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A FRAMEWORK FOR DIABETES DIAGNOSIS BASED ON TYPE-2 FUZZY SEMANTIC ONTOLOGY APPROACH

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Abstract:

Diabetes mellitus is a significant metabolic disorder that may last a lifetime and affects a great number of people throughout the world. Two major critiques that may be levelled at the ontology-based tools that are presently being used to analyse and treat diabetes are an increase in semantic incompatibility and an inability to interpret the information. Both of these complaints have the potential to be severe issues. Furthermore, clinical decision support systems, often known as CDSSs, play an important role in the diagnosis of diabetes. As a consequence, the outcomes of this study project advised that a new semantically intelligent Type-2 fuzzy CDSS for diabetes diagnosis be developed. The following steps are included in the proposed system: feature definition, semantic modelling, type-2 fuzzy modelling, and knowledge reasoning. This research endeavour is critical since there are currently so few works that address the formal integration of ontology semantics with Functional Electrical Stimulation (FES) reasoning, particularly in the medical arena. The ontology is a feature of FES that may be needed or selected as optional. The system that was constructed takes into consideration the ontology-semantic similarity of the concepts that are relevant to diabetes complications and symptoms while doing a fuzzy rule analysis. The proposed approach is put to the test using a real-world dataset, and the results show that it has the potential to help both individuals and medical experts provide more accurate diabetes diagnoses. The suggested technique was tested on a real dataset, and the findings show that it has the potential to help physicians and patients diagnose diabetes mellitus more correctly.

Keywords: *Diabetes mellitus – Clinical decision support system (CDSS) - Ontology reasoning – Functional Electrical Stimulation (FES) - Type-2 Fuzzy.*

I. Introduction

Any healthcare system's clinical diagnosis procedure is the most important and vital component. It is the process of determining the cause and origin of an illness using clinical and laboratory tests, careful examination of the patient's symptoms and indications, and a thorough review of the patient's medical history. The investigation's main emphasis was on the idea of diabetes mellitus (DM). Because insulin is not being released at all, its efficiency has reduced, or both of these reasons are at play, blood glucose levels are dangerously high. According to

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forecasts from the International Diabetes Federation, there will be 642 million diabetics on the planet by 2040. (IDF). Type 1 diabetes (which involves only 10% of diabetics) and type 2 diabetes (which affects 90% of diabetics) are the two types of diabetes, according to the American Diabetes Association (which affects 90 percent of diabetics).

The CDSS [1] is designed to help patients and their treating doctors in a number of contexts, starting with the first consultation and continuing through diagnosis and patient follow-up. These systems are in charge of gathering, processing, examining, disseminating, presenting, and storing information on patients. The clinical decision support systems that are available are divided into two categories: “knowledge-based systems and non-knowledge-based systems”. The essential architecture of a knowledge-based CDSS may be broken down into four main modules: “input, output, knowledge base, and inference (reasoning engine)”. The system considers the patient's symptoms to be trustworthy data. As part of its input, the CDSS gets the vast bulk of the patient's medical history. This information contains the whole medical history of the patient. Clinical diagnoses are created using knowledge bases and inference engines, two of the most important components of a knowledge-based clinical decision support system (CDSS). Information on medical practises and procedures may be found in the knowledge base. In a basic way, the ontology clarifies conceptualizations as well as drawing relationships between concepts obtained from a number of fields. Because knowledge representation lies at the foundation of a decision support system, it has a substantial presence in the field of knowledge-driven decision support systems, which aim to make clinical analysis easier. The capacity to easily exchange and preserve knowledge, as well as its reusability in a variety of scenarios, is one of the most important advantages of using ontologies. The Online Ontology Language, or OWL, is a kind of ontology language that was created with the objective of creating high-level ontologies that give thorough descriptions of material available on the internet. To create these ontologies, first create hierarchies of classes that define concepts inside a domain, and then use attributes to connect the classes and explain how they are connected. Ontology is widely accepted as a critical phase in the process of developing a knowledge-based system, and it is the first step that must be accomplished. Humans and robots may both interpret knowledge in the same way thanks to ontology.

