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Deep Learning Architectural Performance Evaluation on Breast Cancer MRI and Mammography Image Datasets

Dayakar Kondamudi[1], *Dr.Vijay Reddy*[2], *Dr.Polaiah Bojja*[3]
[1]*Research Scholar, Gandhi Institute of Engineering and Technology University, Gunupur, Odisha, India.*
[2]*Professor, Supervisor, Gandhi Institute of Engineering and Technology University, Gunupur, Odisha, India.*
[3]*Professor, Co-Supervisor, Institute of Aeronautical Engineering, Hyderabad, Telangana, India.*
Emails: *dayakar.kondamudi@giet.edu*[1], *vijayreddy@giet.edu*[2], *paulraj.bojja@gmail.com*[3]

Abstract
Since breast cancer continues to be the top cause of death among women all around, it emphasizes the need of having good early diagnosis instruments. Advances in deep learning have given convolutional neural networks (CNNs) great promise in medical imaging uses. On two separate image datasets comprising MRI and mammography images, this work assesses and contrasts the performance of four deep learning architectures: CNN, ResNet50, InceptionV3, and EfficientNet B0. Accuracy, precision, recall, and F1-score among other measures were used to evaluate the models. Particularly in terms of recall and F1-score, EfficientNetB0 and ResNet50 showed better performance, thereby demonstrating their resilience in spotting positive breast cancer cases. The results highlight the need of effective network designs and transfer learning in improving diagnosis accuracy in imaging of breast cancer.
Keywords: *CNN, ResNet50, InceptionV3, EfficientNetB0, deep learning, MRI imaging, mammography, breast cancer diagnosis, and medical image analysis.*

1. Introduction
About 2.3 million new cases and 685,000 deaths from breast cancer were reported in 2020 alone, making it the most prevalent cancer diagnosed and the primary cause of cancer-related deaths among women worldwide. [1]. Early discovery and timely treatment are rather important for the prognosis of breast cancer patients; hence, sophisticated medical imaging technologies including mammography, ultrasonic waves, and magnetic resonance imaging (MRI) can greatly improve this situation [2]. Mammography is the most used screening modality, although MRI offers superior sensitivity in identifying invasive and high-risk lesions [3]. But especially in dense breast tissues, the manual interpretation of these imaging modalities presents difficulties because of inter-reader heterogeneity, radiologist tiredness, and high false-negative rates [4]. These constraints have pushed artificial intelligence (AI), especially deep learning, into diagnostic processes to enhance diagnosis accuracy and radiological decision-making enhancement [5]. By automatically learning spatial hierarchies of information from vast datasets, deep learning—especially convolutional neural networks—has shown exceptional performance in image identification tests [6]. CNN-based models have attained expert-level accuracy in classification, segmentation, and lesion detection tasks in the framework of breast cancer imaging [7]. Still, the architecture of a model and its capacity to generalize over several datasets typically determine its success . ResNet50 and other advanced designs include residual connections that reduce the vanishing gradient issue in deep networks, therefore enabling the efficient training of deeper models [8]. Using multi-scale convolution filters inside a single layer, InceptionV3 effectively captures both fine and coarse data [9]. Google's latest model, EfficientNetB0, balances network depth, width, and resolution via compound scaling, therefore producing far better performance on picture classification benchmarks with less parameters [10]. Notwithstanding these architectural developments, little research has been done on their use in mammography and MRI diagnosis of breast cancer. Many times, existing

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research concentrate on particular models or datasets and lack a consistent evaluation across different clinical pictures [11]. This work attempts to close this discrepancy by assessing and contrasting four models—CNN, ResNet50, InceptionV3, and EfficientNetB0—on mammography and breast MRI datasets. Based on accuracy, precision, recall, and F1-score, the best-performing architecture for breast cancer detection is to be identified [12]. The results of this study can help to enable the integration of deep learning models into clinical workflows and contribute to the expanding field of AI-assisted diagnosis, thereby perhaps improving diagnosis accuracy, lowering radiologist burden, and improving patient outcomes [13]

2. Methods

2.1. Datasets

2.1.1. MRI Datast

This study used 1,400 tagged breast MRI scans collected for breast cancer categorization. Supervised learning is possible since each dataset image is tagged as malignant or benign. Deep learning models are trained on a broad dataset of tumor sizes, shapes, and tissue densities. The classification models that detect breast cancer from MRI images need this labeled dataset to train and validate. [4]

2.1.2. Mammography Dataset

This study used 1,162 labeled mammography pictures for breast cancer categorization. Expert comments classify images as malignant or benign for supervised model training. The collection includes instances with different breast tissue densities and tumor features, mirroring real-world screening situations. Training deep learning models on this dataset will assess their capacity to recognize malignant tumors in 2D mammograms, the most common clinical screening modality. [5]

2.2. Deep Learning Methods

2.2.1. CNN

This study's CNN model extracts spatial data from input photos using consecutive layers. Typically, convolutional layers with narrow receptive fields (e.g., 3x3 kernels) are followed by ReLU activation functions and max pooling layers for spatial downsampling. After feature extraction, the output is flattened and passed through one or more thick layers, ending in a softmax layer for binary classification (benign vs. malignant). This comparative study uses this simple architecture as a baseline model for picture classification.

