

# Breast Cancer Detector

**Mrs. Nayan V. Ahire<sup>1</sup>, Sakshi P. Nikam<sup>2</sup>, Sanskruti S. Ahire<sup>3</sup>, Piyali K. Pagar<sup>4</sup>, Manasi V. Sonawane<sup>5</sup>**

Professor, Computer Engineering, Mahavir Polytechnic, Nashik, India<sup>1</sup>

Students, Computer Engineering, Mahavir Polytechnic, Nashik, India<sup>2-5</sup>

**Abstract:** *Breast cancer is one of the most frequently diagnosed cancers among women and remains a major cause of mortality worldwide. Detecting tumors at an early stage is extremely important because it increases the chances of successful treatment and improves patient survival rates. However, conventional screening methods such as mammography and ultrasound have certain drawbacks, including exposure to radiation, high cost, and reduced detection accuracy in dense breast tissues. This project presents an Artificial Intelligence based Breast Cancer Detection System that utilizes deep learning and image analysis techniques to automatically identify tumor patterns in breast imaging data. The system employs several Convolutional Neural Network (CNN) architectures to extract meaningful features from reconstructed breast images and classify them into normal or cancerous categories.*

*The model is developed using Python and TensorFlow, along with supporting libraries such as OpenCV, NumPy, and Scikit-learn. For training and evaluation, the system uses the University of Manitoba Breast Microwave Imaging Dataset (UM - BMID), which contains microwave scan data obtained from breast phantom models.*

*The primary goal of the project is to design an automated diagnostic support system that assists medical professionals by providing accurate and fast breast tumor detection using advanced artificial intelligence techniques..*

**Keywords:** Artificial Intelligence, Breast Cancer Detection, Deep Learning, Convolutional Neural Network, Medical Image Analysis, Tumor Classification

## I. INTRODUCTION

Breast cancer remains one of the most significant global health challenges, where early and accurate detection plays a vital role in improving survival rates and treatment outcomes. Conventional screening methods, such as mammography, are widely used but have notable limitations, including high costs, radiation exposure, and reduced effectiveness in detecting tumors in dense breast tissue. In recent years, microwave imaging has emerged as a promising alternative due to its non-invasive nature, safety, and ability to capture high-resolution images based on variations in the electrical properties of tissues. Despite these advantages, accurately identifying tumors in microwave images remains difficult because of the complex and irregular structure of cancerous tissues. To overcome these challenges, the proposed system leverages advanced deep learning techniques by integrating multiple convolutional neural network (CNN) architectures for robust feature extraction. Specifically, seven different CNN models are employed to analyze breast images, enhancing the system's ability to capture diverse and subtle patterns. Additionally, a region-based CNN (R-CNN) is utilized for precise localization and detection of tumor regions, improving overall diagnostic accuracy. This multi-model framework provides an automated, efficient, and reliable approach to breast cancer detection. Furthermore, its performance can be enhanced by training on larger and more diverse datasets, enabling better generalization across different patient profiles and imaging conditions. Overall, the integration of microwave imaging with state-of-the-art deep learning techniques demonstrates strong potential to revolutionize breast cancer screening by making it more accurate, accessible, and safer for patients.



## **II. PROBLEM STATEMENT**

Breast cancer continues to be one of the most prevalent and life-threatening diseases among women globally. Traditional diagnostic techniques such as mammography, though effective to some extent, suffer from several limitations including exposure to ionizing radiation, discomfort during the procedure, and decreased accuracy in dense breast tissues. This project aims to address these limitations by proposing a Deep Learning-based approach for breast cancer detection using microwave imaging. Microwave imaging is a promising non-invasive, safe, and cost-effective method capable of capturing dielectric contrasts between healthy and cancerous tissues. Through this project, we aim to develop an accurate and automated system for early breast tumor detection that enhances diagnostic efficiency and reduces human intervention.

