International Journal of Multidisciplinary Research and Growth Evaluation.

# A fuzzy logic-based model for breast cancer prediction

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## Article Info

**ISSN (online):** 2582-7138
**Volume:** 05
**Issue:** 04
**July-August** 2024
**Received:** 22-04-2024;
**Accepted:** 24-05-2024
**Page No:** 19-27

**Abstract**
In Africa, the prevalence of unexpected deaths due to various illnesses highlights the urgent need for improved medical care systems. Breast cancer is a common cancerous infections found among women and also the primary cause of death of females living with cancer around the World. This paper proposes the development of a fuzzy model for cancer of the breast prediction, aiming to mitigate the shortcomings of traditional diagnostic approaches. By leveraging fuzzy logic, the model seeks to improve the precision and reliability in predicting the cancer of the breast, thereby facilitating earlier detection and intervention. In evaluation, the model demonstrates promising performance metrics with an Accuracy of 84%, Precision of 81.8%, Recall of 81.8%, and F1-score of 81.6%. The system was developed using the application development kit of Visual Studio C# for the code construct of forms interaction with EMGU profiler for image processing, training and matching, as well as MS SQL server for its backend to store information. The design of a Fuzzy Model for Breast Cancer Prediction is expected to enhance diagnostic accuracy, providing personalized treatment recommendations. By integrating fuzzy logic, it aims to reduce false results, ensuring timely intervention and minimizing unnecessary medical procedures for patients. The software methodology employed in the system is Object-Oriented Methodology. This research addresses a critical gap in healthcare delivery in Africa, offering a potentially transformative approach to combating the devastating impact of breast cancer through improved predictive analytics.

**Keywords:** Fuzzy Logic, Breast Cancer and Kalman's Filter Algorithm

## 1. Introduction

Humans especially in Africa are facing the delinquent of unexpected deaths due to various sickness which results from unavailability of good medical care system. Medical facilities, traditionally viewed as beacons of hope during times of illness, adhere to meticulous and intricate processes akin to other organizational structures. Recent data has highlighted a concerning rise in the inaccuracies and inconsistencies in medical diagnoses and treatments, exacerbated by patients resorting to self-medication in the absence of hospital visit [1]. Breast cancer stands out as one of the most prevalent malignancies affecting women globally, claiming countless lives each year. Statistics from 2008 revealed approximately 1.38 million cases of breast cancer diagnosed worldwide, with a staggering 50% to 60% of fatalities occurring in developing nations. Disparities in breast cancer survival rates are starkly evident on a global scale, with mortality rates notably higher in underdeveloped regions compared to their more affluent counterparts [2].

Advancements in Information Communication Technology, particularly in domains like Artificial Intelligence, which has brought in a dawn in computer systems supporting clinical diagnostics and treatment decisions tailored to individual patient data [3]. AI technologies complementing medical specialists' expertise are streamlining the healthcare sector by automating repetitive and time-consuming tasks, allowing physicians to focus more on direct patient care. As information systems progressively streamline healthcare delivery, physicians can allocate their attention to more routine patient needs.

The integration of AI holds promise in enhancing proficiency and effectiveness in combating diseases, with ongoing improvements anticipated in successive generations of AI applications [4]. As AI systems continue to evolve, it's evident that machine capabilities will increasingly permeate various aspects of breast cancer care. Rather than resisting this transformation, it's prudent to anticipate and adapt to its impacts, potential benefits, and challenges, preparing our work environments for this new reality [5]. The current diagnostic system outlined in the case study relies on manual processes for diagnosing breast cancer, where patients with suspicious cases often endure long waits to see the assigned physician. Furthermore, the hospital's outdated file storage system frequently leads to the misplacement of patient records, hindering the tracking of medical histories.

