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INVESTIGATING THE EFFECTIVENESS OF THE FUZZY INFERENCE SYSTEM IN DECISION MAKING

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Abstract
Fuzzy inference systems, In order to account for uncertainty and imprecision in decision making, models like the Mamdani and Sugeno models are widely utilised. MATLAB is a well-known programming environment that offers the required tools and techniques for individuals interested in creating and deploying fuzzy inference systems. The Mamdani and Sugeno fuzzy inference systems have been implemented in MATLAB to evaluate Diabetes Mellitus (DM), and this abstract gives a quick overview of how it was done.The Mamdani model uses fuzzy sets to describe uncertain data and is based on language standards. Users of MATLAB can quickly design and simulate Mamdani fuzzy systems using the Fuzzy Logic Toolbox. Users are entirely free to define and create membership functions, fuzzy rule sets, simulations, and Mamdani system optimisations. The behaviour of the system is made clearer by MATLAB's visualisation options, such as the surface plot and the rules plot.The Sugeno, or Takagi-Sugeno-Kang (TSK) model, blends fuzzy rules with linear functions to produce inferences and predictions. The Fuzzy Logic Toolbox in MATLAB can be used to implement Sugeno fuzzy systems. After linguistic variables and membership functions have been used to specify the input-output relationships, the user can define the linear functions connected to each rule. Sugeno fuzzy systems' rule surfaces and output response curves can be quickly assessed, simulated, and displayed in MATLAB. In conclusion, The Mamdani and Sugeno fuzzy inference systems can be effectively built using MATLAB. Rapid system modelling, simulation, and analysis software is available. Fuzzy logic techniques in MATLAB can be used by academics and professionals to deal with uncertainty and imprecision in decision-making procedures.

1. INTRODUCTION

A fuzzy inference system (FIS) is a sort of man-made reasoning innovation that utilizes fuzzy mental stability to talk over with another information. Because it can deal with uncertainty and erroneousness, fuzzy logic is a good analytical foundation for handling difficult questions about the real world. In a Fuzzy surmising framework, the information factors are portrayed as Fuzzy sets, that are depicted by participation works that assign a place of enlistment for each worth in the set. The rules that define how the recommendation variables influence the gain variables are represented using fuzzy sanity, and the crop variables are also depicted as fuzzy sets. The course of determination in a fuzzy surmising framework incorporates three primary advances: rule judgment, defuzzification, and fuzzification. Fuzzification changes over the new proposal values into Fuzzy sets using the cooperation capabilities. Rule judgment determines the degree of participation of the output variables by applying the fuzzy rules to the fuzzy inputs. Finally, defuzzification reverts the fuzzy production sets to new decision-making principles. Fuzzy conclusion orders are frequently utilized in control techniques, where they can be used to model and control complex orders with ambiguous or changing dossier. They are more utilized in dossier thinking and example affirmation utilizes, place they can assist with recognizing complex companionships in bountiful dossier sets. Fuzzy end framework (FIS) is the method involved with arranging the arrangement from a logical proposal to a result using Fuzzy reasoning controllers and Fuzzy principles. Before, the plan provides a foundation from which one can draw inferences or identify a pattern. FIS is individual of extreme unbelievable purposes of Fuzzy sense and Fuzzy set conviction. In Fuzzy set hypothesis, a changing that enjoys a benefit is named semantic variable. The system is primarily distinguished by fuzzy philosophy manipulators of "or" and "and," enrolment functions of recommendation and crop semantic variables, and if-therefore rules. The types of fuzzy sets used to delineate recommendation variables and, furthermore, the configuration of fuzzy rules determine the optimality of the quantity variables. The substance of FIS is laid out their bifold personality of suggestion and benefit factors that they are clever to deal with phonetic thoughts. In light of this substance, FIS have upgrade whole approximates that ready to act non-undeviating weighing center from two focuses data sources and results. The Mamdani-type and the Sugeno-type FIS have been developed using these two FIS strengths. The principal parts of administration are fuzzification interface, derivation engine and Defuzzification.

The structure depicted in Figure 1 for the two inferences of the Mamdani-type and Sugeno-type is basically followed, with fuzzification and deffuzification serving as the two primary processes. The third cycle is deduction process. In Mamdani derivation process, the result is characterized as enrollment capability whereas, in Sugeno deduction process, the result is cleared up by a solitary polynomial with deference for input factors. The Mamdani induction has a typical construction with various rule bases for info and result.

2 LITERATURE REVIEW

Samavat 2023 et al. In order to introduce the ideal regulator for enhancing the output of a planetary group by utilising the two types and learning about their qualifications, the two classes for Mamdani and Sugeno are surveyed. Also considered is what the capacity for information enrolment entails for the regulator's suitability. Along these lines, each fuzzy system model is provided one of two optional information involvement capabilities. It is crucial to note that fuzzy system, a subset of man-made reasoning, was created by inherited calculations due to a human desire to automate certain jobs. On a planetary group, four distinct fuzzy system have thus been created and put to use. The discoveries were evaluated and grouped in MATLAB Simulink. [1].

