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Implementation and Evaluation of A Type-1 Fuzzy Logic Controller for Healthcare Diagnosis and Monitoring

Uduak Umoh* Mfon Ntekop
Department of Computer Science, University of Uyo, PMB 1017, Akwa Ibom State, Nigeria

Abstract
Type-1 fuzzy inference systems have shown potential to improve clinician performance by imitating human thought processes in complex circumstances and accurately executing repetitive tasks to which humans are ill-suited. This paper addresses the implementation of a type-1fuzzy model for pregnancy health risk diagnosis and monitoring to enhance control strategies in the medical discipline of diagnosis and monitoring pregnancy health conditions. 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. The system is developed using NETBEANS IDE, JAVA, MYSQL, etc using Windows Vista as operating system platform. Results indicate that, the study has ascertained the association of the risk factors with pregnancy outcomes. It is observed that, the paper will serve as a tool for medical practitioners in educating the women more about the degree of influence of risk on pregnancy impacted by pregnancy risk factors. Thus encourage them to begin antenatal clinic early in pregnancy. It is believed that our application will reduce doctors' workload during consultation and help to eradicate major negative pregnancy outcomes; thus promoting positive pregnancy outcomes.
Keywords: Type-1 fuzzy inference system, Fuzzy logic decision support, Pregnancy health risk, Infant mortality

1. Introduction

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 centre (Wardlaw and Kessel, 2002) (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, it is 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. Since infant mortality rates are highest during the first four weeks of pregnancy, it is important to put care efforts on the early days of pregnancy life (Kazaura et al, 2006) (March and Dimes, 2015) (Kidanto *et al*. (2006).

Pregnancy risk factors if not controlled, are associated with adverse birth outcomes (e.g., stillbirth, preterm birth, spontaneous abortion, fetal death, sudden infant death syndrome, low birth-weight infants, neural tube defects fetal growth restriction, fetal alcohol spectrum disorders, and other birth defects) (Crocker and Farrell, 2004) (Simpson, 2002)(Gao et al, 2006) (CDC, 2014) (Dahlui et al, 2016). Low birth weight remains a public health problem in many parts of the world. It is associated with a range of health problems, lasting disabilities and even deaths. Promoting preconception health is an important *Healthy People 2020* strategy for preventing adverse pregnancy outcomes and improving women's health overall (US Department of Health and Human Services, 2013).The term preconception health generally refers to the health of women of reproductive age before or between pregnancies (CDC, 2014). Factors affecting pregnancy outcomes are among others one of the most important public health concerns worldwide and is still the leading cause of prenatal and neonatal deaths. Despite intense research conducted on adverse birth outcomes globally, these factors have not been adequately investigated in Nigeria. High-risk pregnancies require close monitoring and sometimes referral to a prenatal centre (Mosha and Philemon, 2010). Diagnosis and monitoring of pregnancy risk and addressing the best prevention strategies will help to avert negative birth outcome.

Fuzzy logic, developed from fuzzy set theory (Zadeh, 1965), is another branch of artificial intelligence techniques which deals with uncertainty in knowledge that simulates human reasoning in incomplete or fuzzy data. Fuzzy set theory makes it possible to define inexact medical entities as fuzzy sets. It provides an excellent approach for approximating medical text. Fuzzy logic has emerged as a tool to deal with decisions in which the phenomena are uncertain, imprecise, partial truth, qualitative decision-making problems etc, to achieve robustness, tractability, and low cost solutions (Umoh et al, 2011). Fuzzy relational inference is applied in medical diagnosis, within the medical knowledge-based system, which is referred to as Clinaid. It deals with diagnostic activity, treatment recommendations and patient's administration (Meng, 1996). In medicine, the principle of "measuring everything measurable and trying to make measurable which has not been measurable so far" (Galileo) is still practiced. Nevertheless, some fundamental limitations are already recognized owing that real world knowledge is characterized by incompleteness, inaccuracy, and inconsistency.

Fuzzy logic reasoning is a solution to avoid instable decisions in case of uncertainty and imprecision (Zadeh (1965). Recently many researchers have applied intelligent techniques (i.e. neural network, fuzzy logic, optimization algorithms, etc.) to solve the healthcare control problem. 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. In (Djam et al. 2011), a fuzzy expert system for the management of malaria (FESMM) is presented for providing decision support platform to malaria researchers, physicians and other healthcare practitioners in malaria endemic regions. The study is 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. Al-Dmour, (2013) investigates a fuzzy logic based patients' monitoring system. He utilizes mobile units that allow for the remote observation and diagnosis of patients in their homes. A remote healthcare monitoring is studied (Medjahedet al. 2012), by learning and recognizing human activities of daily living based on fuzzy logic approach.

