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Research Article

Leveraging AI Models for Breast Cancer Detection: A Case Study with a Proposed Prototype Framework

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A B S T R A C T

Breast cancer is one of the leading causes of death among women globally, with inconsistencies in mammographic screening and delays in diagnostic processing contributing to poor outcomes. In simple terms, it occurs when cells in the breast grow abnormally, eventually turning into malignant tumors and if these cells are left undetected, they spread to the surrounding organs, thereby making detection a pivotal step in the healthcare industry. Recognizing this need, artificial intelligence has emerged as a key player in detecting breast cancer while reshaping the landscape for patients' survival. Recent advancements in artificial intelligence, particularly the use of deep learning (DL) and large language models (LLMs), have created unprecedented opportunities, from improved diagnostic accuracy to efficient clinical workflow. The paper discusses that radiologists may face cognitive burden while reviewing imaging data as conventional methods face limitations such as interpretation errors, diagnostic inaccuracy and financial stress. Leveraging AI in breast cancer detection has shown great potential in addressing the gap. This research paper combines literature on AI-assisted breast cancer detection with an original case study: The GenAI-BCD proposed framework is developed around a convolutional neural network (CNN); the core design of the model is based on EfficientNet-Bo and fine-tuned on CBIS-DDSM data to classify images as malignant or benign. On the held-out test of 645 mammographic images, the model achieved an AUC of 0.796 with a specificity of 75.9%, a sensitivity of 71.2% and an overall accuracy of 74.0%. GenAI-BCD is deployed through a lightweight web application intended to support radiologists by highlighting the cases for further examination and providing interpretable visual reasoning behind each prediction.

Keywords: Breast cancer, Artificial intelligence, Awareness, Large language model, Specialized language model, Machine learning, Malignant cells

1. Introduction

1.1. What is breast cancer?

Cancer, particularly breast cancer, is one of the deadliest diseases known to humankind. For years, mankind has been struggling to find its cure that is viable in today's time. The modern-day definition of breast cancer presented by the healthcare industry is the uncontrolled proliferation of malignant cells inside of the breast, which subsequently form a lump termed a tumor. These cancerous cells infect the surrounding tissues and then gradually spread (metastasis) to other organs of the body[1] Breast cancer is more prevalent among women over the age of 50, but it can also appear in men. The starting point of this disease is tiny structures called ducts and lobules whose only function is to produce and carry milk to surrounding areas. In fact, when you look closely at the anatomy of the breast, it is surrounded by multiple layers of protection; each has a unique function to perform. Beginning from the chest wall to pectoral muscles, which are primarily responsible for support and protection[2] and then moving on to the inner lining containing delicate structures called lobules (glandular tissues) that produce milk and ducts that carry it to the nipples and fatty tissues that surround them. This intricate architecture of the breast makes lesions difficult to detect.

An estimated 2.4 million women are diagnosed with breast cancer, according to the World Health Organization (WHO), surpassing a toll of 694,000 deaths and making it the most diagnosed cancer among women[3]. Apparently, changes in breast cancer are invisible to the naked eye, but its commonly known signs include a lump or swelling in the breast area, blood discharge from the nipples, crusty or flaky skin around the nipple (areola), nipple retraction, chest pain and shape asymmetry. However, these signs vary from person to person, making its detection a more complicated procedure, shedding focus on what factors are responsible for an increased risk of developing breast cancer. Highlighting factors such as age, family history/genetic mutation (BRCA1, BRCA2), unhealthy lifestyle choices, not breastfeeding oral contraceptives, exposure to radiation and hormonal shifts among these. Resulting in the formation of benign and malignant breast lesions, often distinguished by their biological behavior rather than their appearance. Benign are characterized as solid or fluid-filled masses with no potential invasive properties and well-defined borders, whereas malignant tumors have the capacity to invade surrounding stroma and metastasize[4].