Sonia 2023 et al. uses a multi-layer neural network no-property method to create a novel system for classifying the three forms of diabetes mellitus. The two primary information system phases that the algorithm uses are the development phase and the testing phase. Type 1 diabetes comes first in each period, followed by normal and type 2 diabetes, and healthy pregnant women with diabetes come last. A multi-layer neural network is then trained separately using the pertinent traits that were chosen throughout the attribute selection procedure. The architecture of the multi-layer neural network improves classification performance. A confusion matrix is developed following an experiment to evaluate the sensitivity, specificity, and accuracy of diabetes diagnosis. Maximum specificity and sensitivity values of 0.95 and 0.97 were attained. [2]

Shwetha 2023 et al. In addition, preprocessed photographs are used to collect data on 14 variables. Identification of retinal lesions can be aided by methods for the early diagnosis and treatment of diabetic retinopathy, a condition that is frequently seen. provide a novel criterion for locating the optical disc, where we first identify the key blood vessels and then use the points of intersection to locate the optical disc. In the future, localization will use colour features. Show that when utilised properly, a variety of morphological approaches can be used to identify a collection of characteristics, including blood vessels, mucus, micro aneurysms, and haemorrhages. [3]

Sadat Asl 2022 et al. The interval type-2 fuzzy expert system predicts the ICU admission for COVID-19 patients. For this prediction job, a system for adaptive neuro-fuzzy inference (ANFIS) was further developed. Additionally, the results of these fuzzy systems are contrasted with those of other well-known classification methods, including Naive Bayes (NB), Case-Based Reasoning (CBR), Decision Tree (DT), and K Nearest Neighbour (KNN). The findings show that the ANFIS and type-2 fuzzy expert system models compete favourably in terms of accuracy and F-measure when compared to other system modelling approaches. [4]

Sangeetha Devi, 2022. et al. put forward a new A Several fuzzy graph operations, including cycle, union, join, and products, are used to find the Sugeno-Type Fuzzy Graph of Groups. A figure that is representative depending on those vertices in all paths with those vertices as their starts and ends is the minimal number of shared edges chosen by those vertices in the formations that comprise all paths with those vertices as their starts and ends to compare with other paths. The Sugeno dominating path-colouring number, which exists in all sets of shared edges, allows for a range of methods because it exists in all sets of shared edges. With the aid of these new discoveries, several newly created chromatic number graphs are studied. [5]

Kotiyal 2022 et al. Given that a substantial section of the population is affected, big data is relevant to this problem. Deep Learning can solve the issues that Big Data faces, notwithstanding these issues. Big data and deep learning are consequently particularly interesting to academics. In this study, we attempted to employ effective preprocessing and Deep Learning approaches to achieve binary classification of diabetic retinopathy. The experiment makes use of an Indian-sourced Kaggle dataset. The peculiarity of the research is that three models—InceptionV3, Xception, and VGG19—and the performance of the Logistic Regression classifier are contrasted on the Spark platform. The models' precision is compared as a comparison metric. The trial's results show that InceptionV3 is 95% accurate, Xception is 92.50% accurate, and VGG19 is 89.94% accurate. InceptionV3 outperforms the other two models as a result. [6]

Lin, Jing 2022 et al. Grade 1 corresponds to 42.50 percent of the 54 DKD cases, Grades 2, 3a, 3b, and Grade 4 to 18.52 percent, 11.1 percent, 9.2 percent, 18.52 percent, and 18.52 percent, respectively, according to the eGFR grading. Despite there being a negative correlation between blood Hb levels and the course of DKD, blood urea and creatinine levels were considerably positively connected. The main renal artery (MRA), segment renal artery (SRA), and interlobular renal artery (IRA) all had considerably lower Vsmax and Vdmin values than in healthy instances, according to ultrasonography. The IR of the aforementioned arteries was noticeably enhanced, and the changes in the aforementioned data were also more pronounced than those in the lower extremities. The correlation between RI and DKD grades was positive, whereas the correlation between MRA, SRA, and IRA grades was adverse. Although RI of the arteries is negatively connected with kidney health, we found that the level of Hb is positively correlated with it. This is caused by the convergence of RI and Hb level. Conclusions. Indicators of the development of DKD include the haemoglobin (Hb) level and the intrarenal artery resistance index (RI), as evaluated by. [7]

Srivastava 2022 et al. focuses on categorising the common kinds of arrhythmia in Southeast Asian populations. It has been carefully examined how medical information is applied in practise to enhance professional arrhythmia diagnosis. This system is tested to evaluate how well the inputs and outputs match using a satisfied factor. [8]

Abhilash 2022 et al. The two diabetes mellitus disease datasets (DMDDs) used in the integrated dataset on which the system is trained utilising EDL techniques are the Pima Indians Diabetes Dataset (PIDD) and the Hospital Frankfurt Germany Diabetes Dataset (HFGDD). Both the UCI-ML and Kaggle repositories were used to obtain these datasets. The suggested system has been utilised to demonstrate a number of characteristics, including precision, recall, accuracy, F-measure, latency, arbitrator time, jitter, processing time, throughput, energy consumption, bandwidth utilisation, networking utilisation, and more. The IoT-cloud connection is helpful for remotely and instantly diagnosing diabetic patients. The findings highlight the benefits of using FC ideas and the extent to which they can be used to quickly diagnose diabetes patients remotely. The text PACS-key contains a description of the key. written explanation of the PACS-key. [9]

