

Development and Validation of a Type 2 Fuzzy Expert System for Breast Cancer Diagnosis and Treatment Recommendation

Elias Ayinbila Apasiya

elias.apasiya@bolgatu.edu.gh

Prof. Peter Awon-Natemi Agbedemnab

Research Article

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Dr. Elias Ayinbila Apasiya

Bolgatanga Technical University

Post Office Box 767

Bolgatanga,

Upper East Region, Ghana.

West Africa.

Email: elias.apasiya@bolgatu.edu.gh

apasiyaelias@yahoo.com

+233024664089

Prof. Peter Awon-Natemi Agbedemnab

University of Technology and Applied Sciences

Navrongo, Bolgatanga, Upper East Region, Ghana.

Email: pagbedemnab@cktutas.edu.gh

Abstract

Breast carcinoma has been a serious health issue globally, especially in developing countries where specialist care is tough to get, and diagnosing the disease can be tricky. Traditional methods like mammograms, ultrasounds, and biopsies help find it but often face issues with consistency and interpretation errors. This study came up with a better system for diagnosing and treating mammary carcinoma using Type-2 Fuzzy Logic, powered by a Mamdani Deduction Engine and Python. The knowledge from experts was turned into fuzzy variables and IF-THEN rules to help with both diagnosis and treatment recommendations. To test it, they used 100 hospital cases and standard performance checks. The results were impressive, showing 98% accuracy, 86% precision, complete sensitivity and recall, 85.1% specificity, and an F1-score of 92.47%. Compared to what's out there, this new model not only diagnoses better but also guides treatment. The study wraps up by saying that this logic type is great for dealing with uncertainty in medical diagnoses and helps in making decisions. It's a useful and easy-to-understand tool that can improve diagnosis accuracy and patient care results.

Keywords: Breast Cancer, Fuzzy Expert System, Type-2 Fuzzy Logic, Mamdani Inference Engine, Clinical Decision Support System, Diagnosis, Treatment Recommendation.

1.0 Introduction

Nevertheless, breast cancer still remains the most devastating public health problem among females throughout the world, imposing a considerable load on healthcare services after decades of development of medicine. Indeed, breast cancer is the most common cancer among women and one of the leading causes of death from cancer across the world (Abdelwahed et al., 2015). In accordance with the data on global cancer statistics, about 14.1 million cases of cancer were detected worldwide during 2012, which resulted in more than 8.2 million deaths (Boughorbel et al., 2016). As reported by the WHO, cancer was responsible for about 8.8 million deaths in 2015, with a considerable share of those being due to breast cancer (WHO, 2017). Recent statistics show that breast cancer is the most diagnosed cancer type, surpassing lung cancer and causing over 2.3 million new cases each year and about 685,000 deaths (Sung et al., 2021). At present, the risk of a woman suffering from breast cancer throughout her lifetime is equal to about 12%, with the probability increasing dramatically with age, independently of any family history of the disease (Bhardwaj & Tiwari, 2015). Despite the progress made through treatment, which has resulted in better survival chances, early and proper diagnosis is the best way to prevent deaths since successful treatment is highly correlated with early detection before the progression and metastasis of cancer (Daliri, 2012; Polat & Gunes, 2008). Unfortunately, uncertainties about diagnosis, late arrival, lack of accessibility to specialists, and difficult interpretation of clinical risk factors have posed problems for medical professionals, especially in developing nations like Ghana.

In order to overcome these challenges, numerous CI techniques have been employed by researchers, ranging from machine learning algorithms to decision support systems and expert systems based on fuzzy logic. Traditional diagnostic procedures, including mammography, fine

needle aspiration cytology (FNAC), ultrasound, CT scan, and biopsy, have played an important role in diagnosing breast cancer; however, their efficiency have been limited by the breast tissue density, variation in images, subjectivity, and uncertainty in diagnosis (Chen et al., 2011; Feng et al., 2012; Lu et al., 2014). Fuzzy expert systems can be viewed as promising tools since they manage uncertainty and mimic human reasoning. Guo and Neagu (2005) showed the importance of fuzzy logic for decision support systems when solving complicated biological classification problems. Latha et al. (2013) successfully applied fuzzy logic approaches to breast cancer prediction using volatile biomarkers. Okikiola et al. (2019) were able to improve the efficiency of their fuzzy expert system and increase diagnostic accuracy from 80% to 90%. Despite these improvements, many current models suffer from their dependence on the use of Type-1 fuzzy modelling, failure to sufficiently incorporate the expertise of clinical professionals, limitations regarding treatment recommendations, poor uncertainty handling, low interpretability, and lack of validation via real-world clinical data sets. In addition, most studies concentrated only on the problem of diagnosis without incorporating any component of treatment recommendation within the framework of a clinical decision support system. After years of study and advancements in intelligent healthcare systems, the need for an effective type 2 fuzzy expert system which can handle both diagnosis and treatment recommendations has not yet been addressed.

To surmount such challenges, the current study suggests an Enhanced Fuzzy Expert System (EFES) for mammary carcinoma detection and management that employs Type-2 fuzzy theory and expert system techniques. In the suggested approach, expert knowledge gathered from oncologists and radiologists is used together with fuzzy inference systems to account for the uncertainty involved in breast cancer detection. The expert knowledge was translated into linguistic variables, fuzzy membership functions, and rules appropriate for use in Mamdani engines. The constructed

system was then tested using clinical examples provided by hospitals. In particular, the goals of the current research are to (i) develop and design a Type-2 Diagnostic Fuzzy Algorithm to diagnose and treat mammary carcinoma; (ii) develop a clinically validated knowledge base based on expert-derived fuzzy IF–THEN rules; (iii) conduct a validation of the proposed system using actual clinical data; and (iv) produce an intelligent decision support tool that will be able to help health care practitioners make more accurate diagnoses and treatment plans and improve the outcomes of their work with patients. The application of expert knowledge and advanced fuzzy reasoning techniques aims at lowering breast cancer deaths among women.

2.0 Methodology

The study employed a combination of primary expert knowledge, hospital-derived clinical test cases, and secondary scientific information. Primary expert knowledge was obtained from medical professionals, including oncologists and radiologists, through structured, unstructured, and direct-rating approaches. The expert information was used to identify clinically relevant breast cancer risk factors and to construct and validate the Type-2 fuzzy membership functions and IF–THEN rule base.

For system testing and validation, 100 clinical test cases were randomly selected from Upper East Regional Hospital. These cases constituted the principal evaluation dataset for the proposed systems.

Secondary information was obtained from peer-reviewed literature, clinical guidelines, and related scholarly sources accessed through PubMed, IEEE Xplore, ScienceDirect, and SpringerLink. This information was used to support the identification and classification of breast cancer risk factors and to inform the development and refinement of the fuzzy knowledge base, membership

functions, and clinical rules. The approach applied in this research has been through the knowledge engineering and clinical decision support framework involving six major steps: knowledge acquisition, knowledge validation, fuzzy knowledge modelling, rule base formation, implementation, and performance evaluation. This framework has been established to ensure that the clinical experience is systematically translated into a reliable Type-2 knowledge base for diagnosis and recommendation of treatment for breast cancer. To determine the Membership Function (MF), elicited data were gathered to establish the upper and lower bounds. From this, the system parameters were synthesised. The outputs from Type-2 fuzzy logic and the Mamdani Deduction Algorithm determine the malignancy status and suggest treatments. This was carried out using Python algorithms. The procedure is illustrated in Figure 2.1

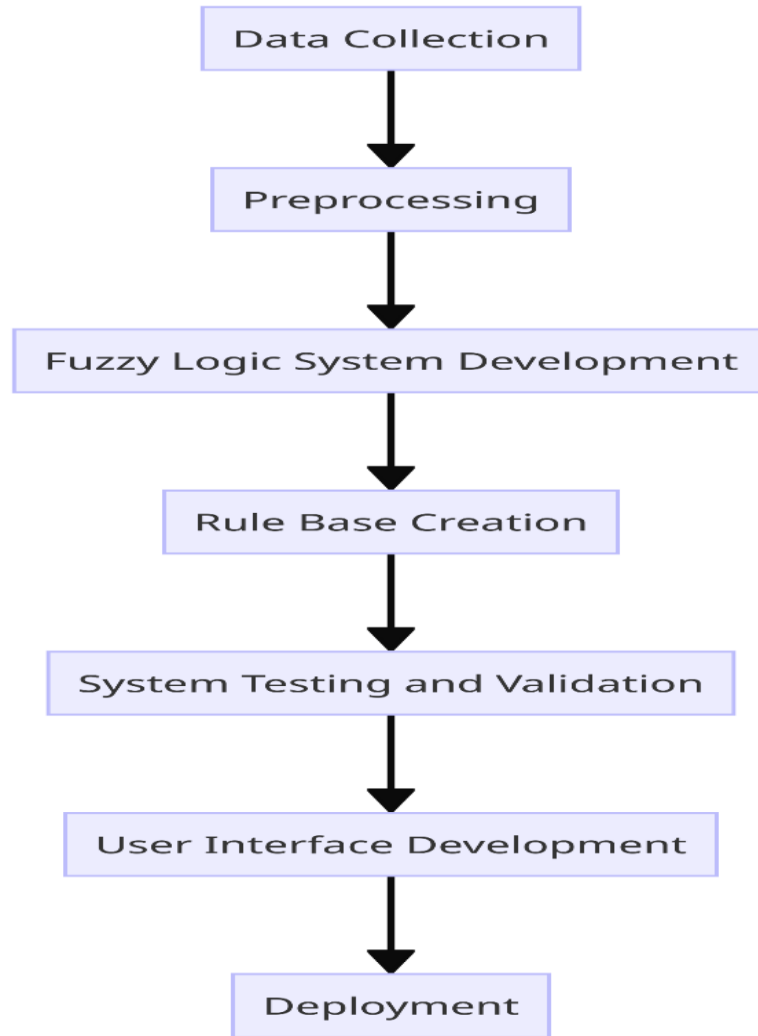


Figure 2.1: Sequence Diagram of the Algorithm

2.1 Data Gathering

In this section, the data needed to design the system were collected and explained. Expert knowledge obtained from clinical experts who have experience in diagnosing and treating patients with breast disease was central to the fuzzy knowledge base framework and architecture. Knowledge acquisition entailed using structured interviews and questionnaires with domain experts such as radiologists and oncology experts.

To identify experts who have many years of experience in treating breast cancer, as well as the knowledge regarding diagnosing breast cancer protocols, an expert sampling procedure was

adopted. Information from the experts served as the source of data regarding the important variables of diagnostics and prognosis, including age, tumour size, symptoms of lump, family history, and severity of symptoms.

In order to ensure that the knowledge collected was reliable, a multi-expert validation technique was applied. The answers of the experts were compared to find out how similar their answers were. In case there was some inconsistency, clarification sessions were carried out to arrive at a common consensus. In addition to this, bias was reduced through combining opinions of the experts, not depending on one source of knowledge. Where variation occurred, the interpretations that were most frequently accepted became part of the fuzzy rule base. This helped to make sure that the system created was a reflection of a balanced clinical approach. The process of converting the expert knowledge into fuzzy rules was systematic. The clinical statements were expressed in fuzzy set concept and then translated into IF...THEN... rules for the use of the Mamdani and Sugeno Fuzzy deduction algorithms. The checking of rule consistency made sure that there were no conflicting rules in the knowledge base. These rules were reviewed and validated by the domain experts. Furthermore, the fuzzy rule base was checked through the simulation of some sample patient data.

2.2. Primary data source

In this study, the method of mixed methodology was employed to collect and analyse the data. By using both methodologies, data validity could be guaranteed in the process of creating the Smartphone Intelligent Decision Support System (SIDSS). The structured and unstructured approach was used in order to gather factual and informational data from the expert medical practitioners (oncologists and radiologists), whose expert knowledge was required in making diagnoses and managing breast cancer cases. Obtaining data from experts when developing an

expert system is an appropriate practice because it is essential for rule-based information (Hasan & Shil, 2022).

Also, another data collection method that was used was the direct rating method, where the medical experts were permitted to allocate a standardised mathematical value to already delineated linguistic variables and fuzzy MFs. A direct rating method is an information-gathering strategy in which the researcher supplies the respondent with a collection of descriptors and variables and expects the respondent to rate or score every item on a defined measurement scale depending on their experience or judgment. A direct rating method allowed for systematic capturing of inferred insight and at the same time, aided in the quantification of expert unpredictability, which is more important in domains involving building fuzzy modes (Regees, 2022).

They were asked to assign a number to the descriptors, including low, medium, and high, on a continuous scale ranging from 0 to 10. For any of these risk factors, the expert assessed the extent of correlation between the factors and breast cancer development based on their experience. These numerical values denote the opinions on breast risk factors in the clinical environment. The study used the lowest and highest numbers to define the footprint of unpredictability for each interval Type-2 fuzzy set, which helped to capture each interval Type-2 fuzzy set. By utilising this methodical approach, where expert insight was formalised, it was possible to apply computational reasoning, consistent with fuzzy system design practices in healthcare (Mendel, 2017).

2.3. Secondary Data Sources

To augment the basic facts obtained from clinical experts, the study carried out a pragmatic assessment of earlier research work as well as clinical data which were pertinent to malignancy identification and survival prediction. To accumulate the required information, credible domains

including **PubMed**, **IEEE Xplore**, **ScienceDirect**, and **SpringerLink** were searched for peer-reviewed journal articles, clinical guidelines, and case reports.

Literature from these sources authenticated the information on risk factors of breast cancer, expert systems and fuzzy logic. Particularly, these studies were related to fuzzy logic, artificial intelligence, or expert systems in medical diagnostics. The secondary information was used to support the creation of fuzzy rules and refine the membership functions, as it provided an in-depth understanding of symptom severity, disease progression, and medical decision-making patterns. The literature additionally assisted in the classification of the 18 linguistic variables that the system used. The rigorous development ensured that the system is anchored in ongoing medical practices and resonates with evidence-based knowledge. By incorporating these authoritative sources, the system was grounded in current clinical practices and aligned with evidence-based knowledge.