(Figure 1) illustrates how cancerous cells affect healthy breast cells. Breast cancer typically begins inside a milk duct, one of the narrow tubes that transports milk to the nipple. Faults in a cell's genetic instructions produce aberrant growth and multiplication. Initially, these aberrant cells remain stuck inside the duct, locked in place by its lining (myoepithelial layer) and outside wall (basement membrane). This early stage is known as ductal carcinoma in situ (DCIS)[5,6]. In some cases, the cells eventually break through the duct wall and grow into the healthy breast tissue around it. At that time, the condition is known as invasive ductal carcinoma[7]. Once they escape the ducts, they enter into the bloodstream or lymph nodes and are carried to other organs. This is not always the case; invasive cancer does not always develop from DCIS. Between 25% and 60% of untreated patients are estimated to eventually do so[7,8]. Moreover, detecting breast cancer is not a simple task. Conventional screening methods of breast cancer include clinical breast examination (CBE), mammography, ultrasound, magnetic resonance imaging (MRI) and tissue biopsy with histopathological analysis.

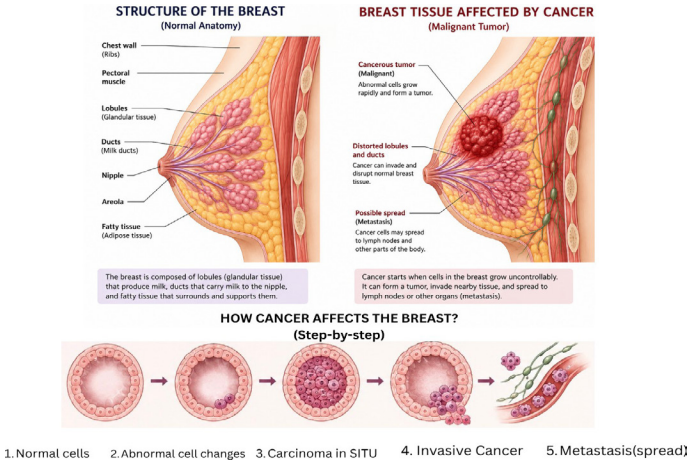

Figure 1: Normal Breast Anatomy and Progression of Breast Cancer.

1.2. How can AI be leveraged to detect breast cancer?

Prior to the adoption of artificial intelligence, breast cancer detection relied on clinical assessments and image interpretation. After reviewing the patient's medical history and physical examination results, doctors go on to imaging, which is often mammography with the help of ultrasound and, in higher-risk situations, MRI[9]. Each of these methods has certain limitations. Mammographic sensitivity drops dramatically from 93% in fatty tissues to 30% in dense breast tissues, where lesions become hidden and both tumor and fibroglandular tissue appear white[10]. Readers' interpretations also differ; in a large multi-site cohort, the sensitivity of individual radiologists varied from 31.6% to 96.2%[11]. As a result, there are undetected tumors on one side and unnecessary biopsies on the other side. Artificial intelligence provides a solution to address these limitations in image interpretation. Deep learning models trained on huge mammographic datasets can identify problematic lesions, give risk ratings and prioritize exams before or alongside radiologist evaluation, providing a reliable second read that is not affected by tiredness, experience or workload. To support this claim with evidence, the Swedish MASAI randomized controlled trial of 105,000 women demonstrated that AI-assisted screenings reduced radiologist workload by 44%[12] and raised the detection rate by 29%, which means from 0.5 to 6.4 cancers per 1000 participants[13] with no rise in false positives. The results of MASAI trials depict higher sensitivity and unhinged specificity. Leveraging AI in the detection of breast cancer reduces radiologists' workload and provides better diagnostic accuracy. It also functions as a decision-support tool to radiologists, flagging lesions and assigning risk scoring that standardizes image interpretation and reduces unpredictability that comes with human reading.