Tian 2022 et al. examined the relationship between CHD and the serum Sestrin2 levels in people with type 2 diabetes. 69 T2DM patients without coronary heart disease participated in the trial. Both clinical characteristics and metabolic markers were discovered. Sestrin2 levels in serum were determined using ELISA. Results: The T2DM-CHD groups had significantly lower serum levels of sestrin2 than the T2DM group (11.17 (9.79, 13.14) ng/mL vs. 9.46 (8.34, 10.91) ng/mL). Serum Sestrin2 levels were shown to be negatively correlated with age ($r = 0.256$, $P = 0.002$), BMI ($r = 0.206$, $P = 0.015$), FBG ($r = 0.261$, $P = 0.002$), and Tyg index ($r = 0.207$, P 0.014) in bivariate correlation analysis. By using binary logistic regression, it was found that there was a significant (P 0.05) correlation between lower blood Sestrin2 levels and a higher risk of T2DM-CHD. In order to predict T2DM-CHD patients, sestrin2 was utilised, and its area under the curve (AUC) achieved 0.724 (95% CI 0.641-0.808, P 0.001). Sestrin2 levels and CHD were strongly correlated in diabetic individuals. Serum sestrin2 may impact the prevalence and progression of diabetic heart disease. [10]

Zhang 2022 et al. a vehicle's suspension can be controlled effectively, more reliably, and with less energy use. Based on bionic nonlinear dynamics, a fuzzy SMC technique for active suspension systems is developed. In contrast to earlier findings, the proposed control strategy effectively makes use of the beneficial nonlinear stiffness or damping of the biomimetic

reference model, resulting in performance that is energy-saving. Furthermore, a number of real-world concerns are carefully considered, such as input saturation, dead zones, unknown/uncertain dynamics, and outside interference. According to theoretical analysis and simulation results, the suggested fuzzy SMC approach based on bionic dynamics may successfully reduce energy consumption, improve ride comfort, and efficiently reduce the vibration of the active suspension system.[11]
Afrash 2022 et al. In an effort to develop a system for decision support (DSS) based on the use of machine learning (ML) for DN diagnosis, it was tried to identify the variables that were relevant in predicting DN. Methods: Retrospective analysis was performed on the medical records of 327 people who had diabetes (types 1 and 2). The predicted variables affecting DN following data processing were identified using the genetic algorithm's (GA) feature choice method. Then, in addition to other ML methods, the support vector machine (SVM), decision tree (DT), K-nearest neighbour (KNN), and artificial neural networks (ANN) were used to train prediction models based on the selected features. The performance of the developed models was then evaluated using the accuracy, specificity, and sensitivity criteria over the course of ten independent runs. [12]
Galo, 2022 et al. This article suggests the application of computational tools for decision-making using fuzzy inference systems as a way to potentially improve the triage procedures in Brazil. We contend that the use of natural language to describe the patient's symptoms makes it simpler for medical personnel to understand the problem and that fuzzy set theory is applicable. We used a pilot test after simulating the issue in a fuzzy system. The model takes into account the symptoms that doctors now utilise to evaluate COVID-19 cases. The findings point to the model's possible use in aiding triage for the classification of the seriousness of COVID-19 cases by showing convergence with the sample data. One advantage of the suggested model . We place particular emphasis on the contributions that reduce the amount of time and personnel needed for triage and the exposure of medical personnel and other patients who may be carrying the virus. In this sense, this study offers a chance to acquire social contributions for the enhancement of services in public hospitals..[13]
Chakraborty 2021 et al. Applying a fuzzy inference system & machine learning techniques, a COVID-19 risk prediction model for diabetes patients is suggested. This study sought to determine the COVID-19 risk level in diabetes individuals without seeking medical advice in order to take prompt action and reduce the multifold COVID-19 mortality rate amongst diabetic patients. Eight factors that were identified as having the greatest influence on diabetic patients' symptoms serve as inputs for the suggested model. Fifteen models were built utilising a range of cutting-edge machine learning techniques, with the rule base serving as the framework. The CatBoost classifier delivers the highest kappa, F1, recall, accuracy, and other measures. The CatBoost classifier achieved 76% accuracy after hyper-parameter optimisation, along with improvements in recall, precision, F1 score, and kappa score. Then, with 75.1% accuracy, came logistic regression and XGBoost. [14].

Liu 2021 et al. This study used bioinformatics approaches to look into how to treat diabetic coronary heart disease. Methods. From the GeneCard database, the associated genes for diabetic CHD and the target genes for the chemical components of Qiweitangping were obtained. The active chemical elements of Qiweitangping were gathered using the TCMSP database. The junction between the drug's target gene and the gene linked to the disease was also found in order to discover possible genes. Next, utilising the STRING and DAVID databases, KEGG enrichment analysis & protein interaction analysis were performed on the candidate genes. The docking of molecules was also used as an additional verification method. By using the Cytoscape tool, a network of "drug component-gene target-pathway" genes was eventually created. Results. In Qiweitangping, 62 active substances, comprising naringin, diosgenin, formogenin, isorolin, and isocryptanshinone, as well as 59 potential target genes, including AKT1, CASP3, and VEGF-A, were discovered. Additionally, the outcomes of two molecular docking tests (CASP-naringenin and STAT3-cryptotanshinone) demonstrated high affinity (-5.00 kcal/mol). Conclusion. Qiweitangping uses the study's findings in a variety of chemical treatments for diabetic CHD. Its operation may be influenced by the signalling pathways PI3K-Akt, ErbB, and HIF-1. The molecular docking method has demonstrated that the Qiweitangping, STAT3, and CASP genes interact well. More experimental studies on the Qiweitangping therapeutic mechanism for diabetic CHD will be theoretically underpinned by the findings of this study.

