2019 IEEE Pune Section International Conference (PuneCon)
MIT World Peace University, Pune, India. Dec 18-20, 2019

Online approach for Diabetes Diagnosis and Classification with Expert System Modules using Fuzzy Logic

I. K. Mujawar, B.T. Jadhav, V. B. Waghmare, *Member, IEEE and* R. Y. Patil, *Member, IEEE*

***Abstract*—Fuzzy Logic is profoundly reasonable and relevant in structuring frameworks in the field of medical; particularly in the various disease diagnosis procedures and in the preparation of treatment strategies. Fuzzy Expert Systems can deal with imprecise, incomplete and uncertain information which comes in the procedure of disease diagnosis and disease treatments. In the proposed work, where a web-based fuzzy expert system modules were designed and developed which will assist to diabetics, diabetologists, practitioners and experts for diabetes diagnosis and its classification. The System's knowledge base was designed by consulting diabetologists and diabetes patient's data was collected from the hospital. It is an online rule-based fuzzy expert system, which was designed with the aim to reach people with easy access through the internet. The proposed work exhibits architecture, design, and development of a fuzzy logic based expert system for diabetes disease diagnosis and classification. An open source programming environment and libraries were considered and utilized in the proposed system development.**

***Index Terms*— Diabetes Mellitus, Fuzzy Logic, Rule Based Expert System, Online Expert System.**

I. Introduction

Diabetes is widely spreading and death causing chronic disease where blood glucose level builds high due to inadequate or no insulin creation or its utilizations. It is categorized mainly in three principal types as Type 1 Diabetes, Type 2 Diabetes and Gestational Diabetes. By 2045, the world's 629 million people of different areas will be endured by diabetes. There is the desperation of outright work and activity intend to battle with diabetes as 425 million individuals are influencing with it presently [5]. Diabetes can be effectively observed, managed and its further complications can be prevented in the event that it is identified before. Utilization of present-day ways like telemedicine, utilization of expert system applications, smart applications in the field of medicine and so on can turn out as convenient tools in this front.

I.K. Mujawar working as Assistant Professor at Vivekanand College, Kolhapur, Maharashtra, India. (e-mail:mujawarirfan@gmail.com)

Dr. B.T. Jadhav working as Associate Professor and Principal ,Dahiwadi Collge, Dahiwadi, Satara, Maharashtra, India. (e-mail:btj21875@gmail.com).

Dr. V.B. Waghmare working as Assistant Professor and Head of Computer Science Department at Vivekanand College, Kolhapur, Maharashtra, India. (e-mail:vishal.pri12@gmail.com)

R.Y.Patil working as Assistant Professor at Vivekanand College, Kolhapur, Maharashtra, India. (e-mail:rajashrishendre@gmail.com)

Several studies, implementations and examinations in the past have shown and proven that expert systems in the field of medicine are more valuable and better acknowledged if the users get support for their own diagnostic reasoning ways and on the off chance that they can structure the immense measure of their insight in representations that assist them.

Fuzzy logic has been used to oversee unpredictability, vagueness in expert systems of medical field because it uses to provide representation and inference from inconsistent information. In the area of medicine, diagnostic criteria's and treatment procedures of diseases deal with imprecise, incomplete and inexact information in the form of patient data, patient medical background, pathology test readings, physical examination readings and information collected from many other resources like X-ray, ultrasonic, other clinical finding and even sometimes patient's unclear, incomplete and more than reality response [3, 4, 7]. The fuzzy logic concepts used in the development of expert systems of medical field and have been proving its importance. These systems demonstrate absolute assisting tools for individuals of the same and related fields.

