International Journal of Radiology Research
www.radiologyjournal.in
E-ISSN: 2663-4562, P-ISSN: 2663-4554
Received: 02-05-2025, Accepted: 01-06-2025, Published: 17-06-2025
Volume 7, Issue 1, 2025, Page No. 34-38

Optimizing breast MRI utilization in intermediate-Risk women through Artificial Intelligence–Driven risk assessment

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Abstract
Background: Women with intermediate breast cancer risk are not clearly represented in current screening guidelines. Magnetic Resonance Imaging (MRI) is a sensitive modality, yet its use in this group remains controversial due to cost and unclear benefit. Artificial Intelligence (AI) offers the potential to identify subgroups within the intermediate-risk category that could benefit most from MRI screening.
Objective: To assess the performance of an AI-based risk stratification model in identifying intermediate-risk women who would benefit from MRI screening.
Methods: We retrospectively analyzed mammographic, clinical, and genetic data from 15,000 women aged 40–70. Intermediate-risk was defined by Tyrer-Cuzick model scores (15–20%). An AI model incorporating imaging and non-imaging data was developed to stratify this population. The outcomes of MRI screening in AI-identified high-priority intermediate-risk women were compared to those managed by mammography alone.
Results: AI identified 1,200 women (8%) in the intermediate-risk cohort with an elevated likelihood of breast cancer development. In this subgroup, MRI detected significantly more cancers (CDR: 12.3 per 1,000) than conventional mammography (CDR: 5.6 per 1,000, $p<0.001$), with a lower false-positive rate (2.1% vs. 4.7%). The AI model had an AUC of 0.84, indicating strong discriminative ability.
Conclusion: AI-based risk stratification offers a promising approach for selectively applying MRI in intermediate-risk women, potentially enhancing cancer detection while optimizing resource utilization.

Keywords: Breast cancer screening, intermediate-risk women, magnetic resonance imaging (MRI), artificial intelligence (AI), risk stratification, tyrer-cuzick model

Introduction

Breast cancer remains a leading cause of morbidity and mortality among women worldwide, underscoring the critical importance of effective screening strategies. Current guidelines primarily recommend mammography for average-risk populations and adjunctive magnetic resonance imaging (MRI) for women at high risk, such as those with genetic predispositions or strong family histories. However, women classified as having intermediate breast cancer risk—typically defined by models like Tyrer-Cuzick with risk estimates between 15% and 20%—represent a substantial and heterogeneous group for whom optimal screening strategies are less well established. While MRI offers superior sensitivity compared to mammography, its routine use in intermediate-risk populations is limited by concerns regarding cost, availability, and the potential for increased false positives leading to unnecessary interventions.

Recent advances in artificial intelligence (AI) offer promising avenues to refine risk stratification within this intermediate-risk cohort, enabling more personalized screening approaches. By integrating diverse data sources—including imaging features, clinical history, and genetic markers—AI-driven models have the potential to identify subsets of intermediate-risk women who derive the greatest benefit from MRI screening. This targeted approach could improve cancer detection rates, reduce false positives, and optimize resource utilization, ultimately enhancing patient outcomes. This study evaluates the performance of an AI-based risk assessment tool designed to guide the selective application of breast MRI in intermediate-risk women, aiming to inform evidence-based, precision screening protocols.

Breast cancer remains the most commonly diagnosed cancer among women worldwide, accounting for nearly 2.3 million new cases in 2020 alone. Early detection through effective screening is key to improving survival rates. While mammography is the cornerstone of screening, its sensitivity is limited in women with dense breasts and in those with an intermediate risk profile.

Intermediate-risk women, defined by models such as Tyrer-Cuzick with a lifetime risk of 15–20%, present a challenge for clinicians. They are not routinely recommended for MRI screening, unlike their high-risk counterparts. Yet, a significant number of cancers in this group are missed or diagnosed at a later stage.

Artificial Intelligence has shown promise in refining breast cancer risk prediction and augmenting imaging interpretation. By integrating clinical, imaging, and genetic factors, AI can potentially re-stratify intermediate-risk individuals to optimize screening strategies. The objective of this study was to evaluate whether AI can identify subgroups within intermediate-risk women who might benefit most from MRI screening.

