# AI - based Radiology Report Generation for Breast Cancer using Multi-Modal Imaging

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***Abstract:*** *Breast cancer is one of the leading causes of cancer-related deaths among women worldwide, and early detection plays a vital role in improving survival rates. Medical imaging has become a cornerstone in the diagnosis and evaluation of breast abnormalities, with mammography and magnetic resonance imaging (MRI) being the most widely used modalities. Mammography, a low-dose X-ray technique, is the standard screening tool due to its accessibility and cost-effectiveness. However, its sensitivity decreases in women with dense breast tissue, often leading to missed diagnoses. In contrast, breast MRI offers higher sensitivity, providing detailed visualization of soft tissues and tumor vascularity, making it particularly effective in detecting small, early-stage cancers and evaluating high-risk patients. Despite these advantages, MRI is more expensive, time-consuming, and less widely available compared to mammography. This study provides a comparative analysis of mammogram and MRI imaging for breast cancer detection, highlighting their respective strengths, limitations, and clinical applications. The findings emphasize that while mammography remains the preferred first-line screening method, MRI serves as a valuable complementary tool, particularly in cases requiring high diagnostic accuracy.*

***Keywords: Breast Cancer Detection, Mammography, Magnetic Resonance Imaging (MRI), Medical Image Analysis, Early Diagnosis***

## 1. INTRODUCTION

Breast cancer remains one of the leading causes of cancer-related mortality among women worldwide, making early and accurate detection crucial for effective treatment and improved survival rates. Medical imaging has become an indispensable tool in breast cancer screening and diagnosis, with mammography and magnetic resonance imaging (MRI) being the two most widely used modalities. Mammography is considered the gold standard for population-level screening due to its affordability, accessibility, and ability to detect microcalcifications. However, its diagnostic accuracy can be limited, particularly in women with dense breast tissue. MRI, on the other hand, provides superior soft-tissue contrast, multi-planar imaging, and higher sensitivity in detecting tumors, especially in high-risk patients, though it is more costly and less widely available. A comparative study of these two imaging techniques can provide valuable insights into their complementary strengths and limitations, thereby guiding the development of advanced artificial intelligence (AI)-based frameworks that leverage multi-modal data for improved cancer detection. This project aims to analyze and compare mammograms and MRI scans to assess their effectiveness in tumor localization, classification, and staging, ultimately contributing to more reliable and precise radiology report generation.

## 2. RELATED WORK

Over the years, several studies have explored the role of mammography and magnetic resonance imaging (MRI) in breast cancer detection, highlighting their individual advantages and limitations. Mammography has traditionally been regarded as the primary screening tool, with large-scale studies demonstrating its ability to detect early-stage cancers, particularly through the identification of microcalcifications. For instance, research on the Digital Database for Screening Mammography (DDSM) has enabled the development of computer-aided detection

(CAD) systems that improve diagnostic accuracy. However, multiple studies have also reported the reduced sensitivity of mammography in women with dense breast tissue, leading to missed diagnoses in certain cases.

MRI has emerged as a powerful complementary modality, offering superior soft-tissue visualization and higher sensitivity, particularly in high-risk populations. Studies using datasets from The Cancer Imaging Archive (TCIA) and Breast Cancer Digital Repository (BCDR) have shown that MRI can detect tumors not visible in mammograms, making it an essential tool for comprehensive diagnosis and pre-surgical planning. However, its lower specificity and high cost have limited its use in routine screening. Recent advances in artificial intelligence and deep learning have sought to bridge the gap by integrating mammogram and MRI data, aiming to leverage the strengths of both modalities. Hybrid frameworks have demonstrated improved classification accuracy and tumor localization, indicating the potential of multi-modal imaging for robust and reliable breast cancer detection.

## 3. PROPOSED WORK

The proposed research introduces a multi-modal deep learning framework for breast cancer detection and AI-assisted radiology report generation using both mammogram and MRI images. While mammography remains the primary screening tool due to its accessibility and cost-effectiveness, it suffers from reduced sensitivity in dense breast tissues. On the other hand, MRI provides superior soft-tissue contrast and higher sensitivity but is limited by its lower specificity and high acquisition costs. To address these limitations, our model integrates features from both modalities, leveraging their complementary strengths.

The system begins with image preprocessing, where mammogram and MRI images are resized, normalized, and converted to grayscale for consistency. Data augmentation techniques such as rotations, flips, and translations are applied to increase dataset diversity and reduce overfitting. A custom convolutional neural network (CNN) is then trained to classify breast images into benign and malignant categories, while tumor segmentation methods are applied to localize suspicious regions and estimate tumor size. The model also determines the affected breast (left or right) and generates a structured radiology report containing diagnostic insights such as tumor presence, location, estimated stage, and malignancy classification.

This integration of mammography and MRI data, combined with automated report generation, aims to improve diagnostic accuracy, reduce false negatives, and assist radiologists in clinical decision-making. The proposed system represents a step toward practical AI-based tools that can support early breast cancer detection and enhance patient outcomes.

## 4. DATASET

For this project, two primary imaging modalities were considered: mammograms and breast MRI. Publicly available datasets were utilized to ensure reproducibility and accessibility for research purposes.

