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A Fuzzy Intelligent Framework for Healthcare Diagnosis and Monitoring of Pregnancy Risk Factor in Women

Uduak Umoh[1] and Emmanuel Nyoho[2]
[1]Department of computer Science, University of Uyo, Nigeria
[2]Department of computer Science, University of Uyo, Nigeria

Abstract
The harmful effect of pregnancy risk factors to the body cannot be underestimated. Pregnancy risk factors are all the aspects that endanger the life of the mother and the baby. The infant mortality rates are still high in developing countries despite national and international efforts to redress this problem of pregnancy risk factors. The operations of the prediction of pregnancy risk factors are complex and risky due to fluctuation in the diagnosis of these risk factors. This is due to the vagueness, incompleteness, and uncertainty of the information used. Also, the health population index, which is based primarily on the result of medical research, has a strong impact upon all human activities. Medical experts are considered best fit for interpretation of data and setting the diagnosis, but medical decision making becomes a very hard activity because the human experts, who have to make decision, can hardly process the huge amount of data. This paper presents a fuzzy logic model for the diagnosis and monitoring of pregnancy risk factor for in order to make accurate reasoning with huge amount of uncertain knowledge. The model is developed based on clinical observations, medical diagnosis and the expert's knowledge. Twenty-five pregnant patients are selected and studied and the observed results computed in the range of predefined limit by the domain experts. The model will provide decision support platform to pregnancy risk factor researchers, physicians and other healthcare practitioners in obstetrical. The study will also guide healthcare practitioners in obstetrical and gynecology clinic regions in educating the women more about the pregnancy risk factors and encouraged them to start antenatal clinic early in pregnancy.
Keyword: Fuzzy inference System, Artificial Intelligence, Expert System, Pregnancy risk factors, Infant mortality, Pregnancy outcome

1. Introduction

Fuzzy logic, a sub-field of intelligent systems is being widely used to solve a wide variety of problems in medical, biological applications. Fuzzy logic deals with reasoning on a higher level, using linguistic information acquired from domain experts. The past few years have witnessed a rapid growth in the number and variety of applications of fuzzy logic (FL). Fuzzy Logic techniques have been used in image understanding applications such as detection of pregnancy risk factors, feature extraction, classification, and clustering. Fuzzy logic poses the ability to mimic the human mind to effectively employ modes of reasoning that are approximate rather than exact. Fuzzy logic is adopted in this research mainly due to its capability to make decisions in an environment of imprecision, uncertainty and incompleteness of information since fuzzy logic resembles human decision making with its ability to work from approximate reasoning and ultimately find a precise solution.

Pregnancy risk factors are all the aspects that endanger the life of the mother and the baby. These factors may include poor nutrition of the woman, child spacing, maternal age (less than 15 years and over 35 years), inadequate prenatal care, lifestyle behaviours e.g. smoking, alcohol consumption, drug abuse and unsafe sex, overweight, obesity and poverty. The processing of medical diagnosis and monitoring revolves around structured stored fact which allows for the development of a healthcare system that monitors and diagnoses as well as makes recommendations as regards treatment of ill health condition based on known symptoms. (Wardlaw & Kessel, 2002) (WHO, 1991) (Bloch et al. 2008). Health monitoring consists of measures taken to prevent diseases, rather than curing them and diagnosis system is a system which can identify diseases through checking out the symptoms. Due to population variability and difference in pregnancy risk factors, there may be flaws in diagnosis. In recent time, computerization in healthcare allows for various clinical support systems to be constructed; that is programs that can perform as the human expert in narrow problem domain (CDC, 2004).

Artificial Intelligent is a branch of computer science that is concerned with the automation of intelligent behavior. Artificial Intelligent methods have significantly been used in medical applications and research efforts have been concentrated on medical expert systems as complementary solution to conventional technique for finding solution to medical problems. This has opened unprecedented opportunities in health care delivery system as the demand for intelligent and knowledge-based systems has increased as modern medical practices become more knowledge intensive (Luger and Stublefield, 1991). An Expert System (ES) is an intelligent computer program that uses the knowledge base of one or more experts and inference procedures for problem solving. Human experts solve problems by using a combination of factual knowledge and reasoning ability. In an expert system, these two essentials are contained in two separate but related components: a knowledge base and an inference engine. The knowledge-base provides specific facts and rules about the subject and the inference engine provides the reasoning ability that enables the expert system to form conclusions. (Adekoya, 2008)

Fuzzy logic is a set of mathematical principles for knowledge representation based on degrees of membership rather than classical binary logic. It is a powerful tool to tackle imprecision and uncertainty and was initially introduced to improved tractability, robustness and low-cost solutions for real world problems. Fuzzy sets have been applied in many fields in which uncertainty plays a key role for which medical diagnosis is an excellent example of vagueness and uncertainty. Fuzzy logic is a promising technique that can easily capture the required medical knowledge and come up with sound diagnosis decisions as it will estimate the risk in getting pregnancy based on the risk factors and the symptoms. It will increase the number of medical consulting point in hospitals as well as giving some recommendation that will suggest the life style that could contribute to the high risk of getting pregnant.

The objective of this research is to develop a fuzzy framework using AI technologies and apply for healthcare diagnosis and monitoring of pregnancy risk factor in women. To achieve our objectives, relevant literatures on fuzzy logic, pregnancy risk factors monitoring and diagnosis, database tools, healthcare system are reviewed and the characteristic of the existing system is studied. Data are gathered through personal interviews with medical experts/consultants as well as personal observation on 25 pregnant patients. Mini- fuzzy inference system and centre of gravity defuzzification is employed in this project. Object oriented design tool is adopted in this system. The proposed system if implemented will provide decision support platform to pregnancy risk factor researchers, physicians. The study will also guide healthcare practitioners in obstetrical and gynecology clinic regions in educating the women more about the pregnancy risk factors and encouraged them to start antenatal clinic early in pregnancy.

The rest of this paper is as follows, section 2 presents literature review, section 3 research methodology; section 4 presents results and discussion. Finally, section 5 gives a conclusion and section 6 presents references.

2. Literature Review

Fuzzy Logic is a problem-solving control system methodology that lends itself to implementation in systems. It provides a simple way to arrive at a definite conclusion based upon vague, ambiguous, imprecise, noisy, or missing input information. Its approach to control problems mimics how a person would make decisions, only much faster. The concept of Fuzzy Logic (FL) was conceived by Lotfi Zadeh (1965), a professor at the University of California at Berkeley, and presented not as a control methodology, but as a way of processing data by allowing partial set membership rather than crisp set membership. Professor Zadeh reasoned that people do not require precise, numerical information input, and yet they are capable of highly adaptive control. If feedback controllers could be programmed to accept noisy, imprecise input, they would be much more effective and perhaps easier to implement. (Russell and Kay, 2004).