In (Imianvan and Obi, 2011), Fuzzy Cluster Means (FCM or Fuzzy C-Mean) analysis is performed to the diagnosis of different forms of hepatitis. The paper involves a sequence of methodological and analytical decision steps that enhances the quality and meaning of the clusters produced. The uncertainties often associated with analysis of a hepatitis test data are eliminated by the proposed system. In (Mosha and Philemon, 2010), maternal knowledge and attitudes regarding the risk factors that adversely affect pregnancy outcomes in Morogoro municipality in Tanzania is investigated. The study is conducted among 157 pregnant women attending antenatal clinics from their second trimesters to term. Socio-economic, demographic, anthropometric, biomedical and obstetric information is collected. Results show that, majority of the pregnant women (> 70%, n = 157) are aware of the risk factors that could adversely affect the pregnancy outcomes, however, they did not know the exact mechanisms by which the risk factors acted to cause the adverse effects. In (Fernando et al., 2002), a fuzzy linguistic model for evaluating the risk of neonatal death is presented. The study is based on the fuzziness of the variables newborn birth weight and gestational age at delivery. In (Abbode, et al. (2001), a survey of utilization of fuzzy technology in medicine and healthcare is investigated.

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. In (Omar et al., 2010), a study is carried out to assess the outcomes and risk factors of adolescent pregnancies in 2 major hospitals in Malaysia with a case-control study of pregnant girls aged 10 through 19 years. The study reveals that adolescent pregnancies are high-risk pregnancies and better sexual health strategies are required to address the associated complications. In (Mirsharif et al., 2014), a fuzzy expert system and neuro-fuzzy system is investigated and applied for gestational diabetes mellitus diagnosis. In (Umoh and Nyoho, 2015), a fuzzy intelligent framework for healthcare diagnosis and monitoring of pregnancy risk factor in women is proposed. Mishra et al, (2013) design a fuzzy based model for breast cancer diagnosis. Shannon and Wong, (2010) investigate risk factors associated with gestational diabetes mellitus. In (Igodan et al. 2013), an online fuzzy-logic knowledge warehousing and mining model for the diagnosis and therapy of HIV/AIDs is carried out. Khooban, et al, (2013) design swarm optimization tuned Mamdani fuzzy controller for diabetes delayed model. (Umoh and Isong, 2015), design a methodology of fuzzy expert system for the diagnosis and control of obesity. Fuzzy Expert Systems (FES) for medical diagnosis is proposed by (Sikchi et al. 2013).

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 and Kessel, 2002) (WHO, 1991). In recent time, computerization in healthcare allows for various clinical support systems to be designed that can perform as the human expert in narrow problem domain (CDC, 2007). However, due to population variability and difference in pregnancy risk factors, there may be flaws in diagnosis. Also, the operations of the prediction of pregnancy risk are complex and risky due to fluctuation in the diagnosis of these risks due to vagueness, incompleteness, and uncertainty of the information used.

This paper aims at implementing and evaluating a type-1fuzzy logic model for pregnancy risk level diagnosis and monitoring. The components of the model include; (1) a prototype of computer aided system for pregnancy risk diagnosis and monitoring that will help medical practitioners and women to identify the level of influence of risk factors associated with pregnancy, (2) a database model implementation to store important information about pregnancy women and pregnancy risk factors. (3) A knowledge base model implementation for obtaining important information that will be used in the development of a decision support system. (4) A type-1 fuzzy logic decision support system for pregnancy risk factor diagnosis and monitoring that will help clinicians in making important decisions to eliminate pregnancy risk factors and thus improve on pregnancy outcomes.

The system is developed using NETBEANS IDE tool, JAVA programming language, MYSQL database management system tool, etc. The proposed system will serve as a tool for medical practitioners, researchers etc, to explore in order to educate and guide the women on the different levels of influence of pregnancy risk and how to eradicate the same, thus increase pregnancy outcomes in our society.

In section 2, the research methodology is presented. Section 3 presents the model implementation, while in Section 4 research evaluation is presented. Section 5 presents results and discussion. Finally in Sections5 and 7 give the conclusion and references.

