Original Article

Breast Cancer Detection With Resnet50,Inception V3, And Xception Architecture

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Abstract

This study proposes the implementation of three different deep learning models - ResNet50, InceptionV3, and Xception - for the purpose of identifying defects in breast thermographic images. The results of the study show that each architecture has its own unique strengths and weaknesses, and that the accuracy and performance of the models can be improved through the use of different optimizers and learning rates. This suggests that these models have the potential to be used in a variety of fields where high accuracy is required. Furthermore, the study compares the accuracy and performance of each model under different conditions. By varying the optimizers and learning rates used in each architecture, the study is able to determine which combination of parameters produces the highest accuracy and performance. Overall, this study suggests that the implementation of deep learning models is a promising approach for identifying defects in breast thermographic images, and that ResNet50, InceptionV3, and Xception are all viable options for achieving high accuracy and performance in this field. The study also emphasizes how crucial thorough parameter adjustment is for maximizing the precision and effectiveness of these models.

Keywords—ResNet50, Inception V3, Xception, Accuracy, Deep Learning, Breast Thermogram, Breast cancer detection, Machine Learning.

I. INTRODUCTION

Breast cancer is the most frequent kind of cancer in women in Tamil Nadu, as reported by J. Radhakrishnan, the Health Secretary. The incidence of cancer in the state has been increasing gradually, which highlights the need for effective diagnostic methods that can detect the disease at an early stage. Mammogram, Breast MRI, Whole breast ultrasound or automated breast ultrasound system (ABUS), and Thermography are some of the methods available to detect breast cancer. Among these, Breast thermography is thought to be painless, non-invasive, and safe. It uses digital infrared thermal imaging (DITI) to detect breast cancer by detecting temperature changes on the surface of the breasts. In India, breast cancer accounts for 14% of all malignancies that afflict women. However, the good news is that the recovery rate is high - up to 75% of patients can be cured if the disease is diagnosed early. This underscores the importance of early detection in improving patient outcomes.Deep learning is a cutting-edge technique that can assist enhance the identification and analysis of breast cancer. In this context, the proposed study aims to use deep learning models such as ResNet50, InceptionV3, and Xception to detect breast cancer at an early stage by identifying flaws in thermographic images. The study will use DITI-based thermographic images to train the models and then ensemble them for better accuracy and results. Overall, this study is significant because it addresses an important health concern in Tamil Nadu and proposes a cutting-edge technology that can help detect breast cancer early, leading to better outcomes for patients.

II. LITERATURE SURVEY

The literature review emphasizes the significance of merging Artificial Intelligence (AI) with Infrared Imaging for breast cancer screening. Machine Learning (ML) algorithms like Artificial Neural Network (ANN) have been demonstrated to be beneficial in the diagnosis of breast tumors. The ability of ANN to give quick assessment and exact findings makes it a preferred classifier above others. Table 4 compares performance evaluations based on standard descriptions for breast cancer diagnosis using infrared imaging.Overall, the use of AI in breast cancer screening is promising and has the potential to revolutionize medical imaging and give patients with more accurate and efficient diagnoses[1]. Thermography has come a long way in matching mammography's accuracy in detecting breast cancer, with a sensitivity of 100%. Thermography can also accurately distinguish between benign and malignant instances, making it a useful tool in avoiding unnecessary biopsies. The low cost and portability of thermography make it a viable alternative to mammography, especially in economically backward and rural areas.Thermography has a substantial chance of detecting breast cancer early with further advancements in technology and computational techniques[2]. This paper presents a standardized protocol for acquiring and interpreting breast thermograms to improve the accuracy of detecting breast cancer early. The study sets up an infrared breast thermogram acquisition setup and analyses heat patterns statistically to find anomalies. Breast thermograms have a greater chance of detecting breast cancer early because to the suggested protocol suite, which can reduce erroneous positives. This study can be useful for researchers and practitioners, when it comes to medical imaging and cancer detection[3]. Through the analysis of breast thermography, this study suggests using Deep Convolutional Neural Network Inception v3 for precise breast cancer detection.To increase the precision of the diagnostic approach, the study proposes several training strategies, such as continuous training, and after closing MATLAB, and training after shutting down the computer. Breast cancer detection using the suggested learning rate of 1e-3 to 2.5e-3 has showed encouraging results, with accuracy rates of 97.816% and 99.928% respectively. The study highlights the When building a deep convolutional neural network, it is crucial to choose the right variables in order to increase accuracy. The suggested method may aid in the creation of extremely precise thermography-based diagnostic procedures for the identification of breast cancer.[4]. Using a convolutional neural network trained on the BreakHis dataset, ResNet-50, the research proposes a computational framework for the detection of breast cancer. The research model utilizes transfer learning technique from a pre-trained ResNet-50 CNN to classify histopathological microscopy images into malignant. The conclusion demonstrate that the model that we have proposed achieved a 99% accuracy compared against other models developed using the similar dataset. This indicates the potential of deep learning approaches, particularly the ResNet-50 CNN, in accurate breast cancer diagnosis, which can have a significant impact on the healthcare sector[5]. This research proposes a deep learning model for identifying and categorizing breast cancer into eight classes. The proposed model achieved a high level of precision, recall, and F1-score. This study highlights the potential of deep learning models as a promising tool for the precise breast cancer detection and categorization[6].

