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An Enhanced Deep Learning Based Model for the Prediction and Diagnosis of Breast Cancer

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ABSTRACT

This article presents an enhanced deep learning-based model for the prediction and diagnosis of breast cancer which has been one of the most serious health concerns worldwide. Traditional diagnostic methods, though effective, often face limitations such as high costs, subjectivity and delays in result interpretation. To address these challenges, this model combines advanced preprocessing techniques with optimized deep learning techniques to extract meaningful features, minimize errors and deliver more reliable results. By leveraging convolutional neural networks (a powerful deep learning approach) the system improves the accuracy speed and consistency of breast cancer detection, making early intervention more achievable and ultimately helping to save lives. The model achieved promising results, with 86% accuracy, precision of 83.5%, a recall of 84 % and an F1-score of 82%, reflecting its diagnostic efficiency. The system was developed using Visual Studio C# for the design of interactive forms, EMGU CV for image processing and Microsoft SQL Server as the backend database. This model is based on Object-Oriented Methodology making it easier to manage and expand. The integration of deep learning in healthcare delivery will assist medical personals to make better decisions and plan treatments that fit individual patients, especially in hospitals with fewer resources.

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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 establishments are seen as figures of hope when one is struck with illnesses and just like other organizations, medical institutions are well-organized, following rigid and complex processes (Merri et al., 2020). In recent years, records have shown increased inaccuracy and imprecision in medical diagnosis and treatment as most patients who could not visit the hospital usually result to self-medication (Basem et al., 2022).

According to Shen et al. (2019), breast cancer is one of the most common cancerous infections found among women and also the primary cause of death of females living with cancer around the World. A statistical analysis of about two million breast cancer cases were diagnosed in recent years with almost 60 percent of deaths occurring in developing countries (Nguyen et al., 2022). There is a huge difference in breast cancer survival rates worldwide, as the rate of death were higher in under develop country than that of its developed counterparts (Muhammad et al., 2017). According to Abunasser et al. (2022), breast cancer affected

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millions of women recently, making it the most prevalent cancer worldwide among women.

On a global scale, approximately very few types of new cancer cases are reported each year, contributing to a rise in morbidity rates (Okikiola et al., 2019). Breast cancer has emerged as a leading cause of mortality among women. The classification of tumors plays a vital role in diagnosing breast cancer. Tumors can be categorized into two types: malignant and benign. Physicians require a dependable diagnostic procedure to accurately differentiate between these tumor types (Dora et al., 2017). However, even experts often face challenges in distinguishing tumors. Therefore, there is a need for automated diagnostic systems to aid in tumor diagnosis. Numerous researchers have explored the application of machine learning algorithms in detecting cancer survivability in humans. These algorithms have demonstrated their efficacy in cancer diagnosis, as supported by research findings (Malasowe et al., 2018).

From the work of Mahesh, (2012), advances in information communication technology most especially in areas like artificial intelligence have led to the development of computer systems that support clinical diagnostics or therapeutic decisions based on personalized patient data. According to Wadkar et al. (2019), artificial intelligence technologies which supports specialists' skills in medicine, brings about an era in which repetitive and time-intensive tasks in the medical sector can be automated and performed by artificial intelligence systems. As information system progressively facilitates the delivery of healthcare in medicine today, physicians can now focus on more common patient care. The use of artificial intelligence to ensure proficiency and efficiency in delivering a sufficient tool to fight against diseases and there is no doubt that these artificial intelligence applications will improve from generation to generation (Kabiraj et al., 2020).

With the progress of artificial intelligence systems, it seems clearly that machine abilities will invade our cubicle, literally and figuratively, in all areas of breast cancer care. Instead of repelling, we should consider preparing ourselves for the impact, the potential, and the drawbacks, and start familiarizing our work environment to this new reality (Joseph, 2020).

According to Park & Han (2018), deep learning is a branch of artificial intelligence that uses layered neural networks to automatically learn patterns from large data, making it highly effective for complex tasks like medical diagnosis and speech recognition. Convolutional neural networks, a key type of deep learning model, are designed for analyzing images. They use filters to detect features such as edges, shapes, and textures, allowing them to recognize subtle patterns in medical scans. In breast cancer detection, convolutional neural networks improve speed, accuracy, and reliability, supporting earlier diagnosis and better treatment outcomes.