## 2. Review of Related Literature

In the study carried out by [6], they created a fuzzy-based system for the diagnostic and treatment advice of breast cancer issues. The study revealed that adding the fuzzy inference system increased the system's accuracy and precision level. It was opined by [7] that the goal is to formulate a mobile system that uses fuzzy expert logic that can forecast an individual's likelihood of acquiring cancer at first. The findings showed that the information that the experts provided functions used in the fuzzy logic of the input, leading to the generation of 36 rules. The system development utilized the rules. 96% accuracy was achieved by the designed MFES. The system design was done using the Mamdani method. The mobile technology was created using a Java expert system shell running on an Android operating system. The study carried out by [8] demonstrated how an early diagnosis of breast cancer can dramatically increase the prognosis and likelihood of survival by encouraging patients to receive timely therapeutic therapy. Patients may avoid receiving needless therapies if benign tumors are classified more accurately. To explore the alertness, risk factors, and self-deluge or self-respond screening practices of breast cancer among female there exists a gap between consciousness and practice of breast cancer screening [9]. To evaluate the influence of cancer of the breast cancer to victims and determine connotations between socio demographic and clinical variables [10]. The results generated through the questionnaire shows that One hundred females were included in the study with most with not up to 5 years of follow-up, low buying power, and low education levels. Poor level style were anticipated based on the subscales of the Cancer Impact Scale. In the work of [11], they expanded the knowledge of breast cancer and its risk factor to the public. Breast cancer causes up to 23% of cancer fatalities that leads to death. To prevent the hazardous effects of synthetic medications. Many patient today finds it difficult to consult a therapy during cancer situation due to the monetary charges involves in getting one [12]. To investigate the causes of cancer and finding out a lasting solution in terms of cure, [13] concluded that cancer is a hereditary illness characterized by aberrant cell development and the spread of cancer to other body areas as a result of genetic or epigenetic abnormalities in somatic cells. To access the knowledge and awareness of the risk factor in breast cancer in India [14] undertook a survey which out found that awareness of risk factors and BSE practices among women in Varanasi is quite poor (Delhi, Mumbai, Himachal Pradesh, Turkey and Nigeria). They concluded that doctors and other health professionals, on the other hand, may encourage them to know their statues early enough. In other to generate a comprehensive report of breast cancer and its useful concerns [15] proposed the etiology of the protective or detrimental effect of variants/mutations should be considered in the context of mtDNAhaplo groups. To give an insight of the risks curtails in breast cancer infection. Its early diagnosis is the first step for effective treatment [16]. Treatment regimen should consist of combination therapy to achieve high cure rate and decrease the risk of recurrence additionally, a qualitative study by [17] explores the psychological and physical impacts of the determination of the cancer of the breast cancer and ways of managing in among female citizens of Ghanaian.

Female of younger age who are diagnosed with breast cancer necessitate interventions and supports from health personnel and their families. In the study conducted by [18], the researchers examined the over 100 publications concerning breast cancer. They utilized data obtained from a search from high profile publications for their investigation. The study involved compiling several cited papers from the initial shortlist, which were then categorized based on journals, study categories, nations, centres, authors, and publication dates. This work emphasizes the continuous rise in the incidence of breast cancer across all regions of the world.

Despite advancements in the detection and treatment of breast cancer, leading to improved mortality rates, there remains a pressing need to explore new therapeutic approaches as well as predictive and prognostic factors [19]. In the study conducted by [20], significant awareness was raised regarding breast cancer and its consequences. Moreover, patients were educated about the molecular and genetic alterations underlying breast cancer progression, laying the groundwork for innovative therapy options. Additionally, [21] reviewed the investigation and management of cancer of the breast which includes several stages.

They suggested that the treatment of patients of breast cancer could be done individually by incorporating the analysis of standard immune-histochemical studies. This comprehensive approach aims to customize the treatment, response and planning assessment. According to [22, 23], there are associations between several hormonal and non-hormonal risk factors of breast cancer and associated molecular types. Additionally, obesity and overweight were found to increase the risk of the triple-negative subtype, particularly in premenopausal women [24].

The variables examined includes the following factors, age, family history, children, period of breast feeding, mensuration cycle, blood group, life style etc. Prediction models indicate a low likelihood of discovering additional high-penetrance genes that have not yet been identified [25]. Currently, standard models for predicting personal life style risk are usually base on family history and clinical records [26].

## 3. Methodology Adopted

The research methodology intended for the development of a Fuzzy Model for Breast Cancer prediction, integrating Kalman's Filter algorithm, commences with an in-depth review of existing literature encompassing breast cancer prediction, fuzzy logic in medical diagnostics, and Kalman Filters in healthcare. Acquisition of a comprehensive dataset from reliable medical sources is the next step, ensuring inclusion of relevant features for breast cancer prognosis, followed by meticulous preprocessing to address missing data, outliers, and inconsistencies. Techniques for feature selection and engineering are employed to identify influential variables and reduce dimensionality. Subsequently, the construction of Fuzzy Inference System is undertaken, incorporating fuzzy logic to handle dataset uncertainties, including the definition of membership functions, fuzzy rules, and inference mechanisms. Integration of the Kalman Filter into the fuzzy model is pursued to refine predictions, managing noise and uncertainties effectively. The resulting model is then trained and validated using suitable datasets to ensure its accuracy and effectiveness in breast cancer prediction.

