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DESIGN AND IMPLEMENTATION OF A MOBILE BASED FUZZY EXPERT SYSTEM FOR PRE BREAST CANCER GROWTH PROGNOSIS

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Abstract:Fuzzy logic has different approaches for enhancing personal health care delivery. Currently, breast cancer is rated as the second leading cause of death among women. Previous studies using fuzzy logic were directed at reoccurrence/survivability. However, there is need for early identification of the predisposing factors of the disease and its elimination. This study focuses on developing a Mobile-based Fuzzy Expert System (MFES) to predict an individual risk of initial cancer growth.

The predisposing risk factors of breast cancer were elicited from four domain experts through direct contact; this was used to generate the fuzzy rules. The fuzzy inference approach was employed to formulate the membership functions.Mamdani approach was used for the system design. The system accommodates imprecision, tolerance and uncertainty to achieve tractability, robustness and low cost. Java expert system shell running on Android operating system was used to achieve the mobile technology aspect. For the purpose of system evaluation, 2500 data were collected from two health care centers in Nigeria using random sampling.

The result indicated that the fact elicited from the experts served as range values for the 12 risk factors for fuzzification of the input and thus, 36 rules were generated. The rules were used for the system development. The developed MFES recorded 96% accuracy.

It is therefore recommended that MFES be used to detect breast cancer risk levels early enough. The main contribution of this work is to reduce the incidence rate in contrast to the existing methods currently applied in the diagnosis of breast cancer.

Keywords**:** Soft Computing, Fuzzy Set, Breast Cancer, Risk Factors, Membership Functions

1. INTRODUCTION

Information Technology (IT), can play a key role in enhancing and enabling health care systems, when linked to specific needs. The initiation of various types of mobile portable computer devices – smartphones has influenced an appreciated positive impact in many works of life which includes the health sector. This has been influenced by the increasing excellence and availability of application software in the health sector [2]. These portable application systems are designed to supplement the experts work in order to deliver a resource that will advance the results for private health monitoring and at the point of care [2]. There are existing medical expert system models and health calculators which include but not limited to Breast Cancer Surveillance Consortium (BCSC), the Breast Cancer Risk Assessment Tool which have not met the need in the health sector. These models did not explore detail risk factors for breast cancer growth, and detail fuzzy rules were not explored as well. Most of the mobile health calculators for breast cancer prognosis are not user friendly, were more on after growth prognosis and are not readily available for personal use.

World Health Organisation (WHO) in 2012 described cancer as a leading cause global deaths. In, 2008 cancer accounted for about 13% (7.6 million) deaths (44). There are divergent views on the exact cause of breast cancer. Though, knowing an individual risk level and preventing the growth of the malignant (breast cancer) could be a preferred approach to tackling this disease because most existing research works have not actually reduced the death rate [14]. This is because reviewed literatures have shown that the existing systems focused on diagnosing/prognosing after tumour growth, the survivability and recurrence of the disease.

Majority of the data applied in medical field are naturally unclear. As a result of the unclear (fuzzy) nature of medical data and models as well as the relationships that exist in the models, fuzzy logic technique is suitable for medical applications. Fuzzy logic (an aspect of soft computing) proposes approach of result production that have the capability of estimated representation of decisions. Hence, fuzzy logic a soft computing methodology has the capability to reduce uncertainty in decision making in medical field. The main objective of this this system is to design and implement a Mobile-based Fuzzy Expert System (MFES) for breast cancer pre-growth prognosis. The designed system would be capable of capturing ambiguous and imprecise information prevalent in breast cancer

1.1 Statement of the Problem

The most recurrent and second leading cause of death in women is breast cancer. The inadequacies of the existing methods, such as Mammography, Magnetic Resonance Imaging (MRI), Self-examination and others, account for the breast cancer high mortality. The shortcomings of the existing models include: Late discovery of the cancerous, Existing models cause patients pains and related and imprecise diagnosis because it involves several layers of uncertainty.

Thousands of people fall victim to breast cancer every year due to limitation of medical services and the inability to use the existing services effectively. Late presentation of cases at advanced stages when little or no benefit can be derived from any form of therapy is the hallmark of breast cancer among Nigerian women. The available breast cancer calculators are only focused on survivability and re-occurence To curtail the worsening incidence of breast cancer deaths, a Mobile-based Fuzzy Expert System (MFES) for breast cancer pre-growth prognosis that would obviate the inadequacies of the existing models, encourage voluntary personal screening and more importantly, detect the risk of developing breast cancer is designed. Pre growth prognosis of a disease like breast cancer is very crucial to a successful reduction of death rate caused by the disease. This article weaved its solution/prognosis intervention around a nature motivated method that is biologically inspired.

1.2 Review of Literature

The advent of mobile phones has dramatically increased the availability of mobile device applications in the hospitals, businesses and home users in the past ten years. In recent time, smaller portable devices such as Personal Digital Assistant's (PDA) and especially medical applications have slowly changed the way humans live and think of computers. They now readily accept and trust medical Computing Systems. Computing is drifting away from just being concentrated on computers and relates more and more towards society, its people and its infrastructures.

- **Mobile Computing**

Mobile computing is a form of human–computer interaction scenario by which computers are expected to be moved from one place to the other when in use. Their characteristics are based on the Software and Hardware type.

- **Benefits of Mobile Applications for Personal Health Care Monitoring**

Many benefits have been provided by mobile devices and applications for Personal Health Care Monitoring (PHCM). Allowing individuals to monitor their health status, increasing the quality of personal health to a large extent reduce the death rate caused by most life threatening disease like cancer. These benefits have been shown to have an encouraging effect on individual health management results, as demonstrated by a decrease in opposing actions and wrong prognosis/diagnosis. Other benefits are convenience, improved accuracy, improved patient engagement and improved patient safety.

- **Android Mobile Application using Java Expert system shell**

Java Expert System Shell (JESS) is an expert system shell and also a scripting language. It is a very good support for the development of rule-based expert systems application which can be tightly coupled to code written in the powerful, portable and platform dependent Java language. This research work being a rule based design JESS became the best rule engine shell that would be used for java platform.

- **The current state of art of Digital Technologies in the health and care sector**

The past and recent decade have recorded speedy advancement and acceptance of expertise in computing which has greatly changed the approach to life of the people. On the other hand the question is – among these new technological know-hows which of them will influnce positively in the health sector? This question has remained a great concern. Some of these technologies are on the horizon – others are readily available in our pockets, our local surgeries and hospitals. None of these technologies has been fully deployed in the health and care sector. Each could represent an opportunity to achieve better outcomes or more efficient in personal health care. These current different technologies are Smarthphone, 8-technologies-8-connected-community, At-home diagnostics, blockchains and wearable body sensor network system (fig.1 & 2), these phones have a very high computing power to sonsor relevant data in the health setcor. Meanwhile these great potentials of these sarthphone has not been fully grasped in the health sector. Smart implantable drug delivery mechanisms are also another development in recent time. This technology can be as an effective result to help manage long-term diseases [10]. Blockchain is a distributed and protected databases that uses encryption, to protect confidential records with respect to necessary data operations on the database over time [10]. The connected community, is also a recent technology and has gone a long way in enabling and facilitating the growth of many societies, organising people together around a societal drive, a public uniqueness, a mutual interest or even a confussed community. Connected communities in the health sector are growing tremendously in association and variety. MedHelp, Patients like me and Health Unlocked are some of these social networks used for health care delivey and discussing health and care information as well as best practices [10]. Either these technologies are not fully utilized or they are not delivering on their premise. Hence, technology research should dwell more on early prognosis before the unset of any disease.