Shwetha et al. (2019) opined that artificial intelligence has undoubtedly made a significant impact on intricate image analysis and has provided automated data for quantitative assessment in the context of breast radiological examinations, eliminating the associated radiation risks. By emulating human reasoning with operational excellence, artificial intelligence offers super intelligence. Leveraging artificial intelligence techniques can be advantageous in instantly incorporating feature learning, processing and managing complex and multidimensional data, as well as accessing diagnostic data from various clinical experiments (Nanglia et al., 2022).

Consequently, medical consultants, academics, and oncologists have acknowledged the potential of artificial intelligence in numerous aspects of breast cancer diagnosis. Recent advancements in artificial intelligence have further fueled this optimism (Dilber et al., 2023 and Oghorodi et al., 2025). Various data mining techniques are widely employed for diagnosing different stages of breast cancer. The identification of cancer, distinguishing between malignant and benign cases, can be achieved through diverse data mining methods (Anazia et al., 2025). Classification and clustering are among the most widely used techniques for organizing and making sense of data. In the medical field, they play a vital role in diagnosis and analysis by helping to reduce false positives and false

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negatives. This, in turn, supports more accurate and reliable decision-making, ultimately improving patient care (Rashim, 2019).

The existing system used in the case study is based on manual process of diagnosing breast cancer where a patient or patients with suspicious cases may have to queue up and wait for the available doctor/physicians that has being allocated to them in other to be diagnosed (Alanazi et al., 2021). And even if it gets to a patient turn to see the doctor, in most cases patients' files are being lost due to the file storage system used by the hospital which makes it almost impossible to track a patient medical history.

STATEMENT OF PROBLEM

This research is designed to address the following problems that are associated with patients' health emergency management: Inability for patient to get prompt report on their test in relation to breast cancer, the present's systems causes stalling in medical centres as patients have to wait in queue for them to be attended to by staffs of the medical care centers, inability for patients to get their recommended drugs for treatment without leaving his/her location and the inability for patients to have a self-service to fasten up breast cancer checks in other to prevent it from growing more infectious.

REVIEW OF RELATED LITERATURE

In the work presented by Aantaki et al. (2021) a culturally grounded intervention aimed at promoting breast health care among women emphasized the importance of tailoring health education to the cultural and contextual realities of the target population. In many countries where breast cancer remains a leading cause of cancer-related deaths among women, such targeted public health education can play a critical role in improving treatment outcomes (Shah et al., 2022 and Oyathelemi et al. , 2023). However, the authors also noted the limited availability of literature to guide the development of culturally sensitive cancer education programs in communities where low awareness and prevailing cultural norms contribute to poor breast health outcomes. It described the formative assessment process, including decisions on target audience, message design, and delivery strategies, followed by the evaluation of both processes and outcomes. The study concluded with recommendations for culturally informed message development, questionnaire design, data collection, and analysis (Mahmood et al., 2020). Also Wang et al. (2022) reviewed the role of widely used health behavior theories in addressing disparities in breast cancer screening across racial, ethnic, immigrant, and low-income populations. The strengths and limitations of these theories, particularly their tendency to focus narrowly on individual cognition while neglecting broader social contexts. Multilevel ecological approaches and the integration of anthropological perspectives to better understand screening behaviors were of great importance (Odiakaose et al., 2025). It was presented that culturally grounded frameworks provide a more comprehensive understanding of disparities and can help design interventions that address both behavioral and sociocultural factors influencing mammography use (Balaha et al., 2022).

As stated by Ali et al. (2022), they presented a process that involves describing, summarizing and critically evaluating scholarly works to establish their relevance to the research problem at hand. Beyond mapping the current state of knowledge, a literature review demonstrates how a study contributes to ongoing academic and practical discussions. Durga et al. (2022) further emphasizes that a well-structured review enables researchers to link their work with broader theoretical and empirical debates, ensuring that new studies build on and extend the field rather than duplicate existing efforts.

In the work carried out by Varsha & Vishal (2023), they investigated the application of machine learning techniques for predicting breast cancer. Their study focused on developing algorithms capable of accurately forecasting the progression of the disease. Among the models tested, both decision tree and XGBoost classifiers achieved a very positive accuracy rate with XGBoost producing an improved area under the curve value.

