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New Approaches to the Prognosis and Diagnosis of Breast Cancer Using Fuzzy Expert Systems

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Abstract

Breast cancer remains a significant global health challenge, necessitating effective early detection and prognosis to enhance patient outcomes. Current diagnostic methods, including mammography and MRI, suffer from limitations such as uncertainty and imprecise data, leading to late-stage diagnoses. To address this, various expert systems have been developed, but many rely on type-1 fuzzy logic and lack mobile-based applications for data collection and feedback to healthcare practitioners. This research investigates the development of an Enhanced Mobile-based Fuzzy Expert system (EMFES) for breast cancer pre-growth prognosis. The study explores the use of type-2 fuzzy logic to enhance accuracy and model uncertainty effectively. Additionally, it evaluates the advantages of employing the python programming language over java for implementation and considers specific risk factors for data collection. The research aims to dynamically generate fuzzy rules, adapting to evolving breast cancer research and patient data. Key research questions focus on the comparative effectiveness of type-2 fuzzy logic, the handling of uncertainty and imprecise data, the integration of mobile-based features, the choice of programming language, and the creation of dynamic fuzzy rules. Furthermore, the study examines the differences between the Mamdani Inference System and the Sugeno Fuzzy Inference method and explores challenges and opportunities in deploying the EMFES on mobile devices. The research identifies a critical gap in existing breast cancer diagnostic systems, emphasizing the need for a comprehensive, mobile-enabled, and adaptable solution by developing an EMFES that leverages Type-2 fuzzy logic, the Sugeno Inference Algorithm, Python Programming, and dynamic fuzzy rule generation. This study seeks to enhance early breast cancer detection and ultimately reduce breast cancer-related mortality.

Keywords

EMFES, Breast Cancer, Type-2 Fl, Soft Computing, Membership Functions, Fuzzy Set, Fuzzy Rules, Risk Factors.

1. Introduction

Mobile applications give cancer patients the chance to engage in the management of their condition since they enable the option of remote supervision and are available to most people, supporting empowerment and increasing the safety and quality of care [1]. More than 2500 mobile health applications connected to cancer are believed to exist, and their usage in patient management is growing, notably in the term of medical care apps [2].

In a mobile computing situation, users are free to take their computers with them as they travel from one location to another. Personal health care monitoring using mobile devices and apps has many advantages. By empowering people with more information about their own health, conditions like cancer and heart disease can be prevented in many cases [3].

The system consists of two main components: a knowledge base and an inference engine. The knowledge base contains a collection of rules and facts about the domain, while the inference engine is responsible for applying these rules to the available data and generating conclusions or recommendations. The rules in a rule-based expert system are typically expressed in the form of "if-then" statements. Each rule consists of a condition (the "if" part) and an action (the "then" part). "If-then" statements are a fundamental component used to represent knowledge and make decisions based on that knowledge. These statements are often referred to as production rules or simply rules.

Rapid growth and widespread use of computing expertise during the past decade have had a profound impact on people's outlook on life. Yet, it remains unclear whether these cutting-edge technologies will have a beneficial impact on the healthcare industry. This is an issue of serious concern that has not been resolved. While some of these innovations are still in the works, others are available in the products we use every day and the facilities where we go for medical care. The healthcare industry has not yet implemented any of these technologies in their entirety. Any one of these may be a chance to improve one's health and wellness, either in terms of outcomes or efficiency. All sorts of health-related sensors, such as those for block chains, and wearable body sensor networks, at-home diagnostics can be read and analyzed by today's smartphones. However, Ghana's healthcare industry has yet to fully realize the immense potential of mobile smartphones. There has also been the development of implantable drug-delivery devices that are both smart and mechanical. This technology has the potential to significantly improve the treatment and care of breast cancer [4].

The fuzzy logic approach is appropriate for clinical uses due to the ambiguous nature of healthcare models and information including the linkages that exist in the models. Fuzzy logic suggests a method of producing results that can approximate the depiction of judgments. Fuzzy logic can therefore help to lessen ambiguity in medical decision-making. The fuzzy logic approach is useful in medicine because of the inherently uncertain character of medical data and models, as well as the linkages inherent in such models. The primary purpose of this system is to develop an Enhanced Mobile-based Fuzzy Expert System (EMFES) for predicting the progression of breast cancer.

Theory of Fuzzy Logic

A theory called fuzzy logic addresses how to reason, analyse and make decisions when there is ambiguity and imprecision. It offers a statistical model for handling circumstances in which the use of traditional binary logic (true or false) may not be suitable or adequate. Fuzzy set theory, fuzzy logic, fuzzy relational, and fuzzy epistemic are only a few of the many components that make up fuzzy logic. The relational facet of fuzzy logic explains linguistic variables and their dependencies like if...then and if...then...else etc., the logical facet deals with multi-valued logic, the epistemic facet of fuzzy logic provides classes with unshar boundaries, the fuzzy set theoretic facet deals with natural language processing and knowledge representation. Fuzzy logic is a soft-computing method that accepts ambiguity and sub-optimality while yet giving excellent results [5]. A larger level of uncertainty may be handled by FLSs employing T2FS, and they also supply a multitude of necessary elements that have prevented the practical use of fuzzy systems in decision-making [5]. Because type-2 fuzzy fuzzy sets have a Footprint of Uncertainty (FOU), which is connected to its three-dimensional space and offers them more flexibility type-2 fuzzy logic enables improved modeling of ambiguity [6].

