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DEVELOPMENT OF WEB-BASED FUZZY EXPERT SYSTEM FOR BREAST CANCER RISK PREDICTION

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ABSTRACT
Research indicates that fuzzy logic offers various approaches to improve the delivery of personal healthcare within the healthcare sector. Presently, breast cancer ranks as the second leading cause of death among women, as reported by the World Health Organization. Previous studies that applied fuzzy logic to breast cancer risk focused on disease recurrence and individual survivability. However, there is a growing necessity to identify the risk factors predisposed to breast cancer growth and mitigate these risks at an earlier stage. Therefore, this study concentrates on the development of an efficient web-based Fuzzy Expert System (WFES) for breast cancer risk prediction. This system aims to predict an individual's risk level, ultimately reducing the high incidence rate of breast cancer. To obtain information regarding the factors that predispose individuals to breast cancer, data were collected from four domain experts through direct contact. This data was then used to formulate relevant fuzzy rules. The fuzzy inference engine was applied to establish membership functions and fuzzy rules, which served as the foundation for designing the WFES. The Mamdani approach was employed for input fuzzification and output de-fuzzification. This system accommodates imprecision, tolerance, and uncertainty to ensure tractability, robustness, and minimal solution cost. Python was utilized for modelling, and JavaScript was used for system implementation. The study's results indicated that the information obtained from experts defined the range values for six risk factors used in input fuzzification, resulting in the generation of fifty rules. These rules formed the basis for the development of the WFES. This work empowers individuals to assess their breast cancer risk level, emphasizing the potential to reduce predisposing risk factors through personal health monitoring.

Keywords: Fuzzy Logic, prediction, Breast cancer and Expert Systems

INTRODUCTION

Fuzzy logic, a mathematical approach that accommodates uncertainty and imprecision, provides a promising avenue for improving the accuracy of risk prediction models (Karahan et al., 2018). Breast cancer, often referred to as the 'silent epidemic,' poses a significant health threat globally. The World Health Organization reports that breast cancer is the second leading cause of death among women (WHO, 2021). Early detection and effective risk prediction are crucial for reducing the incidence and mortality rates associated with this disease. Fuzzy logic offers a unique approach to address these challenges by incorporating vague or uncertain information, making it an ideal candidate for enhancing the accuracy of breast cancer risk prediction (Mamdani & Assilian , 1975; Khezri et al, 2014). By developing a web-based fuzzy expert system, this study aims to provide accessible and user-friendly tools for individuals to assess their breast cancer risk levels.

The importance of such a system is underscored by the potential to reduce the incidence and improve early diagnosis, ultimately leading to better outcomes and survival rates. Previous research in breast cancer prediction primarily focused on the reoccurrence of the disease and the survivability of individuals after diagnosis (Paik, *et al.*, 2004; Sankar & Bai, 2022). While these studies have made valuable contributions to breast cancer research, there is an emerging need to shift the focus towards early identification of predisposing risk factors for breast cancer growth and the subsequent reduction of these risks. This research seeks to build upon these foundations by introducing a web-based fuzzy expert system capable of delivering personalized breast cancer risk predictions, thereby bridging the gap in current research efforts.

MATERIALS AND METHODS

Research Design

This research work adopts a model research methodology that is based on fuzzy expert. Although fuzzy systems can either be modelled as type-1 systems, which are based on mathematical modelling or type-2 systems which are based on fuzzy inference systems or fuzzy logical rules. This study adopts the Mamdani fuzzy inference system model procedure in developing a fuzzy expert system for breast cancer Risk assessment. The processes involved in building the model are:

i. Fuzzification
ii. Rule Base
iii. Inferencing
iv. Defuzzification

Method Of data Collection

Structured interview with medical specialists was used to gain expert knowledge about breast diseases. Medical doctors at two national hospitals of the country, Kogi State Specialist Hospital, Lokoja and University of Abuja Teaching Hospital, Gwagwalada, were sent questionnaires. The questionnaire aided in the collection of knowledge from doctors and breast cancer Experts through pair-wise comparisons of the risk factors used in the risk prediction of breast cancer.

Fuzzification

Fuzzification is a process used in fuzzy logic to convert crisp input values into fuzzy sets. In fuzzy logic, the concept of membership degrees is crucial. Membership degrees represent the degree to which an input belongs to a specific category. These membership functions can take various shapes, such as triangular, trapezoidal and Gaussian. Fuzzification helps to handle imprecise or uncertain data. The factors for designing the fuzzy set for all important input variables for the web-based fuzzy expert system for breast cancer risk prediction stage is given as:

i. Age

ii. Age at first menstrual Circle
iii. Age at last menstrual circle
iv. Age at first Pregnancy
v. Duration of Breast feeding
vi. Body Max Index
vii. Alcohol Intake
viii. Family History

Rule Base

After assigning MF and linguistic variables to all the selected input variables using the intuition method and ranking order method of MF assignment rules are needed to build the knowledge base. The rule-based system is built using the IF-THEN rules, which consist of antecedent and consequences. The antecedents and consequences consist of fuzzy logic statements. The construction of fuzzy rules is the next phase in the fuzzification process. The fuzzy rules for this study were created with the help of domain experts (breast cancer consultants). The knowledgebase contains many fuzzy rules created using combination theory: only the valid rules were picked by domain experts.