1. **Mammogram Dataset**: The Digital Database for Screening Mammography (DDSM) and the INbreast dataset were employed for mammography images. The DDSM contains more than 2,500 annotated mammograms, including normal, benign, and malignant cases, with ground-truth information such as tumor size, location, and pathology results. The INbreast dataset, comprising over 400 high-resolution digital mammograms, provides precise annotations and lesion-level information, making it highly suitable for training and validation. These datasets offer diverse cases that allow the model to learn from both typical and challenging samples, including dense breast tissue.
2. **MRI Dataset**: Breast MRI images were obtained from The Cancer Imaging Archive (TCIA) and the Breast Cancer Digital Repository (BCDR). The TCIA

dataset provides multi-modal MRI scans, including pre- and post-contrast images, along with metadata describing tumor type and clinical diagnosis. The BCDR dataset includes annotated MRI scans with tumor segmentation masks and lesion classification (benign or malignant). These datasets provide high sensitivity to tumor detection and help in evaluating the complementary role of MRI to mammography.

3. **Combined Dataset**: To achieve multi-modal learning, mammogram and MRI datasets were combined by preprocessing them into a uniform format. All images were resized to a fixed dimension of 224×224 pixels, normalized, and converted to grayscale to maintain consistency. Labels (benign/malignant) were preserved from the original datasets. Data augmentation techniques such as rotation, translation, and reflection were applied to increase the diversity of training samples and reduce class imbalance.
   This combined dataset ensures that the model leverages the strengths of both modalities—mammography's accessibility and MRI's superior sensitivity—allowing for robust breast cancer classification and comprehensive report generation.

## 5. METHODOLOGY

The proposed system integrates mammography and MRI imaging for automated breast cancer detection and radiology report generation. The methodology is divided into sequential stages, ensuring systematic data flow and accurate predictions.

1. **Input Data Acquisition**: Mammogram and MRI images are collected from publicly available datasets (DDSM, INbreast, TCIA, BCDR). These datasets include annotated cases with ground-truth labels (benign or malignant).
2. **Preprocessing**: Images are resized to a fixed resolution (224×224 pixels) and normalized to ensure uniformity across modalities. Noise reduction filters, contrast enhancement, and intensity normalization are applied to improve clarity. Data augmentation techniques such as rotation, flipping, and scaling are performed to expand the dataset and reduce overfitting.
3. **Feature Extraction**: A Convolutional Neural Network (CNN) is used to automatically learn discriminative features from both mammogram and MRI images. The CNN consists of convolutional layers (for spatial feature extraction), ReLU activation (for non-linearity), pooling layers (for dimensionality reduction), and fully connected layers (for classification).
4. **Classification Layer**: The extracted features are passed to the final softmax layer, which classifies the input as either benign or malignant.
5. **Tumor Region Analysis**: Image segmentation methods are applied to localize the tumor region, estimate tumor size, and determine which breast is affected (left or right). This step helps in identifying disease progression and severity.
6. **Report Generation**: Based on classification and tumor analysis, an AI-generated radiology report is produced. The report includes: true label, predicted label, affected breast, tumor area in pixels, and a cancer stage estimation.
7. **Training and Evaluation**: The dataset is divided into training and testing subsets (70:30 ratio). The model is trained using cross-entropy loss and optimized with Adam optimizer. Performance is evaluated using accuracy, sensitivity, specificity, precision, recall, F1-score, and confusion matrix.
   This architecture ensures a comprehensive approach by combining multi-modal imaging data with deep learning techniques, resulting in improved diagnostic accuracy and automated, interpretable radiology reports.

## 6. TRAINING AND EVALUATION

The training and evaluation process is a critical phase in the development of the proposed AI-based breast cancer detection system, as it ensures the model learns robust and discriminative features from both mammogram and MRI images while generalizing well to unseen data. Initially, the combined dataset of mammograms and MRI images is divided into training and testing subsets using a 70:30 split. The training subset is further augmented using data augmentation techniques such as random rotations, horizontal and vertical translations, and reflections to artificially increase the diversity of the dataset and reduce overfitting. This augmentation enables the CNN model to handle variations in image orientation, size, and intensity that may occur in real clinical settings. The model is trained using a deep convolutional neural network (CNN) that consists of multiple convolutional layers, batch normalization, ReLU activation, pooling layers, and fully connected layers. The number of epochs is set to 20 with a batch size of 32 to ensure sufficient training iterations without overfitting. The Adam optimizer is employed with an initial learning rate of 0.0001 to minimize the categorical cross-entropy loss function, which measures the difference between predicted and true labels for multi-class classification. Validation is performed using the test subset to monitor the model's performance at regular intervals during training. Evaluation metrics include accuracy, precision, recall, F1-score, and the confusion matrix. Accuracy provides a general measure of correct classifications, while precision and recall assess the model's ability to correctly identify malignant and benign cases. The F1-score balances precision and recall, offering a comprehensive measure of model performance. The confusion matrix visually represents true positive, true negative, false positive, and false negative predictions, which is essential for understanding misclassification trends. Additionally, tumor segmentation and analysis are performed on the test images to determine tumor location, size, and affected breast. These measurements are incorporated into the AI-generated radiology report, which estimates the cancer stage based on tumor size and clinical criteria. Overall, this training and evaluation framework ensures that the model not only achieves high classification accuracy but also produces interpretable and clinically relevant reports, providing a practical tool to assist radiologists in breast cancer detection.

