VOL. 03 NO. 9,
FEBRUARY, 2024
E-ISSN 3026-958X
P-ISSN 3027-1169

African Scholar Publications & Research International
www.africanscholarpub.com

Journal of Science Innovation & Technology Research (JSITR)

Neuro-Fuzzy Expert System for Diagnosis of Breast Cancer with Gini Index Random Forest-Based Feature Importance Measure Algorithm

Mohammed Bello Mohammed[1], L. J. Muhammad[2] & Abubakar Muhammad Al-Amin[3]

[1,3] Department of Mathematics and Computer Science, Gombe State College of Education and Legal Studies, Nafada, Gombe State – Nigeria. [2*]Computer Science Department, Federal University of Kashere, Gombe – Nigeria.
mohammed.bello62@gmail.com

Abstract

Breast cancer is one of the common type cancers and also one of deadliest cancers after lung cancer. The cancer is the most common cancer in women worldwide, in Nigeria, with population of about 187 million people and it represents about 12% of all new cancer cases and 25% of all cancers in women. However, conventional clinical diagnosis process of diseases is often associated with uncertainty and ambiguity due to complexity and fuzziness in the course of diagnosis of most of the deadly diseases such as COVID-19, Coronary artery diseases, breast cancer, diabetes mellitus among other. Therefore, artificial techniques such as fuzzy logic, and neural network can be used to deal with the uncertainty and ambiguity of the diverse nature of clinical and medical diagnosis or decision making. In this work, a hybrid AI intelligent expert system based on neural network and fuzzy logic artificial intelligence techniques for diagnosis of breast cancer has developed so as to provide a promising solution of how to deal uncertainty and vagueness often associated with the clinical and decision making in the course of diagnosis of breast cancer and also to assist the healthcare workers in diagnosing and predicting breast cancer in its early stage. the result of the performance evaluation of the system showed that the system achieved an accuracy of 96.77% for its ability to accurately diagnose healthy, mild and severe

breast cancer patients, and system achieved a sensitivity of 96.77% and a specificity of 97.10% respectively for its ability to correct diagnose health cases of the breast cancer.

Keywords: Fuzzy Logic, Expert System, Neural Network, Artificial Intelligence, Breast Cancer

Introduction

Cancer is a group of diseases characterized by the uncontrolled spread and proliferation of abnormal cells [3], [19]. Therefore, uncontrolled spread and proliferation of abnormal cells can lead to death [4]. Breast cancer is one of the multifactorial genetic diseases possibly associated with the action of multiple genes through a combination of environmental factors and lifestyle [17]. Breast cancer is one of the most common cancer types and also one of the deadliest cancer types after lung cancer [3-4]. However, although it also occurs in men, it is the most common type of cancer in women [3]. Breast cancer occurs when certain cells in the breast become abnormal and grow out of control to form a tumor. Cervical and breast cancers are the two most common cancers among women in Nigeria, and other developing countries contributing significantly to a high morbidity and mortality rate in the country [20 -22, 24]. Breast cancer is the most common cancer in women worldwide, in Nigeria, with population of about 187 million people and it represents about 12% of all new cancer cases and 25% of all cancers in women. However, medical diagnosis is the process that is designed to explain the cause of an illness or patient discomfort, i.e. diagnosing the disease using historical facts and symbols for patients [1, 7-8].

In this work, expert system which is AI based intelligent systems that emulate human experts towards decision making in order to complement human activities in the course of making decisions has been developed with two other AI based techniques which include neural network and fuzzy logic respectively. The system is being developed also to deal with uncertainty and vagueness often associated with decision making of breast cancer. The diagnostic dataset of the breast cancer was also used to develop the system. Neutral network mimics the way human brain works and it also describe as a streamlined mathematical model of human brain like system which consist of distributed artificial neurons to perform parallel computations while fuzzy logic is an AI techniques that is based on "degrees of truth" unlike traditional logic which is based on "true or false" [2, 16, 25, 27, 33]. Recent advancements in AI files have led the emergence of the expert system developed with neural network and logic for medical application especially prediction, classification and diagnosis of the diseases which improve

the abilities and the experiences of medical practitioners for making decision about the patients [1, 23, 28].

Many researches have been done on fuzzy neural network based expert system for prediction, classification or diagnosis of many diseases. In this work, a hybrid AI intelligent expert system based on neural network and fuzzy logic AI techniques for diagnosis of breast cancer would be developed. The system will provide a promising solution of how to deal uncertainty and vagueness often associated with the clinical dataset and decision making. The system will also assist the healthcare workers in diagnosing and predicting breast cancer in its early stage. The system will be a complementary solution to a conventional technique for diagnosing breast cancer in hospitals /clinics and will also serve as diagnostic help tool to fresh or junior healthcare workers in various hospitals and clinics. However, many AI techniques have been used to diagnosis of the breast cancer and other deadly diseases. Nero-fuzzy rules based expert system for diagnosis of breast cancer has been developed in this work. The fuzzy rules have been applied to the Ex-DBC system engine which were generated and discovered using neural network - fuzzy way. Ex-DBC can be used as a solid diagnostic tool with 97% specificity, 76% sensitivity, 96% sensitivity positive and 81% predictable rates of breast cancer. [5] developed a machine learning-based system for cancer screening. This system was developed to diagnose cancer and use artificial neural networks to determine whether the cancer is benign or malignant. The network was trained using a backpropagation algorithm and then a neuro-fuzzy system was developed based on the model. In a study [6], a hybrid expert system representing a combination of incremental fuzzy neural networks and fuzzy linguistics for cancer diagnosis was developed to address uncertainties associated with clinical decision making. A neurofuzzy-based expert system has been proposed for classifying breast cancer. The system was developed using the Wisconsin breast cancer screening data set. This data set contains 683 data sets, each with 9 properties such as clot strength, cell size parallelism, and cell shape similarity. The proposed approach predicted a separation rate of 99.08%, a precision of 99.27% and a sensitivity of 98.74%. Reference [9] developed a neural network fuzzy system for skin cancer identification and classification. The system involved preprocessing and optimization of tumor locations using color detection methods, followed by extraction of colors and corresponding regions. A hypertension classification system based on a neurofuzzy approach was proposed in [10]. The system was tested using sample data from 10 patients each, including parameters such as age, body index (BMI), blood pressure (BP), heart rate, and risk limits as model output variables. rice field. The purpose of this study is to develop a hybrid AI-based intelligent expert system based on neural

network and fuzzy logic technology for breast cancer diagnosis, which will address the uncertainties and ambiguities in the clinical decision-making process.

