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A Comparative Analysis of CNN Models for Breast Cancer Detection

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Abstract: *Breast cancer remains a critical global health issue, with early detection playing a pivotal role in improving survival rates and treatment effectiveness. Deep learning, particularly Convolutional Neural Networks (CNNs), has emerged as a powerful tool in medical image analysis, offering promising results in disease classification. This paper focuses on the application of transfer learning to classify breast cancer using histopathological and mammogram images. Three widely adopted CNN architectures—ResNet-50, VGG16, and InceptionV3—were utilized to differentiate between benign and malignant breast tissue. The study involved training and evaluating these models on a structured breast cancer dataset, leveraging pre-trained networks for optimized feature extraction and classification accuracy. Among the tested architectures, InceptionV3 demonstrated superior performance, achieving a 92% accuracy rate in binary classification. This result underscores the model's ability to identify malignant cases with high precision and reliability, making it a strong candidate for assisting in diagnostic workflows. However, challenges such as dataset bias, variability in imaging quality, and model generalization remain critical concerns. Addressing these issues through techniques like advanced data augmentation, hyperparameter tuning, and integration of multi-modal imaging could further enhance model robustness[1]. Future work will focus on expanding datasets to improve model generalization and exploring hybrid architectures that combine multiple CNN frameworks*

Keywords: breast cancer, deep learning, CNN, ResNet-50, VGG16, InceptionV3, histopathological images, transfer learning, medical image classification, clinical integration, model robustness

I. INTRODUCTION

Breast cancer detection is a pivotal focus in contemporary healthcare, given the disease's widespread impact and the complexities associated with its diagnosis. As one of the most common cancers among women globally, breast cancer poses significant challenges for early detection and effective treatment[2]. Despite advancements in medical technologies, including imaging techniques and screening protocols, many patients are still diagnosed at advanced stages, which adversely affects Recent advances in machine learning (ML) and convolutional neural networks (CNNs**)** have transformed medical imaging by identifying subtle patterns often missed by clinicians. CNNs excel in analyzing mammograms and related images, enhancing diagnostic precision. In India, breast cancer represents a significant public health concern, with a growing number of cases reported annually. The integration of advanced ML techniques into clinical practice could facilitate earlier diagnoses and more personalized treatment plans, ultimately leading to better patient outcomes[3]. This research paper aims to conduct a comparative review of various CNN models utilized for breast cancer detection. By evaluating their effectiveness and performance metrics, this study seeks to provide insights into the most promising approaches for enhancing diagnostic accuracy. The findings will contribute to ongoing efforts to improve breast cancer detection methodologies, fostering a deeper understanding of how technological innovations can transform patient care in oncology[4].

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II. LITERATURE SURVEY

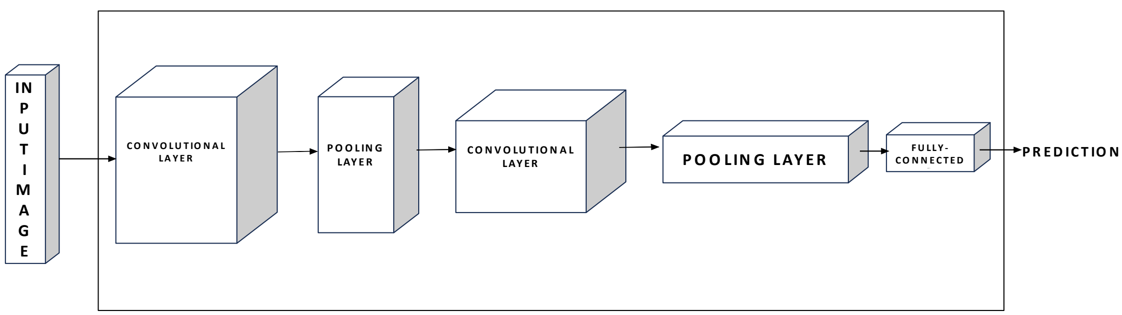
The application of Artificial Neural Networks (ANNs) in breast cancer diagnosis has been explored by , demonstrating their utility despite challenges associated with manual feature design. The various machine learning approaches reviwed, outlining their effectiveness and limitations in breast cancer prediction[5]. The application of Artificial Neural Networks (ANNs) in breast cancer diagnosis has been explored, demonstrating their utility despite challenges associated with manual feature design. In addition to imaging techniques, investigated risk factors and preventive strategies for breast cancer, providing valuable insights that can inform computational approaches in diagnostics [6] proposed advanced machine learning methods for breast cancer detection, showcasing the integration of computational models with domain knowledge. Additionally, reviewed recent advancements in medical imaging, emphasizing the evolution of image processing techniques for diagnostic improvement.

