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Analyzing the Performance of the Fuzzy Inference System in Decision Making

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Abstract— Inference systems that are fuzzy, It is common practise to make use of models such as the Mamdani and Sugeno models in order to take into consideration the presence of uncertainty and imprecision in the decision-making process. MATLAB is a well-known programming environment that provides persons who are interested in developing and implementing fuzzy inference systems with the necessary tools and strategies to accomplish their goals. In order to evaluate Diabetes Mellitus (DM), the Mamdani and Sugeno fuzzy inference systems have been developed in MATLAB. This abstract provides a brief summary of how the evaluation was carried out.The Mamdani model provides a description of uncertain data through the utilisation of fuzzy sets and is founded on language standards. Through the utilisation of the Fuzzy Logic Toolbox, users of MATLAB are able to rapidly construct and simulate Mamdani fuzzy systems. Membership functions, fuzzy rule sets, simulations, and Mamdani system optimisations can all be defined and created by users without any restrictions that are placed on them. The visualisation options that are available in MATLAB, such as the surface plot and the rules plot, help to make the behaviour of the system more understandable.For the purpose of producing inferences and predictions, the Sugeno model, also known as the Takagi-Sugeno-Kang (TSK) model, combines fuzzy principles with linear calculations. It is possible to implement Sugeno fuzzy systems by utilising the Fuzzy Logic Toolbox that is included in MATLAB. The user is able to create the linear functions that are associated to each rule after the information regarding the input-output relationships has been specified through the utilisation of linguistic variables and membership functions. Evaluation, simulation, and visualisation of the rule surfaces and output response curves of Sugeno fuzzy systems can be accomplished in MATLAB in a short amount of time. To summarise, the Mamdani and Sugeno fuzzy inference systems are capable of being constructed in an efficient manner by utilising MATLAB. There is software available for rapid system modelling, simulation, and analysis applications. The techniques of fuzzy logic that are available in MATLAB can be utilised by both professionals and academics in order to address the issue of uncertainty and imprecision in decision-making processes.

Key words : Inference Systems , Fuzzy, Mamdani and Sugeno Models, Diabetes Mellitus, MATLAB, Takagi-Sugeno-Kang .

I. INTRODUCTION

A fuzzy inference system, often known as a FIS, is a type of artificial reasoning invention that makes use of fuzzy mental stability in order to communicate with other information. Fuzzy logic is an excellent analytical basis for dealing with challenging concerns regarding the real world since it is able to deal with erroneousness and uncertainty. In the framework of fuzzy surmising, the information factors are represented as fuzzy sets. These fuzzy sets are indicated by participation works that assign a place of enlistment for each worth in the set. The rules that determine how the recommendation variables effect the gain variables are depicted using fuzzy sanity, and the crop variables are also depicted into fuzzy sets. Fuzzy sets are also used to represent the crop variables. Rule judgement, defuzzification, and fuzzification are the three fundamental advancements that are incorporated into the course of determination in a framework that is based on fuzzy assumption. The new proposal values are transformed into fuzzy sets through the process of fuzzyification, which makes use of the capabilities of cooperation. Rule judgement is the process of applying fuzzy rules to fuzzy inputs in order to establish the degree of participation with which the output variables are involved. At last, the fuzzy production sets are reverted to new decision-making principles through the process of defuzzification. handle approaches make frequent use of fuzzy conclusion orders. These orders can be utilised to describe and handle complex orders that have unclear or shifting dossiers. Fuzzy conclusion orders see widespread application. They are utilised more frequently in the areas of dossier thinking and example affirmation applications, where they might be of assistance in recognising intricate friendships in abundant dossier sets. A fuzzy end framework, also known as a FIS, is a strategy that involves arranging the arrangement from a logical proposal to a result by making use of fuzzy reasoning controllers and fuzzy principles. As was said earlier, the plan serves as a basis from which one might make conclusions or recognise a pattern. Individual of the most astounding purposes of fuzzy sense and fuzzy set conviction, FIS is a member of the fuzzy identity system. Within the framework of the fuzzy set hypothesis, a change that is advantageous is referred to as a semantic variable. Additionally, the system is distinguished by fuzzy philosophy manipulators of "or" and "and," enrolment functions of recommendation and crop semantic variables, and if-therefore rules. These are the primary distinguishing characteristics of the system. In addition, the configuration of fuzzy rules and the forms of fuzzy sets that are utilised to delineate recommendation variables are what determine the optimality of the amount variables. It is the substance of FIS that is laid forth, and it is their bifold personality of suggestion and benefit aspects that they are sophisticated enough to cope with phonetic thoughts. As a result of this substance, FIS has upgraded whole approximates that are prepared to act as a non-undeviating weighing centre from two different sources of data and results. These two FIS strengths have been utilised in the development of the Mamdani-type and the Sugeno-type FIS. The defuzzification engine, the fuzzification interface, and the defuzzification processes are the most important components of administration.