III. Methodolody

The project aims to develop a deep learning model for detecting breast cancer using breast thermographic images. To prepare the data for training, data resizing, data augmentation, and normalization are performed, and a training, validation, and test dataset are created from the data. Three distinct deep learning models are developed, utilizing ResNet50, Inception V3, and Xception architectures, respectively. The best hyperparameters for each model are figured out by testing it on the validation set after it has been trained on the training set. The weights of the models are changed until the necessary level of precision is achieved. The breast cancer dataset used in the project contains about 2088 images of thermograms that are collected under controlled environmental conditions. The dataset consists of two classes for detecting breast cancer: healthy and sick. Finding breast cancer may be done inexpensively, painlessly, and non-invasively with thermography. By monitoring the temperature distribution of the skin, this method finds the presence of breast lesions. Healthy tissues have a specific distribution of temperature, whereas cancer cells generate heat due to accelerated metabolic activity. Thermal cameras, or thermograms, can translate the heat radiated by the breast surface into visual information.

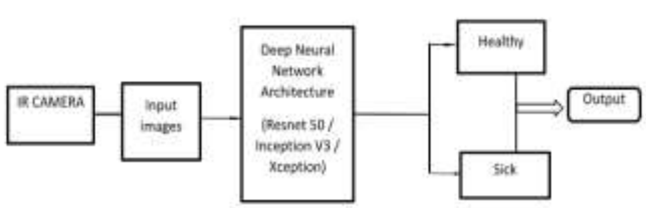


Figure 1. Proposed methodology block diagram

Three deep learning architectures are utilized in the project: ResNet50, Inception V3, and Xception.With hundreds or even thousands of layers, ResNet50 is a convolutional neural network (CNN) variation that enables the construction of very deep networks. Inception V3 is another type of CNN, known for its high accuracy, and utilizes "inception modules" that allow for more efficient computation of convolutions across different scales.With Xception, the standard convolutional layers are swapped out for Convolutions that can be divided by depth, making it a variation of Inception V3,, resulting in a network that is faster and more accurate than Inception V3, particularly on small datasets.The number of photos in the dataset is greatly increased by the use of data augmentation, which aids in the model's ability to rapidly learn features from various regions of the same image and perform better on image data that hasn't been previously seen. The optimizer is initialized with the stated learning rate and decay parameters throughout the training and validation procedure. Comparatively speaking, the selected optimisation strategy almost invariably achieves quicker and improved convergence of the global minimum. The validation accuracy rises in tandem with the training accuracy, while the validation loss falls in tandem with the training loss. By adjusting the learning rate, training the model on more photos, or training it for longer periods of time, better outcomes can be achieved. Overall, this methodology aims to develop a robust deep learning model for detecting breast cancer using thermographic images. Further improvements can be made by adjusting the learning rate, increasing the amount of training data, or training the model for longer periods.