2.4 Data type

The facts that were considered in the scientific process encompassed qualitative expert judgment, which was converted into quantitative fuzzy values as a way to build a Type-2 fuzzy expert algorithm. In a more precise sense, 18 linguistic determinants of breast cancer were considered. The variables include: age, age at first conception, family history, radiation prone, family planning medication, menarcheal age, menopausal age, drinking hard liquor, genetic change inheritance, past information of the individual, hormones, thick breast lump, body mass index (BMI), and postmenopausal hormone treatment. This hybrid type of data, qualitative in source but quantitative in expression, helped the researcher to build MFs for every output. Because the linguistic variables were transformed to numerical values, it permitted the ES to process the imprecise, uncertain, or ambiguous information that was gathered from the expert respondents.

2.5 Programming Language Used

The systems were developed using the Python Streamlit framework. The reason behind selecting the framework is the fact that the Python Streamlit framework provides simple deployment, meaning that the application can be easily shared with other people without setting up any servers. Again, an instantaneous response could be obtained using the Python Streamlit framework algorithm. The specialists will be able to enter their details, and the algorithm will give immediate feedback.

2.6: Software Development Life Cycle (SDLC)

The illustration in Figure 2.2 is a structured SDLC process. The SDLC process is relevant to this research because it provides a structure and process that guarantees the Expert System is medically reliable, technically robust, clinically applicable, scalable, and sustainable. The SDLC process in the study ensures that the developed system is more than just a technical solution, but a reliable and effective medical decision support system for breast cancer diagnosis and prognosis. Figure 2.2 is the SDLC process flow diagram that shows all the processes involved in developing the software solution, the activities, and the procedures. In addition to this, it highlights the need for risk management and also provides project details such as timeline, technologies, and testing parameters. The study made use of SDLC because it gave the researcher a structured approach to building the system. Given that it helps to clearly delineate system and medical requirements, errors were reduced in the process of developing the system. SDLC is suitable for testing and validating systems, which are essential for accuracy and reliability (Kumar & Hiremath, 2023).



Figure 3.2 A General Purpose SDLC

2.7 Expert Knowledge Acquisition

Expert knowledge was elicited from purposively selected oncologists and radiologists through structured interviews, guided questionnaires, and direct-rating exercises. The objective was to capture clinical reasoning patterns, diagnostic criteria, treatment recommendations, and risk assessment procedures associated with breast cancer diagnosis.

2.7.1 Knowledge Validation and Consistency Checking

Elicited knowledge was validated using comparisons between experts and consensus building sessions. Redundancies, contradictions, and inconsistencies in knowledge were excluded. The opinions of the experts were collated to reduce biases and increase reliability. The analysis of rule consistencies followed thereafter.

2.7.2 Type-2 Fuzzy Knowledge Modelling

Validated clinical knowledge was transformed into linguistic variables and represented using Type-2 fuzzy membership functions. The Type-2 fuzzy representation was selected because of its superior capability to model uncertainty and imprecision in clinical information compared with conventional Type-1 fuzzy systems.

2.7.3 Rule Base Construction

Clinical reasoning statements were encoded into fuzzy IF–THEN production rules. The generated rules formed the system's knowledge base and were structured to support both diagnostic reasoning and treatment recommendation processes.

2.7.4 Inference Engine Development

The Mamdani inference mechanism was employed to process the fuzzy rules and derive diagnostic conclusions. Fuzzification, rule evaluation, aggregation, and defuzzification processes were implemented to generate clinically interpretable outputs.

2.7.5 System Validation and Performance Evaluation

The system was developed and tested on 100 breast cancer cases sourced from hospitals and performance measures used to evaluate the performance included accuracy, precision, sensitivity, specificity, recall and F1-score, while comparison tests were carried out to determine the efficacy and applicability of the system. The system knowledge base was built using expert knowledge and variables sourced from the literature on clinical cases. The largest number of cases was in the age range 51-60 years (30%), and this is clinically plausible as breast cancer incidence increases with age, as indicated in Table 2.1.

Simulation test cases were randomly selected from four hospitals, including Bolgatanga Regional Hospital, Tamale Teaching Hospital, Tongo District Hospital and The Rock Hospital, using structured, unstructured and direct ratings methods with involvement of the experts. Approvals for ethical practices in data gathering and testing were obtained using the procedures set by the institution.

2.7.6 Demographic Distributions of Cases

Table 2.1 Age-group breakdown of cases.

Age Group	Cases	Percentage
18–40 years	20	20%
41–50 years	25	25%
51–60 years	30	30%
61–70 years	20	20%
71+ years	5	5%

Table 2.2: Risk Score Distribution table

Risk score	Cases	Percentage
0–4 points	20	20%
5–9 points	25	25%
10–14 points	25	25%
15–19 points	20	20%
20+ points	10	10%

Table 2.3: Diagnostic Distribution of Cases

Diagnosis Type	Cases	Percentage
Recurrent Breast Cancer	15	15%
Angiosarcoma	5	5%
Paget's Disease	15	15%
LCIS	10	10%
DCIS	15	15%
Invasive Lobular Carcinoma	15	15%
Inflammatory Breast Cancer	25	25%

Table 2.3 shows how the cases were distributed across several breast cancer categories.

Clinical epidemiology was not the main focus of this study; instead, expert-system development and performance evaluation. The inclusion and exclusion criteria were not stated as would normally be expected in a clinical study, despite the thesis clearly reporting the 100 hospital-derived test cases and their demographic distribution.

2.8 Proposed System Architecture

Numerous recommendations pertain to each kind of breast cancer, necessitating accurate diagnosis. The system's architectural structure is designed during the fuzzy model development stage. The development involves delineating the model's framework, components, elements, software, and facts to fulfil established standards. The software was designed to be easy to use,

with clear instructions and simple operations suitable for clinical practice. The software was designed using Python. The data objects, the key facts to be written, their nature of storage, the results of the model, the software and applications of the model, and the specifications of the various details determination strategies are all included in the system design. The flow design in Figure 2.3 outlines the framework and processes for developing the expert scheme.

Most of the commendations are associated with all sorts of breast disease, requiring an accurate analysis. The expert model algorithm is developed in the expert modelling development process. The process entails the identification of the model algorithm, the different components, interfaces, and facts necessary to achieve reliable values. The interfaces were created with the help of the Python programming language. The Windows operating system deals with the analysis part. It involves an elaborate description of the different values to be considered, the input data to be kept, how the data will be kept, the expert model display interface, the expert applications, and the needs of different information handling processes. The Algorithm and Processes of the Proposed Expert Model are presented in Figure 3.4. Such values provide information on how the Expert model interprets multifaceted and ambiguous medical information to come up with good advice for the best and correct diagnosis of breast growth.

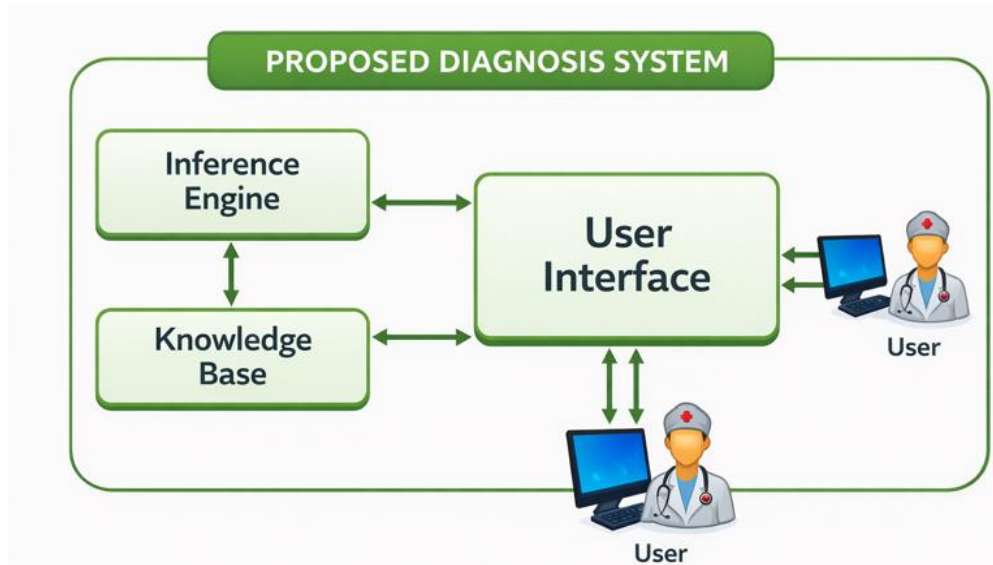


Figure 2.4: Diagram of the Proposed Fuzzy Expert Model

2.8.1 User Interface

Clinicians and authorised users can interact with the improved mobile and window-based fuzzy expert system for breast cancer diagnosis and prediction through the User Interface (UI), which offers a user-friendly and interactive environment. It is made up of neatly arranged displays that facilitate clinical workflows, such as login, patient data entry, diagnostic results, case history, and settings screens. The UI uses basic menus and intuitive navigation to make it easy for users to switch between system functions. A centralised dashboard provides easy access to major functionality as well as diagnostic activity summaries. Structured input forms with dropdowns, validation checks, and guidance prompts ensure that clinical data for fuzzy inference is entered accurately and completely.

Diagnostic and prognostic outputs are given clearly, with accessible linguistic phrases, confidence levels, and graphic summaries to aid in clinical understanding. Usability characteristics, including responsive design, uniform layouts, understandable fonts, and error handling, improve accessibility on both mobile and Windows platforms.

Overall, the user experience stresses simplicity, efficiency, and clarity, allowing users to engage with the system with confidence while also facilitating reliable, rapid clinical decision-making.

2.8.2 The Inference Phase of a Fuzzy Algorithm

Managing the ambiguity and ascertaining the level of cancer growth in the patient is determined by the use of the inference engine. This happens through the application of predefined fuzzy rules to patient input data. The enhanced algorithm would help in ascertaining the time necessary and how urgent it is to find treatment for the type of cancer. Here, the system evaluates the degree of membership of clinical variables across different cancer stages. The Fuzzy Deduction Mechanism uses the Fuzzy reasoning approach to associate variables. It maps input values to fuzzy sets and applies rule-based inference. Since the Inference System generates the fuzzy class outcomes after rule evaluation and defuzzification, which are very necessary for this scientific study work and endeavour, it can be utilised in this situation. Age, breast discomfort, and lump size were all taken into consideration by the membership function. The young, middle-aged, and elderly states were taken into consideration by the age membership function. Age range of 0 to 20 is considered to be young, age 21 to 40 is considered to be middle age and age 41 and above is considered old age. The level of association for cancer disease is classified into mild, modest and severe segregations. The lump size metrics are divided into three segments: small, medium, and huge. There are two categories for the results metrics, which are rate: low and high.

2.8.3 Rule Base and Repository

This is a repository where information obtained from specialists are kept up to date and new information is added for use in the diagnosis process. As a result, the data is retrievable and usable whenever needed. The knowledge base's contents are subject to queries, deletions, and updates.

2.8.4 The Fuzzy Inference Framework

The commands that order information processing are the responsibility of the fuzzy inference system. The IF-THEN commands are utilised in the construction of the expert model to execute the process with the information obtained from the medical professionals. The major types of breast cancer and a lot of diagnostic conclusions were adopted to design the instructions of the model segment of this research.

The membership functions will be determined by using the following ranges;

2.9 Membership degree.

The function $\mu(x)$ characterises the degree of association in a fuzzy aggregation. The degree of association takes a metric x to the level of association in an aggregation, which is normally a figure between 0 and 1. The degree of association determines the level at which a particular value belongs to the function of $\mu_A(x)=1$. The expression shows that the value x is completely an element of the class A . The association level = 1.

The degree of association of $\mu_A(x)$ is considered to govern the extent to which x is part of a vague set A .

$$\mu_A(x) \begin{cases} 0 & \text{if } x \text{ does not belong set } A \\ 1 & \text{if } x \text{ belongs to the set } a \\ \text{some value in } (0,1) & \text{if } x \text{ partially belongs to the set } A \end{cases} \quad (1)$$

The equation shows the level of association between 0 and 1, demonstrating whether x completely, moderately, or doesn't belong to any.

Table 2.4: features of associations

Variables	Fuzzy Categorisation	Array	Dimension/Degree
	Low	[0 – 20]	Membership degree (μ_{Low})
Risk Indicators	Medium	[20 – 50]	Membership degree (μ_{Medium})
	High	[50 – 100]	Membership degree (μ_{High})

$$\mu(x) = \begin{cases} \frac{(b-x)^1; x \leq a}{(b-a)_0; \geq b} & ; a < x < b \end{cases} \quad (2)$$

For very small values ($x \leq 0$), membership is fully “low”, $\mu_{low}(x) = 1$

Values between 0 and 20, membership decreases nearly:

$$\mu_{low}(x) = \frac{20 - x}{20} = 1 - \frac{x}{20}$$

At $x = 0, \mu = 1$

At $x = 20, \mu = 0$

For $x \geq 20$, membership is 0: $\mu_{low}(x) = 0$

$$\mu_{low}(x) = \begin{cases} 1, & x \leq 0 \\ \frac{20-x}{20-0}, & 0 < x < 20 \\ 0, & x \geq 20 \end{cases} \quad (3)$$

$$u(x) = \begin{cases} 0; x \leq a \text{ or } x > c \\ \frac{[x-a]}{[b-a]}; a < x \leq b \\ \frac{[c-x]}{[c-b]}; a < x \leq b \end{cases} \quad (4)$$

$$u_{medium}(x) = \begin{cases} 0, x \leq 20 \text{ or } x > 50 \\ \frac{[x-20]}{15}; 20 < x \leq 35 \\ \frac{[50-x]}{15}; 35 < x \leq 50 \end{cases} \quad (13)$$

$$k(x) = \begin{cases} 0; x \leq a \\ \frac{[x-a]}{[b-a]}; a < x \leq b \\ b < x \end{cases} \quad (5)$$

when $x \leq 50$

the value is:

$$k(x) = 0$$

When $50 < x \leq 100$

The membership increases nearly from 0 to 1

$$k(x) = \frac{x - 50}{100 - 50} = \frac{x - 50}{50}$$

At $x = 50$: $\frac{50-50}{50} = 0$

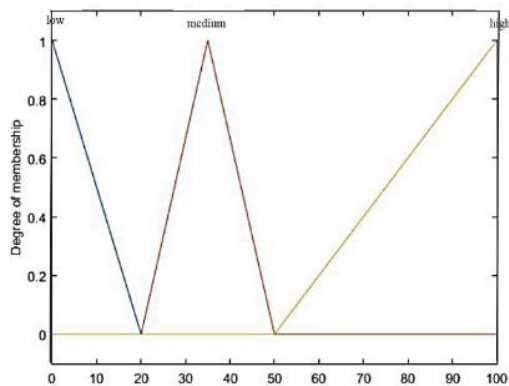
At $x = 100$: $\frac{100-50}{50} = 1$

When $x > 100$

The membership remains at the maximum

$$k(x) = 1$$

$$k(x) = \begin{cases} 0, & x \leq 50 \\ \frac{x-50}{50}, & 50 < x \leq 100 \\ 1, & x > 100 \end{cases} \quad (6)$$



Level of association risk features.