## 4. Analysis of the System

The proposed research endeavors to construct a cutting-edge fuzzy model for cancer of breast prediction integrating Kalman's Filter algorithm, aiming to revolutionize prognostic capabilities in oncology. The comprehensive research analysis commences with an extensive exploration of existing methodologies in breast cancer prediction, fuzzy logic applications in medical diagnostics, and the use of Kalman Filters in healthcare, delineating gaps and opportunities for innovation. The crux of this investigation lies in amalgamating the adaptive nature of fuzzy logic with the filtering prowess of Kalman's algorithm, enabling the creation of a robust predictive framework that adeptly navigates uncertainties inherent in medical datasets. A critical facet involves the curation of a rich dataset, meticulously encompassing diverse patient profiles, tumor characteristics, and historical medical data from reputable sources. This dataset undergoes rigorous preprocessing to handle missing values, outliers, and normalization, preparing it for feature extraction and selection to discern pivotal attributes driving breast cancer prognosis. The subsequent development and implementation of the Fuzzy Model leverage this curated dataset, intricately weaving fuzzy inference mechanisms and membership functions to capture nuanced patterns within the data, thus accommodating uncertainties. The integration of Kalman's Filter within this model becomes the fulcrum for enhancing predictive accuracy, dynamically adjusting estimations by discerning deviations from predicted outcomes. The research entails iterative refinement, encompassing model training, validation, and optimization to ensure robustness and efficacy in breast cancer prediction.