Fuzzy an expert system uses a collection of fuzzy membership functions and rules, instead of Boolean logic, to reason about data. Unlike conventional expert systems, which are mainly symbolic reasoning engines, fuzzy expert systems are oriented toward numerical processing. A typical fuzzy expert system has a fuzzification mechanism, inference engine, more than one rule and the entire group of rules collectively known as a rule base or knowledge base and the defuzzification mechanism. Fuzzy expert systems allow partial matching of a rule's antecedents to provide a systematic way of managing imprecision and uncertainty. Compared to traditional expert systems, fuzzy expert system take less time to develop, reduce maintenance cost and improve user understanding. (Mamdani and Assilian, 1975) (Mamdani, 1976).

The health population index, which is based primarily on the result of medical research, has a strong impact upon all human activities. Medical experts are considered best fit for interpretation of data and setting the diagnosis. But medical decision making becomes a very hard activity because the human experts, who have to make decision, can hardly process the huge amount of data. They could use some expert systems with fuzzy logic to make accurate reasoning with huge amount of uncertain knowledge. The harmful effect of pregnancy risk factors to the body cannot be underestimated (Abbod et al. 2001). Pregnancy risk factors are all the aspects that endanger the life of the mother and the baby. These factors may include poor nutrition of the woman, child spacing, maternal age, inadequate prenatal care, lifestyle behaviors e.g. smoking, alcohol consumption, drug abuse and unsafe sex, overweight, obesity and poverty. The infant mortality rates are still high in developing countries despite national and international efforts to redress this problem of pregnancy risk factors. In a high-risk pregnancy, the mother, foetus, or neonate is at increased risk of morbidity or mortality before or after delivery. Risk factors are assessed systematically because each risk factor presents increases overall risk. High-risk pregnancies require close monitoring and sometimes referral to a prenatal center (Mosha and Philemon, 2010).

Factors that put a pregnancy at risk can be divided into four categories: (i) Existing Health Conditions (ii) Age (iii) Lifestyle Factors (iv)Conditions of Pregnancy. Existing health conditions include high blood pressure, diabetes, kidney disease etc. Age factors include, teen pregnancy, first-time pregnancy after age 35 etc. Lifestyle factors include alcohol use and cigarette smoking. While conditions for pregnancy factors are multiple gestation, gestational diabetes and preeclampsia and eclampsia. Although pregnancy risk factors may be life-threatening, prevention of these risk factors is normally straightforward if proper sanitation practices are followed. Effective sanitation practices, if instituted and adhered to in time, are usually sufficient to stop an epidemic. A multidisciplinary approach is based on prevention, preparedness and response, along with an efficient surveillance system as key to mitigating pregnancy risk factor outbreaks, controlling pregnancy risk factor in endemic areas and reducing deaths. As a result of pregnancy risk factors, (Kazaura et al, 2006) estimated that, about four million out of 130 million infants born worldwide die during the first four weeks of life and more than three million are stillborns.

In (Djam et al. 2011), a fuzzy expert system for the management of malaria (FESMM) is presented for providing decision support platform for healthcare practitioners in malaria endemic regions. The study explores triangular membership function and Root Sum Square (RSS) fuzzy inference methods respectively. The fuzzy expert system is designed based on clinical observations, medical diagnosis and the expert's knowledge. 35 patients with malaria are selected and computed the results that are in the range of predefined limit by the domain experts. In (Umoh and Ntekop, 2013), a fuzzy expert system for the diagnosis and monitoring of cholera is presented for providing decision support platform to cholera researchers, physicians and other healthcare practitioners in cholera endemic regions. Twenty patients with cholera are selected and studied and the observed results computed in the range of predefined limit by the domain experts.

In (Ephzibah, 2011) the automated design of pattern classification is carried out. The proposed system solves the feature subset selection problem. It is a task of identifying and selecting a useful subset of pattern-representing features from a larger set of features. Using fuzzy rule-based classification system, the proposed system proves to improve the classification accuracy. Reis et al, (2004) propose the use of a fuzzy expert system to predict the need for advanced neonatal resuscitation efforts in the delivery room. This system relates the maternal medical, obstetric and neonatal characteristics to the clinical conditions of the newborn, providing a risk measurement of need of advanced neonatal resuscitation measures. The system helps health care staff to make decisions in prenatal care. Felming, et al. (2007) describes an early warning GIS prototype tool aimed at identifying favourable preconditions for cholera outbreaks. These preconditions are defined using an expert system approach. The variables thus identified are input into a spatial fuzzy logic model that outputs risks. The model is based on the assumption that endemic reservoirs of cholera occur and that environmental conditions, especially algal blooms, trigger Vibrio growth in the natural environment.

Fernando et al. (2002) present introduce a fuzzy linguistic model for evaluating the risk of neonatal death. The study is based on the fuzziness of the variables newborn birth weight and gestational age at delivery. The inference used is Mamdani's method. Neonatologists are interviewed to estimate the risk of neonatal death under certain conditions and to allow comparing their opinions and the model values. The results are compared with experts' opinions and the Fuzzy model is able to capture the expert knowledge with a strong correlation (r=0.96). James and Dasarathy (2014) carry out a paper review on medical image fusion to improve the imaging quality and reduce randomness and redundancy in order to increase the clinical applicability of medical images for diagnosis and assessment of medical problems. Multi-modal medical image fusion algorithms and devices shows notable achievements in improving clinical accuracy of decisions based on medical images.

Igodan et al. (2013) presents a model of a web-based system for knowledge warehousing and mining of diagnosis and therapy of HIV/AIDs using fuzzy logic and data mining approach. The model is developed using the predictive modeling technique, for predicting HIV/AIDs and monitoring of patient health status. The fuzzy inference rule and a decision support system based on cognitive filtering are employed to determine the possible course of action to be taken. Shannon and Wong 2010) investigate risk factors associated with gestational diabetes mellitus. Sikchi et al. (2013) develop fuzzy expert systems (FES) for Medical Diagnosis. Leite et al. (2011) design fuzzy model for processing and monitoring vital signs in ICU patients. Umoh et al. (2010) study fuzzy rule based framework for effective control of profitability in a paper recycling plant. Mishra et al. (2013) investigate fuzzy based model for breast cancer diagnosis.

3. Research Methodology

A case study of the anti-natal and post-natal section, University of Uyo Teaching Hospital (UUTH), Uyo, Akwa Ibom State is considered in our study. The hospital is research/training point for medical students from University where data are collected. The pregnant women are required to register and get an identification code for subsequent diagnosis. This registration form contains personal information about patient which is used to maintain a record of patient and trace her health history in the clinic. The proposed system uses this information for the development of a fuzzy logic healthcare diagnosis and monitoring system for pregnancy risk factors. This is used to determine the different levels of severity of risk factors in pregnancy. 30 pregnant women are selected, aged between 25 and 40.