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Similarly, Apoorva et al. (2021) examined approaches to enhance the accuracy of breast cancer prediction using machine learning and deep learning techniques. Their results showed that convolutional neural networks outperformed other models in image-based breast cancer classification tasks. It was stated by Eti et al. (2025) that using numerical datasets on support vector machine delivered better performance compared with classification and regression tree naïve bayes and KNN classifiers. It was further opined that combining convolutional neural networks for image datasets with traditional machine learning classifiers with structured numerical data had a more improved and positive output. It highlighted the importance of selecting model architectures that align with the nature of the dataset to achieve optimal prediction accuracy (Tang et al., 2021).

METHODOLOGY AND MODEL DESIGN

Method of Data Collection

This study follows the Object-Oriented Analysis and Design approach. Data will be sourced from both primary and secondary materials. Primary data will come from anonymized breast cancer patient records, covering details such as age, clinical symptoms, biopsy results, and diagnostic outcomes. Where necessary, ethical approval and consent will be obtained. Structured interviews with healthcare staff will also be conducted to better understand the current diagnostic process and its limitations.
For secondary data, publicly available repositories such as the Wisconsin Breast Cancer Dataset (WBCD) will be used to train and validate the models. Standard preprocessing techniques—feature selection, normalization, and encoding will be applied to prepare the datasets for analysis and model development.

Sampling Techniques

This study will employ a purposive sampling technique. The sampling will target female patients who have undergone breast-related diagnostic procedures within the last five years. Only cases with complete and relevant medical records (such as histopathology, mammography reports, or clinical examinations) will be included to ensure data quality and relevance to the machine learning application.
Where interview data is required, a purposive sample of key healthcare professionals will be selected based on their involvement in breast cancer diagnosis and management within the hospital.

Data Training Requirements

1. Image size: 224×224 or 299×299 (for Inception)
2. Backbone: EfficientNet-B0/B3 for a good speed/accuracy tradeoff
3. Batch size: 16–32 (GPU-dependent)
4. Learning rate: 1e-4 initial, reduce on plateau (factor 0.1)
5. Loss weighting: class_weight = {0:1, 1: w} where w = N_neg / N_pos
6. Threshold tuning: choose operating point by maximizing F1 or by clinician priority (favor recall to reduce missed cancers)
7. Explainability: provide Grad-CAM + top-5 SHAP features per case

Analysis of the Model

The machine learning model offers a data-driven, scalable, and efficient alternative to the existing manual method. It is expected to significantly enhance diagnostic capacity by leveraging historical and real-time patient data to generate predictive insights. The system will function in three primary stages: data input, model prediction, and result interpretation. A user-friendly interface will allow clinicians to enter relevant clinical variables and receive real-time diagnostic recommendations.

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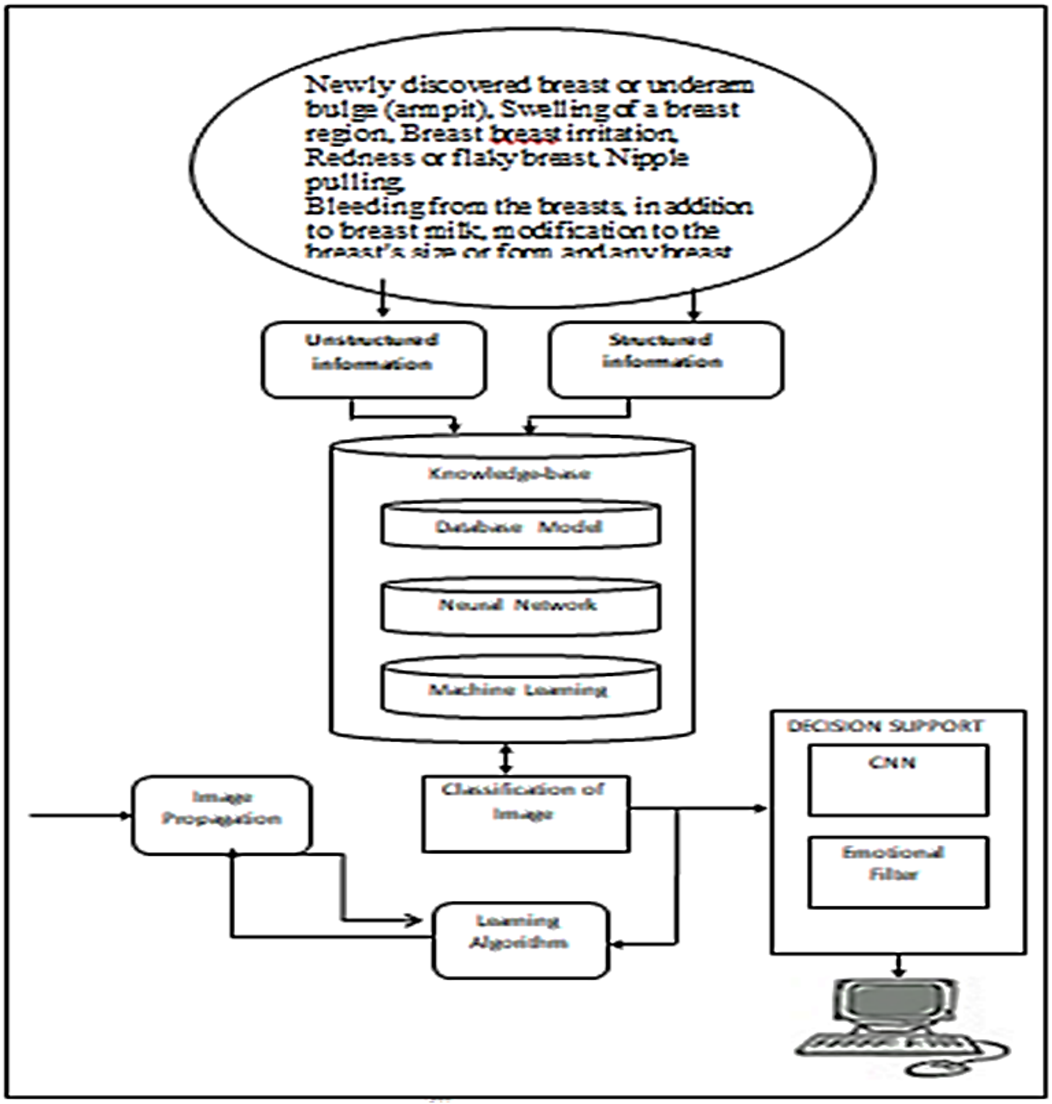