The rule base consists of set of rules that determine the Risk status (High Risk, Intermediate Risk, and Low Risk) based on the above-mentioned input data. Rule base is obviously used in representing expert knowledge, modelling the relationship between the variables used in the risk assessment model and dealing with the uncertainty that exists in this research work. The fuzzy rules that were formulated from the implementation of the fuzzy inference engine model are:

Rule1 = (Age["old"] & AFP["very_early"] & ALMC["average"] & AFMC["very_early"] & DBF["very_short"] & BMI["very_underweight"] & Alcohol["none"] & Smoking["no"],Risk["very_low"])

Rule2 = (Age["old"] & AFP["early"] & ALMC["early"] & AFMC["early"] & DBF["short"] & BMI["underweight"] & Alcohol["low"] & Smoking["no"],Risk["low"])

Rule3 = (Age["average"] & AFP["average"] & ALMC["average"] & AFMC["average"]
& DBF["moderate"] & BMI["normal_weight"] & Alcohol["moderate"] & Smoking["yes"],Risk["moderate"])

Rule4 = (Age["old"] & AFP["late"] & ALMC["late"] & AFMC["late"] & DBF["long"]
& BMI["over_weight"] & Alcohol["high"] & Smoking["yes"],Risk["high"])

Rule5 = (Age["very_old"] & AFP["very_late"] & ALMC["very_late"] & AFMC["very_late"] & DBF["very_long"] & BMI["obese"] & Alcohol["very_high"] &
Smoking["yes"],Risk["very_high"])

The rules presented above are a set of if-then statements that specify the relationship between the input variables (risk factors) and the output variable (breast cancer risk level).

The rules are based on expert knowledge and are designed to capture the complex relationships between the input variables and the output variable. The rules are presented in the form of production rules, where each rule consists of an antecedent (if-part) and a consequent (then-part). The antecedent specifies the conditions under which the rule is triggered, while the consequent specifies the action to be taken when the rule is triggered.

For example, Rule 1 states that if the patient is young and has a age at first pregnancy (AFP) level, and duration of breast feeding (DBF) level, and a normal age at first menstrual circle (ALMC), and does not smoke, and has a normal body mass index (BMI), and does not drink alcohol, then the patient's breast cancer risk level is very low. Similarly, Rule 2 states that if the patient is young and has a normal AFP level, and a normal DBF level, and a normal ALMC, and does not smoke, and has a normal BMI, and drinks alcohol, then the patient's breast cancer risk level is low. The rules continue in this manner, with each rule specifying a different set of conditions and corresponding breast cancer risk level. The rules are designed to be comprehensive and cover a wide range of risk factors and risk levels. Overall, the rules presented provide a clear and concise set of guidelines for breast cancer risk prediction using the developed web-based fuzzy expert system.

Inference

This is the process of drawing inferences from previously collected data. The inference engine is a knowledge processor that is modelled after human expert reasoning. The act of mapping an input set to an output set using the theory of fuzzy sets is known as fuzzy inference in the context of fuzzy logic (Tsoukalas & Uhrig, 1993; Athiyah et al, 2021). This method attempts to gather all necessary facts in order to prove a theory. The fuzzy inference mechanism used in this study is the Mamdani Inference type. The fuzzy inference engine uses the rules in the knowledge-base to get a conclusion. The inference engine used to implement this CDSS will use the forward chaining mechanism to search the knowledge for the breast cancer symptoms. The inference engine technique was employed in this research is the Root Sum Square (RSS).

$$\sqrt{(\sum R)} = \sqrt{(R1\ 2 + R2\ 2 + R3\ 2 + \cdots \ldots + Rn\ 2\ )} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (1)$$

Where R12 + R22 + R32+......+ Rn2 are the strength values (truth values) of various rules that reach the same conclusion. When the inference engine gets a user query, the decision-making process begins. The weights for the inputs are then generated by the inference engine. The entries in this case; symptoms were assessed at this stage to build the fuzzy output set with its relevant compatibility degree.