3.1 System Architecture

The conceptual architecture of the PRFPS proposed in this work is a modification of the model based on Umoh et al. (2010) and Shapiro and Koissi, (2015) and presented in Figure 1. The conceptual architecture comprises of the Knowledge Base which is made of the Database model and Fuzzy logic model and the user interface. The database model is shown in Figure 2, while Figure 3 presents the PRFPS Database Relationship Diagram. Table 1 shows PRFPS Rules Table. Table 2 presents PRFPS Patients Table. Table 3 gives the patient's report table. PRFPS user's table is shown in Table 4.

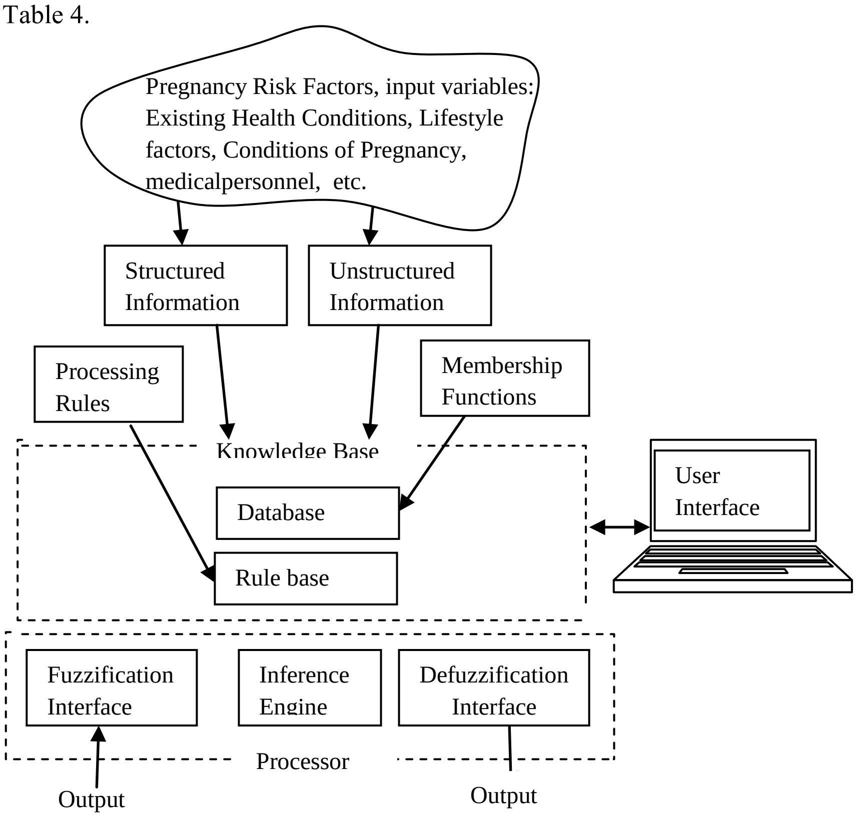

Fig 1: Architecture of Pregnancy risk factors Diagnosis and Monitoring System

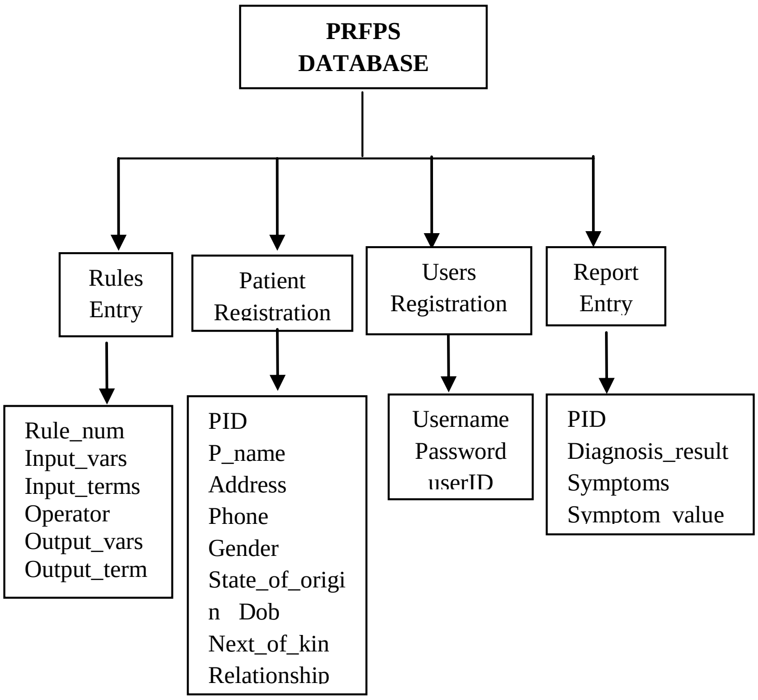

Fig 2: Database Model for Pregnancy Risk Factor Prediction

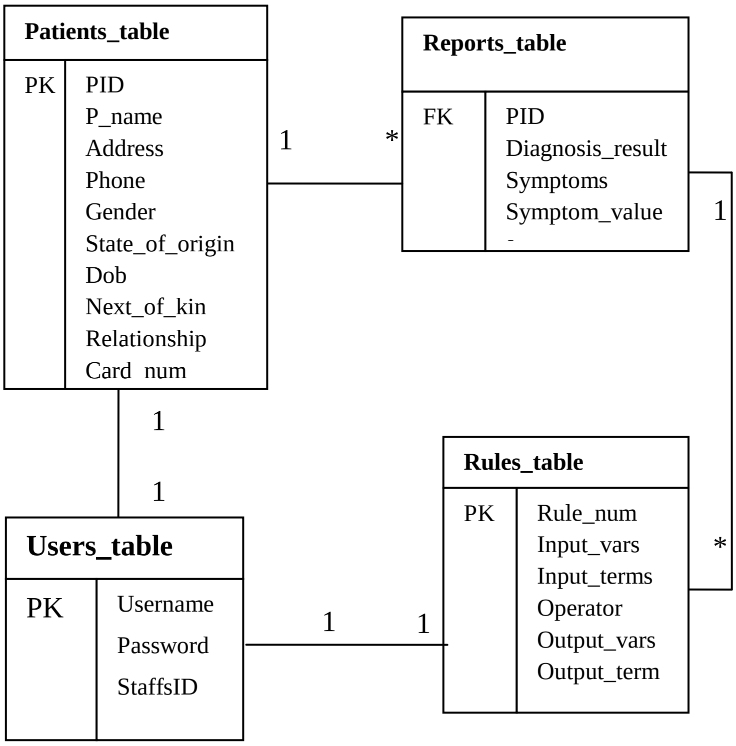

Fig. 3: PRFPS Entity Relationship Diagram

Table 1: PRFPS Rules Table

S/N	FIELNAME	DATA TYPE	SIZE	DESCRIPTION
1	Rule_num	Number	6	Rule number
2	Input_vars	varchar	10	List of input variables
3	Input_terms	Varchar	25	List of input terms
4	operator	Varchar	3	Fuzzy operator (AND, OR)
5	Output_var	Varchar	10	Output variable
6	Output_term	Varchar	25	Output term