2. Design

Our design is based on the work in (Umoh and Nyoho, 2015). Fuzzy logic model comprises of fuzzification, knowledge base, membership function, inference engine and defuzzification modules. Fuzzification module maps the crisp input (symptom's values) to a fuzzy set using a defined membership function. Membership Function (MF) module is a mathematical equation that helps the fuzzification module converts the crisp input into a fuzzy set. Knowledge base is a database of rules (rules are generated from experts' knowledge) and used by the inference engine unit. Inference engine module evaluates the rules in a rule base against fuzzy set received from fuzzification unit to produce yet another fuzzy set. Defuzzification module maps the fuzzy set from inference engine to a crisp output.

First, we focus on Fuzzy Inference Engine (FIE) that is used for fuzzy controller implementation; The FIS requires being stored as HTML files. We implement an Application Programming Interface (API). Different interfaces are defined for the different modules such as, Database, Fuzzifier, Inference Engine, FIS, etc that are involved in our system. For instance a Fuzzifier Interface can be implemented with different classes. FIS Module for example, manages the knowledge base, it has I/O functions to store or read from file (HTML) the definition of the FIS. We can also reference FIS component from a program as a component.

In our system design, we define database class as *Mydatabase.class* to handle database implementation. NFileIO.class defined to read and store data from file. FIS system components are defined to handle FIS implementation by the following classes definitions;*Fuzzifier.class, IMembershipFxn.class, OMembershipFxn.class,* Input and output linguistic terms are both defined by input and output membership functions respectively. The Membership Function class is defined as an abstract class with subclasses to implement Triangular method appropriately. Fuzzy Rule class is defined as *RuleX.class* where each FuzzyProposition instance is associated with an instance of Linguistic Variable and an instance of *InputMembershipFunction* which in turn has a corresponding Linguistic Term.

Inference engine class is defined as *InferenceEngine.class* for the implementation of inference engine module. The study assumes that fuzzy rules have been defined with their corresponding membership functions and the input linguistic variables current values are defined respectively. Inference Engine class perform rule extraction by associating symptom1, symptom2... term1, term2...f, operator, outputTerm and outputVariable. For each rule call, the ruleEval() method of the antecedent is implemented and returns the output. The antecedent instance is an implementation of the FuzzyTerm interface. *Defuzzifier.class* is defined for defuzzification implementation. Parameter diagnosis classes are defined for symptoms diagnosis implementation as; *PDiagnosis.class, PDiagnosis$COP.class,, PDiagnosis$EHO.class, , PDiagnosis$LSF.class,*etc, respectively. We define symptom extractor class as *SymptomXtractor.class* used in the extraction of all symptoms used in the rules.

3. Implementation

Fuzzy intelligent framework for healthcare diagnosis and monitoring of pregnancy risk level in Women based on (Umoh and Nyoho, 2015), is implementation in this paper. The system is implemented using NETBEANS integrated development environment(IDE) tool, JAVA programming language, MYSQL database management tool, tools on Windows Vista platform, etc.

The linguistic variables (and their terms) are defined for three input parameters in (Umoh and Nyoho, 2015) as; Existing Health Condition (EHC) [Low, Moderate, High], Life Style Factors (LSF) [Low, Moderate, High], Condition of Pregnancy (COP) [Low, Moderate, High] and the output parameter is Pregnancy Risk (PR) [Low, Moderate, High]. This example uses the classes described in previous sections.