Isa, Zaidi 2021 et al. The framework's input as well as output language variables were both chosen to use the triangle membership function. Using the methodology's fuzzy aggregation approach, which enables the gathering of professional opinion, a suitable control action can be selected. With the use of a total of 23 rules, including the logical OR operator, the truncation implication, and the Mean of Maxima (MoM) defuzzification method, an effective fuzzy model for forming judgements was created. The framework determines the link between the input and output parameters used in if-then statements or mathematical functions by employing a potent fuzzy arithmetic operator. A Mamdani-style decision framework and an example from a medium-sized project in Malaysia's construction industry are used to discuss the underlying issues with different expert perspectives in the study. We confirm the logic and dependability of the suggested method by comparing it with the outcomes of other experiments. [15]

3 OBJECTIVE OF THE RESEARCH

This Paper main goal is to investigate how membership functions affect Mamdani-type fuzzy inference systems and to identify the key membership function components that influence input-output relationships. It also aims to develop suitable membership functions for both ideal linear inference systems and traditional non-linear inference systems. MATLAB's Fuzzy Logic Toolbox will be used to implement trial and error in this situation. The only criterion that will change in experimental Mamdani fuzzy inference systems is the membership function's features, such as the form, quantity, and overlap ratio of its nearby MFs. Singularity of Input and Output As the most basic model, the Mamdani fuzzy inference system will be examined first in order to draw out the characteristics of membership functions with regard to modifying input-output curves. In order to summarise the consistent impacts of the membership function on both the SISO inference system and the TISO inference system, the two-input single-output inference system will be discussed. A technique for adding weight to a multi-input single-output system will be shown, and a real-world application is anticipated to confirm the viability of the conclusions.

4 RESEARCH METHODOLOGY

DATA COLLECTION

Information gathered from https://www.kaggle.com/datasets/uciml/pima-indians-diabetes-database, where the dataset was originally obtained from the National Institute of Diabetes and Digestive and Kidney Diseases. This collection of diagnostic measurements is intended to aid in the process of diagnosing the presence or absence of diabetes in a patient based on a selection of diagnostic parameters that are present in the dataset. There were a few limitations on how these specific occurrences were chosen from a larger database. To be more precise, all of the patients at this facility are Pima Indian women who are at least 21 years old. The datasets contain several medical predictor factors together with one aim variable that is an outcome variable. The datasets contain several medical predictor factors together with one aim variable that is an outcome variable. Only a few of the predictive variables include the patient's age, body mass index (BMI), insulin level, and the total number of pregnancies.

4.3.2 INPUT AND OUTPUT PARAMETERS

1) In order for a system, model, algorithm, or function to produce an output from an input, it needs to have input parameters. The values you supply for these parameters have an impact on the operation's behaviour or result.The term "input parameters" in the context of fuzzy logic refers to the variables that act as the input to a fuzzy inference system. The task of converting qualitative utterances into numerical input values is carried out by these factors, which are also known as linguistic variables. We can portray the input variables in a more understandable way by utilising words from our own language.The input parameters that were used are listed below.

- Pregnant times (Preg)
- Glucose level (Plas)
- Diastolic BP (Dias)
- Skin Thickness (Tric)
- Serum Insulin (Ins)
- BMI (Mass)
- Pedigree (Pedi)

Age (Age

2) The term "output parameters" describes the elements or variables that represent the result or output generated by a system, model, algorithm, or function. In other words, "output parameters" could also be thought of as "result parameters." These parameters are calculated depending on the internal state of the system and the input parameters, or they are produced from those two variables.The output parameters of fuzzy inference systems serve as representations of the system's conclusion, which was reached using input values and fuzzy logic rules. Any system that makes advantage of fuzzy inference must include this. The output settings that are currently in use are as follows.

- Diabetes Mellitus (DM)

4.3.3 PROPOSED ALGORITHM

1) Input

In order for a system, model, algorithm, or function to generate an output from an input, it must have input parameters. The terms input variables and input factors can also be used to refer to input parameters. Your selections for these parameters will impact both how the operation is carried out and the outcomes it generates.The variables that stand in for the data provided into a fuzzy inference system are referred to as "input parameters" when addressing fuzzy logic.The inputs utilised for the evaluation of the fuzzy set are the letters A1, A2, A3, A4, A5, A6, A7, and A8.

2) Output

The word "output parameters" describes the variables or elements that represent the outcome or output that a system, model, or algorithm produces. So you may think of "result parameters" as an alternative term for "output parameters." These parameters are either generated depending on the input parameters and the system's present condition, or they are calculated based on those same factors.Fuzzy inference systems use input values and fuzzy logic rules to get at a conclusion. The output parameters of the system then reflect this conclusion.For DM, the fuzzy set should be output.

