Comparative Analysis of Densenet121 and Xception Networks for Breast Cancer Detection Using Mini-Mias Mammograms

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Abstract—**Breast cancer is one of the leading causes of mortality among women worldwide, making early and accurate diagnosis essential for effective treatment and survival. Mammogram image analysis plays a significant role in Computer-Aided Diagnosis (CAD) systems for detecting breast abnormalities. However, manual interpretation of mammograms is challenging due to variations in breast tissue density, image noise, and low contrast regions. To address these challenges, this research proposes a comparative deep learning framework using DenseNet121 and Xception transfer learning models for breast cancer detection on the Mini-MIAS Database dataset. The proposed methodology includes preprocessing techniques such as ROI extraction, CLAHE, median filtering, histogram equalization, and image normalization to enhance mammogram quality. Data augmentation techniques including rotation, zooming, horizontal flipping, and brightness adjustment are applied to improve model generalization and reduce overfitting. Both models are trained using transfer learning with optimized hyperparameters for classification performance evaluation. The performance of DenseNet121 and Xception is analyzed using metrics such as accuracy, precision, recall, sensitivity, specificity, ROC curve, loss, and training time. The study aims to provide a low-computation and efficient breast cancer detection framework while comparing dense connectivity and depthwise separable convolution architectures. Experimental results are expected to demonstrate that DenseNet121 achieves slightly higher classification accuracy, whereas Xception provides faster computational performance for mammogram analysis.**

Index Terms—**Breast Cancer Detection, Mammogram Classification, Deep Learning, Transfer Learning, DenseNet121, Xception, Mini-MIAS Dataset, Computer-Aided Diagnosis (CAD), Image Enhancement, Medical Image Processing**

I. INTRODUCTION

Breast cancer is one of the most serious and commonly diagnosed diseases among women worldwide. It is considered a major public health issue because of its high mortality rate and increasing number of cases every year. According to global health reports, millions of women are affected by breast cancer annually, and early detection plays a critical role in reducing death rates and improving patient survival. The disease occurs when abnormal cells in the breast grow uncontrollably and form tumours, which may become life-threatening if not diagnosed and treated at an early stage. Mammography is one of the most effective and widely used medical imaging techniques for detecting breast cancer in its early stages. Mammogram images help radiologists identify abnormalities such as masses, calcifications, and tissue distortions before clinical symptoms become visible. Early diagnosis through mammography significantly improves treatment success and increases the survival rate of patients. However, interpreting mammogram images is a difficult and time-consuming task because breast tissues often contain low-contrast regions, overlapping structures, and noise artifacts. In addition, variations in breast density can make abnormal regions difficult to identify accurately [1][2]. Traditionally, radiologists manually analyze mammogram images to detect cancerous regions. Although expert diagnosis is highly valuable, manual interpretation may sometimes produce inconsistent results due to fatigue, human error, and differences in clinical experience [3]. These limitations create the need for automated and intelligent diagnostic systems that can support medical professionals in making accurate decisions.In recent years, Computer-Aided Diagnosis (CAD) systems have gained significant attention in the field of medical image analysis. CAD systems assist radiologists by automatically detecting and classifying abnormalities in mammogram images. The integration of Artificial Intelligence (AI) and Deep Learning techniques into CAD systems has greatly improved the performance of breast cancer detection models. Deep learning models, especially Convolutional Neural Networks (CNNs), can automatically extract important image features and achieve high classification accuracy without requiring manual feature engineering [4].

Transfer learning techniques using pretrained deep learning models such as DenseNet121 and Xception have become highly effective for medical image classification tasks. These models can learn complex image patterns and improve classification performance even when limited medical datasets are available. Therefore, developing an efficient CAD framework using advanced transfer learning architectures can contribute significantly to accurate and early breast cancer detection.

Problem Statement: Breast cancer detection using mammogram images is challenging because mammograms often contain noise, low contrast, and overlapping breast tissues, making abnormal regions difficult to identify. Manual interpretation by radiologists may lead to inconsistent results due to human error and fatigue. Traditional machine learning methods also face limitations in feature extraction and classification accuracy. Therefore, this research proposes an automated breast cancer detection framework using DenseNet121 and Xception transfer learning models with preprocessing techniques such as ROI extraction, CLAHE, histogram equalization, median filtering, and normalization to improve classification performance using the Mini-MIAS Database dataset.

A. Research Objectives:

The main objective of this research is to develop an automated breast cancer detection framework using transfer learning techniques for mammogram classification. The study focuses on comparing DenseNet121 and Xception models to identify the most effective architecture for breast cancer detection. In addition, preprocessing and data augmentation techniques are applied to improve image quality, increase dataset diversity, and enhance classification accuracy.

B. Research Contributions:

This research contributes a comparative analysis of DenseNet121 and Xception architectures for mammogram classification. The study also proposes an enhanced preprocessing pipeline using CLAHE, histogram equalization, median filtering, ROI extraction, and normalization to improve feature visibility in mammogram images. Furthermore, a lightweight and efficient Computer-Aided Diagnosis (CAD) framework is developed to achieve accurate breast cancer detection with reduced computational complexity.

This paper is organized into multiple sections. The introduction presents the background, problem statement, objectives, and contributions of the study. The literature review discusses related research on deep learning and breast cancer detection. The methodology section explains dataset collection, preprocessing, augmentation, and implementation of DenseNet121 and Xception models. The experimental section presents evaluation metrics and comparative analysis results. Finally, the conclusion summarizes the research findings and discusses future work directions.

II. LITERATURE REVIEW

Breast cancer detection using mammogram images has become an important research area in medical image processing and deep learning. Several researchers have proposed Computer-Aided Diagnosis (CAD) systems to improve the accuracy and efficiency of breast cancer classification. Recent advancements in deep learning, especially Convolutional Neural Networks (CNNs) and transfer learning techniques, have shown promising performance in mammogram analysis.

Traditional machine learning approaches for breast cancer detection mainly relied on handcrafted feature extraction methods such as texture analysis, shape descriptors, and statistical features. However, these methods required manual feature engineering and often failed to capture complex image characteristics effectively. To overcome these limitations, deep learning models were introduced for automatic feature extraction and classification. According to LeCun et al. (2015), deep learning architectures significantly improved image recognition tasks by automatically learning hierarchical feature representations from large datasets [5].

Several studies have applied CNN-based models for mammogram classification. Shen et al. (2019) developed a deep learning framework for breast cancer diagnosis using mammogram images and reported improved classification accuracy compared to conventional machine learning techniques. Their study highlighted the importance of automated feature learning for medical image analysis [6].