Fig. 1 Ginger.io. [12]

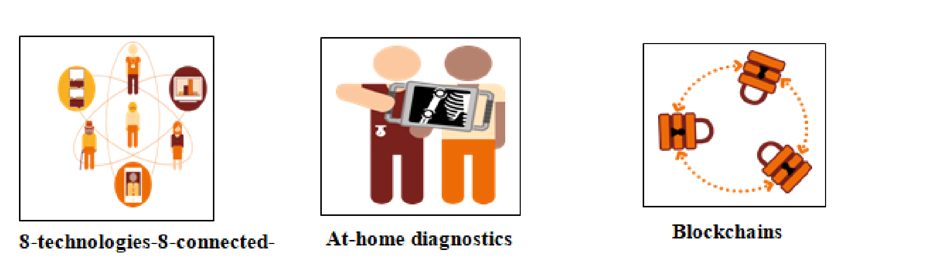

Fig. 2 Digital Technologies in the health and care sector [10]

- **Soft Computing**

According to [57], soft computing (SC) is "an emerging approach to computing, which parallels the remarkable ability of the human mind to reason and learn in an environment of uncertainty and imprecision". Natural courses have continuously been the motivation behind the strategy of soft computing techniques. Further more, [57] states that: "The guiding principle of soft computing is to exploit the tolerance for imprecision and uncertainty to achieve tractability, robustness, and low solution cost". SC is a new multidisciplinary field, to construct a new generation of Artificial Intelligence, known as Computational Intelligence. It has been generally established that the core constituents of Soft Computing are Genetic Algorithms, Probabilistic Reasoning, Fuzzy Logic and Neural Computing [57].

- **Fuzzy logic**

Fuzzy logic an aspect of soft computing is used in modelling human thinking and its applied to real life situations (problems) giving to necessities. It attempts to furnish systems with the skill to process real life data and also work with their past experiences and visions. Human solve problems by creating linguistic (verbal) rules such as "if <event realized> is this, the <result> is that". Fuzzy logic systems use linguistic variables and terms combined with linguistic rules [17]. Linguistic terms and variables in fuzzy systems are articulated accurately as membership degrees and functions.The usage of fuzzy logic provides substitutes to the difficult mathematical modelling of multifaceted non-linear problems. In fuzzy logic, data/information is in linguistic expression as an alternative to numeric values.

- **Fuzzy Logic Theory**

Fuzzy logic is a logic. Logic refers to the study of methods and principles of human reasoning. Classical logic, as common practice, deals with propositions (e.g. conclusions or decisions) that are either true or false. . This classical logic, therefore, deals with combinations of variables that represent propositions. As each variable stands for a hypothetical proposition, any combination of them eventually assumes a truth value (either true or false), but never is a truth value in between or both (i.e., is not true and false at the same time). The main content of classical logic is the study of rules that allow new logical variables to be produced as functions of certain existing variables. The fundamental assumption upon which the classical logic is based is that every proposition is either true or false. Fuzzy sets theory was initiated by [57]. Fuzzy systems play a leading role in soft computing and this stems from the fact that human reasoning is not crisp and admits degrees. The notion central to fuzzy systems is that truth values (in fuzzy logic) or membership values (in fuzzy sets) are indicated by a value on the range [0, 1], with 0 representing absolute falseness and 1 representing absolute truth. Fuzzy Logic incorporates a simple, rule-based IF X AND Y THEN Z approach to solving problem rather than attempting to model a system mathematically. Fuzzy logic provides a simple and clear way to arrive at a near definite conclusion based upon vague, ambiguous, imprecise, noisy, or missing input information.

- **Fuzzy Logic in Breast Cancer**

Fuzzy logic is an extension of Boolean logic that replaces binary truth values with degrees of truth. Reference [6] opined that Fuzzy Logic allows membership values between 0 and 1, arguably it can provide a more realistic representation of data that is inherently noisy and imprecise. The prognosis/diagnosis of breast cancer involves several levels of uncertainty which manifests itself quite differently, depending on the patient and surrounding environment and intensity [37].

1.2.1 Fuzzy Inference System (FIS)

One of the major considerations in the scheme of a fuzzy inference system is the number of fuzzy sets related to a verbal term. Fuzzy inference system as a soft computing technique mimics intellectual reasoning of the human mind based on verbal terms for execution tasks in natural surroundings. Fuzzy inference is the process of formulating the mapping from given input(s) to output(s) using fuzzy logic principles. This mapping provides a basis from which decisions can be made or patterns discerned. A fuzzy inference system with crisp inputs and outputs implements a nonlinear mapping from its input space to output space. This mapping is accomplished by a number of fuzzy if-then rules, each of which describes the local behaviour of the mapping. In particular, the antecedent of a rule defines a fuzzy region in the input space, while the consequent specifies the output in the fuzzy region. Therefore, identifying the processes is a more attractive way which uses the help of expert knowledge. This process requires defining the model input variables and the determination of the fuzzy model type. In general, the main steps performed in FIS are as follows:

1. The fuzzification component transforms each crisp input variable into a membership grade based on the membership functions defined.
2. The inference engine will then control and conducts the fuzzy cognitive procedure by smearing the

suitable fuzzy operators in order to obtain the fuzzy set to be gathered in the output variable.

3. The defuzzifier converts the fuzzy result into a crisp output by applying a precise defuzzification technique.

There are majorly two (2) types of fuzzy inference approaches that are frequently used. They are – the mamdani and sugemo techniques [27]. The Mamdani fuzzy inference process which was adopted for this research work includes four steps [27]; [26]. These are: fuzzification, rule evaluation (knowledge base), aggregate output(s) (inference engine) and defuzzification.

In making decision, fuzzy systems uses linguistic variables (rules), which are judiciously formulated [35]; [24]; [54]. A basic Fuzzy Inference System (FIS) consists of four (4) conceptual components. These are: Fuzzification Interface (contains a selection of fuzzy rules), Knowledge Base (defines the membership functions used in the fuzzy rules), Inference engine (Decision making logic) and Defuzzification Interface (performs the inference procedure upon the rules and given facts to derive a reasonable output or conclusion).

- **Fuzzification -** In this phase, the system reads the input data, scale it to fit the appropriate universe and fuzzify the input data to appropriate linguistic variables. Scaling the input data to map against the universe appropriate for the system that can be done by assigning each membership functions (MF) with an explicit function [22]. To complete fuzzification stage membership function must be determined which involves eliciting knowledge from experts. There are different methods to elicit knowledge from experts for the construction of membership functions (MF) [5]. The direct rating which was adopted is the most straightforward way to come up with a membership function [5]. This approach subscribes to the point of view that fuzziness arises from individual subjective vagueness. The same question is asked to the same subject over and over again, and the membership is constructed using the assumption of probabilistic errors and by estimating a few key parameters as is usual for this type of construction.

- **Knowledge Base**

The knowledge base contains both membership functions, known as the database, and a set of fuzzy rules, known as the rule base. These fuzzy rules define the connection between input and output fuzzy variables. A fuzzy rule has the form: **IF antecedent THEN consequent.**

The **antecedent** is a fuzzy expressions connected by fuzzy operators (and, or) while **consequent** is an expression that assign fuzzy value to the output variables. The **rule base** and the **database** are jointly referred to as the **knowledge base.** The rule base contains a number of fuzzy IF–THEN rules; a database which defines the membership functions of the fuzzy sets is used in the fuzzy rules.

- **Inference Engine**

In the inference engine, the output from the fuzzy rules is joined depending on how the system is designed to behave. The steps of fuzzy reasoning (inference operations upon fuzzy IF–THEN rules) performed by FISs are:

1. Compare the input variables with the membership functions on the antecedent part to obtain the membership values of each linguistic label. (this step is often called fuzzification.)
2. Combine (usually multiplication or min) the membership values on the premise part to get firing strength (deree of fullfillment) of each rule.
3. Generate the qualified consequents (either fuzzy or crisp) or each rule depending on the firing strength.
4. Aggregate the qualified consequents to produce a crisp output. (This step is called defuzzification.)