Figure 1: Architecture of the new model

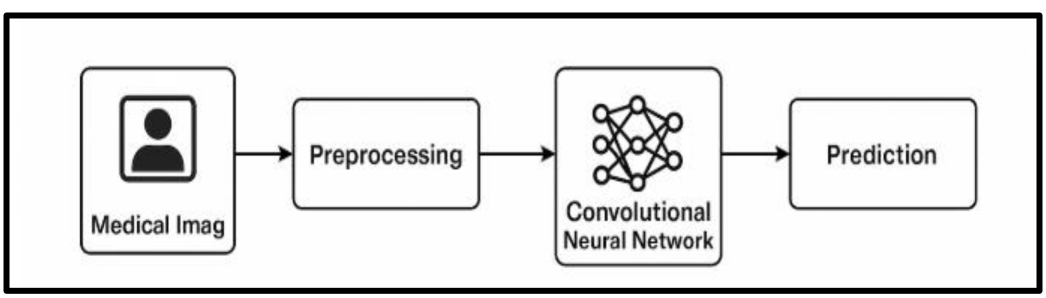

Figure 2: High Level design of the new model

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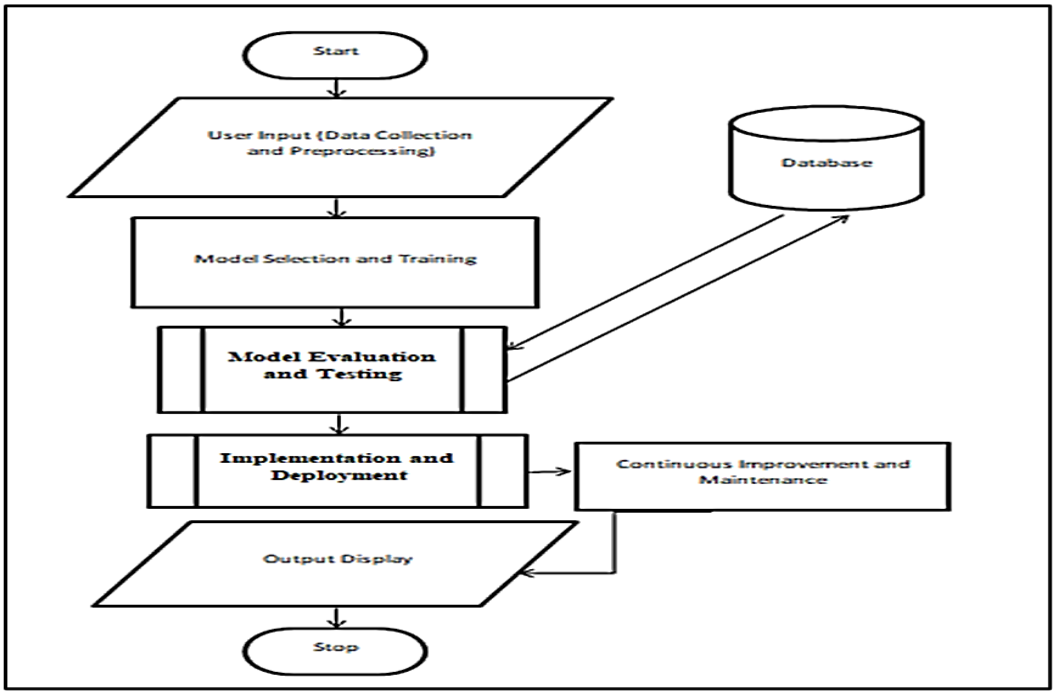

