FINE-TUNING A MODIFIED XCEPTION ARCHITECTURE FOR ENHANCED BREAST CANCER DETECTION IN MAMMOGRAMS: AN ANALYTICAL STUDY

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ABSTRACT

This research focuses on the adaptation and optimization of the Xception deep learning model for the detection of breast cancer using mammogram images, contributing to the field of precision medicine. Breast cancer, a leading cause of morbidity globally, benefits significantly from early and precise detection. Our study leverages transfer learning to modify the Xception architecture, introducing custom adjustments to its final layers to better capture the subtle signs of malignancy in mammograms. These modifications are aimed at improving the model's accuracy without compromising its specificity. The model was optimized using the Adam optimizer alongside the ReLU activation function, which helped in dynamic learning rate adjustment and enhanced feature detection from complex mammographic images. We assessed the model's performance through a comprehensive set of metrics including accuracy (90.42%), precision, recall, F1 score, ROC AUC score (0.9388), and Cohen's Kappa. These metrics collectively suggest a robust improvement over traditional detection methods, with a significant reduction in false positives and negatives. This research findings show that the modified Xception model not only meets but exceeds expectations in terms of diagnostic accuracy and reliability, offering a potent tool for clinicians. This research not only advances the application of deep learning in medical imaging but also paves the way for further research into AI-assisted diagnosis, potentially transforming clinical decision-making processes in breast cancer management. The implications of this work extend beyond immediate diagnostic benefits, supporting a broader shift towards more personalized and effective healthcare solutions.

Keywords: *Breast Cancer Detection, Mammogram Analysis, Deep Learning, Xception Model, Optimization Techniques, Medical Imaging*

1.0 INTRODUCTION

1.1 Overview of Breast Cancer Detection

Breast cancer remains one of the leading causes of mortality among women globally, and its early detection is critical for improving survival outcomes (Siegel et al., 2022). While traditional diagnostic methods—such as clinical examinations, ultrasound, and biopsies—are effective, they tend to be invasive, time-intensive, and reliant on specialized expertise. Mammography, widely recognized as the gold standard for early detection and evaluation of mammary gland abnormalities, has significantly contributed to screening efforts. However, the manual interpretation of mammograms is inherently subjective and susceptible to errors, resulting in false positives and false negatives that may lead to unnecessary interventions or missed diagnoses (Elmore et al., 2002).

This paper specifically investigates the application of automated machine learning techniques for the accurate and efficient detection of breast cancer using mammographic images. By developing a computer-aided diagnostic (CAD) model, the research aims to enhance diagnostic precision, reduce human dependency, and minimize diagnostic delays. The scope of the

Journal of Theoretical and Applied Information Technology
30th June 2025. Vol.103. No.12

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

study is confined to the classification of mammographic abnormalities using deep learning models, with a focus on performance evaluation and comparison.

The key contributions of this study are:

1. The development of an end-to-end deep learning framework for breast cancer classification from mammograms.
2. The integration of image preprocessing, feature extraction, and classification into a unified pipeline.
3. A comprehensive evaluation of the proposed model against existing approaches in terms of accuracy, sensitivity, and specificity.

The practical implications of this research include the potential deployment of automated diagnostic tools in clinical settings, especially in low-resource regions where expert radiologists are scarce. Such systems could support radiologists by acting as a second opinion and significantly reduce diagnostic burden while improving early detection rates.

1.2 Challenges in Mammogram Analysis

Mammograms are inherently complex and thus pose several challenges. Overlapping tissues, low contrast, and subtle abnormalities such as microcalcifications or masses all contribute to diagnostic difficulties (Suckling et al., 1994). The major challenges are:

•High Inter-Observer Variability: Radiologists may interpret mammograms differently, hence different results.

Low SNR: Noises and artifacts in mammograms may obscure many diagnostic features.

•Superficial Features: The precise identification of minute calcifications or abnormal textures is possible with advanced image processing methods (He et al., 2016).