## 5. The System's Architecture

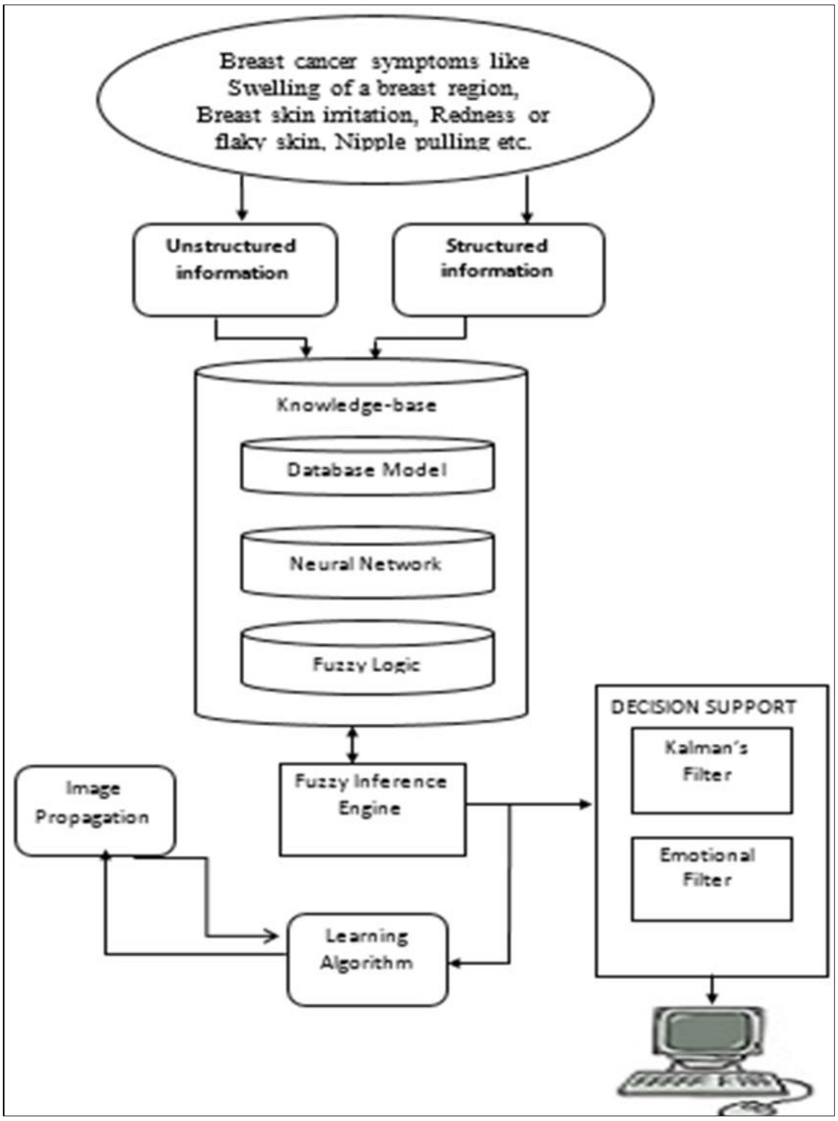


**Fig 1:** The System's Architecture

## 6. Components of the System

**These are the elements that make up the architecture**

1. **Knowledge Base**: A computer system applies a knowledge-base as a technology to store intricately organized and unstructured data.
2. **Fuzzy Inference**: An inference engine, which is a part of the system that applies logical rules to the knowledge base to derive new information, is a concept in artificial intelligence. Expert systems' initial inference engines were included in them. A inference engine and knowledge base are made up the standard expert system.
3. **Decision Support**: A decision support system is an information platform that aids in organizational or corporate decision-making.

## 7. Advantages of the System

1. **Handling Uncertainty**: The proposed system will provide the display of undefined and inaccurate information inherent in medical data. By incorporating fuzzy sets and membership functions, the model can effectively manage the ambiguity present in breast cancer diagnostic factors. Additionally, the integration of Kalman's Filter enhances this capability by dynamically adjusting predictions, refining estimations, and accommodating uncertainties in real-time, leading to more reliable prognoses.
2. **Adaptability and Learning**: Intelligent Fuzzy Models have the capacity to learn and adapt from new information. Through continuous updates and feedback mechanisms enabled by the Kalman Filter, the model evolves and improves its predictions over time. This adaptability ensures that the model remains relevant and accurate in the face of changing medical datasets or emerging diagnostic insights.
3. **Reducing Overfitting**: The Fuzzy Model, coupled with Kalman's Filter, provides a means to combat overfitting, a common issue in predictive models. By leveraging the filter's ability to discern noise and irrelevant data, the model can trim excessive irregularities and outliers from the dataset. Additionally, the fuzzy logic's ability to handle imprecise data assists in reducing the impact of overfitting, leading to a more generalized and robust predictive model for breast cancer prognosis.
4. **Enhanced Predictive Accuracy**: The integration of Fuzzy Logic and Kalman's Filter contributes to heightened predictive accuracy. Fuzzy logic allows for the inclusion of expert knowledge and intuitive reasoning, while the Kalman Filter refines predictions by incorporating both historical data and real-time measurements, resulting in more precise and reliable forecasts of breast cancer outcomes. This combined approach offers a sophisticated method to harness diverse data sources and refine predictions, potentially leading to early and more accurate detection of breast cancer.

## 8. Membership Function

The fuzzy logic contains membership functions which extends the indicator function of classical sets, reflecting the level of truth in fuzzy logic. The Kalman Filter algorithm acts as a recursive mathematical tool for estimating and predicting a system's state, especially in situations involving uncertainty and noisy measurements. This algorithm plays a crucial role in predicting future states by refining estimations iteratively based on both prior states and incoming measurements. Its operation comprises two core steps: prediction and update. During the prediction phase, the algorithm forecasts the next system state using the state transition matrix and control-input matrix, considering any applied control inputs. Concurrently, it computes the error covariance matrix, which signifies the level of uncertainty associated with the estimated state.

## 9. Dataset Used in the System

The datasets were collected from the cancer registry at the Teaching Hospital, University of Calabar, Nigeria covering a span of 24 months. They consist of 213 patient records containing eleven essential features relevant to breast cancer diagnosis. Preliminary examination highlights clear patterns, indicating a higher frequency of malignant diagnoses among patients with larger tumor sizes and invasive nodes, especially among postmenopausal women. This dataset holds promise for statistical and machine learning investigations to identify relationships between patient characteristics and breast cancer diagnosis. It presents an opportunity for developing predictive models aimed at early detection strategies.