Material and Methods

In this study, a hybrid intelligent AI expert system based on neural network and fuzzy logic AI technology was developed for breast cancer diagnosis. Breast cancer clinical datasets were collected in the UCI [University of California] public database [32]. This dataset, called the Wisconsin Breast Cancer Diagnostic Database, has been preprocessed, cleaned, and evaluated to generate knowledge generation rules for the expert system. A Gini Random Forest Based Feature Importance Measure feature selection technique was also used to remove irrelevant, insignificant and redundant features of the dataset in order to build a robust system with lesser uncertainties, ambiguities and heavier burden on the overlay of the network nodes of the system. The MATLAB has been used to develop the system and be evaluated using confusion matric techniques. Figure 1 shows the methodology of the study.

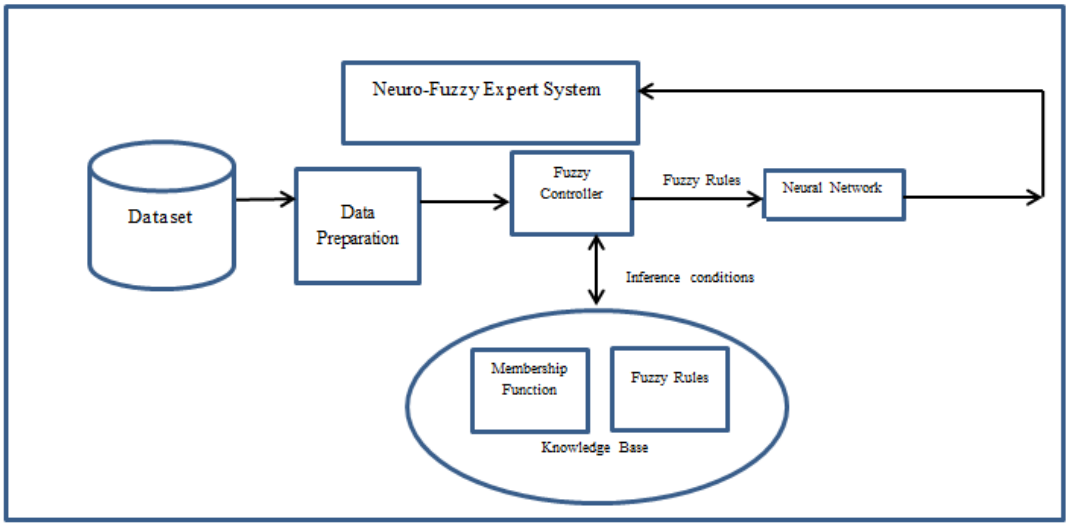


Figure 1: Research Methodology

Collection of dataset

Breast cancer datasets were collected in the UCI [University of California] public database [32]. This dataset is called the Diagnostic Wisconsin Breast Cancer Database and contains 32 functions and 569 instances. At this stage, the dataset went through a cleansing process to remove missing, noisy, and irrelevant data. As shown in Figure 2, there are no missing values in the dataset.

```
radius_mean                0
texture_mean               0
perimeter_mean             0
area_mean                  0
smoothness_mean            0
compactness_mean           0
concavity_mean             0
concave points_mean        0
symmetry_mean              0
fractal_dimension_mean     0
radius_se                  0
texture_se                 0
perimeter_se               0
area_se                    0
smoothness_se              0
compactness_se             0
concavity_se               0
concave points_se          0
symmetry_se                0
fractal_dimension_se       0
radius_worst               0
texture_worst              0
perimeter_worst            0
area_worst                 0
smoothness_worst           0
compactness_worst          0
concavity_worst            0
concave points_worst       0
symmetry_worst             0
fractal_dimension_worst    0
dtype: int64
```

Figure 2: Statistics of the missing values of the dataset' features

There are 32 functions and 569 instances in the dataset, but not all of them are useful in building the system and can affect the system's ability to generalize and overall accuracy. A Gini-based random forest algorithm importance measure is used as the feature selection technique, assigning scores to all input features based on their usefulness and importance in predicting breast cancer. Figure 3 shows the importance measures of the based on Gini-based random forest algorithm importance measure and Figure 4 shows a graphical representation of the ranking values.

Figure 3: Feature ranking Scores

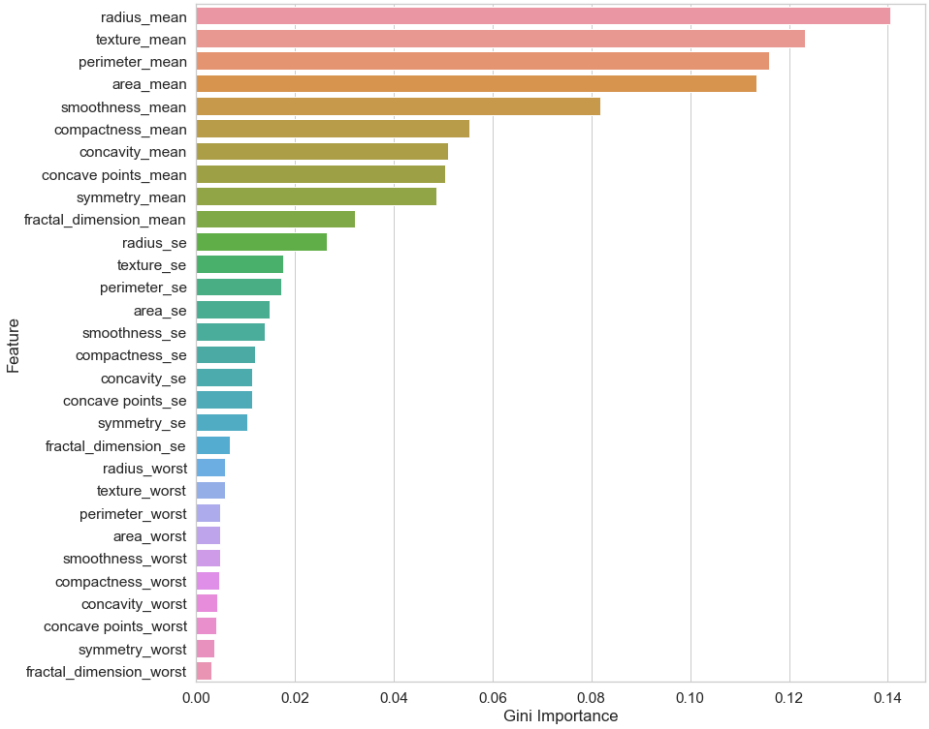


Figure 4: Graphical Presentation of Feature ranking Scores

We select the best five features of the dataset for the development of a fuzzy neural network-based expert system based on the feature importance measure values of the dataset by harnessing random forest Gini-based importance measure. The selected best five features of the dataset include average radius, average texture, average perimeter, average area, and average smoothness. Table 1 shows the units and ranges of features in the data set.