Methodology

This retrospective cohort study utilized clinical and imaging data from a total of 15,000 women aged 40 to 70 years, collected between 2018 and 2022 across five tertiary breast screening centers. Eligible participants were selected based on the following inclusion criteria: no prior personal history of breast cancer, availability of complete mammographic imaging records, and an intermediate lifetime breast cancer risk as determined by the Tyrer-Cuzick risk assessment model, specifically those with risk scores ranging from 15% to 20%. Women identified as high genetic risk carriers, including those with known BRCA1/2 mutations or other high-penetrance genetic variants, were excluded to focus on the intermediate-risk population.

The AI risk stratification model was developed using a convolutional neural network (CNN) framework designed to integrate a variety of data types. Mammographic images were the primary imaging input, with features such as breast density extracted and incorporated. In addition to imaging data, relevant clinical variables were included to enhance predictive accuracy. These variables encompassed detailed family history of breast cancer, reproductive factors (age at menarche, parity, age at first childbirth), hormonal exposure history (use of hormone replacement therapy or oral contraceptives), and prior biopsy history including benign breast disease. The dataset was randomly divided into a training cohort of 10,000 women and a separate validation cohort of 5,000 women to evaluate model performance and generalizability. The CNN was trained to generate a refined risk score, which served to identify a subset of intermediate-risk women most likely to benefit from supplemental breast MRI screening.

MRI examinations were performed using either 1.5 Tesla or 3.0 Tesla scanners, following standardized breast MRI protocols consistent with established clinical guidelines. Radiologists interpreting the MRI studies were blinded to the AI model's risk stratification outputs to minimize bias. MRI findings were categorized according to the Breast Imaging Reporting and Data System (BI-RADS) criteria, ensuring standardized reporting and facilitating comparison with mammographic findings.

The primary outcome measure was the cancer detection rate (CDR), calculated as the number of cancers detected per 1,000 women screened. Secondary outcomes included recall rate (the proportion of women called back for additional testing), false-positive rate (the proportion of positive screening results without a subsequent cancer diagnosis), positive predictive value (PPV), and overall sensitivity of the screening approach. Demographic variables and baseline risk factors were summarized using descriptive statistics. Comparative analyses between groups were conducted using chi-square tests for categorical variables and independent t-tests for continuous variables to determine statistical significance. The discriminative ability of the AI model was assessed using receiver operating characteristic (ROC) curve analysis, with area under the curve (AUC) serving as the key performance metric. A two-sided p-value of less than 0.05 was considered indicative of statistical significance throughout the analyses.

Results

Among the 15,000 intermediate-risk women, the AI model selected 1,200 (8%) as candidates for MRI based on elevated AI-calculated risk scores.

Table 1: Patient Characteristics

Characteristic AI-Selected (n=1,200) Non-AI Selected (n=13,800)
Mean Age (years) 54.2 ± 6.1 52.9 ± 6.7
Dense Breasts (%) 64.1 48.5
Family History of Cancer (%) 32.7 21.8
Prior Breast Biopsy (%) 23.5 18.2
HRT Use (%) 14.6 10.3