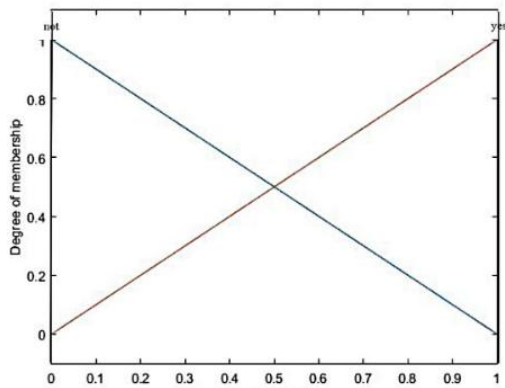
Table 2.5: Tumour association

Variables	Ambiguous Sets	Array	Degree
Lamp size on	1. No	[0—1]	[0—1]
breast	2. Yes		[0—1]

$$u(x)=\begin{cases} 1; x \leq a \\ \frac{[b-x]}{[b-a]}; a < x < b \\ 0; x \geq b \end{cases} \quad (7)$$

$$u(x)=\begin{cases} 20; x \leq 0 \\ \frac{[1-x]}{[2-0]}; a < x < b \\ 0; \geq 20 \end{cases} \quad (8)$$

$$U_{\text{high}}(x)=\begin{cases} 1; x \leq 0 \\ \frac{[x-0]}{[1-0]}; 1 < x < 1 \\ 1 \geq b \end{cases} \quad (9)$$



Level of association of swelling

Table 2.6: Breast Magnitude

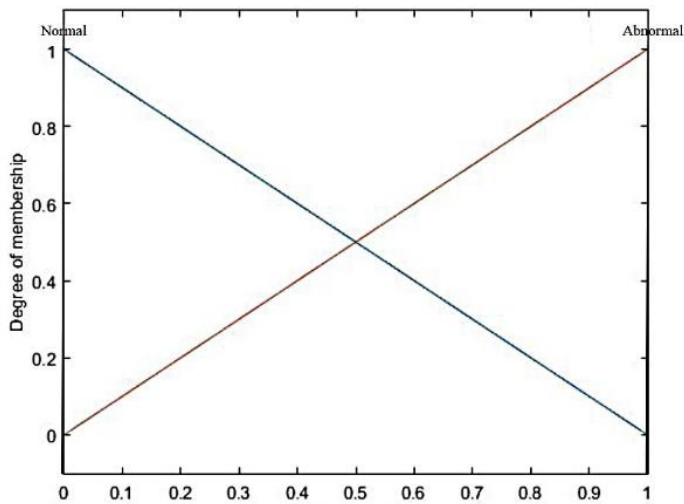
Variables	Fuzzy Sets	Range	Degree
	2. Normal	[0—1]	[0—1]
	2. Abnormal		[0—1]

$$u(x)=\begin{cases} 1; x \leq a \\ \frac{[x-a]}{[b-a]}; a < x < b \\ 0 \geq b \end{cases} \quad (10)$$

$$u_{\text{normal}}(x)=\begin{cases} 1; x \leq 0 \\ \frac{[1-x]}{[1-0]}; 0 < x < 1 \\ 0 \geq 1 \end{cases} \quad (11)$$

$$u(x)=\begin{cases} 0 ; x \leq a \\ \frac{[x-a]}{[b-a]}; a < x < b \\ 1; b \geq x \end{cases} \quad (12)$$

$$(x)=\begin{cases} 0 ; x \leq 0 \\ \frac{[x-0]}{[1-0]}; 0 < x < 1 \\ 1; x \geq 1 \end{cases} \quad (13)$$



Level of association for the magnitude

Table 2.7: Burning sensation

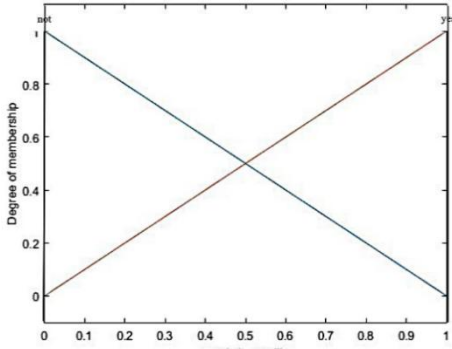
Variables	Ambiguous Sets	Array	Degree
Pain in the breast	1. No	[0—1]	[0—1]
	2. Yes		[0—1]

$$u(x) = \begin{cases} 1, & x \leq a \\ \frac{b-x}{b-a}, & a < x < b \\ 0, & b \geq b \end{cases} \quad (14)$$

$$u_{\text{none}}(x) = \begin{cases} 1 & ; x \leq a \\ \frac{[1-x]}{[1-0]} & ; a < x < 1 \\ 0 & ; b \geq 1 \end{cases} \quad (15)$$

$$u(x) = \begin{cases} 0 & ; x \leq a \\ \frac{[x-a]}{[b-a]} & ; a < x < b \\ 1 & ; b \geq x \end{cases} \quad (16)$$

$$(x) = \begin{cases} 0 & ; x \leq 0 \\ \frac{[x-0]}{[1-0]} & ; 1 < x < 1 \\ 1 & ; b \geq 1 \end{cases} \quad (17)$$



Level of association of discharge

Table 2.8: Malignancy Degree

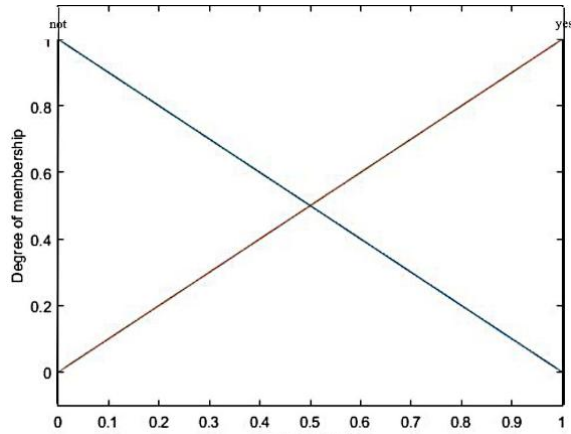
Variables	Ambiguous Sets	Array	Degree
Cancer Rate	1. No	[0—1]	[0—1]
	2. Yes		[0—1]

$$u(x) = \begin{cases} 1, & x \leq 0 \\ 1 - x, & 0 < x < 1 \\ 0, & x \geq 1 \end{cases} \quad (18)$$

$$u_{\text{none}}(x) = \begin{cases} 1, & x \leq a \\ \frac{b-x}{b-a}, & a < x < b \\ 0, & x \geq b \end{cases} \quad (19)$$

$$(x) = \begin{cases} 0, & x \leq a \\ \frac{[b-x]}{[b-a]}, & a < x < b \\ 1, & x \geq b \end{cases} \quad (20)$$

$$\mu(x) = \begin{cases} 0 & ; x \leq a \\ \frac{x-a}{b-a} & ; a < x < b \\ 1 & ; x \geq b \end{cases} \quad (21)$$



Level of association of bump protrusion

2.10 The Mamdani Mechanism Deduction in Fuzzy System

The association function conceptualises the flow variables in the expert model, offering the level of association to varied dialectical ideas based on exclusive arithmetical values. These ambiguous variables, as well as levels of association performance, could be used in expert models for rationalisation and decision-making fields connected to the healthiness of the breast, in which flow variables are used to show ambiguous information.

Table 2.9: Risk Factor description and valuation

FEATURE	DESCRIPTION
Age	Age is a feature
Age at the initial catamenial period	The risk factor rises with the age of the catamenial cycle
Last catamenial cycle Age	Long-term exposure to estrogen and progesterone hormones may contribute to the increased risk.
Age at first gestation	Women who become pregnant below age 20 have less level of developing breast cancer compared to those who become pregnant later in life.
Weight	Females' weight after menopause makes them have high chances of getting breast cancer.
Women who smoke	Females who smoke have an increased chance of getting breast cancer.

2.11 Fuzzy Inference Rules

Figure 3.5 illustrates the nature of inference rules guiding the fuzzy logic operations for the expert system. The fuzzy rules diagram for breast cancer diagnosis explains how the various rules and variables have been brought together by using the rule conditions to evaluate and diagnose the breast cancer malignant level.

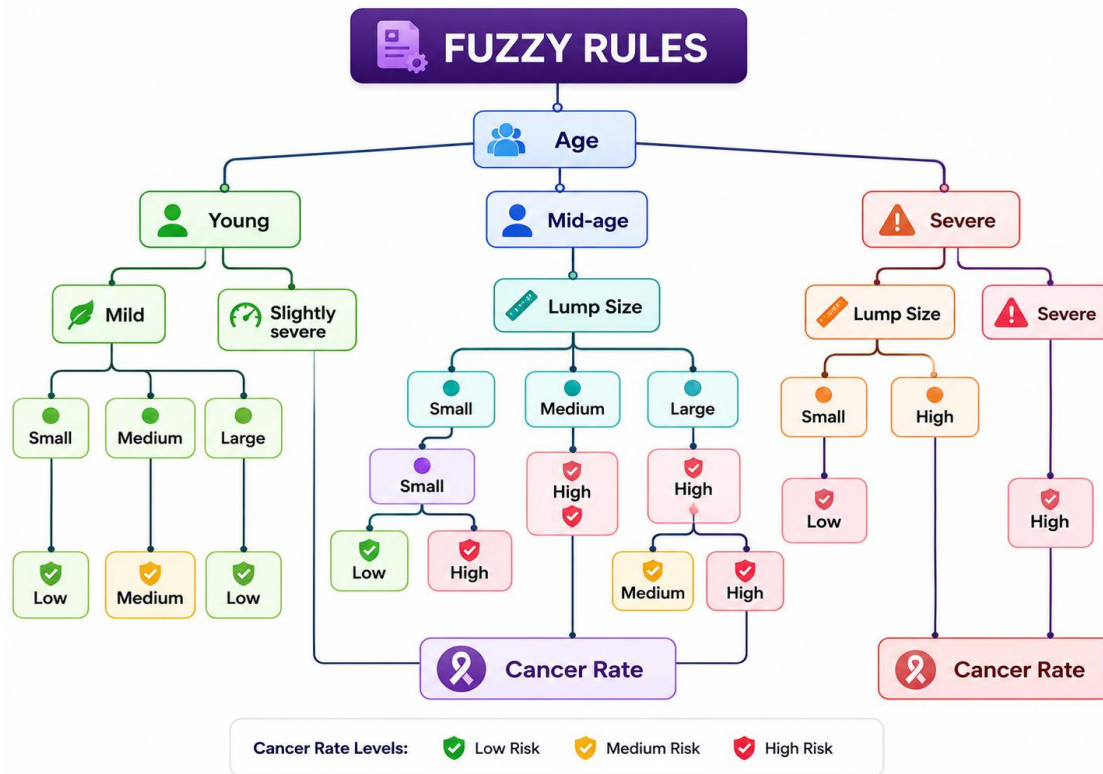


Figure 2.5 A Diagram Illustrating Rules For The Windows Expert System

Figure 2.6 demonstrates how data inputs go through complete fuzzification and reasoning with fuzzy rules and an inference system to produce diagnostic results and recommendations.