Defuzzification

This can only be accomplished after each rule has been evaluated and is permitted to contribute its "weight" in deciding the output fuzzy set. The aggregation method between rules is maximum to combine the output fuzzy set, therefore the fuzzification method is max-min and the defuzzification method is centroid. The system's "goal" is to assess the risk status of breast cancer recurrence or mortality in newly diagnosed patients. The output variable is a number between 1 and 4, denoting Low Risk, Intermediate Risk, and High-Risk status. Tumour risk grows as the value rises. This result has three fuzzy sets: low risk, intermediate risk, and high risk; Table 1 shows the range of these fuzzy sets

Table 1: Fuzzy Set of Output Variable Risk Status Variable

Input Field	Range	Fuzzy set
Risk Status	0-2	Low Risk
	2 – 4	Intermediate Risk
	>=4	High Risk

Algorithm 2: Defuzzification Algorithm (centroid)

Step1: Define the output variable
Step 2: Compute the defuzified value
Step 3: Interpret the defuzified result

Step 4: Output the Assessment result

System Architecture
A system's constituent pieces, their interactions with one another and their surroundings, and the guiding principles that direct its development and evolution all reflect the system's fundamental organisation (Rich, 2009). A picture of the system architecture can be found in Figure 1.

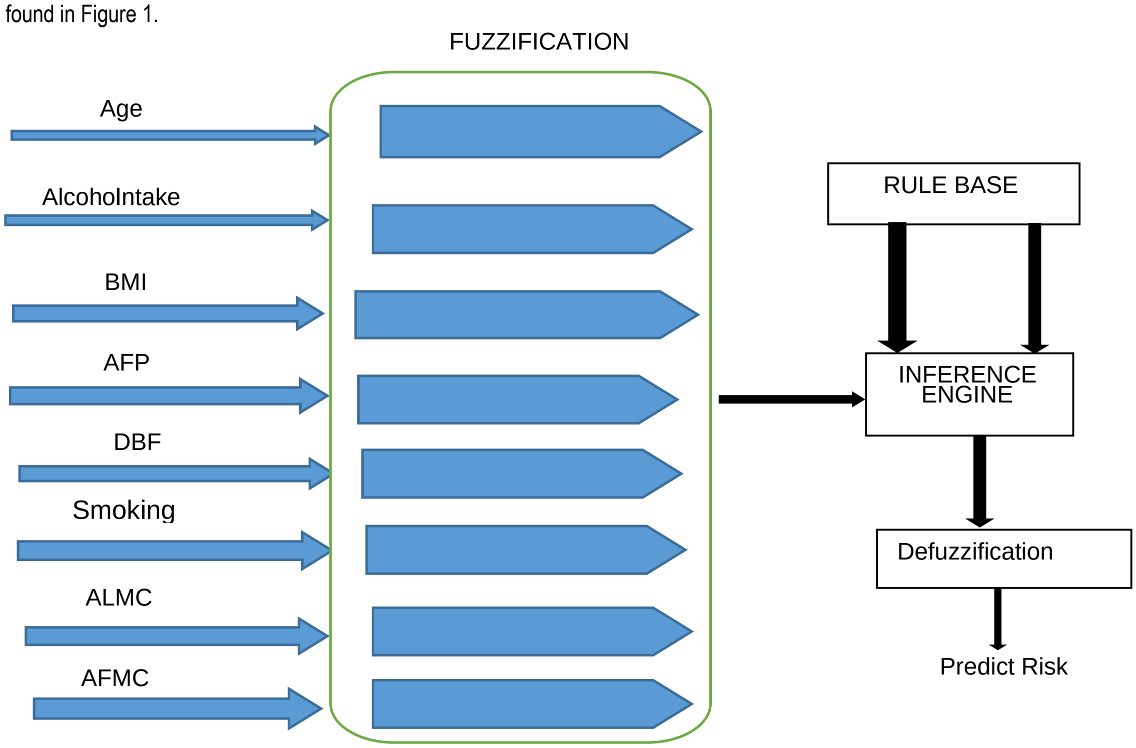

Figure 1: System Architecture

The system architecture presented in Figure 1 illustrates the core components of the developed web-based fuzzy expert system for predicting breast cancer risk. It comprises of three key elements: fuzzification, the rule base with an inference engine, and defuzzification. Fuzzification serves as the initial step, transforming input variables such as age, age at first pregnancy (AFP), duration of breastfeeding (DBF), age at last menstrual cycle (ALMC), alcohol intake, body mass index (BMI), and smoking into fuzzy sets. This allows the system to manage the inherent uncertainty and imprecision of medical data effectively.

At the heart of the system lies the rule base and inference engine, which operates on a set of expert-defined if-then rules. These rules model the intricate relationships between the input factors and the output variable, which is the level of breast cancer risk. The reliance on expert knowledge ensures that the system captures subtle, non-linear connections that traditional models might overlook.

Finally, defuzzification converts the fuzzy output into a crisp, interpretable value that represents the predicted risk level. This step uses a weighted average method, emphasizing the significance of each fuzzy set's contribution.