It's a database of symptoms and diseases accompanied by rules; the rules are organised as If-Then statements for the most part. A usual rule is "IF Vision is Allergy-redness High AND BMI is Very High, THEN Diagnosis is Diabetes." The inference engine has the ability to read. It then makes a decision and creates a diagnostic report based on the findings, taking into account the patient's symptoms as well as the knowledge base's rules. The data supplied assists professionals in making accurate sickness diagnoses and estimating the risks of a variety of illnesses, lowering the chance of human error during manual diagnostic processes. When doing a manual diagnosis, clinicians may be unable to get the whole medical history of their patient, resulting in a decline in diagnostic accuracy. In the aforementioned situations, a clinical decision support system may aid a physician in making better decisions. Furthermore, before coming to a decision, the physician must do a thorough examination of the system's recommendations.

The remaining portions of the study may be divided into the following categories: Section II presents an overview of related field studies. Section III contains an introduction to the System's architecture as well as a basic example of how to implement key features and characteristics that make use of it. The results of the experiments that were analysed are reported in this section. Section V. Some of the results and future work are described in Section V, which is towards the conclusion of the research.

II. Literature Survey

However, Mansourypoor and Asadi [2] failed to tackle the major challenge that exists in the area of diabetes diagnosis when building up a FRBS for diabetes diagnosis. They believed that each of the patient's characteristics could be represented by a number, however this is not the case. The electronic health record, or EHR, has all of the information needed to create the basic FRBS and improve real-time physician inquiries. The usage of FRBSs, which are supposed to display behavior in terms of knowledge representation and reasoning that is intended to be equivalent to that of a qualified medical practitioner, aids the production of interpretable CDSS. In the realm of system modeling, granular computing approaches like FRBS are often utilized for classification and regression analysis. It's a knowledge-based system, and the interpretability of fuzzy rules language is its well recognized invention. In contrast to other machine learning techniques, fuzzy rules language has the ability to acquire some degree of accuracy. They may satisfy the universal approximation property's criteria, and the inference engines they utilize use approximate reasoning. [3] The implementation consists of a series of IF-THEN rules, each of which may be interpreted in a number of ways. [4] Transparency and intelligibility are two notions that are employed in the definition of interpretability. It is critical for these sorts of systems to have a considerable level of human involvement since this aids in the understanding of the system's output. Throughout the design of the FRBS, there are two distinct trends to be recognized. The first technique is known as linguistic fuzzy modeling, although it's also referred to as expert-driven methodology. A human expert enters information directly into the system using this way. The Mamdani model is extensively utilised, and it places a strong focus on the system's interpretability. If the area is complex, there may be several challenges to overcome [5]. The data-driven technique, also known as precise fuzzy modelling (PFM), emphasises system correctness by allowing the system to locate and extract information from experimental data samples on its own. This ensures that the system works as it should. These innovations aren't mutually exclusive; in fact, mixed techniques have been investigated [6].

A1C is high, and the ailment being treated is "Aneurysm," which is not the expected behavior. Anderson et al. [7] used full EHR data (including “medicines, diseases, lab tests, and symptoms”) to examine the influence of DM diagnosis CDSS, and they came to the conclusion that the categorization improved as a direct consequence of their results.

Using the ontology was beneficial in the process of designing automated systems, according to Liaw et al. [8,] and adding EHR data into the diabetes diagnostic CDSS increased the system's accuracy. These two discoveries are mentioned many times in the article. Static solutions to the issue of unstructured data are useless since the resulting system cannot be integrated into the EHR ecosystem or utilized in the mobile health environment, which demands a lower degree of accuracy. It also depends on how similar the concepts included in the patient's profile and those contained in the rule base are to one another. Assume that you have a simple fuzzy rule of the form "IF THEN." The rule will not be invoked if a new case is received with the criteria "Hb."

III. Methodology

3.1 System Architecture

A theoretical framework known as the semantically intelligent Type-2 fuzzy CDSS system has been presented as a direct outcome of the results of this study. It is a reliable approach for identifying whether or not someone has diabetes. In order to construct a full type-2 fuzzy rule foundation for linguistics, information from both experts and CPGs, as well as other forms of training data knowledge and semantic model knowledge, must be included. CDSS now provides a better level of automation and interoperability to its clients as a direct consequence of this activity. In its most basic version, this approach comprises four phases: “data collection and feature definition, semantic modeling, Type-2 fuzzy modeling, and knowledge reasoning”. The recommended organizational architecture for the system is shown in Figure 1. Each of these blocks contains a number of stages, which are detailed below.