We create fuzzifier class where the linguistic variables and their corresponding membership functions are defined and evaluated and finally returns *fuzzySet*. The classes are shortened to limit the space required:


```
String[] sym = {"ehc" , "lsf" , "cop" };

//SYMPTOMS
SymptomXtractor sympX = new SymptomXtractor();
sympX.addNew("ehc", sm[0]+"" , new String[]{"Low", "Moderate" , "High"});
sympX.addNew("lsf", sm[1]+"" , new String[]{"Low", "Moderate" , "High"});
sympX.addNew("cop",  sm[2]+"" , new String[]{"Low", "Moderate" , "High"});


Map<String, String[]> symptoms = sympX.getSymptom();
//MEMBERSHIP DEFINITION | these is general
IMembershipFxn memberFxn = new IMembershipFxn();
Map<String, Map<String, Double[]> > iFxn = memberFxn.memberDefinition(sym);
```


```
String[] sym = {"ehc" , "lsf" , "cop" };

//SYMPTOMS
SymptomXtractor sympX = new SymptomXtractor();
sympX.addNew("ehc", sm[0]+"" , new String[]{"Low", "Moderate" , "High"});
sympX.addNew("lsf", sm[1]+"" , new String[]{"Low", "Moderate" , "High"});
sympX.addNew("cop",  sm[2]+"" , new String[]{"Low", "Moderate" , "High"});


Map<String, String[]> symptoms = sympX.getSymptom();
//MEMBERSHIP DEFINITION | these is general
IMembershipFxn memberFxn = new IMembershipFxn();
Map<String, Map<String, Double[]> > iFxn = memberFxn.memberDefinition(sym);
```


```
public Map<String, Map<String, Double[]> > memberDefinition(String[] symptomNames)
{

    Map<String, Double[]> ehc = new HashMap<>();
    addNew(ehc, "Low", 1, 8.776);
    addNew(ehc, "Moderate", 6.554, 14.4);
    addNew(ehc, "High", 12.4, 20.0);

    Map<String, Double[]> lsf = new HashMap<>();
    addNew(lsf, "Low", 1.0, 4.84);
    addNew(lsf, "Moderate", 3.35, 7.44);
    addNew(lsf, "High", 6.13, 10);

    Map<String, Double[]> cop = new HashMap<>();
    addNew(cop, "Low", 1.0, 7.02);
    addNew(cop, "Moderate", 5.13, 11);
    addNew(cop, "High", 9.13, 15.0);
```

```
//FUZZY INFERENCING
InferenceEngine engine = new InferenceEngine( fuzzySET, tRules);
ArrayList< ArrayList<Object[]> > outputT = engine.startEngine();
```

```
//RULE EXTRACTION
String symptoms[] = rules.get(x).get(0); //symptom array

//System.out.println(" THE SYMPTOM LENGTH HERE IS : "+ symptoms.length);
String terms[] = rules.get(x).get(1); //term array
String o3[] = rules.get(x).get(2); //operrator, outputterm, outputvariable array
String operator = o3[0];
String outputTerm = o3[1];
String outputVariable = o3[2];
```



```
//OUTPUT MEMBERSHIP FUNCTION - NON OVERLAPING
OMembershipFxn oFxn = new OMembershipFxn();
String outputDescr = oFxn.getDescriptn(degree );

System.out.println(" DESCRIPTION " + outputDescr );

return new String[]{(degree)+"", outputDescr };
//DEFFUZIFICATION PROCESS
Defuzzifier defuzz = new Defuzzifier( outputT );
double degree = defuzz.defuzzifyOutput();
```

// CENTER OF GRAVITY EVALUATION

```
public double COG(double l, double m, double h)
{
    double cog = 0;

    double up = (l*(10+20+30) + m*(40+50+60) + h*(70+80+90+100));
    double down = (l*3 + m*3 + h*4);

    if(down!=0)
    {
        cog = up/down;
    }

    return Math.rint(cog);
```

4. Snapshots of the System

The snapshots of the implemented system are presented as follows; Figure 2 shows the proposed system login form. Figure 3 presents the system sign-up form. Figure 4 shows the main menu form. Patient's registration form is shown in Figure 5. Figure 6 shows the pregnancy risk factor diagnosis and monitoring Form. Figure 7 presents the report form with pregnancy risk level of 31%. Figure 8 shows the report form with pregnancy risk level of 50%. Figure 9 gives the report form pregnancy with risk level of 85%.

