian patients using machine learning techniques. *International Journal of Intelligent Engineering & Systems*, 15(1), 453-463.

Mansour, R. F., Alhumyani, H., Khalek, S. A., Saeed, R. A. and Gupta, D. (2023). Design of cultural emperor penguin optimizer for energy-efficient resource scheduling in green cloud computing environment. *Cluster Computing*, 26(1), 575–586.

Nadeem, A., Rizvi, A.A. and Noor, M.Y. (2024). Applying a higher number of output membership functions to enhance the precision of a fuzzy system. *IEEE Transactions on Emerging Topics in Computational Intelligence*, **doi:** 10.1109/TETCI.2024.3425309.

Nguyen, A.-T., Dehak, A., Guerra, T.-M., and Sugeno, M. (2023). Convex stability analysis of Mamdani-like fuzzy systems with singleton consequents. *IEEE Trans. Fuzzy Syst.*, 31(11), 3787–3798.

Noor, Y., Peng, Q., Khokhar, U., Asif, A. and Abid, N. (2019). Low cost and energy efficient fuzzy based kitchen ventilation control system. In *2019 International Conference on Robotics and Automation in Industry (ICRAI)*, 1-6. IEEE.

Othman, K.M.Z. and Zeki, N.M. (2023). Therapeutic management of diseases based on fuzzy logic system-hypertriglyceridemia as a case study. *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, 21(2), 314-323.

Peng, Q., Touqir, R. and Khan, M.S. (2020a) Medical condition monitoring system using fuzzy logic. In *2020 IEEE International Conference on Artificial Intelligence and Information Systems (ICAIIS)*, 211-216. IEEE.

Peng, Q., Asif, A., Noor, M.Y. and Inam, A. (2020b). A simple tuning algorithm of augmented fuzzy membership functions. *IEEE Access*, *8*, 35805-35814.

Peng, Q. and Noor, M.Y. (2023). Output linearization of single-input single-output fuzzy system to improve accuracy and performance. *Computers, Materials & Continua*, *75*(2), 2413-2427.

Pattun, G., Afroaz, K., Siddiqui, A.T. and Ghazala, S. (2023). Prediction of type-I and type–II diabetes: A hybrid approach using fuzzy logic and machine learning algorithms. *Journal of Information Technology Management*, 15, 35-56.

P. P. Phyo and C. Jeenanunta, (2021). Daily load forecasting based on a combination of classification and regression tree and deep belief network, *IEEE Access*, 9, 152226-152242.

Rahman, M.Z., Akbar, M.A., Leiva, V., Tahir, A., Riaz, M.T. and Martin-Barreiro, C. (2023). An intelligent health monitoring and diagnosis system based on the internet of things and fuzzy 10 logic for cardiac arrhythmia COVID-19 patients. *Computers in Biology and Medicine*, 154, p.106583.

Salehi, E., Tahmasbi, S., Tahmasbi, V. and Rahimi, M. (2022). Application of the adaptive neuro-fuzzy inference system (ANFIS) and sobol approaches for modeling and sensitivity analysis of the biosorption of triglyceride from the blood serum. *Iranian Journal of Chemical Engineering*, 19(1), 51-65.

Sai Vyshnavi, T., Prakash, S., Basani, V. and Uma Rao, K. (2022). Cardiac problem risk detection using fuzzy logic. *In Advances in Data Computing, Communication and Security: Proceedings of I3CS2021*, 181-191. Springer Nature, Singapore.

Sohaib, R., Muneeb, A., Bibi, I., Noor, M.Y. and Imran, M. (2023). Automated door to prevent COVID-19 using fuzzy logic. In *2023 International Conference on Electrical, Communication and Computer Engineering (ICECCE)*, 1-6. IEEE.

Wardana, H.K., Ummah, I. and Fitriyah, L.A. (2020). Mamdani fuzzy inference system (FIS) for early diagnosis of diabetes mellitus (DM) and calorie needs. *In International Joint Conference on Science and Engineering (IJCSE)*, 387-394. Atlantis Press.

Yadav, A., Bareth, R., Kochar, M., Pazoki, M. and El'Sehiemy, R.A. (2023). Gaussian process regression-based load forecasting model. IET Generation, Transmission, & Distribution, 18(5), 899-910.

Zhao, Y., Wang, L., Xie, X., Hou, J. and Lam, H.-K. (2024). Double asynchronous switching control for Takagi–Sugeno fuzzy Markov jump systems via adaptive event-triggered mechanism. *IEEE Trans. Syst., Man, Cybern.: Syst.*, 54(5), 2978–2989.