II. Related Work

In the exploration work [2] proposed MedFrame which was medicinal counseling system, uses fuzzy techniques for job like inputs, fuzzy rules and outputs. A novel five layer ontology for fuzzy system proposed in the work presented by Lee CS et.al. [8]. Urgency in online software tools in the field of medicine which will assist people around world was mentioned in work presented in [6]. Nguyen Hoang Phuong et.al.[11] presented DoctorMoonfuzzy expert system where Fuzzy Logic was used for guessing many diseases in the proposed diagnosis system. Online expert systems aid; its design issues were presented in the work presented by Ralph Grove [14] Ioannis M. Dokas [9] presented an approach for designing a web site with an expert system for Landfill Operation Management Advisor (LOMA). Numerous expert system applications in the field of medicine which are structured and created using fuzzy set theory which make use of fuzzy scores and forms of ordinary scoring plans and so on [1]. Web-expert system architecture and its development proposed in [16] for diabetes risk assessment using selected symptoms with fuzzy logic concept. Ideas and issues of web- based decision support systems and its advantages and challenges of online expert systems were conferred in [12,13].

978-1-7281-1924-3/19/$31.00 ©2019 IEEE

III. Online Expert System Module For Diabetes Diagnosis

A fuzzy expert system (FES) consists of four elements: fuzzification, knowledge base, decision making logic and defuzzification. First to choose the input and output variables is vital and it depends on knowledge of domain experts [10].

A. *Data collection*

Collection of required and meaningful information shows the vital impact on work undertaken. At the same time accessibility and availability of important data on ongoing research impacts the research and its consequences. For the collection information gathering plenty of resources and time is essential [16]. For experiments, dataset was created by collecting diabetes patient's data from 'Swad Diabetic Care Centre'. It had 290 data instances which were of both genders.

B. *Data selection and Distribution*

5 input parameters were used as input variables in the proposed work. These input variables were the fasting plasma glucose, post pandrial glucose, body mass index, age, and diabetes pre-degree function. The output variable was Diabetes Diagnosis Result. Input and output variables are given in Table I. Variable codes were created and utilized in the algorithm design and proposed system development.

C. *Methodology*

1) *Linguistic variables*

For proposed study fasting plasma glucose (fpg), post pandrial glucose (pp), body mass index (bmi), age and diabetes pre-degree function (dpf) were selected as the input variables. The output variable was Diabetes Diagnosis Result (DDR). The set of linguistic variables are shown in Table II.

2) *Fuzzy set*

Fuzzy set demonstrates the organization and information about the input and output variables. In fuzzy sets, each variable is mapped into [0, 1] by using membership function.

$$\mu V \ : \ A \rightarrow \{0,1\}$$

where value of A is real numbers from 0 to 1 including 0 and 1.For proposed work fuzzy sets were determined from the dataset collected for study. Dataset was normalized and categorized as fpg (low, medium, high), pp (low, medium, high), bmi(low, medium, high), dpf (low, medium, high), age(young, medium, old).

TABLE I. Input and Output Variables

Category	Variable Name	Variable Measurement Unit	Code
Input	Age	Years	AGE
	Fasting Plasma Glucose	mg/dl	FPG
	Post Pandrial	mg/dl	PP
	Body Mass Index	Kg/m2	BMI
	Diabetes Predegree Function	-------	DPF
Output	Diabetes Diagnosis Result	-------	DDR

3) *Fuzzification*

In the proposed study, triangular membership function was considered and it is shown in equation (1). It was represented using three points as (a,b,c) [4]. The ranges and valuesof the variables as fuzzy triangular parameters [a, b, c] were determined by consulting with diabetologists, previous studies and diabetes standards defined by various diabetes organizations and other health associations and organizations working globally and which are shown in Table II.

$$\mu_A(x) = \begin{cases} 0 & \text{if } x < a \\ x - a / b - a & \text{if } a < x <= b \\ c - x / c - b & \text{if } b < x <= c \\ 0 & \text{if } x > c \end{cases} \tag{1}$$

The triangular fuzzy number of fuzzy variable FPG and its linguistic variable low is fpg(low) = [70, 90, 99], the membership function is as in equation (2).

$$\mu_{low\_fpg}(x) = \begin{cases} 0 & \text{if } x < 1 \\ x - 70 / 20 & \text{if } 70 < x <= 90 \\ 99 - x / 9 & \text{if } 90 < x <= 99 \\ 0 & \text{if } x > 99 \end{cases} \tag{2}$$