Table 2: PRFPS Patients Table

S/N	FIELNAME	DATA TYPE	SIZE	DESCRIPTION
1	PID	Number	6	Patient's ID
2	P_name	varchar	35	Patient's name
3	Address	Varchar	25	Address
4	Phone	Number	11	Phone number
5	Gender	Varchar	6	Gender
6	state	varchar	25	State of origin
7	Dob	Date/Time	6	Date of birth
8	Nok	varchar	25	Next of kin
9	Nokr	varchar	23	Relationship to next of kin
10	Card_num	Number	8	Patient's Card number

Table 3: PRFPS Patient's report table

S/N	FIELNAME	DATA TYPE	SIZE	DESCRIPTION
1	PID	Number	6	Patient's identification number
2	D_result	varchar	10	Diagnosis result
3	Symptoms	Varchar	25	List of patient's symptoms
4	Symp_vals	Varchar	3	List of patient's symptom values

Table 4: PRFPS User's Table

S/N	FIELNAME	DATA TYPE	SIZE	DESCRIPTION
1	Staffs_ID	Number	6	Staff's identification number
2	Username	Varchar	15	Username
3	Password	Varchar	15	User's password

The PRFPS fuzzy logic model is presented in Figure 4.

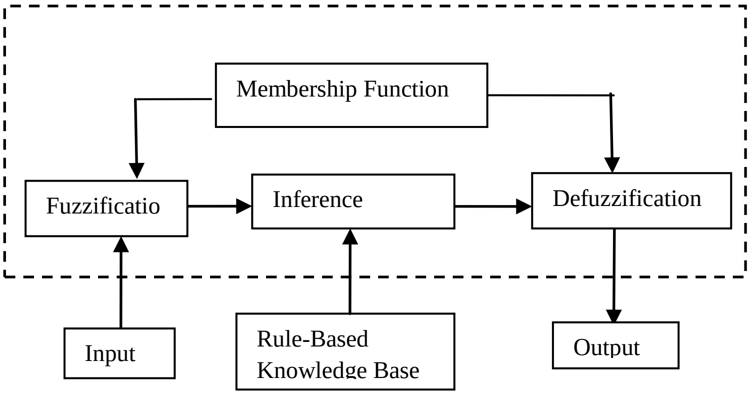

Fig. 4: The PRFPS Fuzzy Logic Model

FIS as shown in Figure 4 can be envisioned as involving a knowledge base and a processing stage. The knowledge base provides Membership Functions (MFs) and fuzzy rules needed for the process. In the processing stage, numerical crisp variables are the input of the system. These variables are passed through a fuzzification stage where they are transformed to linguistic variables, which become the fuzzy input for the inference engine. This fuzzy input is transformed by the rules of the inference engine to fuzzy output. These linguistic results are then changed by a defuzzification stage into numerical values that become the output of the system.
Both input and output linguistic variables (and their terms) used in the PRFPS fuzzy logic model are defined as;

1. Existing Health Condition (EHC) [Low, Moderate, High]
2. Life Style Factors (LSF) [Low, Moderate, High]
3. Condition of Pregnancy (COP) [Low, Moderate, High]
4. Pregnancy Risk [Low, Moderate, High]

The triangular membership function is defined for all input and output parameters based on (1). The universe of discourse is defined for the **PRFPS** input variables to our fuzzy system and is shown in Table 5.

$$f(x;a,b,c) = \begin{cases} 0\,, & x \le a \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ \dfrac{c-x}{c-b}\,, & b \le x \le c \\ 0\,, & c \le x \end{cases} \qquad (1)$$

Table 5: Fuzzy Input's Universe of Discourse

Input Variables and their Universe of Discourse		
Existing Health Condition (EHC)	Life Style Factors (LSF)	Condition of Pregnancy (COP)
[1 , 20]	[1 , 10]	[1 , 15]

We explore Fuzzy logic toolbox in Matlab 7.5.0 to plot the membership functions for our linguistic variables – EHC, LSF, COP and are shown graphically in Figures 5 -.7 respectively. Input membership values for EHC, LSF, COP and output membership values are presented in Tables 6 – 9 respectively. Membership Matrix showing the degree of membership of crisp inputs at various levels in the input membership function defined on the Three (3) input variables (EHC, LSF, COP) for the **PRFPS** system are shown in Tables 10 – 12 respectively.