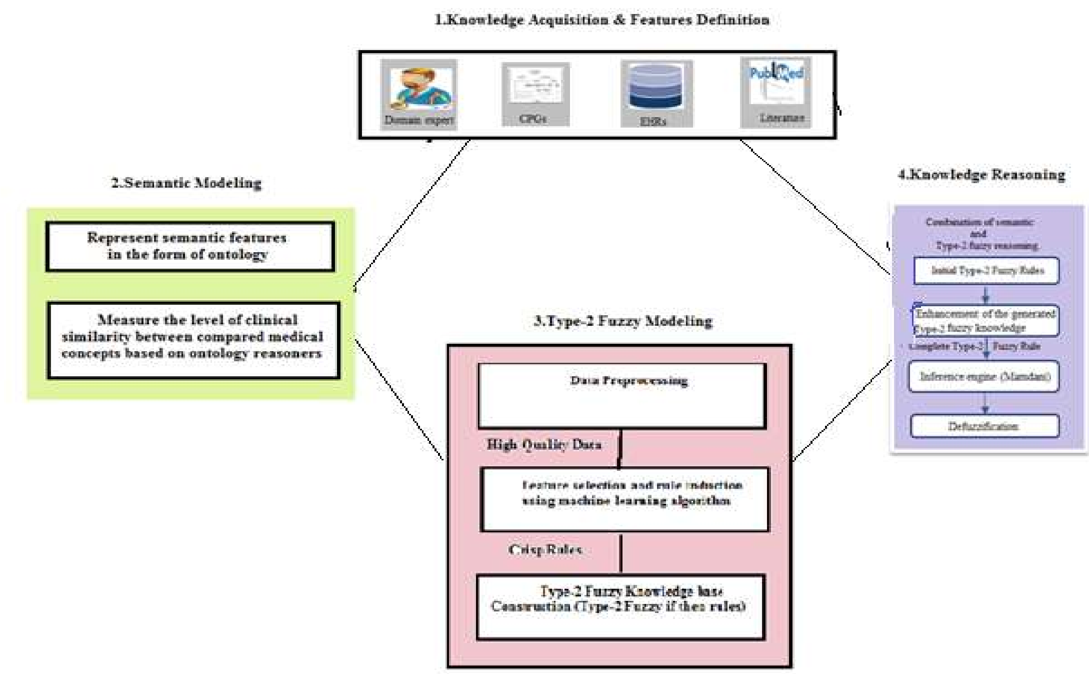


Figure 1: Semantically Intelligent Type-2 fuzzy CDSS System

Knowledge acquisition

Information acquisition, or KA, is a stage in the process of gaining the information needed to successfully diagnose diabetes. This research assembles diabetes information from a variety of sources, including medical experts, recent publications [9], and current clinical practise guidelines (CPGs) issued by the "National Institute for Health and Care Excellence". The information needed to build T2FO comes from five key sources at this point of development, which are detailed in more detail below.

- Med, SpringerLink, and ScienceDirect are all excellent sources of information. A search of the research into the relevant literature was carried out by utilizing a variety of bibliographic databases, one of which being PubMed.
- EPR (Electronic Patient Record) - This software creates personalised treatment plans for individuals based on their current and previous medical issues obtained from a network of electronic health data (EHRs). Lab testing, symptoms, physical exams, existing comorbidities, presently used medicines, and other criteria may all be used to determine these disorders.
- Clinical Practice Guidelines (CPGs) - The goal of this study was to extract TP components, essential concepts and features, SWRL rules, and the relationships between patient characteristics and specific plans.
- This inquiry gathered information regarding type 2 diabetes diagnosis criteria and interactions from a variety of websites.
- Expert in the Field - We sought help from a subject area expert to get a better understanding of the many T2DM treatment types, relationships, principles, and reasoning.

1. Semantic modeling

When we speak about semantic modeling, we're talking about the capacity to express semantic information in the form of ontology and to analyze clinical commonalities across distinct medical theories. For the first requirement, I recommend the OWL2 ontology for diabetes, which is based on the "SNOMED CT" standard medical language. DDO collects and organizes all of the information and risk factors needed to make a diabetes diagnosis. In addition to the 6,444 concepts and 48 traits, this text features 6,356 annotations. The proposed technique focuses mostly on diabetic complications, symptoms, medicines, and chemical substances. Using DDO ontology and an ontology reasoner like "Pellet or Fact++, the semantic similarity between the patient's complications, drugs, and symptoms and the Type 2 fuzzy knowledge base subjects is identified".

