# Comparative Analysis of Transfer Learning Models for Breast Cancer Detection: Leveraging Pre-Trained Networks for Enhanced Diagnostic Accuracy

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**(Breast cancer represents the most prevalent variant of malignancy observed in the female population) 2.3 million were diagnosed with breast cancer in 2022. Early detection enhances the quality of life for breast cancer patients, and one promising approach to achieving this is through the analysis of histopathological images using pre-trained models of convolutional neural networks (CNNs) architectures, namely ResNet152, InceptionV3, and MobileNetV2, all initially trained on the ImageNet dataset. This paper presents an analysis of these architectures applied to the breast cancer dataset, comparing their robustness and effectiveness in detecting breast cancer. The results demonstrate that models pre-trained on ImageNet perform significantly better compared to the same architectures trained from scratch on the breast cancer dataset. This difference in performance highlights the importance of transfer learning in analyzing medical images. It shows that using models already trained on large and varied datasets like ImageNet can greatly improve the ability to identify features in histopathological images. The results help to decide the robustness of the architectures for the given dataset. The results will support researchers working in this domain to understand which architecture yields better results in breast cancer diagnosis.**

Incorporating the applicable criteria that follow. Breast cancer has led to 670000 deaths globally in 2022 (The burden of breast cancer is high), (Especially in nations exhibiting elevated levels of the Human Development Index (HDI)). Breast cancer treatments are more effective when started early. Histopathological images are crucial in diagnosing breast cancer, providing detailed views of tissue samples to identify cancerous cells accurately. These images play a vital role in detecting breast cancer at an early stage, which significantly improves the effectiveness of subsequent treatments.[1]

Breast cancer is the primary cause of mortality for women in developing nations,[2,3,4] With the ratio of health professionals to the population being low in these countries, it is necessary for an automated diagnosis and classification of the disease.[5,6]

With the recent developments in machine learning, and deep learning techniques, researchers have started to use various Conventional Neural Network (CNN) architectures for diagnosis of various diseases as well as classification . The limitation in this is the size of the dataset.[7,8,9]Machine learning techniques require larger datasets for better accuracy . In medical image analysis, the size of the dataset is always small. This leads to overfitting which reduces the test accuracy of any network.[10]

Pre-trained models are proposed by the researchers to address this problem. ImageNet is the largest dataset available and is used for training the CNNs.[11,12] Though the dataset has very few medical images, pre-trained models with this dataset are seen to provide results with improved accuracy of classification. The learning transferred from this dataset increases the accuracy of classification.[13,14]

This paper proposes to analyze breast cancer detection with three state–of–the–art pre-trained models. ResNet152, Mobile NetV2, and InceptionV3 networks. These networks, pre-trained on the ImageNet dataset, are employed to analyze histopathological images of breast cancer. Both the scratch and the pre-trained models are used and are tested with the same dataset for analysis. Pre-trained models yield better results when compared to scratch models highlighting the significance of transfer learning in medical image analysis. The results indicate that researchers can work further in this area to select the optimal network for the specific dataset.

## LITERATURE SURVEY

Several deep-learning models are being proposed by researchers for disease identification and classification. Deep Breast Cancer Net [15] proposes a framework that is validated with standard publicity available dataset with an accuracy claimed of 99.63%. ResNet and InceptionV3 architectures are used as default models [16]and with transfer learning applied from pre-trained models.[17] In this pre-trained model with the dataset, ResNet50 gives the best results considering all the metrics. Feature selection is very important in convolution Neural Networks. Researchers on this to identify the significant features. Nearest Neighbour, Random Forest (RF) and support vector machine are taken for analysis with the RSNA (Radiological Society of North America) dataset.[18]The results are better with MIAS (Mammographic Image Analysis Society) and DDSM (Digital Database for Screening Mammography) datasets than RSNA. LeNet with modified ReLU (Rectified Linear Unit) gives an improved performance with batch normalization.[19]Mobile Net-based architecture gives results with less than 90% accuracy.[20,21]