- **Defuzzification**

The tenacity of this stage is to interpret the present fuzzy output into a crisp value. This is crried out by using procedures. Several methods are used for defuzzification, Centroid defuzzification method was used to determine the point which indicates the center of gravity (COG) of the fuzzy set. Equation (1) was used to calculate the COG [27]; [26]:

$$COG = \int \mu_A(x) * x dx / \int \mu_A(x) dx \qquad \text{(equa. 1)}$$

where, ∫ denotes an algebraic integration and $\mu_A(x)$ is the value of membership function of set A.

In case of FIS design, all of the above mentioned steps must be considered.

1.2.2 Fuzzy Sets- Fuzzy set is an innovative approach to symbolize and operate information and data in which there exist numerous alternate doubts. Fuzzy Inference System (FIS) is based on the concepts of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning. The knowledge (facts) are programmed as a set of clear verbal rules, which is simply understood by individuals without technical knowledge [1]. As fuzzy facts deals with knowledge that is inexact, vague or indefinite, it is therefore very suitable to be used in medical field to represent certain basics as members of sets with some grades of association. The traditional way of representing elements U of a set A is through the characteristic function: $\mu A(u) = 1$, if u is an element of the set A, and $\mu A(u) = 0$, if u is not an element of the set A, that is, an object either belongs or does not belong to a given set. In fuzzy sets an object can belong to a set partially. The degree of membership is defined through a generalized characteristic function called membership function:

$\mu A(u): U \rightarrow 0,1]$, where U is called the universe, and A is a fuzzy subset of U. The membership function, often given the designation of μ, is the essence of fuzzy sets. A membership function is a curve that defines how each point in the input space is mapped to a degree of membership usually taken as a real number in the interval [0,1]. The values of the membership function are real numbers in the interval [0, 1], where 0 means that the object is not a member of the set and 1 means that it belongs entirely. Each value of the function is called a membership degree. Therefore, construction of a fuzzy set is dependent on two things: the identification of a suitable universe of discourse and the specification of an appropriate membership function (Jang & Sun, 1995). Also, the determination of fuzzy sets relies on the knowledge of human experts. Crisp sets is as shown in equa. 2 & 3. Let A be a set of a universe of discourse X then for crisp set:

$$f_A(x) = \begin{cases} 1, & x \in A \quad \text{(equa.2)} \\ 0, & \text{otherwise} \end{cases}$$

$$f_A(x) : \rightarrow \{ 0, 1 \}, \qquad \text{(equa.3)}$$

Therefore, if x is in the set of A, for any component x is in the universe of discourse X, membership function $f_A(x)$ is equal to 1 for crisp set. Conversely, if x is not a member of set A, then $f_A(x)$ is equal to 0. On the other hand, the components of the fuzzy sets belong to a subordinate fuzzy set with a specific degree of membership [57]. For any component x of universe X, if x belongs to set A, membership function μA(x) is equal to the degree to which x belongs to the set. If x is not a member of set A, then the membership function μA (x) is equal to zero. The membership function μA(x) of an element x for a fuzzy set A is expressed as follows:

$$\mu_A(x) \begin{cases} 1, & \text{if x is completely in A} \\ 0, & \text{if x is not in A} \qquad \text{(equa. 4)} \\ 0 < \mu_A(x) < 1, & \text{if x is partially in A} \end{cases}$$

- **Logical Operation on fuzzy set -** Because the standard binary logic is a special case of fuzzy logic where the membership values are always 1 (completely true) or 0 (completely false), fuzzy logic must hold the consistent logical operations as the standard logical operations. The most foundational logical operations are AND, OR and NOT. Unlike standard logical operation, the operands *A* and *B* are membership values within the interval [0, 1]. In fuzzy logical operations, logical AND is expressed by function *min*, so the statement *A* AND *B* is equal to *min* (*A*, *B*). Logical Operator OR is defined by function *max*, thus *A* OR *B* becomes equivalent to *max* (*A*, *B*). And logical NOT makes operation NOT *A* become the operation 1 – *A*.

- **Linguistic variables and Fuzzy Rules**

A linguistic variable is termed by its name and its value which is called fuzzy values or labels, each fuzzy label has a membership function that assign membership degree μ_{Label} (x) to a crisp element x that belong to a predefined range of values, this range known as universe of discourse (UOD) or simply Universe [18]. The value of membership degree ranges from 0 to 1.

However, Gaussian, Sigmoid and other types of linear functions can also be applied to characterize the fuzzy sets. Non-linear functions can also be used but they will cause additional computational complexity to the algorithm [12]. Membership Functions (MF) allow the graphical representation of a fuzzy set. The *x* axis represents the universe of discourse, whereas the *y* axis represents the degrees of membership in the [0,1] interval. A membership function is a curve that defines the feature of fuzzy set by assigning to each element the corresponding membership value, or degree of membership. It maps each point in the input space to a membership value in a closed unit interval [0, 1]. Figure 6 shows a general membership function curve.

1.2.3 Breast Cancer

There exist millions of cells in human body. If these cells are unregulated in their growth it is called cancer (tumour) [43]. Initial protection is very significant for an individual who have not been sick. Currently, greatest number of people who have developed the tumour (breast cancer), report at the health care centres very late (disease advanced stage) which is dangerous to the individual. Tumour that grows at first in the breast is called breast cancer and it is the most frequent cancer all over the world. Recent research, has shown that one in every eight (8) women will eventually have the cancer tumour (breast cancer) [43]. The reason for the increase in breast cancer cases is as a result of contemporary life-style [43]. Knowing the risk level of developing breast cancer and taking appropriate measures will greatly reduce the mortality rate.

- **Risk Factors -** A breast cancer risk factor is anything that makes it more likely for an individual to get breast cancer. Breast cancer is known to be a multifaceted disease. It is then likely to be caused by a group of risk factors. Some of these factors linked to the breast tumour can not be controlled or even be prevented, examples are-age, genetic factor, heredity. Meanwhile, personal choice can change other factors (Preventable), examples are: lack of exercises, early exposure to radiation, overweight and birth contro pills. Research have shown that the following factors are associated with an increased risk of having breast cancer:

1. Being a female
2. Increasing age
3. A personal history of breast cancer
4. A family history of breast cancer
5. Inherited genes that increase cancer risk.
6. Radiation exposure to the chest (before age 30)
7. Use of birth control drugs at an early age
8. Obesity.
9. Beginning mensural period at a younger age. Beginning period before age 12 increases the risk of breast cancer.
10. Beginning menopause at an older age.
11. Having your first child at an older age.
12. Having never been pregnant.
13. Postmenopausal hormone therapy..
14. Drinking alcohol.
15. High Body Mass Index at the onset of menopause.