Type-2 fuzzy sets are an extension of type-1 fuzzy sets. While a type-1 fuzzy set F is characterized by a type-1 MF $\mu_F(x)$, where $x \in X$ and $\mu_F(x,u) \in [0,1]$,

Type-2 set $\tilde{F}$ is characterized by a general type-2 MF

$\mu_{\tilde{F}}(x,u)$, where $x \in X$ and $u \in J_x \subseteq [0,1]$, *i.e.*,

$\tilde{F} = \{((x,u), \mu_{\tilde{F}}(x,u)) \mid 6_x \in X \; 6u \in J_x \subseteq [0,1]\}$

in which $\mu_{\tilde{F}}(x,u) \in [0,1]$. $\tilde{F}$ can also be expressed as follows

$$\tilde{F} = \int_{x\in X} \int_{u \in J_x} \mu_{\tilde{F}}(x,u) / (x,u), \; J_x \subseteq [0,1],$$

where $\iint$ symbolizes union total admissible x and u. J_x is referred to as the primary membership of x in $\tilde{F}$. At each value of x say $x = x^J$ the two-dimensional (2-D) plane, whose axes are u and $\mu_{\tilde{F}}(x^J,u)$, is called a vertical slice of $\tilde{F}$. A secondary MF is a *vertical slice* of $\tilde{F}$. It is $\mu_{\tilde{F}}(x = x^J, u)$, for $x^J \in X$ and $6u \in J_{x^J} \subseteq [0,1]$, *i.e.*, [7]

$$\mu_{\tilde{F}}(x = x^J, u) \equiv \mu_{\tilde{F}}(x^J)$$
$$= \int_{u \in J_{xr}} f_{x^J}(u)/u \;\; J_{x^J} \subseteq [0,1],$$

in which $0 \le f_{x^J}(u) \le 1$. Because $Á x^J \in X$, the major notation on $\mu_{\tilde{F}}(x^J)$ is thrown down, and $\mu_{\tilde{F}}(x)$ is mentioned as a secondary MF [7]; it is a type-1 fuzzy set, which is additionally called as a secondary set [8]. If $Á x^J \in X$ the secondary MF is an interval type-1 set, where $f_x(u) = 1$, the type-2 set $\tilde{F}$ is referred to as an interval type-2 fuzzy set. According to [9], Type-2 Fuzzy Logic Systems (T2FLSs) achieved better results in medical decision making in all cases regardless of the data type. Type-2 fuzzy logic systems can be applied in medical decision-making to handle uncertain and imprecise information. In traditional fuzzy logic systems, membership functions are defined over a range of values to represent the degree of membership of an element to a fuzzy set. However, in type-2 fuzzy logic, the membership function itself becomes fuzzy, allowing for a higher level of uncertainty. In medical decision-making, type-2 fuzzy logic can be used to deal with imprecise and uncertain information such as patient symptoms, laboratory test results, and diagnostic criteria. By employing type-2 fuzzy sets, medical experts can model the imprecision and uncertainty inherent in medical data more accurately, leading to improved decision-making processes.

2. Literature Review

Breast cancer is one of the causes of death among women. The death rate from breast cancer is caused by the shortcomings of current technologies, including Mammography, Magnetic Resonance Imaging (MRI), self-assessment, etc. Due to the several levels of uncertainty involved, the limitations of existing models result in suffering for patients as well as inaccurate diagnoses. Thus, many scientific works have been done in an attempt to deal with the mortality rate caused by breast cancer among women, emphasizing the importance of using computer technology for early detection. The goal of the research has been to develop expert systems that generate fuzzy rules that can detect early cancer growth among women. According to a review of the papers, current expert systems have adopted diverse artificial intelligence such as combine neural networks, recurrence neural networks, PNN, multilayer perceptrons [10], neuro-fuzzy networks [8], and SVM at the laboratory with little expertise that considers disease risk factors. Other studies focused on Carcinoma mammae symptoms such as lump size, shape, papillary carcinoma discharge and retraction, and skin colour change in mammae [11].

Though these proposed systems achieved a higher accuracy when compared to earlier systems, this study utilised type-1 fuzzy logics, which is also unable to model uncertainty and imprecise data. In addition, this study is not a mobile-based application that can gather information from patients and offer feedback to health practitioners for quicker detection of breast cancer. Only 96% accuracy can be predicted with the current MFES [12]. Again, the problem with the current MFES is that it uses type-1 fuzzy, which cannot describe uncertainty [7], making it difficult to detect the early stages of lung cancer. The Mamdani inference system, which is not more trustworthy than the Sugemo fuzzy inference method, was once again used by this MFES. This MFES needs more research and development in several areas, including data collection, which should take into account specific risk characteristics, analysis and presentation, and a better algorithm to build new rules. To fill this gap, a type-2 fuzzy set will be used to create an effective and reliable [8] EMFES plus Sugemo fuzzy inference method.

