Annals of Computing (2025), 1(9):83-89
https: doi.org /10.5281/zenodo.17113507
Research Article

Development of a Web-Based Fuzzy Expert System for Breast Cancer Risk Assessment

Tahir Abdulhakim[1], Collins Ifeanyi Osuji[2] and Christopher Okoro Uzoigwe[3]

[1]Department of Computer Science, Nasarawa State University, Keffi, Nigeria.

[2,3]Department of Computer Science, Federal University, Wukari, Nigeria.

Received 3 August 2025; Acceptance 23 August 2025; Published 13 September 2025.

Abstract

Breast cancer is a leading cause of morbidity and mortality among women worldwide, underscoring the urgent need for reliable, accessible, and cost-effective risk assessment tools. This study developed a Web-Based Fuzzy Expert System (WFES) for breast cancer risk prediction, designed to integrate clinical risk factors into an intelligent decision-support platform. Eight variables—age, age at first and last menstrual cycle, age at first pregnancy, duration of breastfeeding, body mass index, alcohol intake, and smoking—were represented using fuzzy membership functions. A knowledge base of 50 IF–THEN rules, constructed from medical expert input, was implemented through a Mamdani inference engine and deployed via a web application for platform-independent accessibility. The WFES classified patients into five risk levels: very low, low, moderate, high, and very high. Evaluation with 50 patient datasets revealed strong performance, with a Cohen's Kappa coefficient of 0.885, indicating almost perfect agreement with human expert assessments. Beyond its predictive accuracy, the web-based architecture ensures broad usability and scalability, particularly in resource-limited healthcare settings. This study demonstrates that the WFES can serve as a practical and interpretable decision-support system, aiding both clinicians and patients in early breast cancer risk assessment and prevention planning.

Keywords: Web-based system, fuzzy logic, expert system, breast cancer, risk prediction, healthcare technology.

Introduction

Artificial Intelligence (AI) has rapidly evolved in recent years to become one of the most significant and in-demand fields in science and engineering. Its progress has been driven by advances in computer architecture [1], decreasing hardware costs, access to large-scale data, and the expansion of deep neural

Correspondence to: Tahir Abdulhakim; e-mail: abdullahitahir@nsuk.edu.ng

networks. Broadly, AI refers to any technology that incorporates aspects of human intelligence, whether implemented through software or hardware. While definitions vary across industries and among scholars, there is general agreement that AI primarily focuses on enabling machines to replicate human cognitive abilities—such as observation, learning, and problem-solving—without explicit programming [2].

Today, AI applications span diverse sectors worldwide, serving as both general-purpose tools and domain-specific solutions. In healthcare, for example, systems such as IBM Watson Health assist in cancer detection and treatment, while other technologies optimize surgical scheduling for patients [3]. Although artificial general intelligence remains a long-term goal, contemporary AI research and applications emphasize challenges such as planning, knowledge representation, learning, reasoning, and object manipulation. Early AI systems often employed knowledge-based approaches, leading to the development of expert systems. These systems remain valuable due to their interpretability and transparency in logical reasoning tasks [4].

Fuzzy logic, an important branch of AI, seeks to simulate human reasoning by addressing real-world problems through approximate, rather than strictly binary, decision-making. It equips computer systems with the ability to process imprecise inputs while leveraging prior knowledge and human-like reasoning. Humans often solve problems using linguistic rules such as "if [event] occurs, then [outcome] follows." Fuzzy logic formalizes such reasoning by integrating language-based variables with membership functions to represent degrees of truth [5]. Instead of relying solely on numerical data, fuzzy logic systems employ linguistic descriptors, making them particularly suited for handling uncertainty and complexity in nonlinear problems [6].

Cancer, characterized by the uncontrolled growth of abnormal cells, remains one of the leading global health challenges. Among its various forms, breast cancer is the most prevalent, representing a significant threat to women's health worldwide. It typically originates in the breast tissue, with studies indicating that approximately one in eight women will develop the disease during their lifetime [7]. Early detection and preventive strategies are therefore critical.