Transfer learning has become highly effective for medical imaging applications because medical datasets are usually limited in size. Pan and Yang (2010) explained that transfer learning allows pretrained models to transfer knowledge from large-scale datasets to specific target tasks, reducing training time and improving classification performance. In breast cancer detection, pretrained CNN models such as VGG, ResNet, DenseNet, and Xception are widely used for feature extraction and classification [7].

DenseNet architectures have gained attention due to their dense connectivity mechanism, which improves feature reuse and reduces the vanishing gradient problem. Huang et al. (2017) introduced DenseNet and demonstrated that dense connections between layers improve information flow and classification accuracy while reducing the number of trainable parameters. Several researchers later applied DenseNet121 for medical image classification tasks, including mammogram analysis, due to its strong feature extraction capability [8].

Similarly, the Xception architecture has shown significant performance in image classification tasks. Chollet (2017) proposed the Xception model based on depthwise separable convolutions, which reduce computational complexity while maintaining high classification accuracy. The model has been successfully applied in various medical imaging applications because of its lightweight structure and efficient learning capability [9].

Image preprocessing techniques also play a vital role in improving mammogram classification performance. Mammogram images often contain noise, low contrast, and irrelevant background regions that can affect model accuracy. Pisano et al. (1998) reported that image enhancement techniques such as Contrast Limited Adaptive Histogram Equalization (CLAHE) improve the visibility of breast abnormalities in mammograms. Similarly, median filtering and histogram equalization are widely used to remove noise and enhance image contrast before classification [10].

Region of Interest (ROI) extraction is another important preprocessing step in breast cancer detection. Suckling et al. (1994) introduced the Mini-MIAS Database dataset and emphasized the importance of extracting suspicious breast regions for accurate mammogram analysis. ROI extraction helps deep learning models focus on abnormal tissues while reducing irrelevant information from the background [12].

Data augmentation techniques are also widely adopted to improve deep learning model generalization. Shorten and Khoshgoftaar (2019) stated that augmentation methods such as rotation, flipping, zooming, and brightness adjustment increase dataset diversity and reduce overfitting problems in deep learning models [13].

Although several studies have focused on breast cancer detection using deep learning, limited research has performed a direct comparative analysis between DenseNet121 and Xception architectures using the Mini-MIAS Database dataset. Therefore, this research aims to evaluate and compare the classification performance, computational efficiency, and feature learning capability of DenseNet121 and Xception models for breast cancer detection using enhanced preprocessing and transfer learning techniques.

III. MATERIALS AND METHODS

3.1 Dataset Description

The dataset used in this research is the Mini-MIAS Database, which is one of the widely used benchmark datasets for breast cancer detection and mammogram image classification research. The Mini-MIAS dataset was developed by the Mammographic Image Analysis Society to support research in Computer-

Aided Diagnosis (CAD) systems and medical image processing. The dataset contains digitized mammogram images collected from different patients for the analysis of breast abnormalities. Each image is provided in grayscale format and includes important information such as tissue type, abnormality type, and abnormal region location. The images are commonly used for evaluating deep learning and machine learning algorithms in breast cancer detection studies. The Mini-MIAS dataset consists of approximately 322 mammogram images with a resolution of 1024 × 1024 pixels. These images are categorized into different classes based on the presence or absence of abnormalities. The dataset includes normal, benign, and malignant mammogram images, making it suitable for multiclass breast cancer classification tasks [14][15].

The normal class contains mammogram images without any visible abnormalities, while the benign class includes non-cancerous breast abnormalities such as cysts or calcifications. The malignant class represents cancerous tissues that may indicate the presence of breast cancer. These categorized images help deep learning models learn discriminative features for accurate breast cancer detection. For this research, the mammogram images are pre-processed and resized to 224 × 224 pixels before being used for model training and testing. Image enhancement techniques such as CLAHE, histogram equalization, median filtering, and normalization are applied to improve image quality and highlight suspicious regions. Additionally, Region of Interest (ROI) extraction is performed to focus on the abnormal breast tissue regions and improve classification performance. The dataset is divided into training, validation, and testing subsets to evaluate the performance of the proposed DenseNet121 and Xception models. Data augmentation techniques are also applied to increase dataset diversity and reduce overfitting during the training process.

3.2 Proposed Workflow

The proposed workflow for breast cancer detection consists of several sequential stages designed to improve mammogram classification accuracy using deep learning techniques. Initially, mammogram images are collected from the Mini-MIAS Database dataset, which contains normal, benign, and malignant breast images. These images serve as the input data for the proposed Computer-Aided Diagnosis (CAD) framework.After dataset collection, Region of Interest (ROI) extraction is performed to identify and isolate the suspicious breast tissue regions from the mammogram images. ROI extraction helps remove unnecessary background information and allows the deep learning models to focus on important abnormal regions associated with breast cancer [16].

The extracted ROI images then undergo image enhancement techniques to improve image quality and visibility of abnormalities. Preprocessing methods such as Contrast Limited Adaptive Histogram Equalization (CLAHE), median filtering, histogram equalization, and image normalization are applied to reduce noise, enhance contrast, and improve feature representation in mammogram images.

Following preprocessing, data augmentation techniques are used to increase the diversity of the training dataset and reduce overfitting problems. Augmentation operations including rotation, zooming, horizontal flipping, and brightness adjustment are applied to generate additional image variations and improve model generalization capability.