4.3.4 METHOD

Begin **Step1:** Enter the crisp values for the cells A1, A2, A3, A4, A5, A6, and A7.

Step 2: Calculate the equation for the fuzzy number's triangle membership function, then set it. **Step 3:** Constructed the fuzzy numbers for the input set using A1, A2, A3, A4, A5, A6, A7, and A8. **Step 3:** Constructed the uncertain number for DM for the output set. **Step4:** Mamdani's approach is used to perform fuzzy inference analysis.

- The Mamdani approach is well-known for its interpretability as well as its capacity to deal with complicated laws of language. It produces linguistic outputs that are simple enough for humans to comprehend and understand how to interpret. The process of defuzzification, on the other hand, may lead to a reduction in precision and may be computationally expensive for systems that have a high number of rules.
- When the link between the input variables and the output variables can be described using mathematical functions or equations, the Sugeno technique is frequently chosen as the method of choice. In comparison to the Mamdani approach, it is capable of producing results that are both more accurate and less resource intensive to compute. However, due to the fact that it does not directly supply language outputs, the interpretability of the output may be diminished.

Both the Mamdani and the Sugeno approaches have advantages and disadvantages, and selecting one over the other is contingent on the nature of the issue at hand as well as the qualities that are sought for in a fuzzy inference system.

Step 4.1: Enter the rule in the format Rule 1,2,...k. **Step 4.2:** Calculations are made to determine the matching degree of rule using OR fuzzy disjunction for the fuzzy input set (A11, A12, A13, A21, A22, A23, A31, A32, A33, A41, A42, A43, A51, A52, A53, A61, A62, A63, A71, A72, A73, A81, A82, A83, DM1, DM2, and DM3). **Step5:** Using the centroid approach, defuzzify the data into its crisp values. **Step6:** Organize the information so that it is presented in the language of human nature. End.

4.3.4 MEMBERSHIP FUNCTION

The application of membership functions in fuzzy logic allows us to map input or output values to fuzzy sets. A function known as a membership function determines the degree of membership or honesty that an element in a fuzzy collection holds. In order to do this, it gives each element a value between 0 and 1, depending on where it is in the set.

Depending on the type of variable and the type of problem that has to be solved, membership functions can take on a broad range of forms and combinations. Typical examples of membership functions include the following:

1) Triangular:

One of the membership features that is both the simplest to comprehend and the most commonly used is this one. It accomplishes this by producing a triangle-shaped curve with three parameters: the left boundary, the peak, and the right boundary. The value of the membership function linearly increases from the left boundary to the peak, while it linearly decreases from the peak to the right boundary.

2) Trapezoidal:

The left shoulder, the left boundary, the right shoulder, and the right boundary are the four parameters that make up the trapezoidal membership function, which is very similar to the triangle membership function. With a horizontal top between the left and right corners of the pattern, it curls into the shape of a trapezium.

3) Gaussian:

Two parameters—the mean and the standard deviation—define the bell-shaped distribution of the Gaussian membership function. It produces a symmetrical curve with a peak at the mean value. A bell-shaped distribution shows that as the input is pushed more and farther from the mean value, the level of group participation decreases.

4) Sigmoidal:

The sigmoidal membership function uses an S-shaped curve to represent a progressive change between two membership levels. It is characterised by a group of variables that control the shape and steepness of the curve.

Universal bell A generalised bell's membership function is an adaptable curve that can be used to represent a wide range of various forms. The three components that it possesses—the form, the centre, and the width—determine the characteristics of the curve.

There are many different sorts of membership functions available; these are just a few examples. When choosing the membership function to apply, it is important to take into account the type of variable being represented as well as the specific requirements of the fuzzy logic system.It is crucial to remember that the definition of membership functions can be influenced by both expert knowledge and data-driven methodologies. Expert knowledge is the use of one's understanding of a certain domain to design membership functions based on one's intuition and prior experiences. A data-driven approach, on the other hand, makes use of data analysis tools to determine appropriate membership function parameters based on observed data. You have the option of doing this manually or automatically. Since they define the fuzzy sets and the degree of membership that each fuzzy set possesses, membership functions are a crucial part of fuzzy logic systems. Due to the ability to represent imprecise and uncertain information, which is made possible by these components, fuzzy inference systems are able to handle and process subjective or ambiguous inputs.

5 RESULT & DISCUSSION

FUZZY OUTPUT FOR MAMDANI MODEL

Based on the input values and fuzzy rules, a fuzzy inference system will produce a conclusion or decision. The fuzzy output of the system is this conclusion or choice. Given that it is a fuzzy set, the degree to which different output values or linguistic concepts belong to the set is represented by its membership.

You will have an aggregated fuzzy set at your disposal after the rule aggregation procedure is finished, at which time the degrees of activation from each of the rules are joined together, which will constitute the fuzzy output. Each output linguistic phrase from this fuzzy set will have a membership value assigned to it, showing how much each term is appropriate or relevant. The membership value of the set will decide this value.