Breast Thermogram: Thermography is a non-invasive method for detecting breast lesions by monitoring the skin's temperature distribution. Cancer cells accelerate metabolic activity and generate heat, leading to a different distribution of temperature in healthy tissues. Thermal cameras may be used to record and visualize the heat expelled by the breast surface. The automated analysis of thermograms is for the prompt identification of breast carcinoma, it is crucial.

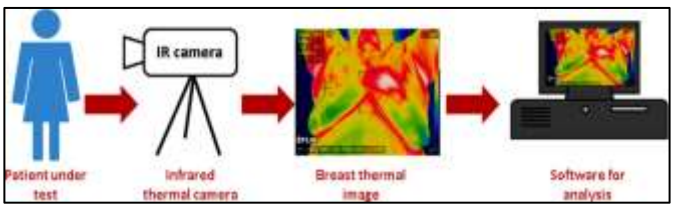


Figure 2.Breast Thermogram

Compared to traditional screening methods like mammography, breast thermography has several advantages. It can detect changes in breast tissue years before a tumor would be large enough to be detected by mammography.

Resnet-50: For image classification tasks, convolutional neural networks with the ResNet-50 architecture are employed. It won the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2015 after being suggested by Microsoft Research. The term "Residual Network," which alludes to the network's usage of "skip connections," is where the name "ResNet" originates. Because residual functions can be optimized more easily than the original mapping, the network can learn them.

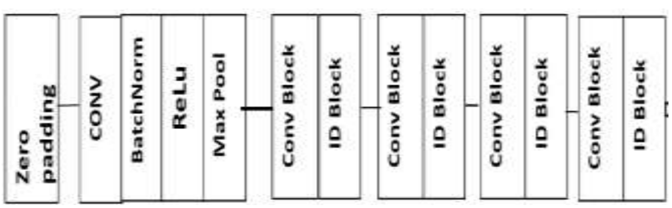


Figure 3. Resnet-50 Architecture.

For a variety of image classification applications, such as object recognition and detection, scene recognition, and fine-grained recognition, ResNet-50 has proven to be quite successful. It has also used as the framework for several computer vision applications, including semantic segmentation and object tracking. Overall, ResNet-50 is a powerful and widely used deep learning architecture that has advances in many image classification jobs have raised the bar.

Inception V3: Deep neural network technology is used in Inception V3 to classify images. It is a development of Google researchers' Inception architecture, which was created in 2014. Inception V3 was developed in 2015 and has since become one of the most extensively used image recognition systems. The key idea behind Inception V3 is to use a variety

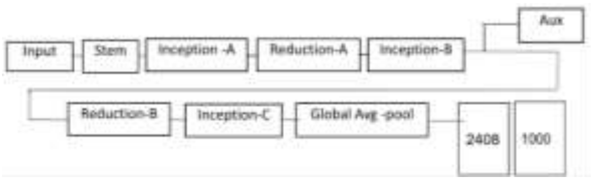


Fig 4. Inception V3 Architecture

of convolutional filters with to simultaneously capture features of various scales in the input image. This is achieved through the use of "Inception modules" that concatenate the outputs of multiple convolutional layers with different filter sizes before passing them on to the next layer. Along with these methods, Inception V3 also makes use of batch normalization, dropout, and auxiliary classifiers to enhance performance and lessen overfitting. Batch normalization is used to normalize the inputs to each layer, which helps to improve training efficiency and lessen overfitting. In order to avoid overfitting, the regularization approach known as dropout randomly removes certain neurons during training. Auxiliary classifiers are additional classifiers inserted at intermediate layers of the network, which help to provide additional training signals and improve gradient flow.The fact that Inception V3 has a comparatively low number of parameters as compared to other cutting-edge models is one of its distinguishing qualities. This is accomplished by reducing the number of channels in the feature maps while maintaining information through the use of dimensionality reduction techniques like 1x1 convolutions. With regard to image classification problems, Inception V3 is a strong and effective architecture that has been employed in a variety of applications, including as identifying objects, recognising faces, and clinical imaging. Its ability to capture features at multiple scales and its efficient use of parameters make it a popular choice for deep learning researchers and practitioners. The Inception v3 architecture offers several significant advantages in computer vision and deep learning applications. Some of these advantages are:

A. Improved accuracy: Inception v3 has shown improved accuracy in image recognition tasks compared to its predecessor, Inception v1. This improvement is due to the incorporation of several novel design features such as factorized convolution, parallel concatenation of filters, and aggressive dimensionality reduction.