2. Literature Review

Breast cancer is one of the leading causes of death among women worldwide. Still, with the integration of artificial intelligence, early detection of malignant tumors becomes possible, as it not only improves the efficiency of the workflow but also aids clinicians in making informed decisions. The

selected literature primarily focuses on its clinical application, performance metrics and methodological rigor. The study also focuses on AI's transformative role in breast cancer screening and diagnosis. AI has revolutionized breast cancer detection by enhancing diagnostic accuracy[14]. Unlike traditional methods that have fixed rules, AI leverages machine learning algorithms to learn from large datasets consisting of complex patterns of imaging data. These AI models act as a supporting tool designed to work alongside radiologists and not as a replacement.

Mckinney, et al. evaluated one of the largest studies on the role of AI in breast cancer screening and found that deep learning models have achieved performance accuracy comparable to human radiologists in some cases. AI systems scored 90% sensitivity and 77% specificity. The result of these findings demonstrates that AI reduces both false-positive and false-negative rates while maintaining other performance metrics. This study highlights the absolute potential of AI models in breast cancer screening and improving diagnostic outcomes by assisting radiologists in marking the subtle abnormalities that may have been overlooked[15].

According to Debellotte, et al., integration of AI offers more accurate and personalized diagnoses of the early stage of breast cancer[16]. The inclusion of AI technology in the detection process spans multiple modalities, including ultrasound, mammography and magnetic resonance imaging, reflecting the reality that breast cancer evaluation requires integration of multiple imaging perspectives. The AI models used in the assistance of breast cancer detection rely on deep learning architectures, especially convolutional neural networks. Shin, et al. study provides support to the claim that the CNN models are exposed to thousands of images. Supervised learning allows algorithms to develop pattern recognition capabilities to identify lesions that are difficult to detect in milliseconds. Unlike human radiologists, who miss subtle findings because of certain limitations[17].

Mahmood, et al. demonstrate that AI models' performance metrics were established in a controlled research setting, which states that AI systems have achieved remarkable accuracy. In addition, researchers examined 902 mammograms to contrast malignant and benign lesions. The results showed that AI models scored 98% training accuracy and 99% sensitivity[18]. Therefore, these results indicate lower false-positive rates than those in a radiologist-led assessment.

AI's impressive technical performance led to its real-world implementation. Lang, et al. conducted a large-scale clinical trial published in The Lancet Oncology in 2023 that provides evidence that leveraging AI in real-world breast cancer detection reduced radiologist workload by 44% while reporting MASAI (Mammography Screening with Artificial Intelligence) trials[12]. The trial also report that the cancer detection rate is 6.4 per 1000 screened with AI as compared to 5.0 per 1000 with standard screening in a sample of 105,000 women aged 50 or older. Hernström, et al., a study elaborating in The Lancet Digital Health found a 29% increase in the cancer detection rate[13]. Moreover, AI enhances breast cancer detection in multiple imaging modalities in real-time settings. AI-trained algorithms detect cancer 29% more accurately than the traditional methods of screening while reducing radiologist reading time. Furthermore, the real-world implementation of AI models demonstrates clinical efficiency while maintaining the final diagnostic authority with the radiologists. AI models have the capability to recognize patterns together with the contextual reasoning of radiologists, resulting in improved diagnostic interpretation without clinicians taking control of decision-making.

Wu, et al. study further demonstrates that AI models can enhance performance when used as a decision-support tool for mammography interpretation. His study also emphasized on the effective clinical approach towards a collaborative system in which AI augments radiologists rather than replacing them in the diagnostic process[19].

Consequently, these developing AI paradigms extend beyond detection and decision support. Vision-language models link high-resolution mammography pictures with clinical reports to assist mass identification and malignancy classification, thereby boosting data efficiency in training computer-aided diagnostic systems[20]. Similarly, Kim, et al. indicated that large language models have been utilized to extract structured characteristics from unstructured pathology reports and link them with electronic medical record data, allowing downstream risk prediction and treatment decision assistance[21]. Lehman, et al. study also indicates that the future deployment of AI models is mostly predictive than reactive. And by incorporating these AI models for longitudinal analysis of screening data, high-risk patients may obtain personalized surveillance protocols before the start of clinical cancer[22].