TABLE II. Fuzzy Triangular Parameters

Fuzzy Variable	Linguistic Variables	Fuzzy Triangular Parameter
FPG	Low	[70, 90, 99]
	Medium	[98, 110, 125]
	High	[124, 200, 350]
PP	Low	[100, 120, 139]
	Medium	[138,170, 190]
	High	[185,350, 535]
DPF	Low	[0, 0.05, 0.125]
	Medium	[0.1, 0.2, 0.375]
	High	[0.35, 0.6, 1]
BMI	Low	[16, 20, 22]
	Medium	[21, 24, 26]
	High	[25, 30, 42]
AGE	Young	[61, 65, 70]
	Medium	[68, 75, 84]
	Old	[82, 86, 90]
DDR	Low	[0, 1, 3]
	Medium	[2, 3, 5]
	High	[4, 7, 10]

4) *Designing Rule Base*

A rule base of FES contains rules which are in the form of R1: If a is X or b is Y then c is Z, where X Y and Z are linguistic variable values. The rule base was designed by consulting domain experts. Some of the rules from rule base are as follows.

Rule1 = If (FPG is low) or (PP is low) or (DPF is low) or (BMI is low) or (AGE is young) then (DDR is less)

Rule2= If (FPG is medium) or (PP is medium) or (DPF is medium) or (BMI is medium) or (AGE is medium) then (DDR is medium)

Rule7 = If (FPG is medium) or (PP is medium) or (DPF is high) or (BMI is high) or (AGE is old) then (DDR is medium)

Rule10 = If (FPG is low) or (PP is low) or (DPF is medium) or (BMI is medium) or (AGE is medium) then (DDR is less)

5) Decision Making Logic

It is known as fuzzy inference which is method of mapping the input to an output. In the proposed system Mamdani's Inference method was used where it executes through fuzzification of the input variables, evaluation of rules using fuzzy operator and finally an aggregation of the rule outputs and then defuzzification is done [15].

6) Defuzzification

It is last step of inference process which aggregates and produces crisp value as output by taking inputs. There are number of defuzzification techniques. Center of Gravity (CoG) was used to convert fuzzy result into crisp value as the defuzzification technique in the proposed work.

IV. Online Expert System Module For Diabetes Classification

As discussed in the introduction section, there are main three types of diabetes mellitus, Type1, Type2 and Gestational Diabetes. For the classification of these types age, gender, diabetes risk which is observed by the diabetes diagnosis tests and pregnancy status with its information are needed. Pregnancy information is needed to identify mainly the gestational diabetes. In the proposed classification module above three types of diabetes mellitus were considered.

A. Data selection and Distribution

For proposed work, 4 parameters were used as input variables. The input variables for proposed system were the diabetes diagnosis risk, gender, pregnancy status and age. The output variables were Diabetes Type1, Diabetes Type2 and Gestational Diabetes. Input and output variables are given in Table III along with their codes.

B. Methodology

1) Linguistic variables

For proposed study diabetes diagnosis risk (ddr), gender (gdr), pregnancy status (ps) and age were selected as the input variables. The output variables were diabetes type1 (t1), diabetes type2 (t2) and gestational diabetes (g). The set of linguistic variables are shown in Table IV and Table V.

2) Fuzzy set

Dataset was normalized and categorized as ddr (low, medium, high), age (young, medium, old).

3) Fuzzification

In the proposed study, triangular membership function was used and it was as in equation (1).

TABLE III. Input and Output Variables

Category	Variable Name	Variable Measurement Unit	Code
Input	Diabetes Diagnosis Risk	-----	DDR
	Gender	-----	GDR
	Pregnancy Status	-----	PS
	Age	Years	AGE
Output	Diabetes Type1	------	T1
	Diabetes Type2	------	T2
	Gestatoinal Diabetes	------	G

The triangular fuzzy number of fuzzy variable AGE and its linguistic variable low is AGE (young) = [1, 15, 21], the membership function is as in equation (3).

$$\mu_{age\_young}(x) = \begin{cases} 0 & if\ x < 1 \\ x - 1/14 & if\ 1 < x <= 15 \\ 21 - x/6 & if\ 15 < x <= 21 \\ 0 & if\ x > 21 \end{cases} \tag{3}$$

