Comparison of Triangular and Trapezoidal Fuzzy Membership Function

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***Abstract*- Classification is one of the important process in clinical trial. Diagnosis leads to analyze the classification of disease and their characters. Medical practitioner makes decision from diagnosis result that is classified. The result of diagnosis has classified based on the clinical trials. The accuracy of classification leads to improve the accuracy of diagnosis. Medical practitioner or research takes decision about experiment, according to the clinical trial reports. Most of the clinical trial reports and results are in uncertainty and vagueness form. In data preparation process, the vagueness value of clinical data has to be change in to crisp form. The fuzzy logic assists to formalize the vagueness value and prepare the data for mining the knowledge. Fuzzy membership function exercises the vagueness value that is in the range between 0 and 1. The objective of this paper is to fuzzify the patient data using triangular and trapezoidal membership function and mining the valuable information. The output of triangular and trapezoidal membership function shows the fuzzified clinical data and measure the performance through mean value of fuzzified data.**

***Keyword*: Datamining, Fuzzy Logic, Fuzzy Set, Trials**

I. Introduction

Clinical trials is one the main process for analyzing the drug molecules and functionalities of drugs. Clinical trials generate the massive amount of uncertainty data. The clinical data having many valuable knowledge and patterns which is clinical informatics [9][10]. The large amount of data collects in clinical trials. In the clinical data, the laboratory results and reports are in uncertainty and vagueness form [1]. When Data mining techniques apply into clinical dataset, the vagueness result value fails to classification of data and make complex the decision making and mining knowledge discovery becomes fail [3]. Fuzzy logic is well known concept and it make sense to process the vagueness value and deals with Boolean logic. A fuzzy number is a generalization of a real number in the sense that it does not connect to one single number but rather to a combines set of possible values, where each possible value has its own range value between 0 and 1 that is called the membership function. Fuzzy set is defined by its ambiguous boundaries. Its properties are described by its membership function μ(x). Membership function helps to change the classify set into fuzzy set. In our proposed method, the fuzzy logic is applied over into the clinical dataset [8]. Triangular membership function assists to fuzzify the clinical data and mine more knowledge about patient medical details [1].

II. TRIANGULAR MEMBERSHIP FUNCTION

The triangular curve is a function of a vector, x, and depends on three scalar parameters [2][8], *a*, *b*, and *c*, as given by

$$\mu_{\tilde{A}}(x:a,b,c)=\begin{cases}\dfrac{x-a}{b-a} & a<x\le b\\[2mm] \dfrac{x-b}{c-b} & b<x\le c\\[2mm] 0 & \text{otherwise}\end{cases}$$

The parameters *a* and *c* locate the base of the triangle and the parameter *b* locates the peak.

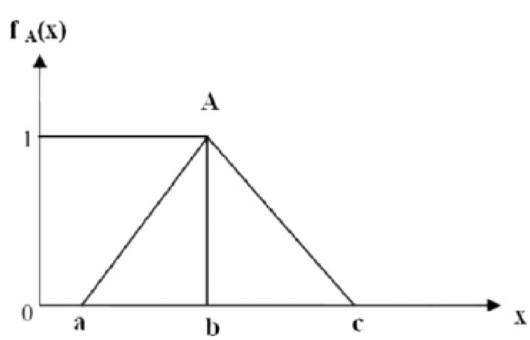

Fig1. Triangular membership function

The three main basic features involved in characterizing membership function are the following.

Core: The core of a membership function for some fuzzy set $\underset{\sim}{A}$ is defined as that region of workspace that is characterized by complete membership function in the set $\underset{\sim}{A}$. The core has elements x of the workspace such that $\mu_A(x). = 1$

Support: The support of a membership function for some fuzzy set $\underset{\sim}{A}$ is defined as that region of universe that is characterized by non-membership function in the set $\underset{\sim}{A}$. The support comprises elements x of the universe such that $\mu_A(x). > 0$

Boundary: The support of a membership function for some fuzzy set $\underset{\sim}{A}$ is defined as that region of universe containing that have a non zero but not complete membership function in the set $\underset{\sim}{A}$. The boundary comprises those elements x of the universe such that

$$0 < \mu_A (x). < 1$$

III TRAPEZOIDAL MEMBERSHIP FUNCTION

The Trapezoidal curve is a function of a vector, x, and depends on four scalar parameters *a*, *b*, c and *d*, as given by

$$\mu_A(x) = \begin{cases} 0, & (x < a) \text{ or } (x > d) \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ 1, & b \le x \le c \\ \dfrac{d-x}{d-c}, & c \le x \le d \end{cases}$$

The parameters are defined by a lower limit a, an upper limit d, a lower support limit b, and an upper support limit c, where a < b < c < d.

