Fuzzy Logic for Diagnosis and Treatment of Lifestyle Diseases

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Abstract: *In this paper we try to study on how fuzzy logic is applicable in the field of Medical Science which encounters with the challenges of uncertainty in diagnostic evaluation and medication monitoring. The main objectives involved in this study are (1) analysis of Type 1 Fuzzy Logic Expert System and Interval Type 2 Fuzzy Logic Expert System for disease diagnosis and medication prediction, (2) construction of rule base corresponding to each disease and (3) compare the output generated by these two fuzzy expert systems to identify the most efficient disease diagnostic and medication prediction expert system.*

Keywords: Type 1 Fuzzy logic expert system, Interval Type 2 fuzzy logic expert system, Disease diagnosis, Medication prediction, Python codes, Rule evaluation

1. Introduction

The field of Medical Science encounters with lots of uncertainty when it comes to the exact diagnosis of disease from varying symptoms. Fuzzy logic can handle imprecision

and can be used to resolve these challenges to attain precise conclusions up to a certain limit. In this paper we try to analyse computer-based interactive disease specific Fuzzy Logic Expert System (FLES) particularly Type 1 Fuzzy Logic Expert System (T1FLES) and Interval Type 2 Fuzzy Logic Expert System (IT2FLES) with the support of a set of fuzzy rules and to have a comparative study upon the outputs put forth by these two FLESs in disease diagnosis and medication prediction. An interactive FLES source codes are programmed and computed using the version 3.8 of Python.

2. Methodology

Here we focus upon the prominent life style disease – Type 2 Diabetes (T2D) and try to analyse these fuzzy expert systems together with a set of rules and also on how these expert systems can be implemented in effectively diagnosing Diabetic Retinopathy (DR), a condition caused due to uncontrolled blood sugar which damages the blood vessels of the eye and affects the vision. The two fuzzy logic systems are also used to predict appropriate medication in the form of exercise, diet control, frequent blood sugar monitoring and insulin injection for those who are positively diagnosed. The main components involved in a FLES are fuzzifier, knowledge base, inference engine and defuzzifier. The fuzzifier converts crisp input values into fuzzy values using trapezoidal membership function.

Rule Evaluation occurs at the inference engine where the fuzzified inputs are matched with the variables under consideration from the knowledge base. In every FLES the key

role is handled by a set of rules that relates the antecedent variables with the consequent variables which varies depending upon the disease. In T1FLES the antecedent variables are ‘Age’, ‘Body Mass Index (BMI)’, ‘Fasting Blood Sugar (FBS)’, ‘Post Prandial Blood Sugar (PPBS)’ and ‘Hemoglobin A1c (HbA1c) test values’. The corresponding consequent variable is T2D stages.

For medication prediction the antecedent variables are ‘Age’, ‘BMI’ and ‘Diabetic Period’. The corresponding consequent variable is the medication classification. The antecedent variables for DR diagnosis are ‘T2D categorization’, ‘Systolic Blood Pressure’, ‘Diastolic Blood Pressure’, ‘LDL Cholesterol’, ‘HDL Cholesterol’, ‘Intraocular Pressure’ and ‘Visual Field’. The corresponding consequent variable is the DR stages. In IT2FLES the antecedent variables are same as that of T1FLES and the consequent variables are degree of truth associated with each antecedent variable.

For IT2FLES type reducer converts type 2 fuzzy output values from the inference engine into type 1 fuzzy values. The final output is obtained at the defuzzifier where the fuzzified outputs from the inference engine after rule evaluation gets converted to crisp output so that human logic can analyse them and arrive at a conclusion. From the fuzzy tool kit packages the basic fuzzy package ’SciKit-Fuzzy’ is implemented in this project for fuzzification and defuzzification processes. The graphs are plotted with the help of ’Matplotlib’ from the Python library.