The two inferences of the Mamdani-type and the Sugeno-type are largely followed, with fuzzification and deffuzification serving as the two fundamental processes. The structure that is illustrated in Figure 1 is basically followed. The process of deduction constitutes the third cycle. In the Mamdani derivation process, the result is referred to as enrollment capability. On the other hand, in the Sugeno deduction process, the result is cleared up by a single polynomial while taking into consideration the input elements. A common construction is used for the Mamdani induction, which includes a number of different rule bases for information and results.

II. LITERATURE REVIEW

In addition to Samavat 2023, etc. The two classes for Mamdani and Sugeno are surveyed in order to introduce the perfect regulator for boosting the output of a planetary group by employing the two types and learning about their qualifications. This is done in order to introduce the ideal regulator. The capability for information enrollment is another factor that is taken into consideration when determining the appropriateness of the regulation. To continue along similar lines, each fuzzy system model is equipped with one of two information involvement capabilities that are totally optional. Note that fuzzy systems, which are a subset of man-made reasoning, were developed by inheriting computations as a result of a human desire to automate specific occupations. This is an extremely important point to keep in mind. The result of this is that four different fuzzy systems have been developed and implemented on a planetary entity. Evaluation and categorization of the findings were carried out in MATLAB Simulink. It is [1].

The creation of a unique system for identifying the three types of diabetes mellitus was accomplished by Sonia 2023 and colleagues through the utilisation of a multi-layer neural network no-property technique. The algorithm makes advantage of the development phase and the testing phase, which are the two fundamental phases of the information system. In each phase, type 1 diabetes is the most prevalent, followed by normal and type 2 diabetes, and finally, healthy pregnant women who have diabetes tend to be the least prevalent. After that, a multi-layer neural network is trained independently by making use of the relevant characteristics that were selected and selected throughout the process of attribute selection. Improvements in categorization performance are brought about by the architecture of the multi-layer neural network. After conducting an experiment to determine the sensitivity, specificity, and accuracy of diabetes diagnosis, a confusion matrix is produced from the results of the experiment. The values of 0.95 and 0.97 for specificity and sensitivity were achieved to their maximum potential. [2]

In addition to Shwetha 2023, etc. Data on fourteen different factors is also collected through the usage of images that have been preprocessed. Methods that are used for the early diagnosis and treatment of diabetic retinopathy, a condition that is frequently observed, can be of assistance in the identification of retinal lesions. a unique criterion for locating the optical disc should be provided, in which the major blood vessels are identified first, and then the points of intersection are used to locate the optical disc. Localization will make use of colour features in the not too distant future. The purpose of this demonstration is to demonstrate that a number of different morphological techniques, when applied appropriately, can be employed to identify a collection of features. These characteristics include blood vessels, mucus, micro aneurysms, and haemorrhages. [3]

In addition to Sadat Asl 2022, etc. Patient admission to the intensive care unit is predicted by the interval type-2 fuzzy expert system for COVID-19 patients. An additional system for adaptive neuro-fuzzy inference (ANFIS) was built in order to fulfil the requirements of this prediction job. In addition, the outcomes of these fuzzy systems are compared to the outcomes of other well-known classification approaches, such as the Naive Bayes (NB) method, the Case-Based Reasoning (CBR) method, the Decision Tree (DT) method, and the K Nearest Neighbour (KNN) method. Based on the data, it can be concluded that the ANFIS and type-2 fuzzy expert system models perform exceptionally well in terms of accuracy and F-measure when compared to alternative approaches to system modelling. [4]