Figure 3: Implementation Procedure of the new model

The system is designed with several key modules that work together to improve usability and accuracy;

1. **User Registration Module**: Handles the creation of user accounts, securely storing details like usernames and passwords, and managing access rights based on roles. It also supports functions such as password reset to keep accounts safe.
2. **Breast Cancer Diagnosis Module**: Uses advanced algorithms and machine learning techniques to analyze patient data such as symptoms, medical history, and test results to provide diagnostic insights and risk assessments that support clinicians in decision-making.
3. **Training Module**: Continuously improves the system's accuracy by learning from historical patient data and medical datasets. This ensures the diagnostic model adapts over time, becoming more reliable and effective in detecting breast cancer.

Algorithms of the Model

1. ***Collect data*** *— gather local anonymized records and public datasets (images + tabular).*
2. ***Preprocess data*** *— clean, normalize, encode; for images: resize, normalize, augment.*
3. ***Split data*** *— train / validation / test (e.g., 70/15/15), consider stratified split.*
4. ***Handle imbalance*** *— use class weights, oversampling (SMOTE) or augmentation.*
5. ***Design model*** *— transfer-learning CNN for images (ResNet/EfficientNet), or hybrid (image CNN + tabular MLP) or ensemble (XGBoost + CNN).*
6. ***Train model*** *— use early stopping, regularization, learning-rate schedule, cross-validation.*
7. ***Post-process predictions*** *— deep learning and a rule-based classifier to refine outputs.*

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8. ***Explainability & validation*** *— use Grad-CAM / SHAP / LIME for clinician-facing explanations and run external validation on holdout / multi-center data.*
9. ***Evaluate*** *— Accuracy, Precision, Recall, F1, AUC; confusion matrix and calibration.*
10. ***Deploy*** *— export model, serve via API or ML.NET PredictionEngine, integrate UI, log predictions and feedback.*
11. ***Monitor & update*** *— monitor drift, retrain periodically with new data, audit fairness/bias.*

Model Design and Implementation

At this stage, the overall architecture of the model is designed. The system is structured as a collection of interconnected subsystems, organized into a hierarchy of classes and objects. The design emphasizes the relationships between these components rather than focusing solely on internal processes. Both the model architecture and the analysis model guide this process, ensuring that each object contributes to a cohesive and scalable diagnostic framework.

The model will be built with ML.NET, using a well-prepared dataset of breast images. After preprocessing (resizing, normalizing, and balancing the data), the model will be trained with transfer learning from proven networks like ResNet or Inception. To improve reliability, a rule-based layer will add clinical logic, while ML.NET's PredictionEngine will enable real-time results through a simple application for doctors. Finally, explainable AI methods will make predictions transparent, helping clinicians trust and use the system effectively.

System's Specification

Below are the requirements needed for developing the model. They have been categorized into Hardware and Software requirements. The development and implementation of the model require a minimum hardware setup consisting of a Core Duo Celeron or any Core series processor, 1 Terabyte of Hard Disk Drive (HDD), and 4 Gigabytes of RAM. On the software side, the system will run on Windows 10 or any compatible operating platform, with Microsoft Visual Studio (2017–2022) used for frontend development and Microsoft SQL Server serving as the backend database management system. The system's database is managed with **SQL Server,** where key tables such as *tblPatient, tblDisease*, and *tblCliniCard* are created to store patient and diagnostic information. Data is accessed through ADO.NET, which provides a simple way to connect the application with the database. SQL statements are then used to query and update records, ensuring smooth and secure data management

