Kabale University Interdisciplinary Research Journal (KURJ)

OPEN ACCESS

Development of a fuzzy-based predictive model for the risk of postpartum hypertension in nursing mothers

***Lawrence O. Omotosho[1], Peter A. Idowu[2], Kudirat O. Jimoh[3] & Ibrahim K. Ogundoyin[4]**

[1]Department of Information Technology, Osun State University, Osogbo, Nigeria
[2]Department of Software Engineering, Osun State University, Osogbo, Nigeria
[3]Department of Computer Science, Osun State University, Osogbo, Nigeria
[4]Department of Computer Science & Engineering, Obafemi Awolowo University, Ile-Ife, Nigeria

**Corresponding Author*
awrence.omotosho@uniosun.edu.ng

KURJ
ISSN 2790-1394

pp. 58 - 69
Vol 2. Issue 4.
Sept 2024

ABSTRACT

Fuzzy Logic has grown in prominence in recent years as its capacity to address a variety of problems in the field of medicine has been demonstrated to be exceptional. This study developed a model to predict risk of postpartum hypertension among nursing mothers. In this study, the variables associated with the risk of postpartum hypertension were identified, formulated a fuzzy-logic model and simulated the predictive model. The variables that were common symptoms associated with the risk of postpartum hypertension were elicited by review of related works on the body of knowledge of postpartum hypertension following which the variables were validated by mental health experts at a Nigerian hospital using the interview method. The variables identified were classified into their respective linguistic labels based on the crisp values assigned to them within the interval of acceptable values while the risk of postpartum hypertension was classified as low, moderate and high risk. Fuzzy-based related functions were used to formulate the fuzzy model for the input variables and the risk of postpartum hypertension. It was also observed that the number of triangular membership function formulated for each variable is a function of the number of classified labels for each variable. The results also showed that a total number of 288 rules were defined by the IF-THEN statements created from the variables identified by the experts. The predictive model developed and simulated can be utilized to aid expert obstetricians in the early detection and treatment of postpartum hypertension in the future.

Keywords: Fuzzy logic, Postpartum Hypertension, Obesity, Defuzzification, Membership Function.

Introduction

Hypertension and other non-infectious diseases or non-transmissible diseases account for at least 20% of all fatalities in Nigeria and about 60% of patients admitted to most tertiary hospitals (Ordinioha, 2016). The epidemiological transition theory was proposed by Omran, (1971) in a series of essays. He stated that as a community or country develops, infectious diseases will be displaced by Non Communicable Diseases (NCDs) as the fore runner causes of morbidity and mortality. In most countries around the world, including Nigeria, this theory has been validated (WHO, 2002; Wokoma and Alasia, 2011; Adefuye *et al.*, 2009; Unachukwu *et al.*, 2008).

High blood pressure, often known as hypertension, is harmful for it can cause strokes, heart attacks, heart failure, kidney illness, as well as a variety of other diseases (Lackland and Weber, 2015). When a person's average arterial pressure throughout one cardiac cycle, systole, and diastole exceeds the upper limit of what is considered normal, this is known as hypertension. An average arterial pressure of 110mmHg is classified as hypertensive (Pouler *et al.*, 2015). When the diastolic blood pressure exceeds 80mmHg (120/80mmHg) and the systolic blood pressure exceeds 120mmHg, this level of mean pressure is reached. Systolic pressure of 160mmHg and diastolic pressure of 100mmHg (160/100mmHg) are considered hypertensive by several cardiologists (Carretero and Osparil, 2000).

Along with several other community studies, the occurrences of hypertension in Nigeria has risen from 11.2% in the 1990s to 27.9% in 2010 in the Niger Delta and 22.6% in 2009 in a sub-urban Christian dominated community in South-West Nigeria (Wokoma and Alasia, 2011; Adefuye *et al.*, 2009). NCDs account for at least 20% of all fatalities in Nigeria (WHO, 2011), and up to 60% of patients admitted to most tertiary hospitals (Unachukwu *et al.*,2008). Furthermore, the poor treatment results for non-communicable diseases are widely noticed, prompting the World Health Organisation to call for a positive and progressive change in health care delivery in favor of preventative and more proactive care (WHO, 2002).

With a prevalence of 5% to 10%, hypertensive disorder are the most common medical consequences of pregnancy, and they are the second largest cause of maternal death in the United States, after venous thromboembolism (Collier and Molina, 2019). Prenatal care and particular attensions paid to the management of hypertension during pregnancy have reduced death rate associated with antenatal hypertension dramatically (Kattah and Garovic, 2013). Hypertension can develop during pregnancy or develop spontaneously in the postpartum period, posing a risk to the mother health. These dangers are amplified because many patients come after being discharged from the hospital and go unnoticed due to a lack of medical supervision following delivery (Ghuman *et al.*, 2009).