3. Current Evidence Synthesis

The available data shows several key results that demonstrate how effective AI models can be in breast cancer detection:

- Breast cancer detection accuracy is demonstrated through meta-analysis of 8 studies, (n=120,950), which shows that AI has an overall AUC of 0.89 when compared to the 0.82 AUC achieved by radiologists. Similarly, the specificity reaches 0.99, indicating that in some cases AI exceeds radiologists' evaluation[23].
- The randomized controlled trials of the MASAI experiment provide strong evidence that leveraging AI in cancer detection increases detection rates by 29% as compared to the usual method of having a radiologist read the images without an increase in the false-positive rate (false positive rate: 1.5% vs. 1.4%, p = 0.92), depicting its real-world effectiveness[12].
- Besides its effectiveness, it has showed potential in real-world screening programs. Integrating AI reduces radiologists' workload by 44%[12]. Instead of replacing conventional screening methods, AI is being used alongside them for interpretation.
- The integration of AI in clinical setup indicates that AI helps as a decision-support tool, but radiologists review and confirm the model's output before the final diagnosis is made. This partnership helps improve diagnostic accuracy[14].

4. Case Study: AI-Powered Model for Breast Cancer Detection

The reviewed literature demonstrated AI's significant potential in the breast cancer detection systems. Models are often created and validated in isolation, thereby resulting in diverse performance metrics across different datasets, imaging and clinical environments. This research paper presents a case study based on a proposed AI-powered model in breast cancer detection, designed to address the gap in diagnostic accuracy.

4.1. Framework overview

The proposed GenAI-BCD (Generative AI for Breast Cancer Detection) framework is an AI-powered model designed to address the gap in breast cancer detection systems and ensure robust outcomes. The published literature demonstrates that breast cancer detection faces challenges related to data interpretation, performance disparities and barriers to its clinical adoption, which affect diagnostic accuracy. This framework consists of four components integrated to enhance the clinician's workflow and performance metrics across demographics. Each component is designed to bridge the gap and increase detection through an AI-assisted model in breast cancer detection. The first component is to process the input by standardizing the imaging data, while the second component accounts for classification and detection by incorporating a core detection model using transfer learning with the EfficientNet-B0. It then classifies the imaging data into two categories, one as benign and the other as malignant, which helps radiologists in decision-making. Interpretability is the third most important component of this proposed model, as it provides, alongside a GRAD-CAM visual heat map which highlights the regions most affected and allows radiologists to verify the reason for an output rather than treating it as a black box in breast cancer detection. The last component emphasizes its clinical deployment, which involves delivering the trained model via a lightweight web application that produces a probability (benign vs. malignant) of the submitted mammograms.

4.2. Datasets

The GenAI-BCD model was trained on the data collected from the CBIS-DDSM. The model was trained on 3,103 full mammographic images divided into 2,458 images for training and 645 images for testing.

4.3. Methods and material

After collecting images, they are then preprocessed and converted into grayscale and contrast-enhanced to improve the visibility details of the images for detection. This is achieved using the CLAHE (Contrast Limited Adaptive Histogram Equalization) technique, as it works on small areas of the image rather than just managing the contrasting details. The images were resized to 384 x 384 and normalized; furthermore, a class-weighted loss function was applied to balance the class of cases, from the most malignant to the benign. The AdamW optimizer was employed to train the network on a GPU (graphics processing unit) while keeping the checkpoint that achieved the highest validation AUC (Area Under the ROC Curve) for evaluation.

4.4. Architecture

By using an EfficientNet-B0 convolutional neural network (CNN) , the model can automatically classify mammograms as malignant or benign and use weights that are trained on ImageNet before tuning to the cancer registry dataset.

4.5. Evaluation metrics

To check models' ability to function on a held-out test, we incorporated several standardized metrics, each evaluated on different aspects of diagnosis.