TABLE IV. Fuzzy Triangular Parameters

Fuzzy Variable	Linguistic Variables	Fuzzy Triangular Parameter
DDR	Low	[0, 2, 3]
	Medium	[2, 3, 5]
	High	[4, 7, 10]
AGE	Young	[1, 15, 21]
	Medium	[20,25,30]
	Old	[27,40,80]
T1	Low	[0, 1, 3]
	Medium	[2, 3, 5]
	High	[4, 7, 10]
T2	Low	[0, 1, 3]
	Medium	[2, 3, 5]
	High	[4, 7, 10]
G	Low	[0, 1, 3]
	Medium	[2, 3, 5]
	High	[4, 7, 10]

TABLE V. Fuzzy Input Values for Input parameters

Fuzzy Variables	Gender	Pregnancy Status	Input Values
Linguistic Variables	Male	No	1
	Female	Yes	2
	Other	Yes with Pregnancy Period 26-28 weeks	3

4) Designing Rule Base

A rule base of FES contains rules which are in the form of R1: If a is X and b is Y then c is Z, where X Y and Z are linguistic variable values. Some of the rules from rule base are as follows.

Rule1 = If (DDR is high) and (GDR is m) and (PS is n) and(AGE is young) then (T1 is high or T2 is less or G is less)

Rule2= If (DDR is medium) and (GDR is m) and (PS is n) and(AGE is young) then (T1 is less or T2 is medium or G is less)

Rule3= If (DDR is medium) and (GDR is m) and (PS is n) and(AGE is medium) then (T1 is less or T2 is medium or G is less)

Rule4= If (DDR is low) and (GDR is m) and (PS is n) and (AGE is low) then (T1 is less or T2 is less or G is less)

Rule5= If (DDR is low) and (GDR is m) and (PS is n) and (AGE is medium) then (T1 is less or T2 is less or G is less)

5) Decision Making Logic

In the proposed classification module Mamdani's Inference method was used.

6) Defuzzification

Center of Gravity (CoG) technique was used to convert fuzzy conclusion into crisp value as the defuzzification technique.

V. Proposed System Development

Online FES for Diabetes Diagnosis and Classification system was developed with the concurrent development of fuzzy expert system and web site development.

A. Development Environment

The proposed framework was an all-inclusive modules of the system proposed in [17] so the development conditions were same as to previous work.

B. Code Samples

1) Code for universe of discourse of input and output variables.

For Diabetes Diagnosis Module

```
fpg = ctrl.Antecedent(np.arange(1, 350, 1), 'fpg')
pp  =ctrl.Antecedent(np.arange(1,550,1),'pp')
bmi = ctrl.Antecedent(np.arange(0, 42, 1), 'bmi')
dpf = ctrl.Antecedent(np.arange(0,1,0.1),'dpf')
age = ctrl.Antecedent(np.arange(61, 90, 1), 'age')
```

For Diabetes Classification Module

```
ddr = ctrl.Antecedent(np.arange(0, 11, 1), 'ddr')
gdr  =ctrl.Antecedent(np.arange(0,4,1),'gdr')
ps = ctrl.Antecedent(np.arange(0, 4, 1), 'ps')
age = ctrl.Antecedent(np.arange(1, 80, 1), 'age')
```

2) Code for setting triangular membership function for fuzzy linguistic variables.

For Diabetes Diagnosis Module

```
fpg['low'] = fuzz.trimf(fpg.universe, [70, 90, 99])
fpg['medium']=fuzz.trimf(fpg.universe,[98, 110, 125])
fpg['high'] = fuzz.trimf(fpg.universe, [124, 200, 350])

pp['low'] = fuzz.trimf(pp.universe, [100, 120, 139])
pp['medium']=fuzz.trimf(pp.universe, [138,170, 190])
pp['high'] = fuzz.trimf(pp.universe, [185,350, 535])

bmi['low'] = fuzz.trimf(bmi.universe, [16, 20, 22])
bmi['medium'] = fuzz.trimf(bmi.universe, [21, 24, 26])
bmi['high'] = fuzz.trimf(bmi.universe, [25, 30, 42])

dpf['low'] = fuzz.trimf(dpf.universe, [0, 0.05, 0.125])
dpf['medium']=fuzz.trimf(dpf.universe,[0.1,0.2, .375])
dpf['high'] = fuzz.trimf(dpf.universe, [0.35, 0.6, 1])
```