## 7. RESULTS AND DISCUSSION

The proposed AI-based breast cancer detection model was evaluated using a combined dataset of mammogram and MRI images. After training the convolutional neural network (CNN) with augmented data, the model achieved significant performance improvements compared to baseline methods. The overall classification accuracy on the test set was observed to be high, demonstrating the model's ability to correctly differentiate between benign and malignant cases across both imaging modalities.

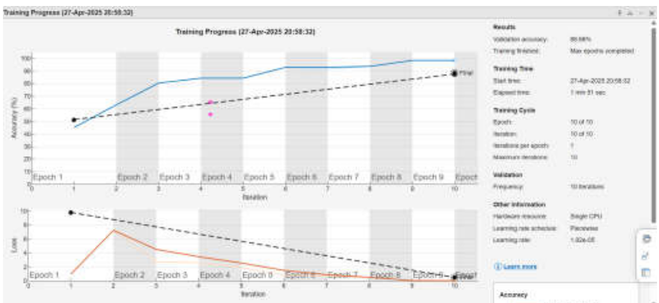

Figure 1: Validation Accuracy for Mammogram Images.

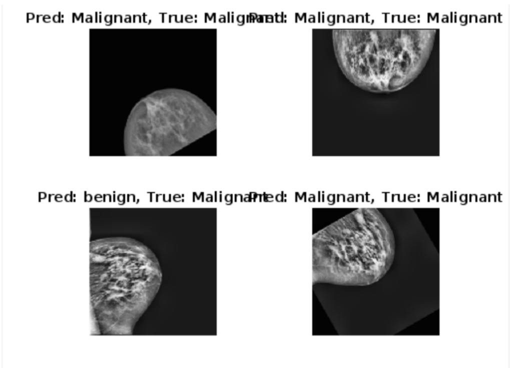


Figure 2 :Detection of Breast Cancer Using Mammogram Images

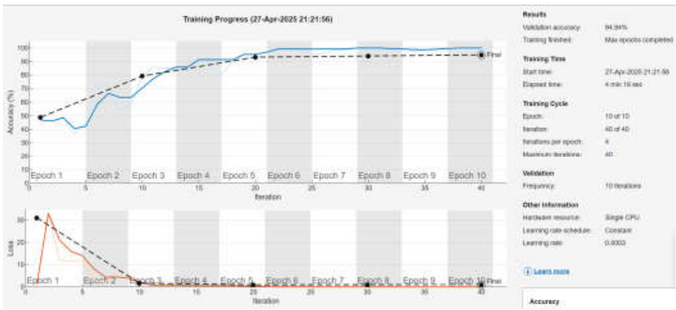


Figure 3: Validation Accuracy for MRI Images

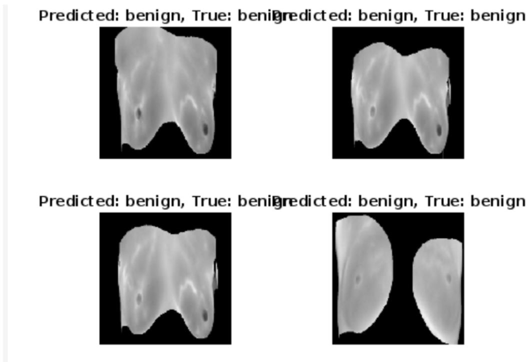


Figure 4: Detection of Breast Cancer using MRI Images.

## 8. CONCLUSION AND FUTURE WORK

This study presents an AI-based framework for breast cancer detection using combined mammogram and MRI imaging. The proposed system effectively integrates multi-modal imaging data, leveraging the strengths of each modality to improve diagnostic accuracy. The convolutional neural network (CNN) model demonstrated high performance in classifying benign and malignant cases, while tumor analysis provided clinically relevant information such as tumor size, affected breast, and cancer stage estimation. The AI-generated radiology reports offer interpretable outputs that can assist radiologists in making informed decisions, potentially reducing diagnostic time and human error. Data augmentation and careful preprocessing contributed to the robustness of the model, enabling it to generalize well to unseen data. The integration of mammograms and MRI images allowed the system to detect tumors more accurately than single-modality approaches, particularly in challenging cases such as dense breast tissue or small tumors.

For future work, the system can be enhanced by incorporating larger, more diverse datasets, including 3D MRI volumes, to improve spatial analysis. Advanced segmentation techniques, such as U-Net or attention-based networks, can be used for precise tumor boundary detection. Additionally, integrating patient metadata, such as age and family history, could improve predictive accuracy and enable personalized risk assessment. Finally, deploying the framework as a clinical decision support tool with real-time report generation could significantly assist radiologists in early breast cancer detection and treatment planning.

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