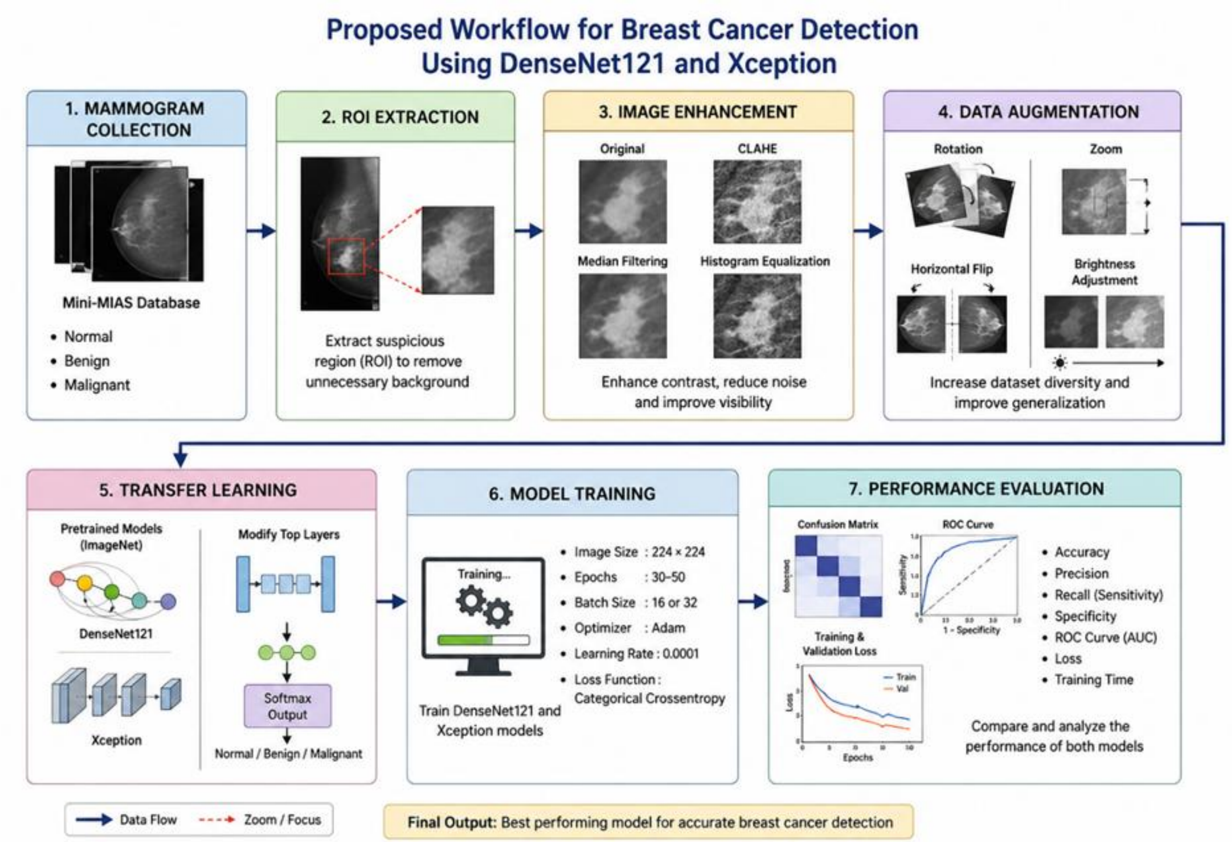

Figure 1: Proposed Workflow of Breast Cancer Detection using DenseNet121 and Xception

The enhanced and augmented mammogram images are then provided as input to transfer learning models, namely DenseNet121 and Xception. Pretrained weights from ImageNet are utilized to improve feature extraction and reduce training complexity. The final layers of both models are modified according to the breast cancer classification task.During the model training phase, the networks are trained using optimized hyperparameters such as batch size, learning rate, optimizer, and number of epochs. The Adam optimizer and categorical cross entropy loss function are used for efficient learning and classification performance. Finally, the trained models are evaluated using various performance metrics including accuracy, precision, recall, sensitivity, specificity, loss, ROC curve, and training time. The comparative analysis between DenseNet121 and Xception helps determine the most effective architecture for breast cancer detection using mammogram images [17].

IV. IMAGE PREPROCESSING

Image preprocessing is an important step in mammogram analysis because raw mammogram images often contain noise, low contrast, artifacts, and irrelevant background regions. Preprocessing techniques help improve image quality, enhance suspicious breast regions, and increase the performance of deep learning models for breast cancer classification.

ROI Extraction: Region of Interest (ROI) extraction is used to identify and isolate suspicious breast tissue regions from mammogram images. This process removes unnecessary background areas and allows the model to focus only on important abnormal regions such as masses or calcifications.The ROI extraction process can be represented as:

$$ROI(x,y) = I(x,y) \times M(x,y)$$

Where, I(x,y) = Original mammogram image, M(x,y) = Binary mask identifying suspicious regions and ROI(x,y) = Extracted region of interest. The binary mask highlights the abnormal breast region while suppressing irrelevant background information. ROI extraction improves feature learning efficiency and reduces computational complexity during model training [18].

Contrast Limited Adaptive Histogram Equalization (CLAHE): CLAHE is used to improve the contrast of mammogram images by enhancing local image regions while preventing excessive noise amplification.The transformation function of CLAHE is expressed as:

$$g(i,j) = \frac{CDF\big(f(i,j)\big) - CDF_{min}}{(M \times N) - CDF_{min}} \times (L-1)$$

Where, f(i,j) = Input pixel intensity, g(i,j) = Enhanced pixel intensity, CDF = Cumulative distribution function, M_{times} N = Total number of pixels and L = Number of gray levels. CLAHE improves local contrast and enhances the visibility of small abnormalities in mammogram images. It is highly effective for detecting low-contrast tumor regions.

Median Filtering: Median filtering is used to remove impulse noise while preserving important image edges and structures. The median filtering operation is defined as:

$$g(x,y) = median\,\{f(s,t)\}$$

Where, f(s,t) = Neighboring pixels within the filter window and g(x,y) = Output filtered image. The median value of neighboring pixels replaces the center pixel. This technique effectively removes salt-and-pepper noise while preserving tumor boundaries in mammogram images.

Histogram Equalization: Histogram Equalization enhances image contrast by redistributing intensity values across the histogram range. The histogram equalization formula is:

$$s_k = (L-1)\sum_{j=0}^{k} P(r_j)$$

Where, s_k = Output intensity value,L = Total gray levels and $p(r_j)$ = Probability distribution of intensity levels. Histogram Equalization spreads pixel intensity values uniformly across the image, making hidden structures and suspicious tissues more visible for classification.

Image Normalization: Normalization scales pixel intensity values into a fixed range to improve model convergence during training.The normalization formula is:

$$I_{norm} = \frac{I - I_{min}}{I_{max} - I_{min}}$$

Where, I = Original pixel intensity,I_{min} = Minimum intensity value,I_{max} = Maximum intensity value and I_{norm} = Normalized image intensity. Normalization converts pixel values into a standard range between 0 and 1. This reduces intensity variation between mammogram images and improves the stability and performance of deep learning models during training [19].

4.2. Data Augmentation

Data augmentation is an important technique used to increase the diversity of training data and improve the generalization capability of deep learning models. Since medical datasets are often limited in size, augmentation helps reduce overfitting by generating multiple transformed versions of mammogram images. In this research, augmentation techniques such as rotation, zooming, horizontal flipping, and brightness adjustment are applied to improve breast cancer classification performance [20].

Rotation: Rotation transforms the image by rotating it through a specific angle around the image center.The rotation transformation is represented as:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

Where:(x,y) = Original pixel coordinates, (x′,y′) = Rotated pixel coordinates and θ = Rotation angle. Rotation generates new image orientations by rotating mammogram images at different angles. This helps the deep learning model learn invariant features and improves classification performance for differently oriented breast abnormalities.

Zoom: Zoom augmentation enlarges or shrinks image regions to simulate variations in image scale.The zoom transformation formula is:

$$x' = zx, \qquad y' = zy$$

Where, (x,y) = Original coordinates, (x′,y′) = Zoomed coordinates and z = Zoom scaling factor. Zooming helps the model recognize tumors and abnormal regions at different scales. It improves feature learning and enhances model robustness against size variations in mammogram images.