Table 1: Unit and Values Ranges of the Features

SN	Features	Units	Range
1	RadiusMean	Mm	6.981 – 28.11
2	TextureMean	Dimensionless	9.71- 39.28
3	PerimeterMean	Mm	43.79 - 188.5
4	AreaMean	μm^2	143.5 – 2501
5	SmoothnessMean	Mm	0.05263 - 0.1634
6	The diagnosis of breast tissues	malignant (0), benign (1)	0,1
µm (micrometer) = 1 x 10^{-6} m			

Splitting of dataset and generation of rules from the dataset

In order to avoid under fitting and over fitting, the dataset has been spitted into 70% and 30% for training and testing respectively. This dataset was used to generate the

rules used for diagnosing breast cancer. In this study, the MALTAB Neuro-Fuzzy Designer Toolbox was used to generate the rules. The dataset was saved in his MATLAB workspace and loaded into the toolbox, as shown in Fig. 5. Figure 6 shows trends in the trained dataset.

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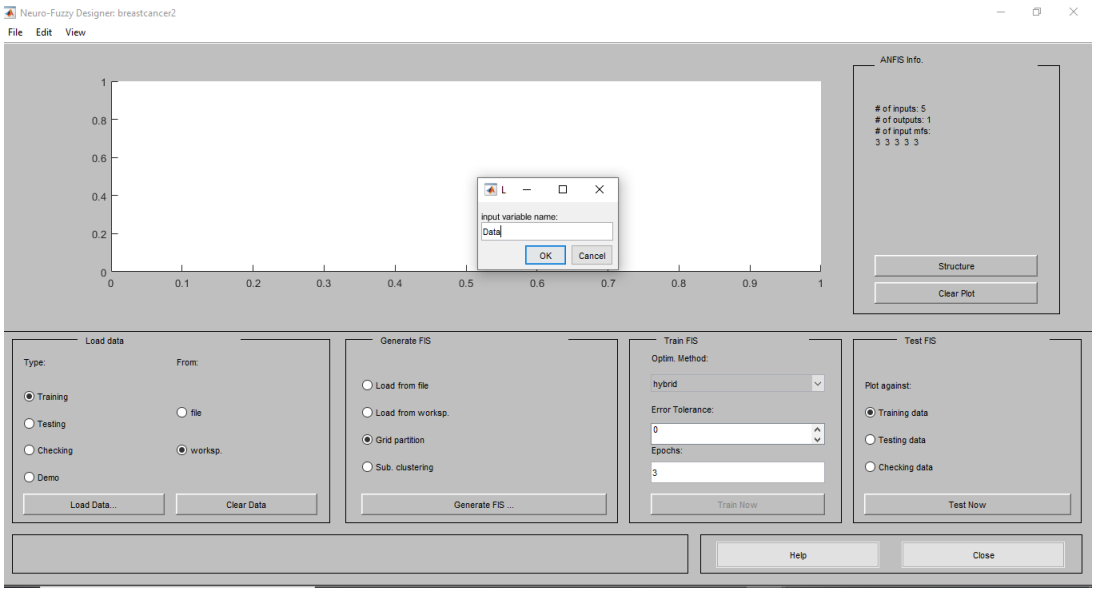


Figure 5: Dataset loading t

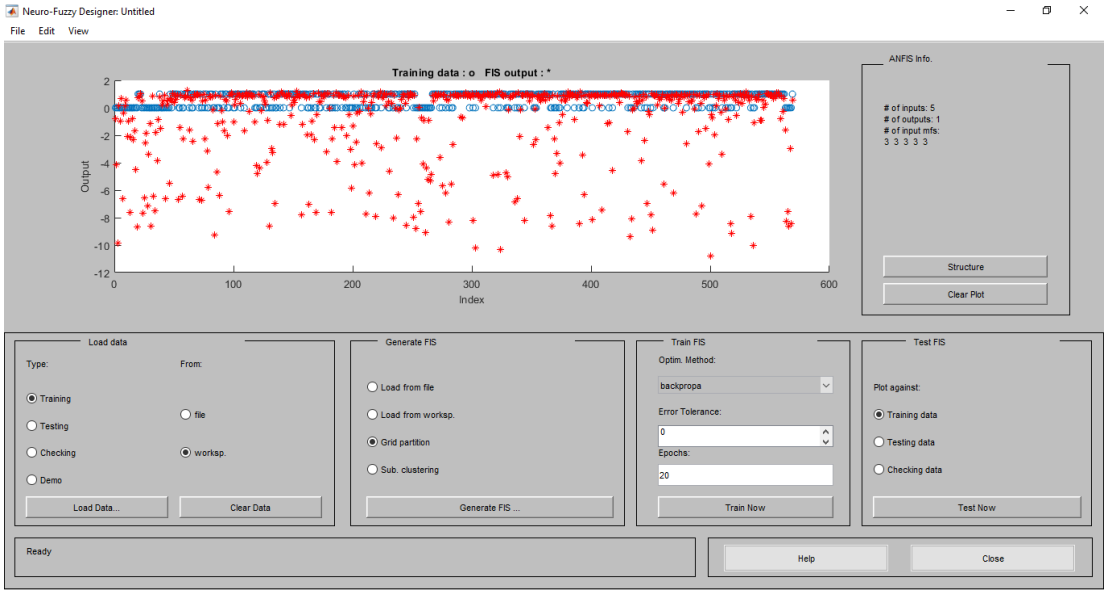


Figure 6: Trained Dataset Trend

Optimization of the rules

In this step, the fuzzy rules generated from the selected training dataset are redefined using neural network techniques. Therefore, redefining fuzzy rules requires the use of

five network neural layers, each layer defining a step in the inference mechanism of a fuzzy neural network-based expert system.

Input layer

The top five features selected from the dataset are the input of the system and have a linear function representing the current state of the system. Inputs to the system therefore include average radius, average texture, average perimeter, average area, average smoothness, and the membership function of each input is determined at the next level.