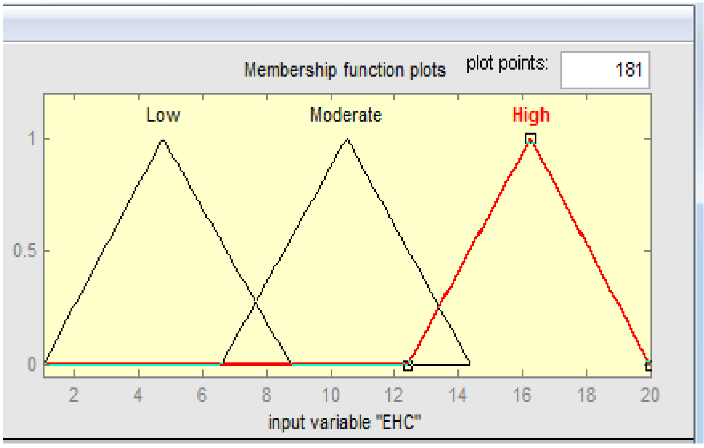

Fig. 5: Membership Function for Existing Health Condition

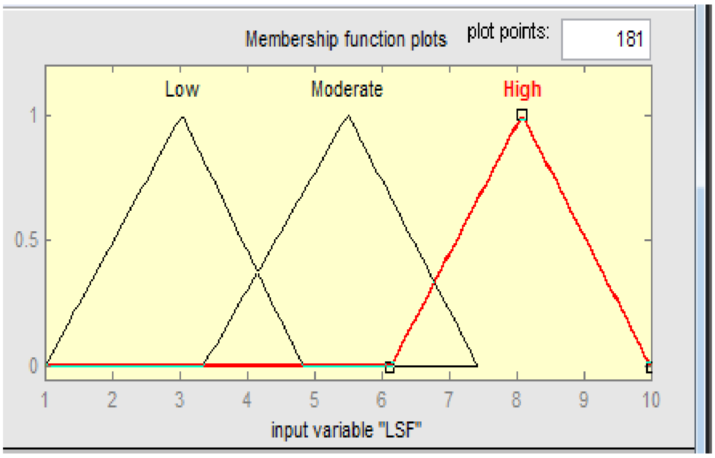

Fig. 6: Membership Function for Life Style Factor

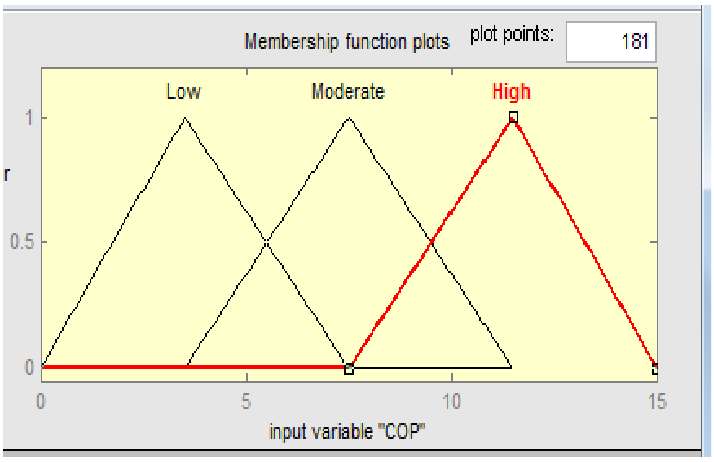

Fig. 7: Membership Function for Condition of Pregnancy

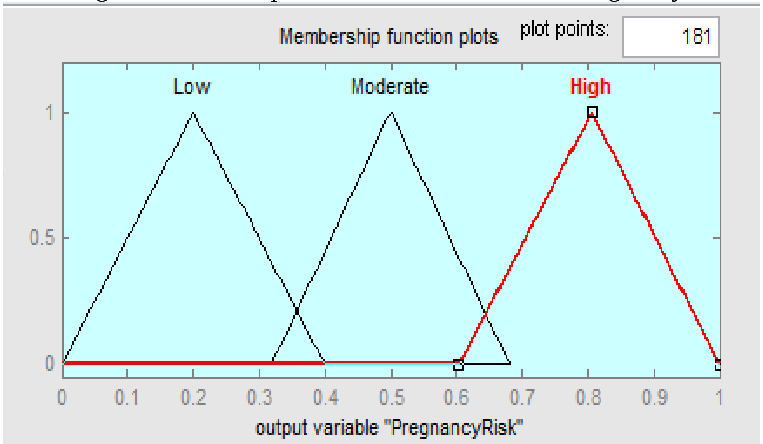

Fig. 8: Output Membership Function (Pregnancy Risk)

Table 6: Membership values for EHC

TERMS	LEFT-LEG	MIDDLE	RIGHT-LEG
Low	1	4.88	8.766
Moderate	6.55	10.4	14.4
High	12.4	16.2	20

Table 7: Membership Values for LSF

TERMS	LEFT-LEG	MIDDLE	RIGHT-LEG
Low	1	2.9	4.85
Moderate	3.35	5.39	7.44
High	6.13	8.06	10

Table 8: Membership values for COP

TERMS	LEFT-LEG	MIDDLE	RIGHT-LEG
Low	0	3.5	7.5
Moderate	3.5	7.5	11.5
High	7.5	11.5	15

Table 9: Membership values for Pregnancy Risk;

TERMS	LEFT-LEG	MIDDLE	RIGHT-LEG
Low	0	0.2	0.4
Moderate	0.32	0.505	0.69
High	0.6	0.8	1

Table 10: Membership Matrix for Existing Health Condition (EHC)

Fuzzy Set	**Crisp Input**									
	2	**4**	**6**	**8**	**10**	**12**	**14**	**16**	**18**	**20**
Lo	0.26	0.77	0.71	0.20	0.0	0.0	0.0	0.0	0.0	0.0
Mo	0.0	0.0	0.0	0.37	0.88	0.61	0.10	0.0	0.0	0.0
Hi	0.0	0.0	0.0	0.0	0.0	0.0	0.42	0.95	0.53	0.0

Table 11: Membership Matrix for Life Style Factors (LSF)

Fuzzy Set	**Crisp Input**									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Lo	0.0	0.5	0.96	0.44	0.0	0.0	0.0	0.0	0.0	0.0
Mo	0.0	0.0	0.0	0.32	0.81	0.70	0.22	0.0	0.0	0.0
Hi	0.0	0.0	0.0	0.0	0.0	0.0	0.45	0.97	0.52	0.0

Table 12: Membership Matrix for Condition of Pregnancy (COP)

Fuzzy Set	**Crisp Input**						
	2	**4**	**6**	**8**	**10**	**12**	**14**
Lo	0.3	0.99	0.34	0.0	0.0	0.0	0.0
Mo	0.0	0.0	0.30	0.97	0.34	0.0	0.0
Hi	0.0	0.0	0.0	0.0	0.30	0.97	0.34

We defined our fuzzy rule based on the conditional statement in the form:
IF *ehc is LOW* AND *lsf is MODERATE* AND *cop is HIGH* THEN *risk is MODERATE,*
Where ehc, lsf and cop are linguistic variables; LOW, MODERATE and HIGH are linguistic values (terms) determined by fuzzy sets on the universe of discourse defined in Table 5. The rules are evaluated based on representation of the expert's knowledge that collected from the University of Uyo Teaching Hospital for the **PRFPS** system. The total number of rules used in this system is 27 (calculated as N^T). Where N is the number of linguistic variables and T is the number of terms. For the sake of our pregnancy risk factor prediction system, we develop an algorithm for the generation of 27 rules presented in Figure 9. The rule generation system uses a pseudorandom number generator in the process.
1: initialize fuzzy input variables *(fv)*
2: initialize fuzzy input terms *(ft)*
3: initialize fuzzy output terms *(fot)*
4: compute rule length as:

$$ruleLen = exponent(tLen, vLen), \quad (2)$$

where *tLen and vLen* are the sizes of input and output terms respectively
5: compute average of minimum terms as;

$$minTermAverage = \{\sum_{i=1}^{tLen} \min(ft_i)\}/tLen \quad (3)$$

6: compute average of maximum terms as;

$$maxTermAverage = \{\sum_{i=1}^{tLen} \max(ft_i)\}/tLen \quad (4)$$

7: compute input to output term ratio as;

$$ioRatio = (\sum(minTermAverage, maxTermAverage))/\text{oLen} \quad (5)$$

8: while loop < ruleLen

a. Generate vLen random number "rand" between 1 and tLen
b. Compute weighted average as;
c.

$$wg = (\sum_{i=0}^{vLen-1} rand_i)/vLen \quad (6)$$

d. Compute consequence as
e.

$$c = wg * ioRatio \quad (7)$$

f. Store $rand_i$ in the input part of the rules and c as the consequence
g. Increment loop variable

Fig. 9: Algorithm for PRFPS Rule Generation

The study employs Mamdani fuzzy inference engine to evaluate the rules from the rule base. The fuzzy inference engine uses the intersection operator (AND) to evaluate the rules. The firing levels of the 27 rules are computed based on (Umoh and Isong, 2013) as presented in (8).

$$\alpha_i = EHC_{i1}(x_0) \wedge LSF_{i1}(y_0) \wedge COP_{i1}(z_0),\ EHC_{i2}(x_0) \wedge LSF_{i2}(y_0) \wedge COP_{i2}(z_0), \ldots EHC_{in}(z_0) \wedge LSF_{in}(y_0) \wedge COP_{in}(z_0) \quad (8)$$