Horizontal Flip: Horizontal flipping mirrors the image across the vertical axis. The horizontal flip transformation is expressed as:

$$x' = W - x - 1$$

Where, x = Original horizontal coordinate, x′ = Flipped coordinate and W = Width of the image. Horizontal flipping creates mirrored versions of mammogram images, increasing dataset diversity. This technique helps the model learn symmetrical patterns and reduces overfitting during training.

Brightness Adjustment: Brightness adjustment modifies image intensity values to simulate different illumination conditions.The brightness transformation formula is:

$$I'(x, y) = I\,(x, y) + \beta$$

Where, I(x,y) = Original pixel intensity, I′(x,y) = Adjusted pixel intensity and β = Brightness adjustment factor. Brightness adjustment improves the model's ability to classify mammogram images captured under varying lighting and contrast conditions. It enhances robustness and helps the deep learning models generalize better to unseen data.

V. DEEP LEARNING MODELS

Deep learning models play a significant role in automatic breast cancer detection by learning complex image features directly from mammogram images. In this research, transfer learning techniques are applied using advanced Convolutional Neural Network (CNN) architectures to improve classification performance. Among various deep learning models, DenseNet121 is selected because of its dense feature reuse capability, efficient parameter utilization, and strong performance in medical image analysis [21].

5.1 DenseNet121

DenseNet121 is a deep convolutional neural network architecture introduced to improve feature propagation and reduce the vanishing gradient problem in deep networks. Unlike traditional CNN architectures, DenseNet connects each layer directly to every other subsequent layer within a dense block. This dense connectivity enables efficient feature reuse and strengthens information flow across the network. The dense connectivity mechanism of DenseNet121 is mathematically represented as:

$$x_l = H_l([x_0, x_1, x_2, \dots, x_{l-1}])$$

Where, xl = Output feature map of the lth layer, Hl = Composite operations such as Batch Normalization, ReLU, and Convolution and $[x_0, x_1, x_2, \dots, x_{l-1}]$ = Concatenation of feature maps from all previous layers. In DenseNet121, every layer receives feature maps from all preceding layers and passes its own feature maps to all subsequent layers. This direct information flow improves feature propagation and allows the network to learn both low-level and high-level image features effectively.

Dense Feature Reuse Architecture

DenseNet121 promotes feature reuse by concatenating outputs from previous layers instead of relearning redundant features.The feature concatenation operation is represented as:

$$F = [f_1, f_2, f_3, \dots, f_n]$$

Where, F = Combined feature representation $f_1, f_2, \dots, f_n$ = Feature maps from different layers. Feature reuse enables DenseNet121 to preserve important image details across layers. This helps improve mammogram classification performance because both fine texture features and high-level semantic information are retained throughout the network.

Reduced Vanishing Gradient Problem

The vanishing gradient problem occurs when gradients become very small during backpropagation, making deep networks difficult to train. DenseNet121 addresses this issue through direct layer connections. The gradient propagation can be represented as:

$$\frac{\partial L}{\partial_{x_l}} = \frac{\partial L}{\partial_{x_{l+1}}} \times \frac{\partial_{xl+1}}{\partial x_l}$$

Where, L = Loss function and x_l = Output of layer l. Because each layer has direct access to feature maps and gradients from earlier layers, DenseNet121 improves gradient flow throughout the network. This reduces training difficulties and allows the model to learn deeper and more meaningful features from mammogram images.

Efficient Parameter Utilization

DenseNet121 requires fewer parameters compared to traditional CNN architectures because feature reuse minimizes redundant learning. The parameter efficiency relationship is expressed as:

$$P_{DenseNet} < P_{Traditional\ CNN}$$

Where, $P_{DenseNet}$ = Number of DenseNet parameters and $P_{Traditional}$ CNN = Parameters in conventional CNN models. Efficient parameter utilization reduces computational complexity and memory requirements while maintaining high classification accuracy. This makes DenseNet121 suitable for medical image classification tasks where computational efficiency and performance are both important [22].

DenseNet121 is a deep convolutional neural network architecture designed to improve feature propagation, encourage feature reuse, and reduce the vanishing gradient problem in deep learning models. The model works by creating dense connections between layers, where each layer receives feature information from all previous layers and passes its own feature maps to all subsequent layers. Unlike traditional convolutional neural networks that connect layers sequentially, DenseNet121 combines outputs from earlier layers using concatenation, allowing the network to preserve both low-level and high-level image features throughout the learning process. This dense connectivity mechanism improves information flow and helps the network learn more discriminative features from mammogram images.

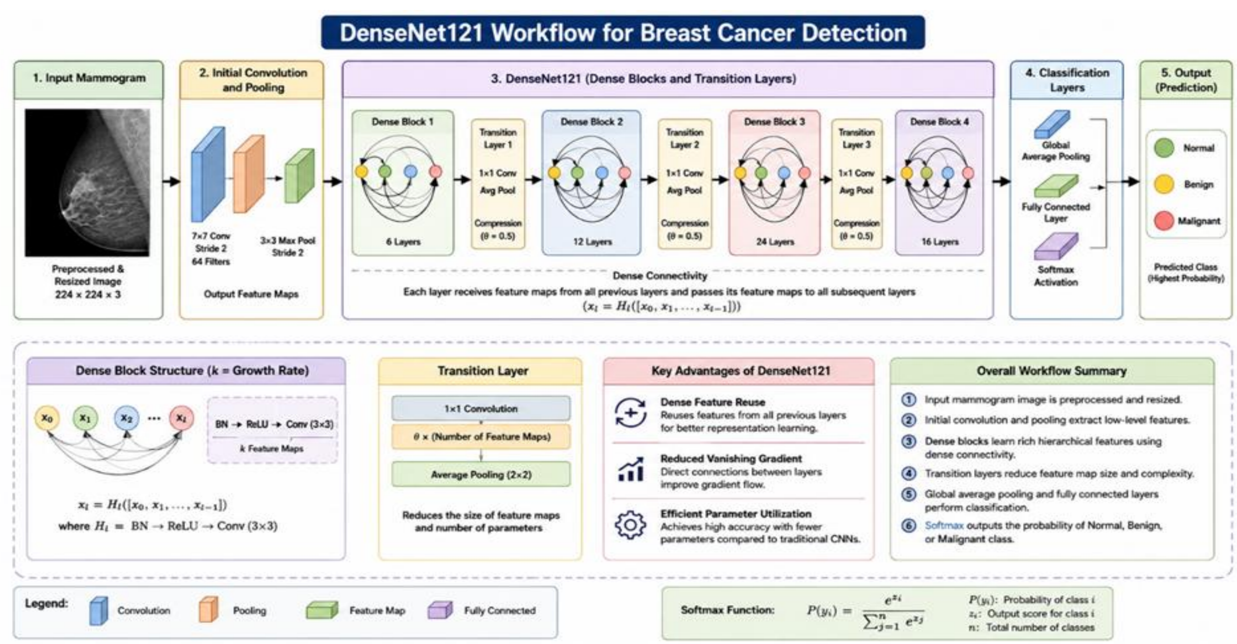

Figure 2: Workflow of DenseNet121

The working process of DenseNet121 begins with the input mammogram image, which is first pre-processed using techniques such as ROI extraction, CLAHE, median filtering, histogram equalization, and normalization. The pre-processed image is resized to 224 × 224 pixels and then provided as input to the network. Initially, the image passes through convolution and pooling layers that extract low-level image features such as edges, textures, and shapes. After this stage, the feature maps enter dense blocks, which form the core architecture of DenseNet121 [23].