While some may argue that traditional statistical models could suffice, such approaches often lack the flexibility to handle ambiguity and linguistic uncertainty in patient data. Fuzzy logic-based architecture offers a more nuanced and adaptive framework, making it particularly suitable for complex healthcare applications.

RESULTS AND DISCUSSION

A. Data Presentation

Data are presented using tables and graphs to show the validity of the results. It is important to state that the research work used fuzzy logic for the modelling of breast cancer Risk assessment.

Age

Linear Membership Function
Age, as illustrated in Figure 1, has five MF and has a range of 0% to 100%. Each MF has three coordinates: a, b, and c. The coordinates for each MF are shown in Table 1 together with their respective MF values. Age is a significant factor in breast cancer diagnosis, as breast cancer characteristics can vary based on a person's age. Although breast cancer can develop at any age, the risk rises with advancing years. Women over 50 are diagnosed with breast cancer in most cases. However, breast cancer can also strike younger women.

Table 2: Age MF Linguistic Variable with Coordinates

S/N	Linguistic Variable	Description	Fuzzy Range for Age	Coordinates of Trigonometric MF	Membership Function value
1	VLR	Very Young	0-44	(A:0) (B:22) (C:44)	0≤ x ≤0.2
2	LR	Young	22-66	(A:22) (B:44) (C:66)	0.2< x ≤ 0.4
3	MR	Medium	44-88	(A:44) (B:66) (C:88)	0.4< x ≤0.6
4	HR	Old	66-110	(A:66) (B:88) (C:110)	0.6< x ≤ o.8
5	VHR	Very Old	88-132	(A:88) (B:110) (C:132)	0.8< x ≤ 1.0

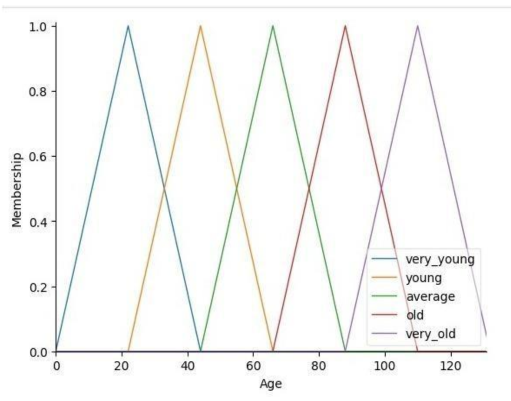

Figure 2: Age Membership Function

Table 3: ALMC MF Linguistic Variable with Coordinates

S/N	Linguistic Variable	Description	Fuzzy Range for AFMC	Coordinates of Trigonometric MF	Membership Function value
1	VE	Very Early	0-7	(A: 0) (B:3.5) (C:7)	0≤ x ≤0.2
2	E	Early	3.5-10.5	(A:3.5) (B:7)(C:10.5)	0.2< x ≤ 0.4
3	A	Average	7-14	(A:7) (B:10.5) (C:14)	0.4< x ≤0.6
4	L	Late	10-17.5	(A:10.5) (B:14) (C:17.5)	0.6< x ≤ o.8
5	VL	Very Late	14-20	(A:14) (B:17.5) (C:20)	0.8< x ≤ 1.0

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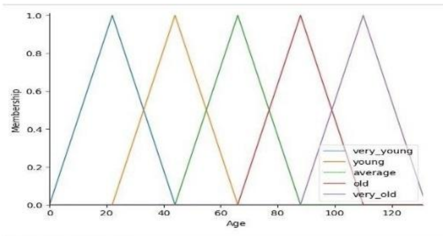

Figure 3: Age Membership Function

Age at First Menstrual Circle (AFMC) Linear Membership Function
AFMC, as illustrated in Figure 3, has five MF and has a range of 0% to 100%. Each MF has three coordinates: a , b, and c. The coordinates for each MF are shown in Table 3 together with their respective MF values. The age of menarche considerably raises the risk of breast cancer. According to research by Ries, Eisner, and Kosary (2000), risk factors reduce by up to 23% for people whose first menstruation age is 15 or older. According to research, women who menarche early (begin their menstrual cycles at a young age) may be at higher risk for breast cancer than those who menarche later. The extended lifetime exposure to hormones like estrogen may be the cause of this.