Complications such as heart failure, cerebrovascular accidents, and acute oliguric renal failure have been recorded as risk factors in women with postpartum hypertension (Ojogwu and Ofili, 2011). Hypertension specialists are frequently relied upon to advise obstetricians on how to manage hypertension in the postpartum period, it is important for them to become familiar with the examination and treatment of women during postpartum period (Ghuman *et al.*, 2009). Due to the great complexity of medical problems and cognitive limitations, physicians are prone to making mistakes. Medical decision-making is difficult since even seemingly basic problems necessitate a great amount of knowledge (Hall and Walton, 2004). There is currently no effective model for assessing the likelihood of postpartum hypertension risk by the identification of key variables.

Fuzzy Logic has grown in prominence in recent years as its capacity to address a variety of problems in the field of medicine has been demonstrated to be exceptional. It has been used in medical domains such as medical diagnostics, pregnancy risk, and feature extraction. Fuzzy logic is used to model and manipulate imprecise and subjective knowledge in the same way as humans do (Wanqing et al., 2010). This study developed a model to predict the risk of postpartum hypertension in Nigerian nursing mothers, with a high, well-balanced sensitivity and specificity, to be able to predict during the first four weeks following childbirth. This model can be utilized to aid expert obstetricians in the early detection and treatment of postpartum hypertension in the future.

Related Works

Baheti (2016) performed a review of related work regarding the "application of fuzzy logic in the diagnosis of various diseases. The study involved the identification of the need for a framework via which expert systems for medical diagnosis could be presented. The review revealed a great number of applications of fuzzy logic to disease diagnosis especially terminal and cardiovascular diseases. The study was limited to the applications of fuzzy logic to diseases management in India.

Sarumi (2015) developed a "cardiovascular disease monitoring system using a combination of fuzzy logic theory and Web technologies". The study was limited in scope to the monitoring of the risk of heart failure by considering stages A, B and C. The developed system was able to classify the risk of the stages of heart failure based on the assessment of risk factors (if any), laboratory tests taken (if any) and the symptoms observed (if any). The study was not able to validate the model using a live dataset and as a result of this, the performance of the model in monitoring the risk of heart failure was not assessed. Obahiagbon and Odigie (2015) proposed a "framework for the intelligent remote monitoring and control of blood pressure in developing nations". Application of wireless communication and remote sensing technologies were used in the study to monitor the vital signs of individuals with high blood pressure. The study only monitor high blood pressure with no adherence to the effect of high blood pressure on the individuals monitored, for example, hypertension risk assessment. Apart from blood pressure, there are other important vital signs in the human body that requires monitoring.

Bolaji (2014) proposed a "health monitoring system for hypertensive patients in rural Nigeria". The design of the data model for the monitoring system was done using Unified Modeling Languages (UML), while the system was implemented using JAVA. A simulation of a real time mobile health monitoring system was proposed using GPRS-enabled technology. The result of the study showed that medical data could be routed from mobile sensor implants using GPRS to patients' records which will be explained by the specialists. The system can only be used for storage and retrieval of information, while human intervention is required to process information.

Srivastava *et al*. (2013) applied soft computing technique to the classification of diseases. The study involved the use of fuzzy logic technique in influencing decision making concerning the classification of hypertension. Membership functions were used to formulate the models using the variables identified for monitoring the risk of hypertension. The results of the study showed that the models proposed had the capacity to effectively classify the risk of hypertension, but was not validated using live datasets.

Srivastava and Srivastava (2012) applied fuzzy logic technique to the problem of diagnosing hypertension. Triangular and trapezoidal membership functions were used to formulate the fuzzy logic system using the values of the risk factors considered for the study. The results of the study showed that the model was able to determine the percentage of the risk of hypertension in an individual, but was not validated using live patient datasets. Apart from the risk factors of hypertension, there are other variables necessary for diagnosing hypertension like possible target organ damage or clinical conditions.

- Djam and Kimbi (2011) presented a "Web-based fuzzy logic system for the management of hypertension". Fuzzy membership functions were used to formulate the model, while PHP and

SQL were used to implement the Web-based system and the integration of the model using the blood pressure, BMI, and age of the individual. The results of the study showed that the system could be used to determine the percentage of the risk of hypertension. The model was not validated prior to its integration into the web-based utilizing the model as the business logic for the system.