B. Efficient computation: The inception v3 architecture utilizes depthwise separable convolutions, which are computationally efficient compared to regular convolutions. This makes it possible to perform more complex tasks with less computational resources, making it a suitable architecture for use in resource-constrained environments.

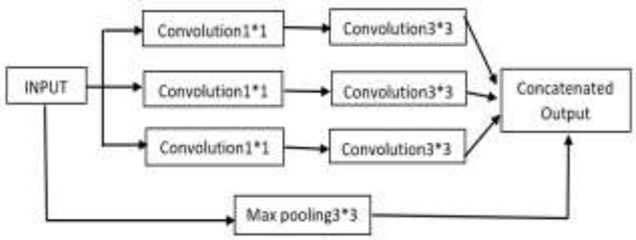
C. Transfer learning: Inception v3 was trained on the large-scale ImageNet dataset, and as such, it has learned general features that are useful for many different computer vision tasks. These features can be fine-tuned for specific applications with smaller datasets, making it easier to develop new applications with fewer training samples.

D. Robustness to image variations: Inception v3 is designed to be robust to image variations such as rotation, scaling, and translation. This is achieved through the use of max-pooling layers, which can extract invariant features from images.

E. Pre-trained models: Pre-trained Inception v3 models are readily available, making it easier for researchers and developers to use the architecture in their applications. These pre-trained models may be used to a variety of tasks, including separating images, identifying faces, and recognising objects.

Xception: As an alternative to the Inception family of designs, Xception is an advanced neural network architecture. François Chollet, the mind behind the Keras deep learning package, made the suggestion. The term "Extreme Inception" (abbreviated as "Xception") refers to an CNN (convolutional neural network) design that employs complexity-wise differentiated transformations to minimise the training requirements in terms of parameters and computation.

Figure 5. Xception Architecture



Xception uses a series of blocks that contain depth wise separable convolutions.In order to avoid the issue of disappearing gradients that can arise in neural networks with deep layers, these blocks are connected by skip connections that permit the gradients to flow directly through the network. There is an additional wise layer of convolution in each block., followed by a pointwise convolution layer, and then a skip connection that connects the input to the output of the block. A two-step convolution method called the deep separable convolution factors the ordinary convolution into a convolution based on depth and a point-by-point convolution. The point-by-point convolution applies a one-by-one convolution to merge the output of the depthwise convolution, whereas the convolution with depth applies a single convolutional filter to each input channel. The advantages of using depth wise dividable convolutions in Xception are that they require fewer parameters and computations than standard convolutions, which makes the network more efficient and easier to train. Additionally, the use of skip connections helps to preserve information from the input throughout the system, which may aid in enhancing the model's accuracy.With fewer parameters and operations than other architectures, Xception achieves outstanding accuracy on numerous benchmark image classification datasets. This is because the depthwise separable convolutions have fewer parameters and require fewer computations compared to standard convolutions. This reduction in parameters and computations leads to faster training and inference times, making it a practical choice for real-world applications. The Xception architecture offers several significant advantages in computer vision and deep learning applications. Some of these advantages are:

A.Improved accuracy: Compared to more established deep learning architectures like Inception and ResNet, Xception architecture has shown higher accuracy. On a number of image classification benchmarks, it produced cutting-edge outcomes.

B. Parameter efficiency: Xception architecture reduces the number of parameters required for training, which can significantly reduce the training time and memory requirements. This makes it an ideal architecture for resource-constrained environments.

C. Computational efficiency: The use of depthwise separable convolution in Xception architecture makes it computationally efficient.The network can learn temporal and stream-wise information independently, reducing the computational complexity.

D. Transfer learning: Xception architecture has been conditioned on big datasets like Image Network, making it a suitable architecture for instructional transfer. A smaller dataset may be utilised for improving the already trained network for a particular job via adaptive learning.

E. Robustness: Xception architecture is robust to occlusion and deformation of objects in the input image, making it suitable for object detection and segmentation tasks.