Numerous models for breast cancer risk prediction have been proposed [1,8,9]. However, most rely on traditional statistical and mathematical approaches that often struggle to capture the inherent complexity and multifactorial nature of the disease. Moreover, the global burden of breast cancer underscores the need for scalable and cost-effective risk assessment tools [10]. To address this gap, this study explores the application of fuzzy logic in breast cancer risk prediction, aiming to provide a more flexible and human-like approach to assessment.

Methodology

This study employed a model-based approach using a Mamdani fuzzy inference system (FIS) to develop a Web-based Fuzzy Expert System (WFES) for breast cancer risk prediction. Expert knowledge on risk factors was obtained through structured interviews and questionnaires administered to medical doctors at

Kogi State Specialist Hospital, Lokoja, and University of Abuja Teaching Hospital, Gwagwalada. Their responses informed the selection of eight input variables: age, age at first and last menstrual cycle, age at first pregnancy, duration of breastfeeding, body mass index, alcohol intake, and smoking. These variables were expressed in linguistic terms and modeled with triangular, trapezoidal, or Gaussian membership functions.

A total of 50 IF–THEN rules were constructed from expert input and refined through consultations with oncologists. The rules mapped combinations of input factors to five output categories: very low, low, moderate, high, and very high risk. The Mamdani inference engine was applied using forward chaining and Root Sum Square aggregation, while outputs were defuzzified with the centroid method. The final crisp results were classified into three categories: low (0–2), intermediate (2–4), and high (≥4).

The system was implemented as a web-based application using Laravel (PHP) for the backend, MySQL for data management, JavaScript for interactivity, and Python for the inference engine. Performance was evaluated against expert judgment using Cohen's Kappa coefficient, with agreement levels interpreted on the standard scale from slight (0.01–0.20) to almost perfect (0.81–1.00).

Results and Discussion

The developed fuzzy expert system classified patients into five breast cancer risk levels: Very Low, Low, Moderate, High, and Very High**.** Test cases demonstrated that the system could reliably distinguish between these categories. Figure 1 presents an example of a system-generated risk classification output, illustrating how an individual's risk factors are processed into a final prediction.

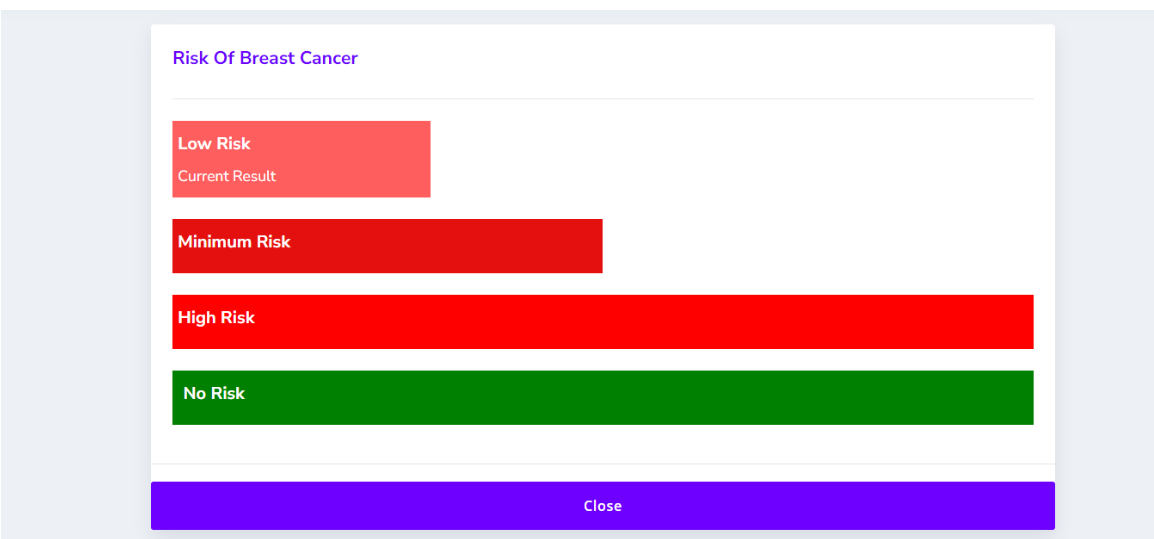

Figure 1. System-Generated Output of Breast Cancer Risk Prediction.