For breast histopathology classification, a study comparing CNN and DenseNet121 based on transfer learning revealed that DenseNet121 obtained 86.6% accuracy at 100X magnification with 128×128 scaling, whereas training accuracy was improved by 16.4% with transfer learning.[22]FA-VGG16, a deep network for classifying images of breast histopathology that is based on Forward Attention. It greatly outperformed standard VGG16, with 97.7% accuracy for binary classification and 92.4% accuracy for quaternary classification.[23]Deep Learning (DL) improves cancer diagnosis in histopathology by more accurately and quickly analysing whole slide images (WSI) of stained tissues. DL compares its performance to human experts, highlighting challenges and opportunities in breast cancer detection and medical image analysis.[24]Pretrained models [25,26]are applied with optimization algorithms like Advanced AI-Birum Earth Radius to boost the classification performance. Additional statistical tests are also conducted to evaluate the results and the model is robust.[27]

Inception V3, a sophisticated deep convolutional neural network architecture, for automatic breast cancer detection through thermography with average classification accuracies obtained (at epochs 3, 5, and 6) were (98.104%, 98.712%, and 97.816%) respectively.[28]A concatenated transfer learning model designed for breast cancer histopathology utilizes pre-trained convolutional neural networks such as VGG-16, MobileNetV2, ResNet50, and DenseNet121 to derive deep features, which are then combined into a unified feature vector for classification purposes.[29]By leveraging pre-trained models and advanced feature selection methods, researchers can enhance the accuracy and robustness of diagnostic tools, ultimately contributing to better early detection and treatment outcomes for breast cancer patients.[30,31]

Xception achieved the best accuracy of 90.86%, surpassing prior state-of-the-art results, and transfer learning using InceptionV3 and Xception on the BreakHis dataset surpassed training from scratch.[32] Using the BreakHis dataset of histological images, transfer learning model of DenseNet121 achieved the highest breast cancer classification accuracy of 0.965 compared to other transfer learning models like (DenseNet201, VGG16, VGG19, InceptionV3, MobileNetV2).[33] The BreakHis dataset was used to test seven transfer learning models (LeNet, VGG16, DarkNet53, DarkNet19, ResNet50, Inception, and Xception) without any preprocessing or augmentation. On the unbalanced dataset, DarkNet53 had the best Balanced Accuracy (87.17%), whereas Xception had the highest accuracy (83.07%).[34] A learnable adaptive resizer for breast cancer classification using the BreakHis dataset to address data loss resulting from downsizing high-resolution histopathology images. Using a variety of convolutional neural networks, including DenseNet201, the method produced a high accuracy of 98.96% at 448x448 resolution.[35]

Hybrid approaches combining hand-crafted features like HOG (Histogram of Oriented Gradients) and LBP (Local Binary Pattern) with deep learning features from a CNN, breast cancer classification using mammograms outperforms the state-of-the-art techniques for breast cancer classification on the CBIS-DDSM dataset.[36] CNNs are the most accurate and widely used models for breast cancer diagnosis, evaluated mainly using accuracy metrics. The Wisconsin Breast Cancer Dataset (WBCD) was used, with 273 out of 569 samples for testing and the remaining for training and validation.[37] Two methods based on ResNet are used to categorise histopathology images of breast cancer: one uses self-supervised contrastive learning with limited labeled data, while the other combines ResNet50 with Inception modules to create an effective architecture. The model achieved 98% accuracy at 40X and 200X magnifications, and 94% at 100X and 400X, with a significantly reduced parameter count of 3.6 million.[38] Fusion of hybrid deep features (FHDF) using multiple CNNs, such as VGG16, VGG19, ResNet50, and DenseNet121, specifically tackling the issues of multilabel classification and unequal dataset distributions. The method detects different severities of breast cancer with high classification accuracies of 98.7%, 97.7%, and 98.8%, respectively, when applied to three public datasets (MIAS, CBIS-DDSM, and INbreast).[39]