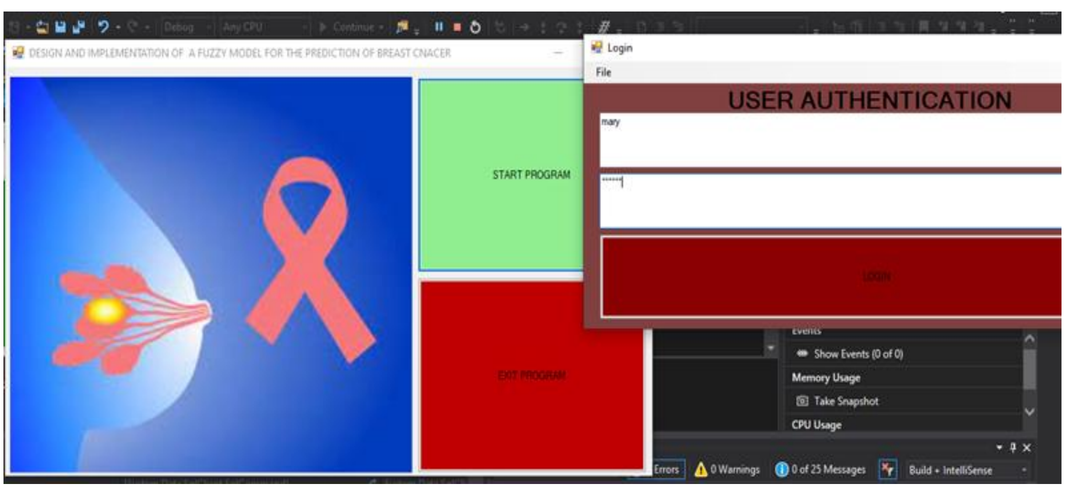

Figure 4: Login Module of the new model

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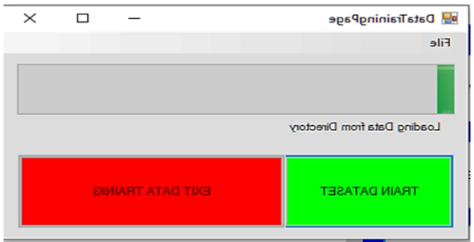

Figure 5: Mammogram Data Training Page

Following training, the model was evaluated using a test dataset to assess its performance. Results below 0.5 indicated potential overfitting, while scores above 0.5 suggested satisfactory performance and readiness for further validation with real-world data. The evaluation incorporated both simulated (programmer-developed) and actual patient dataset.