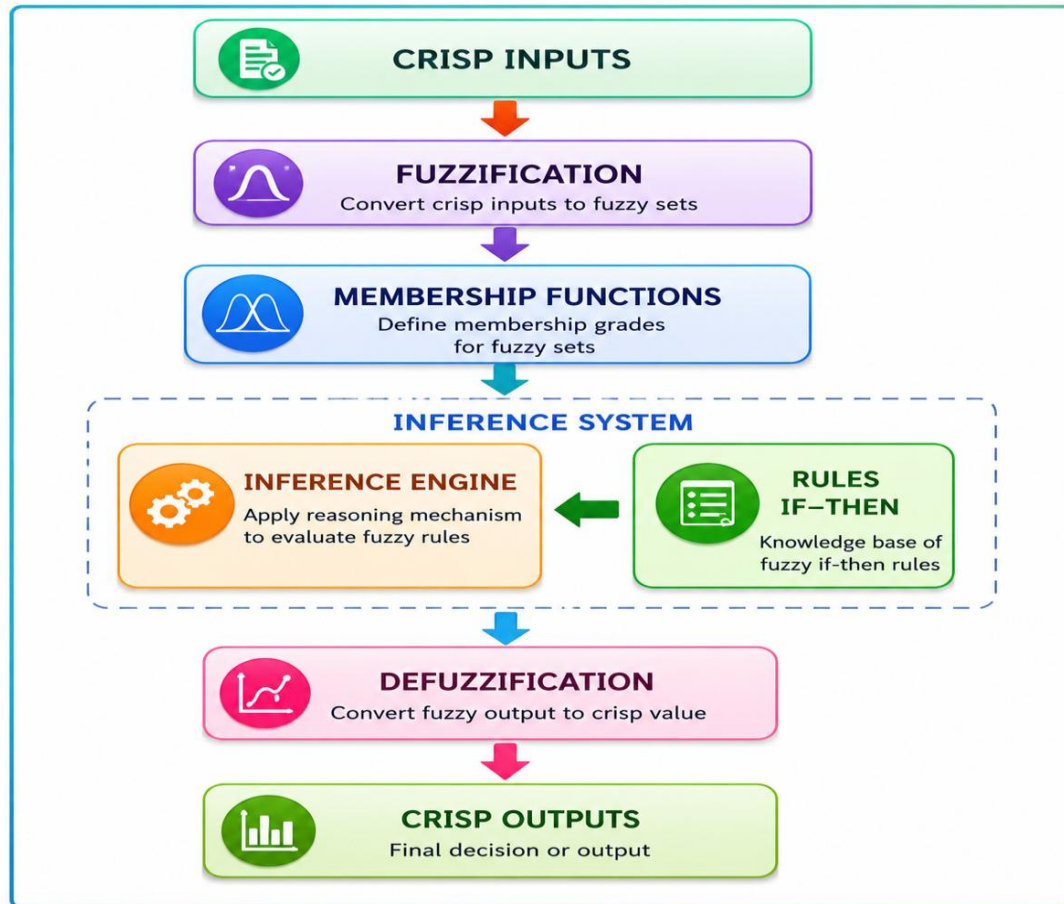


Figure 2.6: Rules and Flow Algorithm of Expert Model

2.12 The Inference Engine

The Mamdani Mechanism diagram is represented in Figure 2.7. To determine the level of ambiguity and how a woman is affected by breast cancer, the fuzzy mechanism algorithm is used. An ailment could occur and not get to a stage in which stringent action advice is needed. The ambiguous additional aspect supports in ascertaining how important it is to take treatment measures. The Mamdani Deduction Model has been a system that is frequently employed in fuzzy mechanism processes and fuzzy models. Professor Ebrahim Mamdani, who propounded the Mamdani Deduction Mechanism in 1975, is largely used as a result of its instinctive method of modelling and accepting data and producing outcomes.

2.13 Function of the Mamdani Inference Deduction

The first step is fuzzification, where quantities decode participation standards and ideals.

Secondly, Fuzzification empowers the scheme to handle inaccurate and ambiguous information by showing participation variables as grades of association, namely, low, medium, and high.

Another function of the Mamdani Mechanism Deduction is rule evaluation, which uses the IF-THEN statement in inputting fuzzy information. Every instruction is evaluated for the purpose of examining how secure the participation facts meet the instruction's statement. It also uses fuzzy operators such as AND, OR, and NOT in order to compose the diverse backgrounds in the conditional statement and instruction.

Another function is rule firing and triggering, and that is the level at which a rule activates to determine fuzzified metrics. A combination of the instructions' outcomes is also performed.

Defuzzification: Turns the combined fuzzy output back into a clear value that may be used in real life. It also converts common methods to Centroid, Bisector, *and* Mean of Maximum. The defuzzified result is an exact number that helps the system make decisions, such as changing a control parameter, setting the speed of a motor, or providing a suggestion.

Interoperability is one of the benefits of the Mamdani Deduction Mechanism. The intuitive "IF-THEN" criteria and language phrases like "low," "medium," and "high" make it simple to imbibe and consistent with how humans think.

Specialist know-how, which is typically expressed in qualitative terms, may be efficiently stored and utilised by the system. This makes it appropriate for uses where human judgment or experience is the primary factor in decision-making.

Managing Complex Issues: The Mamdani excels at solving complex, nonlinear problems when it is difficult to pattern the relationships between inputs and outputs using conventional mathematical techniques.

Processing with many Inputs and Outputs: The Mamdani deduction algorithm can handle many input variables and provide a variety of output constructions. Because of this, it is suitable for complicated systems where several determinants should be taken into account at once.

Simultaneous Rule Evaluation: This ensures that all relevant rules are evaluated at the same time, making sure that key-in facts are taken into account when making judgments.

System tuning: Here, the fuzzy instructions and level of association could be adjusted as time goes on, to advance accuracy and efficacy based on the algorithm's performance and results.

The advantage of this system is hinged on its interpretability, capacity to tackle complicated and uncertain data and adaptability in projecting medical facts and information, thereby ear marking it being generally functional in different requests and submissions.

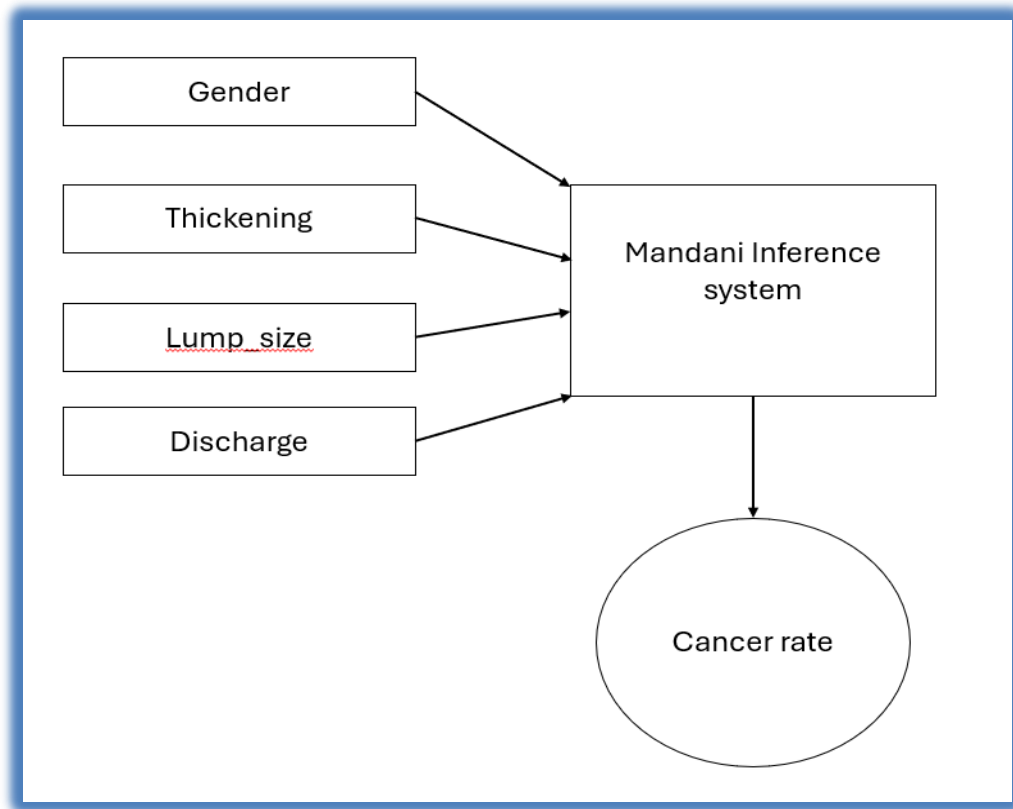


Figure 2.7: Mamdani Deduction Engine

2.14 Design of the Model

In designing the architecture, the patterning of the expert algorithm is carried out at the design phase. The process involves delineating the architectural gamut of the system, the various categories and information that match up benchmarked stipulations. It is likely that a professional doctor may not be skilled when it comes to computer use, the software was created to ensure convenient use. The system was designed using Python. This encompasses giving details on the recorded facts, documented variables, storage arrangements, results created, the software, and lastly, the definitions of the detailed information operation plans.

A systematic evaluation procedure is required to evaluate fuzzy expert systems' performance and compare it to existing systems to ensure their dependability, accuracy, and utility in actual physical environments, applications, such as medical diagnosis. It involves a System comparison (research procedure), Accurate and precise measurement (assessment dimensions), utilising the identical dataset (data facts), Equitable model implementation (implementation procedure), and displaying findings in charts and tables (visualisation). This guarantees a fair, transparent, and scientific comparison between current solutions and the proposed fuzzy expert system. The evaluation procedure is made systematic, understandable, and scientific as indicated in **Table 2.10**.

Table 2.10 A Compact Performance Evaluation Process of Fuzzy Expert Systems

Step	Description	Purpose
1. System Comparison	Research procedure to compare fuzzy expert systems with existing systems.	To identify similarities, differences, and performance gaps.
2. Accurate, Precision, Specificity and sensitivity Measurement	Use of metrics such as accuracy and precision.	To assess diagnostic reliability and correctness.
3. Utilising Identical Dataset	Both systems are tested with the same dataset.	To ensure fairness, homogeneity, and unbiased analysis.
4. Equitable Model Implementation	Implement models with comparable tools, algorithms, and platforms.	To maintain consistency and equal testing conditions.
5. Displaying Findings in Charts & Tables	Presenting results visually in tables and bar charts	To enable clear interpretation and transparent comparison.

The flowchart shows a step-by-step approach to the assessment of the expert model. It provides a clear, structured pathway for assessing the expert system, ensuring fairness, transparency, and scientific rigour in comparisons. This demonstrates where improvements are needed and how reliable the system is in real-world diagnosis.

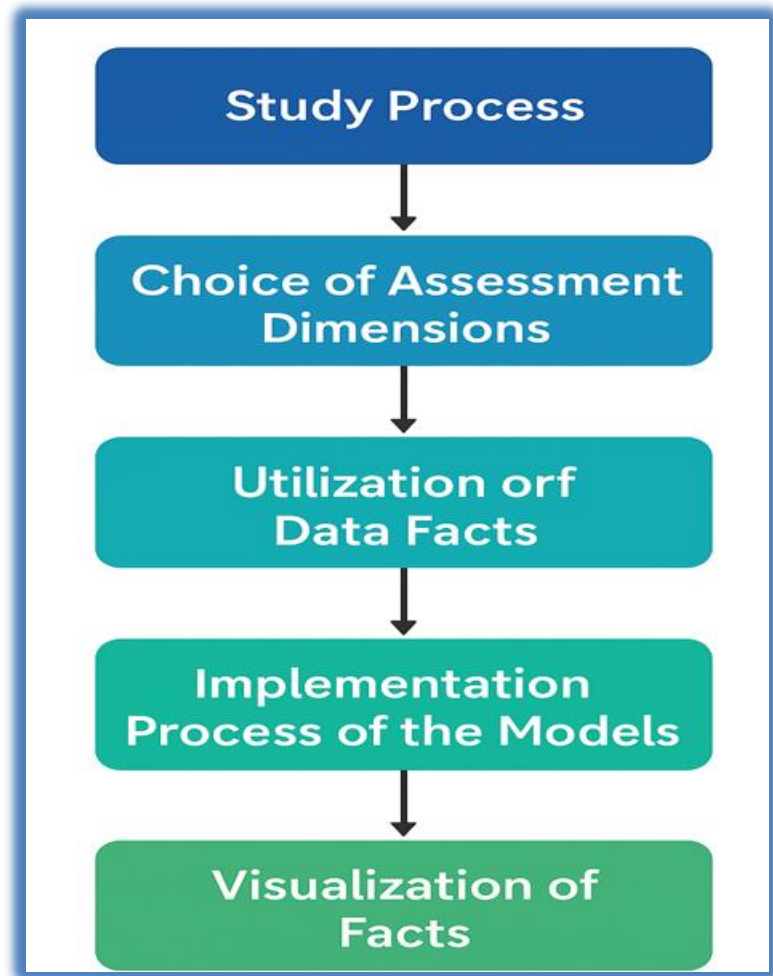


Figure 2.8 Performance Evaluation Process of Fuzzy Expert System

2.15 Study Process (comparison assessment)

The assessments of the system was conducted through a comparative analysis to ascertain its aggregate performance. The research assessed the resemblances and variances of the system performance results and conclusions.

2.16 Choice of Assessment Dimensions

The study employed dimensions of accuracy, precision, specificity and sensitivity values in terms of salient metrics. The metrics selected were as a result of the fact that they give a clear viewpoint in terms of diagnostic analysis. Accurate values comprise the proportion of every case which was assessed and correctly detected, and this does not exclude truthful positive values and truthful negative values. The precision proportion refers to positive outcomes amongst all the model's positive outcomes.

3.17 Utilisation of Data Facts

In order to make sure that there is homogeneity and impartiality in the analysis procedure, the systems have undergone simulation with various breast cancer risk variables, as indicated in the flowchart in Figure 3.9. In the middle are the core factors, that is, the risk indicators, illustrating all the linguistic variables that can cause breast cancer growth.