2. The Type-2 fuzzy modeling

The proposed system's Type-2 fuzzy aspects are developed in this stage. It is required to consider a number of aspects while developing the type-2 fuzzy model, including the description of type-2 fuzzy features and the type-2 fuzzy words that are connected with them, type-2 fuzzy rules, and the type-2 fuzzy inference engine that will be utilised. CPGs, domain physician knowledge, and EHR data processing are three possible sources of information for developing the Type-2 fuzzy model. There are several studies focusing just on expert knowledge [10], and it is typical practise for experts in a certain subject to communicate their knowledge using IF-THEN rules. Creating type-2 fuzzy knowledge from EHR data may be done in a number of ways, including the ones listed below:

i. Convert a crisp DT to type-2 fuzzy rules using induction
ii. The formation of a type-2 fuzzy DT.

However, each of these approaches is insufficient on its own. A comprehensive type-2 fuzzy system can be created by combining this strategy. Type- 2 fuzzy knowledge can be generated from the processing of “medical data”, and then domain expert is added and CPGs knowledge to it. The next sections go into the specifics of each phase.

1. Raw EHR data preprocessing

When dealing with medical data, the first step is to double-check that all of the information is accurate and current. The following procedures were carried out as part of the research: Data cleansing, outlier elimination, encoding, discretization, normalization, and unit unification are all steps in the data processing process (UoMs).

2. Features definition and fuzzification

This strategy is primarily reliant on domain specialists' knowledge, as well as a thorough review of relevant literature and the most recent CPGs like CDA. An initial list of risk factors for diabetes diagnosis is developed after a thorough evaluation of both the CPGs and the relevant published research.

The characteristics Fuzzification is the term used to describe type-2 fuzzy variables, as well as their language names and MFs. The experts' intuition is used to decide the forms, numbers, and sizes of the fuzzy sets that are utilised. The accuracy and interpretability of the resulting system are determined by these parameters.

3. *Features selection and DT induction*

There are a variety of approaches available for obtaining this “information, including extracting rules from experts, formulating CPGs into rules, extracting rules and learning MFs from learning data using data mining techniques such as DT, type-2 fuzzy DT, neural networks, and evolutionary algorithms, among others”.

4. Knowledge reasoning

1. Initial fuzzy knowledge base construction

Making the procedures and decision limits more difficult to grasp using MFs makes the obvious rules less evident. T-norm is established for both AND and OR, and t-conorm is made for both. The study conducts a fuzzification of all problematic operations in line with the membership functions that were described. The rules are divided into many categories, each of which relates to a different set of thinking and decision-making duties. An expert's fuzzy IF (condition) THEN (conclusion) rules are the most popular way to convey type-2 fuzzy knowledge. The material that makes up the diagnostic criteria in the knowledge base comes from diabetes clinical practise guidelines (CPGs), diabetes electronic health record (EHR) data, and domain expert knowledge.

2. Enhancement of the generated fuzzy knowledge

Although the CDSS knowledge base is one of the most significant mechanisms, it is also one of the most time-consuming to develop. As a result, this process requires a number of steps in order to ensure that the fuzzy knowledge base is comprehensive. With a thorough and exact type-2 fuzzy rule base, the system's accuracy and interpretability are both enhanced. The induction of type-2 fuzzy rules from training data is the basis for the two approaches that have been established. The only features that are included in the training data sets are those that were selected previously. For any combination of qualities, the most common way for analysing data based on regions is to utilise fuzzy decision trees, commonly known as FDTs. The use of Type-2 Fuzzy-DT improves the “robustness, noise immunity, and applicability” of the generated rules.

3. The inference engine

This section makes use of fuzzy logic to convert a certain input into an output. Several inference procedures are available, including “Mamdani, Takagi-Sugeno, and Tsukamoto”. The “Mamdani” fuzzy inference strategy, which is the most often utilized technique, was applied in this work. The “Takagi-Sugeno” paradigm is intuitive, adaptive, and propositions are the outcomes of fuzzy rules. It's ideal for applying the t-conorm or s-norm operator to the RLFVs that result from medical classifications. The s-norm is a type s relation:, [0, 1] On all of the RLFVs, the aggregation operator, which might be union, max, or sum, is the one that is used the most as a t-conorm operator. Finally, the A-FATI (first aggregate, then infer) method is used to defuzzify the data.