To convert the murky output value into a clear one, you must employ a defuzzification method. The most common method of defuzzification is the centroid approach, which finds the centroid, often known as the centre of gravity, of the aggregated fuzzy set. The centroid, which represents the crisp output value, can be used to make a precise decision or choose the best course of action based on the fuzzy output. The defuzzification procedure yields a single numerical value that represents the system's ultimate output or conclusion. The fuzzy output, which was previously represented by membership values across linguistic concepts, is now represented by this number.

It is critical to remember that the specific problem at hand as well as the linguistic ideas associated to the output variables influence how the fuzzy output should be interpreted and applied. Fuzzy logic systems can become more adaptable and human-like in their line of reasoning thanks to the fuzzy output, which provides a method of conveying uncertainty and imprecision in the decision-making process.

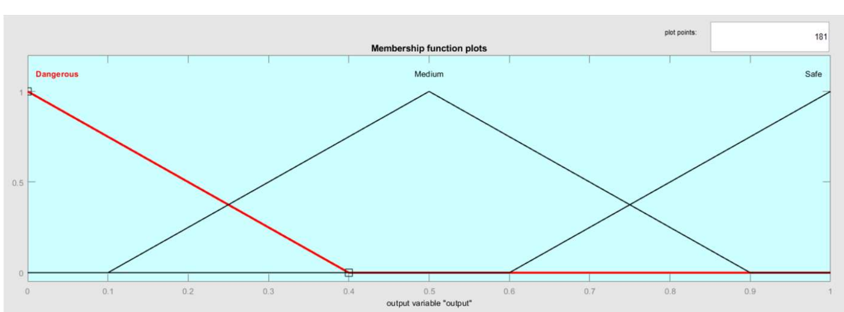

Figure 5.1 Membership function of output variable Diabetes Mellitus (DM)

The graphical illustration of the Membership function of output variables, including Diabetes Mellitus (DM), may be shown in Figure 30.

OUTPUT GRAPHS WITH ALL DIFFERENT VARIABLES INPUT OF SUGENO

In a system that is governed by the Sugeno rules, the input variables may be of a variety of sorts depending on the nature of the problem that is being described. The following is a list of typical varieties of input variables that are utilized in Sugeno systems:

1. Crisp Variables: These are your standard variables, and each of their values is very specific. For instance, the present temperature, the intended temperature, or the occupancy status (such as occupied or unoccupied) could all serve as crisp input variables in a system that regulates the temperature of a room.
2. Fuzzy Variables: Fuzzy variables are a representational tool that can be utilized for linguistic concepts and phrases. They are distinguished by fuzzy sets, which give varying degrees of membership to the elements they contain. For instance, the input variable "temperature" can be represented by fuzzy sets such as "low," "medium," and "high" with membership functions that describe the degree to which one belongs to each group.
3. Linguistic Variables: Linguistic variables are comparable to fuzzy variables and represent qualitative phrases or linguistic labels. These labels, which are connected to fuzzy sets, provide a linguistic explanation of the input variables and are related with those sets. For the purpose of expressing the level of humidity, for example, you may use phrases such as "low," "medium," and "high" rather of relying on a precise numerical figure.
4. Continuous Variables: Sugeno systems are also able to deal with continuous variables, which are variables that can take any real value within a given range of values. In a financial system, for instance, input variables like income, age, and investment amount can all be continuous variables.
5. Discrete Variables: Discrete variables represent a finite or countable set of possible values. They are used to represent data that is categorized or nominal. For instance, the input variable "genre" in a recommendation system could be a discrete variable with categories such as "action," "comedy," or "drama."

It is essential to keep in mind that although Sugeno rules permit many kinds of input variables, the rule consequences are often expressed as crisp (non-fuzzy) values or linear functions that are based on the input variables. This is something that should be kept in mind. One of the most important distinctions that can be made between Sugeno rules and other methods to fuzzy logic, such as Mamdani-type systems, is that the latter make use of fuzzy sets and linguistic variables throughout the rules, including the consequences. Sugeno rules do not do this.