Using dataset to create fuzzy rules and a fuzzy inference system would be necessary to build a successful fuzzy-expert model for diagnosing breast cancer. The system would then make use of these guidelines to assess fresh patient data and offer diagnoses based on linguistic and fuzzy logic factors, taking into consideration the ambiguity and uncertainty present in medical diagnosis. The proposed fuzzy-expert model's dataset for diagnosing breast cancer are:

1. **Clinical Observations**: This includes any symptoms that the patient has described, results from physical exams, and observations like palpating breast lumps.
2. **Diagnostic Result**: The ultimate determination of whether a patient has breast cancer, often expressed as binary values (positive/negative or 1/0).
3. **Age**: The patient's age upon diagnosis, which is crucial in determining the risk that breast cancer will develop.
4. **Family History**: Details regarding the patient's family's breast cancer history, particularly any close relatives who may have been affected. A person's risk might rise if their family has a history of breast cancer.
5. **Genetic Factors**: Information relating to a person's genetic makeup, such as the existence of particular gene mutations (such as BRCA1, BRCA2), which are linked to a higher risk of developing breast cancer.

## 10. Result and Discussion

### 10.1. Algorithm for implementing the breast cancer diagnosis using fuzzy model

**Step 1: Data Gathering and Processing**

1. Collect diverse datasets containing information about breast cancer risk factors like genetics, patient details, medical history, and diagnostic results.
2. Prepare the data by handling missing values, ensuring accuracy, and normalizing features.

**Step 2: Defining Membership Functions**

1. Establish linguistic variables representing breast cancer-related factors (e.g., age, genetic markers).
2. Create membership functions to translate numerical data into linguistic terms (e.g., young, middle-aged).

**Step 3: Fuzzification**

1. Apply fuzzification to map each data point to its corresponding linguistic term using the defined membership functions.

**Step 4: Formulating Rule Base**

1. Construct IF-THEN rules linking input variables and linguistic terms to predict the probability of breast cancer.

**Step 5: Inference Engine**

1. Utilize Kalman Filter algorithm to process rules and make predictions.
2. Employ fuzzy logic operations (e.g., fuzzy AND, fuzzy OR) to evaluate rules and generate fuzzy output.

**Step 6: Defuzzification**

1. Convert fuzzy output into a clear value or interpretation using methods like centroid defuzzification.

**Step 7: Model Assessment**

1. Evaluate the model's performance using metrics such as accuracy, sensitivity, specificity, and validate it with cross-validation or separate datasets.
2. Refine the model based on evaluations to enhance predictive capabilities.