Sangeetha Devi, 2022, along with other researchers, proposed a novel A. In order to locate the Sugeno-Type Fuzzy Graph of Groups, a number of fuzzy graph operations, such as cycle, union, join, and products, are utilised. A figure that is representative of those vertices in all pathways with those vertices as their beginnings and ends is the smallest number of common 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. This figure is used to determine whether or not those vertices are representative across all paths. Given that the Sugeno dominating path-coloring number is present in every set of shared edges, it is possible to implement a variety of different ways. This is because it is present in every set of shared edges. As a result of these recent discoveries, a number of chromatic number graphs that have recently been generated are being investigated. [5]

According to Kotiyal 2022 and others. Due to the fact that a sizeable portion of the population is impacted, big data is pertinent to the issue at hand. Despite these challenges, Deep Learning has the potential to resolve the problems that Big Data is now facing. Big data and deep learning are hence of great interest to the academic community. Within the scope of this investigation, we endeavoured to achieve binary classification of diabetic retinopathy by utilising efficient preprocessing and Deep Learning techniques. The experiment makes use of a Kaggle dataset that was sourced only from India. The originality of the study lies in the fact that many models, namely InceptionV3, Xception, and VGG19, as well as the performance of the Logistic Regression classifier, are compared on the Spark platform. As a comparison metric, the precision of the models is evaluated and compared. According to the findings of the experiment, InceptionV3 has an accuracy rate of 95%, Xception has an accuracy rate of 92.50%, and VGG19 has an accuracy rate of 89.94%. As a consequence of this, InceptionV3 performs better than the other two models.[6]

Lin, Jing 2022, and others. According to the eGFR grading, Grade 1 accounts for 42.50 percent of the 54 cases of diagnosis of chronic kidney disease (DKD), while Grades 2, 3a, 3b, and 4 account for 18.52 percent, 11.1 percent, 9.2 percent, 18.52 percent, and 18.52 percent, respectively. Blood urea and creatinine levels were significantly positively related, in contrast to the fact that there was a negative correlation between blood Hb levels and the progression of diabetic kidney disease (DKD). According to the findings of the ultrasonography, the values of the major renal artery (MRA), segment renal artery (SRA), and interlobular renal artery (IRA) were much lower than those found in healthy individuals. In addition to the fact that the alterations in the aforementioned data were more pronounced than those in the lower extremities, the IR of the arteries that were described earlier was noticeably enhanced. On the other hand, the correlation between MRA, SRA, and IRA grades was negative, whereas the association between RI and DKD grades was an indication of a favourable relationship. We discovered that the amount of haemoglobin has a positive correlation with the RI of the arteries, despite the fact that the RI of the arteries has a negative connection with kidney function. The convergence of RI and Hb level is the root cause of this phenomenon. I will conclude. According to the results of the evaluation, the haemoglobin (Hb) level and the intrarenal artery resistance index (RI) are both indicators of the development of diabetic kidney disease (DKD).[7]

The research conducted by Srivastava 2022 and colleagues focuses on classifying the many types of arrhythmia that are prevalent in Southeast Asian communities. In order to improve the accuracy of professional arrhythmia diagnosis, the manner in which medical knowledge is implemented in practise has been thoroughly investigated. Using a satisfied factor, this system is put through its paces in order to determine how effectively the inputs and outputs mesh together. [8]