Recent research has focused on enhancing deep-learning frameworks for the classification of histopathological images pertaining to breast cancer. Deep transfer learning models like ResNet50 are used for breast cancer detection using histopathology images, with ResNet50 outperforming other models with 90.2% accuracy, 90.0% AUC, 94.7% recall rates, and a marginal loss of 3%.[40,41] The breast cancer images from the ICIAR (International Conference on Image Analysis and Recognition) 2018 histopathological dataset are used, utilizing the ResNet-152v2 CNN architecture to extract features for distinguishing various types of breast cancer (normal, benign, in situ carcinoma, and invasive carcinoma) from histopathological images.[42] Deep transfer learning models for breast cancer histopathology classification that use ResNet50 and DenseNet121, optimised with ImageNet pre-trained weights and data augmentation. The models outperformed earlier CAD (Computer Aided Diagnosis) systems, achieving 100% accuracy in binary classification and 98% accuracy in multiclass classification.[43] The CNN model achieved a higher accuracy (92%) and F1-score (92%) on a dataset consisting of 57 patients in thermal breast imaging, outperforming state-of-the-art architectures like ResNet50, SeResNet50, and Inception.[44] CNN commonly employed to develop an efficient breast cancer classification model.[45]

### TRANSFER LEARNING

Transfer learning is a machine learning technique in which a model trained on one task is repurposed as the foundation for a model on a related task. This method is especially valuable when the dataset for the second task is limited, as it builds on the knowledge gained from the first task. Nowadays, it is very hard to see people training whole convolutional neural networks from scratch. Instead, it is typical to use a pre-trained model, often trained on diverse images for similar tasks such as models trained on ImageNet (1.2 million images across 1,000 categories) and leverage their features to address new tasks.

### Pre-trained Model Representation

Assume there is a pre-trained model

denoted as Mpre, which has been trained on a source task with a dataset Dsource. This model can be represented as a function that maps input data Xsource to predicted labels Ysource, denoted in equation (1).

$$M_{pre}(X_{source}) = Y_{source} \qquad ..(1)$$

In neural networks, this can be represented as shown in equation (2).

$$Y_{source} = f_{pre}(X_{source}; \theta_{pre}) \qquad ...(2)$$

where $\theta_{pr}$ represents the pre-trained model's parameters.

**Feature Extraction**

To transfer knowledge from Mpre, to a new task with a dataset Dtarget, are extracted features from the pre-trained model. Let the extracted features be denoted as mentioned in equations (3) and (4).

$$F_{source} = M_{pre}(X_{source}) \qquad ...(3)$$

$$F_{source} = M_{pre}(X_{Target}) \qquad ...(4)$$

where $X_{target}$ is the input data for the target task.

In neural networks, this is represented as shown in equations (5) and (6).

$$F_{source} = g_{pre}(X\,source; \theta_{pre}) \qquad ...(5)$$

$$F_{target} = g_{pre}(X_{target}; \theta_{pre}) \qquad ...(6)$$

where gpre represents the feature extraction function.

## MATERIALS AND METHODS

**Dataset**

The histopathological images of breast cancer are collected from the Kaggle database. 3928 images are taken from the Kaggle database out of which 2,627 images utilized for training the network, 656 images set aside for validation, and 645 images allocated for testing. The data is collected from the given link: https://www.kaggle.com/datasets/obulisainaren/multi-cancer.

**Data Pre-Processing**

The Breast Cancer dataset collected from the Kaggle database is initially pre-processed. Collected images are resized to 224 X 224 pixels and augmented and used for training.

**CNN Architectures**

In deep learning, pre-trained models serve as invaluable resources for tasks such as image classification, where extensive computational resources and labeled datasets are required for training. This paper conducted a comprehensive comparative study of three state-of-the-art pre-trained models: ResNet152, InceptionV3, and MobileNetV2, initialized with weights trained on the ImageNet dataset. Each model explores their unique characteristics and advantages. Furthermore, evaluating the performance of these models on ImageNet, a widely recognized benchmark dataset for image classification tasks.