4. The defuzzification process

Defuzzification is an optional step that may be skipped if desired. There are many different defuzzification techniques from which to pick. The words used to describe these locations are the “center of gravity (CG), the maximum center average (MCA), the largest of maximum (LOM), the mean of maximum (MOM), the centroid average (CA), and the smallest of maximum (SOM)” (Yaguinuma et al., 2013). The settings that have been fine-tuned and reflect the most often utilized technique (Papadopoulos et al., 2011).

Table 1 outlines the data set that the Fuzzy Rule Based System utilises to diagnose diabetes and can be accessed here. (FRBSs).

Table 1: Data Set Description.

Feature groups for FRBSs	Feature name	Data type	Unit of measurement	Min-mean-max
Symptoms	“Urination frequency”	C	-	{normal, +, ++}
	“Vision”	C	-	{normal, +, ++}
	“Thirst”	C	-	{normal, +, ++}
	“Hunger”	C	-	{normal, +, ++}
	“Fatigue”	C	-	{normal, +, ++}
	“Residence”	C	-	{ Urban, Rural}

	"Gender"	C	-	{Male, Female}
	"Age"	N	year	29-48-74
	"BMI"	N	kg/m2	20-33.117-45
Complications	"Ten features for patient's current and historical complications"	C		Collection of diseases
Diagnosis	"Diabetes diagnosis"	C		{Diabetic, Non-Diabetic}

Table 2 represents the feature group of FRBSs in order to find out the values ofType 1 and Type 2 fuzzy set for diabetics.

Table 2: Type 1&2 Fuzzy Set for Diabetics

NO	ITEM	MESSAGE
1	**Fuzzy Concept** **Fuzzy Variable** **T1FS** **T2FS**	People {Age, Sex} {{Young, Middle, Old},{Male, Female}} {Boy, Man, Old Man, Girl, Women, Old Women}
2	**Fuzzy Concept** **Fuzzy Variable** **T1FS** **T2FS**	BP (mmHg) { Systolic blood pressure, diastolic blood pressure } {Normal, Prehypertension, Hypertension} {Low, Low_normal, Normal, High_Normal, High, Very_High, Too_High
3	**Fuzzy Concept** **Fuzzy Variable** **T1FS** **T2FS**	BMI (kg/m^2) {Independent, Dependent, Controlled] {Low , Medium, High} {Underweight ,Normal_Weight, Over_Weight, Obese}
4	**Fuzzy Concept** **Fuzzy Variable** **T1FS** **T2FS**	Smoking {Independent, Dependent} {Yes, No} {Safe, Caution, Danger}
5	**Fuzzy Concept** **Fuzzy Variable** **T1FS** **T2FS**	Alcohol {Independent, Dependent} {Yes, No} {Safe, Caution, Danger}

6	**Fuzzy Concept** **Fuzzy Variable** **T1FS** **T2FS**	Family History {Independent, Dependent} {Yes, No} {Either or both parents diabetic, Both parents non-diabetics}

Table 3 provides the sample of linguistic variables, linguistic fuzzy sets, Shape and Parameters for the category to detect diabetes.

Table 3: Sample of Linguistic Variables and Fuzzy Sets used for Diabetes Diagnosis.