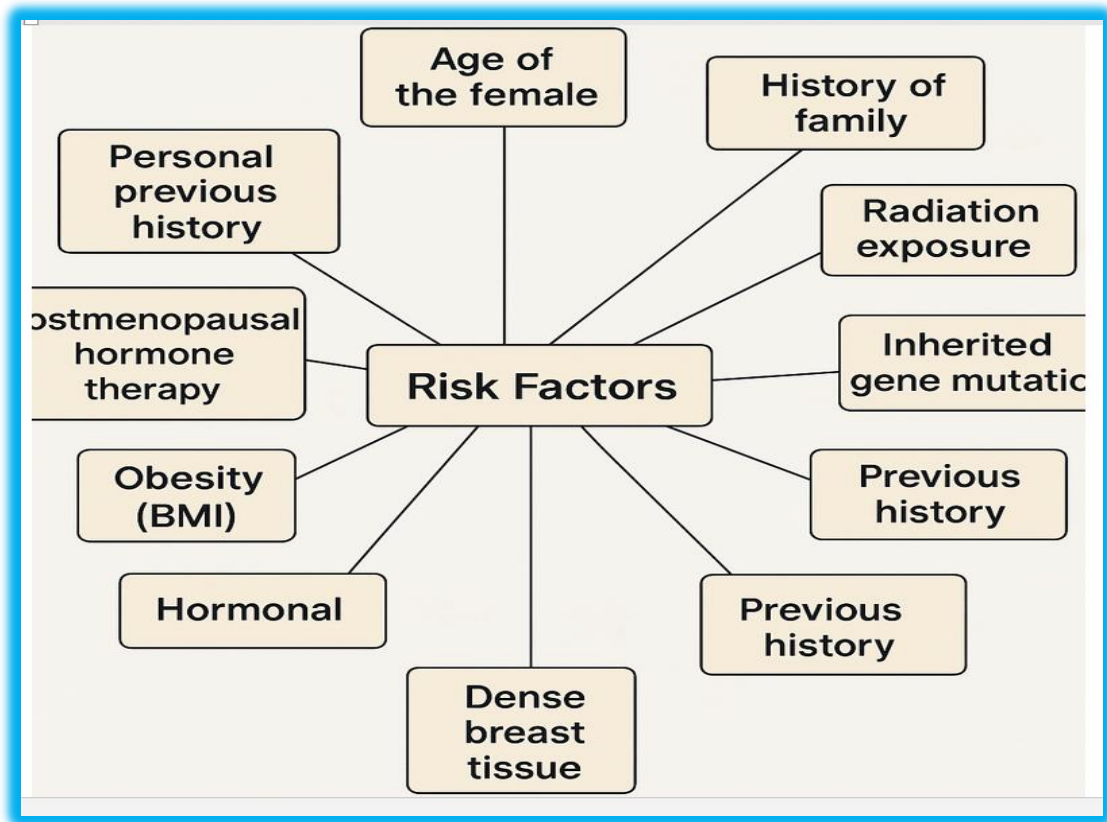


Figure 2.9 A Block diagram expressing the various variables

Fundamentally, the pictorial diagram visually organises all causative indicators in one view for simple understanding.

2.18 Visualisation of Facts

The presentation standards illustrated to help with more understanding include:

A uniquely tabular representation to distinguish between the model and existing ones. Table 3.1 explains the variance. This table explain the tools and instruments used to develop the model. A bar diagram is also used to enhance the easy interpretation of the data. This diagram is used to pictorially represent both the standards assessment

In this research, the performance measures were assessed as a way to establish the benefits plus shortcomings of the expert models, backed with past reviews. The level of performance was proven based on accurate and precise values. This meant the system demonstrated effective dependability with regard to providing correct diagnostics, while mitigating false positives. Accurate values are essential in expert model reliability, as they reveal the accuracy measurements projections from all other projections that are obtained. On the other hand, precision reveals the accuracy of the system in detecting positive values. The measurement is essential to reduce the likelihood of untrue fears while ensuring that true positive values are maintained. This study's ability to assess the efficacy of both systems and proffer good judgments with regard to medical contexts is premised on these analytic standards.

Accuracy: shows how effectively an algorithm correctly identifies or projects results

$$A = \frac{TP + TN}{T}$$

Precision (Positive Predictive Value): shows the number of positive diagnostic values are right.

$$P = \frac{TP}{TP + FP}$$

Sensitivity: This is the measure of the system's ability to correctly detect patients who truly have breast cancer.

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

Specificity: This is the measure of the algorithm to uniquely and appropriately classify non-cancer cases as negative. This is a performance measure that indicates how well a diagnostic system correctly identifies patients who don't have a disease.

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

Recall: This is mathematically the same as Sensitivity (True Positive Rate).

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

The F1-score is mostly useful in medical diagnosis because it balances the ability to detect disease (Recall) with the ability to avoid false alarms (Precision).

$$\text{F1 - Score} = \frac{2 * P * R}{P + R}$$

Where:

TP=True Positives

TN=True Negatives

T=Total Number of Cases

FP=False Positives

2.8 Structural Framework

In designing the architecture, the patterning of the expert algorithm is carried out at the design phase. The process involves delineating the architectural gamut of the system, the various categories and information that match up benchmarked stipulations. It is likely that a professional doctor may not be skilled when it comes to computer use; the software was created to ensure convenient use. The system was designed using Python. This encompasses giving details on the

recorded facts, documented variables, storage arrangements, results created, the software, and lastly, the definitions of the detailed information operation plans.

2.9 Testing and Validation Framework of the Enhanced Fuzzy Expert System (EFES)

The diagram in Figure 3.10 illustrates the complete testing and validation process used to assess the functions of the proposed Enhanced Fuzzy Expert System (EFES) for breast cancer diagnosis and treatment. It presents a sequential workflow beginning with data collection and ending with performance evaluation. This approach for testing and validation guarantees that the Enhanced Fuzzy Expert System is thoroughly assessed using actual clinical data. The procedure confirms that the system can accurately diagnose problems, mimic expert thinking, and manage ambiguity. The study illustrates the efficacy and usefulness of the suggested breast cancer diagnostic and prognosis system in healthcare settings by comparing system outputs with expert diagnoses and computing performance measures.

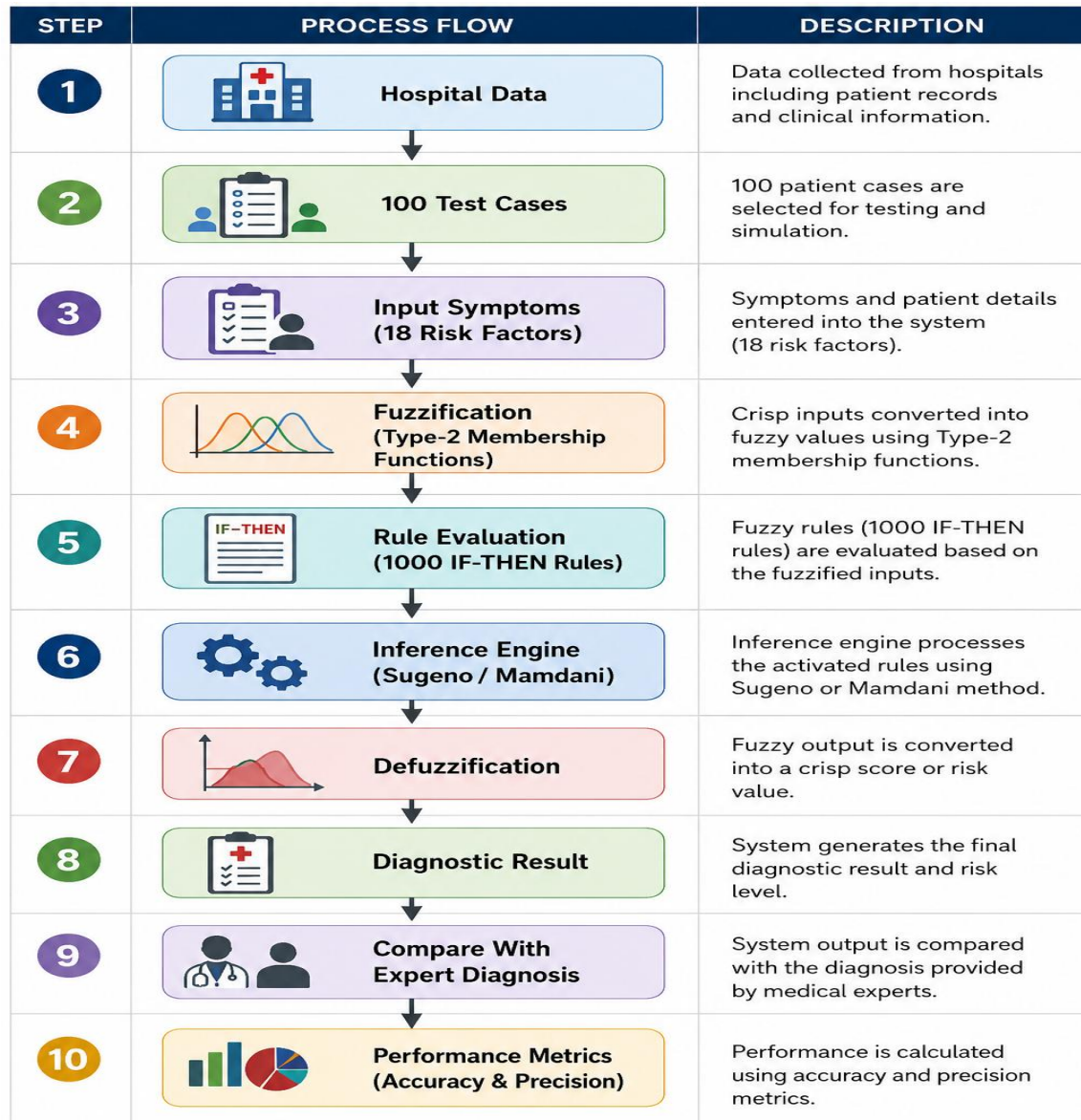


Figure 2.10: Testing and Validation Framework for the Enhanced Fuzzy Expert System (EFES)

3.0 Results and Discussion

The fuzzy model was developed and simulated utilising a staged clinical decision-support deployment strategy. In this approach, the proposed expert system is meant to supplement and improve existing diagnosis and treatment techniques rather than fully replace them. The technology works with existing clinical practices to help healthcare professionals improve diagnostic accuracy, prognosis evaluation, and decision-making efficiency. The suggested fuzzy expert system use Type-2 uncertainty modelling, expert-driven rule creation, weighted multi-variable rule inference, and threshold optimisation to reduce false positives and false negatives. The System also mitigates False Positives and False Negatives through: Type-2 Fuzzy Logic, Multi-Variable Risk Assessment, Weighted Rule-Based Inference, Threshold Optimisation, Expert Knowledge Integration, and Multiple Inference Validation. The approach maintains sensitivity to questionable clinical markers while reducing overclassification. Furthermore, all predictions need clinical validation because the system functions as a clinical decision support tool rather than an independent diagnostic substitute. From a regulatory standpoint, the system is developed and modified to comply with frameworks like ISO 13485, ISO 14971, IEC 62304, and healthcare data protection regulations to guarantee safety, dependability, transparency, and clinical accountability. It also conceptually aligns with Software as a Medical Device standards. Python was used as a programming tool to model the proposed system. This kind of takeover method is convenient, cost-effective, and reduces the risk of a direct takeover. The system implementation ensured that the designed fuzzy expert system was translated into a fully functional application, rigorously tested, deployed, and validated for clinical decision support in breast disease diagnosis and treatment. This involved the planning process, installation and configuration of hardware, software, and system infrastructure, which is known as environment setup, system modules,

database setup, which involves building and populating knowledge bases, integration, testing, deployment, training and documentation, and evaluation and maintenance. The computer systems and the operating systems specifications needed in all units should be well established to enable a successful deployment and changeover. The study execution stage is aggregated into three major sections, which include the access regulation section, the expert section, and the analysis and results sections

Access Regulation: The access regulation part determines who should have access to the expert model. The right managers and doctors should have access to the model platform analysis. Figure 3.1 shows the model.

Breast Cancer Diagnosis System
Early Detection • Accurate Diagnosis • Better Treatment

[Login](#) [Register](#)

Your Health, Our Priority

A smarter way to detect, diagnose and treat breast cancer.

Welcome Back!

Please login to access your account

Username

Enter your username

Password

Enter your password

☒ Remember me [Forgot Password?](#)

Login

Secure & Confidential
Your data is protected

Expert Support
Backed by medical experts

Accurate Results
AI-powered analysis

Better Outcomes
Timely diagnosis saves lives

Figure 3.1: Registration Section of the Expert Model

Assessment Section of the Expert System: The assessment section of the system performs an important function in ascertaining the outcome of the diagnosis. Medical experts will enter their details in order to have access to the system. The system is available for live verification at

<https://9q3ytysrgq4akutwxbzcdv.streamlit.app/>. The analysis phase contains the list of the signs and symptoms, where the physician selects the number of signs exhibited by the patient, and then clicks on the diagnosis dialogue box below the screen and finally, the outcome is displayed for the necessary decision. The results section highlights the number of signs chosen by the physician, the type of cancer, and the suggested treatment steps. The expert model may also add further actions to be taken as a result of the analysis outcome by suggesting additional examination and testing, and preventive steps. The expert model assessment page is shown in Figure 3.2.

Figure 3.3 shows the outcome section for the necessary actions.

The image shows a web interface titled "Symptoms Assessment". It contains 12 symptoms arranged in two columns. Each symptom has a dropdown menu with a blue checkmark icon and a downward arrow. The selected options are: Swollen breast (Yes), Itching breast (No), Swollen lymph nodes (No), Nipple pain (No), Reddish skin colour (Yes), Breast discharge (Yes), Burning sensation (Yes), Painful breast (No), Lump in the armpit (No), Rashes (No), Sores (No), and Thickening (Yes).