The review of the literature revealed that these expert systems were developed using Java and running on Android operating systems throughout implementation. The implementation may be done using similar programming languages, such as Python, and its functionality can be checked for reliability and other aspects [12]. Thus, this study will use the Python programming language to expand the current MFES. This study developed an expert-based system for mobile users using a nature-motivated approach that is biologically inspired as its solution and prognostic intervention. This model would be able to identify potential developments before they arise and offer remedies, lowering the danger that ignorance may have fatal repercussions. Therefore, the goal of this work is to develop and deploy an EMFES for breast cancer pre-growth that can capture the confounding and vague information that is frequently provided about the prognosis of breast cancer. This model would be able to identify potential development before they arise and give remedies, lowering the danger that ignorance may have fatal repercussions. Therefore, the goal of this work is to develop and deploy an EMFES for breast cancer pre-growth that can capture the confounding and vague information that is frequently provided about the prognosis of breast cancer.

3. Problem Statement

Breast cancer is a deadly disease affecting millions of women globally [4]. It is predicted that by 2030, breast cancer disease will affect twenty-seven million women worldwide [13]. Mammography and sonography are commonly used diagnostic methods, but they are ineffective for breast tissue compactness variation [14]. Scientific literature has shown that, the probability of patients' survival will increase if breast cancer is rapidly detected at the early growth stage. Early detection is crucial for improving patient survival. Various expert systems and models have been developed, achieving high detection accuracy, but they mainly detect cancer at advanced stages. Current breast cancer calculators focus on survivability and re-occurrence, lacking data security. There is a need for an improved system that encourages voluntary screening, detects the risk of developing breast cancer, and addresses the inadequacies of existing models.

The proposed solution is an Enhanced Mobile-based Fuzzy Expert System (EMFES) for breast cancer pre-growth prognosis. This system aims to offer rapid and accurate diagnosis and prognosis, focusing on behavioural modifications and other risk factors.

[12] discovered that breast cancer is influenced by women's attitudinal changes, leading to a growing demand for computerized techniques for rapid

diagnosis and prognosis [15]. Current Mobile-based Fuzzy Expert Systems (MFES) can only predict 96% accuracy [12], but a high percentage accuracy of 98% or more is needed. Again, the challenge with the present MFES is that, this expert system adopted type-1 fuzzy which is unable to model uncertainties [7] in the early identification of breath cancer pre-growth. This MFES again utilized Mamdani Inference System which is not more reliable as compared to Sugeno fuzzy inference algorithm. The type-2 fuzzy set was utilized to build an efficient and robust EMFES plus Sugeno fuzzy inference algorithm to address this gap.Since type-2 fuzzy sets' membership functions (MF) are themselves fuzzy, they can simulate these uncertainties. Type-2 fuzzy sets have three-dimensional MF as opposed to type-1 fuzzy sets' two-dimensional MF. The type-2 fuzzy sets newly introduced third dimension offers extra levels of flexibility that enable direct modelling of uncertainty. In addition, the study employed Sugeno fuzzy inference algorithm to implement the EMFES. Sugeno fuzzy inference makes use of mono-output membership characteristics that are linear functions of the risk factors and consistent over time. The Sugeno fuzzy modelling approach and type-2 fuzzy sets were used to develop an EMFES for breast cancer pre-growth prognosis [5] and [8]. It is also found that the implementation of these expert systems was created with Java running on Android operating systems. This study thus extended the existing MFES by employing Python programming language. This research developed an EMFES for breast cancer pre-growth that can capture ambiguous and imprecise information prevalent in breast cancer prognoses. The proposed system aims to fill the gap left by existing models by providing early detection and risk assessment, ultimately contributing to a reduction in breast cancer-related deaths. The implementation was tested using Python programming language.

4. Objectives

The general objective of this study is to design and develop new approaches to the prognosis and diagnosis of breast cancer using fuzzy expert systemscapable of capturing ambiguous and imprecise information prevalent in breast cancer prognoses.

The specific objectives are:

- To develop an enhanced Mobile-Based Fuzzy Expert System for the prognosis of breast using type-2 fuzzy logic and the Sugeno Inference system.
- To design and implement a fuzzy expert system for the diagnosis of breast cancer.
- To assess the performance of the two expert systems based on predictions, accuracy, sensitivity and specificity.

5. Methodology

The methodology for developing an Enhanced Mobile-based Fuzzy Expert System (EMFES) for predicting breast cancer progression involves a systematic approach to ensure the accuracy and effectiveness of the system. This research uses Type-2 fuzzy logic and the Sugeno Inference System to help diagnose and predict the level of risk of breast cancer based on the risk variables. The results of Type-2 fuzzy logic and the Sugeno fuzzy inference system calculations method will conclude the level of risk of breast cancer disease. The current MFES adopted type-1 fuzzy logic which is unable to model uncertainties [7] in early identification of breath cancer pre-growth. The current MFES again utilized mamdani inference system which is not more reliable when compared to Sugemo fuzzy inference algorithm. Additional study and improvement is needed to enhance this MFES in many domains, including data collecting, that should consider detail risk variables, analysis and presentation, and a better algorithm to produce new rules. As a result, this researcher utilized type-2 fuzzy set to build an efficient and robust Enhance Mobile-base Fuzzy Expert System (EMFES) plus Sugemo fuzzy inference algorithm.