Abhilash 2022 and others also published. The Pima Indians Diabetes Dataset (PIDD) and the Hospital Frankfurt Germany Diabetes Dataset (HFGDD) are the two diabetes mellitus disease datasets (DMDDs) that are utilised in the integrated dataset on which the system is trained using EDL approaches. Both of these datasets are used to train the system. The UCI-ML repository as well as the Kaggle repository were utilised in order to get these datasets. In order to illustrate a variety of characteristics, the system that was suggested was employed. These characteristics include precision, recall, accuracy, F-measure, latency, arbitrator time, jitter, processing time, throughput, energy consumption, bandwidth utilisation, networking utilisation, and more. The connection between the Internet of Things and the cloud is useful for detecting diabetes patients remotely and in real time. The findings provide light on the advantages of utilising FC concepts and the extent to which they can be utilised to assist in the rapid diagnosis of diabetic patients through distant means. A description of the key is included in the text component of the PACS-key. A written explanation of the PACS-key is provided! [9]

Researchers Tian 2022 and colleagues investigated the connection between coronary heart disease and the levels of serum sestrin2 in individuals who had type 2 diabetes. Participants in the trial included 69 people with type 2 diabetes who did not have coronary heart disease. It was established that clinical traits as well as metabolic markers already existed. Through the use of ELISA, the levels of sestran2 in serum were determined. End Result: The serum levels of sestrin2 in the T2DM-CHD groups were substantially lower than those in the T2DM group (11.17 (9.79, 13.14) ng/mL versus 9.46 (8.34, 10.91) ng/mL). In the course of conducting a bivariate correlation study, it was discovered that serum Sestrin2 levels exhibited a negative connection with age ($r = 0.256$, $P = 0.002$), body mass index ($r = 0.206$, $P = 0.015$), fasting blood glucose ($r = 0.261$, $P = 0.002$), and Tyg index ($r = 0.207$, P 10%). It was discovered through the utilisation of binary logistic regression that there was a significant (P 0.05) link between decreased blood Sestrin2 levels and an increased risk of type 2 diabetes and coronary heart disease. Sestrin2 was used to predict people with type 2 diabetes and coronary heart disease, and its area under the curve (AUC) had a value of 0.724 (95% confidence interval [CI]: 0.641-0.808, p 0.001). Sestrin2 levels and coronary heart disease were found to have a high correlation in diabetic patients. It is possible that serum sestrin2 has an effect on the prevalence of diabetic heart disease as well as its progression. [10]

According to Zhang 2022 et al., the suspension of a vehicle can be managed in a manner that is more efficient, more dependable, and requires less energy. It is possible to design a fuzzy SMC technique for active suspension systems by using bionic nonlinear dynamics as the driving force. In contrast to the findings that were discovered before, the control method that has been developed makes efficient use of the advantageous nonlinear stiffness or damping that is present in the biomimetic reference model. This results in performance that is more efficient in terms of energy consumption. In addition, a variety of factors that are relevant to the real world are taken into careful consideration. These include input saturation, dead zones, unknown or unpredictable dynamics, and interference from the outside. The fuzzy SMC technique that was offered, which is based on bionic dynamics, has the potential to successfully reduce energy consumption, increase ride comfort, and effectively reduce vibration of the active suspension system, as indicated by the results of theoretical analysis and simulations.[11]

The researchers Afrash 2022 et al. In an effort to construct a decision support system (DSS) for the diagnosis of DN that is based on the use of machine learning (ML), it was attempted to determine the variables that were significant in predicting DN. Techniques: An examination of the medical records of 327 individuals who were diagnosed with diabetes (types 1 and 2) was carried out in a retrospective manner. Through the utilisation of the genetic algorithm's (GA) feature choosing approach, the variables that were expected to have an effect on DN after the processing of the data were found. Then, in addition to other machine learning techniques, the support vector machine (SVM), decision tree (DT), K-nearest neighbour (KNN), and artificial neural networks (ANN) were utilised in order to train prediction models that were based on the features that were chosen. After that, the performance of the models that were generated was evaluated using the criteria of accuracy, specificity, and sensitivity over the course of 10 separate runs. [12]