Symptom	Selected Option
Swollen breast	Yes
Itching breast	No
Swollen lymph nodes	No
Nipple pain	No
Reddish skin colour	Yes
Breast discharge	Yes
Burning sensation	Yes
Painful breast	No
Lump in the armpit	No
Rashes	No
Sores	No
Thickening	Yes

Figure 3.2: Symptoms assessment Section

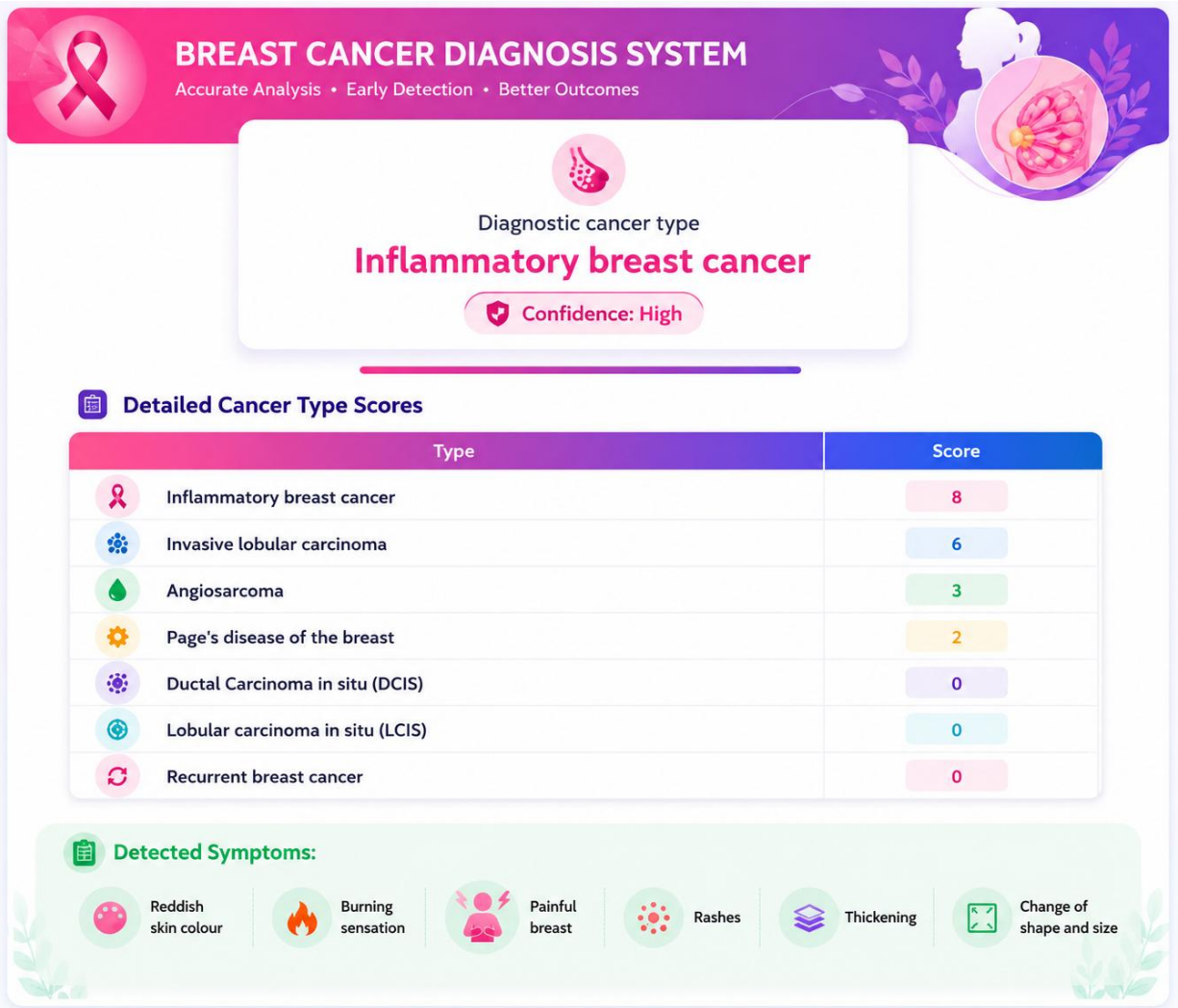


Figure 3.3: Diagnostic analysis phase

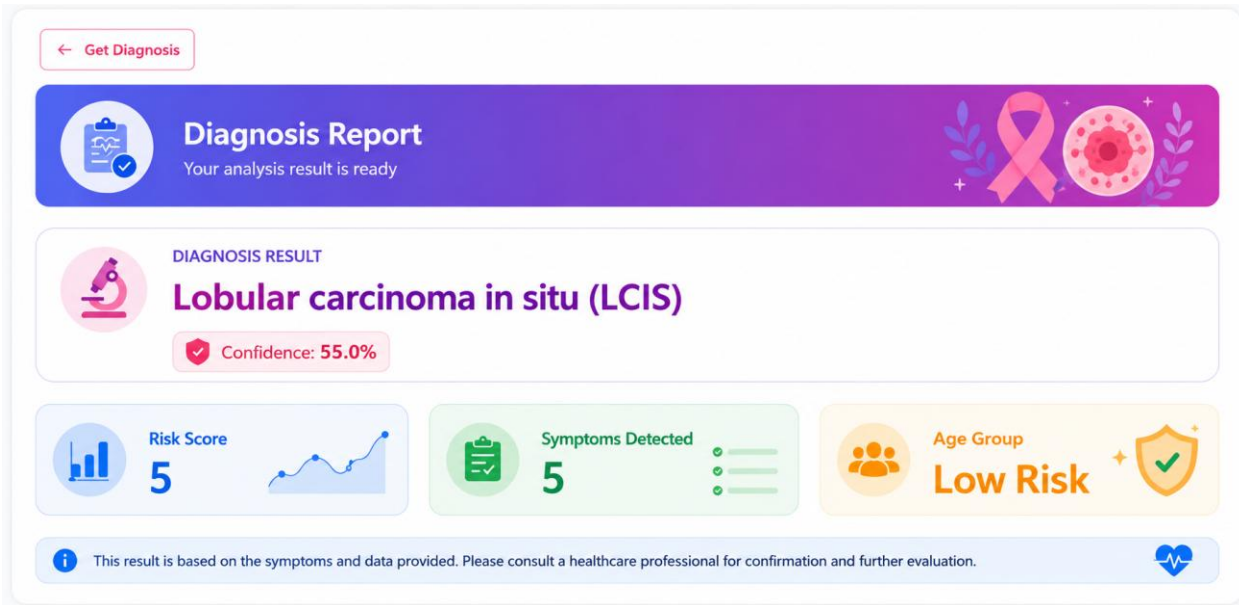


Figure 3.4: Diagnosis results screenshot

As demonstrated in Figure 4.4, the screenshot depicts the outcome phase of the diagnostic system, which is the last stage of the inference algorithm, in which the expert model makes available the outcome information based on the set of instructions and rules used. The results shown on the screen are very important because it provide analytic information for decision-making. The roles include:

Defuzzification: The outcome section changes the classified outcome of the fuzzy inference algorithms into specific quantities for decision-making, and this process is called defuzzification.

Demonstration of Outcome

The expert model gives the end-stage analysis in a way that is more understandable and simpler to imbibe. In most instances, the outcome section adds certain images and pictorial information which support professionals to get the right information for users' consumption. This visualisation supports in interpreting the findings, particularly in multifaceted algorithms and situations.

Provision of necessary steps.

Knowledge and understanding: The outcome section offers decisive understanding and provides advisory information as a result of the expert model outcome observations. The expert system can provide certain key steps to be taken to analyse breast cancer and suggest treatment.

Directions for More Achievement: The outcome section delivers directions about the move, which include adding further examination, taking steps to curb and making appropriate decisions. The kind of software designed matters in this regard.

Description and Clarification

Basis About the Outcome: The outcome section mostly comprises a description and validation of the results delivered. This may comprise specifying which rules were triggered, how they were brought together, and why the exact outcome was selected.

Confidence Levels: The model may also offer assurance levels and the extent of certainty with the outcomes, assisting professionals in gauging the trustworthiness and importance of the results.

Feedback for System Improvement

Response Integration: The outcome section contains devices for beneficiaries to offer a response to the model's results. This response could form the basis and means to enhance the accuracy and effectiveness level of the fuzzy model as time goes on.

Logging and Reporting

Result Logging: The expert model may record the outcomes, which could form the basis for referencing in future. This is very crucial for situations in which past information is valued, with regard to clinical analysis and projecting upkeep.

Report: The outcome section could include producing outcomes that summarise the results, approvals, and motivation and the motivation that formed the choices taken by the model. These reports can be used for storage, compliance, and further scrutiny.

System Outcome Delivery

External Communication: In most instances, the outcome stage includes bringing the results to peripheral models or parts, such as the conveyance of a regulator indication to a mechanism, refining the information management repository, and activating any signal.

Automation: For any automatic algorithm, the outcome stage may straightforwardly activate activities without any manipulation by someone, as a result of the fuzzy expert model observations. The outcome stage of a fuzzy model is a situation in which the algorithm brings the end results, changes unclear information to a clear understanding, offers descriptions, and draws conclusions. It makes sure the deduction processes culminate in better, understandable, and practical results for medical professionals.

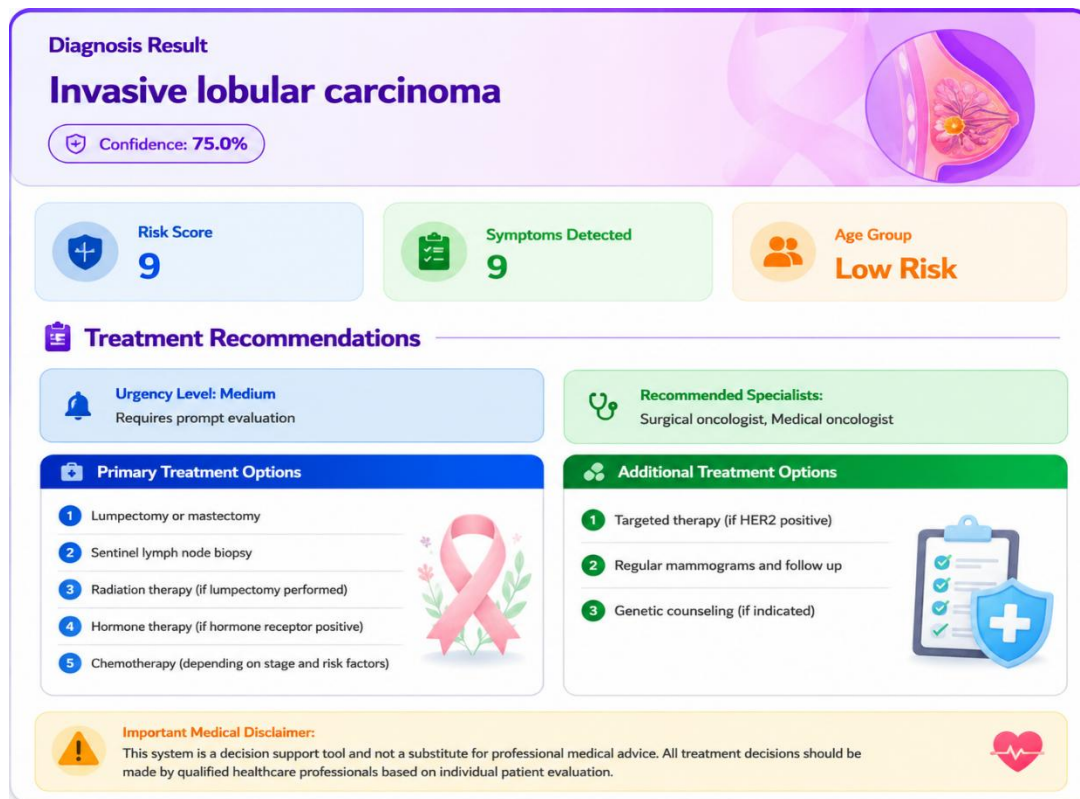


Figure 3.5 Screen view of the treatment recommendation phase

As the last step in the system's decision-making process, as shown in Figure 3.5, the treatment recommendation phase of the Enhanced Fuzzy Expert System (EFES) for breast cancer diagnosis offers a suitable treatment plan customised to the patient's particular condition based on the diagnostic findings. The recommendation phase employs fuzzy logic principles to suggest individualised treatment alternatives that balance efficacy, safety and patient-specific characteristics once the diagnosis phase has established the likelihood, kind, and severity of breast cancer. Diagnostic results and patient information are sent to the treatment suggestion phase, including cancer stage, size and distribution of the tumour (local, regional, metastatic), type of tumour, Patient characteristics, age, menopause, health, and preferences. The main course of

treatment that is advised, either hormone therapy, targeted therapy, radiation, chemotherapy, surgery, or combinations of these, is displayed in the recommendation phase of the expert system.

Administrative Component: This component includes activities offered by the applications that update the current development of new signs and symptoms and other changes, as well as provide treatment advice. To input new development and commendations, the administrator presses on the operator display dialogue box at the top left side of the screen, and the display list will be shown. The administrator now presses on the analysis dialogue box to accomplish the new changes and development. The manager could observe happenings and control user approachability to the proposed model. Figure 4.5 displays the managerial viewer of the model.

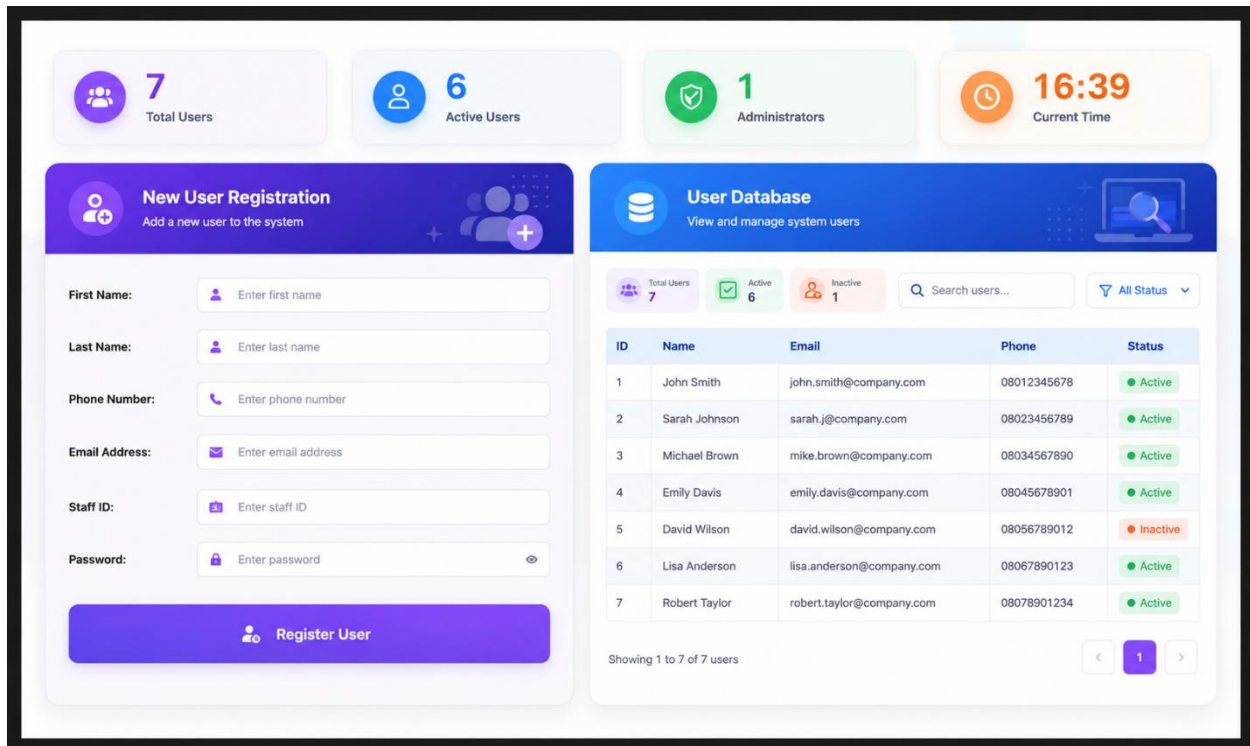


Figure 3.5: Interface screen view of the Manager

Figure 3.6 demonstrates the screen pictorial view of the internet host of the fuzzy specialist model.