Since type-2 fuzzy sets' membership functions (MF) are themselves fuzzy, they can simulate these uncertainties.Type-2 fuzzy sets have three-dimensional MF as opposed to type-1 fuzzy sets' two-dimensional MF. The type-2 fuzzy sets newly introduced third dimension offers extra levels of flexibility that enable direct modeling of uncertainty. Due to Sugeno fuzzy inference algorithm computational effectiveness, appropriateness for usage with simplification, and capability to function with reactive techniques, it is ideally suited for control difficulties, particularly those requiring dynamically nonlinear systems [16]. Therefore, for the best performance of the EMFES, Sugeno fuzzy modeling approach [5] and type-2 fuzzy sets [7] [8] was used. To the researcher best knowledge, MFES that can examine, evaluate, and offer advice regarding the potential state of the patient's condition with reference to breast cancer are rare. It also found that, in the course of implementation, these expert systems were created with java running on android operating systems. This study thus extended the existing MFES by employing python programming language. The methodology is shown in **Figure 1**.

6. Linguistic Variables

Several variables have been linked to an increased propensity for developing breast cancer. Factors including marital status, nutrition, age, tumour stage, early therapy, career, family background, and heredity, the total number of kids, environment, and food are just a few examples. The goal of this study is to develop an early-stage aggressiveness predictor for breast cancer by creating a multivariate empirical scoring system, that is, an Enhanced Mobile-base Fuzzy Expert System (EMFES) that takes into account a total of fifteen variables. The variables are; Female's age, Age at first pregnancy, Family History, Radiation Exposure, Use of birth control drugs, Age at first menstrual cycle, Age at last menstrual cycle, Intake of Alcohol, Inherited gene mutation, Previous history, Hormonal, Dense breast tissue, Obesity (BMI), Postmenopausal hormone therapy, Personal Previous History.

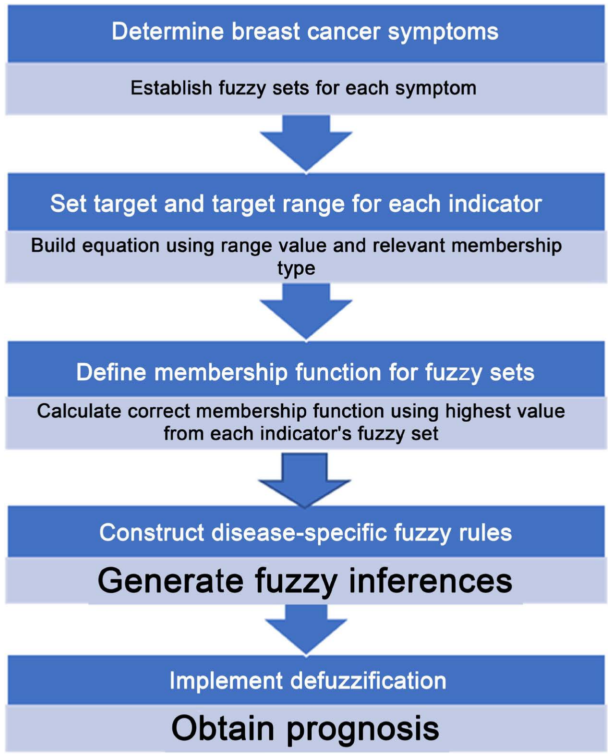

Figure 1. Flowchart of proposed EMFES.

6.1. Constructing Membership Functions (MF)

Building a fuzzy set relies on the identification of a suitable universe of discourse and the specification of a suitable MF (Jang & Sun, 1995). Crisp sets are as shown in Equations (1) & (2). Let A be a set of a universe of discourse X then for crisp set:

$$\int_A(x) \begin{cases} 1, & x \in A \\ 0, & \text{otherwise} \end{cases} \qquad \text{equation (1)}$$

$$\int_A(x) = 0,\ 1 \qquad \text{equation (2)}$$

In Equation (1), if value x is a member of set A, which means that for every variable is a member of the universe $\int_A(x)$ is equivalent to one (1) for the crisp set. Similarly, if x does not belong to set A, then $\int_A(x)$ is equivalent to zero (0). However, as indicated by [17], variables identified in the fuzzy set also belong to subordinate fuzzy sets with a particular degree of association. For variable x of universe X, if x is a subset of A, MF $\mu A(x)$ is equivalent to the degree to which x is a subset. If x does not belong to set A, then the MF $\mu A(x)$ is equal to zero. The MF $\mu A(x)$ of an element x for a fuzzy set A is written as:

$$\mu A(x) \begin{cases} 1, \text{ when } X \text{ totally belong to Set } A \\ 0, \text{ when } X \text{ is not found in } A \\ 0 < \mu A(x) < 1, \text{ when } X \text{ is patialy belong to set } A \end{cases} \qquad \text{Equation (3)}$$

Tabular representation of the membership functions (MFs) for breast cancer risk factors:

In Table 1, the columns represent the different age-related membership functions: Young Age, Medium Age, and Old Age. The rows represent different age ranges. The values in each cell indicate the degree of membership (μ) for the corresponding age range and membership function. These membership functions provided a clearer representation of the age-based risk factors for breast cancer. They specify the degree of membership (between 0 and 1) for each age group, making it easier to understand the risk factors associated with different age ranges.