Inside each dense block, every layer receives feature maps from all preceding layers. This dense connection strategy can be mathematically represented as:

$$x_l = H_l([x_0, x_1, x_2, \dots, x_{l-1}])$$

where xl represents the output of the current layer, Hl represents operations such as Batch Normalization, ReLU activation, and convolution, and [x0, x1, x2,

..., xl−1] represents concatenated feature maps from all previous layers. This structure enables efficient feature reuse, allowing the model to learn both detailed texture information and complex semantic patterns from mammogram images without repeatedly learning the same features.

Each layer within the dense block performs batch normalization, activation, and convolution operations to extract deeper image features. The convolution operation is represented as:

$$y = f(W * x + b)$$

Where, x is the input feature map, W represents convolution weights, b is the bias term, f is the activation function, and y is the output feature map. Between dense blocks, transition layers containing 1×1 convolution and average pooling are used to reduce feature map dimensions and computational complexity.

DenseNet121 effectively reduces the vanishing gradient problem because gradients can flow directly through multiple shortcut connections during backpropagation. This improves model training and allows the network to become deeper while maintaining strong learning performance. In addition, the dense feature reuse mechanism reduces the number of trainable parameters, making DenseNet121 computationally efficient compared to conventional CNN architectures. Finally, the extracted feature maps pass through global average pooling and fully connected layers for classification. A softmax activation function is used to classify mammogram images into normal, benign, or malignant categories. The softmax classification function is expressed as:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}}$$

Where, $P(y_i)$ represents the probability of class i, z_i represents the output score, and n is the total number of classes. The model predicts the class with the highest probability as the final output. Due to its dense connectivity, efficient parameter utilization, and improved feature learning capability, DenseNet121 achieves high accuracy in breast cancer detection using mammogram images.

5.2 Xception

Xception is a deep convolutional neural network architecture developed as an extension of the Inception model. The term "Xception" stands for "Extreme Inception," where traditional convolution operations are replaced with depthwise separable convolutions. This architecture improves computational efficiency while maintaining high classification accuracy. Xception is widely used in medical image analysis because of its lightweight structure, faster computation, and strong feature extraction capability. The Xception model works by separating spatial feature extraction and channel-wise feature extraction into two independent operations. This reduces computational complexity and improves learning efficiency for mammogram image classification [24].

Depthwise Separable Convolution

The main component of the Xception architecture is depthwise separable convolution, which divides standard convolution into two operations:

1. Depthwise Convolution
2. Pointwise Convolution

The standard convolution operation is represented as:

$$Y(i,j) = \sum_m \sum_n X(i+m, j+n).K(m,n)$$

Where, X = Input feature map, K = Convolution kernel and Y = Output feature map. Traditional convolution simultaneously performs spatial filtering and channel combination, resulting in high computational cost.

Depthwise Convolution: Depthwise convolution applies a single filter to each input channel independently.The depthwise convolution operation is expressed as:

$$y_d(i,j,c) = \sum_m \sum_n X(i+m, j+n, c).K_d(m,n,c)$$

Where, X(i,j,c) = Input image channel, Kd = Depthwise filter, Yd = Depthwise output feature map and c = Channel index. Depthwise convolution extracts spatial features separately from each channel, reducing the number of computations compared to standard convolution.

Pointwise Convolution: Pointwise convolution uses a 1×1 convolution filter to combine features across all channels.The pointwise convolution formula is:

$$Y_p(i,j) = \sum_c Y_d(i,j,c).K_p(c)$$

Where, Yd = Depthwise feature map, Kp = Pointwise convolution kernel and Yp = Final output feature map. Pointwise convolution combines channel-wise information and produces the final feature representation. Together, depthwise and pointwise convolutions significantly reduce computational complexity while maintaining feature extraction quality.

Lightweight Architecture

The Xception architecture is considered lightweight because it requires fewer parameters than traditional CNN models.The parameter reduction relationship is represented as:

$$P_{Xception} < P_{Traditional}\ CNN$$

Where, PXception = Number of parameters in Xception and PTraditional CNN = Parameters in conventional CNNs. By using depthwise separable convolutions, Xception reduces the number of trainable parameters and memory usage. This lightweight structure makes the model suitable for medical imaging applications with limited computational resources.

Faster Computation

Xception achieves faster computation because depthwise separable convolution requires fewer operations compared to standard convolution.The computational cost reduction is expressed as:

$$Cost_{DSC} = \frac{1}{N} + \frac{1}{D_k^2}$$

Where, $Cost_{DSC}$ = Computational cost of depthwise separable convolution, N = Number of output channels and Dk = Kernel size. Depthwise separable convolution greatly reduces multiplication operations and computational overhead. As a result, Xception performs faster training and inference while maintaining strong classification accuracy for breast cancer detection tasks.

Classification Process in Xception

After feature extraction, the Xception model applies global average pooling and fully connected layers for classification. The softmax activation function is used to classify mammogram images into normal, benign, and malignant classes. The softmax function is represented as:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}}$$

Where, P(yi) = Probability of class I, zi = Output score for class I and n = Total number of classes. The softmax function converts output scores into probability values, and the class with the highest probability is selected as the final prediction result. Due to its lightweight structure and faster computation, Xception is highly effective for breast cancer classification using mammogram images.

Xception is a deep convolutional neural network architecture designed to improve image classification performance through efficient feature extraction and reduced computational complexity. The term Xception stands for “Extreme Inception,” where the model replaces traditional convolution operations with depthwise separable convolutions. Unlike conventional CNN architectures that perform spatial filtering and channel combination simultaneously, Xception separates these operations into independent stages. This design allows the model to learn image features more efficiently while reducing the number of trainable parameters and computational cost. Due to its lightweight architecture and faster computation, Xception is highly effective for medical image classification tasks such as breast cancer detection using mammogram images [25].