As well as Galo, 2022, etc. This study proposes the utilisation of computer tools for decision-making that make use of fuzzy inference systems as a potential means of enhancing the triage procedures that are currently in place in Brazil. We argue that the utilisation of natural language in the description of the patient's symptoms makes it easier for medical workers to comprehend the issue, and that fuzzy set theory is applicable in this context. After simulating the problem in a fuzzy system, we used a pilot test to test our hypothesis. The model takes into account the symptoms that are currently being used by medical professionals to evaluate instances of COVID-19. Because the findings demonstrate that the model is converging with the sample data, they suggest that the model might be utilised to assist in the triage process for the classification of the severity of COVID-19 cases. One of the benefits of the model that was suggested. We place a special emphasis on the contributions that result in a reduction in the amount of time and personnel required for triage, as well as the exposure of medical workers and other patients who may be carrying the virus. Consequently, this research presents an opportunity to gain social contributions for the purpose of improving the quality of services provided by public hospitals.[13]

Chakraborty 2021 and others, etc. It has been suggested that a COVID-19 risk prediction model for diabetic patients be developed by utilising a fuzzy inference system and several machine learning approaches. In order to take immediate action and lower the multifold COVID-19 death rate among diabetic patients, the purpose of this study was to evaluate the COVID-19 risk level in individuals who had diabetes without seeking the advice of a medical professional. As inputs for the proposed model, there are eight elements that were found to have the greatest influence on the symptoms that diabetic patients experience. It was determined that the rule base would serve as the basis for the construction of fifteen models, which were constructed using a variety of cutting-edge machine learning approaches. It has been demonstrated that the CatBoost classifier achieves the maximum kappa, F1, recall, accuracy, and other related metrics. Following the implementation of hyper-parameter optimisation, the CatBoost classifier was able to attain an accuracy of 76%, in addition to gains in recall, precision, F1 score, and kappa score. Then, logistic regression and XGBoost came along, each of which had an accuracy of 75.1% [14].

The authors Liu 2021 et al. In this work, bioinformatics methods were utilised to investigate potential treatments for coronary heart disease in diabetic patients. Techniques. The genes that are connected with diabetic coronary heart disease (CHD) and the genes that are specifically targeted for the chemical components of Qiweitangping were collected from the GeneCard database. Through the utilisation of the TCMSP database, the active chemical components of Qiweitangping were investigated. Additionally, in order to identify potential genes, the junction between the gene that the medicine is intended to target and the gene that is associated with the disease was discovered. The candidate genes were then subjected to KEGG enrichment analysis and protein interaction analysis, both of which were carried out with the assistance of the STRING and DAVID databases. As an alternative way of verification, the docking of molecules was also utilised. In the end, a network of genes that are associated with "drug component-gene target-pathway" was developed through the utilisation of the Cytoscape tool. The outcomes. It was discovered in Qiweitangping that there are 62 active compounds, which include naringin, diosgenin, formogenin, isorolin, and isocryptanshinone, in addition to 59 possible target genes, which include AKT1, CASP3, and VEGF-A. An additional point of interest is that the results of two molecular docking studies (CASP-naringenin and STAT3-cryptotanshinone) showed a high affinity (-5.00 kcal/mol). Final thoughts. Within a wide range of chemical treatments for diabetic coronary heart disease, Qiweitangping makes advantage of the findings of the study. Additionally, the signalling pathways PI3K-Akt, ErbB, and HIF-1 have the potential to have an effect on its operation. This was demonstrated by the molecular docking approach, which showed that the Qiweitangping, STAT3, and CASP genes interact in a positive manner. It is anticipated that the outcomes of this study will serve as a theoretical foundation for more experimental studies on the Qiweitangping treatment mechanism for diabetic coronary heart disease.