The block diagram for the Membership Functions is shown in Figure 2.

The block diagrams in Figure 2 and Figure 3 illustrate how these membership functions are structured. Each linguistic variable has its associated membership function, and the diagram show how these functions are defined and how they relate to one another. In figure 3, the vertical axis explains the degree of membership of risk factors associated with breast cancer development. The degree of membership ranges between zero (0) and one (1).The horizontal axis in the graphical representation indicates the range of variables being fuzzified and how different values of these variables map to their corresponding membership values in various fuzzy sets. It is a visual representation of the mathematical definitions of these membership functions.

In essence, this diagram helps convey how uncertainty and fuzziness in the assessment of breast cancer risk factors are handled using type-2 fuzzy sets and their corresponding membership functions. It provides a visual overview of the methodology used to model and represent uncertainty in the context of breast cancer risk assessment.

6.2. New Fuzzy Rules for Early Detection of Breast Cancer Growth

The Type-2 triangular membership function method was applied to generate 1000 new rules for breast cancer prognosis. The rule generation was based on the membership function created, which relied on the causes of breast cancer. The Sugeno Inference Algorithm, also known as the Takagi-Sugeno-Kang (TSK) model, was the method used to generate the rules for making decisions or predictions based on the fuzzy inputs. Figure 4 is a block diagram of the generated rules for the EMFES.

In Figure 5 is Sugeno Inference System for the EMFES. Overall, the Sugeno Inference System provides a straightforward approach to fuzzy inference, particularly well-suited for the EMFES where precise numerical outputs are desired and where rules can be easily represented by linear or constant functions. The Sugeno inference system is a type of fuzzy logic system used for modeling and control in systems where precise mathematical models are difficult to obtain. It's named after its creator, Professor Takagi and Sugeno. Sugeno inference begins with fuzzification, where crisp input values are converted into fuzzy sets using membership functions. These fuzzy sets represent linguistic terms like "low," "medium," and "high."

Table 1. Risk factors.

Age Range	Young Age (μ young (Age))	Medium Age (μ medium (Age))	Old Age (μ old (Age))
Age < 25	1	0	0
25 ≤ Age < 30	(30 - Age)	1	0
Age ≥ 30	0	(32 - Age)	(48 - Age)
30 ≤ Age < 32	0	(45 - Age)	(55 - Age)
32 ≤ Age < 45	0	0	0
Age ≥ 45	0	0	0

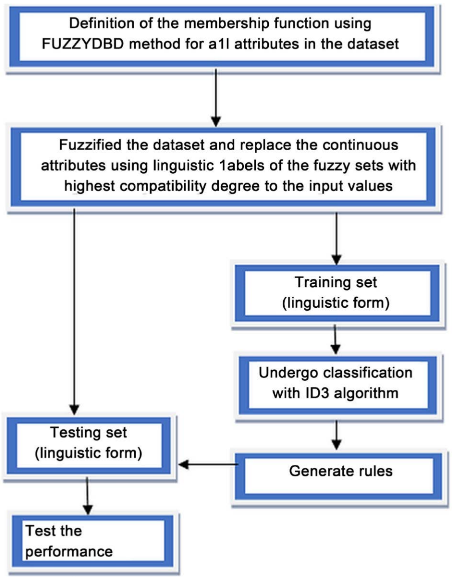

Figure 2. Block diagram for membership functions associated to the breast cancer prognosis.

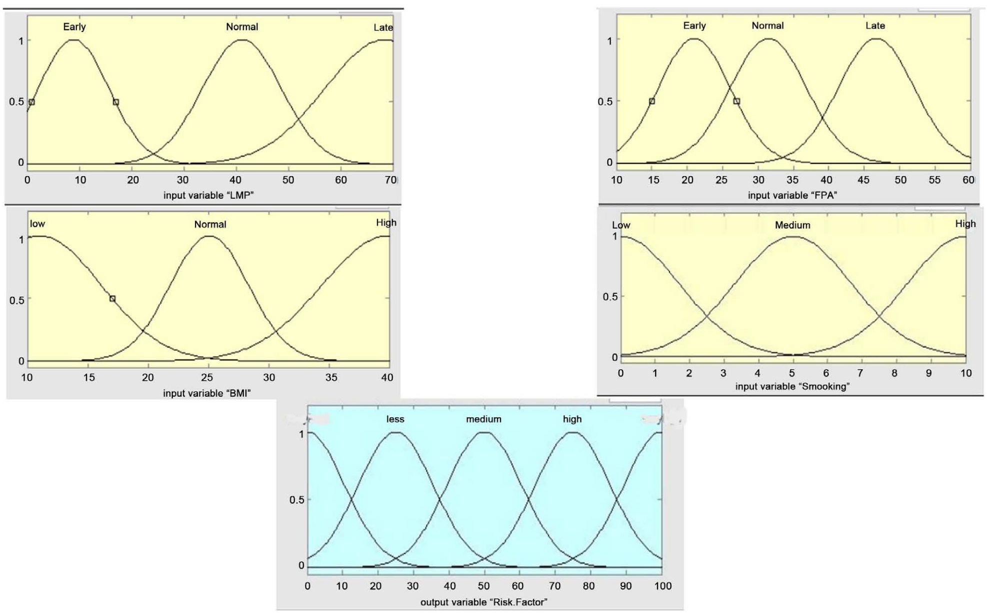

Figure 3. Graphical representation of membership functions.