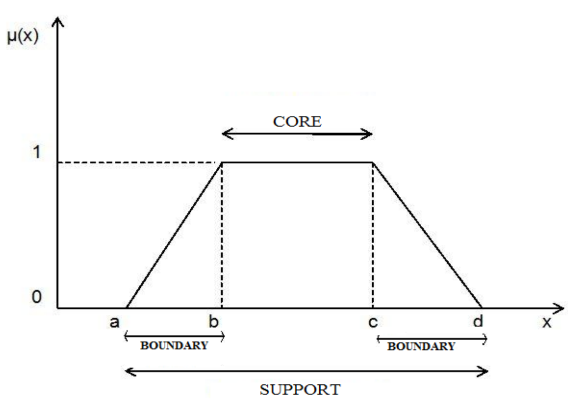

Fig2. Trapezoidal membership function

The three main basic features involved in characterizing membership function are the following.

Core: The core of a normal fuzzy set $\underset{\sim}{A}$ is the crisp set that contains all the elements of x that have the membership grades of one in $\underset{\sim}{A}$,such that

$$core(A) = \{x \in X|\mu A(X) = 1\}$$

Boundary: The boundary is the crisp set that contains all the elements of x that have the membership grades of $0 < \mu A(x) < 1$ in $\underset{\sim}{A}$, such that

$$Bnd(A) = \{x \in X \vee 0 < \mu A(x) < 1\}$$

Support: The support of a normal fuzzy set consists of a single element $x°$ of X, which has the property such that $Supp(A) = core(A) = \{x°\}$

IV PROPOSED METHOD

The classification process is too complex due to uncertainty value. So the valuable information does not come in to picture. When applying the datamining techniques. The classification process the uncertainty value fails to project the data in classification model. The complexity of classification takes the way of clinical trials leads to poor decision making. Fuzzy logic makes comfortable for classifying the vagueness value and change the uncertainty value in crisp form. Fuzzy logics handle the vagueness value for exposing into fuzzy set. Generally the values are in the form of classical view which is in the nature of uncertainty and vagueness. The analysis of clinical trials is too complex due to the vagueness value. So the valuable information becomes uncertainty when apply the datamining in the clinical trial dataset. The vagueness value abandoned the discovery knowledge and makes hard decision making. Data classification process is too difficult while the large amount of data is in vagueness form. For overcome this complexity, in our proposed method applies the fuzzy logic into the clinical trial dataset when prepare the data for mining process. Generally, the laboratory reports and trial results are in crisp set format. The crisp set with their operations and properties are focusing the classical logic which leads to attain the vagueness results [6][9]. So the decision making becomes hard and fails in better knowledge discovery. The fuzzification is the process of transforming the crisp set into fuzzyset. For fuzzifying the clinical trial data, in our proposed method applies the triangular membership function. It's consolidated the vagueness value and converts into fuzzy set. Table 3 shows the sample clinical trial dataset. The boundary values have to be setup for all attributes except PatientID, Gender and Blood group attributes. The membership value [0,1] of each attribute values associate with boundary value. For example, if patient causes diabetes disease, the blood sugar metric value is important for diagnosis. The range value of blood sugar shown in below

Table 1.Blood sugar level chart

Low	Normal	High
< 30	30 <=100	>100

The boundary value of sugar is based on the chart. In fig1, a, c are boundary value and b is core value. Therefore a=30, b=100 and c=320 (maximum value). In table 1, the sugar level of PatientID is 230. The fuzzification executes as per equation which derived in section 2. The implementation is given below

Triangle (230:30,100,320) = (230-100) / (100-30)

= 130/70

= 1.8571

= (320-230) / (320-100)

= 90/220

=0.4090

$f(x)$= max (min(1.8571,0.4090),0) = 0.4090

Figure 3 shows the result in the triangular membership shape.

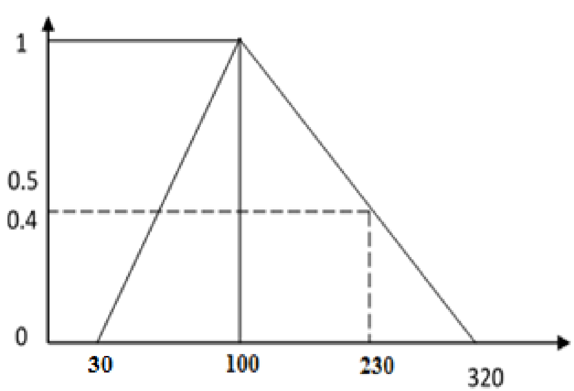

Fig3. Indication of fuzzy value in triangular membership shape

The fuzzy value of sugar metris 230 is 0.4090. It is observed that the calculation, the PatientID 116 causes diabetes in severe condition. The result has suggested, the patient ID 116 has to be taken treatment immediately. This formulation applies into values of all attributes except PatientID, Gender and Blood group attributes.