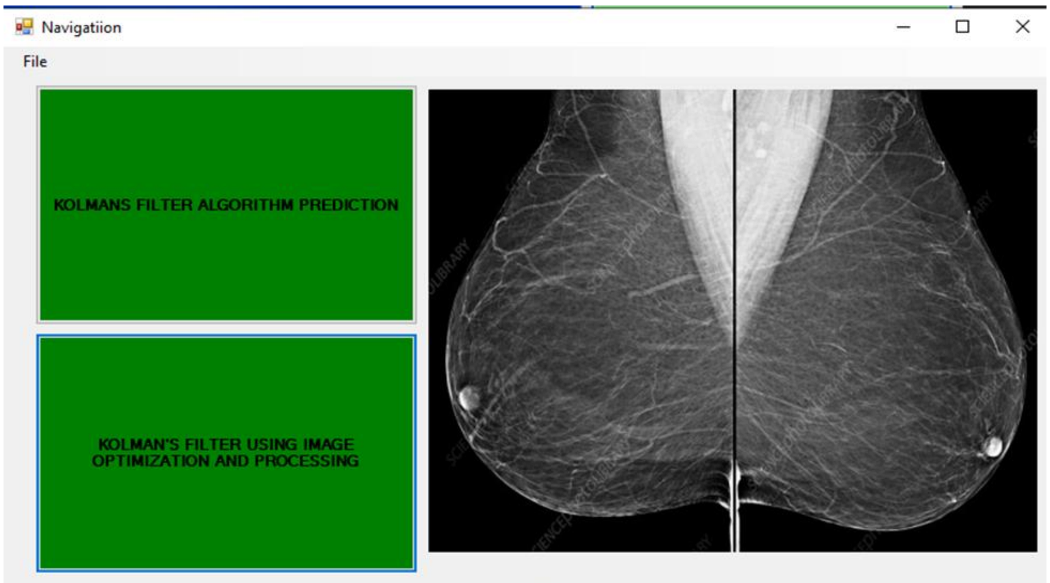

Figure 6: Diagnosis Main Page

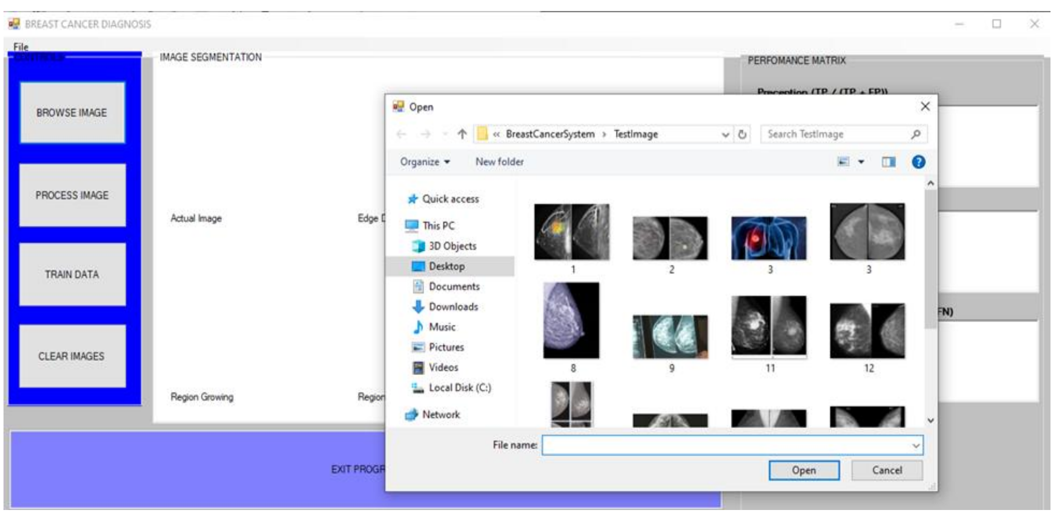

Figure 7: Output Using Mammogram Page

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Analysis and Discussion of Findings

The system achieved promising results, with 86% accuracy, precision of 83.5%, a recall of 84 % and an F1-score of 82%, indicating strong potential for breast cancer prediction. While these metrics highlight effectiveness, the evaluation would be strengthened by more context on the dataset, possible biases, and the model's generalizability to diverse populations. The development process, which integrated Visual Studio C#, EMGU Profiler, and MS SQL Server, reflects a solid software framework.

Table 1. Comparison of Existing and new Model

Aspect	Existing System (Manual & Paper-Based)	Machine Learning Model
Predictive Capability	Absent; cannot identify risk in asymptomatic or high-risk patients	Predictive analytics for early detection and risk stratification
Error Risk	High chance of human error and misdiagnosis	Minimizes error through algorithm-driven predictions
Efficiency	Time-consuming record retrieval; delays in decision-making	Faster workflow, reduced workload, and quicker clinical decisions
Diagnosis Process	Relies on subjective judgment, physical exams, and delayed referrals	Automated predictions using patient data; real-time diagnostic recommendations
Data Management	Records stored in physical folders; prone to loss, damage, or delay in access	Centralized digital storage; fast, secure, and easy retrieval
Overall Impact	Slows down care, reduces accuracy, and limits innovation	Enhances accuracy, supports evidence-based care, and drives digital transformation
Adaptability	Rigid, limited by lack of infrastructure	Scalable; can integrate image analysis, mobile access, and future AI modules