Table 4: AFMC MF Linguistic Variable with Coordinates

S/N	Linguistic Variable	Description	Fuzzy Range for AFMC	Coordinates of Trigonometric MF	Membership Function value
1	VE	Very Early	0-7	(A: 0) (B:3.5) (C:7)	0≤ x ≤0.2
2	E	Early	3.5-10.5	(A:3.5) (B:7)(C:10.5)	0.2< x ≤ 0.4
3	A	Average	7-14	(A:7) (B:10.5) (C:14)	0.4< x ≤0.6
4	L	Late	10-17.5	(A:10.5) (B:14) (C:17.5)	0.6< x ≤ o.8
5	VL	Very Late	14-20	(A:14) (B:17.5) (C:20)	0.8< x ≤ 1.0

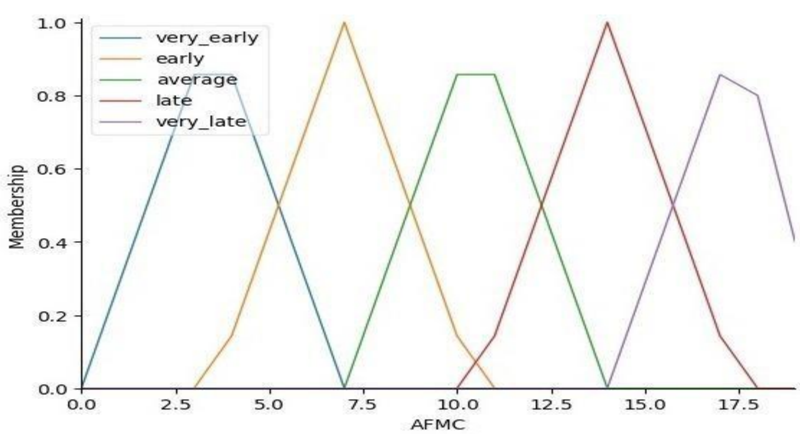

Figure 4: AFMC Membership Function

Age at Last Menstrual Circle (ALMC) Linear Membership Function
ALMC, as illustrated in Figure 4, has five MF and has a range of 0% to 100%. Each MF has three coordinates: a, b, and c. The coordinates for each MF are shown in Table 4 together with their respective MF values. As the menopause is postponed after the age of 45, the risk factor rises by 3% annually. Longer lifetime exposure to the hormones progesterone and estrogen may be the cause of the increased risk (Brinton, Schaiere, & Hoover 1988).

Table 5: ALMC MF Linguistic Variable with Coordinates

S/N	Linguistic Variable	Description	Fuzzy Range for ALMC	Coordinates of Trigonometric MF	Membership Function value
1	VE	Very Early	0-20	(A: 0) (B:10) (C:20)	0≤ x ≤0.2
2	E	Early	10-30	(A:10) (B:20)(C:30)	0.2< x ≤ 0.4
3	A	Average	20-40	(A:20) (B:30) (C:40)	0.4< x ≤0.6
4	L	Late	30-50	(A:30) (B:40) (C:50)	0.6< x ≤ o.8
5	VL	Very Late	40-60	(A:40) (B:50) (C:60)	0.8< x ≤ 1.0

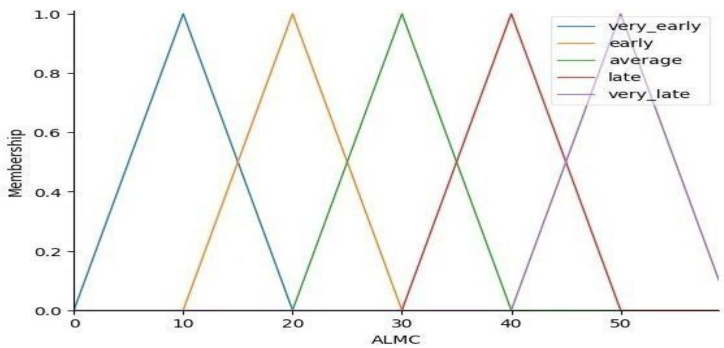

Figure 5: ALMC Membership Function

Age at First Pregnancy (AFP) Linear Membership Function

Hormone receptor, as illustrated in Figure 5, has five MF and has a range of 0% to 100%. Each MF has three coordinates: a, b, and c. The coordinates for each MF are shown in Table 5 together with their respective MF values. Pregnancy before the age of 20 is associated with a lower risk of breast cancer than pregnancy beyond the age of 20 (McTiernan, Kooperberg & White, 2003).