The internet host in a fuzzy specialist algorithm is vital for keeping, manipulating, recovering, and

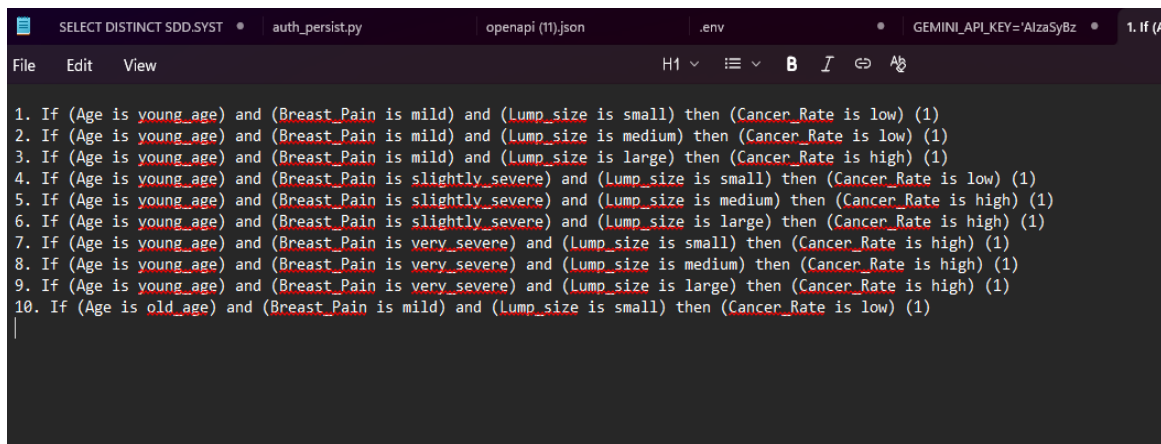
safeguarding the details and facts the algorithm depends on to carry out its activities. It makes sure the model operates efficiently, competently, and steadily. The information provider (Host) keeps specialist data, such as fuzzy instructions, variable associations, outcomes produced by the inference algorithm and some associated information which defines the model judgments. If a problem occurs, the internet provider delivers a process to retrieve information, which ensures the continuous process of the model processes. As a fuzzy expert model can include multifaceted calculations and a huge number of data classes, the internet host must effectively manipulate and update the cumulative effect of information.

ID	Name	Email	Phone
1	John Smith	john.smith@company.com	08012345678
2	Sarah Johnson	sarah.j@company.com	08023456789
3	Michael Brown	mike.brown@company.com	08034567890
4	Emily Davis	emily.davis@company.com	08045678901
5	David Wilson	david.wilson@company.com	08056789012
6	Lisa Anderson	lisa.anderson@company.com	08067890123
7	Robert Taylor	robert.taylor@company.com	08078901234

Figure 3.6: Windows outlook of a Host Provider

Figure 3.7 exhibits the windows outlook view of the fuzzy instructions of the specialist algorithm. Rules are a major aspect of a fuzzy model, showing an important function in the decision-making steps by demonstrating how data are refined to generate results. Fuzzy rules define how the model

construe instructions, refines ambiguous information, makes inferences and produces outcomes. Health professionals can simply review and update fuzzy rules to enhance the algorithm's activities and adapt to new situations, making the model manageable and allowing scalability. The expert model can process complex, ambiguous and inaccurate data via the fuzzy rules, making it appropriate for a real-time decision-making process.



```

1. If (Age is young_age) and (Breast_Pain is mild) and (Lump_size is small) then (Cancer_Rate is low) (1)
2. If (Age is young_age) and (Breast_Pain is mild) and (Lump_size is medium) then (Cancer_Rate is low) (1)
3. If (Age is young_age) and (Breast_Pain is mild) and (Lump_size is large) then (Cancer_Rate is high) (1)
4. If (Age is young_age) and (Breast_Pain is slightly_severe) and (Lump_size is small) then (Cancer_Rate is low) (1)
5. If (Age is young_age) and (Breast_Pain is slightly_severe) and (Lump_size is medium) then (Cancer_Rate is high) (1)
6. If (Age is young_age) and (Breast_Pain is slightly_severe) and (Lump_size is large) then (Cancer_Rate is high) (1)
7. If (Age is young_age) and (Breast_Pain is very_severe) and (Lump_size is small) then (Cancer_Rate is high) (1)
8. If (Age is young_age) and (Breast_Pain is very_severe) and (Lump_size is medium) then (Cancer_Rate is high) (1)
9. If (Age is young_age) and (Breast_Pain is very_severe) and (Lump_size is large) then (Cancer_Rate is high) (1)
10. If (Age is old_age) and (Breast_Pain is mild) and (Lump_size is small) then (Cancer_Rate is low) (1)

```

Figure 3.7: Windows View of the Sytem's Rules

The pictorial view in Figure 3.8 demonstrates the rules display of the fuzzy expert algorithm. The instructions View in a fuzzy deduction mechanism is an important component for presenting visual details and creating more clarity of the algorithm mechanism, input data and uses the fuzzy instructions to produce results. The instructions component of the expert system demonstrates a generic visualisation of the rules. It displays the extent to which every rule is activated as a result of the key-in details. This is normally displayed in a shaded form, showing the magnitude and degree of rules and how greatly a specific instruction determines the outcome. It helps in finding and fixing errors as well as adjusting parameters, settings and configurations, making sure that there is transparency and reliable results of the expert system.

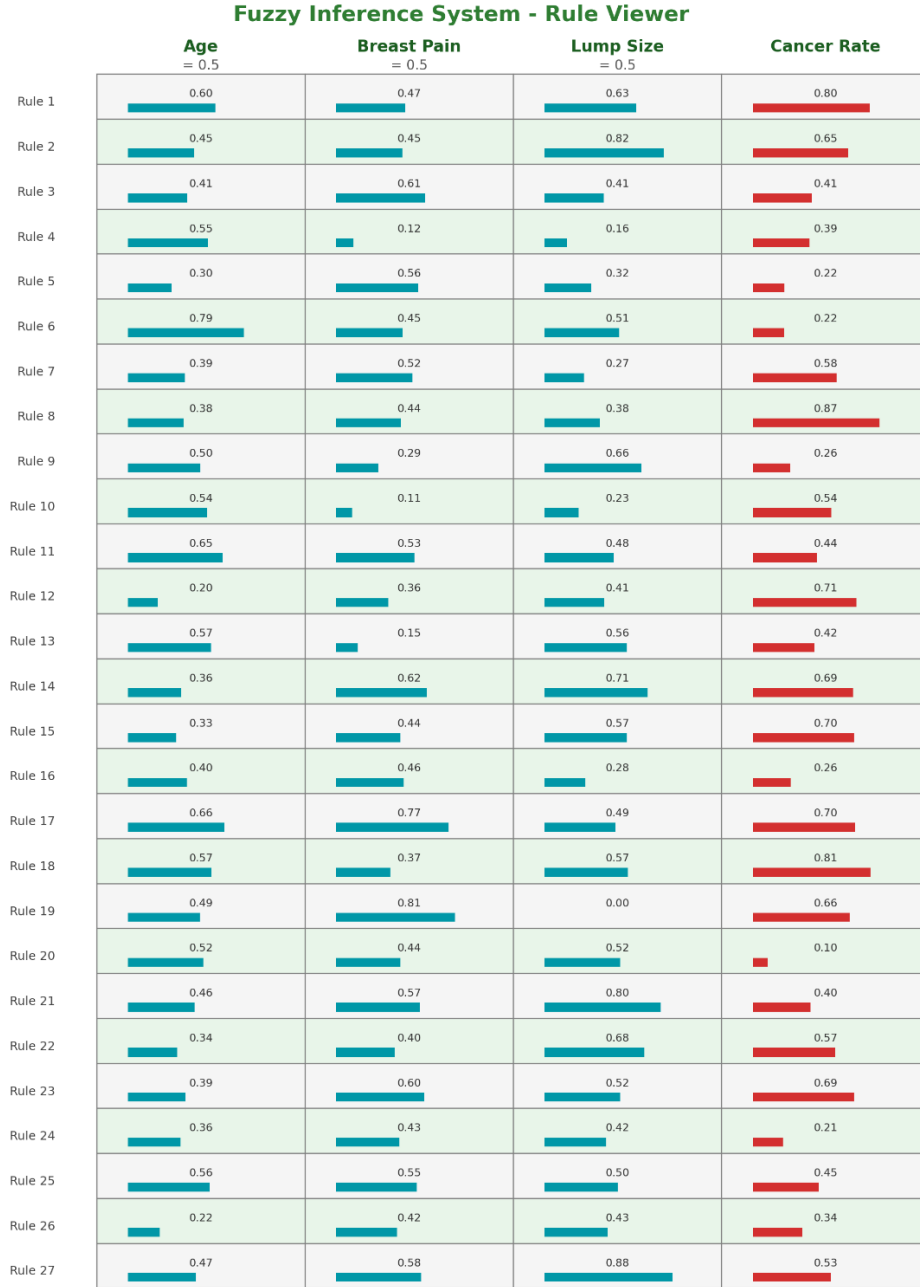


Figure 3.8: Decision Rule Visualizer

3.1 Performance Analysis

Table 3.1 demonstrate the indicators of the Enhanced Fuzzy Expert System (EFES). The system was developed using Python programming language, Type-2 Fuzzy Logic (T2FL), and the Mamdani Inference Engine. The empirical findings indicate that the algorithm got an accuracy of

98%, precision of 86%, Sensitivity 100%, Specificity 85.1%, Recall 100%, and an F1-Score 92.47%. These results show the efficacy of the inference mechanism and the suitability of the selected technologies for breast cancer diagnosis and treatment recommendations.

Table 3.1: Technical Features and Performance Metrics of the Enhanced Fuzzy Expert System (EFES)

	Descriptions
Tools	EFES
Platform	Windows
Kind of Fuzzy Logic	T2FL
Inference Mechanism	Mamdani
Programming Code	Python
Accuracy	98%
Precision	86%
Sensitivity	100%
Specificity	85.1%
Recall	100%
F1-Score	92.47%

3.2 Metrics Analysis

The effectiveness of the developed algorithm was assessed using benchmark metrics, which are accuracy, precision, sensitivity, specificity, recall, and F1-score. These metrics were employed to determine the performance and reliability of the algorithms.

A total of 100 hospital-derived breast cancer cases were used for system testing and simulation. The developed system correctly identified 18 positive cases (True Positives) and 80 negative cases (True Negatives). Furthermore, the system recorded 14 False Positives and no False Negatives.

The performance evaluation yielded an accuracy of 98% and a precision of 86%. The system's exceptional accuracy in diagnosing BC is largely due to its use of type-2 fuzzy logic, the Mamdani inference engine and the Python programming language. The Mamdani inference engine and type-2 fuzzy logic improve the system's capacity for making difficult judgments because of its reputation for flexibility and efficiency when working with complex and ambiguous data (Feizollahzade, 2020). Another reason for the model's 98% accuracy is that it can identify complex patterns in the dataset because of the engine's ability to produce precise and context-aware rules. Python's extensive ecosystem made it possible to integrate many modules and libraries seamlessly, making it easier to create a complex diagnostic model (Khoirom et al 2020). The results were obtained using the same dataset, fuzzy membership functions, rule base, and inference settings throughout all experiments. A detailed and accurate diagnosis result is achieved by taking into account a broad spectrum of diagnoses, which guarantees that the model considers different facets of a patient's medical history, demography, and lifestyle (Bustillo et al. 2022).

In addition, all experimental conditions, including input ranges, fuzzy rules, inference architecture, and evaluation parameters, were maintained consistently to ensure reproducibility. Consequently, researchers applying the same methodology, dataset, and parameter settings should obtain comparable results.

Accuracy: Accuracy is a benchmark the overall ability of the system to correctly classify breast cancer cases.

$$A = \frac{TP + TN}{T}$$

Precision, measures the proportion of predicted positive cases that are correctly identified.

$$P = \frac{TP}{TP + FP}$$

Where:

A=Accuracy

P=Precision

TP=True Positives

TN=True Negatives

T=Total Number of Cases

FP=False Positives

Therefore:

$$A = (18+80)/(100) = 98\%$$

$$P = (86)/(86+14) = 86\%$$

Sensitivity: This is the measure of the system's ability to correctly recognise patients who truly have breast cancer.

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

Specificity: Specificity represents the benchmark of the system's ability to rightly recognise individuals who do not have breast cancer.