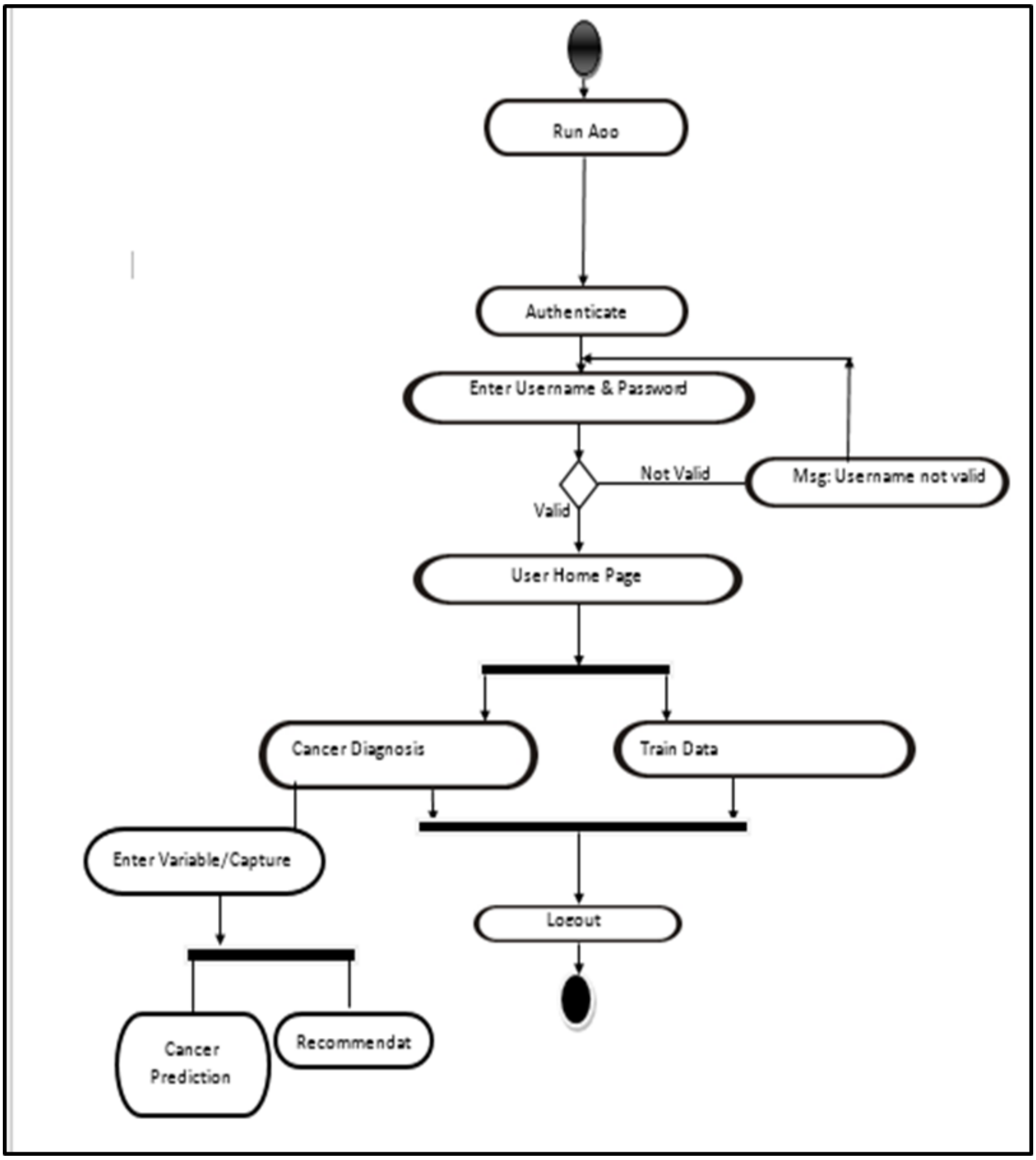


**Fig 2:** Activity Diagram for Cancer Diagnosis Process

### 10.2. Testing Data Output

The accuracy of testing data is 84%, the recall value is 0.818 for detected cancer. Precision for breast cancer prediction dataset is 81.8% and F1-score is approximately 81.6%.

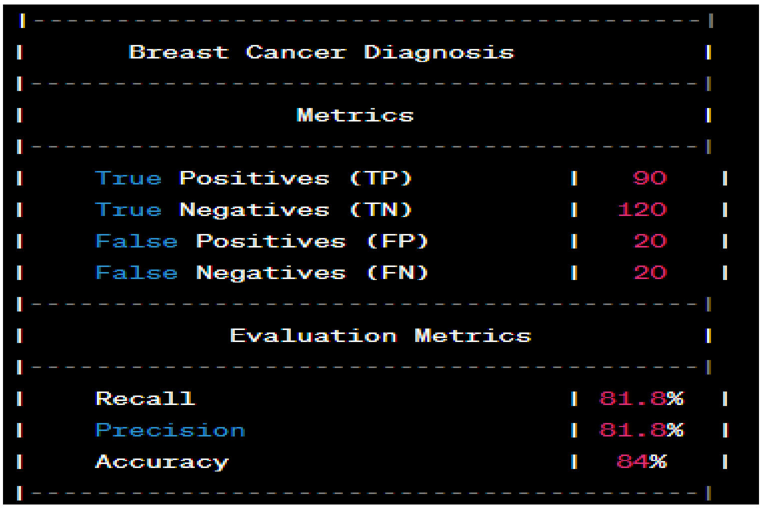


**Fig 3:** Testing Data Output

**Table 1:** Performance Matrix

| Model | Accuracy | Precision | Recall | F1-score. | Training time (seconds) |
|---|---|---|---|---|---|
| Kolman's Algorithm | 84% | 81.8% | 81.8% | 81.6% | 5 mins |

**Accuracy** – The accuracy of the classification is given as:

$$AC = \frac{TP + TN}{TP + TN + FP + FN} * 100$$

The Accuracy gave 84%

**Precision Rate** – The percentage of all correctly classified attack packets, given as:

$$PR = \frac{TP}{TP + FP} * 100$$

The Precision rate is 81.8%.

**Recall** – The percentage of all rightly classified attacks in the dataset. This is given as:

$$RC = \frac{TP}{TP + FN} * 100$$

The Recall is 81.8%.