Fig. 2: The Proposed System Login Form

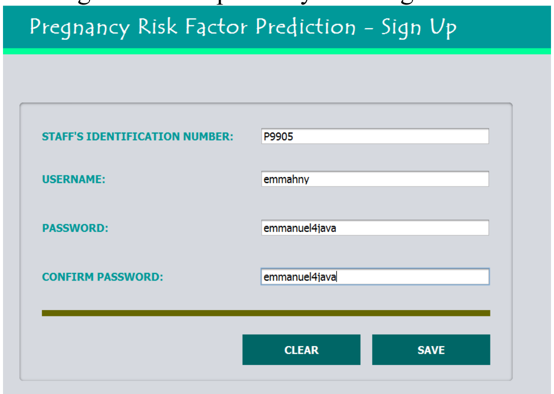

Fig 3: The System Signup Form

Fig. 4: The Main Menu Form

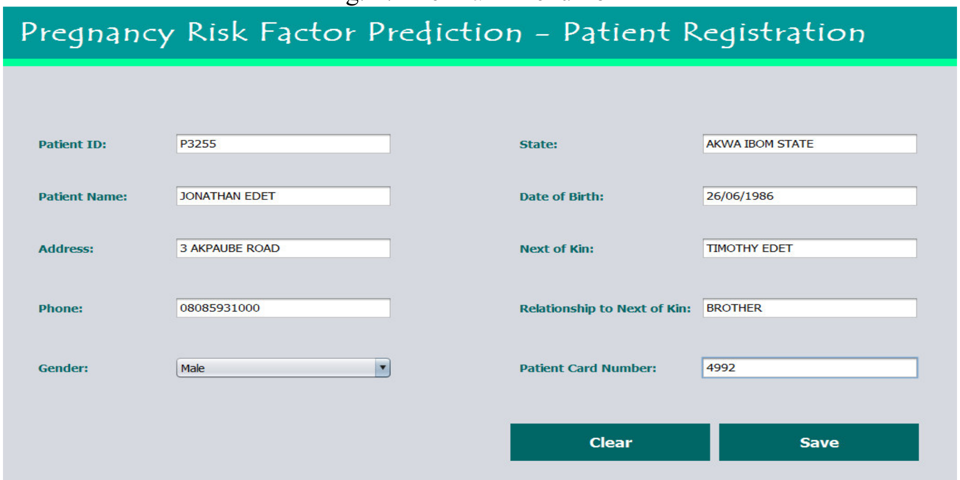

Fig. 5: The Patients' Registration Form

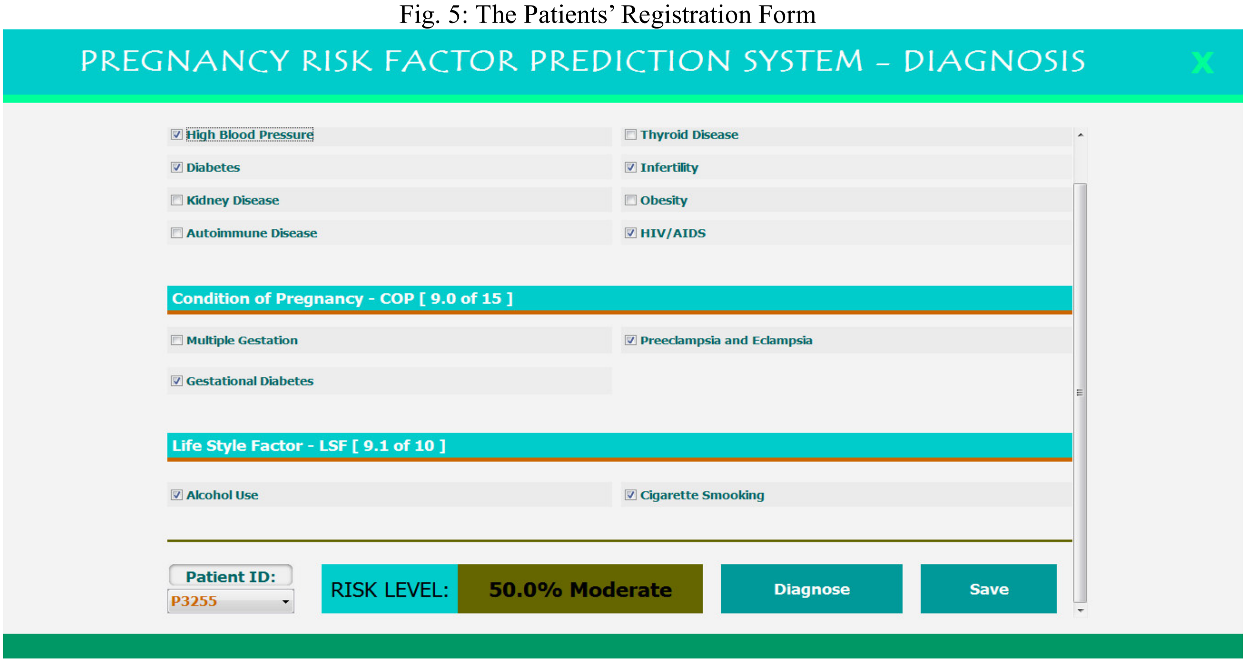

Fig. 6: The Pregnancy Risk Diagnosis and Monitoring Form

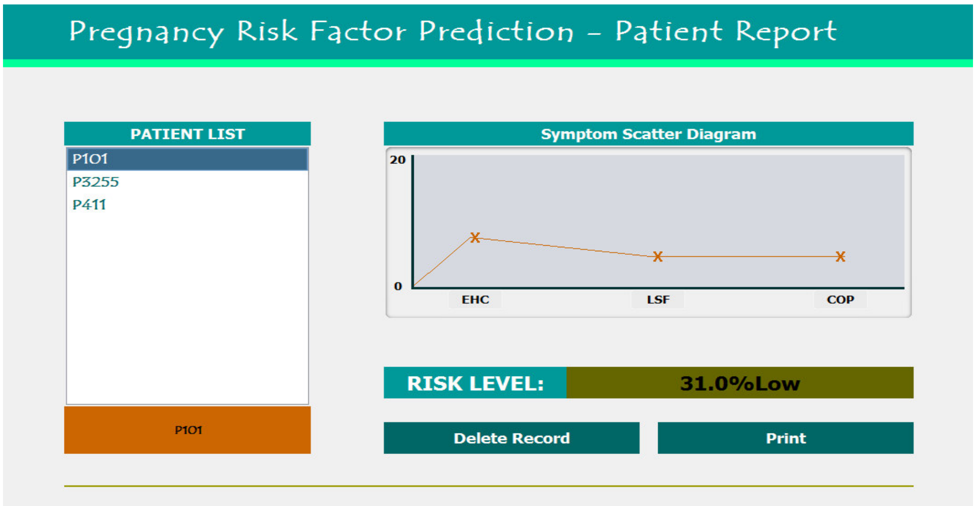

Fig. 7: The Report Form with pregnancy risk level of 31.0%

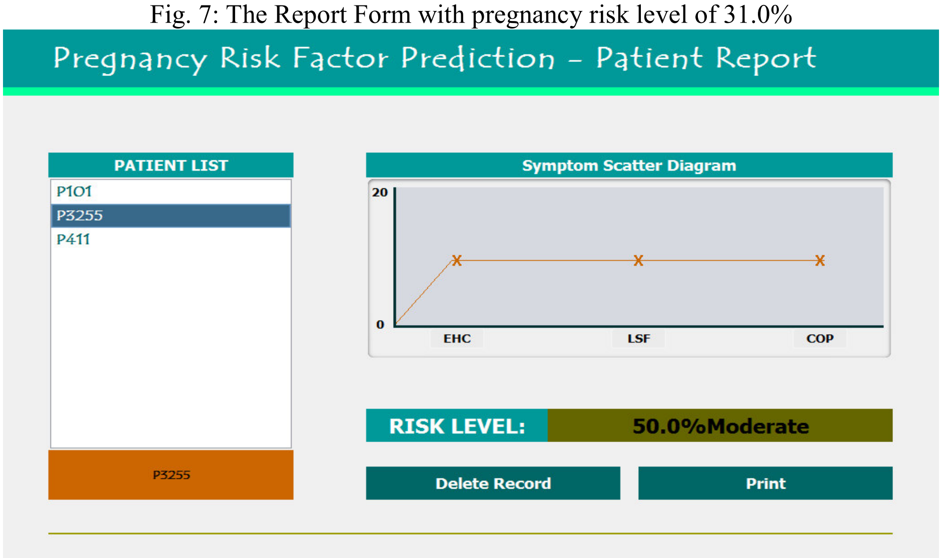

Fig. 8: The Report Form with pregnancy risk level of 50.0%

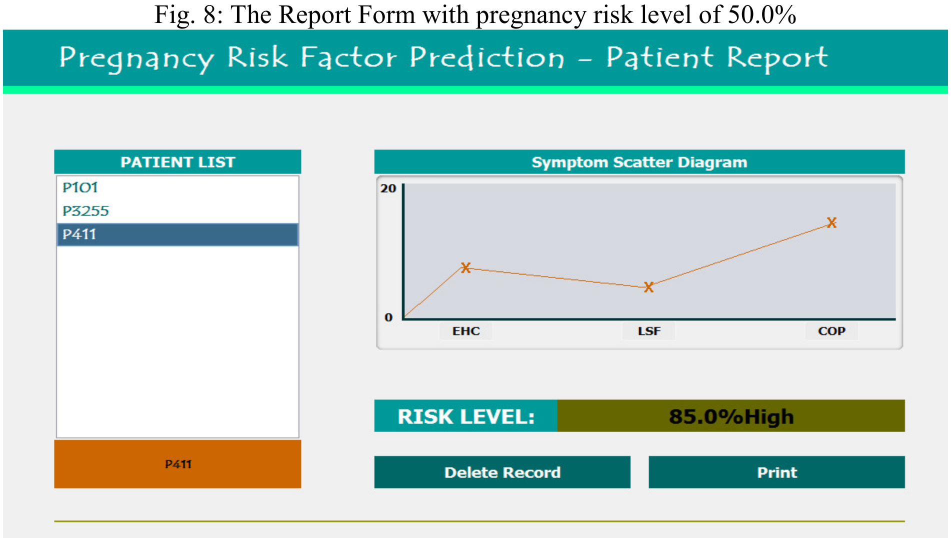

Fig. 9: The Report Form with Pregnancy Risk level of 85.0%

The proposed system login form in Figure 2 authenticates a user by accepting a username and password from the user. It loads a login database, searches for a match in other to grant access. This form helps the hospital to introduce an application level security to the system which prevents unauthorized staffs from accessing the database. The sign-up form of Figure 3 helps the user (Staffs of University of Uyo Teaching Hospital) to get registered into the system in other access the system. The form accepts staffs identification number, username and password and submits same to the database using the "submit" button. Figure 4 provides the main navigation to the pregnancy risk prediction system. The user is required to select any of the three (3) tabs in other to access a particular module.

From Figure 5, the patient registration form keeps record of patient's information such as patients' ID, state, patient's name, date of birth, address, next of kin, phone, gender, and patient's card number. This information is then stored in the database for use during patient diagnose. Figure 6 accepts user values and present the diagnose level to the user. The values are selected by the use of a "JCheckedBox" component. These values are passed to the fuzzy logic module when the "Diagnose" button is clicked. The result is then instantly displayed in a "JLabel" component. The "Save" button saves the diagnose result.