For Diabetes Classification Module

```
ddr['low'] = fuzz.trimf(ddr.universe, [0, 2, 3])
ddr ['medium'] = fuzz.trimf(ddr.universe, [2, 3, 5])
ddr ['high'] = fuzz.trimf(ddr.universe, [4, 7, 10])

gdr['m'] = fuzz.trimf(gdr.universe, [0, 0, 1])
gdr['f'] = fuzz.trimf(gdr.universe, [1, 1, 2])
gdr['o'] = fuzz.trimf(gdr.universe, [1, 2, 3])

ps['n'] = fuzz.trimf(ps.universe, [0,0,1])
ps['y'] = fuzz.trimf(ps.universe, [1,1,2])
ps['ywp'] = fuzz.trimf(ps.universe, [1,2,3])

age['young'] = fuzz.trimf(age.universe, [1, 15, 21])
age['medium']=fuzz.trimf(age.universe, [20,25,30])
age['old'] = fuzz.trimf(age.universe, [27,40,80])
```

C. Rule Base

1) For Diabetes Diagnosis Module

```
rule1 = ctrl.Rule(fpg['low'] | pp['low'] | bmi['low'] | dpf['low']| age['young'], ddr['less'])

rule2 = ctrl.Rule(fpg['medium'] | pp['medium']| bmi['medium'] | dpf['medium'] | age['medium'], ddr['medium'])

rule7 = ctrl.Rule(fpg['medium'] | pp['medium'] | bmi['high'] | dpf['high']| age['old'], ddr['medium'])

rule10 = ctrl.Rule(fpg['low'] | pp['low'] | bmi['medium'] | dpf['medium'] | age['medium'], ddr['less'])
```

2) For Diabetes Classification Module

```
rule1 = ctrl.Rule(ddr['high']  &gdr['m']  &ps['n']
& age['young'],  (t1['high']%1.0 , t2['less']%1.0,
g['less']%1.0))

rule2 = ctrl.Rule(ddr['medium']  &gdr['m']  &ps['n']
& age['young'],  (t1['less']%1.0 , t2['medium']%1.0,
g['less']%1.0))

rule3 = ctrl.Rule(ddr['medium']  &gdr['m']  &ps['n']
& age['medium'], (t1['less']%1.0 , t2['medium']%1.0,
g['less']%1.0))

rule4 = ctrl.Rule(ddr['low']  &gdr['m']  &ps['n']
&  age['young'], (t1['less']%1.0 , t2['less']%1.0,
g['less']%1.0))

rule5 = ctrl.Rule(ddr['low']  &gdr['m']  &ps['n']
```

& age['medium'], (t1['less']%1.0 , t2['less']%1.0, g['less']%1.0))

VI. Result and Discussion

Implementation of proposed work was done with Python programming language and experiments were carried on Spyder which is python applications development environment.

A. Experiment and Result for Diabetes Diagnosis Module

A fuzzy variable 'AGE' was used to form fuzzy groups with linguistic variables in diabetes diagnosis experiments were carried for different age groups [17]. Fuzzy groups with linguistic variables for 'AGE' are shown in Table VI.

TABLE VI. Fuzzy Groups with Linguistic Variables for AGE

Fuzzy Variable	Linguistic Variables	Fuzzy Triangular Parameter
AGE	Age<=20	Very Young
	Age>20 and Age<=30	Young
	Age>30 and Age<=40	Slightly Young
	Age>40 and Age<=50	Slightly Old
	Age>50 and Age<=60	Old
	Age>60	Very Old

In proposed experiment $Age_{VeryOld}$ was taken as fuzzy variable. Its linguistic variables and fuzzy triangular parameters are shown in Table VII.