F. Scalability: Xception architecture can be easily scaled up or down to accommodate various input image sizes, making it flexible for different applications.

G. Compatibility: Xception architecture is compatible with various types of input data, including images, audio, and video,used in a variety of applications.

V. RESULTS AND DISCUSSION

Traditional methods for breast cancer detection can be inaccurate or require invasive procedures, leading to discomfort and increased risk. Deep learning techniques have emerged as a promising approach to improve breast cancer detection accuracy while minimizing patient discomfort. We suggested a deep learning-based method for breast tumor diagnosis in this work using breast thermographic images. We utilized three popular deep learning models: ResNet50, Inception V3, and Xception, and trained them on a breast thermographic image dataset. The models were trained using different optimizers, including SGD, Adam, Adagrad, and Rmsprop. The proposed system was developed with the goal of benefiting the medical field, specifically by detecting breast tumors earlier with high accuracy. The system was implemented in Python, achieving an accuracy of approximately 80%. By utilizing Google's GPU for processing, both the accuracy and speed of the system can be further improved. Analysis of the results obtained from training the models using different optimizers showed that the accuracy of the model improved as the precision of training increased. In a similar vein, as the training loss shrank, so did the precision of the validation.The system's accuracy might be raised by changing the learning rate, adding additional training photos, retraining the model for longer periods of time, or all three. The outcomes of this study showed the promise of techniques using deep learning for the early diagnosis of breast tumors. Future study can concentrate on adding more features or methods to boost the precision of the suggested system. The suggested approach has the ability to help in early identification and management of breast carcinoma, which would eventually improve patient results and standard of life. The application of methods based on deep learning to the diagnosis of breast tumors has shown significant promise and can potentially revolutionize the medical field. The accuracy and speed of the proposed system can be further improved by using more advanced optimization techniques and larger datasets. The results of this study can be used as a basis for future research in developing more robust and accurate deep learning models for breast cancer detection. The relevance of these results resides in the possibility that stronger and more sophisticated deep learning models for breast cancer detection may be created in the future. This research provides a starting point for future research in the construction of more sophisticated deep learning models.

SIMULATION RESULTS:

Optimization	**LR**	**Epoch**	**Train Accuracy**	**Test Accuracy**
SGD	0.001	1	0.97	0.93
SGD	0.1	5	1.00	0.96
ADAM	0.001	8	1.00	0.93
ADAM	0.1	9	1.00	0.96
ADAGRAD	0.001	2	0.98	0.93
ADAGRAD	0.1	9	1.00	0.96
RMSPROP	0.001	4	0.99	0.93
RMSPROP	0.1	2	1.00	0.96

Table 1. Simulation result for Resnet-5

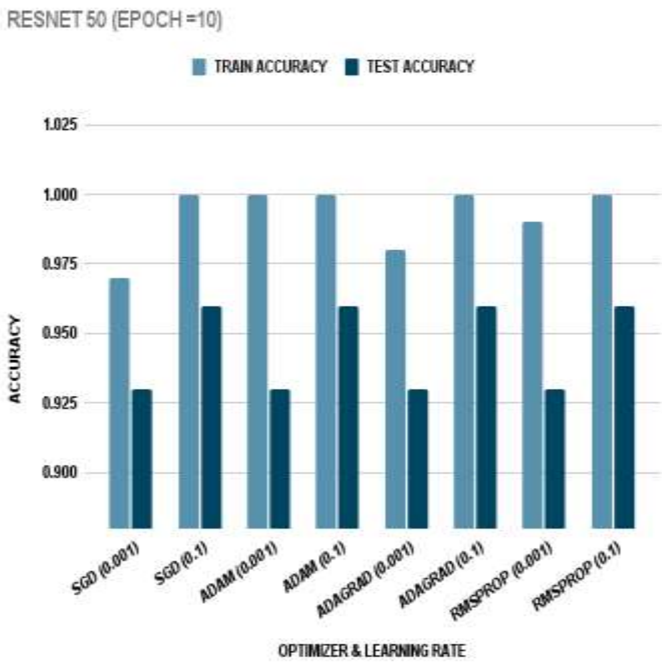


Figure 6. Resnet-50 graph

Optimization	LR	Epoch	Train Accuracy	Test Accuracy
SGD	0.001	10	0.97	0.87
SGD	0.1	10	1.00	0.83
ADAGRAD	0.001	10	1.00	0.95
RMSPROP	0.001	8	1.00	0.96