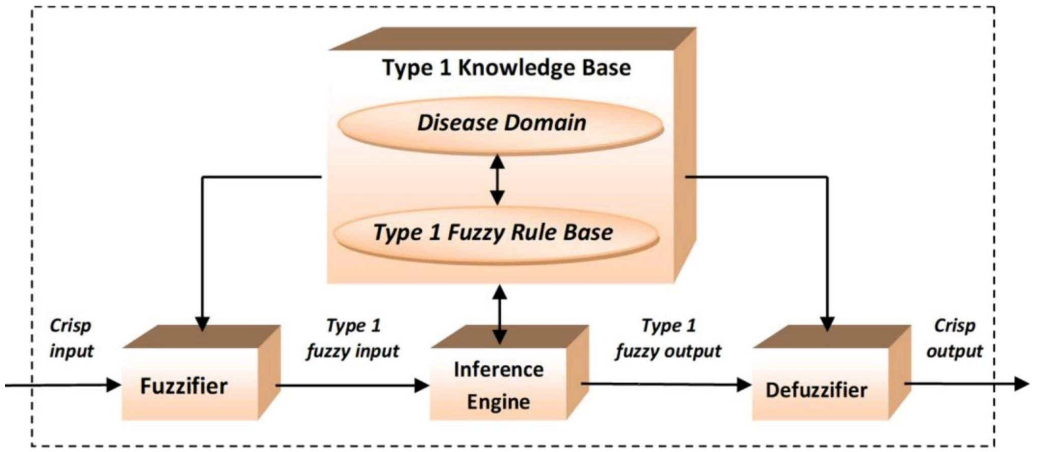


Figure 1: Type 1 Fuzzy Logic Expert System

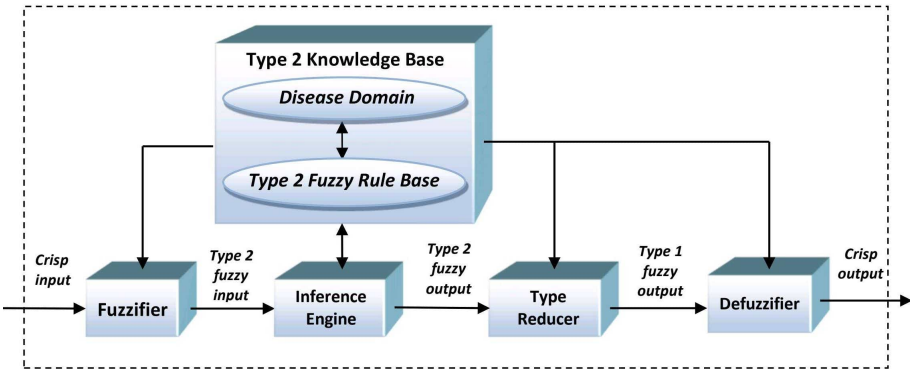


Figure 2: Interval Type 2 Fuzzy Logic Expert System

T2D Diagnosis	Inputs (Antecedent Variables)					Clinical Report	Defuzzified Outputs		Accuracy (%)		
	Age	BMI (kg/m^2)	FBS (mg/dL)	PPBS (mg/dL)	HbA1c (%)		T1FLES	IT2FLES	T1FLES	IT2FLES	
	25	17	105	119	4.5	Normal	0.1662	0.1639	92.86%	78.57%	
	32	17	107	162	5.6	Pre-Diabetic	0.4949	0.4949			
	29	26	127	190	11	Diabetic	0.8122	0.8178			
	44	17.6	103	114	5.7	Normal	0.1662	0.1639			
	47	21.3	115	192	10	Diabetic	0.8122	0.8178			True Positive
	48	28.7	167	243	9.7	Diabetic	0.8237	0.831			True Negative
	52	27.9	154	257	7.5	Diabetic	0.8237	0.831			False Positive
	59	16.7	101	132	6	Normal	0.1707	0.1735			False Negative
	62	15.4	108	136	8	Pre-Diabetic	0.4949	0.1681			
	65	23.7	119	162	7.8	Pre-Diabetic	0.4949	0.4236			
	57	22.3	105	256	7.5	Pre-Diabetic	0.4949	0.8187			
	69	21.8	174	215	10	Diabetic	0.8237	0.831			
	71	28	117	163	7.2	Pre-Diabetic	0.4949	0.1719			
	62	17	110	140	7	Normal	0.4949	0.1667			