Fuzzification Layer

The top five selected features of the dataset that is the input to the system (radius mean, texture mean, perimeter mean, area mean, smoothed mean, etc.) are fuzzified in this layer. Input comes from neurons in this layer. This is the scalar value of the input features received from the input layer. Therefore, the corresponding fuzzy values should be determined using membership functions. Fuzzification is the process of converting a scalar value of a system's input into its fuzzy equivalent. This process is performed using fuzzy logic [21, 26, 29, 30-31]. Fuzzy logic is multi-value logic, unlike traditional logic where the values are 0 or 1, but there are infinitely many values between 0 and 1 in fuzzy logic [11-12]. In fuzzy theory, the fuzzy set B of Y is defined as the set of ordered pairs =, ( ) ∈. where μB(x) is called the membership function of set B.

$$M_B(y): \rightarrow \{0,1\}, where\ \mu\beta(y) = 1\ is\ totally\ in\ \ B; \quad (1)$$

$$M_B(y) = 0\ if\ y\ is\ not\ is\ B; \quad (2)$$

$$0 < \mu\beta(y) < 1\ if\ y\ is\ party\ in\ \ B. (3)$$

Fuzzy logic allows many options and choices. For each element y of the set Y, the membership function of μB(u) is equal to the degree to which y is an element of the set Y [13,15,18]. Therefore, an infinite number of values between 0 and 1 are considered and called the membership order function. Membership functions express ambiguity and uncertainty through value overlap to avoid the problem of distinct value boundaries [14, 34]. Therefore, although there are many membership function distributions, the trapezoidal membership function distribution is used for the input features of the system and the triangular membership function distribution is used for the output features of the system. A trapezoidal membership function distribution is represented as a trapezoid (x;a,b,c,d). The membership function values at x=a, x=b, x=c, x=d are set to 0.0, 1.0, 1.0, 0.0 respectively. Table 2 shows the input and output

characteristics, the range of language terms, and the membership functions. The trapezoidal membership function is given by Equation (4) below.
-

$$trapezoid\ (x; a, b, c, d) = \max\left(\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right). \quad (4)$$

The triangular membership function is provided by triangle(x;a,b,c). The membership function values at x=a, x=b, x=c are set to 0.0, 1.0, 0.0 respectively. The triangle membership function is given by Equation (5) below:

$$triangle\ (x; a, b, c) = \max\left(\min\left(\frac{x-a}{b-a}, 1, \frac{c-x}{c-b}\right), 0\right) \quad (5)$$

Table 2: Input and output features, ranges with linguistic terms and membership function

Input (Features)	Range	Linguistic Term	Membership Function
RadiusMean	< 10	Smaller	Trapezoid
	7 - 28	Normal	
	> 21	Larger	
TextureMean	< 15	Smaller	Trapezoid
	10–30	Normal	
	> 25	Larger	
PerimeterMean	< 40	Smaller	Trapezoid
	30 - 180	Normal	
	> 160	Larger	
AreaMean	< 150	Smaller	Trapezoid
	130 - 2200	Normal	
	> 2300	Larger	
SmoothnessMean	< 0.04	Smaller	Trapezoid
	0.06- 0. 14	Normal	
	> 0.12	Larger	
Diagnosis	< 1	Mild	Triangle
	1- 2	Healthy	
	> 2	Severe	

Trapezoidal membership function distributions are used for system inputs and outputs and are computed and visualized in the MATLAB Fuzzy Logic Toolbox. Figures 7, 8, 9, 10, and 11 show visualizations of the membership functions of the linguistic variables radius mean, texture mean, perimeter mean, area mean, and smoothed mean

of the input features of the system. I'm here. Figure 12 shows a visualization of the membership functions of the output functions of the linguistic variables.

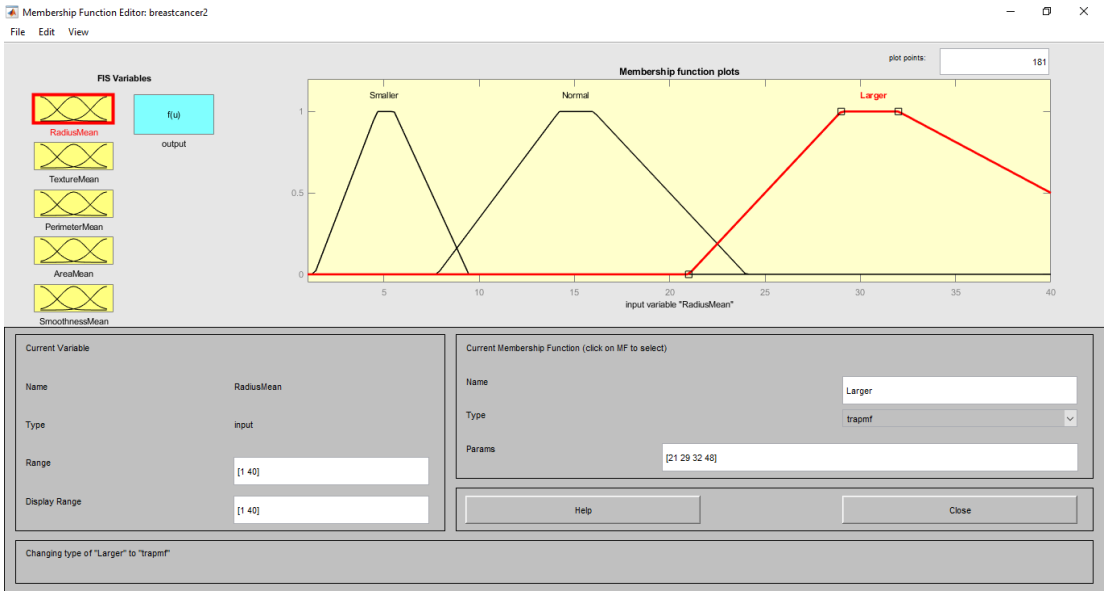


Figure 7: Membership functions of the linguistic variables of the radius mean input