Table 2. Simulation result for Inception V3

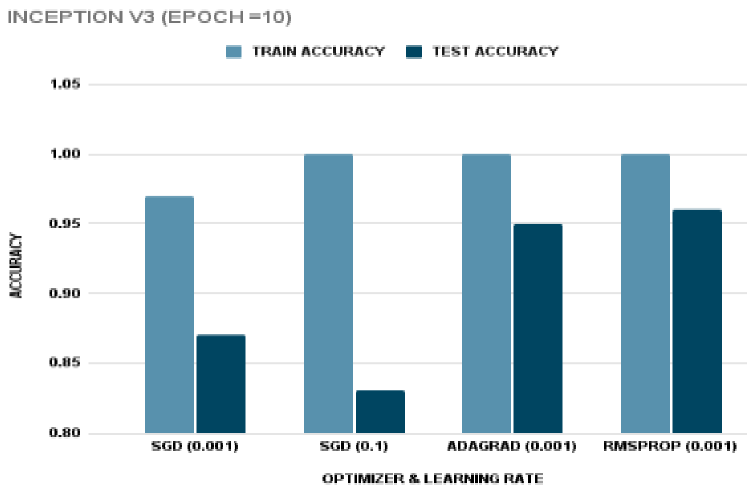


Figure 7.Inception V3 graph

Optimization	LR	Epoch	Train Accuracy	Test Accuracy
SGD	0.001	10	0.72	0.84
SGD	0.1	8	1.00	0.96
ADAM	0.001	9	0.99	0.95
ADAM	0.1	2	1.00	0.96
ADAGRAD	0.001	10	0.80	0.93
ADAGRAD	0.1	4	1.00	0.96
RMSPROP	0.001	10	1.00	0.96
RMSPROP	0.1	6	1.00	0.96

Table 3. Simulation result for Xception Architecture

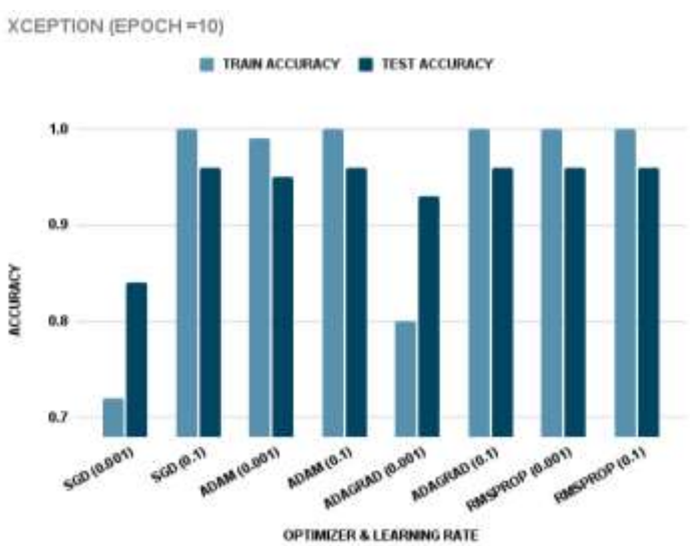


Figure 8. Xception graph

V CONCLUSION

The present research suggested utilising thermographic pictures to train a deep-learning algorithm to speed up carcinoma of breast diagnosis. The system was developed using ResNet50, Inception V3, and Xception models trained on a breast thermographic image dataset. Different optimizers were used for training, including SGD, Adam, Adagrad, and Rmsprop. The suggested method has an accuracy of about 80%, which may be increased by adjusting the pace of learning or doing additional practise on photos. Overall, the results indicate that deep learning models can provide better predictability than traditional methods for breast cancer detection.

VI ACKNOWLEDGEMENT

This work is original and has not been published elsewhere, nor is it currently under consideration for publication elsewhere.

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