Where, α_i is the matching degree of a given input which satisfies the condition of the *ith* rule and i= 1, 2,.., 27. Then α_i is assigned to the rule's consequence C_i (w) as in (9).

$$C_i(w) = \alpha_i \quad (9)$$

We obtain the individual rule outputs as in (10).

$$C'_i(w) = (\alpha_{i1} \wedge C_{i1}(w)), (\alpha_{i2} \wedge C_{i2}(w)), \ldots (\alpha_{in} \wedge C_{in}(w)) \quad (10)$$

where Li(w) is the individual rule's consequence.
The overall system output is computed by aggregating the individual rule outputs from all the rules using OR operator as in (11);

$$C(w) = C'_1(w) \vee C'_2(w) \vee C'_3(w) .. \vee C'_n(w) \quad (11)$$

For example, crisp inputs vales are selected for EHC, LSF and COP and corresponding degrees of membership, the fired rules, and consequences are computed as shown in Tables 13 – 15 repectively.

Table 13: Rule Base Evaluation for EHC = 8, LSF = 7, COP = 2

Rule No.	**Crisp Inputs**			**Consequence (non- zero)**
	EHC	LSF	COP	Risk
24	0.197	0.215	0.332	0.197 Low
7	0.368	0.215	0.332	0.215 Moderate
23	0.197	0.447	0.332	0.197 Moderate
18	0.368	0.447	0.332	0.332 Moderate

Table 14: Rule Base Evaluation for EHC = 15, LSF = 5, COP = 6

Rule No.	**Crisp Inputs**			**Consequence(none zero)**
	EHC	LSF	COP	Risk
6	0.68	0.8	0.62	0.62 Moderate
17	0.68	0.8	0.4	0.4 Moderate

Table 15: Rule Base Evaluation for EHC = 9.8, LSF =8.43, COP = 9

Rule No.	**Crisp Inputs**			**Consequence(none zero)**
	EHC	LSF	COP	Risk
11	0.82	0.811	0.4	0.4 High
21	0.82	0.811	0.62	0.62 Moderate

In order to obtain a deterministic control action, we apply a defuzzification method is used. There are several defuzzification techniques, the paper explore centroid (or center of gravity) technique given by the formula in (12).

$$COG = \frac{\sum_x^b \mu_A(x)x}{\sum_x^b \mu_A(x)}, \qquad (12)$$

Where, $\mu_A(x)$ is the degree of membership of x in a set A.
Figure 10 shows the rule generation system for diagnosis and monitoring pregnancy risk factor. Figures 11 - 13 present the simulated view of the rule base evaluation impact of pregnancy risk factor based on different selected input values. Figures 14 show surface view with inputs LSF and EHC with their expected Pregnancy risk, while the surface view with inputs EHC and COP with their expected Pregnancy risk is shown in Figure 15.

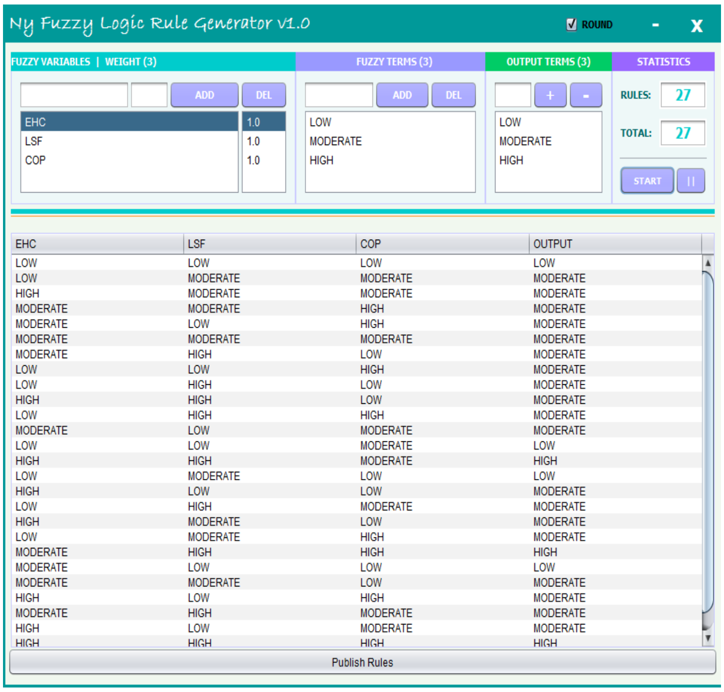

Fig. 10: The PRFPS rule generation system

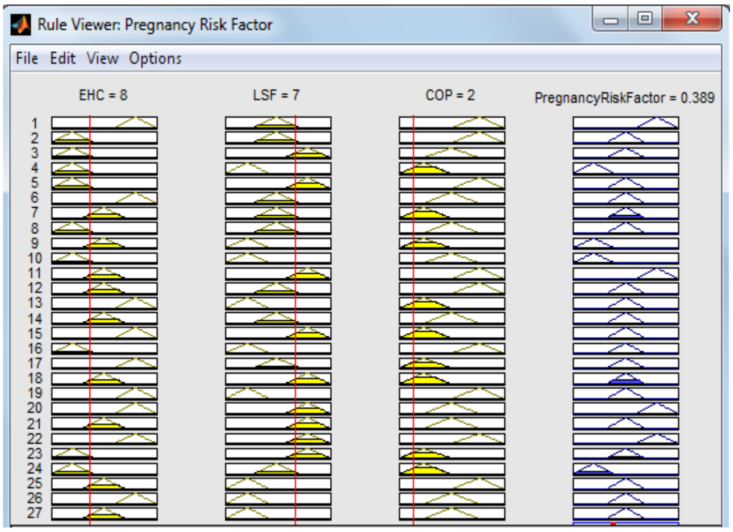

Fig. 11: Simulated View of the Rule Base Evaluation – Impact of |Pregnancy Risk Factor|

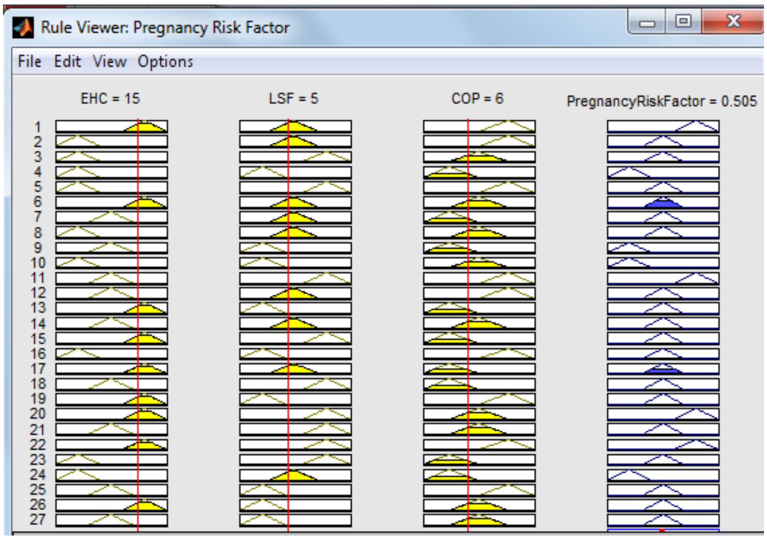

Fig. 12: Simulated View of the Rule Base Evaluation – Impact of |Pregnancy Risk Factor|