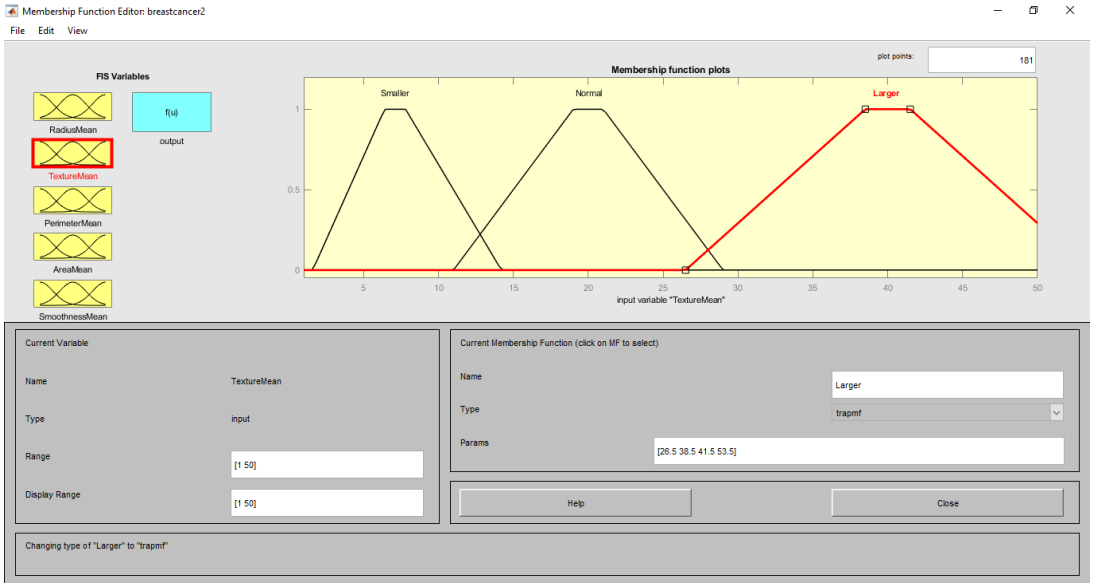


Figure 8: Membership functions of the linguistic variables of texture mean input

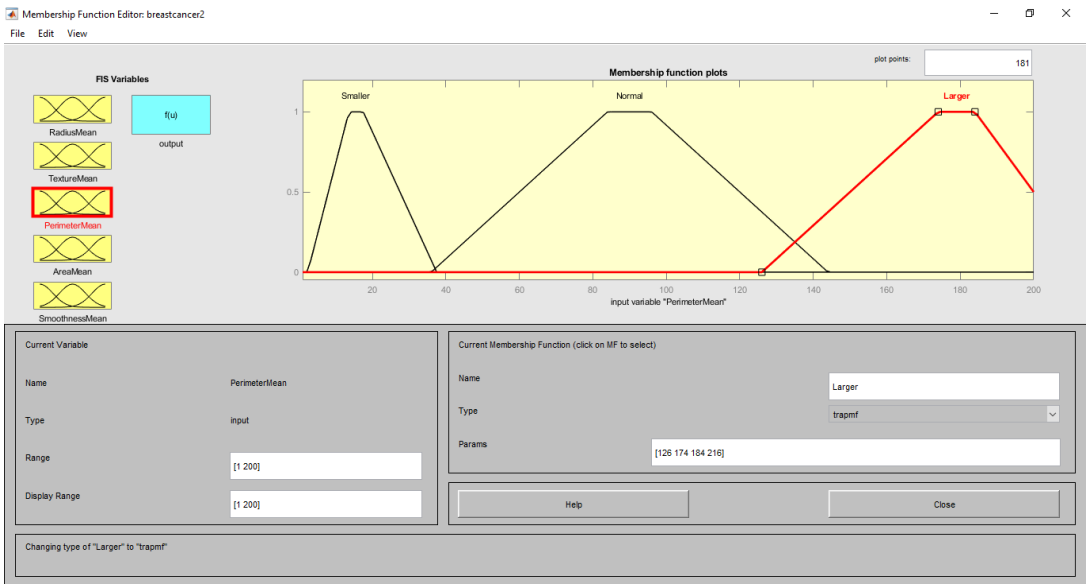


Figure 9: Membership functions of the linguistic variables of perimeter mean input

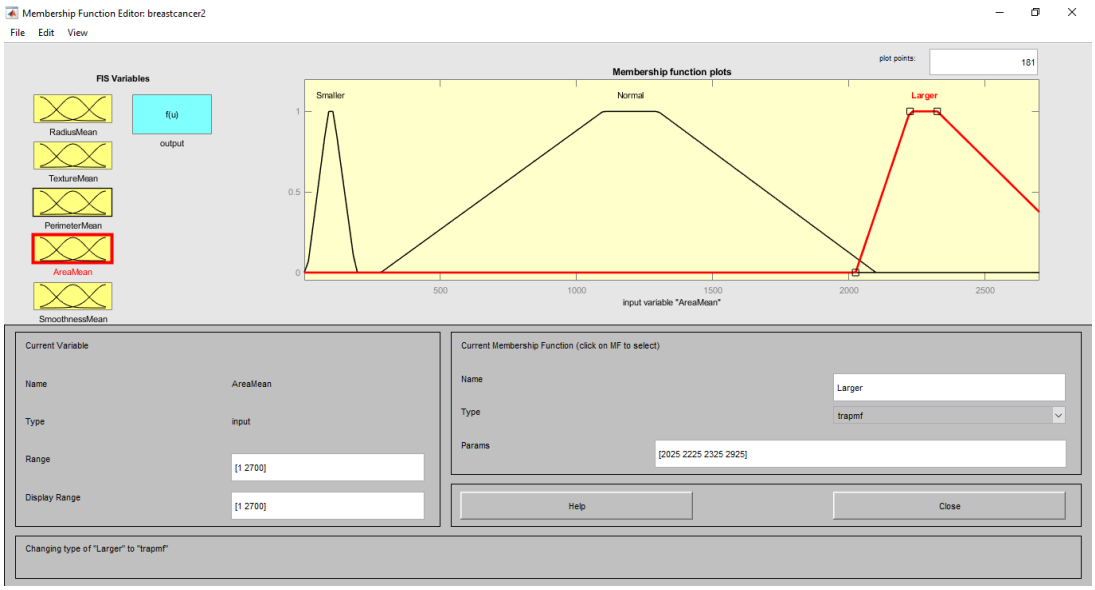


Figure 10: Membership functions of the linguistic variables of area mean input

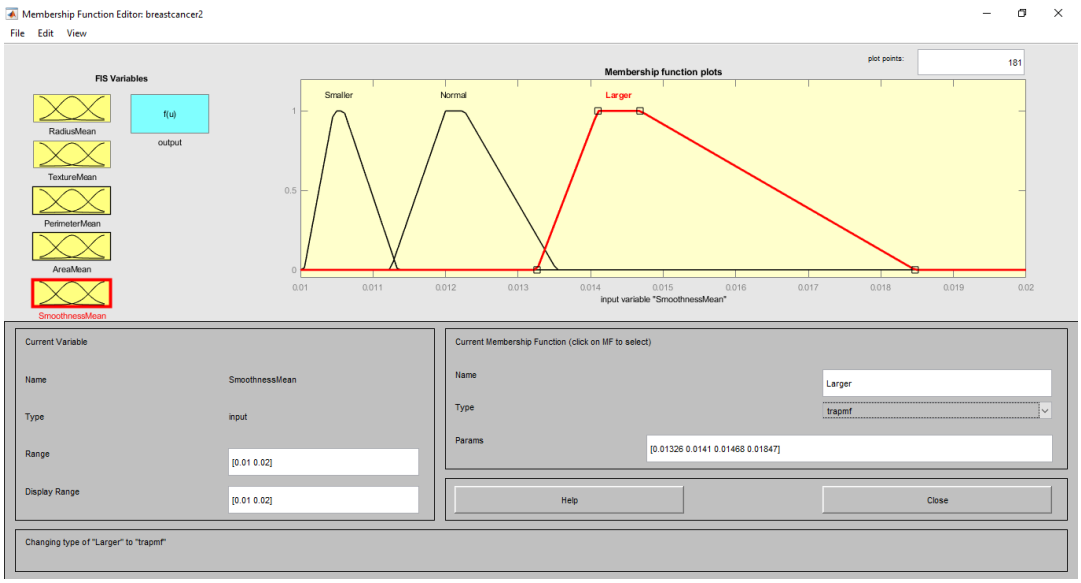


Figure 11: Membership functions of the linguistic variables of and smoothness mean input