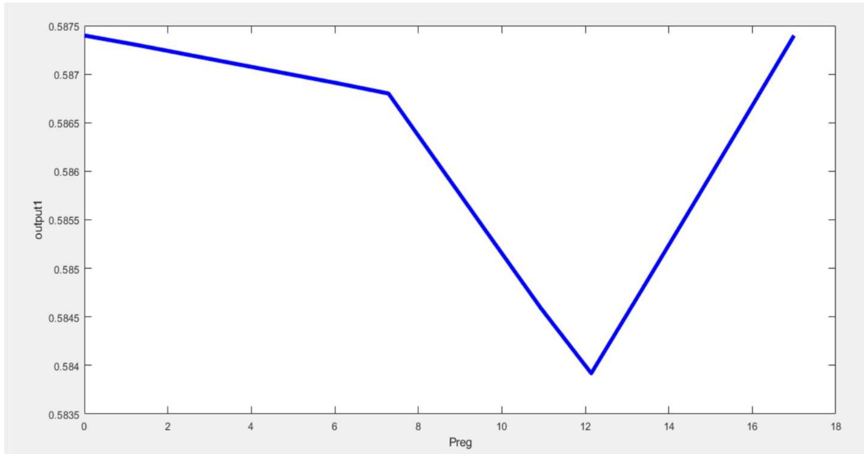

Figure 5.2 Output Graph of Preg

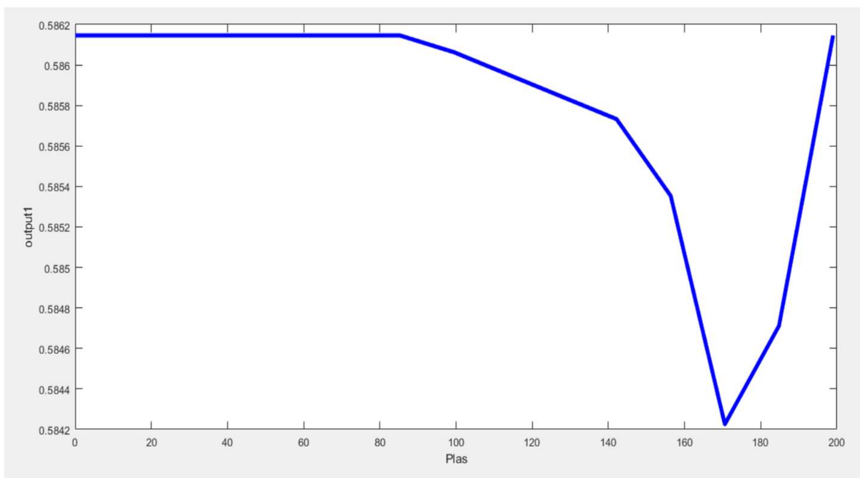

Figure 5.3 Output Graph of Plas

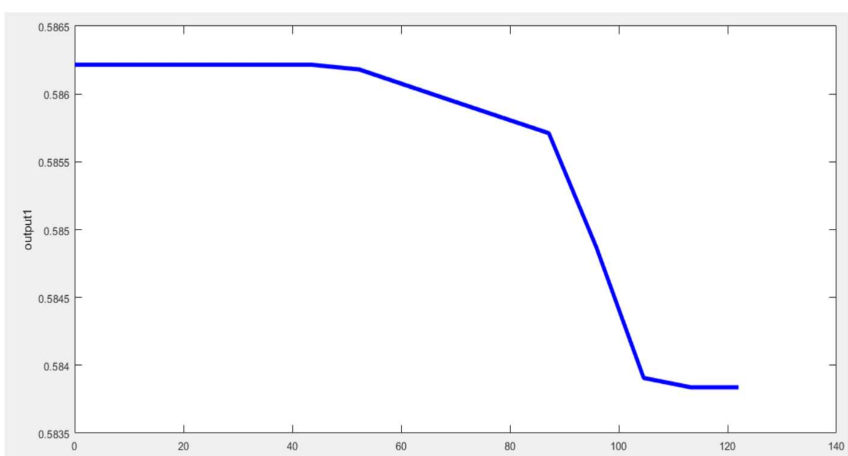

Figure 5.4 Output Graph of Dias

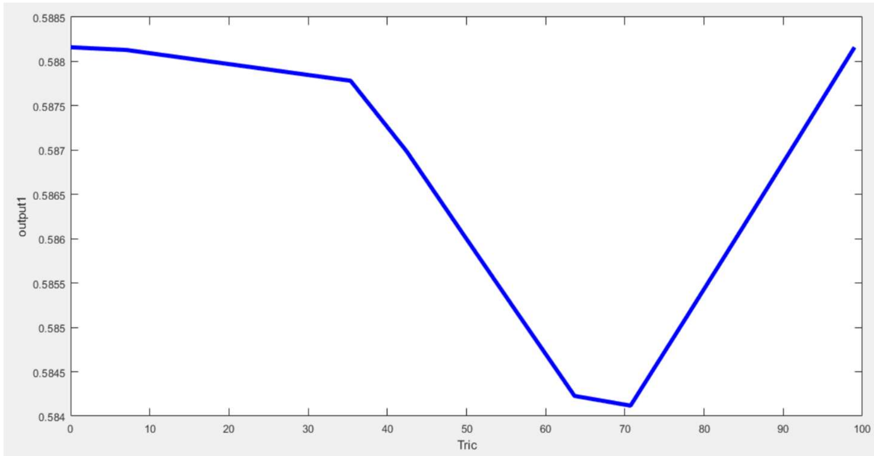

Figure 5.5 Output Graph of Tric

6 CONCLUSIONS

In conclusion, In the industry, the Mamdani and Sugeno fuzzy inference systems are often used as a means of putting fuzzy logic to use in a range of applications. These methods allow for the simple design and implementation of fuzzy inference systems with the aid of MATLAB, which offers a convenient environment. Important information on the MATLAB-created Mamdani and Sugeno fuzzy inference systems is listed below:Fuzzy Inference System by Mamdani: The Mamdani fuzzy inference system employs fuzzy sets to describe uncertainty and imprecision. The linguistic conventions that underpin this system. Fuzzy logic evaluation, rule aggregation, fuzzy logic defuzzification, and fuzzy logic fuzzification are all included in this procedure. Users can design and model Mamdani fuzzy systems using a comprehensive collection of tools and functions provided by the Fuzzy Logic Toolbox, which is accessible through MATLAB. The Takagi-Sugeno-Kang (TSK) model, also known as the Sugeno fuzzy inference system, uses a combination of fuzzy rules and linear functions to generate judgements or projections. In conclusion, the combination of MATLAB's powerful processing capabilities and user-friendly interface makes it possible to develop, simulate, and analyse the Mamdani and Sugeno fuzzy inference systems in a welcoming environment. It doesn't matter if you're working with rule-based models with linear functions (Sugeno) or rule-based models with linguistic rules and fuzzy sets (Mamdani), MATLAB offers the necessary tools and functions to rapidly develop and investigate fuzzy logic-based systems.