1.2.4 Related Works

The prognosis/diagnosis of breast cancer comprises several layers of ambiguity and imprecision this makes traditional methods unsuitable. Soft Computing methodology - Fuzzy Logic has been used widely to model expert behaviours in the health sector as well as other works of life. In 1999, reference [34] studied the performance of fuzzy rule generation approach on Wisconsin breast cancer data (WBCD). The problem was combined with fuzzy genetic approach to evaluate system accurate recognition of breast cancer tumour. 97% accuracy was recorded. Reference [4] in 2006 have used three data mining techniques decision tree algorithm, neural network and Naïve Bayes for the breast cancer survivability studies. Fuzzy logic was applied to study the breast cancer stage. Four(4) Fuzzy rules were formed and the performed Fuzzy rules predicted the seriousness of the breast cancer at their respective stages. Reference [32] proposed fuzzy logic model to predict breast cancer using volatile biomarkers. Data mining technique Fuzzy Logic was applied in their study to interpret the risk of breast cancer stages. Laboratory data was used as input data for the proposed system. In 2007, reference [29], discussed about new segmentation method for breast cancer detection based on the mammography. Reference [16], used an adaptive fuzzy inference system (ANFIS) methodology in the estimation of breast cancer survival prediction of patients. In another research the correlation between patient and the prognostic risk of developing breast cancer was developed by reference [9] in 2010 using fuzzy system. Reference [3] in 2011, proposed a fuzzy logic technique for the estimate of the risk of breast cancer based on selected set of fuzzy rule that support the decision making process for the treatment of a supposed breast cancer patient. Furthermore, reference [8] recommended a method - fuzzy logic to predict the risk of breast cancer which was centred on a set fuzzy rules utilizing patient age and automatically extracted tumour features. Reference [25]; [20], proposed an computerized and precise hybrid system for identification of breast cancer using Machine Vision and Image Processing (MVIP). Fuzzy feature was used to increase the accuracy of their proposed system and this system tested against the data of WBCD. A research work carried out by [55], designed a fuzzy logic model to calculate the risk of individuals having breast cancer and proposed possible prospects to extinguish these risk. After assessing the risk level of the tumour (breast cancer) in individuals, the effect of stress to cancer tumour was also reported. Reference [41], used eight (8) sets of fuzzy rules, the Mamdani max-min inference mechanism was implemented. Tumour size, number of nodes and the metastasis were used as input parameters and the breast cancer risk was obtained as an output. Reference [7] developed a model using a set of fuzzy rules that can process the relevant data of breast cancer cases in order to give a breast cancer risk prognostic factor comparable to the one the expert gives. These models are more applicable for post prognostic purpose, growth stage identification of the cancer and survivability rather than pre prognosis.

To therefore tackle this life threatening disease (breast cancer) this research work is distinctive in the following ways: Detail and appropriate risk indicators that predisposes a woman to breast cancer were used, Detail risk factors were used to judiciously formulate rules for the expert system, A good number of rules were used to build the knowledge base of the system, Sample data is not needed from the tumour for the system to work, The system is not web based and its personally used (This supports the ethical issues of the right of who has access to individuals personal information).

2. BODY TEXT

2.1 The Design and Implementation of Mobile-based Fuzzy Expert System (MFES) for Breast Cancer Growth Prognosis

This design adopted the Mamdani method to develop the mobile system. The mobile aspect of the designed MFES was developed using Java expert system shell which runs on android operating system. In order to develop a MFES for breast cancer pre-growth prognosis, the following steps were followed:

- Identification of the indicators of the disease (Breast Cancer) and defining the fuzzy sets for each indicator
- Preparation of the range value for each of the indicators
- Construction of the equation using the range value. (using appropriate type of membership)
- Definition of membership function for the fuzzy sets using the appropriate equation.
- Generation of the appropriate membership function by taking maximum from the fuzzy sets of each indicator
- Construction of fuzzy rules for the disease.
- Generation of fuzzy inference
- Application of defuzzification
- Obtaining of the prognosis

2.2 Breast Cancer Prognosis Features Specification

Breast cancer ailment is related to many issues, which are marital status, diet, age, stage of cancer tumour, earlier treatment, profession, family history, inheritance, number of offspring, environmental factors and diet [39]. This research designed a MFES for breast cancer pre-growth prognosis that consisted of twelve (12) input variables. These are

1. Age
2. Age of first menstrual cycle
3. Age at last menstrual cycle
4. Age at first pregnancy
5. Duration of breast feeding
6. Body Mass Index
7. Family History
8. Early Radiation Exposure
9. Use of birth control drugs
10. Postmenopausal hormone therapy
11. Alcohol Intake (% per drink)

These parameters were identified with the help of four experts (two Surgeons, two Oncologists and from liteature). This enabled the research to cover all possible ranges of values for a given membership function selection. However, most of the features were in agreement with other similar studies [56], [36]. The output zone of the model revealed the level of risk for breast cancer in the female under observation. The model classified the risk into four categories: low, medium, high and very high. The mobile system will also refer an individual for further screening if the risk is high and very high or recommend healthy attitude if the risk factor is medium in order to reduce the risk level. Fig.2.1 shows the diagramatical representation of the Mobile-based Fuzzy Expert System (MFES) model process. The requirement of breast cancer risk evaluation and their descriptions used for the design of the MFES is as shown in Table 3.1

2.3 Design stages of the Mobile-based Fuzzy Expert System (MFES)

The mobile based expert system was built using Java Expert System Shell (JESS) which runs on Android Operating system. The sytem function is based on the rules modelled into the application to understudy the user by interrogation, analysis and then provides advisory about the possible state of the patient's health status as regards breast cancer. Android was the most desired platform because it ranks the highest in computing usage even amongst mobile devices like itself.

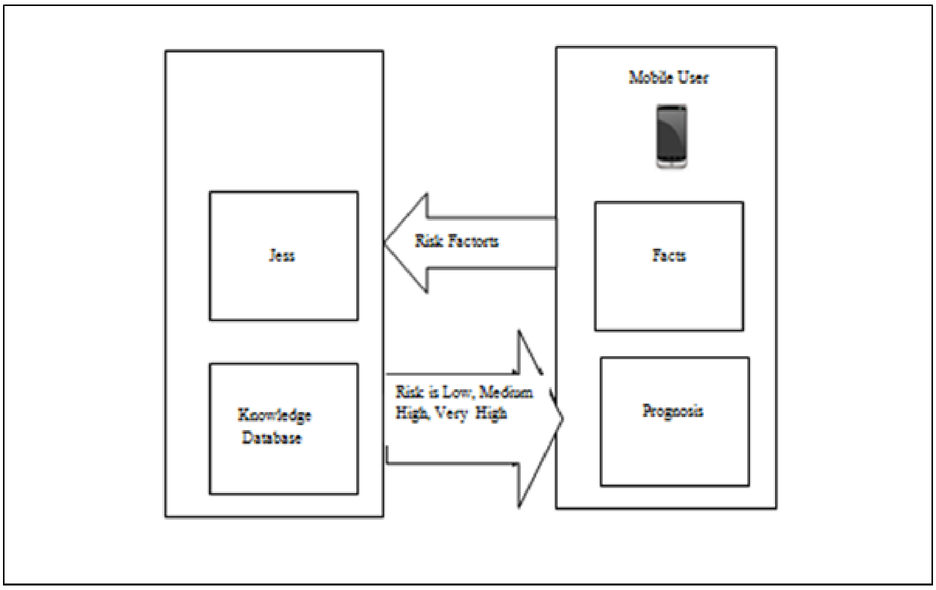

Fig 2.1The Mobile-based Fuzzy Expert System (MFES) model process

In practice generally, formulating the range values classical set fuzzy is required for fuzzy set (Table 2.1 & 2.2), logic and system procedures [37], [14]. For this reason, it is considered that all of the elements that may be present in a range have various values between 0 and 1. Convenience of fuzzy sets depends on the skill of being able to form membership degree functions appropriately to different concepts. In order to complete this stage membership function must be formulated. Some of the risk factors (indicators) and their acronyms used to formulate the membership function were:

1. Age. (Young/Medium/old)
2. Age at first menstrual cycle (AFMC). (Early/normal/Above Normal)
3. Age at last menstrual cycle (ALMC). (Normal/Above Normal)
4. Age at first pregnancy (AFP) . (early/Normal/late)
5. Duration of breast feeding (DBF) Not Normal /Normal
6. Body Mass Index (BMI). (Low/Medium/High/Very High)
7. Family History (FH). (Yes/No)
8. Early Radiation Exposure (ERE). (yes/no)
9. Use of birth control drugs (BCD). (yes/ no)
10. Postmenopausal hormone therapy (PMHT). (yes /no)
11. Alcohol Intake (% per drink). Low/ Moderate/High
12. Smoking (Yes/No)