According to Isa, Zaidi 2021, and others. Both the input and output language variables of the framework were predetermined to make use of the triangle membership function. It is possible to choose an appropriate control action by employing the fuzzy aggregation approach of the technique, which makes it possible to collect the opinions of competent professionals. In order to develop an efficient fuzzy model for the formation of judgements, a total of 23 rules were utilised. These rules included the logical OR operator, the truncation implication, and the Mean of Maxima (MoM) defuzzification approach. Through the utilisation of a powerful fuzzy arithmetic operator, the framework is able to ascertain the connection that exists between the input and output parameters that are contained within if-then expressions or mathematical functions. For the purpose of discussing the underlying difficulties with a variety of expert views, the study makes use of a decision framework in the style of Mamdani as well as an example from a medium-sized project in the construction industry in Malaysia. By contrasting the results of the given approach with those of previous trials, we are able to demonstrate that said method is both logical and reliable. [15]

III. OBJECTIVE OF THE RESEARCH

The primary objective of this paper is to study the ways in which membership functions influence Mamdani-type fuzzy inference systems and to determine the component parts of membership functions that have the most significant impact on input-output connections. The development of membership functions that are appropriate for both ideal linear inference systems and typical non-linear inference systems is another objective of this project. In this particular circumstance, the Fuzzy Logic Toolbox of MATLAB will be utilised to carry out the process of trial and error. For experimental Mamdani fuzzy inference systems, the sole criterion that will be subject to change is the characteristics of the membership function. These characteristics include the form, quantity, and overlap ratio of the MFs that are located nearby. Both the input and the output are singular. The Mamdani fuzzy inference system, which is the most fundamental model, will be investigated first in order to determine the properties of membership functions in relation to the modification of input-output curves. The two-input single-output inference system will be addressed in order to provide a concise summary of the consistent impacts that the membership function has on both the SISO inference system and the TISO inference system. The presentation will include a demonstration of a method for incorporating weight into a multi-input single-output system, and it is hoped that a real-world application will be used to validate the validity of the findings.

IV. RESEARCH METHODOLOGY

4.1 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.

4.2 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 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.

4.3.1 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.

4.3.2 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.

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V. RESULT & DISCUSSION

5.1 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.

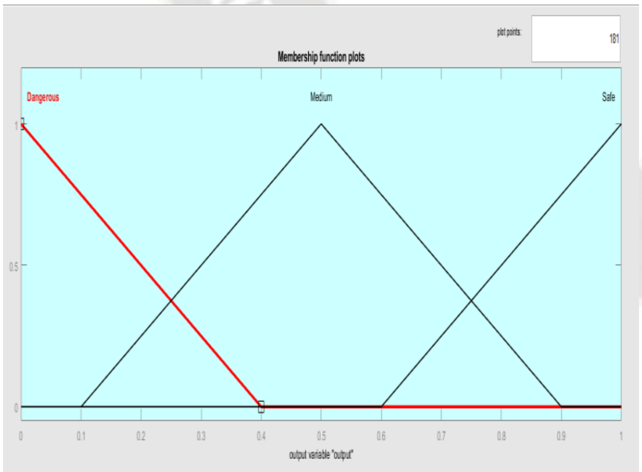

Figure 1 Membership function of output variable Diabetes Mellitus (DM)

The graphical illustration of the Membership function of output variables, including Diabetes Mellitus (DM), may be shown in Figure 1.

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.

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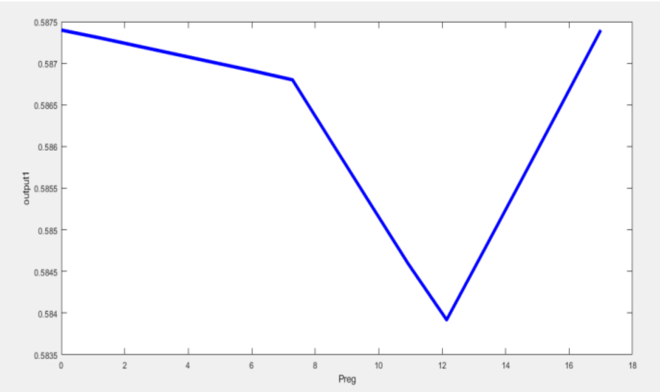