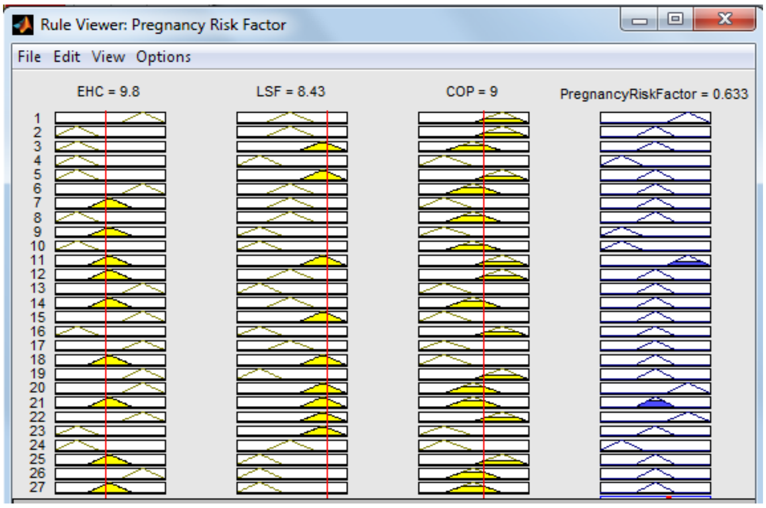

Fig. 13: Simulated View of the Rule Base Evaluation – Impact of |Pregnancy Risk Factor|

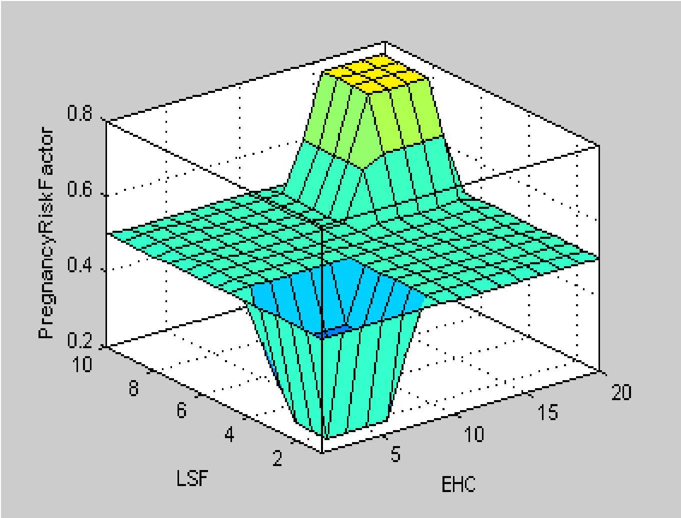

Fig 14: Surface view with inputs LSF and EHC with their expected Pregnancy risk

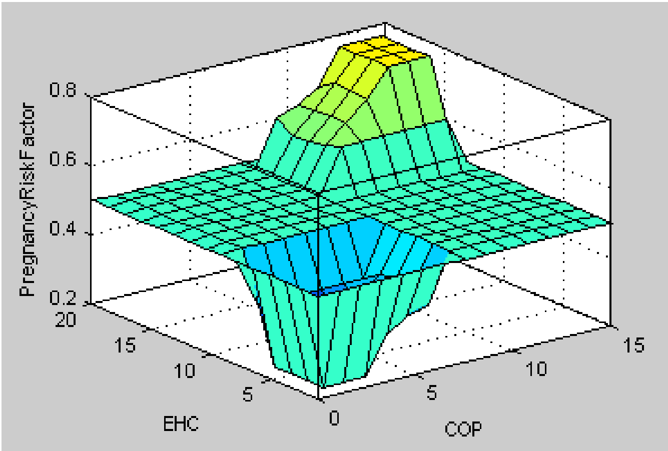

Fig. 15: Surface view with inputs EHC and COP with their expected Pregnancy risk

4 Results And Discussion

The pregnancy risk factor diagnosis and monitoring model is based on fuzzy logic model. This system consists of three input variables: EHC, SLF and LSF. We have 27 rules in our rule base used to determine the three output parameter values: low pregnancy risk, moderate pregnancy risk and high pregnancy risk, according to the three input values. We employ triangular membership function method for membership function evaluation. The rule base is designed based on knowledge of domain experts. The study adopts Mamdani's inference engine technique and center of gravity method for the defuzzification. We explore fuzzy inference system in order to remove uncertainty, ambiguity and vagueness inherent in healthcare diagnosis and monitoring. The study assigns linguistics variables such as low, moderate and high and evaluates the degree of lowness, moderateness and highness to the diagnosis and monitoring of pregnancy risk.

In order to validate the fuzzy logic approach used in construction of PRFPS, the study perform an extensive simulation using MATLAB based on variation defined in the membership function as a rule viewer, surface view etc. We simulate designed FIS to identify the output parameter- the factors of pregnancy risk in a pregnant woman. The snapshot of our fuzzy rules for the pregnancy risk prediction system is shown in Figure 10. Simulated Views of the Rule Base Evaluation – Impact of Pregnancy Risk Factor based on Tables 13 – 15 are shown in Figures 11 – 13 respectively. In our study, the surface views are generated showing the three dimensional view curves that represent the mapping for all the input parameters with the output parameter of pregnancy risk as shown in Figures 14 and 15.

Pregnancy Risk surface viewer is used to view the dependency of the output on two of the inputs, generates and plots an output surface map of the system. The outputs, low pregnancy risk, mild pregnancy risk and moderate pregnancy risk show the dependences on the inputs parameters. Through surface viewer, our system can be seen in micro form which is not possible with the help of rule viewer. We evaluate surface view by filling all the X, Y and Z) axis representing two inputs and one output (EHC, COP and Pregnancy Risk) respectively. The surface viewing grid helps us to see our system in actual form, thus helps to monitor the pregnancy risk based on the variations of the risk factors from time to time. The results show a good performance, being in the range of the pre-defined limits by the domain experts.