Table 6: AFP MF Linguistic Variable with Coordinates

S/N	Linguistic Variables	Description	Fuzzy Range for AFP	Coordinates of Trigonometric MF	Membership Function value
1	VE	Very Early	0-15	(A: 0) (B:7.5) (C:15)	0≤ x ≤0.2
2	E	Early	7.5-22.5	(A:7.5) (B:15)(C:22.5)	0.2< x ≤ 0.4
3	A	Average	15-30	(A:15) (B:22.5) (C:30)	0.4< x ≤0.6
4	L	Late	22.5-37.5	(A:22.5) (B:30) (C:37.5)	0.6< x ≤ o.8
5	VL	Very Late	30-45	(A:30) (B:37.5) (C:45)	0.8< x ≤ 1.0

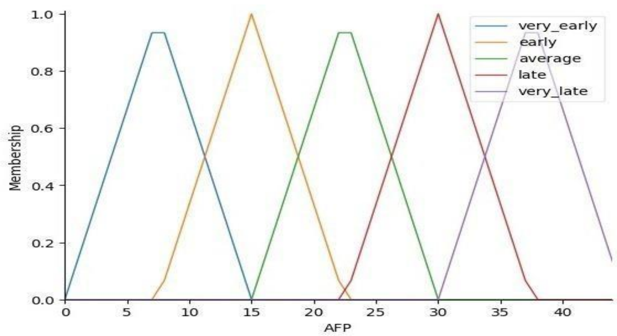

Figure 6: AFP Membership Function

Duration of Breast feeding (DBF) Linear Membership Function

DBF, as illustrated in Figure 6, has five MF and has a range of 0% to 100%. Each MF has three coordinates: a, b, and c. The coordinates for each MF are shown in Table 6 together with their respective MF values. Women who breastfeed are less likely to acquire breast cancer. According to some studies, nursing reduces a woman's risk of developing breast cancer marginally, especially if she breastfeeds for one and a half to two years. The risk of breast cancer dramatically decreased the longer the mother breastfed her kid.

Table 7: DBF MF Linguistic Variable with their Coordinates

S/N	Linguistic Variables	Description	Fuzzy Range of DBF	Coordinates of Trigonometric MF	Membership Function value
1	VS	Very Short	0-12	(A: 0) (B:6) (C:12)	0≤ x ≤0.2
2	S	Short	6-18	(A:6) (B:12)(C:18)	0.2< x ≤ 0.4
3	M	Moderate	12-24	(A:12) (B:18) (C:24)	0.4< x ≤0.6
4	L	Long	18-30	(A:18) (B:24) (C:30)	0.6< x ≤ o.8
5	VL	Very Long	24-36	(A:24) (B:30) (C:36)	0.8< x ≤ 1.0

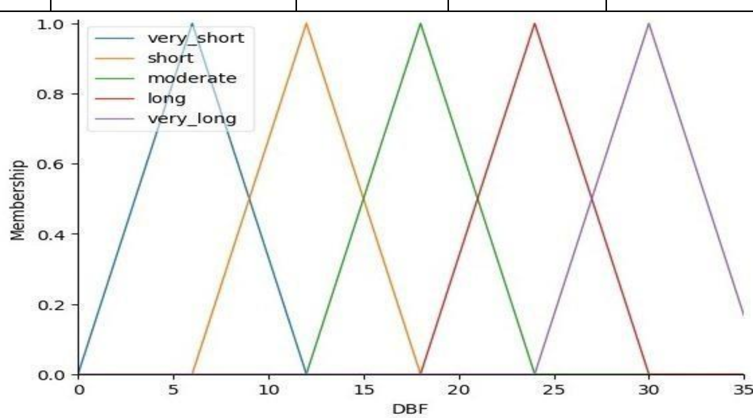

Figure 7: DBF Membership Function

Implementation of Body Mass Index (BMI) Linear Membership Function

BMI, as illustrated in Figure 13, has five MF and has a range of 0% to 100%. Each MF has three coordinates: a, b, and c. The coordinates for each MF are shown in Table 13 together with their respective MF values. Breast cancer risk is increased by a woman's BMI after menopause. Weight gain from the time a person is 18 years old until they are between the ages of 50 and 60 has consistently been linked to an increased risk of breast cancer after menopause.

Table 8: BMI MF Linguistic Variable with Coordinates

S/N	Linguistic Variables	Description	Fuzzy Range for BMI	Coordinates of Trigonometric MF	Membership Function value
1	VU	Very Underweight	0-13	(A: 0) (B:6.5) (C:13)	0≤ x ≤0.2
2	U	Underweight	6.5-19.5	(A:6.5) (B:13)(C:19.5)	0.2< x ≤ 0.4
3	NW	Normal Weight	13-26	(A:13) (B:19.5) (C:26)	0.4< x ≤0.6
4	OW	Overweight	19.5-32.5	(A:19.5) (B:26) (C:32.5)	0.6< x ≤ o.8
5	O	Obese	26-40	(A:26) (B:32.5) (C:40)	0.8< x ≤ 1.0