Figure 3: Samples used for T2D diagnosis in T1FLES and IT2FLES

Type 2 Diabetes Classification	**Defuzzified Output**
Normal	≤ 0.2
Pre-Diabetic	$0.2 < x \leq 0.5$
Diabetic	> 0.5

Figure 4: Classification of defuzzified output in TD2 diagnosis

3. Salient Research Achievements

In this study 14 sample data were considered for T2D diagnosis and among them 10 were positively diagnosed as Pre-Diabetic and Diabetic as per clinical report. These 10 samples were considered for DR diagnosis and for appropriate medication prediction.

The T1FLES analysed in this paper is 92.86% accurate in T2D diagnosis, 80% accurate in DR diagnosis and 90% accurate in medication prediction whereas the IT2FLES is 78.57% accurate in T2D diagnosis, 70% accurate in DR diagnosis and 80% accurate in medication prediction.

Medication	Inputs (Antecedent Variables)			Clinical Report	Defuzzified Outputs		Accuracy (%)		
	Age	BMI (kg/m^2)	Diabetic Period (in years)		T1FLES	IT2FLES	T1FLES	IT2FLES	
	32	17	2	Middle	0.1662	0.4949	90.00%	80.00%	
	29	26	6	High	0.8237	0.7897			
	47	21.3	4	Middle	0.4949	0.495			
	48	28.7	8	High	0.8237	0.831			True Positive
	52	27.9	1	Low	0.1662	0.8266			True Negative
	62	15.4	1	Middle	0.4949	0.495			False Positive
	65	23.7	3	Middle	0.495	0.5672			False Negative
	57	22.3	2	Middle	0.495	0.5216			
	69	25.8	20	Very High	0.8237	0.4949			
	71	28	6	Very High	0.8237	0.831			

Figure 5: Samples used for medication prediction in T1FLES and IT2FLES

Medication Classification	**Defuzzified Output**
Low	≤ 0.3333
Middle	$0.3333 < x \leq 0.6$
High/Very High	> 0.6

Figure 6: Classification of defuzzified output in medication prediction

Medication Classification	**Medication Prediction**
Low	Exercise + Diet Control
Middle	Medicine + Exercise + Diet Control
High	Medicine + Exercise + Diet Control + Frequent Blood Sugar Check-up
Very High	Medicine + Exercise + Diet Control + Frequent Blood Sugar Check-up + Insulin

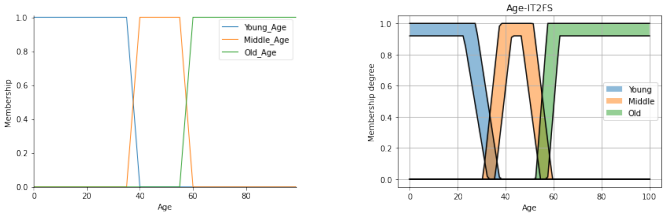
Figure 7: Classification of medication prediction

	Inputs (Antecedent Variables)							Clinical Report	Defuzzified Outputs		Accuracy (%)		
	T2D Grade	BP_SYS (mm Hg)	BP_DIAS (mm Hg)	CHL_LDL (mg/dL)	CHL_HDL (mg/dL)	IOP (mm Hg)	VF		T1FLES	IT2FLES	T1FLES	IT2FLES	
DR Diagnosis	0.5	61	62	52	21	6	8	Mild Non Proliferative	0.1383	0.1642	80.00%	70.00%	
	0.53	91	73	77	47	12	7	Moderate Non Proliferative	0.8829	0.4949			
	0.501	147	110	134	78	28	4	Proliferative	0.8824	0.8275			True Positive
	0.503	156	72	53	50	27	5	Severe Non Proliferative	0.65	0.8275			True Negative
	0.55	163	71	145	25	15	5	Proliferative	0.8824	0.8275			False Positive
	0.7	97	74	82	147	6	6	Severe Non Proliferative	0.65	0.1708			False Negative
	0.75	168	119	156	159	26	3	Proliferative	0.8824	0.8275			
	0.9	112	73	76	53	26	4	Mild Non Proliferative	0.1383	0.8275			
	0.8	150	90	148	90	29	3	Proliferative	0.7348	0.8242			
	0.85	65	82	75	25	25	5	Proliferative	0.8795	0.8242			