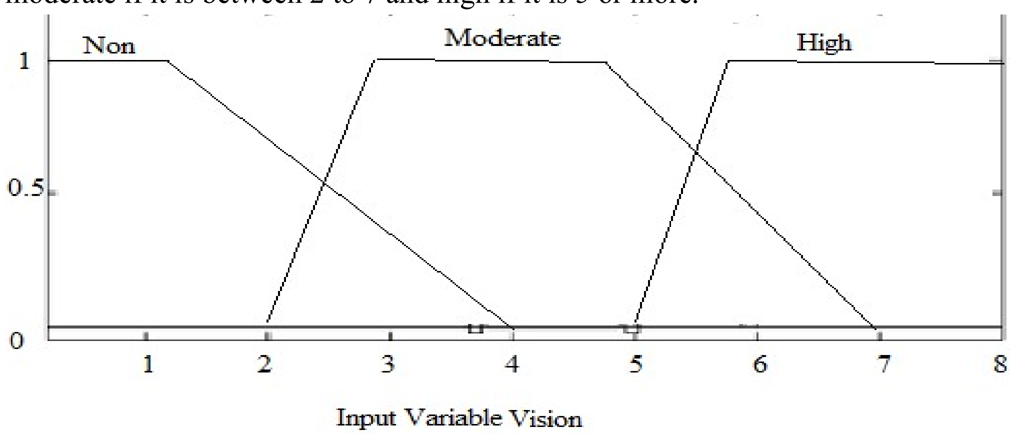
Category	Linguistic variable	Linguistic fuzzy set	Shape	Parameters
Symptoms	Vision Fatigue, Hunger, Thirst, Urination Frequency Residence Gender	{Non, Blurred-vision, Allergy-redness} {Normal, High, Very High} {Urban, Rural} {Female, Male}	Singleton Singleton Singleton Singleton	{1, 2, 3} {1, 2, 3} {1, 2} {1, 2}
	BMI Age	Very Low Low Average High Very High Very Low Low Average High Very High	Trapezoidal Triangular Triangular Triangular Trapezoidal Trapezoidal Triangular Triangular Triangular Trapezoidal	[20, 20, 24.585, 28.941] [24.585, 28.941, 32.275] [28.941, 32.275, 37.813] [32.275, 37.813, 42.071] [37.813, 42.071, 45, 45] [29, 29, 29, 35.266] [29, 35.266, 40.862] [35.266, 40.862, 51.738] [40.862, 51.738, 74] [51.738, 74, 74, 74]
(Complications)	Nephropathy, Shrunken Kidney,	{False, True}	Singleton	{0, 1}

	Splenomegaly, Retinopathy			
Diagnosis	Diabetes Diagnosis	{Normal, Diabetic}	Singleton	{1, 2}

IV Experimental Result

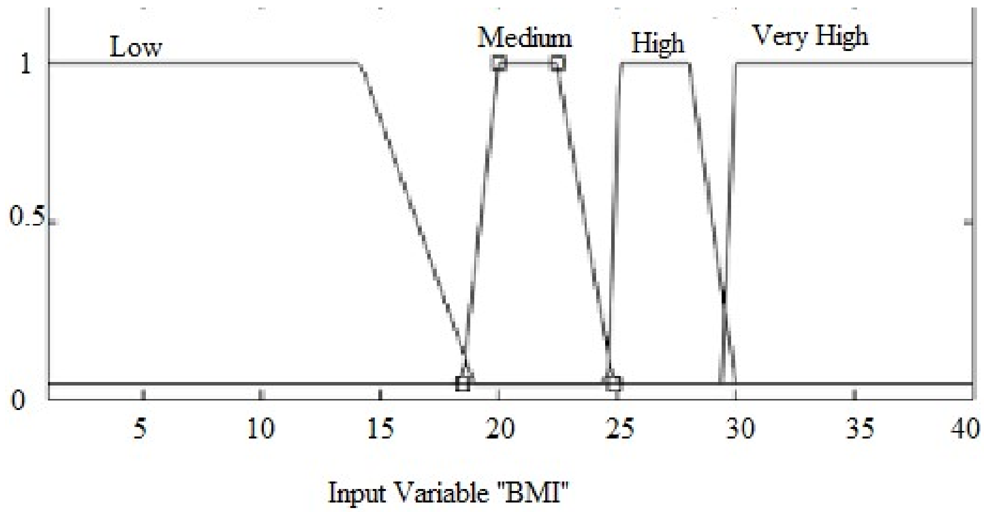
Vision

Diabetic macular edema is the inflammation that arises in the macula as a consequence of diabetes. Diabetes is a medical condition. Over time, this disorder has the potential to obliterate crisp vision in the afflicted area of the eye, resulting in either peripheral vision loss or complete blindness. It has three variables. A vision of the person is normal if it is less than 5, non moderate if it is between 2 to 7 and high if it is 5 or more.



Body Mass Index (BMI)

For diabetes patient diagnosis, the BMI is a simple and therapeutically essential piece of information. A person's body mass index is calculated by multiplying their weight by the square of their height. There are four distinct variables in it. A person's body mass index (BMI) is called medium if it is less than 19. Their BMI is termed high if it is between 18.5 and 24.9. Their BMI is regarded very high if it is between 24.6 and 30.