**ResNet152**

ResNet-152 introduces the idea of residual connections, often referred to as skip connections or shortcut connections. These connections enable the network to bypass certain layers and propagate the input directly to deeper layers. By implementing this approach, ResNet-152 is able to learn residual mappings, which capture the difference between the input and the target output. This effectively addresses the vanishing gradient problem often faced when training very deep neural networks, enabling better optimization and training of the model.

Compared to shallower architectures, such as ResNet-50 or VGG-16, ResNet-152 has a larger capacity to capture intricate patterns and details in the data.

**InceptionV3**

InceptionV3 introduces a series of inception modules, which are convolutional modules with several parallel branches. Each branch performs convolutions of varying sizes (1x1, 3x3, and 5x5) to capture features across various spatial scales. These parallel branches are concatenated together to form the output of the inception module, enabling the network to capture both local and global features efficiently.

InceptionV3 employs factorized convolutions to reduce computational complexity and memory requirements. Instead of performing a single convolution with a large kernel size, factorized convolutions split the operation into

smaller convolutions, such as 1x3 and 3x1 convolutions, which are less computationally expensive. This allows the network to achieve better performance.

**MobileNetV2**

MobileNetV2 is a convolutional neural network architecture designed for mobile and embedded vision applications. MobileNetV2 introduces two hyperparameters, width multiplier, and resolution multiplier, which allow for flexibility in controlling the model's size and computational complexity. MobileNetV2 replaces the standard ReLU activation function with ReLU6 in the bottleneck layers. It helps to mitigate the problem of vanishing gradients and exploding activations, especially in deeper networks.

**Proposed Method**

The proposed block diagram for breast cancer prediction is shown in Figure 1. Pre-trained models such as ResNet152, InceptionV3, and MobileNetV2 are initially chosen. These models have undergone pre-training on the ImageNet dataset, which contains many images across a wide range of categories. The features learned by these models during training on ImageNet can be valuable for extracting meaningful features from breast cancer images.

The pre-trained models serve as feature extractors. The convolutional layers of these models act as feature extractors that can effectively capture meaningful patterns and features from breast cancer images. The images are passed through the pre-trained models, and the output of the last convolutional layer is extracted as features. After feature extraction, fine-tuning is done by adding a new layer on top of the pre-trained model for the classification process. The fine-tuned models are then trained on the breast cancer dataset. The dataset is typically split into training, validation, and testing sets. The dataset is customarily partitioned into training, validation, and testing subsets. The model undergoes training utilizing the training subset, while its efficacy is assessed on the validation subset to oversee potential overfitting and ascertain the appropriate cessation of training. Finally, the trained model's performance is evaluated on the testing set to find the ability and accuracy in classifying breast cancer images.

## RESULTS

The pre-trained models are trained for 25 epochs with a learning rate of 0.0001 using a Adam optimizer and binary cross entropy loss function. The training dataset consists of 2,627 images. Once the model is trained the same model is validated with 656 images. A batch size of 32 is used for training, and the activation function is sigmoid. The training and validation process is carefully monitored throughout all 25 epochs, ensuring the model's performance is continually
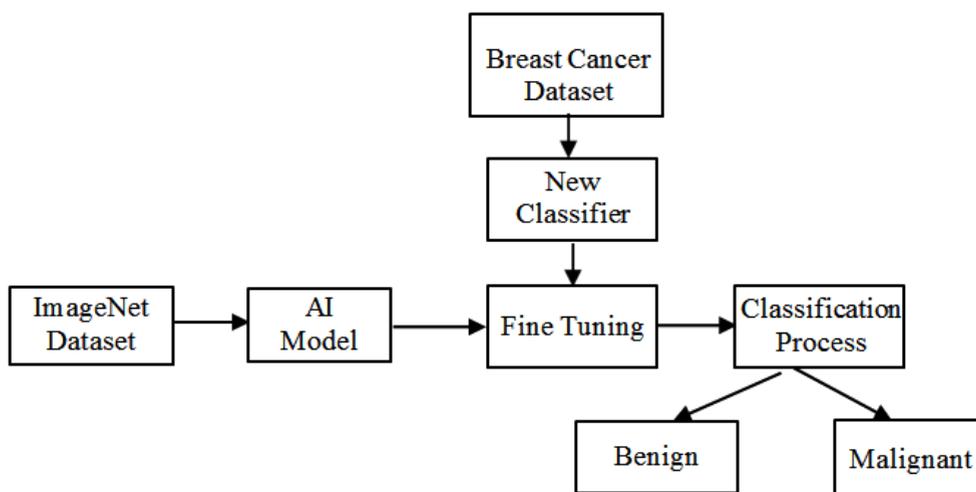