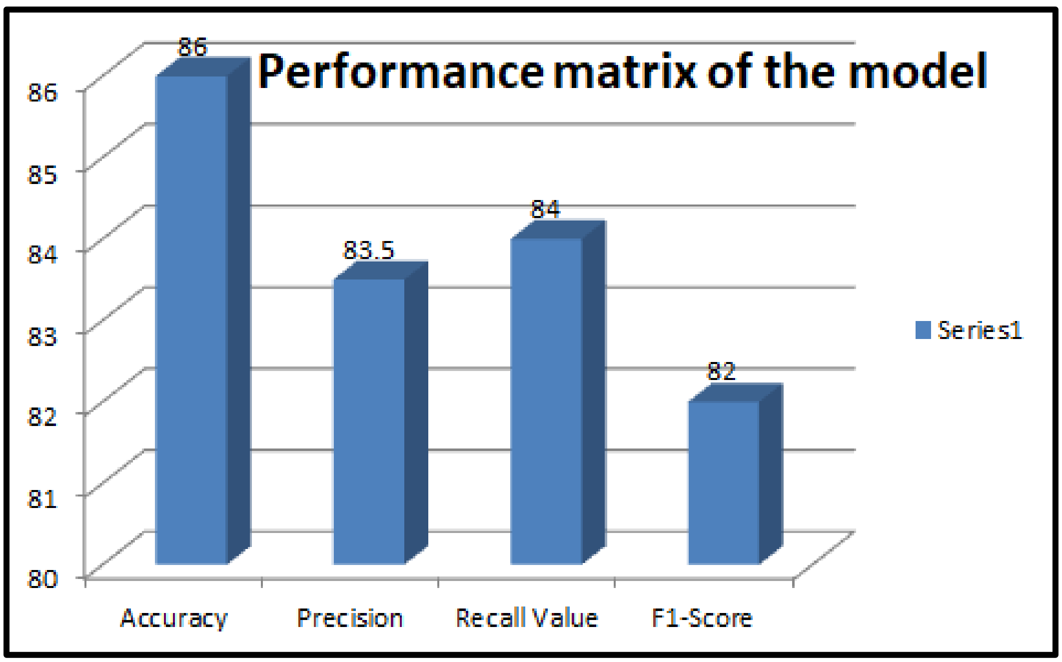

Figure 8: Performance Metrics of the model

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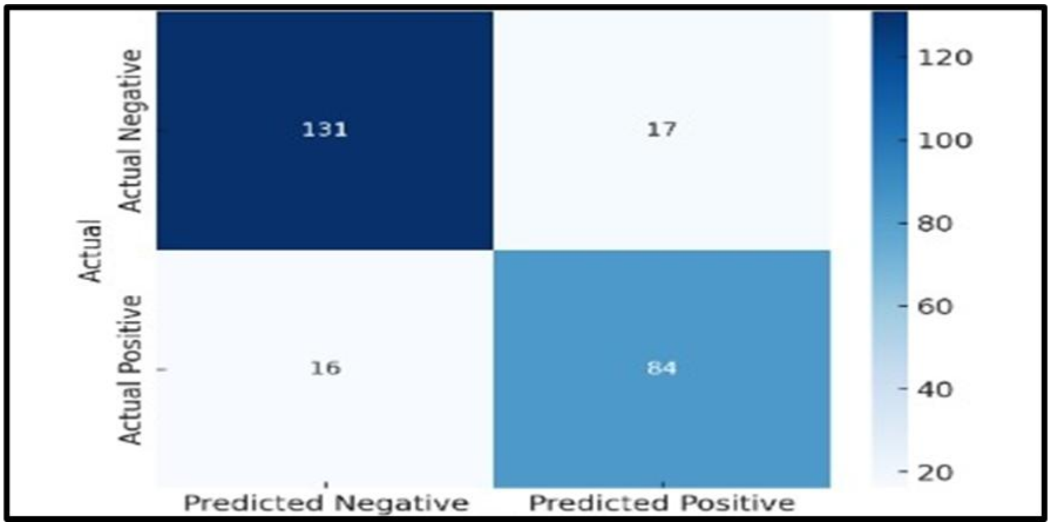

Figure 9: Confusion Matrix of the model

CONCLUSION

This study introduced an enhanced deep learning model for predicting and diagnosing breast cancer, developed using the Object-Oriented Model (OOM) as the system design approach. The model addresses key limitations of traditional diagnostic methods such as high costs, subjectivity, and delays by integrating deep learning techniques with robust data preprocessing. Core modules, including patient data management, diagnostic prediction, and model training, work together to provide timely, evidence-based insights for healthcare professionals. The system was built using C# with ASP.NET, Bootstrap 3.5, CSS, JavaScript, JQuery, and SQL Server.

Evaluation results were promising, with 86% accuracy, precision of 83.5%, a recall of 84 % and an F1-score of 82%, demonstrating strong potential for reliable breast cancer prediction. By effectively handling complex medical data and minimizing diagnostic errors, the system can serve as a valuable clinical decision support tool. Its flexible design also allows for adaptation to other medical conditions, highlighting its scalability and relevance for broader healthcare applications. With further refinement and validation in real-world settings, this model offers a significant step toward AI-powered healthcare solutions that improve early detection, support clinical decision-making, and ultimately save lives.

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