Methodology

The methodological approach starts by identifying the various variables relevant for identifying the risk of postpartum hypertension followed by the process of model formulation using the fuzzy membership functions and rule-base required for the inference engine of the fuzzy inference system was also elicited using the variables identified for the risk of postpartum hypertension. The specific methods are described as follows:

- Data collection and Interview with gynecologists and cardiologists following the review of related works was conducted.
- Identifying and analyzing the factors responsible for causing postpartum hypertension in order to understand and establish their relationship with postpartum hypertension risk.
- Fuzzification of all variables (input factors and output), MATLAB Fuzzy logic Toolbox was used as the simulation environment.
- The membership function which corresponds to each respective labels of every identified variables were identified.
- The fuzzy inference system was developed to formulate the predictive model for the risk of postpartum hypertension.

Development of Fuzzy Inference Model for Postpartum Hypertension Risk

The Fuzzy Inference System (FIS) is a rule-based system. It is a tool used to represent different forms of knowledge about a problem. FIS is used to model the interactions and relationships that exist between variables of a domain field. FIS takes into consideration all the fuzzy rules in the rule base and learnt how to transform a fuzzified set of inputs to their corresponding fuzzified outputs as shown in Figure 1. FIS consists of four sub processes which are:

I. Fuzzification: This Fuzzification of variables involved the conversion of the crisp values assigned to the variables (both input and output) into their respective fuzzy logic linguistic variables defined by a mathematical model called a membership function;
II. Rule production: Rule Definition which involved identifying all possible rules which make clear by explanation the relationship between the values of input variables and the value of the output variables using IF-THEN rules – based on knowledge elicited from experts;
III. Aggregation of Fuzzy Rules: Aggregation involved the combination of all the fuzzified output mappings generated from the rules defined in the inference engine into a single fuzzified output map of linguistic value; and
IV. Defuzzification: Defuzzification is the conversion of single output fuzzy linguistic values created by aggregation into the original crisp values of the output variable for determining the class to which the risk of post-partum hypertension is classified.

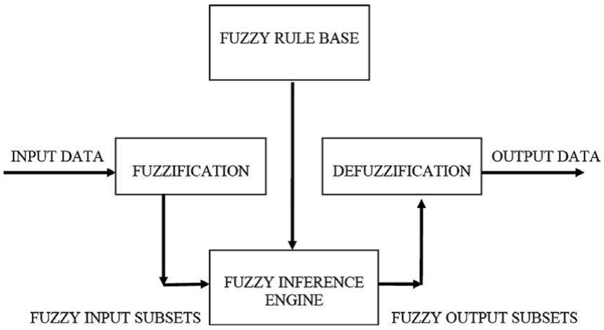

Figure 1: Schematic diagram showing a fuzzy inference system

Formulation of Fuzzy Logic Model for Post-partum Hypertension

For the purpose of fuzzification of the identified variables, it was important to create a crisp value for which linguistic variables will be allocated to a set of intervals within the defined crisp value. Figure 2 shows a triangular membership function for the fuzzification process. The triangular membership function used represents each linguistic variable defined within an interval [x, z] using the function in Equations 1 and 2.

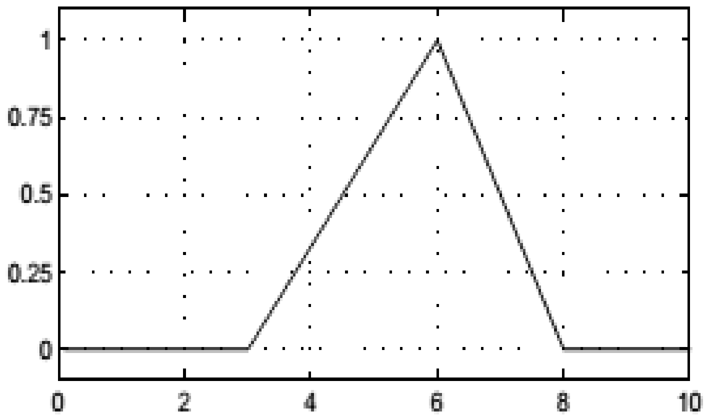

Figure 2: Triangular membership function with (x, y, z) equal to (3, 6, 8)

$$f(a; x, y, z) = \begin{cases} 0, & a \leq x \\ \frac{a-x}{y-x}, & x \leq a \leq y \\ \frac{z-a}{z-y}, & y \leq a \leq z \\ 0, & z \leq x \end{cases} \quad (1)$$

$$f(a; x, y, z) = \max\left(\min\left(\frac{a-x}{y-x}, \frac{z-a}{z-y}\right), 0\right) \quad (2)$$

The interval [x,y,z] is the horizontal crisp value of the triangular membership function such that b located at the centre is usually in line with the apex of the triangle, while a and c are the extreme points (minimum and maximum) of the triangle where z > x and all points lie within the horizontal interval of [x, z]. All the input and output variables were fuzzified using the triangular membership function. All variables were divided into linguistic variables (labels) for which a triangular membership function was formulated for each label.