Table 2.Blood sugar level chart

Low	Normal	High	Very High
< 30	30 <=100	100>110	>110

The boundary value of sugar is based on the chart. In fig2, a, d are boundary value and b and c is core value. Therefore a=30, b=100, c=110and d=320 (maximum value). In table 2, the sugar level of PatientID is 230. The implementation is given below

Triangle (230:30,100,110,320) = (230-30) / (100-30)

= 200/70

= 2.8571

= (320-230) / (320-110)

= 90/210

=0.4285

$f(x)$= max (min(2.8571,0.4285),0,0) = 0.4285

Figure 4 shows the result in the trapezoidal membership shape.

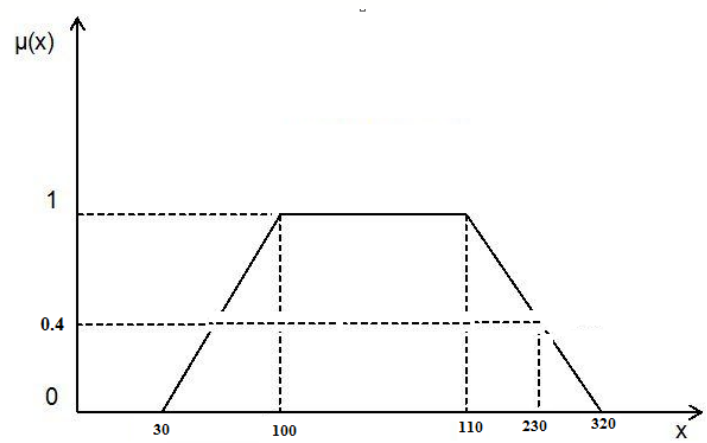

Fig4. Indication of fuzzy value in trapezoidal membership shape

The fuzzy value of sugar metris 230 is 0.4285. It is observed that the calculation, the PatientID 116 causes diabetes in severe condition. The result has suggested, the patient ID 116 has to be taken treatment immediately. This formulation applies into values of all attributes except PatientID, Gender and Blood group attributes.

V EXPERIMENTAL RESULT

Our proposed method is applied over sample clinical dataset. In sample dataset of following attributes such as Patient ID, Gender, Age, Blood Group, Weight, Fever (F^0C), Sugar and BloodPressure (BP). The Sample dataset has shown in the below table. In table 3, the attribute name ID represent the patient ID, 'G' represent the Gender, 'B' represent the Blood group, 'W' represent the weight, 'A' represent the age, 'BP' represent the Blood Pressure, 'F' represent the Fever (F^0C) and 'S' represent the Sugar.

Table3. Sample clinical dataset

P-ID	Age	Gen	BG	W	S	F	BP
111	18	M	5	54	108	101	90
112	32	M	1	65	123	104	80
113	43	M	3	70	116	97	60
114	54	F	2	84	94	90	100
115	65	F	7	66	82	107	110
116	36	M	3	66	237	107	120
117	47	F	1	72	109	92	140
118	68	M	6	81	58	100	105
119	79	F	2	69	71	100	100
120	40	M	7	40	85	99	86

Let a,b,c are membership variables as shown in the Fig 1.The boundary and core value of membership assign into following attributes

BP = {a=60,b=100,c=200}

Fever(F^0C) ={a=90,b=97,c=107}

Sugar={a=30,b=100,c=320}

Age= {a=18,b=54,c=90}

Weight= {a=40, b=54,c=92}

Blood Group= {a=0,b=4,c=7}

In sample data, fuzzify the values by using triangular member function. The result shows in the table4.