To validate performance, the system was evaluated using a sample of 50 patient records. Predictions were independently compared with human expert assessments. The analysis yielded the following outcomes:

- **Observed Agreement (Po):** 0.985
- **Expected Agreement (Pe):** 0.870
- **Cohen's Kappa:** 0.885 (≈89%)

According to established benchmarks, this value indicates almost perfect agreement between the system and human experts. Overall, the results demonstrate that the web-based fuzzy expert system provides a highly accurate and consistent tool for breast cancer risk prediction. Its ability to replicate expert judgments while offering efficiency and scalability supports its potential for clinical and public health applications.

Discussion of Findings

This study developed and evaluated a Web-based Fuzzy Expert System (WFES) for breast cancer risk prediction using a Mamdani fuzzy inference system. The results demonstrate that the system provides accurate and consistent predictions, achieving a Cohen's Kappa coefficient of 0.885, which indicates almost perfect agreement with human expert judgments. This finding confirms the WFES as a reliable decision-support tool for breast cancer risk stratification.

The strength of fuzzy logic lies in its ability to manage uncertainty and approximate reasoning, which are common in medical data [11,12]. Unlike conventional statistical and mathematical models that rely on rigid assumptions [13], fuzzy logic allows knowledge representation through linguistic variables and rules that closely mimic human reasoning [5,6]. In this study, 50 IF–THEN rules were constructed based on expert knowledge, enabling the system to handle multiple risk factors simultaneously and to classify patients into five distinct risk levels. This granular classification expands upon earlier models, which often relied on binary or three-tier outputs [14,15].

The findings align with previous applications of fuzzy systems in healthcare, where interpretability and transparency were emphasized as key advantages [4]. For instance, Gupta et al. [1] and Deng & Yang [4] have highlighted the value of knowledge-based AI approaches, particularly in domains requiring explainable reasoning. Unlike black-box machine learning models that demand large datasets and offer limited interpretability [9], fuzzy logic systems—such as those developed by Solikah [8] and Yilmaz & Ayan [16]—demonstrate strong diagnostic potential even with relatively small datasets. This makes the WFES suitable for settings where large-scale medical data is scarce, a common challenge in low- and middle-income countries.

From a clinical perspective, the system accurately accounted for critical risk factors such as age, reproductive history, breastfeeding duration, BMI, alcohol intake, and smoking—factors that are widely documented in the epidemiological literature [10, 17]. The classification into very low, low, moderate, high, and very high risk levels provides clinicians with actionable insights that can inform tailored preventive strategies. This aligns with global calls for scalable and cost-effective solutions to reduce the burden of breast cancer [3].

A significant innovation of this study is the deployment of the system as a web-based application, ensuring accessibility across devices and locations. Prior studies have mostly focused on offline models [18], limiting their scalability. The web-based nature of the WFES expands its applicability in real-world healthcare, particularly in resource-limited environments where breast cancer remains a leading cause of mortality [10,19]. Moreover, the adaptability of fuzzy systems allows for easy integration of additional risk factors—such as genetic predisposition, family history, or hormonal influences—making the system future-proof [20,21,22].

Overall, this discussion demonstrates that the WFES is not only accurate but also interpretable, scalable, and practical. Its capacity to replicate expert reasoning while ensuring transparency distinguishes it from many contemporary AI models. With further validation using larger datasets, the WFES could become a valuable component of breast cancer screening and prevention programs, particularly in regions with limited access to oncology specialists.

Conclusion

This study successfully developed a web-based fuzzy expert system (WFES) for breast cancer risk prediction. The system demonstrated high predictive accuracy and consistency, with a Cohen's Kappa coefficient of 0.885, indicating almost perfect agreement with human experts. By incorporating multiple risk factors and a robust rule base, the WFES provides a reliable tool for categorizing individuals into very low, low, moderate, high, or very high risk levels.

The web-based design enhances accessibility, allowing patients and healthcare professionals to use the system across different platforms, making it especially valuable in resource-limited settings where early detection and preventive interventions are crucial. To maximize its impact, healthcare providers can integrate the system into screening programs, while policymakers and institutions may adopt it as part of broader cancer prevention strategies. Future work should incorporate additional risk factors, larger datasets, and ongoing clinical validation to further improve the model's adaptability and accuracy across diverse populations.

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