III. METHODOLOGY

Workflow in Convolutional Neural Networks (CNNs)

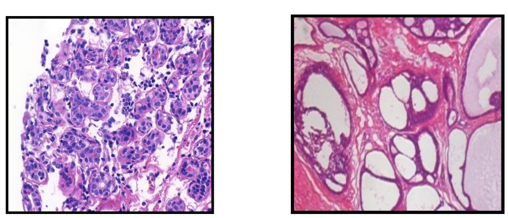
Convolutional Neural Networks (CNNs) represent a specialized subset of artificial neural networks explicitly designed to handle structured grid-like data, particularly images. Their architecture is inspired by the hierarchical processing of the human visual cortex, enabling them to effectively analyze, recognize, and classify complex patterns in visual data. CNNs have significantly advanced various applications, including image classification, object detection, medical diagnostics, and automated image processing. By leveraging a deep learning framework with multiple hidden layers, CNNs automatically extract essential features from raw input data without requiring manual feature engineering.

A typical CNN workflow follows a sequential process, encompassing image preprocessing, feature extraction, and classification. Each stage is essential in ensuring optimal model performance and accuracy in diverse image-based applications.



CNN ARCHITECTURE

Input Image: The model receives a raw image as input. This image is usually represented as a matrix of pixel values, possibly with multiple channels (e.g., RGB).The model receives a raw image as input. This image is usually represented as a matrix of pixel values, possibly with multiple channels (e.g., RGB. In this case we are using Histological Slides Which is obtained after performing biopsy of the patient. Here are some reference images of the two distinct type of the tumour which help in detecting breast cancer.



BENIGN MALIGNANT

Fig 2. Histological Images of different tissues

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Convolutional Layer: This layer applies a set of learnable filters (also called kernels) to the input image. Each filter slides over the image and captures spatial hierarchies by detecting low-level features such as edges, textures, and patterns. The result is a set of feature maps

Pooling Layer: Pooling (commonly max pooling) reduces the spatial dimensions of the feature maps. This helps in Reducing computational cost. Controlling overfitting., Retaining the most important features.

Second Convolutional + Pooling Layers: The process of convolution followed by pooling is repeated to extract more complex features from the previous layer's output. Deeper layers capture higher-level abstractions such as shapes or object parts...

Fully Connected Layer: The feature maps from the last pooling layer are flattened and passed through one or more fully connected (dense) layers. These layers integrate the extracted features and perform the final reasoning.

Output (Prediction): The final layer produces the prediction result. For classification problems, this could be a SoftMax layer that outputs the probability distribution over various classes.

Models for Breast Cancer Detection

CNNs are widely used in medical imaging for tasks like breast cancer detection, offering precise analysis of mammogram and histopathology images. Among various architectures, VGG16, InceptionV3, and ResNet-50 are notable for their accuracy, design, and efficiencyVGG16

VGG16:

(Visual Geometry Group 16) is a convolutional neural network (CNN) architecture known for its deep yet straightforward design. Developed by Simonyan and Zisserman in 2014 at the University of Oxford, VGG16 became one of the top-performing models in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC features 16 layers using 3x3 convolutions and 2x2 max-pooling. Its deep yet simple design captures complex patterns with fewer parameters.. The key design principle of VGG16 is the use of small receptive fields (3x3) stacked in depth, rather than using larger kernels.