Figure 8: Samples used for DR diagnosis in T1FLES and IT2FLES

Diabetic Retinopathy Classification	**Defuzzified Output**
Mild Non-Proliferative	< 0.2
Moderate Non-Proliferative	$0.2 \leq x < 0.5$
Severe Non-Proliferative	$0.5 \leq x < 0.8$
Proliferative	≥ 0.8

Figure 9: Classification of defuzzified output in DR diagnosis



(i) Type 1 fuzzy set (ii) Interval Type 2 fuzzy set

Figure 10: Fuzzy set corresponding to the antecedent variable Age

3.1. New observations

1. For a T1FLES having n variables under consideration where,

$$n = \text{No. of antecedents+No. of consequents} \tag{1}$$

If n^{th} variable has n_{p} choices, then

$$\text{the total no. of rules in T1FLES} = n_1 \times n_2 \times n_3 \times \ldots \times n_{\text{p}} \tag{2}$$

where $n_{\text{i}} \in \mathbb{N}$ and $i = 1, 2, 3, \ldots, p; p \in \mathbb{N}$. For an IT2FLES having m no. of antecedents where the 1^{st} antecedent variable has m_1 choices, 2^{nd} variable has m_2 choices, 3^{rd} variable has m_3 choices, $\ldots$, m^{th} variable has m_{q} choices. Then,

$$\text{the total no. of rules in IT2FLES } = m_1 \times m_2 \times m_3 \times \ldots \times m_{\text{q}} \tag{3}$$

$m_{\text{i}} \in \mathbb{N}$ and $i = 1, 2, 3, \ldots, q; q \in \mathbb{N}$.

2. For each expert system the structure and the number of rules vary.

3. T1FLES has more number of rules than IT2FLES.

4. The T1FLES and IT2FLES are disease specific and have almost equal range of performance. By comparing the outputs generated from these systems we can not explicitly predict one is better than the other.

3.2. Innovations/Technologies generated

For the analysis of computer-based interactive type 1 and interval type 2 FLESs in disease diagnosis and medication prediction all the antecedent variables and consequent variables undergo fuzzification process using trapezoidal membership function.

Here the fuzzy rules are constructed using IF-THEN statements. In T1FLES a knowledge base consisting of 729 rules were constructed for Type 2 Diabetes diagnosis, 81 rules were constructed for medication prediction and 8748 rules were constructed for Diabetic Retinopathy diagnosis. In IT2FLES 243 rules were constructed for Type 2 Diabetes diagnosis, 27 rules were constructed for medication prediction and 2187 rules were constructed for Diabetic Retinopathy diagnosis. The Center of Sums (CoS) method is employed for defuzzification in T1FLES. In IT2FLES the Karnik-Mendel algorithm is selected as type reduction algorithm employed for evaluating the output generated after rule evaluation and the Centroid method is used for defuzzification process.

3.2.1. Algorithm for rule generation in T1FLES

Step 1: Import the following Python packages and modules[9];

```
import numpy as np

import skfuzzy as fuzzy

from skfuzzy import control as ctrl

import matplotlib.pyplot as plt
```

Step 2: Define the range of antecedent variables and consequent variables.

Step 3: Classify the antecedent variables and consequent variables using trapezoidal membership function.