## **III. LITERATURE REVIEW**

Recent studies highlight the growing role of machine learning and deep learning in breast cancer detection. Traditional classifiers such as SVM, Random Forest, and Logistic Regression have been effective for structured patient data, while convolutional neural networks (CNNs) excel in analyzing medical images, capturing subtle lesions and microcalcifications. Transfer learning with pre-trained architectures like ResNet, Dense Net, Inception, and NASNet has improved performance, especially for limited datasets. Explainable AI techniques, including Grad-CAM, SHAP, and LIME, have enhanced model interpretability and clinician trust. Despite these advances, challenges such as high computational cost, dataset bias, and regulatory constraints continue to limit large-scale clinical deployment. Microwave imaging has emerged as a non-invasive, radiation-free method for breast tumor detection, but accurate tumor identification requires advanced image reconstruction and CNN-based analysis.

## **IV. PROPOSED SYSTEM**

This Enhanced Breast Cancer Diagnosis Using Machine Learning on Patient Data and Deep Learning proposes an intelligent and hybrid breast cancer diagnostic framework that integrates machine learning techniques applied to structured patient data with deep learning models applied to medical imaging. The proposed system aims to improve diagnostic accuracy, reduce false-positive and false-negative rates, and provide clinically interpretable decision support. By combining the strengths of machine learning and deep learning approaches, the system addresses the limitations of single-modality diagnostic methods identified in existing literature. The proposed system is designed as a multi-stage diagnostic pipeline consisting of data acquisition, preprocessing, feature extraction, classification, and decision fusion. The framework supports multiple data modalities, including clinical attributes, radiological images (mammography, ultrasound, and MRI), and histopathological images.

1. The data acquisition layer gathers diverse data sources, including structured patient information and unstructured medical images like mammograms, ultrasound scans, MRI scans, and histopathology slides. These are collected from hospital systems as well as publicly accessible datasets.
2. In the preprocessing layer, patient records are cleaned through normalization, handling of missing values, and noise removal. Medical images are processed with resizing, contrast enhancement, and data augmentation to ensure consistent and high-quality inputs for later analysis.
3. The feature extraction and learning layer consists of two parallel modules. The machine learning module focuses on structured patient data, applying feature selection methods feeding the results into classifiers such as Support Vector.



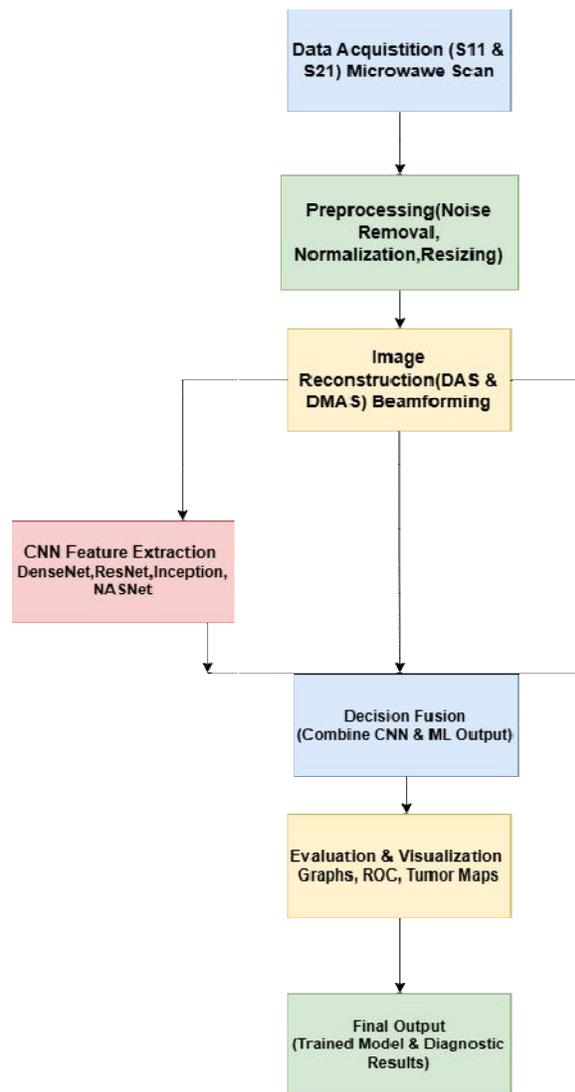


Fig. System Architecture

## V. METHODOLOGY

The system uses structured data (patient features like age, tumor size, texture, shape, biomarkers) and unstructured data (mammograms, ultrasound, MRI, histopathology images).