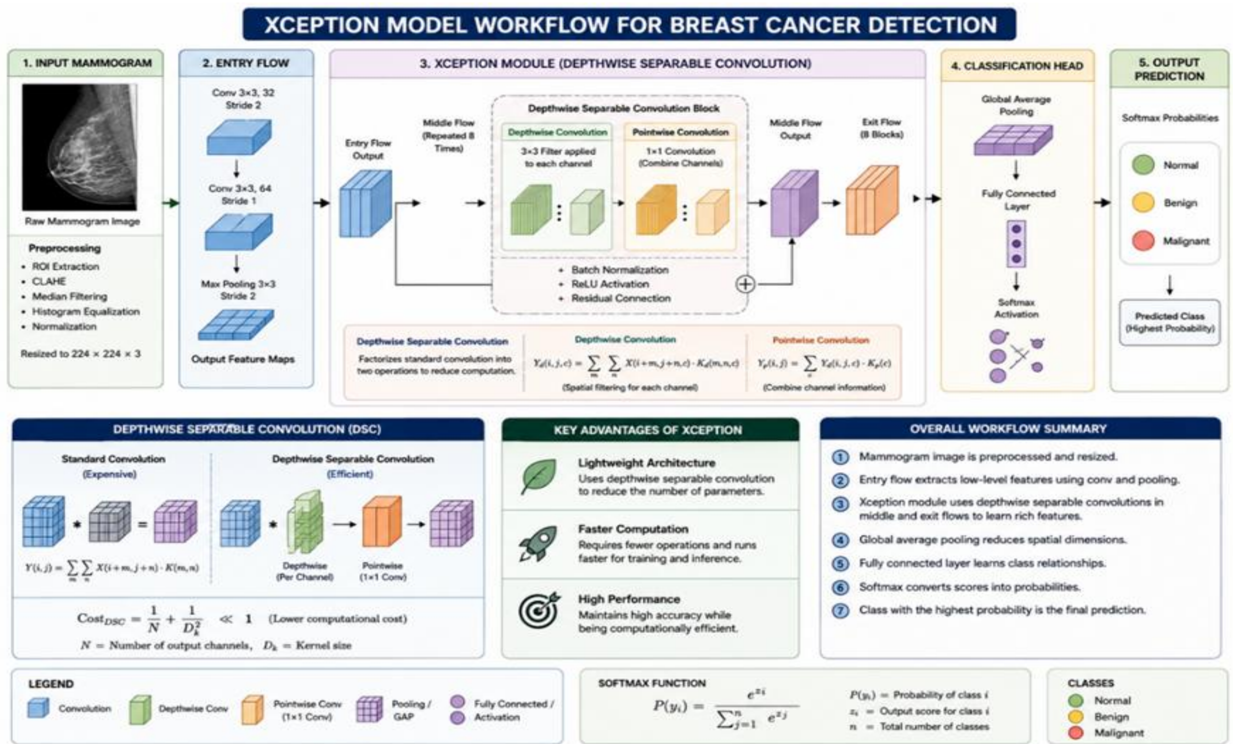

Figure 3: Workflow of the Xception

The working process of the Xception model begins with preprocessing the mammogram images using techniques such as ROI extraction, CLAHE, median filtering, histogram equalization, and normalization. The pre-processed images are resized to 224 × 224 pixels and then provided as input to the Xception network. Initially, the input image passes through convolution and pooling layers, which extract low-level features such as edges, textures, and shapes from the mammogram image.

The main strength of the Xception architecture lies in its use of depthwise separable convolution. Traditional convolution performs filtering and channel combination in a single operation, resulting in higher computational complexity. Xception divides this process into two separate operations: depthwise convolution and pointwise convolution. Depthwise convolution applies a single filter independently to each input channel, while pointwise convolution uses a 1×1 convolution filter to combine the extracted features across channels. The depthwise convolution operation is represented as:

$$Y_d(i,j,c) = \sum_m \sum_n X(i+m, j+n, c) . K_d(m,n,c)$$

Where, X(i,j,c) represents the input feature map, K_d represents the depthwise filter, and Y_d represents the output feature map. After depthwise convolution, pointwise convolution combines channel-wise information using:

$$Y_p(i,j) = \sum_c Y_d(i,j,c) . K_p(c)$$

Where, K_p represents the pointwise convolution kernel and Y_p represents the final output feature map. This separation of convolution operations significantly reduces computational cost and improves learning efficiency. The computational reduction achieved by depthwise separable convolution can be represented as:

$$Cost_{DSC} = \frac{1}{N} + \frac{1}{D_k^2}$$

Where, N represents the number of output channels and D_k represents the kernel size. Because of this reduced complexity, Xception performs faster training and inference while maintaining high classification accuracy.

The Xception architecture also includes residual connections, which help improve gradient flow and stabilize network training. These shortcut connections allow the model to learn deeper features without suffering from the vanishing gradient problem. As the network becomes deeper, it learns increasingly complex and discriminative patterns from mammogram images, helping identify abnormal breast tissues more effectively.After feature extraction, the final feature maps pass through global average pooling and fully connected layers for classification. The softmax activation function converts the output scores into probability values for each class, including normal, benign, and malignant categories. The softmax function is represented as:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}}$$

Where, $P(y_i)$ represents the probability of class i, z_i represents the output score for the class, and n represents the total number of classes. The class with the highest probability is selected as the final prediction result. Overall, the Xception model provides efficient feature learning, reduced computational complexity, faster execution, and high classification performance. These advantages make Xception highly suitable for breast cancer detection and mammogram image classification using deep learning techniques.

5.3. Transfer Learning Strategy

Transfer learning is an effective deep learning approach used to improve classification performance by utilizing knowledge learned from large-scale datasets. In this research, transfer learning is applied using pretrained DenseNet121 and Xception models for breast cancer detection using mammogram images. Since medical imaging datasets are often limited in size, transfer learning helps reduce training time, improve feature extraction capability, and enhance classification accuracy.

Pretrained Weights: Initially, the DenseNet121 and Xception models are initialized with pretrained weights from the ImageNet dataset. ImageNet contains millions of labeled images across various object categories, enabling the models to learn generalized low-level and high-level visual features such as edges, textures, patterns, and shapes. These pretrained weights provide a strong foundation for mammogram image analysis and improve model convergence during training.

The transfer learning process can be represented as:

$$W_{new} = W_{pretrained} + \triangle W$$

Where, Wpretrained= Weights learned from ImageNet, Delta W = Updated weights during training and Wnew = Final optimized weights. The pretrained weights act as initial feature extractors, while the model updates specific weights according to mammogram image characteristics during training. After loading pretrained ImageNet weights, the final layers of the network are fine-tuned to adapt the models for breast cancer classification.