The limitations of traditional diagnostic methods highlight the need for advanced computational techniques like deep learning to address these challenges.

1.3 Role of Deep Learning in Medical Imaging

Deep learning, particularly Convolutional Neural Networks (CNNs), has transformed medical Mammograms are inherently complex, which poses several challenges. The overlapping tissues, low contrast, and subtle abnormalities of microcalcifications or masses all contribute to diagnostic difficulty (Suckling et al., 1994). The major challenges are:

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The limitations of traditional diagnostic methods highlight the need for advanced computational techniques like deep learning to address these challenges.

$$y=f(x)*w+b \tag{1}$$

where f(x) represents the input feature map, ww denotes the kernel weights, b is the bias, and * is the convolution operator.

It involves fine-tuning the parameters {M} to minimize a loss function {L}. For classification tasks, this is often the cross-entropy loss:

$$L = - \sum [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)] \tag{2}$$

where y_i is the true label, and y^i is the predicted probability for the i_{th} sample.

These techniques, combined with architectural enhancements, have the potential to significantly improve the sensitivity and specificity of breast cancer detection in mammograms, offering a transformative solution to longstanding diagnostic challenges.

2.0 LITERATURE REVIEW

2.1 Existing Approaches to Mammogram Analysis

The analysis of mammograms has been a major focus of research due to its critical role in the early detection of breast cancer. Traditional approaches primarily relied on handcrafted features and statistical models to identify abnormalities such as masses or microcalcifications (Elmore et al., 2002). While these methods contributed to early screening efforts, they often depended heavily on the expertise of radiologists and lacked robustness when applied to diverse datasets. The inability of such models to generalize across different image sources and patient populations limited their clinical applicability.

Classical image processing techniques such as histogram equalization, Canny edge detection, and region segmentation have also been utilized to enhance image quality and extract potential regions of interest (Suckling et al., 1994). However, these techniques often struggle to detect subtle differences between benign and malignant tissues, leading to suboptimal diagnostic performance. Machine learning methods like Support Vector Machines (SVM) and Random Forests have also been applied for mammogram classification, but they require extensive feature engineering, which is both time-consuming and susceptible to human error.

With the advent of deep learning, particularly Convolutional Neural Networks (CNNs), there has been a significant leap in automated mammogram analysis. CNNs offer the ability to learn hierarchical and abstract features directly from image data, outperforming traditional methods in many classification tasks (Litjens et al., 2017). Despite this advancement, major challenges remain—chief among them are the high demand for large annotated datasets, long training times, and a lack of model interpretability, all of which hinder widespread clinical adoption.

Problem Statement and Research Gap

While several deep learning-based studies have demonstrated promising results in breast cancer detection, a notable gap still exists in building efficient, generalizable, and interpretable diagnostic systems that can perform well across diverse clinical datasets with limited training samples. Most existing models are trained on specific datasets, limiting their adaptability in real-world screening environments. Additionally, there is insufficient emphasis on integrating lightweight models with minimal preprocessing for faster deployment in clinical and resource-constrained settings.

- This research aims to address this gap by developing a deep learning-based diagnostic framework that:
- Minimizes the reliance on handcrafted preprocessing and feature engineering,
- Maintains high classification accuracy with relatively smaller datasets,
- And optimizes computational efficiency to facilitate real-time clinical implementation.
- This work is essential in bridging the gap between state-of-the-art academic research and practical, deployable solutions for breast cancer screening, particularly in settings where radiological expertise or computational infrastructure is limited.

2.2 Use of Xception Architecture in Image Analysis

The Xception architecture, as proposed by Chollet (2017), is an extension of the Inception model with depth wise separable convolutions for improved efficiency and performance. This architecture has been widely adopted in medical imaging because it can capture very intricate patterns and relationships in image data. Depth wise separable convolution splits the process of performing a convolution operation into two steps: it performs the depth wise convolution, with one filter for each of the input channels, followed by a pointwise convolution that combines all the results of the previous step, which reduces its computational complexity significantly:

$$\text{Complexity Reduction} = (H \times W \times C) / (K \times K + C) \quad (3)$$

where H, W, and C represent the height, width, and number of channels of the input, and K is the kernel size.