Therefore, a variable with two labels would be given crisp values with centres 0 and 1 with intervals [-0.5 0 0.5] and [0.5 1 1.5] respectively while variables with three labels would be assigned crisp values with centres 0, 1 and 2 with intervals [-0.5 0 0.5], [0.5 1 1.5] and [1.5 2 2.5] with which Equation 1 was used to assign the respective fuzzified linguistic value based on the crisp value which lie along all points within the crisp interval defined for each triangular membership function.

Identification of variables

Following an extensive interview with expert cardiologists and obstetricians for understanding of the factors relevant for the identification of the risk of postpartum hypertension in nursing mothers. To accomplish this task, a number of variables were identified alongside their respective labels. The variables identified from literature reviewed and the interviews with experts having their own identifiable labels were fuzzified using the triangular membership function with their respective crisp interval defined. The identifiable variables with their labels are presented as follows:

- **High Blood Pressure during last pregnancy**: It is a measure of the systolic and diastolic blood pressure of the body, the risk of postpartum hypertension increases with the development of gestational hypertension. The variables have two nominal values No and Yes which were assigned crisp values of 0 and 1 respectively.
- **Obesity**: It is a measure of the worst state of the nutritional status of a woman which was measured using the weight and height, the risk of postpartum hypertension increases with the likelihood of a nursing mother being obese. The variables have two nominal crisp values No and Yes which were assigned crisp values of 0 and 1 respectively;
- **Family History of post-partum hypertension**: Having a first-degree family member (mother or sister) increases the likelihood of postpartum hypertension. The variables have three nominal crisp values No which was assigned 0, Second Generation which is assigned 1 and First Generation which was assigned 2.

Age: The risk of postpartum hypertension increases for women aged younger than Fuzzification was the first process in the process of modelling the fuzzy logic system for post-partum hypertension in nursing mothers. The first step in the modelling of the controller was the fuzzification of crisp values (labels) of the input and output variables to be accepted by the fuzzy inference system. In the process of Fuzzification, each value of a variable (input and output) was mapped with a membership function in order to establish the degree of membership for which the crisp values of variables are mapped to fuzzified values of a triangular membership function. Table 1 gives a description of the input and output (risk of post-partum hypertension) variables identified, their respective linguistic values (labels) as presented alongside the crisp values to be assigned for the fuzzification of each value of the – two membership functions were used for a variable with two labels while three was used for a variable with 3 labels.

- **20 or older than 40 years of age**. The variables have three nominal crisp values: between 20 and 40 years which was assigned 0, below 20 years which was assigned 1 and above 40 years which was assigned 2.
- **Having multiple births**: having twins or more babies increases the risk of postpartum hypertesion in nursing mothers. The variables have two nominal crisp values: No which was assigned 0 and Yes which was assigned 1.

- **History of Smoking**: Having a history of smoking increases the risk of having postpartum hypertension. The variables have nominal crisp values No which was assigned 0 and Yes which was assigned 1
- **History of alcohol**: Having a history of alcohol increases the risk of having postpartum hypertension. The variables have two nominal crisp values No which was assigned 0 and Yes which was assigned 1.
- **Risk of post-partum hypertension**: This is the output variable to be determined from the values of the input variables identified. The variable was defined using four (4) labels namely: no risk, low risk, moderate risk and high risk based on the intensity of the risk of post-partum hypertension in the nursing mother.

Fuzzification of variables

Table 1: Fuzzification of the variables for Post-partum Hypertension

Variable Type	Variable Name	Linguistic Variable	Crisp value	Interval
INPUT	High Blood Pressure during last pregnancy	No		[-0.5 0.0 0.5]
		Yes		[0.5 1.0 1.5]
	Obesity	No		[-0.5 0.0 0.5]
		Yes		[0.5 1.0 1.5]
	Family History	No		[-0.5 0.0 0.5]
		Second Generation		[0.5 1.0 1.5]
		First Generation		[1.5 2.0 2.5]
	Age	20 to 40 years		[-0.5 0.0 0.5]
		Below 20 years		[0.5 1.0 1.5]
		Above 20 years		[1.5 2.0 2.5]
	Having Multiples	No		[-0.5 0.0 0.5]
		Yes		[0.5 1.0 1.5]
	History of Smoking	No		[-0.5 0.0 0.5]
		Yes		[0.5 1.0 1.5]
	History of Alcohol	No		[-0.5 0.0 0.5]
		Yes		[0.5 1.0 1.5]
OUTPUT	Risk of Postpartum Hypertension	No		[-0.5 0.0 0.5]
		Low		[0.5 1.0 1.5]
		Moderate		[1.5 2.0 2.5]
		High		[2.5 3.0 3.5]

Development of the IF-THEN rules of inference engine

In the central part of the Fuzzy Inference System model developed for the risk of post-partum hypertension in nursing mothers lies the Inference Engine which holds the rules that define the mapping for a combination of input variables to an output variable. These rules were presented by the medical experts which were interviewed earlier in the study and they compose of the combination of the labels (or crisp values) of the input variables needed for determination of the respective risk of post-partum hypertension in nursing mothers.