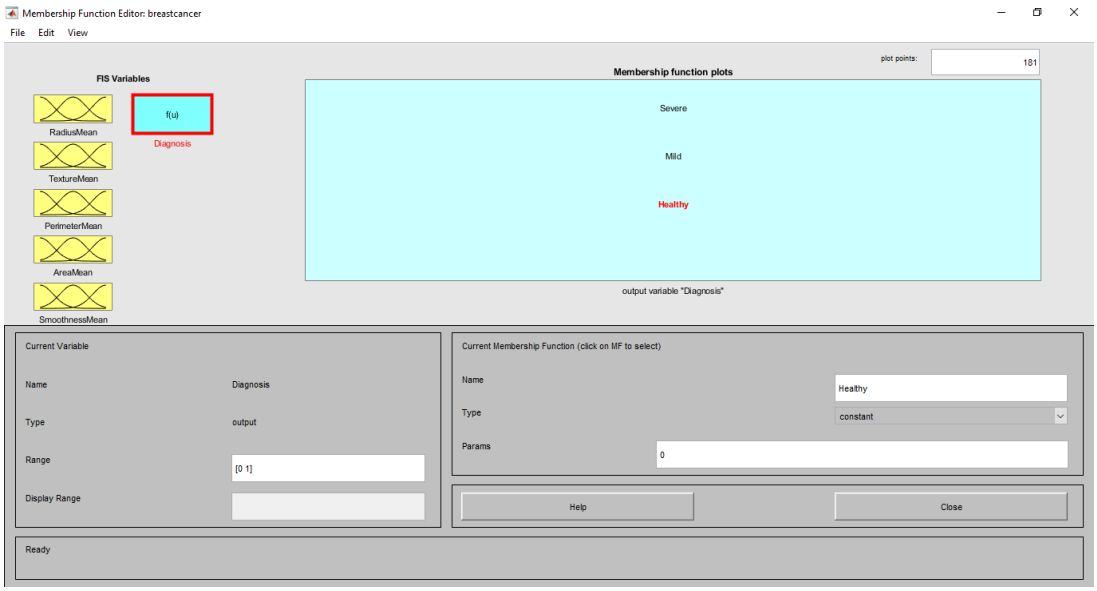


Figure 12: Membership functions of the linguistic variables output feature

Fuzzy rules layers

Fuzzy rules are generated at this layer called the knowledge base of predicates. This is because it contains all possible combinations of all fuzzy values of the system inputs for which a logical AND operation has been performed. In fuzzy logic, the universal set Y looks like this:

Y→[0,1] is called the discourse universe, or simply the universe. The implicit Y→[0,1] is shorthand for the IF-THEN rule.
"If y is in Y, then its MF is μY(y) in [0,1]." where $\mu Y(x)$ is the membership function of y. Universe Y can contain either discrete or continuous values.

The neurons in this layer therefore represent the fuzzy rules of the system, and the number of neurons equals the number of fuzzy rules. The main function of the neurons in this layer is to perform a logical AND operation on the results of their respective input characteristics of the system and pass the output to the next layer. Below is an example of a fuzzy rule.

Inference Layer

In this layer, neurons identify triggered rules that correspond to a set of system input features. A neuron therefore represents an output member set, and each neuron ANDs all input features. Therefore, each neuron's output represents an extension of its input rule. Figure 13 shows how each neuron ANDs all its input features.

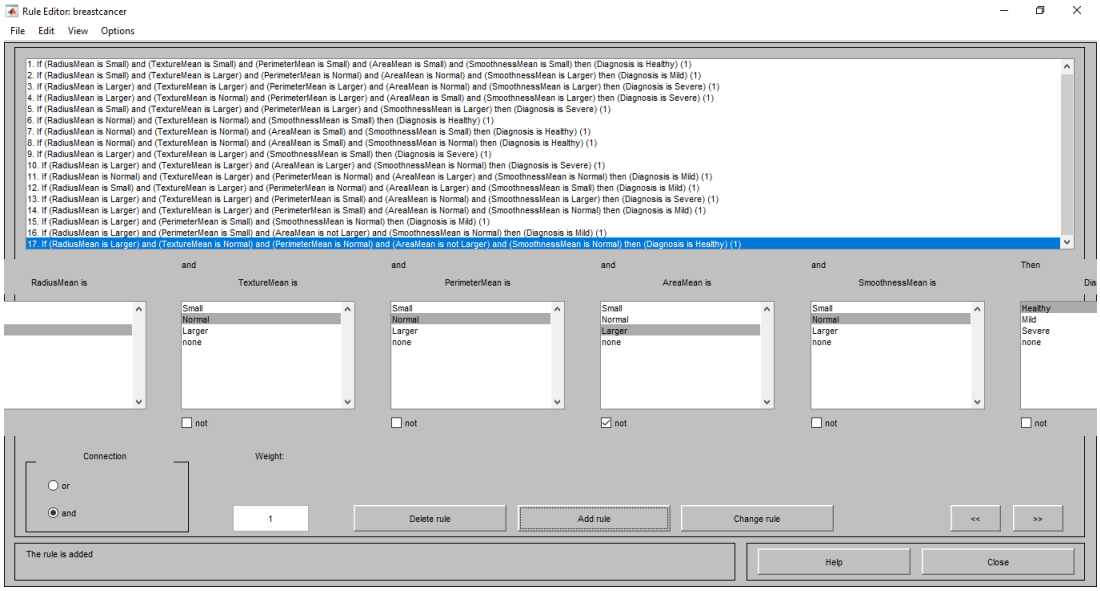


Figure 13: Neuron combines all input functions with an AND operation.