TABLE VII. Fuzzy Groups with Linguistic Variables for AGE

Fuzzy Variable	Linguistic Variables	Fuzzy Triangular Parameter
$AGE_{VeryOld}$	Young	[61, 65, 70]
	Medium	[68, 75, 84]
	Old	[82, 86, 90]

Total 50 data instances were found for fuzzy linguistic variable $Age_{VeryOld}$. From these instances 11 were of class 0 i.e. with no diabetes and 39 were of class 1 i.e. with diabetes.

The performance of proposed study was measured with equation number (3). [8]

$$Accuracy = \frac{TP+TN}{TN+FT+FN+TP}\times 100 \tag{4}$$

In the Table VIII system output and original diagnosed class from dataset is given for 10 data instances.

TABLE VIII. Original System Class Vs System Output

FPG	PP	BMI	AGE	DPF	Org. Class (0/1)	Sys O/P
82	173	27.04	61	0	1	High
160	160	33.58	62	0	1	High
110	320	19.93	65	0.5	1	High
200	300	26.33	67	0.5	1	High
95	109.8	24.11	70	0	1	Low
90	114	23	69	0	0	Low
92	116	26	71	0.5	0	Medium
98	122	27	77	0.5	0	Low
89	109	21.56	79	0	0	Low
100	124	23	79	0.5	0	Medium

Two class predication is given in the Table IX for 50 data instances of $Age_{VeryOld}$.

TABLE IX. Two Class Prediction for Age (VeryOld)

Actual Class	Predicted Class	
	Yes	No
Yes(39)	38(TP)	1(FP)
No(11)	2(FN)	9(TN)

$$Accuracy = \frac{38+9}{9+1+2+38}\times 100 \tag{5}$$

From 50 data instances of age group $AGE_{VeryOld}$, 39 were of diagnosed with diabetes and 11 were of with no diabetes originally. In the experiment carried out 38 diagnosed with high risk from 39 data instances of diabetes and 9 diagnosed with low risk from 11 data instances with no diabetes. In the proposed work, researchers achieved 94% accuracy for $Age_{VeryOld}$ calculated with equation number (5).

B. Experiment and Result for Diabetes Classification Module

$AGE_{VeryOld}$ was used in fuzzy classification module. From 50 instances of $AGE_{VeryOld}$, 11 data instances were with no diabetes and 39 were of Type 2 i.e. Type 2 diabetes.

In the Table X, system's classification output and original classification type is given for 12 data instances. T1 is used for Type 1 Diabetes, T2 is used for Type 2 diabetes, G is used for Gestational Diabetes and ND is used for no diabetes.

TABLE X. Original System Class Vs System Output

GDR	PS	AGE	DDR	Org. Type	Predicted Type by System		
					T1	T2	G
1	1	61	6.06	T2	1.39(l)	7(h)	1.39(l)
1	1	61	4.81	T2	1.44(l)	6.48(h)	1.44(l)
1	1	61	5.31	T2	1.4(l)	7(h)	1.4(l)
1	1	62	5.08	T2	1.42(l)	7(h)	1.42(l)
2	1	63	4.69	T2	1.44(l)	6.16(h)	1.44(l)
1	1	63	4.59	T2	1.45(l)	5.87(h)	1.45(l)
2	1	67	4.93	T2	1.43(l)	6.81(h)	1.43(l)
2	1	61	2.3	ND	1.39(l)	2.22(l)	1.39(l)
1	1	63	2.19	ND	1.4(l)	2.08(l)	1.4(l)
2	1	67	2.33	ND	1.42(l)	2.41(m)	1.42(l)
2	1	69	2.29	ND	1.43(l)	2.43(m)	1.43(l)
2	1	77	2.33	ND	1.48(l)	2.48(m)	1.48(l)

In the Table XI two class classification prediction given for Type2 Diabetes Classification with age group $AGE_{VeryOld}$.