Table 2. 1 Experts Rating for the Indicators (Risk Factors) of the Breast Cancer disease

Field (Input)	**Range Values**				
	First Expert	Second Expert	Third Expert	Fourth Expert	Fuzzy Set (Chosen by this current work)
Age	<=30	<=25	<30	<28	Young
	34	40	43	46	Medium
	>= 54	>= 55	>= 52	>= 60	old
Age at first mensural cycle (AFMC).	>=10 - <=12	>=11 - <=13	>=11 - <=13	>=12 - <= 14	Early
	>=12 - <=14	>=13 - <=15	>=13 - <=15	>=14 - <=15	Normal
	>=14 - <=16	>=15 - <=16	>=15 - <=16	>=15 - <=16	Above normal
Age at last menstrual cycle (ALMC).	<=40	<=39	<=40	<=40	Normal
	>=40	>=39	>=40	>=40	Above Normal
Age at first pregnancy (AFP) .	<=20	<=21	<=21	<=21	early
	>=20 - <=30	>=21- <=30	>=21 - <=30	>=21- <=30	Normal
	>=30	>=30	>=30	>=30	late

The experts rating for the Indicators (Risk Factors) of the breast cancer disease and the fuzzy set chosen for the design of the Fuzzy Mobile-based Expert System are given in Table 1. The Direct Rating method was used to elicit data from experts for the fuzzification stage of the model.

Equation (4) was used to calculate all the membership functions for each of the risk factor identified shown below:

$$\mu_A(x) \begin{cases} 1, & \text{if x is completely in A} \\ 0, & \text{if x is not in A} \\ 0 < \mu_A(x) < 1, & \text{if x is partially in A} \end{cases}$$

Membership Function Calculation of the risk indicators of Breast Cancer:

The experts rating for the Indicators (Risk Factors) of the breast cancer disease and the fuzzy set chosen for the design of the Fuzzy Mobile-based Expert System are given in Table 1. The Direct Rating method was used to elicit data from experts for the fuzzification stage of the model.

Equation (4) was used to calculate all the membership functions for each of the risk factor identified shown below:

$$\mu_A(x \begin{cases} 1, & \text{if x is completely in A} \\ 0, & \text{if x is not in A} \\ 0 < \mu_A(x) < 1, & \text{if x is partially in A} \end{cases}$$

Membership Function Calculation of the risk indicators of Breast Cancer:

$$\mu_{young}(Age) = \begin{cases} 1 & \text{if} \quad Age<25 \\ (30-Age)/5, & \text{if} \quad 25 <=Age<30 \\ 0, & \text{otherwise} \end{cases}$$

$$\mu_{medium}(Age) = \begin{cases} 1 & \text{if} \quad Age = 30 \\ (Age - 34)/6 & \text{if} \quad 34 <= Age <30 \\ (46 - Age)/4 & \text{if} \quad 30<= Age <46 \\ 0, & \text{Otherwise} \end{cases}$$

$$\mu_{Old}(Age) = \begin{cases} 1, & \text{if} \quad Age = 46 \\ (Age - 52)/6 & \text{if} \quad 46<= Age <52 \\ (60-Age)/4 & \text{if} \quad 46<=Age< 60 \\ 0, & \end{cases}$$

$$\mu_{Early}(AFMC) = \begin{cases} 1, & \text{if} \quad AFMC =10 \\ (14 - AFMC)/4 & \text{if} \quad 10<= AFMC <=14 \\ 0, & \text{Otherwise} \end{cases}$$

Table 2.2 Range values for the fuzzified output

Fuzzy Input Variables	**Range**
Age	Young <=30
	Medium =30 to <= 46
	Old >=46 to >=60
Age at first mensural cycle (AFMC).	Early >=10 to <=14
	Normal >=14 to <=15
	Above Normal >=15 to <=16
Age at last mensrual cycle (ALMC)	Normal <=40

	Above Normal >=40
Age at first pregnancy (AFP)	Early <=20
	Normal >=20 to <=30
	Late >=30
Duration of breast feeding (DBF)	Not Normal < 1 year
	Normal > 1 years
Body Mass Index (BMI) (kg/m2)	Low >=10 to <=20
	Medium >=20 to <=30
	High >= 30 to <= 40
	Very High >=40 to <=50
Family History (FH).	Yes/No
Early Radiation Exposure (ERE).	Yes/No
Use of birth control drugs Drugs (BCD).	Yes/No
Postmenopausal hormone therapy (PMHT).	Yes/No
Alcohol Intake (% per drink)	Low >=1 to <=1 1/2
	Moderate >= 2 to <= 4
	High> 4

2.3.1 Rules for the Mobile-base Fuzzy Epert System for breast cancer growth prognosis

If (age is young) and (AFMC is normal) and (ALMP is early) and (AFP is early) and (BMI is High) then (risk factor is very low)
If (age is young) and (AFMC is normal) and (ALMP is normal) and (AFP is normal) and (BMI is low) then (risk factor is very low)
If (age is very young) and (FMC is normal) and (LMP is normal) and (AFP is normal) and (BMI is high) then (risk factor is low)
If (age is very young) and (FMC is early) and (LMP is normal) and (AFP is early) and (BMI is high) then (risk factor is low)
If (age is young) and (FMC is early) and (LMP is normal) and (AFP is late) and (BMI is high) and (smoking is medium) then (risk factor is high low)
If (age is young) and (FMC is normal) and (LMP is late) and (FPA is normal) and (BMI is high) and (smoking is medium) then (risk factor is medium)
If (age is old) and (FMC is late) and (LMP is late) and (FPA is normal) and (BMI is high) and (smoking is low) then (risk factor is high)
If (age is very old) and (FMC is late) and (smoking is high) and (AFP is early) and (ERE is Yes) and (FH is positive) then (risk factor is high)
If (age is very old) and (FMC is early) and (LMP is late) and (AFP is normal) and (BMI is high) and (smoking is High) then (risk factor is very high)
If (age is old) and (FMC is early) and (LMP is late) and (AFP is not normal) and (BMI is high) and (smoking is high) then (risk factor is very high)
If (age is young) and (FMC is early) and (LMP is late) and (AFP is not normal) and (FH is positive) then (risk factor is very high)
If (age is young) and (FMC is early) and (LMP is late) and (AFP is not normal) and (BC is early) then (risk factor is very high)
If (age is old) and (FMC is early) and (LMP is normal) and (AFP is earlyl) and (BMI is high) and (BCD is early) then (risk factor is very high)
If (age is old) and (FMC is early) and (LMP is late) and (AFP is not normal) and (BMI is high) and (ERE is early) then (risk factor is very high)
If (age is young) and (FMC is early) and (LMP is late) and (AFP is not normal) and (FH is positive) then (risk factor is very high)
If (age is young) and (FMC is early) and (ERE is yes) and (AFP is not normal) and (FH is positive) then (risk factor is very high)
If (age is young) and (FMC is early) and (ERE is No) and (AFP is normal) and (FH is negative) then (risk factor is medium)
If (age is old) and (FMC is early) and (ERE is No) and (AFP is normal) and (PMHT is positive) then (risk factor is high)
If (age is old) and (ALMC is early) and (ERE is Yes) and (AFP is late) and (PMHT is yes) then (risk factor is high)
If (age is old) and (BMI is high) and (ERE is Yes) and (BCD is yes) and (PMHT is yes) then (risk factor is very high)
If (age is old) and (FH is yes) and (ERE is Yes) and (AFP is late) and (PMHT is yes) then (risk factor is very high)
If (age is old) and (Smoking is yes) and (ERE is Yes) and (AFP is late) and (PMHT is yes) then (risk factor is very high)
If (age is old) and (AFMC is early) and (ERE is Yes) and (AFP is late) and (PMHT is yes) then (risk factor is high)
If (age is old) and (FH is yes) and (ERE is Yes) and (AFP is late) and (PMHT is positive) then (risk factor is very high)
If (age is old) and (BCD is yes) and (ERE is Yes) and (AFP is late) and (PMHT is positive) then (risk factor is very high)
If (age is medium) and (AFMC is Above Normal) and (ALMC is above normal) and (BMI is Low) and (DBF is Normal) then (risk factor is medium)