- **AUC (Area under the ROC curve):** measures the model's capability to differentiate between benign and malignant cases. The 0.1 score represents discrimination, whereas the 0.5 score depicts no better performance than just a random chance.
- **Specificity:** measures models' proportion performance in correctly catching non-cancerous cases as benign. When it is low, it indicates suspicious benign cases, which leads to unnecessary follow-ups.
- **Sensitivity:** It measures the proportion of actual cancer cases as malignant ones, since a false negative is riskier in a clinical setting.
- **Precision:** It identifies how many cases the model labeled as malignant cases with utmost precision, as a positive prediction is significant to the model.
- **F1 Score:** It's a balanced combination of precision and sensitivity. It is beneficial when both false negatives and false positives carry consequences.

These metrics were carefully selected, as accuracy alone can be misrepresenting in imaging tasks.

5. Results

The model performance on the held-out test set reached an AUC of 0.796. Having achieved a balanced operating threshold, it has 71.2% sensitivity, 75.9% specificity, 67.1% precision, 70.9% and an F1-score at 69.1%. The model achieved an overall accuracy of 74.0% in correctly identifying 188 of 264 cancer types and 289 of 381 benign cases.

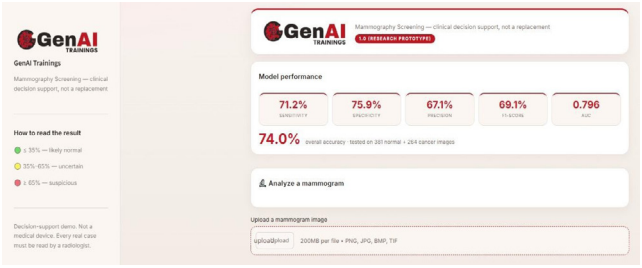

Table 1: GenAI-BCD model performance on the held-out CBIS-DDSM test set.

Metrics	Values
AUC	0.796
Sensitivity	71.2%
Specificity	75.9%
Precision	67.1%
F1-score	69.1%
Accuracy	74.0%

6. Discussion

The GenAI-BCD model performance is viewed as a realistic yet honest outcome, which is significant in medical research. Earlier published models have significantly higher figures, but their real-world applicability is different. This proposed model was trained on 3,103 mammographic images with standard hardware, reflecting constraints many researchers still face in this day. In that setting, an AUC metric of 0.796 genuinely reflects a valuable signal well above the chance that sometimes even the radiologist's performance varies. The gap between specificity and sensitivity values reflects that breast cancer detection comes at a cost, as missing a malignancy carries greater risk than a false alarm. Given the proposed model performance, it acts as a decision-support tool that complements radiologist work, narrowing attention toward high-risk cases. While at the same

time, it reduces cognitive load on human radiologists in resource-limited settings. The model identifies suspicious patterns that were missed by radiologists during image screening. Though radiologists are skilled professionals, they have higher risks of making errors and leading to misinterpretation of data, ultimately affecting the diagnostic accuracy. For future reference, more research is being carried out on improving AI capabilities in breast cancer detection, as they are fully functional and operational in performing tasks. Thus, leveraging AI in detecting breast cancer improves the survival rate of the patients and lowers the false positive rates and unnecessary follow-up procedures.

7. Conclusion

Leveraging AI algorithms in early detection of breast cancer proves to be pivotal in the healthcare industry. The synergy between human radiologists and AI models doesn't act as a replacement; it rather provides support. Resultantly, reducing the cognitive load improves sensitivity, reducing false positives, enhancing the diagnostic workflow and maintaining accuracy. This research paper concludes that leveraging AI in breast cancer detection improves outcomes in the healthcare sector. By leveraging AI models, disparities in the healthcare system can be bridged and breast cancer detection can be achieved. Future work should validate the model on larger datasets and integrate demographic fairness monitoring the test performance with radiologists using these tools in practice.