The report forms indicating different pregnancy risk levels diagnosis, presenting in Figures 7 to 9 have the following components; (i) The JList Component – this is used to display the list of patient to which diagnosis is conducted for. It helps the user to view the diagnose result of a particular patient. (ii) The Bar Chart Panel – this panel is used to display the degree of severity of each symptom that is selected during patient diagnosis. It uses the "Graphics" Class (java.awt.Graphics) to draw the chart. (iii) The Diagnose Level Label – this component is used to display the diagnose level of Pregnancy Risk of a patient. (vi)The Delete Button – this button is used to delete an unwanted patient's record from the database. (v) The Print Button – this component is a member of the javax.swing package of the java SDK. It helps in initiating the print command, which prints the diagnose result.
The three major categories of pregnancy risk factors (existing health conditions (EHC), conditions of pregnancy (COP) and lifestyle factors (LSF)) are considered and these form the input parameters to the our system. To calculate the prediction of a pregnancy risk level by using the prediction evaluator, we illustrate three different samples of scenarios as follows.
Scenario 1: A pregnant woman has 36% low and 20% moderate existing health conditions when selecting thyroid, autoimmune disease, obesity and15% low and 85% moderate lifestyle factors on selecting alcohol use and 83% moderate condition of pregnancy when selecting multiple gestation. All these arguments are entered into and evaluated in the fuzzy logic based prediction system in our application as shown in Figure 6. The result shows that existing health condition (EHC) affects pregnancy with 40% level of severity, lifestyle factors (LSF) impact negatively on pregnancy with30% level of influence and condition of pregnancy (COP) factor affects pregnancy with 30% possibility. The overall output of this scenario shows that the pregnancy is at 31% risk indicating a low level risk as shown in Figure 7.