**Fig. 1.** Proposed Block Diagram

assessed and optimized. The models are trained using an NVIDIA GeForce RTX 4090 GPU with 24 RAM, ensuring efficient computation. This iterative process involves training the selected pre-trained models such as ResNet152, InceptionV3, and MobileNetV2 on the histopathological images sourced from Kaggle. The same hyperparameter values are given to train the scratch model of the same architecture.

After the completion of each epoch, the accuracy curves are plotted for both the training and validation datasets. Graphs [1-2] shows the comparison of training and validation accuracy plots of ResNet152 while Graphs [3-4] depicts the same for Inception V3 and Graphs [5-6] for MobileNetV2

## DISCUSSION

Once the training process is completed, the resultant trained models are subjected to testing using a separate set of 656 test images. These images are unseen by the model during training and validation, serving as an independent evaluation of its performance. Table 1 gives the metrics of accuracy, F1-score, Precision, and Recall for the scratch model. The scratch models' performance indicates that ResNet152V2 and InceptionV3 perform similarly, with training accuracies of 47.13% and 47.05% and validation accuracies of 47.19% and 47.50%, respectively. An F1-score of 0.74 and a testing accuracy of 59.22% are attained by both models, suggesting balanced precision
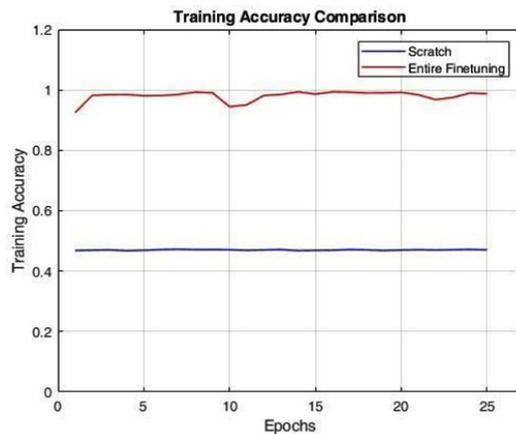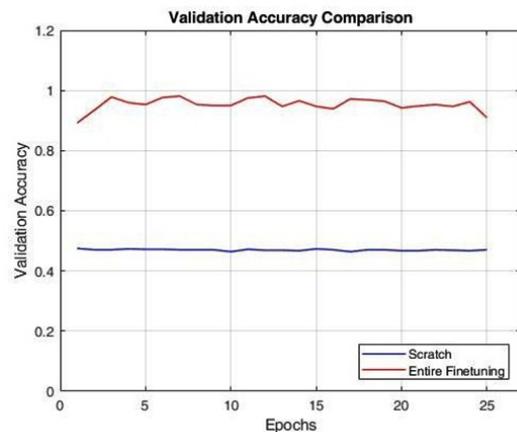