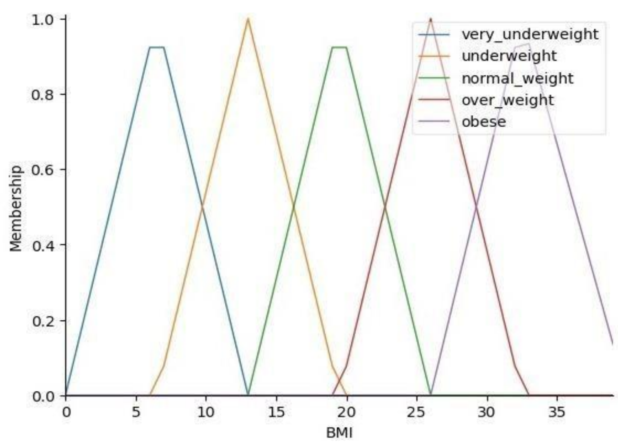

Figure 8: BMI Membership Function

Alcohol Intake Linear Membership Function
Alcohol intake, as illustrated in Figure 4.13, has five MF and has a range of 0% to 100%. Each MF has three coordinates: a, b, and c. The coordinates for each MF are shown in Table 8 together with their respective MF values. As alcohol accelerates the metabolism of carcinogens like acetaldehyde, it may raise the risk of breast cancer

Table 9: Alcohol Intake MF Linguistic Variable with Coordinates

S/N	Linguistic Variable	Description	Fuzzy Range for Alcohol intake	Coordinates of Trigonometric MF	Membership Function value
1	N	None	0-34%	(A: 0) (B:17) (C:34)	0≤ x ≤0.2
2	L	Low	17-51%	(A:17) (B:34) (C:51)	0.2< x ≤ 0.4
3	M	Moderate	34-68%	(A:34) (B:51) (C:68)	0.4< x ≤0.6
4	H	High	51-87%	(A:51) (B:68) (C:87)	0.6< x ≤ o.8
5	VH	Very High	68-100%	(A:68) (B:87) (C:100)	0.8< x ≤ 1.0

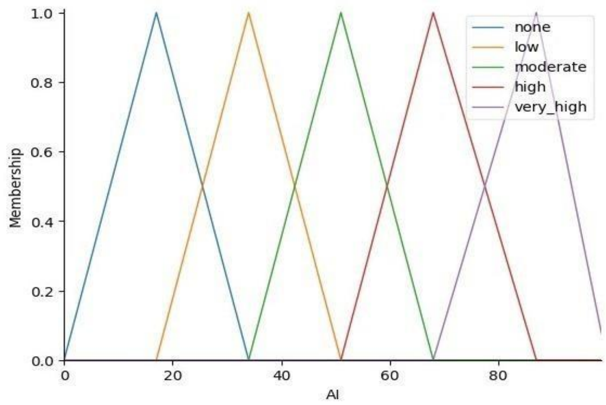

Figure 9: Alcohol Intake Membership Function

Smoking Linear Membership Function
Smoking, as illustrated in Figure 10, has two MF and has a range of 0 to 1.

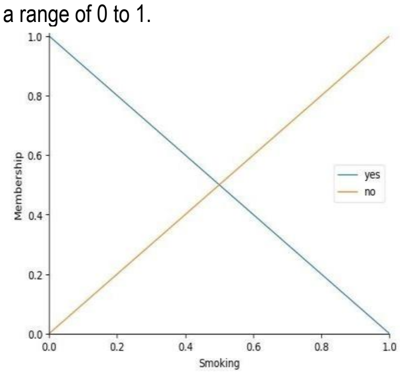

Figure 10: Smoking Membership Function

B. Presentation of Result
In this paper, the goal is to predict breast cancer risk using breast cancer risk factors. Considering this, the expected result are of different levels which include very low, low, moderate, High and very high. Furthermore, the implementation of the model using and intuitive user interface comprises of the registration page, logging page, profile page, risk assessment page and result page. The results demonstrating these levels of breast cancer risk are shown below:

Very High Risk
The graph in Figure 11 shows the result of an individual who has a very high risk of breast cancer

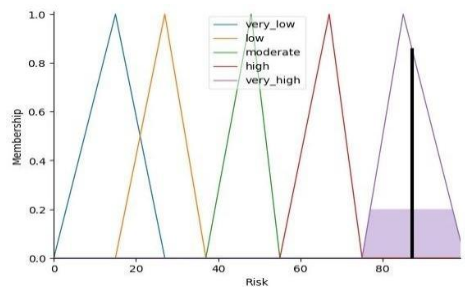

Figure 11: Very High Risk

High Risk
The graph in Figure 12 shows a result of an individual who has a high risk of breast cancer

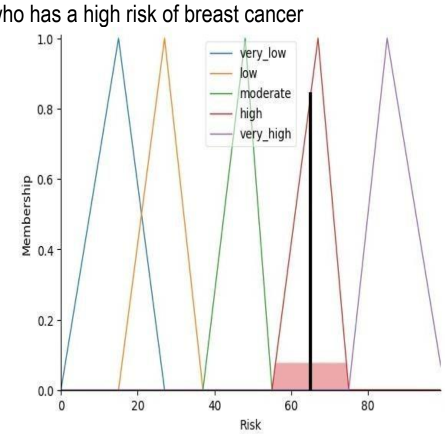

Figure 12: High Risk

Moderate Risk
The graph depicts in Figure 13 shows the result of an individual with moderate risk of breast cancer