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5. Conclusion

The study has successfully developed a proposed fuzzy framework for pregnancy risk factor diagnosis and monitoring for providing decision support platform to pregnancy risk factor researchers, physicians. The study will also guide healthcare practitioners in obstetrical and gynecology clinic regions in educating the women more about the pregnancy risk factors and encouraged them to start antenatal clinic early in pregnancy. The model is developed based on clinical observations, medical diagnosis and the expert's knowledge. Twenty-five pregnant patients are selected and studied and the observed results computed in the range of predefined limit by the domain experts. Both the design model and simulation result are same. Our fuzzy system consists of three inputs, membership function curves which describe the curves of both inputs and output. The whole system is based on 27 rules. Our system can be viewed through Rule viewer and Surface viewer. While Rule viewer helps us to see the whole functioning of the system, the Surface viewer helps us to see the whole system in micro form. The medical knowledge in this field is characterized by uncertainty, imprecision and vagueness. As the pregnancy risk factors are very fuzzy in nature, the use of linguistic approximation enables knowledge to be represented in a more meaningful way.

In our study, low pregnancy risk, moderate pregnancy risk and high pregnancy risk are all dependents on the inputs EHC, LSF and COP. Similarly, in the future, the system can be defined with more than three inputs to achieve more efficient human diagnose and monitoring results. The performance of the proposed system can be improved in future by integrating fuzzy logic with particle swarm optimization tool.

6. References

G. Wardlaw and M. Kessel "Perspectives in Nutrition". 5th Ed. Mc Graw Hill. Boston Burr Ridge. Pp 157 – 198, 2002.

WHO ''Sample size determination in Health Studies. A practical manual". WHO, Geneva, 1991.

[M. Bloch, F. Althabe, M. Onyamboko, C. Kaseba-Sata, E. Castilla, S. Freire, A. Garces, S. Parida, S. Goudar

M. Kadir, N. Goco, J. Thornberry, M. Daniels, J. Bartz, T. Hartwell, N. Moss, and R. Goldenberg, "Tobacco use and second-hand smoke exposure during pregnancy: an investigative survey of women in 9 developing nations". American Journal of Public Health 98, 87 – 96, 2008.

CDC " Malaria during pregnancy". Centre for Diseases Control and Prevention, 2004. [http://www.cdc.gov/malaria.htm] site visited on 20/6/2015

G. Luger, and W. Stubblefield "Artificial intelligence."In MacMillan Encyclopedia of Computer Science. New York, NY: MacMillan, , 1991.

A. Adekoya, A. Akinwale and O. Oke, "A medical expert system for managing tropical diseases". Proceedings of the Third Conference on Science and National Development, 74-86, 2008.

L. Zadeh, "Fuzzy Sets". Information and Control 8: 338–353, 1965.

R. Russell and B. Kay "Medical entomology: changes in the spectrum of mosquito-borne disease in Australia and other vector threats and risks", 1972–2004. Aust J Entomol 43:271–282, 2004.

E. Mamdani, and S. Assilian, "An experiment in linguistic synthesis with a fuzzy logic controller", International Journal Man-Machine Studies, 1975, 7,1-13.

E. Mamdani, ".Advances in the Linguistic Synthesis of Fuzzy Controller". International Journal of Man-Machine Studies. 8(6): 669–678, 1976

M. Abbode, D. von Keyserlingk, D. Linkens, M.,Mahfouf 2001, Survey of utilization of fuzzytechnology in Medicine and Healthcare, Fuzzy Setsand Systems, 120(2):331–349.

T. Mosha and N. Philemon "Factors influencing pregnancy outcomes in Morogoro Municipality, Tanzania". Tanzania Journal of Health Research Volume 12, Number 4, pp 1-14, October 2010

Kazaura, M.R., Kidanto, H.L. & Massawe, S.N. "Levels, trends and risk for early neonatal mortality at Muhimbili National Hospital, Tanzania, 1999-2005". *East African Journal of Public Health* 3 , 10 -13, 2006

X. Djam, G. Wajiga, Y. Kimbi, and N. Blamah, "A Fuzzy Expert System for the Management of Malaria". Int. J. Pure Appl. Sci. Technol., 5(2) (2011), 84-108,

U. Umoh, and M. Ntekop, M. M. (2013), a Proposed Fuzzy Framework for Cholera Diagnosis and Monitoring. *International Journal of Computer Applications* 82(17):1-10.

E. P. Ephzibah, Cost Effective Approach on Feature Selection Using Genetic Algorithms and Fuzzy Logic for Diabetes Diagnosis. International Journal on Soft Computing (IJSC), Vol.2, No.1, February 2011, 1-10.

M. Resis, N. Ortega and P. Silveiral "Fuzzy expert system in the prediction of neonatal resuscitation". Brazilian Journal of Medical and Biological Research, 2004, 37, 755-764.

[G. Fleming, M. van der Merwe, G. McFerren "Fuzzy expert systems and GIS for cholera health risk prediction in southern Africa". Environmental Modelling & Software 22 (2007) 442-448.

L. Fernando, C Nascimentoa and N. Ortegab "Fuzzy linguistic model for evaluating the risk of neonatal death". Rev Saúde Pública 2002;36(6):686-92.

A. James and B. Dasarathy, "Medical Image Fusion: A survey of the state of the art", Information Fusion, 2014, 1-45.

C. Igodan O. Akinyokun and O. Olatubosun "Online Fuzzy-Logic Knowledge Warehousing And Mining Model for the Diagnosis and Therapy of Hiv/Aids. International Journal of Computational Science and Information Technology (IJCSITY) Vol.1, No.3, August 2013, 27-41.

A. Shannon and C. Wong "Risk Factors Associated with Gestational Diabetes Mellitus". INT. J. Bioautomation, 2010, 14(1), 15-26.

S. Sikchi, S. Sikchi, and M. Ali, "Fuzzy Expert Systems (FES) for Medical Diagnosis". International Journal of Computer Applications (0975 – 8887) 63(11), 7-17, 2013..

monitoring vital signs in ICU patients". BioMedical Engineering OnLine 2011, 10:68, 1-17, 2011..

U. Umoh, E. Nwachukwu and O. Obot, "Fuzzy Rule based Framework for Effective Control of Profitability in a Paper Recycling Plant". Global Journal of Computer Science and Technology, (10)10: 56-67, 2010.

M. Mishra, T. Abirami, S. Soundarya, and R. Sulochana "A Fuzzy Based Model for Breast Cancer Diagnosis". International Journal of Scientific and Research Publications, 3(3), 1-6, 2013.

U. Umoh, E. Nwachukwu, and O. Okure (2010). "Fuzzy Inference System for Control of Profitability in Paper recycling plant: Mamdani's Design approach". Pacific Journal of Science and Technology. 10(2):391-407

F. Arnold, F. Shapiro and M. Koissi "Risk Assessment Applications of Fuzzy Logic". © 2015 Casualty Actuarial Society, Canadian Institute of Actuaries, Society of Actuaries, All Rights Reserved. Pp. 28. 2015)

U. Umoh, and B. Isong, "Fuzzy Logic Based Decision Making for Customer Loyalty Analysis and Relationship Management. International Journal on Computer Science and Engineering (IJCSE), 5(11), 919-932, 2013.

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