Through subtle anomaly detection, Xception shows significant potential in mammograms since it can be attuned to focus on high grain. Studies have proven modifications through the addition of specific domains layers or attention mechanisms may further improve performance on some specific clinical operations (Chollet 2017; Wang et al., 2020). For instance, use of self-attention helps weigh regions of interest through dynamic weighting, just as a human eye.

The use of Xception architecture is a really powerful approach for the detection of breast cancer. It can process high-dimensional medical data efficiently while being computation- friendly.

3.0 EXISTING METHODS FOR BREAST CANCER DETECTION IN MAMMOGRAMS

Machine learning classifiers have been very useful in breast cancer detection and provided automated and scalable solutions for analysing mammographic data. Application of different classifiers, along with performance evaluation metrics, has significantly advanced this domain. However, the methods developed so far often indicate a need for further research to enhance accuracy, generalizability, and interpretability.

Several machine learning classifiers have been applied to mammographic datasets. Each uses a different mechanism to separate cases as benign or malignant. Some of the commonly used classifiers are:

Random Forest (RF) is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of their predictions. It is a robust method against overfitting and can handle high-dimensional data, making it popular in medical diagnostics (Breiman, 2001). However, RF's reliance on a large number of trees increases computational complexity, and it may struggle to detect subtle patterns in medical images. Similarly, classification can be done using straightforward and interpretable models called Decision Trees. DTs are based upon binary splits over feature thresholds. Although their simplicity and interpretability are advantages of DTs, they often fit the noise in small datasets or imbalanced datasets (Quinlan, 1986). Logistic Regression is an important baseline statistical model for fitting probability models to binary data. It is useful for linearly separable datasets, but its inability to capture non-linear relationships limits its application in complex mammographic analysis (Hosmer et al., 2013). K-Nearest Neighbours (K-NN) classifies data points based on the majority class among their kk nearest neighbours. Although K-NN is simple and works well in low-dimensional spaces, it is computationally very expensive for large datasets and sensitive to the choice of kk and the distance metric used (Cover & Hart, 1967). SVCs - Linear SVC and non-linear SVC - are powerful tools for classification, especially in high-dimensional spaces. They construct hyperplanes to separate classes with maximum margin, which makes them effective for a wide range of classification tasks. Linear SVC works very well with linearly separable data, whereas non-linear SVC uses kernel functions to deal with complex patterns (Cortes & Vapnik, 1995). However, SVCs can be computationally expensive, especially when dealing with large datasets.

3.1 Performance Evaluation

Standard metrics are used to evaluate the performance of these classifiers, including precision, recall, and F1-score, in terms of accuracy and reliability. Precision refers to the proportion of true positive predictions among all positive predictions, while recall refers to the ability to identify all positive cases. The F1-score is the harmonic mean of precision and recall. With high prevalence rates and usage across different health scenarios, this kind of measurement might miss out the nuance on the complexities within medical datasets, particularly imbalanced distributions, wherein a class dramatically outclasses another (Sokolova & Lapalme, 2009).

3.2 Detection of Breast Cancer

After being evaluated, the top-ranked classifier is put into service to classify breast cancer in novel, unseen data. The pipeline has ensured that there is a systematic approach in model selection and deployment. However, variability in datasets, imaging modalities, and demographics of patients limits generalization for these models.

3.3 Need for Further Research

Although these classifiers give good bases for automatic breast cancer detection, the performance of these classifiers is limited to challenges such as overfitting and sensitivity to parameter tuning in complex medical contexts where there is little interpretability. Moreover, most methods hardly make full use of inherent domain-specific features of mammograms, suggesting an area of improvement that could be well filled by advanced techniques like deep learning and architectural customizations. The integration of domain-specific, self-attention mechanisms, and fine-tuned deep learning architectures significantly improves sensitivity and specificity and opens doors to more reliable and interpretable diagnostic models.