Step 4: Define rule$i$ from ctrl. Rule connecting the antecedent variables and consequent variables as

$$\texttt{IF } a_1 \texttt{ is } A_1 \texttt{ and } a_2 \texttt{ is } A_2 \texttt{ and } \cdots \texttt{a}_n \texttt{ is } A_n \texttt{ THEN } c \texttt{ is } B_1.$$

Here a_{i}'s and c represents the antecedent and consequent variables while A_{i}'s and B_{i}'s represents the fuzzified antecedent and consequent variables where i, $n \in \mathbb{N}$.

3.2.2. Algorithm for rule generation in IT2FLES

Step 1: Import the following Python packages and modules[1]

```
from pyit2fls import IT2FS, trapezoid_mf, IT2FS_plot, IT2 Mamdani,
min_t_norm, max_s_norm, TR_plot,crisp
import numpy as np
from numpy import linspace
```

Steps 2 & **3** is same as that of T1FLES.

Step 4: Define the Interval Type 2 Mamdani Fuzzy Logic Expert System as [1].

```
name_IT2FLES = IT2Mamdani(min_t_norm, max_s_norm, method = "Centroid",
algorithm= "KM")
```

Step 5: Add input and output variables using the function add_input_variable and add_output_variable as[1]

`name_IT2FLES.add_input_variable("`i_j`") name_IT2FLES.add_output_variable("`o_j`")`

Step 6: Define the rule connecting the antecedent variables and consequent variables as follows

$$\texttt{IF } i_1 \texttt{ is } A_1 \texttt{ and } i_2 \texttt{ is } A_2 \texttt{ and } \cdots \texttt{i}_n \texttt{ is } A_n,$$

$$\texttt{THEN } o_1 \texttt{ is } B_1 \texttt{ and } o_2 \texttt{ is } B_2 \texttt{ and } \cdots \texttt{o}_n \texttt{ is } B_n.$$

Here i_{j}'s and o_{j}'s represent the input antecedent and output consequent variables while A_{j}'s and B_{j}'s represents the fuzzified input antecedent and output consequent variables where $j,\ n \in \mathbb{N}$.

3.3. Application potential

This paper gives a comparative study on the efficiency of performance put forward by T1FLES and IT2FLES on accurately diagnosing the lifestyle diseases particularly Type 2 Diabetes and Diabetes Retinopathy and to predict an appropriate medication in those people who are positively diagnosed.

The T1FLES and IT2FLES analysed in this paper with the help of programming language Python are above 75% accurate. Hence these systems are highly capable to handle uncertain medical statements in disease diagnosis and medication prediction.

In order to compare their efficiency of performance the defuzzified outputs generated

from these two expert systems corresponding to each sample are plotted and the area under the graph is analysed.

