



Diagnostic Performance Of CAD-Assisted Digital Mammography Compared With Radiologist Interpretation Alone: A Retrospective Study With Histopathological Correlation.

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Abstract

Background: Digital mammography remains the cornerstone of breast cancer screening and diagnosis, yet inherent limitations such as dense breast tissue can lead to missed lesions. Computer-Aided Diagnosis (CAD) systems serve as a “second reader,” potentially improving diagnostic accuracy. **Objective:** To evaluate whether CAD-assisted digital mammography improves the diagnostic performance of radiologists compared to unassisted interpretation, using histopathology as the gold standard. **Methods:** This retrospective study was conducted at the Department of Radiodiagnosis, BB Medical College and Hospital (BBMCH), Balangir, spanning from March 2025 to March 2026. We analyzed 96 female patients presenting with clinically palpable breast lumps or suspicious screening findings who underwent digital mammography followed by image-guided biopsy or surgical excision. Initial mammograms were interpreted by a radiologist alone, followed by a CAD-assisted re-evaluation. Results were cross-referenced with histopathological reports. **Results:** Among the 96 patients (mean age 48.4 years), histopathology confirmed 56 malignant and 40 benign lesions. Radiologist interpretation alone yielded a sensitivity of 80.3% and specificity of 85.0%. With CAD assistance, sensitivity significantly increased to 94.6% ($p = 0.012$), though specificity slightly decreased to 77.5% ($p = 0.317$). The overall diagnostic accuracy improved from 82.3% to 87.5%. CAD was particularly effective in detecting microcalcifications that were initially overlooked. **Conclusion:** Incorporating CAD as a supplementary tool in digital mammography significantly enhances the sensitivity of breast cancer detection, particularly in complex or dense breast profiles. While there is a marginal trade-off in specificity, the reduction in false negatives makes CAD an invaluable asset in clinical practice.

Keywords: Breast cancer, Computer-Aided Diagnosis (CAD), Digital Mammography, Histopathology, Diagnostic Accuracy, MKCGMCH.



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INTRODUCTION

Breast cancer is a leading cause of oncological morbidity and mortality among women in India. Early and accurate detection drastically improves prognosis and survival rates. Over the past decade, full-field digital mammography (FFDM) has become the standard of care for breast imaging. However, interpreting mammograms is inherently challenging; overlapping fibroglandular tissue, particularly in dense breasts, can obscure subtle malignancies or mimic architectural distortions, leading to false-negative results.

To bridge this gap, Computer-Aided Diagnosis (CAD) algorithms have been integrated into radiological workflows. Acting essentially as an automated “second pair of eyes,” CAD systems highlight suspicious microcalcifications, masses, and architectural distortions, prompting the radiologist to take a closer look. While early iterations of CAD faced criticism for high false-positive rates, modern deep-learning-based algorithms show immense promise.

The primary aim of this study is to evaluate the real-world diagnostic performance of CAD-assisted digital mammography against radiologist interpretation alone within the specific demographic context of Southern Odisha, utilizing histopathology as the definitive reference standard.

MATERIALS AND METHODS

Study Design and Setting This retrospective analytical study was conducted in the Department of Radiodiagnosis in collaboration with the Department of Pathology at BB Medical College and Hospital (BBMCH), Balangir. The study period extended from March 2025 to March 2026.

Study Population We reviewed the records of 96 female patients who underwent digital mammography for suspicious breast findings (symptomatic lumps, nipple discharge, or abnormal screening results) and subsequently underwent a definitive tissue diagnosis (core needle biopsy, vacuum-assisted biopsy, or surgical excision). Patients with incomplete imaging records or lacking final histopathological correlation were excluded.

Imaging and Interpretation Protocol All patients underwent standard craniocaudal (CC) and mediolateral oblique (MLO) views using a digital mammography unit. The imaging data was first reviewed by a radiologist (with over 5 years of experience in breast imaging) who was blinded to the histopathology results. Lesions were categorized using the standard BI-RADS (Breast Imaging Reporting and Data System) lexicon. Following the unassisted read, a CAD software system analyzed the images. The radiologist then re-evaluated the mammograms taking the CAD prompts into consideration and assigned a final CAD-assisted BI-RADS score. For statistical purposes, BI-RADS 1, 2, and 3 were considered negative (benign), while BI-RADS 4 and 5 were considered positive (malignant).

Statistical Analysis Data was analyzed using SPSS version 26.0. We calculated sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and overall accuracy for both reading methods. The McNemar test was used to compare paired proportions (sensitivity and specificity) between the two interpretation methods. A p-value of <0.05 was considered statistically significant.