These rules were presented as a set of IF-THEN statements written in such a way that the IF-part that holds the condition giving a value is called the antecedent, while the THEN-part that holds the conclusion to the value(s) of the condition is called the consequent. A typical fuzzy rule is of the form

$$\mathrm{IF}(in1=label)\mathrm{and}(in2=label)\mathrm{and}\cdots(inN=label)\ \ \mathrm{THEN}\ (out=label).$$

Where label is the linguistic value of each variable

If an inference engine has i variables each with a number of linguistic values (labels) then the possible number of rules that can be determined is a product of the number of labels for all variables considered for the problem as shown in Equation 3 where $n(labels_{variable,i})$is the number of labels for $variable_i$:

$$\#Rules = n(labels_{variable,1}) * n(labels_{variable,2}) *..* n(labels_{variable,i}) \quad (3)$$

For the purpose of this study, the total number of possible rules was elicited as a product of all the labels for each variable identified for this study. The final set of possible rules that shows the possible combination of the labels of each variable with respect to the risk of post-partum hypertension in nursing mothers was elicited form the expert based on the experience in the area of identifying postpartum hypertension risk in nursing mothers.

Aggregation

Each rule of the fuzzy inference engine gives an output fuzzified thus resulting in multiple output fuzzified functions (triangular membership functions) which is based on the number of rules presented. All thee output fuzzified membership functions must be combined into a single output triangular membership function using the process called aggregation. Two methods are commonly used to arrive at aggregation, namely: minimum which returns the lowest fuzzified value from all the values of the input for a rule and the product which returns the product of fuzzified values from all the values of the input for a rule operation method. The minimum method was used for the aggregation of the fuzzified output of all the rules generated in the fuzzy inference engine to produce a single output triangular membership function.

Defuzzification

Since the output of aggregation is a single output triangular membership function which must be converted using defuzzification into a crisp value within the crisp interval of the output variable – the risk of post-partum hypertension in nursing mothers. In this study, centroid method was applied for the defuzzification of the final output aggregated triangular membership function and identifying the crisp value of the risk of post-partum hypertension in nursing mothers.

Results and discussion

The results of the simulation using the MATLAB Fuzzy Logic Tool-Box was presented showing the surface plots and the rules plots used for testing the values of the identified variables for the validation of the rules proposed by the experts. Figure 2 shows the schematic diagram of the Fuzzy Inference System (FIS) representing the predictive model for postpartum hypertension risk. The Figure consists of six inputs representing the risk factors of postpartum hypertension risk on the left side while the output postpartum hypertension risk is shown on the far-right hand side of the diagram. The centre consists of the inference engine which contains the rule base – set of IF-THEN rules that show the relationship that exists between the set of input variables and the output variable.