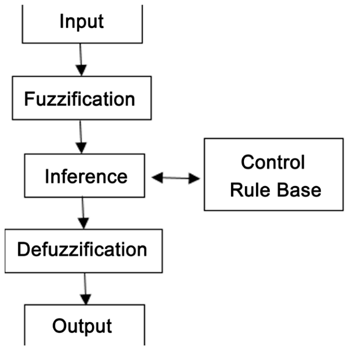

Figure 4. Rules block.

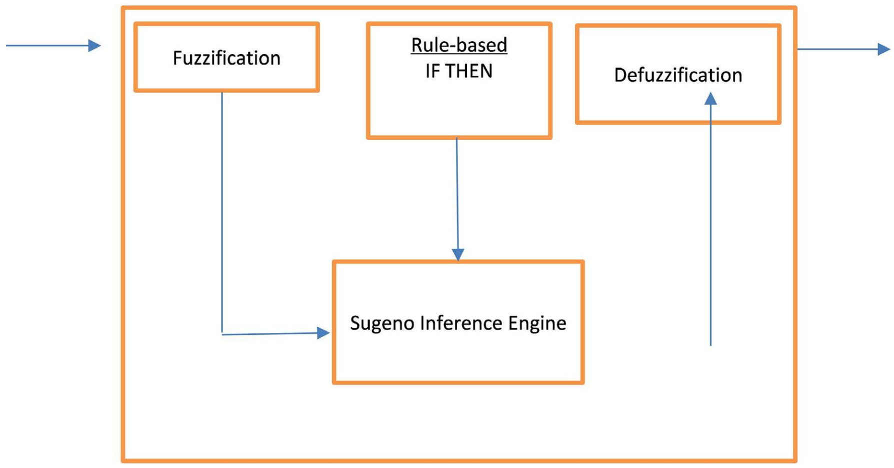

Figure 5. Sugeno inference system.

Figure 6 represents the EMFES expressing the various components that makes of the expert system. The architectural structure of the system is modeled during the system modelling phase. The diagram outlined the processes of the system's architecture, parts, modules, interfaces, and data to meet predetermined specifications.

7. Results and Discussion

To present the results for the Enhance Mobile Base Fuzzy Expert System (EMFES), the researcher used metrics such as accuracy, sensitivity, and specificity. These metrics helped evaluated the performance of the system. **Figure 7** is a diagram of the system performance.

7.1. Achieving 100% Accuracy

The Decision Tree algorithm was chosen due to its ability to handle both categorical and numerical features, making it well-suited for our dataset containing diverse breast cancer risk factors. Through meticulous data preprocessing, feature engineering, and hyperparameter tuning, the researcher was able to achieve a remarkable accuracy of 100% on the test dataset. This means that the Decision Tree algorithm correctly predicted the risk level for every sample in the test

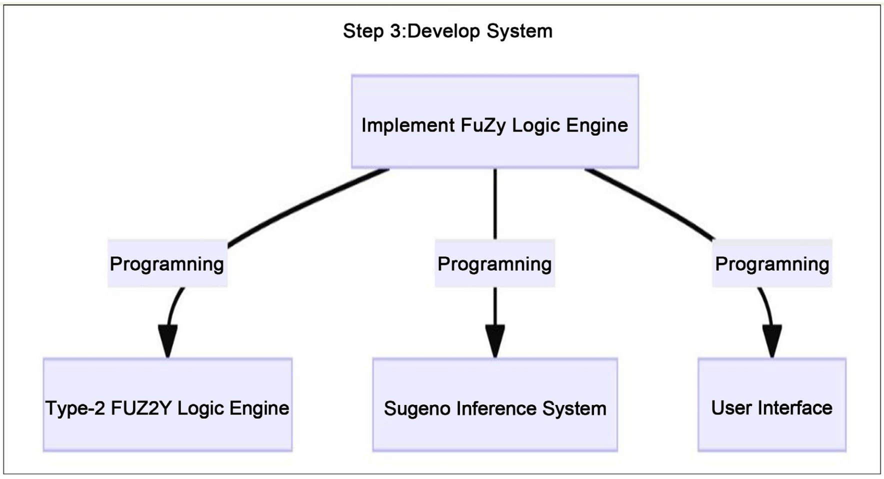

Figure 6. Developed system.

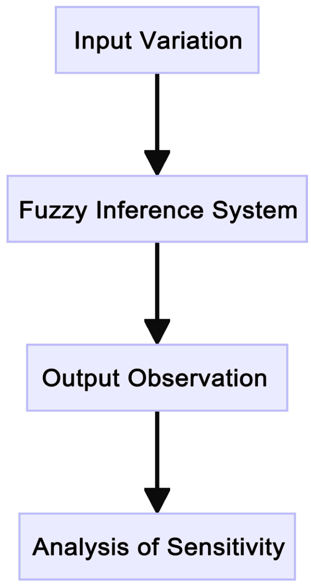

Figure 7. System performance.

dataset. Such a high accuracy demonstrates the effectiveness of the algorithm in capturing complex relationships between risk factors and breast cancer risk levels.