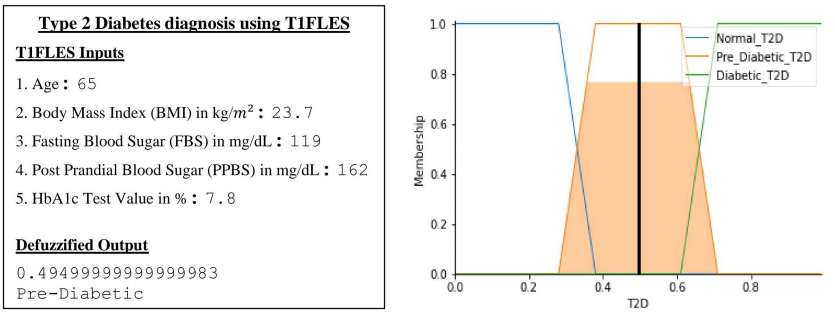


Figure 11: Defuzzified output from T1FLES using CoS method in T2D diagnosis

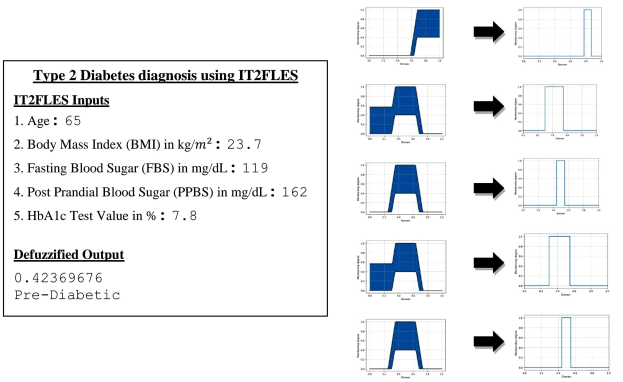
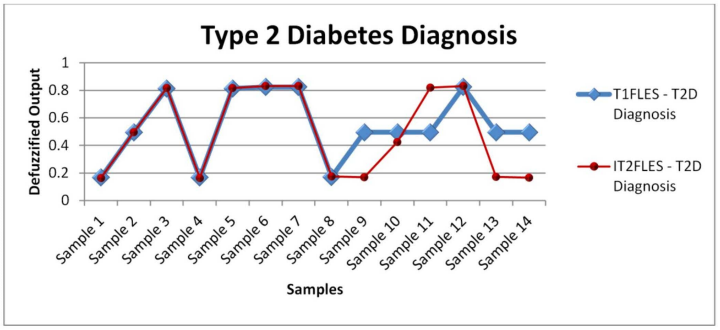
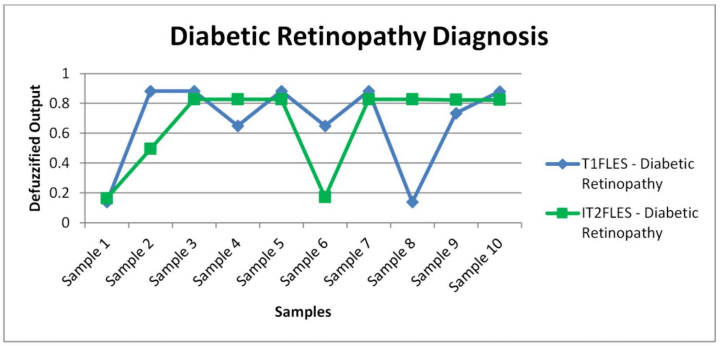


Figure 12: Interval Type 2 and type reduced outputs from IT2FLES in T2D diagnosis

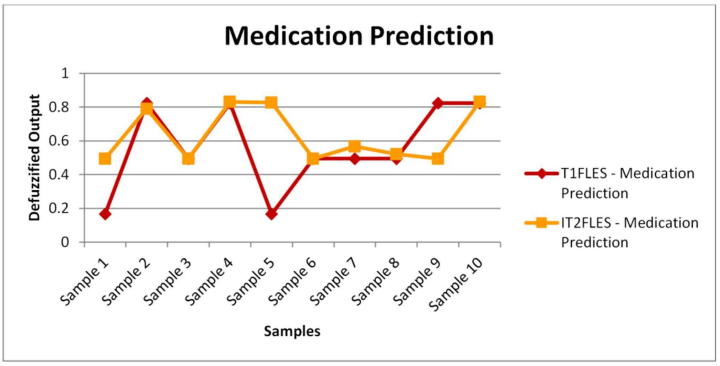
By comparing the area under the graph corresponding to each disease and medication prediction we can conclude that type 1 and interval type 2 fuzzy systems have almost equal performance level.



(i) Comparison of efficiency in T2D diagnosis



(ii) Comparison of efficiency in DR diagnosis



(iii) Comparison of efficiency in medication prediction

Figure 13: Efficiency comparison of T1FLES and IT2FLES by graphical analysis

4. Conclusion

Type 1 Fuzzy Logic Expert System and Interval Type 2 Fuzzy Logic Expert System has almost equal performance level in disease diagnosis and medication prediction. It can't be concluded that one is beyond the other in general. Each method of approach has its own performance level depending upon the nature of disease and its clinical symptoms.

Acknowledgement

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