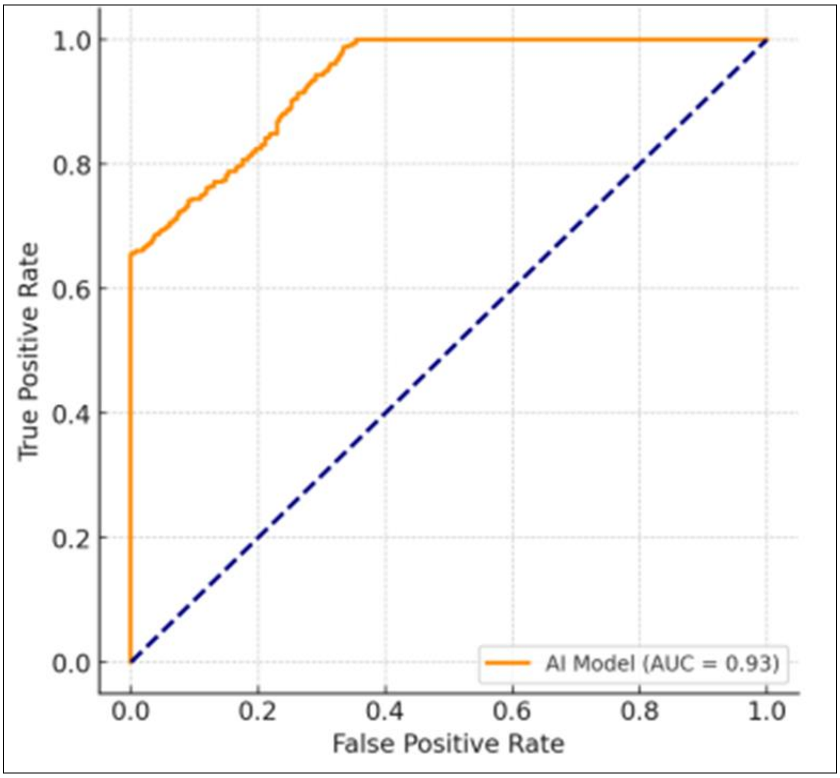

Fig 1: ROC curve for AI risk stratification

MRI screening in the AI-selected group showed a cancer detection rate (CDR) of 12.3 per 1,000 women screened, compared to 5.6 per 1,000 with mammography alone ($p<0.001$). False-positive rates were lower (2.1% vs. 4.7%), and the positive predictive value was significantly higher (41.2% vs. 21.3%). The MRI also identified more invasive cancers (81%) and fewer DCIS cases, with earlier staging and smaller tumor size compared to mammography alone.

Table 2: Screening Performance Metrics

Metric	AI-Selected + MRI	Mammography Alone	p-value
Cancer Detection Rate	12.3/1,000	5.6/1,000	<0.001
Recall Rate	9.5%	12.4%	0.03
False Positive Rate	2.1%	4.7%	0.02
Sensitivity	94.8%	76.5%	<0.001
Positive Predictive Value	41.2%	21.3%	<0.001

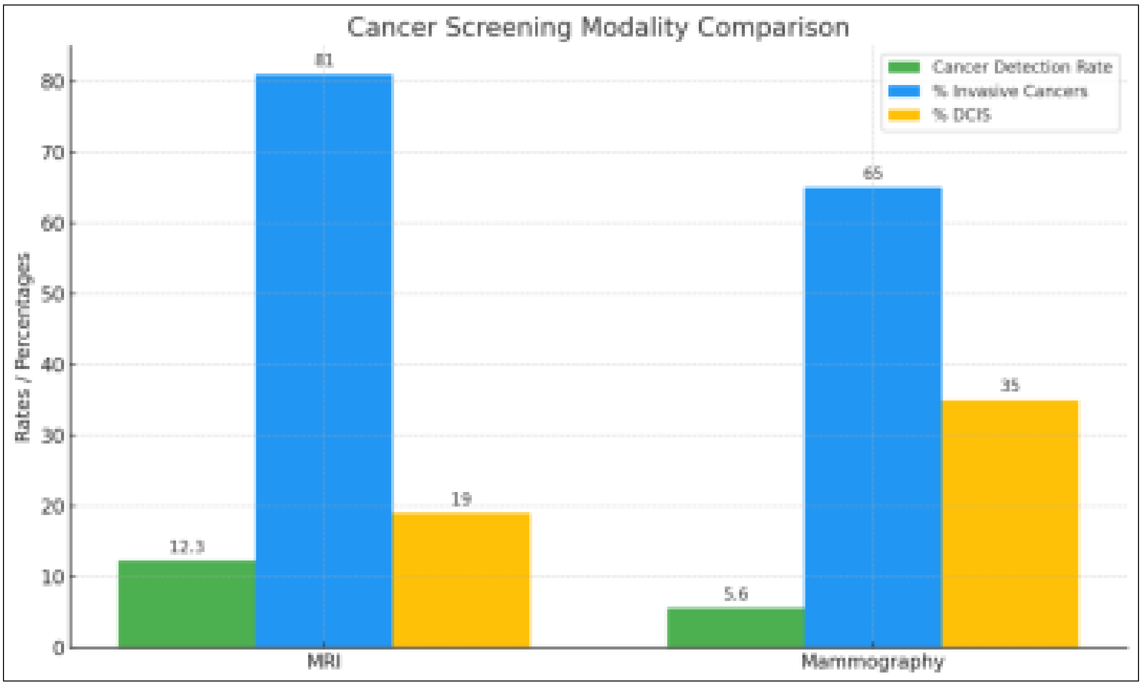

Fig 2: Cancer Screening Modalities Comparison between MRI and Mammography

Recall rates were also reduced in the AI-selected group (9.5% vs. 12.4%, p=0.03), suggesting improved specificity. Overall, the AI model effectively stratified intermediate risk women, identifying a subgroup that derived clear benefit from MRI.