Feature extraction is done using statistical/morphological descriptors for patient data and multi-scale CNNs for histopathology images. Outputs from machine learning and deep learning modules are combined via decision-level fusion, using weighted scores or a meta-classifier for optimal prediction.

## VI. ALGORITHM

1. Data Acquisition: Collect S11 and S21 microwave scan data of the breast phantom.
2. Preprocessing: Remove noise, normalize data, and enhance image quality.
3. Image Reconstruction: Use DAS and DMAS beamforming to create 2D/3D breast images.



4. Feature Extraction: Apply multiple CNN architectures (DenseNet201, ResNet50, InceptionV3, etc.)
5. to extract tumor features.
6. Classification: Train CNNs to classify tumors as benign or malignant; evaluate using accuracy, loss, and AUC.
7. Decision Fusion (Optional): Combine CNN predictions with structured patient data using weighted aggregation or a meta-classifier.
8. Data Augmentation: Apply techniques such as rotation, flipping, scaling, and noise injection to increase dataset diversity and improve model generalization, especially when dealing with limited microwave imaging data
9. Hyperparameter Tuning: Optimize learning rate, batch size, number of epochs, and optimizer selection (e.g., Adam, SGD) to enhance CNN performance and prevent overfitting.
10. Cross-Validation: Use k-fold cross-validation to ensure the robustness and reliability of model performance across different data split



## VII. CONCLUSION

This project successfully demonstrates that microwave imaging combined with deep learning can play a vital role in non-invasive breast cancer detection. By comparing multiple CNN architectures, NASNetLarge was identified as the most effective model, achieving an accuracy of 88.41% and an AUC of 0.786. The approach provides a radiation-free and safer alternative to traditional mammography, with strong potential to improve early-stage cancer diagnosis and patient outcomes. In addition, the integration of advanced beamforming techniques such as DAS and DMAS with deep learning models enhances the accuracy of tumor localization and classification. The system also shows promise as a cost-effective and portable screening solution, making it particularly beneficial for deployment in resource-limited or rural healthcare settings. Furthermore, the use of multiple CNN architectures strengthens feature extraction capabilities, enabling better detection of complex tumor patterns in microwave images. The framework can be extended by incorporating patient clinical data for improved decision-making and personalized diagnosis. Future work includes integrating ensemble learning techniques to boost performance, applying model interpretability methods such as saliency maps and Grad-CAM to improve transparency, and validating the system on larger, real-world clinical datasets. Additional improvements may involve optimizing computational efficiency for real-time applications and ensuring ethical considerations such as data privacy, fairness, and model reliability are addressed for successful clinical.

## REFERENCES

- [1]. Patel, Priyam, and Anant Raina. 'Comparison of Machine Learning Algorithms for Tumor Detection in Breast Microwave Imaging.' IEEE Confluence, 2021
- [2]. Qasem, Ashwaq, et al. 'Breast cancer mass localization based on machine learning.' IEEE Colloquium on Signal Processing and its Applications, 2014.
- [3]. Lu, Min, et al. 'Detection and Localization of Breast Cancer Using UWB Microwave Technology and CNN-LSTM Framework.' IEEE Transactions on Microwave Theory and Techniques 70.11 (2022): 5085.
- [4]. A. Rezi and M. Allam, "Techniques in array processing by means of transformations," in Control and Dynamic Systems,
- [5]. Vol. 69, Multidimensional Systems, C. T. Leondes, Ed. San Diego: Academic Press, 1995, pp. 133 -180.
- [6]. G. O. Young, "Synthetic structure of industrial plastics," in Plastics, 2nd ed., vol. 3, J. Peters, Ed. New York: McGraw- Hill, 1964, pp. 15-64.
- [7]. S. M. Hemmington, Soft Science. Saskatoon: Univ. of Saskatchewan Press, 1997.



- [8]. P. Patel and A. Raina, "Comparison of Machine Learning Algorithms for Tumor Detection in Breast Microwave Imaging," IEEE Confluence, 2021.
- [9]. A. Qasem et al., "Breast cancer mass localization based on machine learning," IEEE Colloquium on Signal Processing and its Applications, 2014.