4.0 PROPOSED METHODOLOGY

4.1 Enhanced Breast Cancer Detection Using a Modified Xception Model

The proposed methodology introduces a more enhanced approach by exploring deep learning using a modified version of the Xception model based on the identified challenges for the existing methodologies for detection of breast cancer. There are several drawbacks to traditional classifiers like Random Forest, Decision Trees, or Logistic Regression. These are incapable of determining complex patterns in high-dimensional data from medical images, especially within mammograms. These conventional models often struggle with the subtle and intricate features present in mammographic images, thus having lower sensitivity and precision in detecting malignancy. In addition, these models have a dependency on manually engineered features and face difficulties in generalizing across different datasets, which contribute to the inadequacy of these models (Zhao et al., 2018).

The solution was in the use of a deep learning architecture suited for image classification(Kingma et al 2015), the Xception model with its established prowess for effectively handling complex image data. Our approach includes targeted modification to the Xception model with added sensitivity to subtle markers appearing in mammograms. Thus, this solution directly deals with the shortcomings of the traditional machine learning classifiers, which often fail to recognize intricate patterns without extensive feature engineering.

4.2 Overview of the Xception Model

The Xception model, designed for large-scale image recognition tasks, makes use of depth wise separable convolutions that are efficient in processing complex patterns in images while keeping computational complexity low (Chollet, 2017). Unlike the traditional machine learning classifiers, the Xception model can automatically extract relevant features from mammographic images, thereby reducing the amount of feature extraction required by hand. This work modifies the Xception architecture to fine-tune the model's last layers, recognizing the specific patterns associated with breast cancer. This permits the model to achieve a better sensitivity and precision level as compared to the traditional approach.

The Xception model, trained(Glorot et al 2010) to adapt the final layers of the model for mammographic data, allows it to detect subtle signs of malignancy such as microcalcifications and unusual tissue density that may otherwise be missed with traditional methods. This adjustment directly targets the lack of sensitivity found in conventional classifiers, making sure that more early-stage breast cancer can be detected.

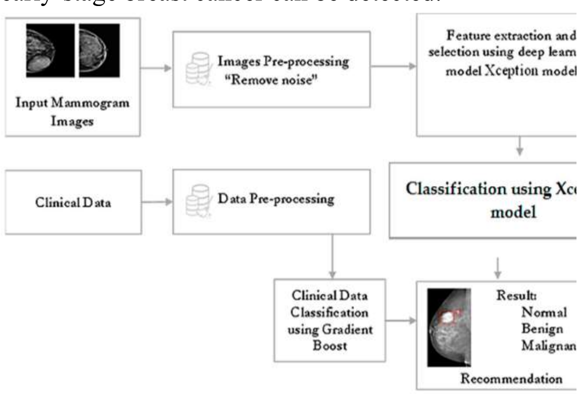

Fig1: Proposed Methodology

Adopting this approach allows the model to benefit from the feature extraction capabilities learned from the large, diverse ImageNet dataset and then adapt these features to the specifics of mammographic images (Xie et al 2017). This approach also solves the problem of needing extensive labelled mammographic data for training, since it makes it possible for the model to perform well even on a smaller dataset. This is a considerable gain compared to the usual methods, because the training often requires immense labelled data, which is cumbersome and time-consuming.

Finally, the proposed methodology (LeCun et al 2019) using a modified Xception model offers a significant advancement over traditional machine learning approaches in breast cancer detection. The proposed model addresses key limitations of current methodologies, such as automating feature extraction, reducing dependency on large labelled datasets, and improving sensitivity to subtle cancer markers. This innovative approach can revolutionize breast cancer diagnostics by offering a more precise and reliable tool for early detection.