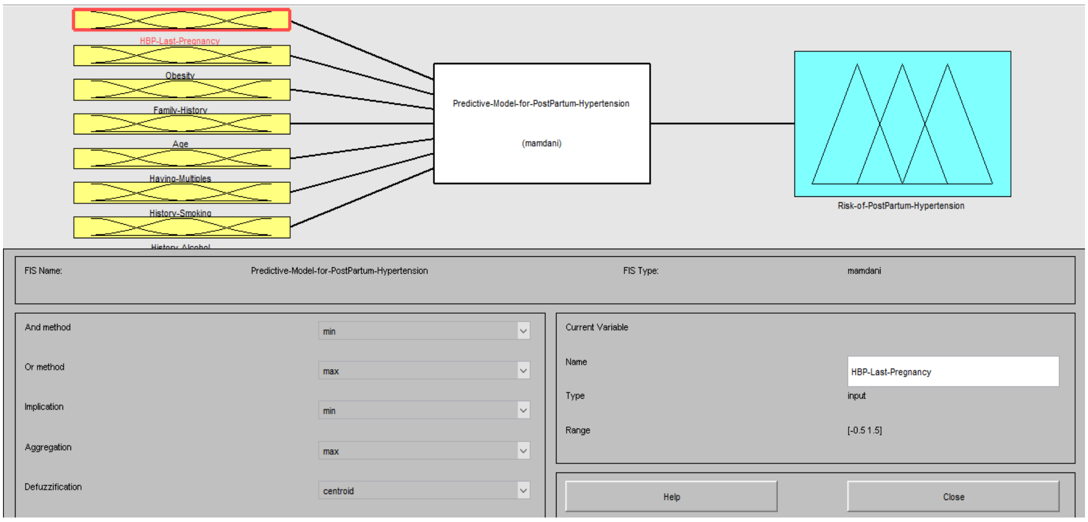

Figure 3: Fuzzy Inference System for Postpartum hypertension Risk

There are two main stages required in the process of fuzzification, which included the derivation of the membership functions for both the input and output variables alongside the linguistic representation of these functions. The triangular membership functions were adopted for this study because of the variation in the data representing the variables which did not require any non-linear description. The input variables that were used in developing the selected fuzzy logic model for postpartum hypertension risk prediction used a number of triangular membership function that was proportional and equal to the number of values of each respective variable considered for the risk of postpartum hypertension while the fuzzification parameters for the triangular membership function were proposed. The formulation of the triangular membership functions used for the variables identified for the study are describes as follows.

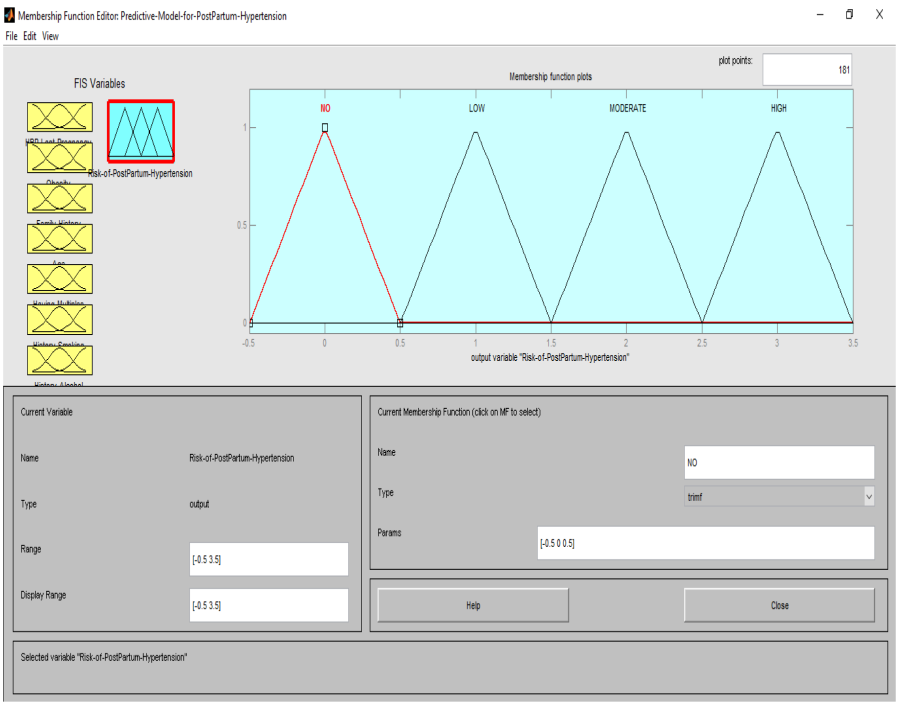

Figure 4: Fuzzification of Postpartum hypertension Risk

The fuzzy sets that were defined using membership functions were also manipulated using fuzzy operators with the use of rules that define the required relationship. The IF-THEN rules formulated were used to define the conditional statements that comprise the fuzzy logic. These conditional statements are domain specific information which was provided by the health physician via knowledge elicitation process which in this case involved the use of a structured interview. Figure 3 shows a description of the rule editor interface used in inserting all 288 rules elicited from the expert into the inference engine of the fuzzy model for the prediction of postpartum hypertension risk. The values of each variable were selected from the bottom part of the interface where each attribute was defined and the rules were added following the selection of the required values for the rules provided.