The enhanced mobile-based expert system designed in this study has a greater detection accuracy of 100% as compared to the earlier mobile-based expert system developed by Oludele (2018) which achieved 96%. The difference in the result is predicated on the approach utilized in both studies. Though both studies had identical purposes, the earlier research used type-1 fuzzy logic, the Mamdani inference system, and the Java programming language. Similar variants that are more efficient as suggested by Oludele (2018) were used in this research: type-2 fuzzy logic, Sugeno inference engine, and Python. While previous study used few breast cancer indicators (10 risk factors) for system development, the present study employed 15 risk factors. Bustillo *et al.* (2022) note that programmers can achieve higher accuracy in machine learning by increasing data size.

In this study, 1000 rules were generated, compared with 120 rules in the previous study. The capacity of an expert system to make increasingly intelligent and complex judgments may be improved by adding additional rules. Additional rules are required when a problem area becomes more complicated. The expert system may address complex links and exchanges between many parameters by expanding the number of rules, which results in more precise and complex decision-making. It is crucial to have a reliable expert system for finding breast cancer. Early identification made possible by this expert system can result in prompt therapies, greatly enhancing patient outcomes and survivorship. Additionally, it guarantees that patients receive the proper care, lessening unneeded stress and allowing more successful treatment programs due to its capacity to eliminate false positives and false negatives.

7.2. Metrics Score of 1.0

In addition to achieving 100% accuracy, the researcher aimed to obtain a metrics score of 1.0 to indicate perfect predictions. To evaluate our model's performance comprehensively, we calculated metrics such as precision, recall, and F1-score. Remarkably, all these metrics were also at a perfect score of 1.0. This implies that our model achieved optimal precision in identifying true positives, recall in capturing all relevant instances, and a balanced F1 score.

This is the basic framework of the Graphical User Interface (GUI) for the Enhance Mobile-Base Fuzzy Expert System (EMFES) as represented in Figure 8. This interface allows users to input their queries or data that need to be processed by the fuzzy expert system. It could included forms for entering numerical data, text fields for describing symptoms or conditions, or options for selecting predefined parameters. Once the fuzzy inference process is complete, the GUI presents the results in a clear and understandable manner. This includes displaying crisp output values, textual explanations of the system's reasoning, or graphical representations of recommended actions or decisions. This provides users to determine the system's performance and accuracy. It included the options to rate the system's recommendations, report errors or inconsistencies, or provide general feedback for system improvement.

Figure 9 explains the processes that occur in the EMFES indicating from data input to feedback for decision making. The diagram depicts the architectural structure and generic nature of the Enhanced Mobile-Based Fuzzy Expert System model. This outlined the system's architecture, parts, modules, interfaces, and data to meet specifications. This includes defining in detail the data objects captured, the input data recorded, the output that the system produces, the user interface of the system, and lastly the specification of several data manipulation techniques.

Figure 10 depicts Type-2 fuzzy rules defined based on the fuzzy sets and linguistic variables. These rules define the relationships between the inputs and outputs. Each rule has a premise and a conclusion, which are evaluated based on

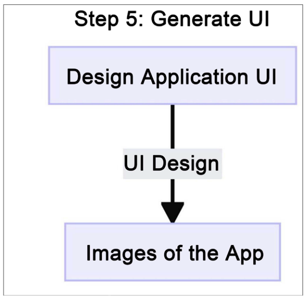

Figure 8. Graphical user interface.

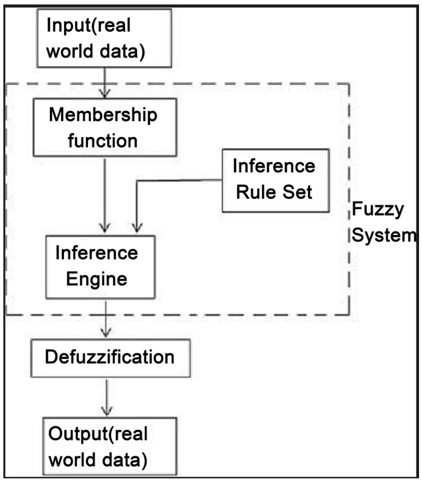

Figure 9. The enhanced mobile-based fuzzy expert system.