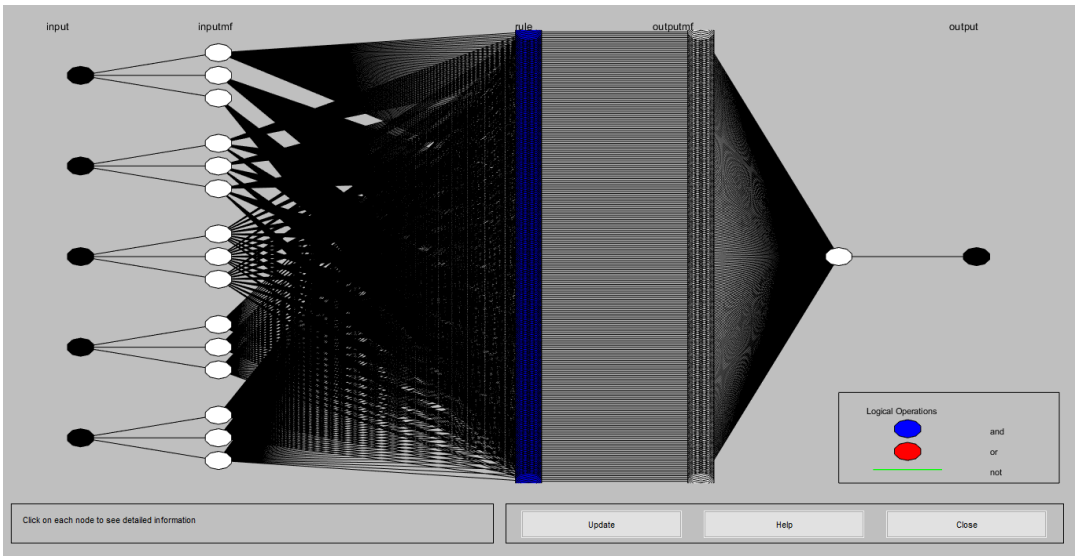


Figure 14: Neuro-Fuzzy Expert System for Diagnosis of Breast Cancer

In this study, centroids, called centroids or centroids, are used for defuzzification. where z is the output feature and (z) is the membership function of the aggregate fuzzy set A associated with z. The centroid method defuzzifies the diagnostic results of the system, i.e. the indeterminate values of the system's output, into very crisp values. Figure 15 shows the defuzification layer of the system.

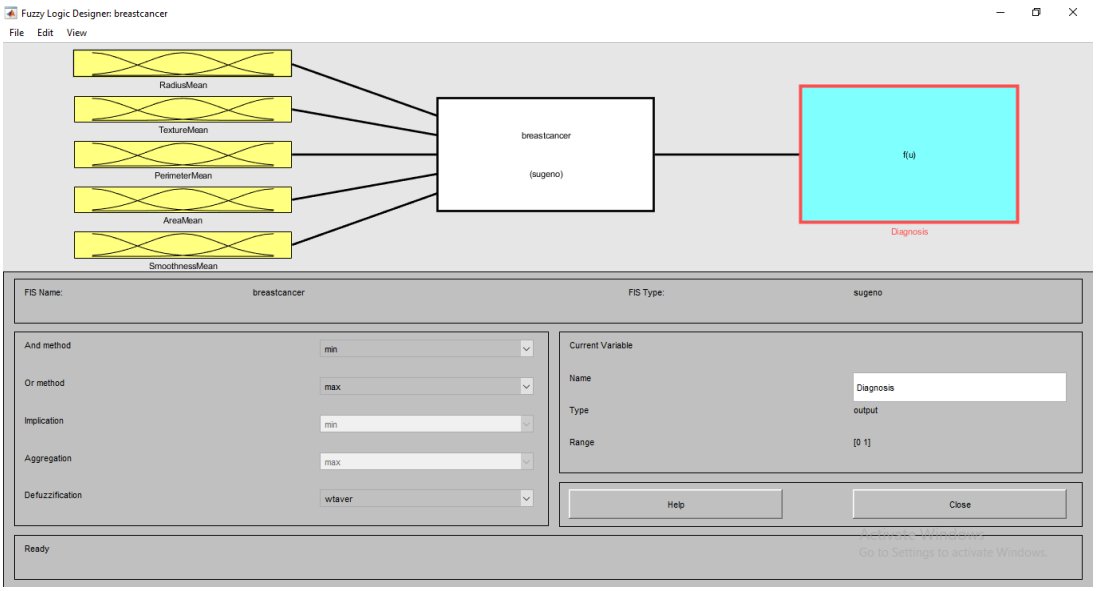


Figure 15: Defuzzification Layer

System performance evaluation

A breast cancer expert system developed in this study has been carefully evaluated to determine its accuracy and efficiency. The system was used to diagnose breast cancer cases from 100 randomly selected instances of the Wisconsin breast cancer diagnostic data set, and only the top five random Gini-based importance features were Considered. Features include radius averages, texture averages, perimeter averages, area averages, and smoothed averages. Figures 16, 17, and 18 show how the system diagnoses breast cancer based on the three linguistic variables, which include Healthy, Mild, and Severe.