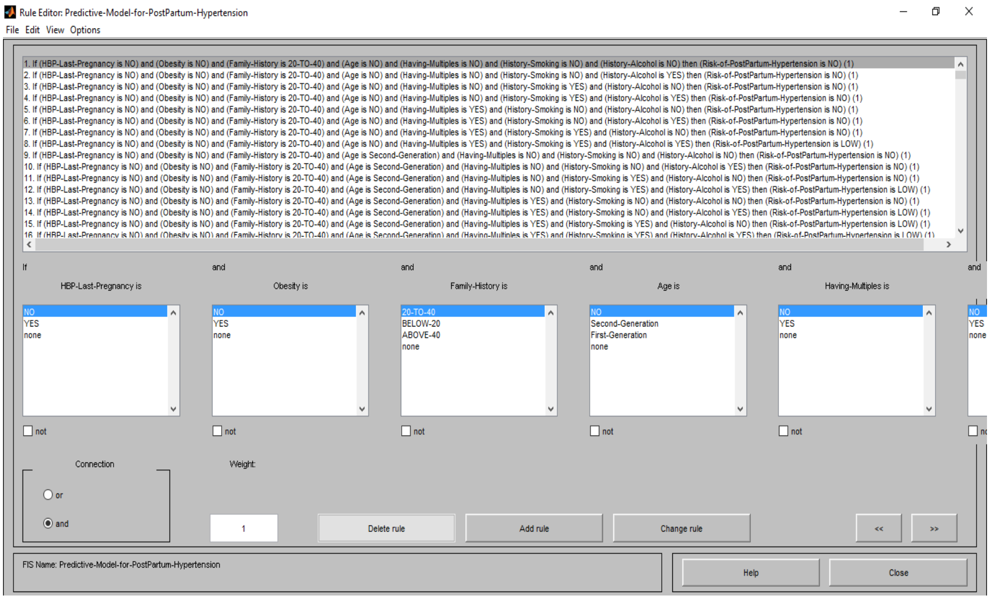

Figure 4.3: Rule Base consisting of the Inference engine

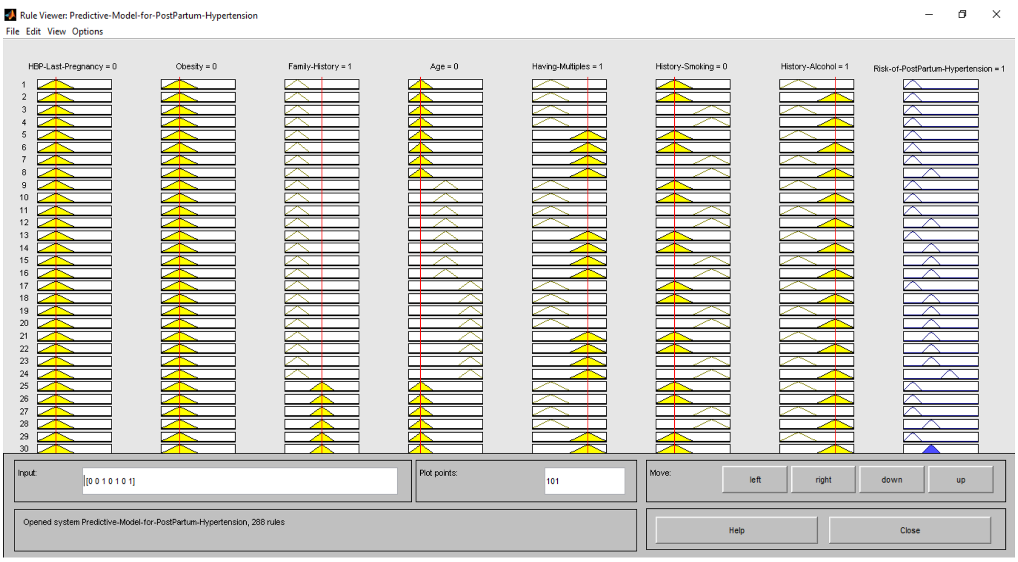

Figure 4.4: Aggregation and defuzzification of Postpartum Hypertension Risk

Summary and Conclusion

Postpartum hypertension is a serious problem to nursing mothers today in most developing nations and its threat is a serious deadly disease in Nigeria, especially those with insufficient health facilities which are inadequate to cater for the necessary health needs. It is responsible for the deaths of many Nigerians including children and nursing mothers. In this study, monitoring the risk of postpartum hypertension among Nigerian nursing mothers has been provided and thus a means to alleviate the risk of the deadly scourge of the disease. The results of the study revealed that fuzzy logic-based models capture the vagueness of real-life measurements with simplicity using membership functions. The results further revealed that the triangular membership function served as a good model for representing the fuzzification of the variables. It was also observed that the number of triangular membership function formulated for each variable is a function of the number of classified labels for each variable. The results also showed that a total number of 288 rules were defined by the IF-THEN statements created from the variables identified by the experts. The study concluded that fuzzy logic models are effective for the formulation of the real-life variables using fuzzification which can be later defuzzified following the process of inference rule generation and the aggregation of rule outputs. The study also noted that the fuzzy logic model can be integrated into existing health information systems used in monitoring the identified variables for the early detection of postpartum hypertension among nursing mothers. The study has implication in improving the decision-making process that affects the early detection of postpartum hypertension.

References

Adefuye, B.O., Adefuye, P.O., Oladapo, O.T., Familoni, O.B. and Olurunga, T.O. (2009). Prevalence of hypertension and other cardiovascular risk factors in an African sub-urban religious community. *Niger Med Pract* 55: 4-8.