**10.3. Result Evaluation Performance**

The evaluation of the breast cancer diagnosis model reveals promising performance metrics, demonstrating strong accuracy (84%), precision (81.8%), recall (81.8%), and an F1 score of approximately 81.6%. These metrics underscore the model's effectiveness in accurately predicting positive cases and ensuring overall correctness in its classifications. Specifically, out of the 110 actual positive instances (True Positives (TP) + False Negatives (FN) = 90 + 20), the model correctly identifies 90 True Positives, confirming its ability to flag cases with breast cancer accurately. However, the presence of 20 False Negatives highlights areas for improvement, indicating instances where the model fails to detect breast cancer when present. Addressing these missed diagnoses is crucial to enhance the model's sensitivity and prevent undetected cases of breast cancer. While the model demonstrates a recall rate of approximately 81.8%, indicating its capacity to capture a significant portion of actual positive cases among the total positives, refining its performance to reduce False Negatives is essential for accurate and timely diagnoses. Improving the F1 score further validates the model's balanced performance by considering both precision and recall, thereby promoting better outcomes in breast cancer detection and patient care.

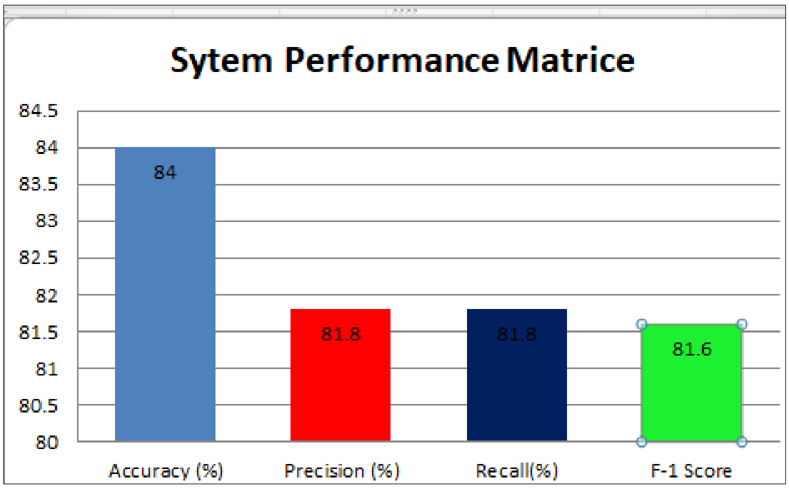


**Fig 4:** Bar Chart for Performance Metrics

## 11. System Requirement

Below are the requirements needed for developing the system they have been categorized into Hardware and Software requirements.

### 11.1. Hardware Specification/ System Software Specification

The following minimum requirements are needed: Computer System with the following hardware configurations and accessories: Core Duo Celeron and any Core series processor, 1 Terabyte of HDD, 4 Gigabyte of RAM, An Operating System (Window 10 Operating System or any other platform), Microsoft Visual Studio 2017 to 2022 (Front end) and Microsoft SQL Server (back end).

## 12. System Implementation

Implementing a system involves outlining the structure for assembling the information framework, including both hardware and software components. It also involves ensuring the effective use of the information system and aligning it with high-quality standards through quality assurance protocols.

**Table 2:** Actual Test Result versus Expected Test Result

| Actual Test Done | Expected Result |
|---|---|
| **Training Module:** the training module was tested using programmer's developed data and also real data generated via information form the case study. | The training phase was a success as every tiny detail of ailment or cancerous disease was well filtered through the inference engine and outputs where given accordingly. |
| **User Registration Module:** this stage was tested with several data generated by the programmer and as well real data from the hospital as well. These data are basic data that identifies a patient. | The registration module worked as expected but some mobile devices do not display the UI/UE as expected but tracing the Cascading Style Sheet involves in that module, the issue was solved. |
| **Training Module:** the training module was tested using programmer's developed data and also real data generated via information form the case study. | The training phase was a success as every tiny detail of automobile fault was well filtered through the inference engine and outputs where given accordingly. |
| **User Registration Module:** this stage was tested with several data generated by the programmer and as well real data from the hospital as well. These data are basic data that identifies a valid user. | The registration module functioned correctly; however, certain mobile devices did not display the user interface/user experience (UI/UE) as anticipated. Upon investigating the Cascading Style Sheet (CSS) associated with that module, the issue was resolved |