Model Algorithm:

Step 1: Load Dataset: Set paths and load images with Image Data Generator, resized to **224×224**
Step 2: Preprocess: Normalize and augment images.
Step 3: Load Model: Load VGG16 pretrained on ImageNet.
Step 4: Compile: Use Adam Optimizer, Binary crossentropy, track metrics: accuracy, precision,
Step 5: Train: Use Early Stopping and Model Check point for validation monitoring.
Step 6: Evaluate: Predict on test set, compute confusion matrix and classification report

InceptionV3

InceptionV3 is an advanced deep learning model designed for efficient feature extraction. Developed by Google, it builds on the original Inception architecture, improving computational efficiency and accuracy. Unlike VGG16, which uses uniform-sized convolutional layers, InceptionV3 employs parallel convolutional operations with varying filter sizes (1x1, 3x3, 5x5) in the same layer. Techniques like factorized convolutions and label smoothing improve accuracy and reduce complexity. It is widely applied in medical imaging.

Model Algorithm:

Step 1: Load Dataset: Set paths and load images with Image Data Generator, resized to **224×224**
Step 2: Preprocess: Normalize and apply heavy Data augmentation on images.
Step 3: Load Model: Load VGG16 pretrained on ImageNet.
Step 4: Compile: Use Adam Optimizer, Binary crossentropy, track metrics: accuracy, precision,
Step 5: Train: Use Early Stopping and Model Check point for validation monitoring.
Step 6: Evaluate: Predict on test set, compute classification report

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ResNet-50:
(Residual Network with 50 layers) is a deep CNN model designed to address the vanishing gradient problem, which occurs when training very deep neural networks. Developed by Microsoft Research, ResNet-50 introduced the concept of residual learning, which allows deeper networks to be trained effectively by using skip connections, also called residual connections. **ResNet-50** designed to overcome vanishing gradients via *residual connections*, which allow identity mappings across layers. This enables deeper networks with stable training and high accuracy, making it ideal for medical imaging.

Model Algorithm**:**

Step 1: Load Dataset: Set paths and load images with Image Data Generator, resized to **224×224**
Step 2: Preprocess: Normalize and augment images.
Step 3: Load Model: Load VGG16 pretrained on ImageNet.
Step 4: aCompile: Use Adam Optimizer, Binary crossentropy, track metrics: accuracy, precision,
Step 5: Train: Use Early Stopping and Model Check point for validation monitoring.
Step 6: Evaluate: Predict on test set, compute confusion matrix and classification report

IV. RESULT & DISCUSSION

Table 1: Comparative Review of CNN Models

Models	VGG16	InceptionV3	ResNet-50
Accuracy (%)	74.79	92	55.76
Precision (%)	74.5	92.5	56
Key Features	Simple 3×3 convolutions; heavy (~138M params).	Multi-scale filters; efficient (~23.8M params).	Residual blocks; handles deep nets (~50 layers).
Training Time	Slow; uses residuals to handle vanishing gradients.	Fast; compact and efficient architecture.	Moderate skip connections improve convergence.

The Table 1 present experiment evaluation focused on three widely-used convolutional neural network (CNN) architectures—VGG16, InceptionV3, and ResNet-50—to assess their performance in classifying breast cancer images into benign and malignant categories

InceptionV3 achieved the highest classification performance with an **accuracy of 92%** and **precision of 92.5%**. Its architectural efficiency utilizing mixed convolutional filters of different sizes enabled multi-scale feature extraction while maintaining a relatively small parameter count (~23.8M). This allowed for **faster training** and better generalization, making it particularly suitable for medical image classification where detail at multiple scales is crucial.