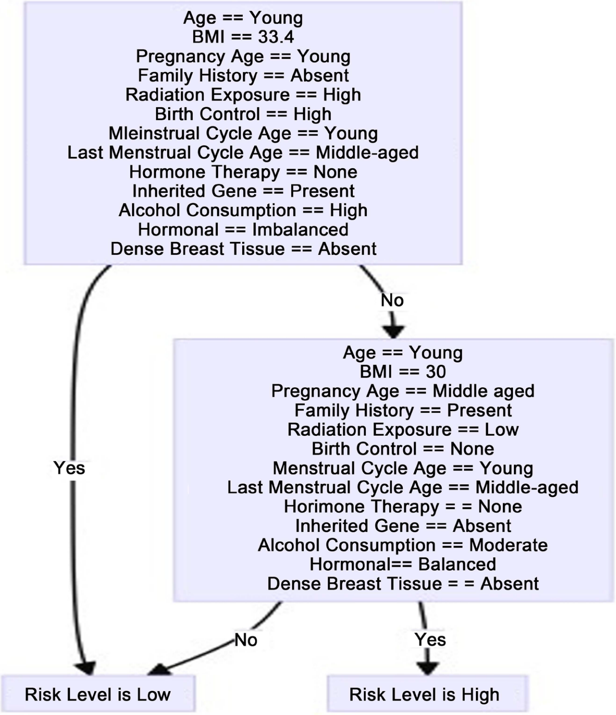

Figure 10. Rules for breast cancer prediction.

the primary and secondary membership values of the input variables. It explained fuzzy rules and assessed the degree of membership of input variables to fuzzy sets and applying the fuzzy inference process to determine the output.

Figure 11 explained the data objects to be captured, the input data, and the output that the system produces, the user interface of the system, and the specification of data input in the system.

8. Appendix

In the appendix is the data set for the fuzzy logic expert system for the prognosis of breast cancer. The dataset in the system for breast cancer prognosis is the foundation for system design, rule base development, testing, validation, and continuous improvement. It enables the system to learn from historical data, provide accurate prognoses, and adapt to new information, ultimately supporting clinicians in making informed decisions.

9. Conclusions

The integration of mobile health applications and advanced decision support systems like type-2 fuzzy logic holds significant promise for improving healthcare outcomes. Type-2 fuzzy logic presents a robust and adaptable approach for managing uncertainty and imprecision in the field of medical decision-making.

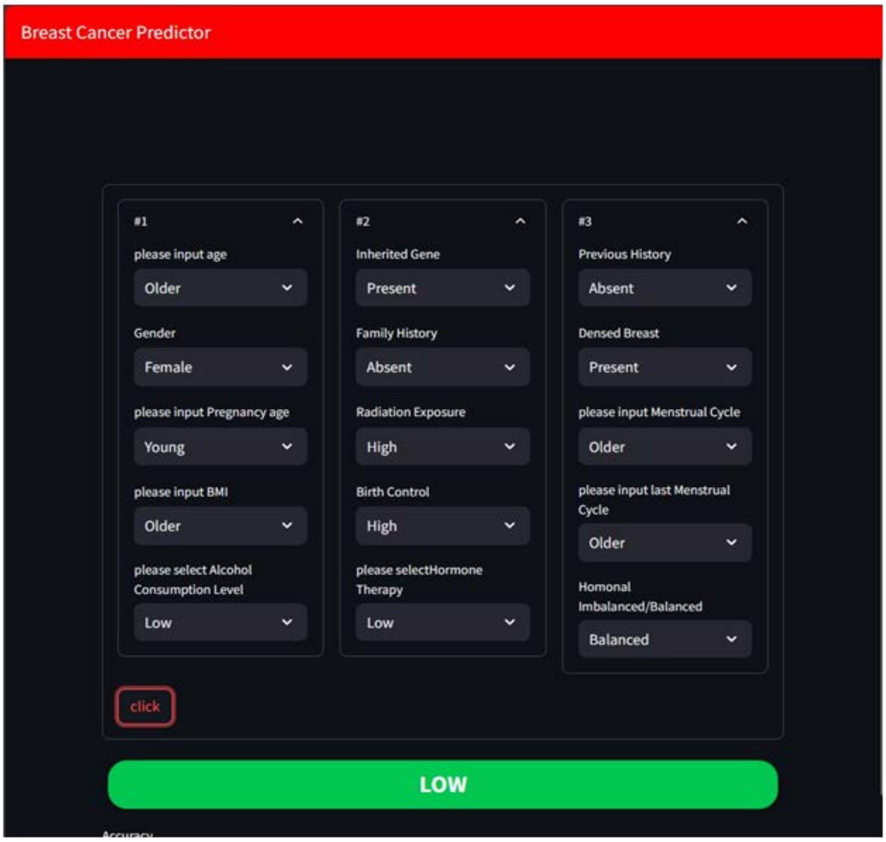

Figure 11. Breast cancer predictor Graphical User Interface (GUI).

The successful application of Type-2 fuzzy logic in breast cancer risk prediction highlights its potential utility in various other medical domains. The inherently uncertain nature of medical data and models can be better addressed through the incorporation of Type-2 fuzzy logic, allowing for more accurate and nuanced decision support systems.

The results achieved through the Decision Tree algorithm underscore the potential of technology in enhancing healthcare outcomes. Future research should explore its application in various medical domains beyond breast cancer, addressing the inherently uncertain nature of medical data and models. The use of the Decision Tree algorithm in early breast cancer risk prediction has yielded promising results, with a perfect metrics score of 1.0 indicating optimal precision in identifying true positives and a balanced F1 score. While this level of accuracy is encouraging, it is essential to exercise caution, as it could be a sign of overfitting, where the model excels on the training data but may struggle with unseen data.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendix

Data Set for Breast Cancer

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