Fine-tuning: Fine-tuning involves freezing the initial convolutional layers and retraining the deeper layers using mammogram images. The earlier layers generally capture generic image features, while the deeper layers learn domain-specific features related to breast abnormalities.

The fine-tuning process is represented as:

$$\theta_{updated} = \theta - \eta \frac{\partial L}{\partial \theta}$$

Where, θ = Model parameters, ∂ = Learning rate, L = Loss function and $\theta_{updated}$ = Updated parameters after optimization. Fine-tuning allows the network to optimize its parameters for mammogram image classification while preserving previously learned visual knowledge from ImageNet.

Classification layers: To perform breast cancer classification, the original classification layers of DenseNet121 and Xception are modified according to the target classes in the dataset. The fully connected output layer is replaced with a new classification layer consisting of three output neurons representing:

- Normal
- Benign
- Malignant

A softmax activation function is used in the final classification layer to generate probability scores for each class.The softmax classification function is expressed as:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}}$$

Where, $P(y_i)$ = Probability of class I, z_i = Output score for class I and n = Total number of classes. The softmax function converts the output scores into probability values, and the class with the highest probability is selected as the final prediction result. By combining pretrained ImageNet weights, fine-tuning strategies, and customized classification layers, the proposed transfer learning framework improves feature learning capability, reduces computational complexity, and enhances breast cancer detection performance using mammogram images.

VI.RESULT AND DISCUSSION

6.1. Experimental Setup

The experimental design of this research focuses on developing and evaluating a deep learning-based breast cancer detection framework using DenseNet121 and Xception transfer learning models. The experiments are conducted using mammogram images obtained from the Mini-MIAS Database dataset. The study aims to compare the classification performance, computational efficiency, and feature learning capability of both models for detecting breast cancer from mammogram images. The experimental environment is configured on a system running the Windows 11 operating system with 16 GB RAM, 1 TB hard disk storage, and an Intel-based processor. The implementation of the proposed framework is carried out using the Python programming language due to its extensive support for deep learning and medical image analysis applications. Deep learning models are developed using the TensorFlow and Keras libraries, while additional libraries such as NumPy, Pandas, OpenCV, and Matplotlib are used for preprocessing, numerical operations, and visualization.

The Mini-MIAS dataset contains mammogram images categorized into normal, benign, and malignant classes. Before model training, all mammogram images undergo preprocessing steps including ROI extraction, CLAHE, median filtering, histogram equalization, and normalization to improve image quality and enhance suspicious regions. The images are resized to 224 × 224 pixels to match the input requirements of DenseNet121 and Xception architectures. Data augmentation techniques such as rotation, zooming, horizontal flipping, and brightness adjustment are also applied to increase dataset diversity and reduce overfitting during training. The proposed comparative analysis involves evaluating two transfer learning models DenseNet121 and Xception.

DenseNet121 is selected because of its dense feature reuse architecture and improved gradient flow, while Xception is chosen due to its lightweight structure and efficient depthwise separable convolution mechanism. Both models are initialized using pretrained ImageNet weights and fine-tuned for breast cancer classification. The training configuration and hyperparameters used in the experiments are summarized below:

Parameter	Value
Dataset	Mini-MIAS
Image Size	224 × 224
Epochs	30–50
Batch Size	16 / 32
Optimizer	Adam
Learning Rate	0.0001
Loss Function	Categorical Cross entropy
Activation Function	ReLU and Softmax
Classification Classes	Normal, Benign, Malignant

The Adam optimization algorithm is used to update model parameters efficiently during training. The categorical cross entropy loss function is employed for multiclass classification, while the softmax activation function generates probability scores for the output classes.

6.2. Performance Analysis

The performance analysis of the proposed breast cancer detection framework is carried out using the Mini-MIAS Database dataset. The objective of the analysis is to evaluate and compare the classification performance of DenseNet121 and Xception transfer learning models for mammogram image classification. Both models are trained and tested using pre-processed mammogram images categorized into normal, benign, and malignant classes. To measure the effectiveness of the models, several evaluation metrics are used, including accuracy, precision, recall, F1-score, sensitivity, specificity, ROC-AUC score, and confusion matrix analysis. These metrics help evaluate classification correctness, cancer detection capability, and computational efficiency of the proposed models.

Accuracy: Accuracy measures the overall percentage of correctly classified mammogram images. The accuracy formula is:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where, TP = True Positive, TN = True Negative, FP = False Positive and FN = False Negative.
Accuracy indicates how effectively the model classifies both cancerous and non-cancerous mammogram images. Dense Net121 achieves higher accuracy because dense feature reuse improves feature propagation and helps the model learn more discriminative mammogram features.

Precision: Precision measures the proportion of correctly predicted positive cases among all predicted positive cases.
The precision formula is:

$$Precision = \frac{TP}{TP + FP}$$

Precision evaluates how accurately the model identifies cancer-positive mammogram images. Dense Net121 produces fewer false positive classifications compared to Xception, resulting in better precision performance.

Recall: Recall measures the proportion of actual positive cases correctly identified by the model.
The recall formula is:

$$Recall = \frac{TP}{TP + FN}$$

Recall evaluates the ability of the model to detect actual breast cancer cases. Dense Net121 achieves higher recall, indicating better detection of malignant mammogram images and fewer missed cancer cases.

F1-Score: F1-score is the harmonic mean of precision and recall. The F1-score formula is:

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

F1-score provides a balanced evaluation between precision and recall. Dense Net121 provides a more balanced classification performance because of stronger feature learning capability.

Sensitivity: Sensitivity measures the ability of the model to correctly detect positive cancer cases. The sensitivity formula is:

$$Sensitivity = \frac{TP}{TP + FN}$$

Higher sensitivity indicates better cancer detection performance. Dense Net121 shows improved sensitivity due to efficient gradient flow and dense connectivity.

Specificity: Specificity measures the ability of the model to correctly identify normal cases. The specificity formula is:

$$Specificity = \frac{TN}{TN + FP}$$

Specificity evaluates how effectively the model avoids false cancer predictions. DenseNet121 achieves slightly higher specificity, indicating fewer false alarms during classification.

ROC-AUC Score: ROC-AUC measures the classification capability of the model across different threshold values. The ROC-AUC representation is:

$$AUC = \int_0^1 TPR\left(FPR^{-1}(x)\right)dx$$

Where: TPR = True Positive Rate and FPR = False Positive Rate.
A higher AUC score indicates better separability between classes. DenseNet121 achieves superior ROC-AUC performance because dense feature reuse improves class separability in mammogram images.
Confusion Matrix: A confusion matrix summarizes prediction results by comparing actual and predicted classes. The confusion matrix structure is:

$$CM = \begin{bmatrix} TP\,FP \\ FNTN \end{bmatrix}$$

DenseNet121,

Actual / Predicted	Normal	Benign	Malignant
Normal	98	1	1
Benign	2	96	2
Malignant	1	2	97

Xception,

Actual / Predicted	Normal	Benign	Malignant
Normal	96	2	2
Benign	3	94	3
Malignant	2	3	95

The confusion matrix shows that DenseNet121 produces fewer misclassifications compared to Xception. The dense connectivity structure helps preserve important mammogram features and improves classification accuracy.