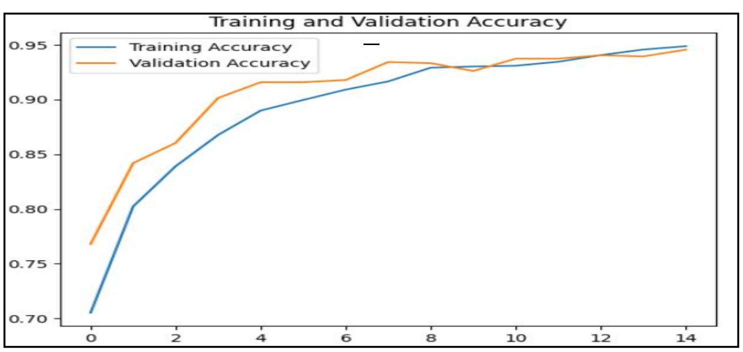

Fig 3. Inception V3 Accuracy graph

VGG16 shows a moderate performance with **74.79% accuracy** and **74.5% precision**. Although it is a simpler and well-established architecture, its computationally heavy design (~138M parameters) led to **slower convergence** and longer training times. Its stacked convolutional layers work well in general image tasks but appear less effective in capturing subtle variations in medical imaging without further fine-tuning.

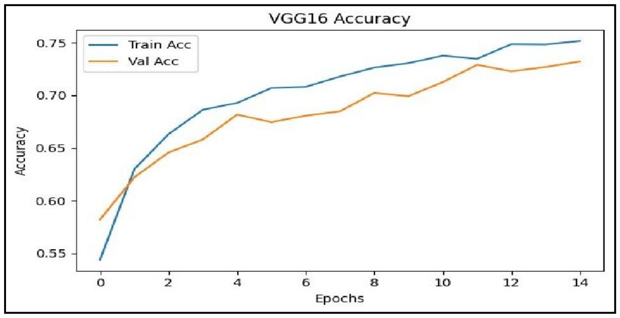

Fig 4. VGG16 Accuracy graph

ResNet-50 surprisingly yielded the **lowest performance**, with only **55.76% accuracy** and **56% precision**. While it is designed to tackle the vanishing gradient problem in deep networks through residual connections, it may have **overfit or underfit** on the relatively smaller dataset, or not benefited from the architectural depth due to insufficient training epochs or suboptimal hyperparameter tuning.

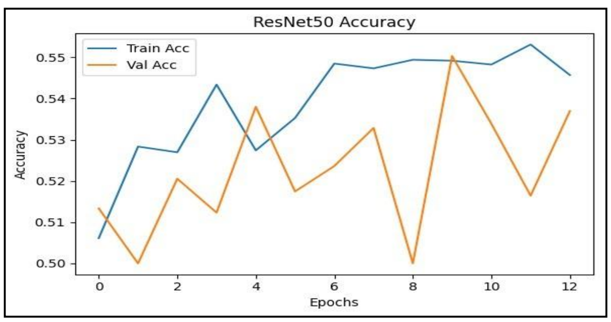

Fig 5. ResNet Accuracy graph

Based on the comparative analysis, **InceptionV3 is the most suitable model** for breast cancer detection in this study. It produced a balance between accuracy, precision, training time, and computational cost. Its superior performance validates the importance of architectural efficiency and multi-scale feature extraction in the context of medical imaging.

V. CONCLUSION

This research compares the performance of three well-established Convolutional Neural Network (CNN) models—VGG16, ResNet-50, and InceptionV3—in identifying breast cancer. Each architecture demonstrates distinct advantages in terms of accuracy and reliability, which influence their relevance for clinical deployment. The results suggest that modern CNN models hold significant promise in supporting early breast cancer diagnosis, thereby contributing to improved patient care. Future investigations should prioritize refining these architectures and examining their seamless adoption into healthcare environments to enable swift and precise diagnostic support.

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