Example of type- 2 Fuzzy Rules Generated for FRBS

- IF Vision is Allergy-redness High AND BMI is Very High THEN Diagnosis is Diabetic [Weight= 0.1703]
- IF Vision is Allergy-redness Low AND BMI is Low THEN Diagnosis is Normal [Weight= 0.1703]

Table 4: Identify Diabetics / Normal by Type-2 FRBS fuzzy rules

S.No	Vision	BMI	Diabetic / Normal
Patient 1	7.2	63.1	Diabetic
Patient 2	5.4	45.8	Diabetic
Patient 3	0.2	32.1	Normal
Patient 4	2.1	22.4	Normal
Patient 5	6.6	70	Diabetic
Patient 6	8.2	57.5	Diabetic

V Measurement of overall efficiency of proposed system

During the ontology's development phase, each step is evaluated in order to identify the amount of progress and compare the results. Following that, type-1 and type-2 fuzzy ontologies are employed to determine the results.

The given formulas are used to calculate the results.

Precision (P) =Ae/Ae + Fe *100%

Recall (R) = Ae/Ae + Te *100%

Accuracy (A) =Ae+Te/Ae+Te+Fe * 100%

Function measurement (FM) = Execution Time (ET) /Accuracy (A) * 100%

In the above equations,

Ae – “elicited total number of records”
Te- “true and false elicited record elements”.
Fe – “False record elements”.

The entire results of each scenario's true and false elicited components, which were utilized to generate the scenario, are shown in Tables 8–10. The average accuracy and function measurement are computed at the end of each occurrence in order to perform a system analysis. For each occurrence, the value of the function as measured by the function measurement is shown. When compared to T2FO, the crisp ontology's exact output can be seen.

Table 8
The proposed system results in the case of a crisp ontology.

	Total elicited data from ontologies (Ae)	Elicited true elements (Te)	Elicited False elements (Fe)	Precision (P) %	Recall (R) %	Total execution time (T) in min	Accuracy (A) %	Function measure (FM) %
Case 1	369.00	163.00	206.00	64.100	69.300	11.500	72.000	15.900
Case 2	579.00	215.00	364.00	61.300	72.900	9.200	68.500	13.400
Case 3	383.00	144.00	239.00	61.500	72.600	12.300	68.700	17.900
Case 4	455.00	98.00	357.00	56.000	82.200	6.500	60.700	10.700
Case 5	525.00	231.00	294.00	64.100	69.400	8.400	72.000	11.600

Table 9
The proposed system results in the case of a T1FO.

	Total elicited data from ontologies (Ae)	Elicited true elements (Te)	Elicited False elements (Fe)	Precision (P) %	Recall (R) %	Total execution time (T) in min	Accuracy (A) %	Function measure (FM) %
Case 1	369.00	195.00	174.00	67.900	65.000	7.300	76.300	9.500
Case 2	579.00	323.00	256.00	69.300	64.100	10.500	77.800	13.300
Case 3	383.00	209.00	174.00	68.700	64.600	8.200	77.200	10.600
Case 4	455.00	212.00	243.00	65.100	68.700	5.100	73.300	6.900
Case 5	525.00	340.00	185.00	73.900	60.000	9.000	82.300	10.900

Table 10
The proposed system results in the case of a T2FO.

	Total elicited data from ontologies (Ae)	Elicited true elements (Te)	Elicited False elements (Fe)	Precision (P) %	Recall (R) %	Total execution time (T) in min	Accuracy (A) %	Function measure (FM) %
Case 1	369.00	301.00	68.00	86.00	55.00	8.40	90.70	9.20
Case 2	579.00	499.00	80.00	87.00	53.70	13.10	93.00	12.00
Case 3	383.00	294.00	89.00	81.00	56.50	9.20	88.30	9.40
Case 4	455.00	384.00	71.00	86.00	54.20	6.10	92.10	6.40
Case 5	525.00	469.00	56.00	90.00	52.80	9.40	94.60	9.10