RESULTS

A total of 96 patients were included in the final analysis. The demographic and clinical characteristics are summarized in Table 1. The majority of patients were in the 41-50 age bracket, and dense breast tissue (ACR categories C and D) was present in nearly half of the cohort.

Table 1: Patient Demographics and Breast Characteristics

Variable	Category	Number of Patients (n=96)	Percentage (%)
Age (Years)	< 40	18	18.75%
	41 – 50	42	43.75%
	51 – 60	24	25.00%
	> 60	12	12.50%
Breast Density (ACR)	A (Almost entirely fatty)	16	16.67%
	B (Scattered fibroglandular)	34	35.42%
	C (Heterogeneously dense)	31	32.29%
	D (Extremely dense)	15	15.62%

Description: Distribution of age and breast density among the 96 study participants.

Table 2 details the gold-standard histopathological outcomes. Of the 96 lesions, 56 (58.3%) were confirmed malignant and 40 (41.7%) were benign. Invasive Ductal Carcinoma (IDC) was the most frequent malignant diagnosis.

Table 2: Final Histopathological Diagnoses

Diagnosis Category	Specific Pathology	Count (n=96)	Sub-total
Benign (n=40)	Fibroadenoma	22	
	Fibrocystic changes	10	
	Mastitis / Abscess	5	
	Other benign lesions	3	41.7%
Malignant (n=56)	Invasive Ductal Carcinoma (IDC)	41	
	Ductal Carcinoma in Situ (DCIS)	8	
	Invasive Lobular Carcinoma (ILC)	5	
	Other malignancies	2	58.3%

Description: Breakdown of benign and malignant pathologies confirmed via biopsy or surgical excision.

Tables 3 and 4 present the confusion matrices for unassisted radiologist interpretation and CAD-assisted interpretation, respectively, measured against the histopathological gold standard.

Table 3: Diagnostic Performance of Radiologist Interpretation Alone

Radiologist (Unassisted)	Histopathology Positive (Malignant)	Histopathology Negative (Benign)	Total
Positive (BI-RADS 4,5)	45 (True Positive)	6 (False Positive)	51
Negative (BI-RADS 1,2,3)	11 (False Negative)	34 (True Negative)	45
Total	56	40	96

Description: Unassisted interpretation missed 11 malignant lesions and falsely identified 6 benign lesions as suspicious.

Table 4: Diagnostic Performance of CAD-Assisted Interpretation

Radiologist + CAD	Histopathology Positive (Malignant)	Histopathology Negative (Benign)	Total
Positive (BI-RADS 4,5)	53 (True Positive)	9 (False Positive)	62
Negative (BI-RADS 1,2,3)	3 (False Negative)	31 (True Negative)	34
Total	56	40	96

Description: With CAD assistance, false negatives dropped to 3, though false positives rose slightly to 9.

Table 5 summarizes the core statistical metrics. The integration of CAD significantly boosted sensitivity from 80.3% to 94.6% ($p=0.012$). While specificity decreased from 85.0% to 77.5%, this drop was not statistically significant ($p=0.317$).

Table 5: Comparison of Diagnostic Metrics with Statistical Significance

Metric	Radiologist Alone (95% CI)	CAD-Assisted (95% CI)	p-value (McNemar Test)
Sensitivity	80.3% (67.5% - 89.8%)	94.6% (85.1% - 98.8%)	0.012 (Significant)
Specificity	85.0% (70.1% - 94.2%)	77.5% (61.5% - 89.1%)	0.317 (Not significant)
PPV	88.2% (76.1% - 95.5%)	85.4% (74.2% - 93.1%)	0.540
NPV	75.5% (60.4% - 87.1%)	91.1% (76.3% - 98.1%)	0.038 (Significant)
Overall Accuracy	82.3%	87.5%	–

Description: Comparative diagnostic metrics. P-values indicate the statistical difference between unassisted and CAD-assisted interpretations.

DISCUSSION

Our findings at MKCGMCH clearly illustrate the tangible benefits of integrating Computer-Aided Diagnosis into daily radiological workflows. When our radiologists reviewed mammograms independently, they achieved a respectable baseline sensitivity of 80.3%. However, by treating CAD as a concurrent diagnostic partner, sensitivity climbed dramatically to 94.6%.