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

Where:

S= Sensitivity

S= Specificity

Given the reported matrix values:

TP = 18, TN = 80, FP = 14, FN = 0

Sensitivity: = $18 / (18 + 0) = 100\%$

Specificity: = $80 / (80 + 14) = 85.1\%$

Recall: Recall is mathematically equivalent to Sensitivity and represents the percentage of real positive results rightly recognised by the system.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

TP = 18, FN = 0

Therefore: Recall = $18 / (18 + 0) \times 100 = 100\%$

The F1-score is the harmonic mean of Precision and Recall. It enables an equilibrium benchmark of an algorithm's ability to detect positive cases while minimizing false alarms.

$$\text{F1 - Score} = \frac{2 * P * R}{P + R}$$

Precision = 86% = 0.86, Recall = 100% = 1.00

Mathematically:

$$\text{F1} = (2 \times 0.86 \times 1.00) \div (0.86 + 1.00)$$

$$\text{F1} = 1.72 \div 1.86$$

$$\text{F1} = 0.9247$$

$$\text{F1-Score} = 92.47\%$$

Table 3.2: Comparative Performance Analysis

Authors	Accuracy (%)	Precision (%)	Specificity (%)
Miranda & Felipe (2015)	76.7	-	-
Khalil et al. (2022)	90.0	86.0	-
Nagarajasri & Padmavathamma (2013)	97.0	-	-
Thani & Kasbe (2022)	90.3	-	87.3
Das & Bhattacharya (2008)	87.0	-	-
Ghayumizadeh et al. (2014)	95.0	-	-
EFES	98.0	86.0	85.1

Table 3.2 compares the EFES with selected expert systems reported in the literature. The Enhanced Fuzzy Expert System had an accuracy of 98%, outperforming several existing systems.

The developed EFES significantly exceeded the performance of the model proposed by Miranda and Felipe (2015), which achieved an accuracy of 76.7%. Similarly, the systems developed by Das and Bhattacharya (2008) and Thani and Kasbe (2022) reported accuracies of 87% and 90.3%,

respectively, which are lower than the 98% achieved by the proposed system. Ghayumizadeh et al. (2014) reported an accuracy of 95%, which remains below that of the EFES.

The peak proficiency of the proposed model may be attributed to the integration of Type-2 Fuzzy Logic, expert-driven rule construction, the Mamdani inference mechanism, and the computational capabilities provided by Python. These features enhance the system's ability to manage uncertainty and support accurate clinical decision-making.

Although the difference between the proposed system and Nagarajasri and Padmavathamma (2013), who reported an accuracy of 97%, is relatively small, the proposed EFES still demonstrates improved performance. Furthermore, unlike several existing models that focus solely on diagnosis, the developed system also provides treatment recommendations, thereby enhancing its practical value in clinical settings.

Figure 4.8 visually exemplified the comparative veracity of the proposed model against existing systems. The figure clearly demonstrates that the EFES demonstrated enhanced diagnostic reliability compared with existing approaches.

It should be noted that the primary objective of this study was system development and proof-of-concept validation. Although the results obtained from hospital-derived cases demonstrate the feasibility and effectiveness of the proposed system, future studies should validate the model using larger and internationally recognized benchmark datasets to improve generalizability and reproducibility.



Figure 3.8: A bar chart illustrating the percentage accuracy of the EFES and existing systems

3.3 Discussion

The empirical findings indicate that the enhanced algorithm demonstrated an enhanced veracity of 98%, a precision of 86%, a sensitivity of 100%, a specificity of 85.1%, a recall of 100%, and an F1-Score of 92.47%. demonstrating strong diagnostic capability. These performance outcomes can be attributed to several factors.

First, the integration of Type-2 Fuzzy Logic enabled the system to effectively handle uncertainty, ambiguity, and imprecision commonly encountered in medical diagnosis. Unlike conventional Type-1 fuzzy algorithm, Type-2 fuzzy algorithm provides an additional degree of flexibility in representing uncertain clinical information.

Second, the Mamdani Inference Engine contributed significantly to the system's effectiveness. The Mamdani approach is widely recognized for its ability to process complex rule-based reasoning

and generate interpretable diagnostic outcomes. Its suitability for handling nonlinear and uncertain medical data enhanced the overall reliability of the system (Feizollahzade, 2020).

Third, Python provided a robust and flexible development environment that facilitated the implementation of sophisticated fuzzy reasoning algorithms and seamless integration of supporting libraries (Khoirom et al., 2020).

Another important factor contributing to the system's performance is the comprehensive rule base developed from expert knowledge. The extensive set of fuzzy IF–THEN rules enabled the system to capture complex relationships among patient demographics, symptoms, risk factors, and clinical indicators. Consequently, the model was able to generate more comprehensive and context-sensitive diagnostic recommendations (Bustillo et al., 2022).

Overall, the findings demonstrate that the combination of Type-2 fuzzy reasoning, expert knowledge representation, and Mamdani inference provides a reliable framework for mammary carcinoma identification and treatment recommendation.

4. Conclusion

This study was done to help address a crucial medical problem which has attracted global attention. The researcher adopted T2FL, the Mamdani Deduction Mechanism and Python Programming Language to accomplish the development of the EFES for the diagnosis of breast disease as per the various variables. The suggested fuzzy expert systems use Type-2 uncertainty modelling, expert-driven rule creation, weighted multi-variable rule inference, and threshold optimisation to reduce false positives and false negatives.

The problem is that breast cancer affects many women, with an estimate showing that by 2030, 27 million women will suffer from the disease (Hasan, 2020). Despite the urgency of this situation, present diagnostic methods like mammography and sonography have limited detection abilities. In addition, even though early detection is very important to increase survival rate, the current available expert systems and algorithms primarily identify malignancy levels rather than providing comprehensive treatment guidance. This study has directly responded to these gaps by developing an Enhanced Fuzzy Expert Systems (EFES) that improves on the existing detection models. The study successfully improved on accuracy, precision, sensitivity, specificity, recall and F1-score, the ability to handle uncertainty, poor accessibility, and insufficient integration of multiple risk factors.

This study has improved on the accuracy of the earlier systems by Miranda and Felipe (2015), which achieved an accuracy of 76.7%. Similarly, the systems developed by Das and Bhattacharya (2008) and Thani and Kasbe (2022) reported accuracies of 87% and 90.3%, respectively, which are lower than the 98% achieved by the proposed system. Ghayumizadeh et al. (2014) reported an accuracy of 95%, which remains below the performance of the Enhanced Fuzzy Expert System (EFES) which reported 98% accuracy.

This provides a noteworthy advantage in medical practices. Therefore, medical experts are more assured as a result of the Enhanced Fuzzy Expert System's high accuracy, which tends to eliminate false positives and inappropriate diagnostic outcomes.

Hitherto, its intended goal was achieved because it improved on the early expert systems.

Ethics Approval and Ethical Considerations

This study was conducted by a researcher affiliated with **Bolgatanga Technical University, Ghana**, using clinical data obtained from the **Upper East Regional Hospital, Bolgatanga, Ghana**. Ethical approval for the study was obtained from the **Ghana Health Service Ethics Review Committee (GHS-ERC)**. The study was conducted in accordance with the ethical requirements and procedures of the Ghana Health Service Ethics Review Committee. Appropriate measures were taken to protect the privacy and confidentiality of the patients whose clinical information was used in the study. Patient-identifying information was excluded from the dataset used for analysis, and the data were used solely for research purposes.

Consent to Participate: All human participants in the study were adequately informed about the purpose, procedures, potential benefits, and risks associated with their participation. Participation was entirely voluntary, and participants provided informed consent before taking part in the study. Participants were informed that they had the right to decline participation or withdraw from the study at any time without penalty or adverse consequences. All information obtained from participants was treated as confidential and used solely for research purposes. Personally identifiable information was not disclosed in the reporting or publication of the findings. Children were not among the participants in the study since the inclusion criteria for this study begin at 18 years and above.

For the systematic literature review: Since the manuscript is primarily a review of previously published studies and does not involve direct recruitment or interaction with human participants, no new participant consent was required for the review component. However, where the reviewed underlying studies involved human participants, only studies reporting appropriate ethical

approval and/or informed consent procedures were considered eligible, subject to the review's inclusion criteria.

Funding: There was no funding for the research.

Clinical trial number: not applicable.

This study did not involve the registration or conduct of a prospective interventional clinical trial. The study used 100 clinical/hospital-derived test cases for the evaluation and simulation of the proposed breast cancer diagnostic and prognostic systems; therefore, the number of test cases should not be presented as a clinical trial registration number.

Consent to Publish Declaration: not applicable.

Data Availability

The data used in this study were obtained from clinical and hospital sources and contain sensitive health information. Due to patient privacy, confidentiality, and ethical considerations, the individual-level clinical data cannot be made publicly available. The data may be available in a de-identified and aggregated form from the corresponding author upon reasonable request, subject to approval by the relevant institutional or ethical authority and compliance with applicable data protection requirements. The datasets used for testing and validation are described in sufficient detail within the manuscript to support the interpretation and reproducibility of the study findings.

Dataset Clarification

The dataset used in this study is a **primary clinical dataset** obtained from hospital sources for the purpose of developing, testing, and validating the proposed Type 2 fuzzy expert system for breast

cancer diagnosis and treatment recommendation. The dataset comprised 100 clinical test cases derived from hospital records and included the relevant breast cancer risk factors and clinical variables used as inputs to the system.

The dataset was not obtained from a publicly available secondary database, and therefore there is **no public database link** associated with the dataset. Because the dataset contains sensitive clinical and health-related information, the individual-level data cannot be made publicly accessible due to patient confidentiality, privacy, and ethical considerations. The data were used solely for research and system evaluation purposes in accordance with the applicable ethical and institutional requirements.

Dataset type: Primary clinical dataset

Number of test cases: 100

Source: Hospital clinical records

Publicly available database: No

Public database link: Not applicable

Secondary Data Analysis and Dataset Clarification

Secondary Data Analysis: The study did not use a publicly available web-based secondary dataset for the development, testing, or validation of the proposed fuzzy expert systems. The primary evaluation dataset consisted of 100 clinical test cases randomly selected from hospital sources, with expert participation, and was used under the applicable institutional and ethical procedures.

Secondary information obtained from previously published studies, clinical literature, guidelines, and scholarly databases including PubMed, IEEE Xplore, ScienceDirect, and SpringerLink was used to support the identification of breast cancer risk factors, development of the knowledge base,

construction of fuzzy IF–THEN rules, and refinement of membership functions. These sources were used as scientific and clinical evidence rather than as the patient-level testing dataset.

Consequently, **accession numbers or direct web links to a publicly available patient-level dataset are not applicable to the primary evaluation dataset used in this study.** The hospital-derived clinical data cannot be made publicly available because of patient confidentiality, privacy, ethical restrictions, and institutional requirements. Therefore, no accession number or public database URL is applicable to the dataset used for the primary evaluation.

Component	Source	Role in the study	Classification
Expert Knowledge	Oncologists/radiologists	Rule and membership-function development.	Primary Data
100 clinical cases	Upper East Regional Hospital, Bolgatanga.	Testing and validation.	Hospital-derived clinical data.
Published Literature	PubMed, IEEE Xplore, ScienceDirect, SpringerLink.	Clinical knowledge, risk factors, rules and membership functions.	Secondary information.

Some Aspects of the Breast Cancer Dataset.

Family History	Radiation Exposure	Birth Control	Hormone Therapy	Alcohol Consumption	Inherited Gene	Previous History	Hormonal	Dense Breast Tissue	Risk	Age	Pregnancy Age	Last Menstrual Cycle Age	Menstrual Cycle Age
Absent	High	High	None	High	Present	None	Imbalanced	Absent	Low	Young	Young	Middle-aged	Young
Present	Low	None	None	Moderate	Absent	None	Balanced	Absent	High	Young	Middle-aged	Middle-aged	Young
Present	High	None	None	Low	Absent	None	Balanced	Absent	Moderate	Young	Middle-aged	Middle-aged	Young
Present	High	None	Low	High	Present	None	Balanced	Present	High	Young	Young	Middle-aged	Young
Absent	High	Moderate	None	Moderate	Present	Present	Balanced	Present	Low	Young	Middle-aged	Middle-aged	Older
Absent	Low	None	Moderate	Moderate	Present	None	Imbalanced	Present	Low	Young	Middle-aged	Middle-aged	Older
Present	Moderate	High	Low	None	Absent	Present	Balanced	Absent	High	Young	Young	Middle-aged	Young
Present	Moderate	Moderate	Moderate	Low	Present	None	Balanced	Absent	High	Older	Young	Middle-aged	Young
Present	Moderate	High	None	High	Absent	None	Balanced	Absent	High	Older	Young	Middle-aged	Young
Present	High	Low	Moderate	Moderate	Absent	Present	Imbalanced	Present	Moderate	Young	Young	Middle-aged	Young
Present	Moderate	Moderate	Low	Low	Present	None	Imbalanced	Absent	Low	Young	Middle-aged	Middle-aged	Young
Present	Moderate	None	Moderate	Low	Present	None	Imbalanced	Present	Low	Young	Middle-aged	Middle-aged	Young
Absent	High	Moderate	Moderate	Moderate	Present	None	Imbalanced	Absent	Moderate	Young	Young	Middle-aged	Young
Present	Low	Moderate	Low	High	Absent	Present	Imbalanced	Present	High	Young	Young	Middle-aged	Older
Absent	High	Low	High	Moderate	Absent	None	Imbalanced	Present	High	Young	Middle-aged	Middle-aged	Young
Present	Moderate	Low	None	None	Absent	None	Balanced	Present	Moderate	Older	Young	Middle-aged	Young
Present	Low	Low	Low	None	Present	Present	Imbalanced	Present	Low	Older	Young	Middle-aged	Young
Present	Moderate	None	Low	Low	Present	Present	Balanced	Absent	High	Older	Middle-aged	Middle-aged	Young

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