**Graph 1.** Training Accuracy Plot-ResNet152
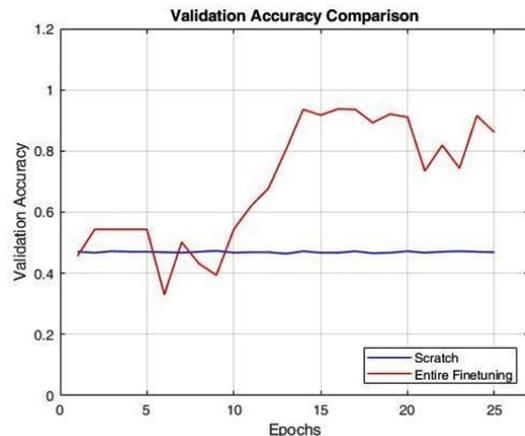


**Graph 2.** Validation Accuracy Plot- ResNet152
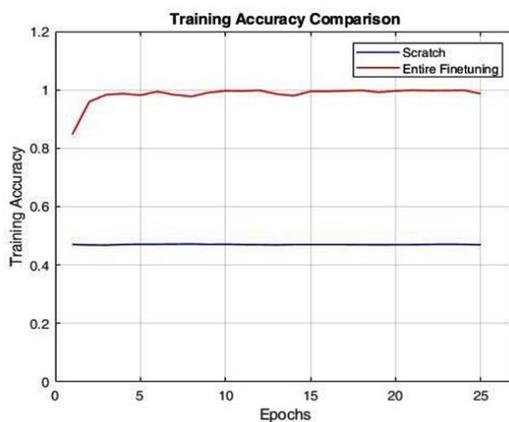


**Graph 3.** Training Accuracy Plot-InceptionV3



**Graph 4.** Validation Accuracy Plot- InceptionV3

(0.58) and recall (1.0). According to this, they may over predict positive cases but are skilled at spotting them. MobileNetV2, on the other hand, exhibits a substantially lower testing accuracy of 75.50% but a significantly better training accuracy of 94.03% and validation accuracy of 93.59%). Together with a precision of 0.59 and recall of 0.37, the model's F1-score of 0.45 indicates that it has trouble generalizing and does not detect all relevant positive examples during testing.
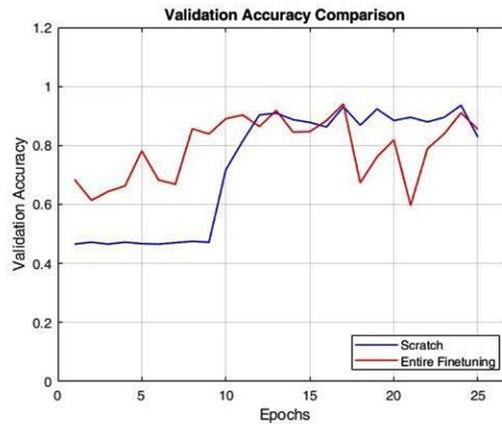
The Pre-trained model performance gives the metrics of accuracy, F1-score, Precision, and Recall, as shown in Table 2. InceptionV3 stands out as the leading model with the highest testing accuracy of 96.74%, alongside a remarkable F1-score of 0.96, a precision of 0.99, and a recall of 0.93, signifying its strong ability to both recognize positive cases and reduce false

positives. ResNet152V2 also shows commendable results, achieving a training accuracy of 99.38%, a validation accuracy of 93.75%, and a testing accuracy of 83.10%. Its F1-score stands at 0.83, with a precision of 0.95 and a recall of 0.75, demonstrating a reasonable balance with a slight compromise in recall. MobileNetV2 records a testing accuracy of 90.07%, with an F1-score of 0.92, a precision of 0.86, and an ideal recall of 1.0, indicating its exceptional ability to capture all relevant positive cases. InceptionV3 excels in performance, followed by MobileNetV2 and then ResNet152V2.