Table4. Triangular Fuzzy clinical dataset

Patient id	Age	Gender	BloodGrp	Weight	Sugar	Fever	Bp
111	0.0	Male	0.6666	1.0	0.9636	0.6	0.75
112	0.3888	Male	0.0	0.7105	0.8954	0.3	0.5
113	0.6944	Male	0.75	0.5789	0.9272	1.0	0.0
114	1.0	Female	0.5	0.2105	0.9142	0.0	1.0
115	0.6944	Female	0.0	0.6842	0.7428	0.0	0.9
116	0.5	Male	0.75	0.6842	0.3772	0.0	0.8
117	0.8055	Female	0.25	0.5263	0.9590	0.2857	0.6
118	0.6111	Male	03333	0.2894	0.4	0.7	0.95
119	0.3055	Female	0.5	0.6052	0.5857	0.7	1.0
120	0.6111	Male	0.6666	0.0	0.7857	0.8	0.65

Search Record Press 1 to Continue
Exit Press 2
1
Enter Patient-ID: 113

P-ID	Age	Gender	BloodGrp	Weight	Sugar	Fever	BP
113	0.6944	Male	0.75	0.5789	0.9272	1.0	0.0

Age :Young Adult
Weight :Heavy Weight
Blood group :A-ve
Fever :No Risk
Sugar :Medium
BP :Very Low Bp

Enter the choice 1 for Sugar - 2 for BP - 3 for Fever - 4 for Weight
2
Enter the value Medium

P-ID	Age	Gender	BloodGrp	Weight	Sugar	Fever	BP
115	65.0	Female	7.0	66.0	82.0	107.0	110.0
115	0.6944	Female	0.0	0.6842	0.7428	0.0	0.9

Age: Old
Gender: Female
Blood Group: AB+ve
Weight: Heavy Weight
Fever: Very High
Sugar: Low
BP: Medium

P-ID	Age	Gender	BloodGrp	Weight	Sugar	Fever	BP
116	36.0	Male	3.0	66.0	237.0	107.0	120.0
116	0.5	Male	0.75	0.6842	0.3772	0.0	0.8

Age: Young Adult
Gender: Male
Blood Group: A-ve
Weight: Heavy Weight
Fever: Very High
Sugar: High
BP: Medium

P-ID	Age	Gender	BloodGrp	Weight	Sugar	Fever	BP
118	68.0	Male	6.0	81.0	58.0	100.0	105.0
118	0.6111	Male	0.3333	0.2894	0.4	0.7	0.95

Age: Old
Gender: Male
Blood Group: A+ve
Weight: Over Weight
Fever: High
Sugar: Low
BP: Medium

Let a,b,c,d are membership variables as shown in the Fig 2.The boundary and core value of membership assign into following attributes

Fever= {a=90, b=96, c=101, d=107}

Sugar= {a1=30, b1=100, c1=110, d1=320}

BP= {a2=60, b2=90, c2=110, d2=200}

Age= {a3=18, b3=49, c3=57, d3=90}

Weight= {a4=40, b4=50, c4=54, d4=92}

Blood Group= {a5=0, b5=3, c5=4, d5=7}

In sample data, fuzzify the values by using trapezoidal member function. The result shows in the table5.

Table5. Trapezoidal Fuzzy clinical dataset

Patient id	Age	Gender	BloodGrp	Weight	Sugar	Fever	Bp
111	0.0	1	0.6666	1.0	0.0	1.0	1.0
112	0.4516	1	0.0	0.7105	0.9380	0.5	0.6666
113	0.8064	1	1.0	0.5789	0.9714	0.0	0.0
114	0.0	0	0.6666	0.2105	0.9142	0.0	0.0
115	0.7575	0	0.0	0.6842	0.7428	0.0	1.0
116	0.5806	1	1.0	0.6842	0.3952	0.0	0.8888
117	0.9354	0	0.3333	0.5263	0.0	0.3333	0.6666
118	0.6666	1	0.3333	0.2894	0.4	0.0	0.0
119	0.3333	0	0.6666	0.6052	0.5857	0.0	0.0
120	0.7096	1	0.6666	0.0	0.7857	0.0	0.8666

If u want to search record press 1 to continue

1

Enter patient id: 112

P-ID	Age	Gender	BloodGrp	Weight	Sugar	Fever	BP
112	0.4516	1	0.0	0.7105	0.9380	0.5	0.6666

Age :Teenage
Weight :Heavy Weight
Bloodgroup :AB-ve
Fever :high
Sugar :Medium
BP :low Bp

Enter the choice 1 for Sugar - 2 for BP - 3 for Fever - 4 for Weight

2

Enter the value Medium

P-ID	Age	Gender	BloodGrp	Weight	Sugar	Fever	BP
116	36.0	1	3.0	66.0	237.0	107.0	120.0
116	0.5806	1	1.0	0.6842	0.3952	0.0	0.8888

Age: young Adult
Gender: 1
Blood Group: O-ve
Weight: Heavy Weight
Fever: very high
Sugar: high
BP: Medium

P-ID	Age	Gender	BloodGrp	Weight	Sugar	Fever	BP
120	40.0	1	5.0	40.0	85.0	99.0	86.0
120	0.7096	1	0.6666	0.0	0.7857	0.0	0.8666