8. References

1. Arravalli T, Chadaga K, Muralikrishna H. et al. Detection of breast cancer using machine learning and explainable artificial intelligence. Sci Rep, 2025;15: 26931.
2. Ghosh A, Mallick S. Anatomy of the Breast. In: Mallick, S., Sharma, C.K. (eds.), Evidence in Breast Cancer. Springer, 2024.
3. World Health Organization. Breast cancer, 2026.
4. World Health Organization. Breast Tumors: WHO Classification of Tumors of the Breast. 5th ed. Geneva: WHO Press, 2019.
5. Cowell CF, Weigelt B, Sakr RA, et al. Progression from ductal carcinoma in situ to invasive breast cancer: Revisited. Molecular Oncology, 2013;7: 859-869.
6. National Cancer Institute. What is ductal carcinoma in situ (DCIS)? National Institutes of Health, 2026.
7. Tomlinson-Hansen SE, Khan M, Cassaro S. Breast ductal carcinoma in situ. In StatPearls. StatPearls Publishing, 2023.
8. Wang J, Li B, Luo M, et al. Progression from ductal carcinoma in situ to invasive breast cancer: Molecular features and clinical significance. Signal Transduction and Targeted Therapy, 2024;9: 83.
9. Saslow D, Boetes C, Burke W, et al. American Cancer Society Breast Cancer Advisory Group. American Cancer Society guidelines for breast screening with MRI as an adjunct to mammography. CA Cancer J Clin. 2007;57(2): 75-89.
10. Brown AL, Vijapura C, Patel M, et al. Breast cancer in dense breasts: Detection challenges and supplemental screening opportunities. RadioGraphics, 2023;43: e230024.
11. Elmore JG, Jackson SL, Abraham L, et al. Variability in interpretive performance at screening mammography and radiologists' characteristics associated with accuracy. Radiology, 2009;253: 641-651.
12. Lång K, Josefsson V, Larsson A-M, et al. Artificial intelligence-supported screen reading versus standard double reading in the Mammography Screening with Artificial Intelligence trial (MASAI): A clinical safety analysis of a randomized, controlled, non-inferiority, single-blinded, screening accuracy study. The Lancet Oncology, 2023;24: 936-944.
13. Hernström V, Josefsson V, Sartor H, et al. Screening performance and characteristics of breast cancer detected in the Mammography Screening with Artificial Intelligence trial (MASAI): a randomised, controlled, parallel-group, non-inferiority, single-blinded, screening accuracy study. Lancet Digit Health, 2025;7(3): 175-183.
14. André S, Bandiwadekar S, Pattarkine M. Enhancing breast cancer detection with AI for early diagnosis and recurrence prediction. Oncoscience, 2026;13.
15. McKinney SM, Sieniek M, Godbole V, et al. International evaluation of an AI system for breast cancer screening. Nature, 2020;577(7788): 89-94.
16. Debellotte O, Dookie RL, Rinkoo F, et al. Artificial intelligence and early detection of breast, lung and colon cancer: A narrative review. Cureus, 2025;17: 79199.
17. Shin HC, Roth HR, Gao M, et al. Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning. IEEE Transactions on Medical Imaging, 2016;35: 1285-1298.
18. Mahmood T, Li J, Pei Y, et al. Breast lesions classifications of mammographic images using a deep convolutional neural network-based approach. PLoS ONE, 2022;17: e0263126.
19. Wu N, Phang J, Park J, et al. Deep neural networks improve radiologists' performance in breast cancer screening. IEEE Transactions on Medical Imaging, 2020;39: 1184-1194.
20. Ghosh S. Mammo-CLIP: A Vision Language Foundation Model to Enhance Data Efficiency and Robustness in Mammography. In Medical Image Computing and Computer Assisted Intervention MICCAI 2024.
21. Integrating Large Language Models with Deep Learning for Breast Cancer Treatment Decision Support. Diagnostics, 2026;16: 394.
22. Changes in AI Mammogram Risk Scores Over Time Help Predict Future Breast Cancer. Radiological Society of North America (RSNA), 2026.
23. Hashim HT, Alhatemi AQM, Daraghma M, et al. Artificial intelligence versus radiologists in detecting early-stage breast cancer from mammograms: A meta-analysis of paradigm shifts. Polish Journal of Radiology, 2025;90: 1-8.