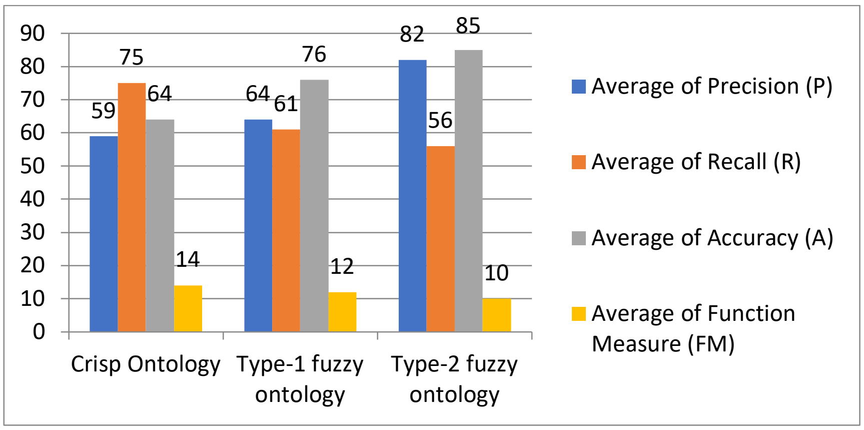


Figure : A graphical representation of crisp, type-1, and type-2 fuzzy ontology performance.

Table 11 Comparison between existing and proposed system.

	The "increasing accuracy (%) in the fuzzy-based existing system"	The "increasing accuracy (%) in the T2FO-based proposed system"
Case 1	13.20	32.20
Case 2	9.50	24.80
Case 3	10.10	20.50
Case 4	13.10	31.40
Case 5	12.30	22.60

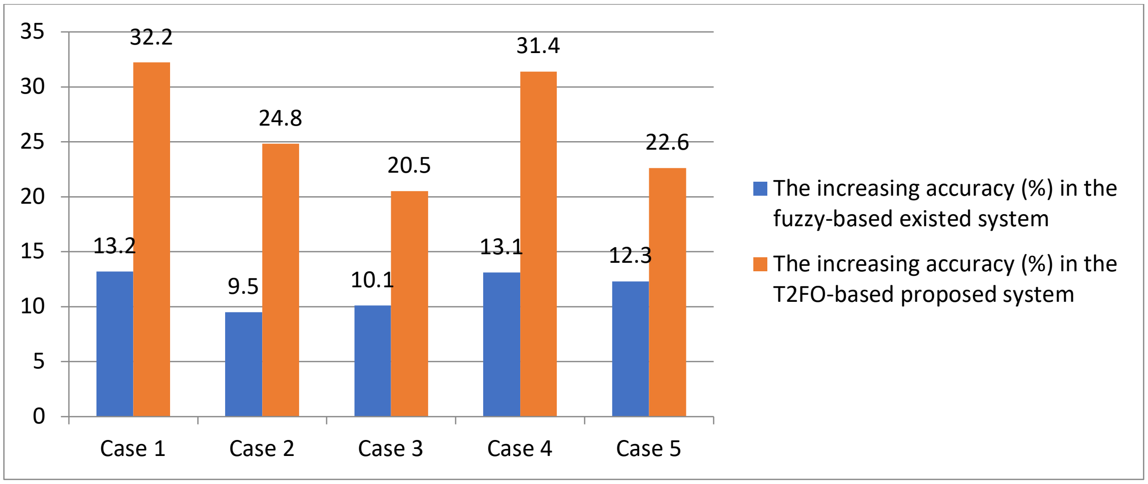


Figure : A graphical representation of accuracy performance

V Conclusion

Because of the disease's intricacy, diagnosing diabetes is a difficult task. It's possible that you'll be given the wrong diagnosis and, as a consequence, get the wrong therapy. As a consequence of this research, a semantically intelligent type-2 fuzzy expert system is suggested. This method has the potential to aid both experts and non-specialists in the evaluation of diabetes patients. The clinical test ranges serve as the basis for the Type-2 fuzzy expert system's development. In addition, this study gives a response surface map of the many input parameters employed in the process of diagnosing the illness.This approach has the ability to offer exact information on a patient's present state of health. At this moment, it is unreasonable to expect the newly created Type-2 fuzzy expert system to be able to replace individual specialists' experience or a group of doctors' pooled knowledge. Rather than being a replacement for the excellent work that doctors currently do, this may be a beneficial tool for them to employ when making decisions. Furthermore, all that is needed to operate this medical expert system is a computer and the necessary software. As a result, the method might be employed in hospitals that have limited access to specific resources, as well as in areas where there aren't many hospitals nearby.

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