If (age is medium) and (AFMC is Above Normal) and (ALMC is above normal) and (BMI is Medium) and (DBF is Not Normal) then (risk factor is High)
If (age is Old) and (AFMC is Above Normal) and (ALMC is above normal) and (BMI is High) and (DBF is Not Normal) then (risk factor is High).
If (age is young) and (FMC is early) and (ERE is yes) and (AFP is not normal) and (DBF is Not Normal) then (risk factor is high)
If (age is young) and (FMC is early) and (ERE is No) and (AFP is normal) and (DBF is normal) then (risk factor is medium)
If (age is medium) and (AFMC is Above Normal) and (ALMC is above normal) and (BMI is Low) and (Alcohol Intake is Low) then (risk factor is medium)
If (age is medium) and (AFMC is Above Normal) and (ALMC is above normal) and (BMI is Medium) and (Alcohol Intake is High) then (risk factor is High)
If (age is medium) and (AFMC is Above Normal) and (ALMC is above normal) and (BMI is Very High) and (Alcohol intake is Moderate) then (risk factor is High).
If (age is old) and (AFMC is Above Normal) and (ALMC is above normal) and (BMI is very High) and (Alcohol Intake is High) then (risk factor is Very High)
If (age is Old) and (AFMC is Above Normal) and (DBF is not normal) and (BMI is High) and (Alcohol Intake is High) then (risk factor is Very High)
If (age is Old) and (AFMC is Normal) and (DBF is normal) and (BMI is Low) and (Alcohol Intake is Low) then (risk factor is low)

2.4 Structure of the MFES

The designed model is based on the idea that real life problems are solved by applying their knowledge (expressed as production rules) to a given problem at hand and represented by the specific information of the problem. These production rules are stored in the long-term memory and the problem-specific information or facts in the short-term memory. In a rule-based expert system, the knowledge is represented as a set of rules. Each rule specifies a relation, recommendation, strategy or directive and has the IF (condition) THEN (action) structure. When the condition part of a rule is satisfied, the rule is said to fire and the action part is executed.

The matching of the rule to the facts produces inference chains. The inference chain cycle indicates how an expert system applies the rules to reach a conclusion. The chain cycle (forward chaining technique) gathers information and then inferring necessary information from the data. When fired, the rule adds a new fact in the database. The match-fire cycle automatically stops when no further rules can be fired. This cycle continues until all the risk indicator have been applied. (**Fig. 2.6**)

2.4.1 The Aggregation of the outputs rule

This is the process of unification of the outputs of all rules. The input of the aggregation process is the list of scaled consequent membership functions, and the output is one fuzzy set for each output variable Using knowledge of inputs values the functions for each breast cancer risk factors were obtained and also a set of functions for each and every rule for every output class. These various rules were used to generate the final output. The final output is affected by each rule and by the decided membership functions. The work of aggregating all the rules together to form a single output is done by the aggregation operator, which is visualized as a summation of the various rules to get the final output.

2.4.2 The MFES User Interface

The user interface is self explanatory; it requires the user to enter personal data by selecting from the on screen list of options and touch sensitive display on a mobile device. The user interface focuses on human concerns such as simplicity of use and reliability.(Fig. 2.2, 2.3, 2.4 & 2.5)

Figure 2.2 The first input section of the designed MFES

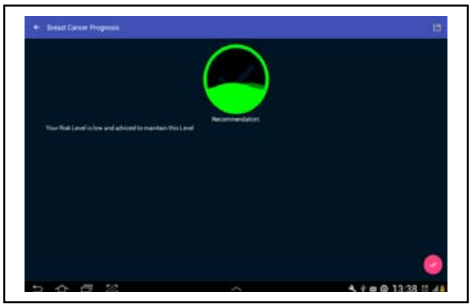

Figure 2.3.The output section of the designed MFES

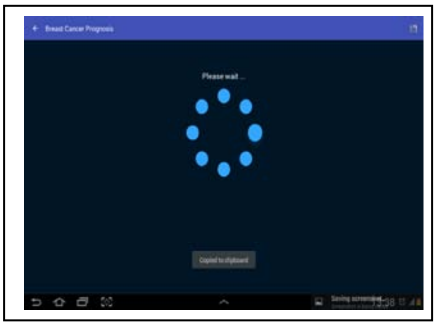

Figure 2.4 The processing page of the designed MFES

Figure 2.5 The output section of the designed MFES.

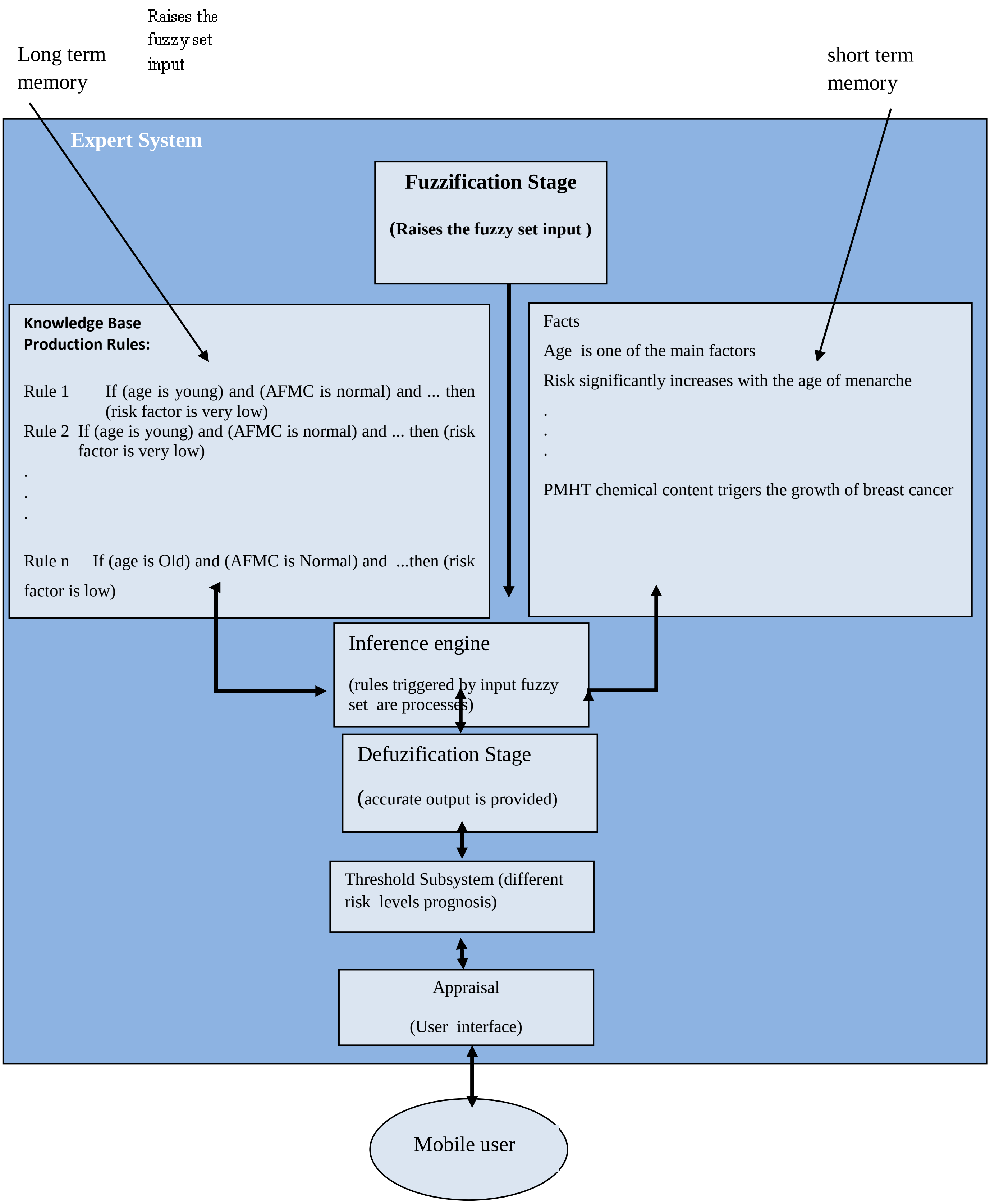

Figure 2. 6. Architectural framework of the Mobile-base Fuzzy Epert System for breast cancer growth prognosis (showing the functional modules)