## 13. Some Major Modules/Output of the System

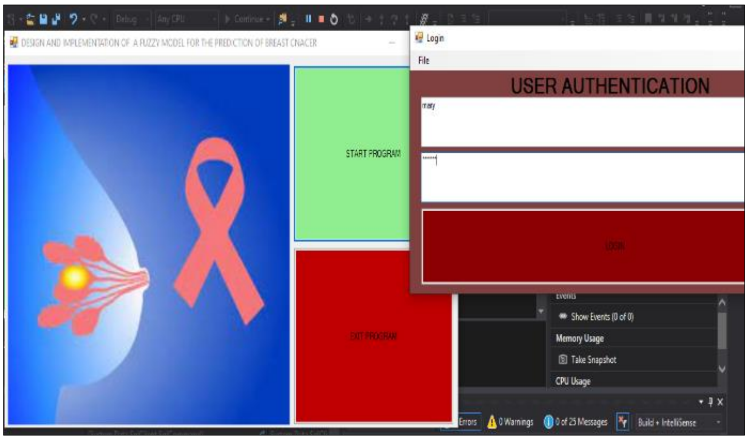

**Fig 5:** Login Module

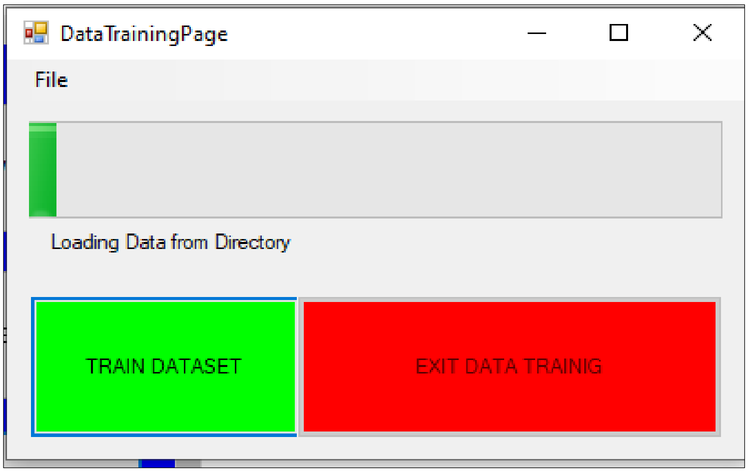

**Fig 6:** Mammogram Data Training


**Fig 7:** Diagnosis Main Page

## 14. Summary

The work's primary objective was to develop a Breast Cancer system capable of conducting cancer infection diagnosis. Throughout the study, fundamental concepts such as fuzzy logic and genetic algorithms were explored. Additionally, cancer infections were extensively discussed, and the research methodology employed was the Object-Oriented Model (OOM) as the System Development Methodology. The work aimed to integrate all hospital operations into a unified computer system to facilitate data sharing, enhance security features, and reduce software costs. The results obtained from the system were satisfactory, indicating its potential for further configuration to diagnose other illnesses. The system's scalability allows for expansion to handle various types of diseases beyond cancer infections. Furthermore, it can be re-implemented using a more advanced programming language. The system was implemented using C# based ASP.Net, Bootstrap 3.5, CSS, JavaScript, JQuery, and SQL Server.

## 15. Conclusion

This work has successfully developed a Fuzzy Model for the prediction of Breast Cancer, incorporating Kalman's Filter Algorithm to address and mitigate the inherent limitations of traditional diagnostic approaches. By integrating fuzzy logic with Kalman's Filter, our model offers a more refined and effective framework for handling the inherent uncertainty and variability present in medical diagnosis. The implementation of fuzzy logic, complemented by Kalman's Filter Algorithm, has significantly enhanced the accuracy and reliability of breast cancer predictions. This improvement stems from the model's ability to process ambiguous and imprecise data, which are common in medical scenarios, and to generate outputs that align more closely with the complex nature of human decision-making. In conclusion, the development of this Fuzzy Model with Kalman's Filter Algorithm marks a substantial progress in medical diagnostics. By improving the accuracy and reliability of breast cancer predictions, this model if fully implemented will improve the quality of care for patients worldwide. Continued research and refinement of this model could further enhance its capabilities, solidifying its role as a valuable asset in the fight against breast cancer.

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