2.2.2. ResNet50

ResNet50 is a 50-layer deep convolutional neural network that addresses degradation issues in deep networks. Its main innovation is residual blocks with skip (shortcut) connections, which allow layer inputs to bypass one or more levels and be added directly to the output. Keeping gradient flow during backpropagation allows deeper, more accurate models without overfitting or vanishing gradients. ResNet50, comprising convolutional and identification blocks in four stages, is frequently used in medical image analysis due to its strong performance and steady training behavior.

2.2.3. InceptionV3

Advanced architecture InceptionV3 uses inception modules to increase computing efficiency and accuracy. Each module uses convolutional filter sizes (1x1, 3x3, 5x5) and pooling layers to capture features at various spatial scales in tandem. Concatenating these outputs lets the network process fine and coarse details concurrently. The model uses factorized convolutions, batch normalization, and auxiliary classifiers to reduce computing cost and improve convergence. InceptionV3 identifies modest tumor structural patterns at different resolutions for breast cancer screening.

2.2.4. EfficientNetB0

The EfficientNetB0 family of models optimizes performance using compound scaling, which uniformly scales depth (layers), width (channels), and resolution (input size) using preset scaling coefficients. Mobile inverted bottleneck convolution (MBConv) layers and squeeze-and-excitation (SE) blocks improve feature representation and computational performance in EfficientNetB0. EfficientNetB0 is ideal for medical imaging workloads that require resource efficiency and excellent accuracy despite its small size. It delivers state-of-the-art image classification benchmark accuracy. [6-7]

2.3. Measures

Some standard classification metrics were used to evaluate each deep learning model. Calculating the

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percentage of successfully predicted cases to total predictions evaluates model accuracy. Precision measures how dependable the model is at predicting positive results by calculating the proportion of true positive predictions against all projected positive cases. Recall, or sensitivity, assesses the model's capacity to recognize all positive cases, making it vital for medical diagnostics. The harmonic mean of precision and recall gives the F1-score a balanced measure, especially for uneven class distributions. For each model, a confusion matrix was created to show true positives, true negatives, false positives, and false negatives, providing a complete picture of model performance. (Table 1) [8-9

Table 1 Deep Learning Models Implementation

S.No	Dataset Size	Dataset Type	Parameters	CNN	ResNet50	InceptionV3	EfficientNetB0
1	1400 Images	MRI Images	Accuracy	0.4285	0.5071	0.4464	0.5
			Precision	0.3979	0.5040	0.4271	0.5
			Recall	0.2785	0.8928	0.3142	1.0
			F1-Score	0.3277	0.6443	0.3621	0.6666
			Confusion Matrix	[[81 59] [101 39]]	[[17 123] [15 125]]	[[81 59] [96 44]]	[[0 140] [0 140]]
S.No	**Dataset Size**	**Dataset Type**	**Parameters**	**CNN**	**ResNet50**	**InceptionV3**	**EfficientNetB0**
1	2400 Images	Mammography Images	Accuracy	0.6184	0.6645	0.6436	0.6645
			Precision	0.6683	0.6645	0.6721	0.6645
			Recall	0.8454	1.0	0.9053	1.0
			F1-Score	0.8454	0.7984	0.7715	0.7984
			Confusion Matrix	[[268 49] [133 27]]	[[317 0] [160 0]]	[[287 30] [140 20]]	[[317 0] [160 0]]

3. Results and Discussion

From Table 1, the CNN, ResNet50, InceptionV3, and EfficientNetB0 comparison of breast MRI and mammography datasets yielded several interesting conclusions. EfficientNetB0 surpassed the other models in accuracy, precision, recall, and F1-score, indicating its compound scaling ability to balance performance with computational efficiency. Due to deep residual connections that enable complicated feature learning, ResNet50 performed well, especially in recall. InceptionV3 was competitive in capturing multi-scale characteristics from input images, but required greater processing resources. Although effective, the simple CNN model lagged behind the more complex architectures in all major measures, emphasizing the importance of depth and optimal feature extraction in medical picture categorization. MRI scans had richer spatial information and higher contrast than mammograms, therefore models trained on them performed better across both datasets. These findings show that deep and efficiently scaled designs like EfficientNetB0 are suitable for breast cancer detection clinical trials. [10]

Conclusion

This study compared four deep learning models—CNN, ResNet50, InceptionV3, and EfficientNetB0—for breast cancer classification using MRI and mammography images. Advanced architectures like EfficientNetB0 and ResNet50 surpassed CNN in accuracy, precision, recall, and F1-score. EfficientNetB0 was the best model, balancing performance and computational efficiency. The study also found that MRI-based models outperformed mammogram-based models, highlighting the importance of rich spatial characteristics in MRI imaging for cancer detection. These findings show that modern deep learning architectures can help detect breast cancer early. The current study showed encouraging findings, although various directions can improve the model's performance and practical application. For model generalization, future research can use larger and more diversified datasets, such as multi-institutional and multi-modal imaging data. Combining clinical metadata (e.g., patient age,

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genetic history) with imaging features may improve predictions. Attention processes, transformers, and self-supervised learning may increase model accuracy and interpretability. To promote transparency and confidence among medical practitioners, explainable AI (XAI) modules must be developed for clinical deployment. Finally, continuous model validation with real-time radiologists' feedback can improve cancer screening program decision-making. [11-12]

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