2.5 Data Collection

Different data collection methods exist in research. In designing FIS, there are six primary methods to elicit knowledge from experts for the construction of a Membership Function (MF). This current study used the direct rating method because it is the most direct means of collecting data for constructing a membership function (MF). In this method, the data (subject) are presented in a series of data (objects) to the domain experts and asked to rate the membership function for each. In order to construct a MF, the responses taken from four experts were aggregated. The lowest and highest value were considered to make the ranges for MF formulation. The lowest value was used as the minimum and highest value as the maximum. All collected data fall within the highest and lowest range, in other to remove any chance of losing data. Four Oncology departments in hospitals were visited to collect data from their medical specialist in breast cancer (Surgeons and Oncologist).

Also, data were collected from the two hospitals (in Nigeria) for the performance evaluation of the designed model (Appendix 1). Data in the health sector is so enomous and coupled with the rate at which breast cancer is on the increase, the data that relates to breast cancer were much. Two thousand five hundred individual data set were collected. The data were stratified into 25 groups (strata), each strata containing 100 data each. Five individual data were collected from each strata randomely which were used to run on the system. This current work also obtained data directly from the individuals for the 100 healthy individuals which included 50 post natal mothers and 20 single females through interview method. The other (healthy dataset) were collected from women at post natal clinic at the general hospital and others were gotten from church gatherings in lagos. It was difficult to get the data because individuals were not sure of what the data was to be used for and they were particular about their personal privacy. During data collection from the individuals, it was observed that a few number of the individuals were not too sure of their first menstrual date and were not too sure to the extent they took birth control pills. As a result of this the system could not record 100% success.

2.6 System Implementation

The designed system (MFES) has a user friendly interface that makes it easy for use. The entry of data is achieved via the keypad. Information from the individual serves as the input data. This information is supplied to the mobile system during run time by the individual with the aim of obtaining relevant feedback such as the disease risk level and advice to take neccssary precaution.

3 Results and Discussion

In modelling real life situation, like breast cancer, the relationships that exist between input variables (risk factors) and output (risk level) and also the connection between each indentified input variables (risk factors) are somewhat complex, hence it is grim to express interactive relationships. Therefore, the benefits of the designed mobile based fuzzy expert system for breast cancer pre-growth prognosis model approach stands out, because the If-then rule based inference mechanism can be defined directly by real familiarity. Fuzzy inference greatly simplifies and fast-tracks the computing procedure for a real life situation modelling because most optimal result from accurate mathematical expressions is tough to get. As the designed MFES produces a result which is good enough for use and referencing.

The main benefits of our designed mobile based fuzzy expert system for breast cancer pre-growth prognosis compared to other similar works on prognosis/diagnosis are:

1. Detail and appropriate risk indicators that predisposes a woman to breast cancer was used. With this, the system can pick the smallest possible information to prevent the initial growth.
2. The detail risk factors were used to judiciously formulate fuzzy rules for the MFES.
3. A good number of rules was used to build the knowledge base of the system. This will account for all contributing factors to the tumour growth.
4. Sample data is not needed from the tumour for the system to work.
5. The designed system is both theoretical and practical.
6. The system is not web based and its personally used. This support the ethical issues of the right of who has access to individuals personal information.
7. It does not require expert analysis for the individual use.

4 Conclusion

The Mobile-based Fuzzy Expert System for breast cancer pre- growth prognosis which runs on android operating system was successfully designed and implemented using risk factors that predispose's a female to breast cancer growth. The system could be used by healthy females (those not diagnosed of breast cancer tumour) to monitor their personal health risk of breast cancer.

Based on the uncertainty nature in the prognosis/diagnosis of breast cancer and with the late presentation of cases at the health care centres. This has created very big problem especially in developing countries like Nigeria where there are insufficient specialists in the area. Fuzzy logic has been found to be a very useful technology in modelling present day issues. The designed MFES provides decision support platform to assist individuals, new researchers, physicians and other health practitioners to prevent the pain and death caused by the disease. If the designed MFES in this study is used smartly, the system could be an effective technique for pre growth prognosis.

The MFES for breast cancer pre-growth prognosis was implemented using data of those already diagnosed of breast cancer. This was to ascertain if actually the risk factors used for the design were actually responsible for the tumour growth. The performance evaluation was 96% and the 4% was as a result of incomplete data given by patient.

Incomplete data because these patients was brought at a very critical state and no family member around to give detail data about the patient. This approach will provide individuals the opportunity to personally monitor their personal health status and in the long run reduce the incidence rate caused by the disease.

The superiority of fuzzy logic model approach in this research work was to achieve an overall result by using risk factors that do not require laboratory test. This approach delivers the fastest solution to the problem at hand and averts loss of time and death as with other methods. Comparing the result in a fuzzy system modelling real life situation, it gives more exact result than using only mathematical models for the same problem. Meanwhile, the designed system recorded 96% success. Also, the risk factors used in the design of the fuzzy expert system was confirmed to be a contributing factor to the growth of breast cancer tumour which was present in patients.

This research work found that breast cancer is anchored on behavioural modification of individuals (women). Therefore the output zone of the mobile expert system is advisoral which enables one to take necessary steps in reducing their risk if it is high or very high.

4.1 Recommendations

Given the existing different fuzzy logic approaches in the bid to control the life threatening disease (breast cancer) which concentrated mainly on survivability of individuals and recurrence of the disease, used few risk factors and most approaches caused pain on individuals. These approaches were applicable only when tumour has grown which in no doubt didnt handle the high incidence rate caused by the disease as recorded by [43]. Hence, this research work strongly recommends the use of the designed MFES. Based on the nature of the disease, it is better presented before the initial growth of the tumour. The designed MFES for breast cancer pre growth prognosis is applicable before the initial growth of the tumour, takes into consideration twelve detailed risk factors, does not cause pain on individual, it is mobile and personally help individuals to monitor their personal risk level. MFES model is therefore highly recommended for global use given that:

1. It is personally used;
2. Usage does not come with pains or side effects as with existing systems;
3. It elicits critical information of individuals and output appropriate output that would help dividuals to embrace necessary action(s) based on the output information;
4. Prevent breast tumour growth and
5. Ultimately, the use of MFES would reduce the projected high death rate attributed to breast cancer.

4.2 Suggestion for Further Studies

As a future research direction, this research can be an initial step towards dealing with fuzziness in modelling real life situation. This study used Mamdani fuzzy inference system to develop the mobile FIS. It is possible to extend the research by choosing other method - Sugeno as mentioned in chapter 2. In the case of implementation, the system was developed using Java running on android phones. It is possible to do the implementation using other programming languages like Python and test their functionality with regards to reliability and other capabilities. Other fuzzy tools such as Fuzzy Structured Query Language (FSQL) can be used to observe the difference and outcomes of different implementation languages. In the future, the system with larger fuzzy rule sets can be implemented. Therefore, the system can also be extended for more research on other cancer types. The number of rules can be incresed as well.