When compared to the scratch model, the Pre-trained model utilizing ImageNet demonstrates superior performance across all metrics, emphasizing the importance of transfer learning in the field of medical image analysis.
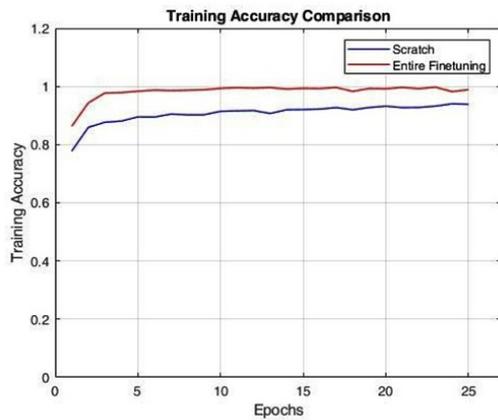


**Graph 5.** Training Accuracy Plot-MobileNetV2          **Graph 6.** Validation Accuracy Plot- MobileNetV2

**Table 1.** Performance Analysis For Scratch Model

| CNN | Training | Validation | Testing | F1-Score | Precision | Recall |
|-----|----------|------------|---------|----------|-----------|--------|
| RESNET152V2 | 47.13 | 47.19 | 59.22 | 0.74 | 0.58 | 1.0 |
| INCEPTIONV3 | 47.05 | 47.50 | 59.22 | 0.74 | 0.58 | 1.0 |
| MOBILENETV2 | 94.03 | 93.59 | 75.50 | 0.45 | 0.59 | 0.37 |

**Table 2.** Performance Analysis For Pre-trained Model

| CNN | Training | Validation | Testing | F1-Score | Precision | Recall |
|-----|----------|------------|---------|----------|-----------|--------|
| RESNET152V2 | 99.38 | 93.75 | 83.10 | 0.83 | 0.95 | 0.75 |
| INCEPTIONV3 | 99.81 | 96.88 | 96.74 | 0.96 | 0.99 | 0.93 |
| MOBILENETV2 | 99.61 | 94.06 | 90.07 | 0.92 | 0.86 | 1.0 |

Within this Pre-trained model, InceptionV3 shows strong results for breast cancer histopathological images, attaining a testing accuracy of 96.74% and an AUC of 98.97%.

## CONCLUSION

When compared to models trained from scratch, pre-trained models on the ImageNet dataset demonstrate significantly superior performance, underscoring the value of transfer learning in medical image analysis. Specifically, the InceptionV3 model, when pre-trained on ImageNet and fine-tuned for breast cancer histopathological images, exhibits remarkable results. This model achieves a testing accuracy of 96.74% and an Area Under the Curve (AUC) of 98.97%. Further, planned to utilize this model to be deployed in the Jetson Nano Development Kit. The Jetson Nano Development Kit is specifically designed for edge computing applications, offering a balance between computational power and energy efficiency. By deploying the InceptionV3 model on this platform, researchers can take advantage of its computational capabilities while minimizing resource consumption, making it well- suited for edge deployment scenarios where computational resources are limited. Furthermore, the InceptionV3 model's ability to accurately classify breast cancer images on the Jetson Nano underscores its suitability for real-world applications in healthcare and medical imaging. The combination of computational efficiency and accuracy ensures that the model can provide timely and accurate diagnoses, ultimately improving patient care and outcomes.

## ACKNOWLEDGMENT

**Conflict of interest**

The author(s) declares no conflict of interest.

**Data availability statement**

The dataset used in this research was obtained from Kaggle and is publicly available. All data preprocessing, analysis, and model development were conducted based on this dataset. The specific dataset can be accessed at https://www.kaggle.com/datasets/obulisainaren/multi-cancer

**Ethics statement**

This research did not involve human participants, animal subjects, or any material that requires ethical approval.

**Informed consent statement**

This study did not involve human participants, and therefore, informed consent was not required.

**Clinical trial registration**

This research does not involve any clinical trials.

**Permission to reproduce material from other sources**

Not Applicable.

**Author's contribution**

Jayanthi K.B : Conceptualization, Study design; Premalatha R : Methodology development, Literature review; Rajasekaran C : Interpretation of results, manuscript review; Sureshkumar R: Data collection, Data analysis.

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