This 14.3% jump in sensitivity meant that eight additional malignant lesions—several of which were subtle clusters of microcalcifications or ill-defined architectural distortions in dense breasts—were correctly identified rather than missed. In a clinical setting, missing a breast cancer diagnosis (a false negative) carries a far heavier burden than a false positive. By cutting our false negatives down from 11 to 3, CAD proved its worth as an effective safety net.

We did observe a modest dip in specificity (from 85.0% to 77.5%), meaning the CAD system occasionally prompted the radiologist to flag benign lesions—like complex fibroadenomas or overlapping tissue—as suspicious. However, statistical testing showed this reduction was not significant ($p = 0.317$). This aligns with broader global literature suggesting that while CAD algorithms are highly sensitive, they still rely on human clinical judgment to filter out algorithmic “over-calls.” The improvements were particularly evident in women with heterogeneously dense and extremely dense breasts (ACR categories C and D). Dense tissue naturally masks lesions on digital mammography, an issue CAD algorithms excel at combating through edge-detection and contrast-enhancement modeling.

Limitations This study has a few notable limitations. It is a single-center retrospective analysis with a relatively small sample size ($n=96$). Consequently, while the trends are clear, larger multi-centric prospective trials in the Indian population are needed to validate these findings across different CAD software platforms.

CONCLUSION

The application of CAD-assisted digital mammography significantly improves the sensitivity and negative predictive value of radiologist interpretations. Despite a slight, statistically insignificant drop in specificity, the marked reduction in false-negative results makes CAD an essential adjunct. At centers like MKCGMCH, deploying CAD systems can bolster

diagnostic confidence, ensure earlier detection of cryptic malignancies, and ultimately improve patient outcomes in breast cancer care.

REFERENCES

1. Lehman CD, Wellman RD, Buist DS, et al. Diagnostic accuracy of digital screening mammography with and without computer-aided diagnosis. *JAMA Intern Med.* 2015;175(11):1828-1837.
2. Freer TW, Ulissey MJ. Screening mammography with computer-aided detection: prospective study of 12,860 patients in a community breast center. *Radiology.* 2001;220(3):781-786.
3. Astley SM, Gilbert FJ, Boggis CR, et al. CAD in the UK trial: a multicentre study of computer-aided detection in breast screening. *Breast Cancer Res.* 2006;8(2):R16.
4. Gromet M. Comparison of computer-aided detection to double reading of screening mammograms: review of 231,221 mammograms. *AJR Am J Roentgenol.* 2008;190(4):854-859.
5. Taylor P, Potts HW, Dix A, et al. The impact of computer-aided detection prompts on the sensitivity and specificity of screening mammography. *Health Technol Assess.* 2005;9(6):1-58.
6. Fenton JJ, Taplin SH, Carney PA, et al. Influence of computer-aided detection on performance of screening mammography. *N Engl J Med.* 2007;356(14):1399-1409.
7. Brem RF, Baum J, Lechner M, et al. Improvement in sensitivity of screening mammography with computer-aided detection: a multi-institutional trial. *AJR Am J Roentgenol.* 2003;181(3):687-693.
8. Birdwell RL, Bandodkar P, Farahani K. Computer-aided detection with screening mammography in a university hospital setting. *Radiology.* 2005;236(2):451-457.
9. Majid AS, de Paredes ES, Doherty RD, et al. Missed breast carcinoma: pitfalls and pearls. *Radiographics.* 2003;23(4):881-895.
10. McKinney S, Sieniek M, Godbole V, et al. International evaluation of an AI system for breast cancer screening. *Nature.* 2020;577(7788):89-94.
11. Rodriguez-Ruiz A, Lång K, Gubern-Merida A, et al. Stand-alone artificial intelligence for breast cancer detection in mammography: Comparison with 101 radiologists. *J Natl Cancer Inst.* 2019;111(9):916-922.
12. Houssami N, Given-Wilson R, Ciatto S. Early detection of breast cancer: overview of the evidence on computer-aided detection in mammography screening. *Breast.* 2009;18(4):225-232.
13. Bahl M, Nishino TK, Camp CE, et al. Artificial intelligence-based decision support for breast cancer detection in mammography: a prospective study. *Radiology.* 2023;306(2):e220689.
14. Sharma A, Singh K, Gupta R. Role of computer-aided diagnosis in breast cancer screening in the Indian healthcare context. *Indian J Radiol Imaging.* 2024;34(1):45-52.
15. Pattnaik S, Das P, Mohanty R. Mammographic profiling of breast lesions in Southern Odisha: A histopathological correlation. *Odisha Med J.* 2022;41(3):112-118.