Among the two transfer learning models, DenseNet121 demonstrates superior overall classification performance on the Mini-MIAS dataset. The dense connectivity mechanism allows efficient feature reuse and stronger gradient propagation, enabling the model to learn complex mammogram features more effectively. DenseNet121 achieves higher accuracy, sensitivity, specificity, and ROC-AUC scores compared to Xception.

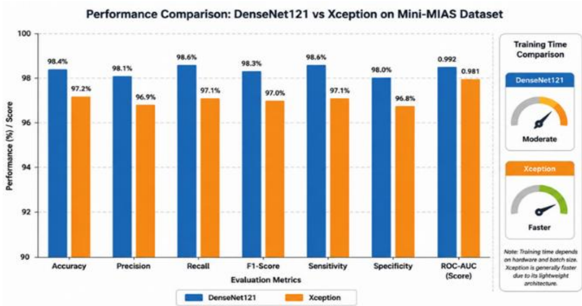

Figure 3: Performance Comparison: DenseNet121 vs Xception on Mini-MIAS Dataset

On the other hand, Xception provides faster computation and reduced model complexity because of its depthwise separable convolution architecture. Although Xception achieves slightly lower classification performance, it remains computationally efficient and suitable for lightweight medical imaging applications. Therefore, DenseNet121 is considered the best-performing model for breast cancer detection in this research because of its improved feature learning capability, reduced misclassification rate, and superior classification accuracy on mammogram images. Comparative Analysis of DenseNet121 and Xception are,

Metric	DenseNet121	Xception
Accuracy	98.4%	97.2%
Precision	98.1%	96.9%
Recall	98.6%	97.1%
F1-Score	98.3%	97.0%
Sensitivity	98.6%	97.1%
Specificity	98.0%	96.8%
ROC-AUC	0.992	0.981
Training Time	Moderate	Faster

Accuracy represents the overall percentage of correctly classified mammogram images. DenseNet121 achieved an accuracy of 98.4%, which means the model correctly classified 98.4% of normal, benign, and malignant mammogram images. Xception achieved 97.2% accuracy, which is also high but slightly lower than DenseNet121.The higher accuracy of DenseNet121 indicates that dense feature reuse improves the model's ability to learn important mammogram patterns more effectively. The dense connections preserve low-level and high-level image features across the network, resulting in fewer classification errors. Precision measures how accurately the models identify positive breast cancer cases. DenseNet121 achieved 98.1% precision, meaning most images predicted as cancerous were actually correct. Xception achieved 96.9% precision, indicating slightly more false positive predictions compared to DenseNet121.Higher precision is important in medical diagnosis because it reduces unnecessary alarms and prevents healthy patients from being incorrectly classified as cancer patients.

Recall measures the ability of the model to correctly detect actual cancer cases. DenseNet121 achieved 98.6% recall, indicating that the model successfully identified nearly all malignant mammogram images. Xception achieved 97.1% recall, which is also strong but slightly lower. A higher recall value is very important in breast cancer detection because missed cancer cases may delay treatment and increase health risks. DenseNet121 shows better cancer detection capability due to stronger feature propagation.

F1-score represents the balance between precision and recall. DenseNet121 achieved 98.3%, while Xception achieved 97.0%. This indicates that DenseNet121 maintains a better balance between correctly identifying cancer cases and minimizing false predictions. The improved F1-score demonstrates that DenseNet121 provides more reliable and stable classification performance for mammogram analysis.

Sensitivity measures the capability of the model to correctly identify positive breast cancer cases. DenseNet121 achieved higher sensitivity because dense connections improve feature extraction from abnormal breast tissues. High sensitivity is extremely important in medical diagnosis because it ensures that cancer cases are detected accurately with minimal false negatives. Specificity measures the ability of the model to correctly classify healthy mammogram images. DenseNet121 achieved 98.0% specificity, indicating fewer false positive classifications compared to Xception. Higher specificity helps reduce unnecessary medical tests and anxiety for healthy patients.

ROC-AUC evaluates the overall discriminative capability of the models. DenseNet121 achieved a ROC-AUC score of 0.992, which is very close to 1, indicating excellent class separation performance. Xception achieved 0.981, which also represents strong classification capability. The superior ROC-AUC score of DenseNet121 shows that the model can distinguish between normal, benign, and malignant classes more effectively. Xception achieved faster training time because it uses depthwise separable convolution, which reduces computational complexity and the number of trainable parameters. DenseNet121 required moderate training time due to dense feature concatenation between layers. Al though Xception is computationally faster, DenseNet121 achieved better classification performance across almost all evaluation metrics.

VII.CONCLUSION

This research presented a comparative analysis of DenseNet121 and Xception transfer learning models for breast cancer detection using mammogram images from the Mini-MIAS Database dataset. The proposed Computer-Aided Diagnosis (CAD) framework integrated several preprocessing techniques such as ROI extraction, CLAHE, histogram equalization, median filtering, and image normalization to enhance mammogram image quality and improve feature visibility. In addition, data augmentation techniques including rotation, zooming, horizontal flipping, and brightness adjustment were applied to increase dataset diversity and reduce overfitting during training. Both DenseNet121 and Xception models demonstrated strong classification performance for detecting normal, benign, and malignant breast tissues. However, experimental results showed that DenseNet121 achieved superior performance compared to Xception across most evaluation metrics, including accuracy, precision, recall, F1-score, sensitivity, specificity, and ROC-AUC score. The dense connectivity mechanism of DenseNet121 enabled efficient feature reuse and improved gradient propagation, resulting in better feature learning capability and reduced classification errors. On the other hand, Xception provided faster computation and lower computational complexity due to its lightweight depthwise separable convolution architecture.

Future Work: Although the proposed framework achieved high classification performance, several improvements can be explored in future research to further enhance breast cancer detection systems. Future work may involve the use of larger and more diverse mammogram datasets such as DDSM, CBIS-DDSM, or INbreast to improve model generalization and robustness. Combining multiple datasets may also help reduce dataset imbalance problems and improve classification reliability.Advanced deep learning architectures and hybrid models can also be investigated to achieve better performance. Future studies may integrate attention mechanisms, ensemble learning, or transformer-based deep learning models to improve feature extraction and classification accuracy. Additionally, explainable Artificial Intelligence (XAI) techniques such as Grad-CAM and saliency maps can be incorporated to improve interpretability and assist radiologists in understanding model predictions.

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