Figure 2 Output Graph of Preg

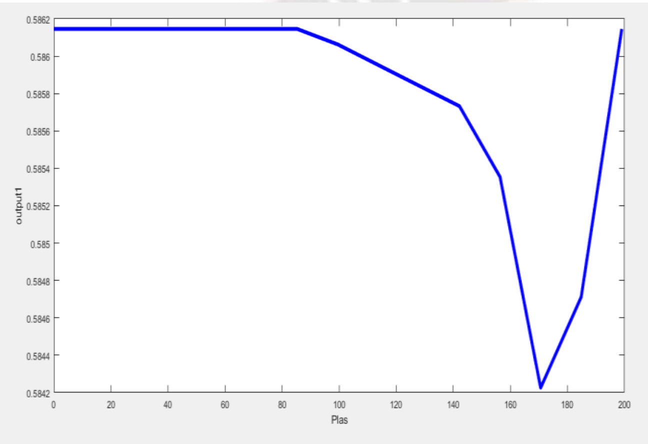

Figure 3 Output Graph of Plas

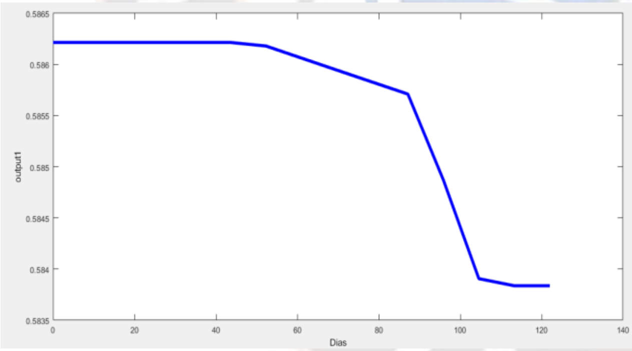

Figure 4 Output Graph of Dias

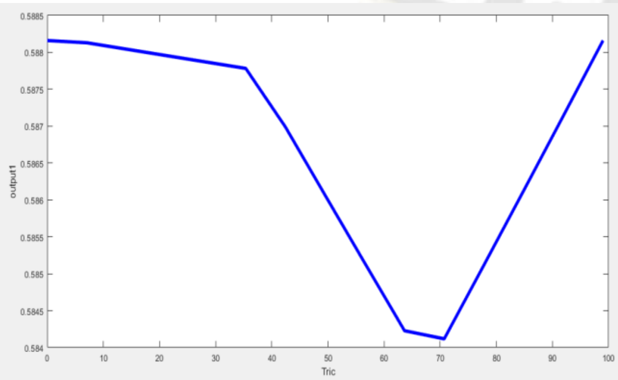

Figure 5 Output Graph of Tric

VI. CONCLUSIONS

As a conclusion, the Mamdani and Sugeno fuzzy inference systems are frequently utilised in the business world as a means of putting fuzzy logic to use in a variety of applications. With the assistance of MATLAB, which provides a comfortable environment, these methods make it possible to build and deploy fuzzy inference systems in a straightforward yet straightforward manner. The following is a collection of important information regarding the Mamdani and Sugeno fuzzy inference systems that were constructed using MATLAB:Mamdani's Fuzzy Inference System is as follows: Fuzzy sets are utilised by the Mamdani fuzzy inference system in order to provide a description of uncertainty and imprecision. The several linguistic conventions that serve as the basis for this system. This process incorporates a number of different fuzzy logic operations, including rule aggregation, fuzzy logic evaluation, fuzzy logic defuzzification, and fuzzy logic frizzification. Users are able to construct and model Mamdani fuzzy systems by utilising the Fuzzy Logic Toolbox, which is accessible through MATLAB. This toolbox offers a comprehensive collection of tools and functions specifically designed for this purpose. In order to create judgements or projections, the Takagi-Sugeno-Kang (TSK) model, which is often referred to as the Sugeno fuzzy inference system, employs a combination of fuzzy rules and linear functions. MATLAB's extensive processing capabilities and user-friendly interface make it possible to create, simulate, and analyse the Mamdani and Sugeno fuzzy inference systems in a welcoming environment. In conclusion, this is made possible by the combination of these advantages. It makes no difference whether you are working with rule-based models with linear functions (Sugeno) or rule-based models with linguistic rules and fuzzy sets (Mamdani) because MATLAB provides the tools and functions that are required to rapidly construct and explore fuzzy logic-based systems.

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