Scenario 2: A pregnant woman has 82% moderate existing health conditions when considering high blood pressure, thyroid, autoimmune and obesity. She has15% low and 85% moderate lifestyle factors of cigarette smoking and 68% moderate condition of pregnancy when selecting multiple gestation, preeclampsia and eclampsia. All these arguments are entered into the prediction evaluator in Figure 6. The evaluation result shows that existing health condition (EHC) affects pregnancy with 50% level of severity, lifestyle factors (LSF) impact negatively on pregnancy with 50% level of influence and condition of pregnancy (COP) factor affects pregnancy with 50% possibility. The output of this scenario as shown in Figure 8 indicates an overall outcome of pregnancy risk of 50% moderate level of severity, indicating that the pregnant woman has 50% pregnancy risk.
Scenario 3: A pregnant woman has 54% moderate existing health conditions when high blood pressure, diabetes, thyroid, infertility, obesity are considered, 15% low and 85% moderate lifestyle factors considering alcohol use and high condition of pregnancy taking into consideration, multiple gestation, gestational diabetes, preeclampsia and eclampsia, with 51% possibility. All these arguments are entered into and evaluated in the fuzzy logic based prediction system in Figure 6. The result shows that existing health condition (EHC) affects pregnancy with 40% level of severity, lifestyle factors (LSF) impact negatively on pregnancy with 20% level of influence and condition of pregnancy (COP) factor affects pregnancy with 80% possibility. The outcome of this scenario shows that the pregnancy is at 85% risk, indicating a high level risk as shown in Figure 9.