Age: young Adult
Gender: 1
Blood Group: A+ve
Weight: underweight
Fever: No Risk
Sugar: low
BP: Medium

Table: 6 Performance of triangular membership function

Fuzzy variable	Mean value for accuracy
Blood pressure	0.7082
Fever	0.4885
Sugar	0.7090
weight	0.5896

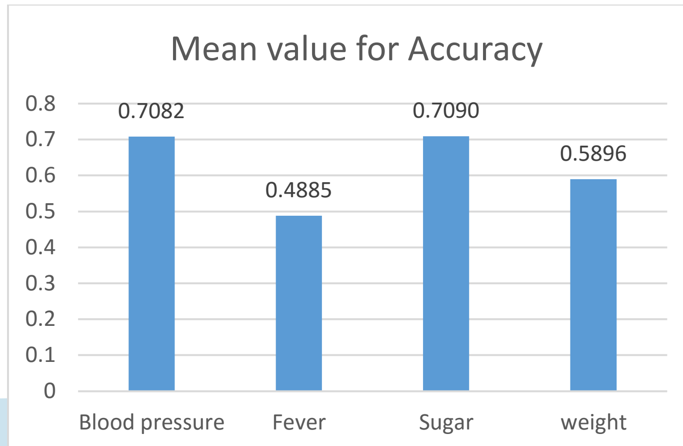

Fig 5. Mean values of fuzzy variables (Triangular membership function

Table 7: Performance of Trapezoidal membership function

Fuzzy variable	Mean value
BP	0.4853
Fever	0.3866
Sugar	0.6102
Weight	0.5210

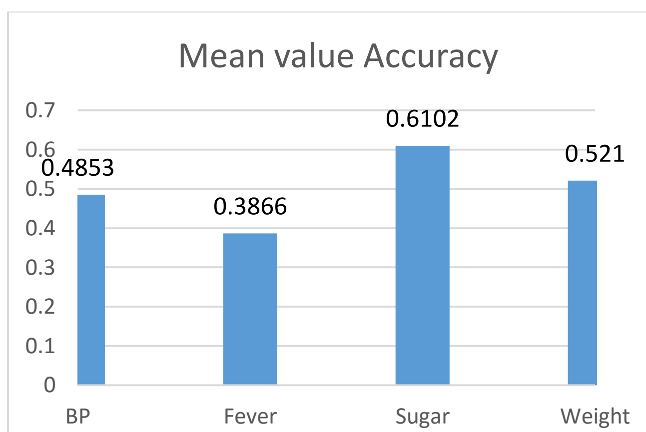

Fig 6. Mean values of fuzzy variables (Trapezoidal membership function

Table 8: Memory Size of Triangular membership function

Variable size	Data size	Program size	Total Program size	Operations
155 bytes	1425 bytes	17876 bytes	19456 bytes	- 48 times / 24 times

Table 9: Memory Size of Trapezoidal membership function

Variable size	Data size	Program size	Total Program size	Operations
167 bytes	1425 bytes	18816 bytes	20408 bytes	- 48 times / 24 times

In table 8 shows the memory size of variable which is assigned for triangular membership function, Program size is 18816 bytes and data size of process occupy 1425 bytes in memory, for variable size occupy 155 bytes in memory. In arithmetic operation of triangular membership function, 48 times of minus operation and 24 times of division operation are performed. When the memory and performance of arithmetic operation compares to trapezoidal operation, the trapezoidal is moderate complex than triangular membership function. It takes more memory size for variable and program size. Even it is complex process, the classification performance is better than triangular membership function. As per the space complexity triangular membership function is better than trapezoidal membership function. After fuzzification, the vagueness value convert into crisp value. The measurement of deviation that is variance between classical values to fuzzy value. If the mean value of fuzzy variables is less, the fuzzy value is nearly to the classic value. In table 6, the mean value of fuzzy variables are higher than trapezoidal member function. So its output having more mean error. In table 7, the mean value of fuzzy variables are lower than triangular member function. Fig5 and fig6 show the mean error value variation is between triangular fuzzy and trapezoidal fuzzy. As per experiment analysis, trapezoidal member function performs as good as triangular membership function.

VI CONCLUSION.

In our proposed method, the clinical data converted into fuzzy data. The vagueness value change in to fuzzy values by using triangular membership function and trapezoidal membership function. The fuzzification process produce fuzzified value that assists to discover more knowledge accurately and avoid complexity of data classification. The performance of trapezoidal function encourages than triangular membership function. In future, Clinical data will be applied into guassian membership function [4][5] for improving the performance of fuzzification.

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