Further research and development will aim at improving this mobile based expert system in many areas such as the information gathering, which should take many more detail risk factors into consideration, the analysis and the reporting. Also, it can also be extended to other deadly diseases. Such development will reduce the incident rate caused by these diseases to the barest minimum upon further development and release to public.

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Appendix I: Breast Cancer Dataset

	Age	Age of first menstrual cycle	Age at last menstrual cycle	Age at first pregnancy.	Duration of breast feeding (years)	Body Mass Index	Family History (Yes/No)	Early Radiation Exposure (Yes/No)	Use of birth control drugs Drugs (Yes/No)	Postmenopausal hormone therapy (Yes /No)	Alcohol Intake (Yes/No)	Smoking
1	60	14	52	30	2		No	No	Yes	Yes	Yes	No
2	59	16	49	38	11/2		No	No	Yes	Yes	Yes	No
3	45	13	42	24	1		No	No	Yes	Yes	Yes	No

4	56	13	50	31	1		Yes	No	Yes	Yes	Yes	No
5	34	11	Nill	Nill	Nill		Yes	No	Yes	Nill	Yes	No
6	37	12	Nill	32	1 and 2 months		No	Yes	Yes	Nill	Yes	No
7	45	14	Nill	40	1		Yes	No	Yes	Nill	Yes	No
8	39	12	Nill	30	1		No	No	Yes	Nill	No	No
9	40	13	Nill	29	1		Yes	No	Yes	Nill	Yes	Yes
10	24	14	Nill	Nill	Nill		No	No	Yes	Nill	Yes	No
11	43	13	Nill	40	11/2		No	Yes	Yes	Nill	Yes	No
12	30	14	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
13	19	12	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
14	37	13	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
15	39	12	Nill	30	1		No	No	Yes	Nill	Yes	No
16	40	14	Nill	32	1		Yes	No	Yes	Nill	No	No
17	12	40	Nill	Nill	1		No	No	Yes	Nill	No	Yes
18	13	56	50	39	1		No	No	Yes	Yes	No	No
19	14	60	54	Nill	Nill		No	No	No	Yes	No	Yes
20	12	60	52	28	1		No	No	Yes	Yes	Yes	No
21	13	58	50	43	1		Yes	Yes	Yes	Yes	Yes	No
22	1	30	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No

	2											
23	13	28	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
24	12	30	Nill	29	1		No	Yes	Yes	Nill	Yes	No
25	12	23	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
26	43	13	Nill	40	11/2		No	Yes	Yes	Nill	Yes	No
27	30	14	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
28	19	12	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
29	37	13	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
30	39	12	Nill	30	1		No	No	Yes	Nill	Yes	No
31	40	14	Nill	32	1		Yes	No	Yes	Nill	No	No
32	12	40	Nill	Nill	1		No	No	Yes	Nill	No	Yes
33	13	56	50	39	1		No	No	Yes	Yes	No	No
34	14	60	54	Nill	Nill		No	No	No	Yes	No	Yes
35	13	58	50	43	1		Yes	Yes	Yes	Yes	Yes	No
36	12	30	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
37	13	28	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
38	12	30	Nill	29	1		No	Yes	Yes	Nill	Yes	No
39	12	23	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
40	43	13	Nill	40	11/2		No	Yes	Yes	Nill	Yes	No
41	3	14	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No

	0											
42	1 9	12	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
43	3 7	13	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
44	3 9	12	Nill	30	1		No	No	Yes	Nill	Yes	No
45	6 0	14	52	30	2		No	No	Yes	Yes	Yes	No
46	5 9	16	49	38	11/2		No	No	Yes	Yes	Yes	No
47	4 5	13	42	24	1		No	No	Yes	Yes	Yes	No
48	5 6	13	50	31	1		Yes	No	Yes	Yes	Yes	No
35	1 3	58	50	43	1		Yes	Yes	Yes	Yes	Yes	No
36	1 2	30	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
37	1 3	28	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
38	1 2	30	Nill	29	1		No	Yes	Yes	Nill	Yes	No
39	1 2	23	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
40	4 3	13	Nill	40	11/2		No	Yes	Yes	Nill	Yes	No
41	3 0	14	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
42	1 9	12	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
43	1 3	58	50	43	1		Yes	Yes	Yes	Yes	Yes	No
44	1 2	30	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
45	1 3	28	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
46	1	30	Nill	29	1		No	Yes	Yes	Nill	Yes	No

	2											
47	12	23	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
48	43	13	Nill	40	11/2		No	Yes	Yes	Nill	Yes	No
49	30	14	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
50	19	12	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
51	60	14	52	30	2		No	No	Yes	Yes	Yes	No
52	59	16	49	38	11/2		No	No	Yes	Yes	Yes	No
53	45	13	42	24	1		No	No	Yes	Yes	Yes	No
54	56	13	50	31	1		Yes	No	Yes	Yes	Yes	No
55	34	11	Nill	Nill	Nill		Yes	No	Yes	Nill	Yes	No
56	37	12	Nill	32	1 and 2 months		No	Yes	Yes	Nill	Yes	No
57	45	14	Nill	40	1		Yes	No	Yes	Nill	Yes	No
58	39	12	Nill	30	1		No	No	Yes	Nill	No	No
59	40	13	Nill	29	1		Yes	No	Yes	Nill	Yes	Yes
60	24	14	Nill	Nill	Nill		No	No	Yes	Nill	Yes	No
61	43	13	Nill	40	11/2		No	Yes	Yes	Nill	Yes	No
62	30	14	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
63	19	12	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
64	37	13	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No

65	39	12	Nill	30	1		No	No	Yes	Nill	Yes	No
66	40	14	Nill	32	1		Yes	No	Yes	Nill	No	No
67	12	40	Nill	Nill	1		No	No	Yes	Nill	No	Yes
68	13	56	50	39	1		No	No	Yes	Yes	No	No
69	14	60	54	Nill	Nill		No	No	No	Yes	No	Yes
70	12	60	52	28	1		No	No	Yes	Yes	Yes	No
71	13	58	50	43	1		Yes	Yes	Yes	Yes	Yes	No
72	12	30	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
73	13	28	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
74	12	30	Nill	29	1		No	Yes	Yes	Nill	Yes	No
75	12	23	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
76	43	13	Nill	40	11/2		No	Yes	Yes	Nill	Yes	No
77	30	14	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
78	19	12	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
79	37	13	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
80	39	12	Nill	30	1		No	No	Yes	Nill	Yes	No
81	40	14	Nill	32	1		Yes	No	Yes	Nill	No	No
82	12	40	Nill	Nill	1		No	No	Yes	Nill	No	Yes
83	13	56	50	39	1		No	No	Yes	Yes	No	No

84	14	60	54	Nill	Nill		No	No	No	Yes	No	Yes
85	13	58	50	43	1		Yes	Yes	Yes	Yes	Yes	No
86	12	30	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
87	13	28	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
88	12	30	Nill	29	1		No	Yes	Yes	Nill	Yes	No
89	12	23	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
90	43	13	Nill	40	11/2		No	Yes	Yes	Nill	Yes	No
91	30	14	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
92	19	12	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
93	37	13	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No
94	39	12	Nill	30	1		No	No	Yes	Nill	Yes	No
95	60	14	52	30	2		No	No	Yes	Yes	Yes	No
96	59	16	49	38	11/2		No	No	Yes	Yes	Yes	No
97	45	13	42	24	1		No	No	Yes	Yes	Yes	No
98	56	13	50	31	1		Yes	No	Yes	Yes	Yes	No
99	13	58	50	43	1		Yes	Yes	Yes	Yes	Yes	No
100	12	30	Nill	Nill	Nill		No	Yes	Yes	Nill	Yes	No