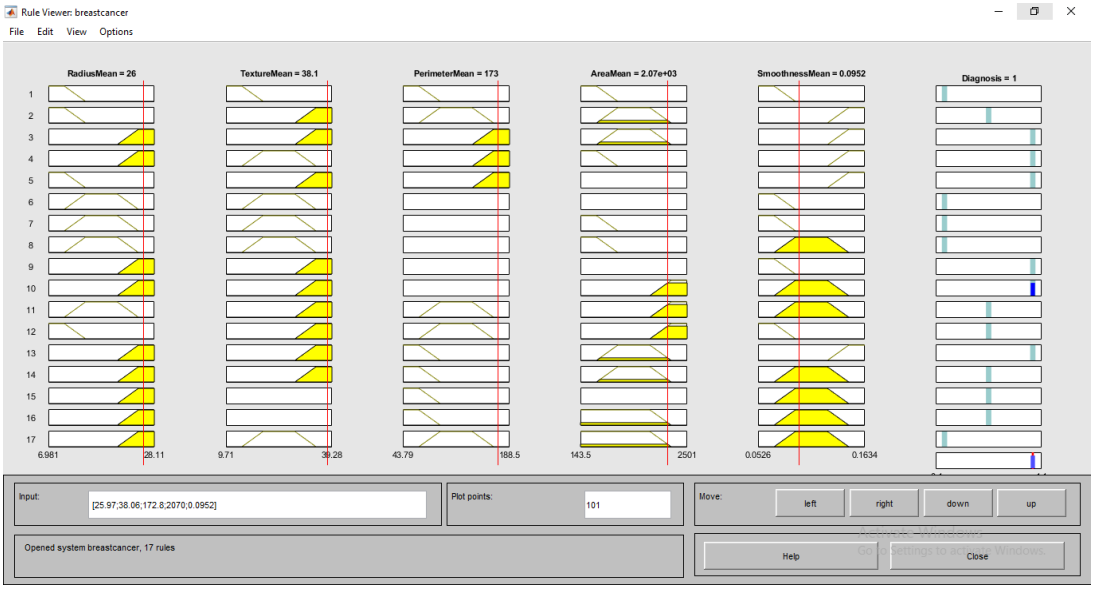


Figure 16: Severe Cases Diagnoses

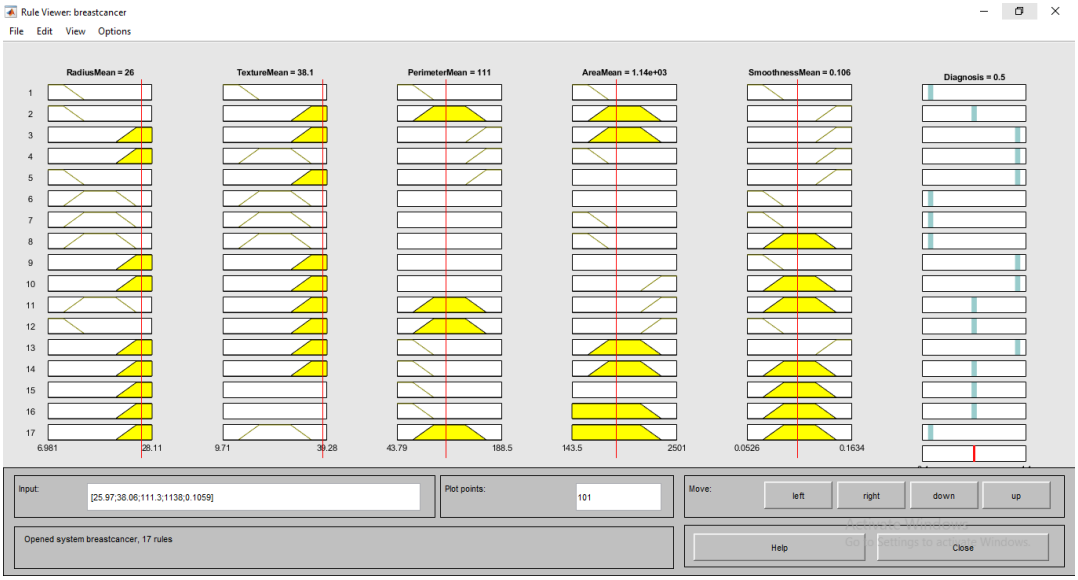


Figure 17: Mild Cases Diagnoses

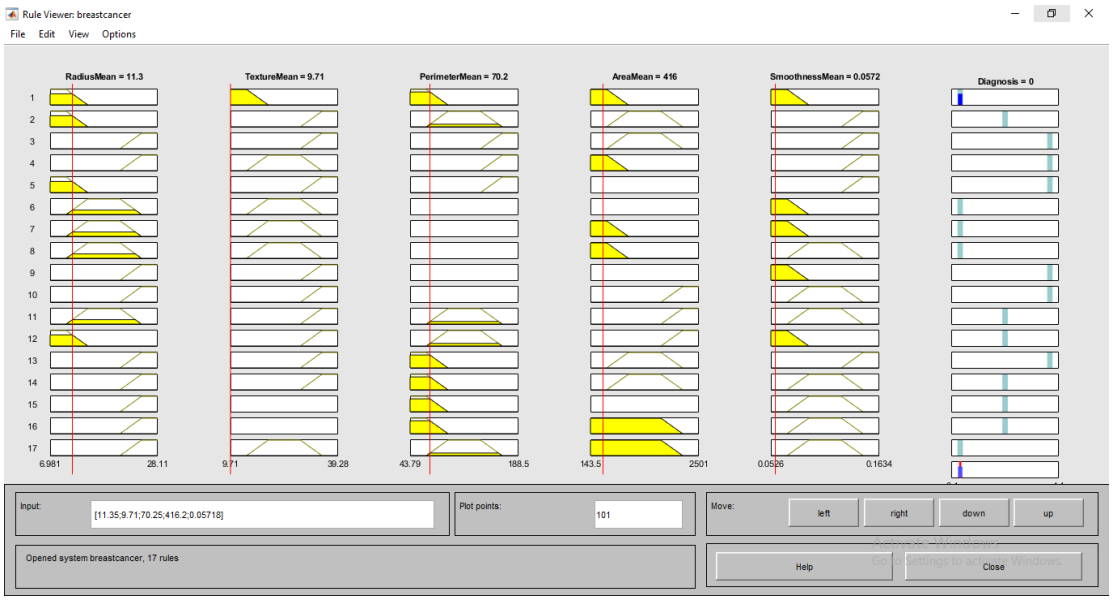


Figure 18: Health Cases Diagnoses

Table 3 shows the results of breast cancer system diagnosis based on healthy, mild, and severe breast cancer cases compared with 100 randomly selected cases from the Wisconsin breast cancer diagnostic dataset.

Table 3: Breast Cancer Diagnosis Outcomes

Class	No. of instances	No. of corrected prediction	No. of wrong prediction
Healthy	31	30	1
Mild	40	39	1
Severe	29	28	1
Grand Total	100	97	3

This system was used to diagnose breast cancer cases based on the following performance evaluation techniques.

i. Accuracy: It is used to determine the efficiency of the system based on the proportion of suspected breast cancer patients who were being diagnosed by the system correctly compared to the total number of cases available.

ii. Sensitivity: It is used to determine the efficiency of the system based on the proportion of mild and severe cases in breast cancer patients who were being diagnosed by the system correctly compared to the total number of positive cases.

iii. Sensitivity It is used to determine the efficiency of the system based on the percentage of healthy cases in breast cancer patients who were being diagnosed by the

system correctly compared to the total number of negative cases in breast cancer patients.

Table 4: System performance evaluation

Accuracy	Specificity	Sensitivity
96.77 %	97.10%	96.77%

Table 4 shows the performance evaluation results of the expert system. The system is shown to achieve 96.77% accuracy for the ability to correctly diagnose healthy, mild and severe cases, and ability to diagnose the mild and severe cases in breast cancer patients correctly, the system achieved a sensitivity of 96.77% and also achieved a specificity of 97.10% in its ability to correctly diagnose healthy cases in breast cancer patients.

Conclusion

Breast cancer is one of the most common cancer types and one of the deadliest cancer types after lung cancer. Cancer is the most common cancer in women worldwide, accounting for approximately 12% of all new cancer cases and 25% of all cancers in women in Nigeria, a population of approximately 187 million. However, the diagnostic process for most fatal diseases such as breast cancer, coronary artery disease, diabetes, and water-borne diseases is complex and ambiguous, so the conventional clinical diagnostic process for diseases is often fraught with uncertainty and ambiguity. . In this study, a neurofuzzy expert system for breast cancer diagnosis using a Gini exponential random forest-based feature importance measurement algorithm was developed to address the uncertainties and ambiguities commonly associated with breast cancer diagnosis and superimpose relieved the heavy burden of the overlay of the network nodes of fuzzy neural network. The system provides promising solutions of how to deal uncertainty and vagueness often associated with the clinician dataset and decision making. The system also assist the healthcare workers in diagnosing and predicting breast cancer in its early stage, be a complementary solution to conventional technique for diagnosing breast cancer in

various hospitals /clinics and also serve as diagnostic help tool to fresh healthcare workers in the hospitals and clinics respectively.

Acknowledgments

This work was supported by the Tertiary Education Trust Fund, Nigeria (TETFUND), as an Institution Based Research Fund (IBR) for Gombe State College of Education and Legal Studies, Nafada, Gombe State, Nigeria

Conflict of interest

The authors declare they have no competing interests

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