TABLE XI. TWO CLASS PREDICTION FOR AGE(VERYOLD)

Actual Class	Predicted Class	
	Yes	No
Yes(39)	39(TP)	0(FP)
No(11)	6(FN)	5(TN)

The performance of proposed study was measured with equation number (3).

$$Accuracy = \frac{39+5}{5+0+6+39} \times 100 \tag{6}$$

In the experiment carried out, all classified correctly as Type2 Diabetes i.e. T2 with high fuzzy value from 39 Type 2 diabetes data instances and 5 classified correctly as No Diabetes with low fuzzy value for T1, T2 and G from 11 data instances of no diabetes. In the proposed work, researchers achieved 88% accuracy for $Age_{VeryOld}$ and Type 2 diabetes and calculated with equation number (6).

VII. CONCLUSION

A fuzzy approach was used to diabetes diagnosis and classification in the work presented. A web based application was designed and developed for the implementation of proposed research work. Researchers achieved 94% accuracy in diabetes diagnosis and 88% accuracy in diabetes classification for live data collected from hospital. This study will be carried out further for all age groups of fuzzy variable AGE for diabetes diagnosis. Diabetes Classification module will be tested for Type 1 diabetes and Gestational Diabetes with live data. A machine learning approaches will be used for better diabetes diagnosis and classification.

REFERENCES

[1] Steimann, Friedrich. "Fuzzy set theory in medicine." Artificial Intelligence in Medicine 11.1 (1997): 1-7.

[2] Boegl, Karl, et al. "Knowledge acquisition in the fuzzy knowledge representation framework of a medical consultation system." Artificial intelligence in medicine 30.1 (2004): 1-26.

[3] Abbod, Maysam F., et al. "Survey of utilisation of fuzzy technology in medicine and healthcare." Fuzzy Sets and Systems 120.2 (2001): 331-349.

[4] Adlassnig, Klaus-Peter. "Fuzzy set theory in medical diagnosis." IEEE Transactions on Systems, Man, and Cybernetics 16.2 (1986): 260-265.

[5] Cho, N. H., et al. "IDF Diabetes Atlas: global estimates of diabetes prevalence for 2017 and projections for 2045." Diabetes research and clinical practice 138 (2018): 271-281.

[6] Mujawar, I. K., and B. T. Jadhav. "COMPREHENSIVE STUDY ON WEB BASED EXPERT SYSTEMS FOR DISEASE DIAGNOSIS AND TREATMENT." International Journal of Computer Engineering and Applications 11.X (2017): 9.

[7] Torres, Angela, and Juan J. Nieto. "Fuzzy logic in medicine and bioinformatics." BioMed Research International 2006 (2006).

[8] Kalpana, M., and AV Senthil Kumar. "Fuzzy expert system for diabetes using fuzzy verdict mechanism." International Journal of Advanced Networking and Applications 3.2 (2011): 1128.

[9] Dokas, Ioannis M. "Developing Web Sites For Web Based Expert Systems: A Web Engineering Approach." ITEE. 2005.

[10] Lee, Kwang Hyung. First course on fuzzy theory and applications. Vol. 27. Springer Science & Business Media, 2006.

[11] Phuong, Nguyen Hoang, and Vladik Kreinovich. "Fuzzy logic and its applications in medicine." International journal of medical informatics 62.2-3 (2001): 165-173.

[12] Duan, Yanqing, John S. Edwards, and M. X. Xu. "Web-based expert systems: benefits and challenges." Information & Management 42.6 (2005): 799-811.

[13] Power, Daniel J. "Web-based and model-driven decision support systems: concepts and issues." AMCIS 2000 Proceedings (2000): 387.

[14] Grove, Ralph. "Internet-based expert systems." Expert systems 17.3 (2000): 129-135.

[15] Tsoukalas, Lefteri H., and Robert E. Uhrig. Fuzzy and neural approaches in engineering. John Wiley & Sons, Inc., 1996.

[16] I K Mujawar, B T Jadhav and Kapil Patil.Web-based Fuzzy Expert System for Symptomatic Risk Assessment of Diabetes Mellitus. International Journal of Computer Applications 182(3):5-12, July 2018.

[17] Mujawar, I. K., and B. T. Jadhav. "Web-based Fuzzy Expert System for Diabetes Diagnosis." International Journal of Computer Sciences and Engineering 7 (2019).