5. System Evaluation

This system is evaluated by carrying out the fuzzy process with different set of crisp inputs. Different symptoms are selected and their severity level which is the resulting crisp output (Pregnancy Level) is computed as shown in Table 1.

Table 1: System Evaluation using Symptoms versus Pregnancy Risk Level

Symptoms						Risk Level
EHC		COP		LSF		
Indicators	Severity	Indicators	Severity	Indicators	Severity	
Autoimmune disease, Obesity	Low(0.99)	Multiple gestation	Low(0.8)	Alcohol use	Low (0.15), Moderate (0.85)	20.0% Low
Thyroid, Obesity Autoimmune disease,	Low(0.36) Moderate (0.20)	Multiple gestation	Low (0.83)	Alcohol use	Low (0.15), Moderate (0.85)	31.0% Low
Diabetes, HIV/AIDs Autoimmune, Thyroid, Obesity,	Moderate (0.54)	Multiple gestation	Low (0.83)	Alcohol use	Low (0.15), Moderate (0.85)	44.0% Low
High blood pressure, thyroid, Autoimmune, Obesity	Moderate (0.82)	Multiple gestation, preeclampsia, eclampsia	Moderate (0.68)	Cigarette Smoking	Low(0.15), Moderate (0.85)	50.0% Moderate
Diabetes, Thyroid, Autoimmune disease	Low (0.36) Moderate (0.20)	Multiple gestation, Gestational diabetes, preeclampsia, eclampsia	High (0.51)	Alcohol use, Cigarette smoking	High (0.46)	65.0% Moderate
High blood pressure, infertility, obesity	Low (0.36) Moderate (0.20)	Gestational diabetes, multiple gestation	Moderate (0.68)	Cigarette Smoking	Low (0.15), Moderate (0.85)	75.0% High
High blood pressure, diabetes, thyroid, infertility, obesity	Moderate (0.54)	Multiple gestation, gestational diabetes, preeclampsia and eclampsia	High (0.51)	Alcohol use	Low (0.15), Moderate (0.85)	85.0% High

6. Conclusion

This paper presents the implementation and evaluation of a type-1fuzzy model for diagnosing and monitoring pregnancy risk based on symptoms. Although, real world knowledge (medical) is characterized by incompleteness, inaccuracy, and inconsistency, type-1fuzzy logic in automated medical diagnosis is necessary to proffer solutions to medical problems.Type-1 fuzzy inference systems have shown potential to improve clinician performance by imitating human thought processes in complex circumstances and to accurately executing repetitive tasks to which humans are ill-suited. Also, type-1fuzzy logic system has the ability to handle uncertainty and the impreciseness of human observed data and reasoning. In this paper, type-1 fuzzy logic model in (Umoh and Nyoho, 2015) is implemented and evaluated. The study implements fuzzy logic model in the diagnosis and monitoring of risk level in pregnancy and have satisfied all formal constraints commonly adopted to define fuzzy sets transparency. Twenty-five pregnant patients are selected and studied and the observed results computed in the range of predefined limit by the domain experts.

Results indicate that, the study has ascertained the association of the risk factors with pregnancy outcomes. It is found out that, the relations between pregnancy risk factors diagnoses and their symptoms are hardly ever one-to-one and differentiation of diagnoses that share an overlapping range of symptoms is therefore inherently difficult. It is also observed that, although majority of the pregnant women are aware that the risk factors that could influence pregnancy outcomes, however, they did not know the degree of influence by which the factors can negatively affect their pregnancy outcomes. It is observed that, the application will help to enhance control strategies in the medical discipline of diagnosis and monitoring pregnancy of health conditions.

Our study reveals that, medical practitioners can use the application as a guide in educating the women more about the degree of influence of pregnancy risk posed by the pregnancy risk factors and therefore can advice the pregnant women to avoid these risk factors. From our results, the pregnant women are encouraged to begin antenatal clinic early in pregnancy in order to check occurrence of these risk factors. It is believed that our application will reduce doctors' workload during consultation and help to eradicate major negative pregnancy outcome, thus, promoting positive pregnancy outcomes. In the future, the study can be extended by addition of more input parameters. Type-2 fuzzy logic system can be applied to eliminate the drawbacks that are associated with type-1 (conventional) fuzzy logic system. Also, fuzzy logic can be integrated with neural network or particle swarm optimization tool for a better performance.

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