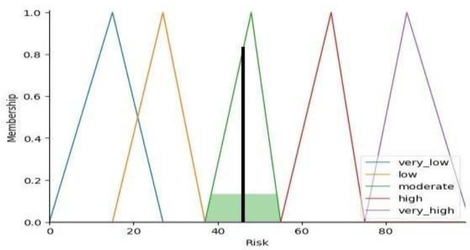

Figure 13: Moderate Risk

Low Risk

The graph depicts in figure 14 shows the result of an individual with low risk of breast cancer

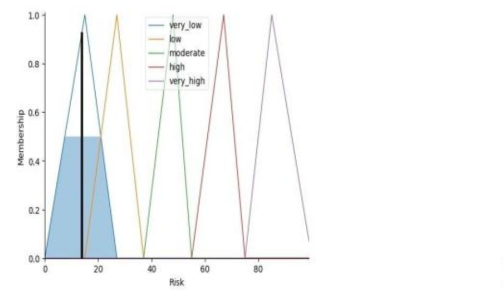

Figure 14: Low Risk

Conclusion and Future Works

It is tasked to express interactive relationships when simulating real-world situations, such as breast cancer risk assessment, because there are complex relationships between input variables (risk factors) and output variables (risk level), as well as connections between each identified input variable's (risk factor) connections. As a result, the advantages of the developed web-based fuzzy expert system for breast cancer risk assessment model approach stand out since the If-then rule based inference mechanism can be directly specified by actual familiarity. Because it is difficult to obtain the best answer using precise mathematical expressions, fuzzy inference substantially streamlines and simplifies the computer process for modelling real-world situations. Due to the intended WFES producing results that are suitable for use and referencing. The primary advantages of our developed web-based fuzzy expert system for breast risk assessment over other comparable works on risk assessment are that it is comprehensive and appropriate with risk indicators that predispose a woman to breast cancer, and a sizable number of rules were used to build the knowledge base of the system. This will take into account every element that influenced the growth of the tumor.

Using risk factors that raise a woman's risk of acquiring breast cancer, the Web-based Fuzzy Expert System (WFES), a web-based tool for assessing breast cancer risk, was successfully developed and put into use. The technology allows healthy females (those without a diagnosis of a breast cancer tumour) to monitor their own individual breast cancer risk. Due to the late presentation of cases to healthcare facilities and the murky nature of the breast cancer risk assessment. Major problems have resulted from this, especially in developing nations like Nigeria where there aren't enough specialists in the area. Fuzzy logic has been found to be a very beneficial technology for simulating contemporary problems. The WFES was created to provide a decision support tool to help people, new researchers, doctors, and other healthcare professionals stop the suffering and demise brought on by the disease. If the WFES developed for this study is applied wisely, the system could be a useful tool for determining breast cancer risk.

The WFES for breast cancer risk assessment was implemented using data of those that have not been diagnosed of breast cancer. This was to ascertain if actually the risk factors used for the design were responsible for breast cancer. The use of risk factors without the necessity for laboratory testing to provide an overall result was made possible by the fuzzy logic model technique in this study. This methodology offers the shortest response to the problem at hand while avoiding time loss and fatality as with other methods. The outcomes from a fuzzy system imitating real-life scenarios are more accurate when compared to using just mathematical models to handle the same problem.

This study concluded that breast cancer is caused by behavioral changes in people's (women's) conduct. The online expert system's output zone is consequently advisory, allowing users to lower risk if it is high or extremely high by taking the necessary action.

Recommendation

Given the many fuzzy logic techniques now employed in the battle to treat the lethal illness (breast cancer), the majority of which caused agony to patients and were primarily centred on survivorship and disease recurrence rates. These treatments only worked once the tumour had already formed, therefore they were clearly insufficient to address the high incidence rate of the illness that the WHO has recorded. The research strongly advises using the WFES that has been developed. Given the nature of the condition, it is best to present it before the tumour begins to spread.

i. The created WFES for breast cancer risk prediction is non-invasive, web based, and enables patients monitor their personal risk level.

ii. It is applicable prior to the initial growth of the tumour and takes seven distinct risk factors into account.

ii. Therefore, it is highly recommended that the WFES model be implemented internationally.

Suggestion for Further Studies

This study can serve as a starting point for future research on how to model fuzziness in real-world scenarios. The Mamdani fuzzy inference system was employed in this study to create the web-based FIS. By utilising other techniques, such as the Sugeno method, the research can be expanded.

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