Baheti, M. (2016). Study of Need and Framework of Expert Systems for Medical Diagnosis. *IOSR Journal of Computer Engineering* (IOSR-JCE) 13: 45 – 48.

Bolaji, A. (2014). Simulation of a Real-Time Mobile Health Monitoring System Model for Hypertensive Patients in Rural Nigeria. *African Journal of Computing and ICT* 7(1): 95 – 100.

Carretero, O.A. and Oparil, S. (2000). Essential hypertension, Part I: definition and etiology. *Circulation* 101(3): 329–35. doi: 10.1161/01.CIR.101.3.329.

Collier, A. Y., and Molina, R. L. (2019). Maternal Mortality in the United States: Updates on Trends, Causes, and Solutions. *Neo Reviews*, 20(10), e561–e574. https://doi.org/10.1542/neo.20-10-e561

Djam, X.Y., and Kimbi, Y.H. (2011). Fuzzy Expert System for the Management of Hypertension. *The pacific Journal of Science and Technology* 12(1): 390 – 402.

Lackland, D.T. and Weber, M.A. (2015). Global burden of cardiovascular disease and stroke: hypertension at the core. *The Canadian journal of cardiology* 31(5): 569–71. doi: 10.1016/j.cjca.2015.01.009.

Ghuman N, Rheiner J, Tendler BE, and White WB. (2009). Hypertension in the postpartum woman: clinical update for the hypertension specialist. *J Clin Hypertens* (Greenwich). 11(12):726-33. doi: 10.1111/j.1751-7176.2009.00186. x. PMID: 20021530

Hall, A. and Walton, G. (2004). Information overload within the health care system: A literature review. *Health Information and Libraries Journal*, 21(2), 102-108

Kattah, A. G., and Garovic, V. D. (2013). The management of hypertension in pregnancy. *Advances in chronic kidney disease*, 20(3), 229–239. https://doi.org/10.1053/j.ackd.2013.01.014

Obahiagbon, K and Odigie, B.B. (2015). A Framework for Intelligent Remote Blood Pressure Monitoring and Control System for Developing Countries. *Journal of Computer Sciences and Applications* 3(1): 11 – 17.

Ordinioha, B. (2016). The prevalence of hypertension and its modifiable risk factors among lecturer of a medical school in Port Harcourt, south-south Nigeria: Implications for control effort. *Nigerian Journal of Clinical Practice* 16(1): 1 – 4. doi: 10.4103/1119-3077.106704.

Omran, A.R. (1971). The epidemiologic transition: A theory of the epidemiology of population change.*Milbank Mem Fund* Q 49: 509-38.

Ojogwu LI, and Ofili UG (1993). Morbidity and mortality from post-partum hypertension in Nigerian women. *Afr J Med MedSci*. 22:11–16.

Poulter, N.R., Prabhakaran, D. and Caulfield, M. (2015). Hypertension. *Lancet* 386(9995): 801–812. doi:10.1016/s0140-6736(14)61468-9

Sarumi, O.A. (2015). *Development of a Web-Based cardiovascular disease monitoring system* (Unpublished MSc Thesis of the Department of Computer Science and Engineering) Obafemi Awolowo University, Ile-Ife, Nigeria.

Srivastava, P and Srivastava, A. (2012). Spectrum of Soft Computing Risk Assessment Scheme for Hypertension. *International Journal of Computer Applications* 44 (17): 23 – 30.

Srivastava, P., and Srivastava, A., Burande, A. and Khandelwal, A. (2013). A Note on Hypertension Classification Scheme and Soft Computing Decision Making System. *ISRN Biomathematics*: 1 – 11. Retrieved from http://dx.doi.org/10.1155/2013/342970 on July 12, 2016.

Unachukwu, C.N., Agomuoh, D.I. and Alasia, D.D. (2008). Pattern of non-communicable diseases among medical admissions in Port Harcourt, Nigeria. *Niger J Clin Pract* 11: 14-17.

Wanqing, L., Lilua, M. and Dong, W. (2010). Data mining based on rough sets in risk decision-making: Foundations and Application. *Transactions on computers Issue* 2(9): 113 – 121.

Wokoma, F.S. and Alasia, D.D. (2011). Blood pressure pattern in Barako: a rural community in Rivers State, Nigeria. *Niger Health J* 11: 8-13.

World Health Organization, WHO (2002). T*he World Health Report: 2002: Reducing the Risks, Promoting Healthy Life*. World Health Organization, Geneva.

World Health Organization, WHO (2011). *WHO Maps: Non-communicable disease trend in all countries*. World Health Global Report, World Health Organization.