REFERENCES

[1] Samavat*et al.*, “Research Article A Comparative Analysis of the Mamdani and Sugeno Fuzzy Inference Systems for MPPT of an Islanded PV System,” vol. 2023, 2023.

[2] J. J. Sonia, P. Jayachandran, A. Q. Md, S. Mohan, A. K. Sivaraman, and K. F. Tee, “Machine-Learning-Based Diabetes Mellitus Risk Prediction Using Multi-Layer Neural Network No-Prop Algorithm,” *Diagnostics*, vol. 13, no. 4, pp. 1–16, 2023, doi: 10.3390/diagnostics13040723.

[3] G. K. Shwetha, U. K. R. K. R, J. A. Rathod, and B. P. Sathyaprakash, “INTELLIGENT SYSTEMS AND APPLICATIONS IN Diabetic Retinopathy Prediction using Modified Inception V3 Model Structure,” vol. 11, no. 1, pp. 261–268, 2023.

[4] A. A. Sadat Asl, M. M. Ershadi, S. Sotudian, X. Li, and S. Dick, "Fuzzy expert systems for prediction of ICU admission in patients with COVID-19," *Intell. Decis. Technol.*, vol. 16, no. 1, pp. 159–168, 2022, doi: 10.3233/IDT-200220.

[5] A. Sangeetha Devi, "An Extensive Study on Graph Colourings and Dominator Chromatic Number of Sugeno-Type Fuzzy Graphs," *Math. Probl. Eng.*, vol. 2022, 2022, doi: 10.1155/2022/3135201.

[6] Bk. Otiyal and H. Pathak, "Diabetic Retinopathy Binary Image Classification Using Pyspark," *Int. J. Math. Eng. Manag. Sci.*, vol. 7, no. 5, pp. 624–642, 2022, doi: 10.33889/IJMEMS.2022.7.5.041.

[7] J. Lin, G. Liu, Y. Lin, C. Wei, S. Liu, and Y. Xu, "Ultrasonography Combined with Blood Biochemistry on the Early Diagnosis of Diabetic Kidney Disease," *Dis. Markers*, vol. 2022, 2022, doi: 10.1155/2022/4231535.

[8] P. Srivastava, N. Sharma, and C. S. Aparna, "Fuzzy Soft System and Arrhythmia Classification," *Chinese J. Math.*, vol. 2014, pp. 1–12, 2014, doi: 10.1155/2014/164781.

[9] A. Pati*et al.*, "Diagnose Diabetic Mellitus Illness Based on IoT Smart Architecture," *Wirel. Commun. Mob. Comput.*, vol. 2022, 2022, doi: 10.1155/2022/7268571.

[10] X. Tian*et al.*, "The association between serum Sestrin2 and the risk of coronary heart disease in patients with type 2 diabetes mellitus," *BMC Cardiovasc. Disord.*, vol. 22, no. 1, 2022, doi: 10.1186/s12872-022-02727-1.

[11] M. Zhang and J. Zhang, "Fuzzy SMC Method for Active Suspension Systems with Non-ideal Inputs Based on a Bioinspired Reference Model," *IFAC-PapersOnLine*, vol. 55, no. 27, pp. 404–409, 2022, doi: 10.1016/j.ifacol.2022.10.547.

[12] M. R. Afrash, F. Rahimi, H. Kazemi-Arpanahi, M. Shanbezadeh, M. Amraei, and F. Asadi, "Development of an intelligent clinical decision support system for the early prediction of diabetic nephropathy," *Informatics Med. Unlocked*, vol. 35, no. May, p. 101135, 2022, doi: 10.1016/j.imu.2022.101135.

[13] N. R. Galo, M. P. Roriz Junior, and R. P. Tóffano Pereira, "A fuzzy approach to support decision-making in the triage process for suspected COVID-19 patients in Brazil [Formula presented]," *Appl. Soft Comput.*, vol. 129, p. 109626, 2022, doi: 10.1016/j.asoc.2022.109626.

[14] G. S. Chakraborty, D. Singh, M. Rakhra, S. Batra, and A. Singh, "Covid-19 and Diabetes Risk Prediction for Diabetic Patient using Advance Machine Learning Techniques and Fuzzy Inference System," *Proc. 5th Int. Conf. Contemp. Comput. Informatics, IC3I 2022*, vol. 2022, pp. 1212–1219, 2022, doi: 10.1109/IC3I56241.2022.10073256.

[15] Z. Isa, "Experts' Judgment-Based Mamdani-Type Decision System for," vol. 2021, 2021.