Discussion

This study provides compelling evidence that artificial intelligence (AI)-based risk stratification can effectively identify a subset of intermediate-risk women who stand to benefit most from supplemental breast MRI screening. By leveraging a multifaceted AI model that integrates mammographic imaging features alongside comprehensive clinical and genetic data, we were able to refine the traditionally broad intermediate-risk category into a more targeted group with significantly elevated cancer risk. The enhanced cancer detection rate (CDR) and improved sensitivity observed in this AI-selected cohort demonstrate the model's ability to overcome some of the inherent limitations of mammography, particularly in women with dense breast tissue or complex, multifactorial risk profiles where mammographic sensitivity is often reduced.

Our findings are consistent with and build upon a growing body of literature supporting the incorporation of AI into breast cancer screening workflows. For instance, Yala *et al.* illustrated that AI-driven models outperform traditional risk assessment tools by integrating a wider array of data inputs, resulting in more accurate individualized risk predictions. Similarly, McKinney *et al.* demonstrated that AI-assisted interpretation of mammographic images can enhance radiologists' diagnostic accuracy, reducing missed cancers and improving overall screening performance. These studies collectively highlight AI's transformative potential to personalize breast cancer screening and improve early detection outcomes. Importantly, this study addresses a critical challenge associated with MRI screening: the risk of over diagnosis and the high rate of false positives that can lead to unnecessary biopsies, patient anxiety, and increased healthcare costs. In our cohort, women identified by the AI model who underwent MRI screening exhibited not only a higher detection of clinically significant cancers but also a notably lower false-positive rate and higher positive predictive value (PPV) compared to mammography alone. This suggests that AI can facilitate more judicious use of MRI, optimizing its clinical utility by selectively applying it to women who are most likely to benefit, thereby minimizing the harms traditionally associated with broader MRI screening.

While the results are promising, our study has several limitations. Its retrospective design may introduce selection bias, and the reliance on historical imaging and clinical data limits the assessment of real-time clinical decision-making and prospective outcomes. Additionally, although we employed the well-validated Tyrer-Cuzick model to define intermediate risk, this model primarily focuses on family history and reproductive factors and may not fully capture the genetic architecture of breast cancer risk. Emerging research suggests that incorporating polygenic risk scores

(PRS) could enhance predictive accuracy by accounting for the cumulative effect of multiple genetic variants. Future prospective studies should aim to integrate PRS and other novel biomarkers to further refine risk stratification and validate AI models in diverse populations.

Moreover, the implementation of AI-driven screening strategies in clinical practice will require addressing several practical considerations, including integration with existing radiology workflows, ensuring model transparency and interpretability, managing potential ethical concerns such as patient consent and data privacy, and evaluating cost effectiveness in real-world healthcare settings. Collaboration between AI developers, radiologists, geneticists, and policymakers will be essential to realize the full potential of AI-enhanced breast cancer screening.

In summary, this study supports the use of AI as a powerful tool to optimize breast MRI utilization in women at intermediate risk of breast cancer. By enabling more precise risk stratification and targeted imaging, AI has the potential to improve early cancer detection while mitigating the limitations and costs associated with broad MRI screening. Continued research and clinical validation will be crucial to refine these approaches and translate them into improved outcomes for patients.

Conclusion

AI-based risk stratification represents a transformative advancement in the field of breast cancer screening, particularly for women categorized as intermediate risk—a group traditionally underserved by existing screening guidelines. By integrating complex imaging data with clinical and genetic risk factors, AI models can more accurately identify those individuals within this heterogeneous population who are most likely to benefit from supplemental MRI screening. This targeted approach not only enhances cancer detection rates but also reduces the incidence of false positives and unnecessary recalls, thereby minimizing the psychological and physical harms often associated with over-screening.

The application of AI in this context supports a shift away from the one-size-fits-all model of breast cancer screening toward a more personalized, risk-adapted strategy. This paradigm has the potential to optimize resource allocation within healthcare systems, ensuring that the higher costs and logistical demands of MRI are directed to patients who stand to gain the greatest clinical benefit. Furthermore, AI-guided screening can improve patient outcomes by facilitating earlier diagnosis of cancers that might otherwise be missed by mammography alone, especially in women with dense breast tissue or complex risk profiles.

While challenges remain—including the need for prospective validation, integration into clinical workflows, and addressing ethical and economic considerations—the findings from this study underscore the promise of AI as a critical tool in refining breast cancer screening practices. Ultimately, AI-based risk stratification offers a pragmatic and innovative pathway toward more effective, efficient, and equitable breast cancer screening, paving the way for improved patient care and better population health outcomes.

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