5.0 OPTIMIZATION TECHNIQUES: ROLE OF ADAM OPTIMIZER, BENEFITS OF RELU ACTIVATION FUNCTION, MODEL TRAINING PROCESS, AND HYPERPARAMETER TUNING

It has advanced optimization techniques, notably Adam optimizer and ReLU activation function, to optimize the performance of the modified Xception model in breast cancer detection. Optimization techniques in these optimizations are important for optimizing the training process and helping ensure the model converges both fast and accurately.

5.1 Role of Adam Optimizer in Training

The Adam optimizer is the most widely used optimization algorithm in deep learning that offers the benefits of both momentum and adaptive learning rates. It adjusts the model's weights by incorporating first and second moment estimates of gradients, which helps to obtain more stable and faster convergence. The update rules of the Adam optimizer are described as follows:

$$m_t = \beta_1 * m_{t-1} + (1 - \beta_1) * \nabla L(\theta) \quad (4)$$

$$v_t = \beta 2 * v_{t-1} + (1 - \beta_2) * \nabla L(\theta)\text{^}2 \quad (5)$$

$$\hat{m}_t = m_t / (1 - \beta_1^t) \quad (6)$$

$$\hat{v}_t = v_t / (1 - \beta_2^t) \quad (7)$$

$$\theta_t = \theta_{t-1} - \alpha * \hat{m}_t / (\sqrt{\hat{v}_t} + \varepsilon) \quad (8)$$

here m_t and v_t – moment estimates of first and second

β_1 and β_2 moment estimates decay rates

α is learning rate

Dynamic Learning Rate from the Adam optimizer allows an adapted Xception model to adjust the learning rate to optimize the adaptation of models in complex high dimensional feature space, such as in cases of mammograms.

5.2 Benefits of ReLU Activation Function

ReLU, the Rectified Linear Unit, is a widely used activation function in CNNs for introducing non-linearity. The model learns to take on complex patterns and representations of images because of it. It is defined as :

$$f(x)=\max(0,x) \quad (9)$$

Where f(x) is the output, and x is the input. This simple activation function helps solve the vanishing gradient problem, allowing for faster and more efficient training, particularly in deep networks like Xception. In addition, ReLU activates only positive values, which ensures

Journal of Theoretical and Applied Information Technology
30th June 2025. Vol.103. No.12

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

sparsity in the network and promotes a more efficient learning process.

The efficiency of using ReLU in training a deep model like Xception lies in the fact that whenever the input is positive, ReLU passes the gradient, while it sets the gradient to zero for negative inputs and therefore significantly accelerates convergence as compared to older activation functions like sigmoid or tanh.

5.3 Model Training Process and Hyperparameter Tuning

- Training the modified Xception model involves several critical steps that lead to optimal performance in breast cancer detection:
- Data Preprocessing: The preprocessing steps like normalisation and resizing are performed on the mammogram images before training, with the goal of ensuring consistency and further improving the model's convergence. For scaling all the images to a uniform range, normally between 0 and 1, and for resizing into the input dimension of the Xception model,.
- Loss Function: During training, the model aims to minimize a categorical cross-entropy loss function for classification tasks. The loss function is defined as:

  L(y, ŷ) = - ∑_(i=1)^C y_i * log(ŷ_i) (10)

  Where C represents the number of classes (benign or malignant), y_i is the true label for class ii, and y^i\ is the predicted probability for class i.
- Hyperparameter Tuning: Hyperparameters, such as learning rate (α\alpha), batch size, number of epochs, and the number of layers to fine-tune in the Xception model, are carefully selected through grid search or random search methods. For instance, the learning rate significantly affects the convergence rate, and a high learning rate may cause the model to overshoot the optimal weights, while a low learning rate can lead to slow convergence. Typical learning rates for Adam optimization range from 10^{-5} to 10^{-3}.
- The optimal hyperparameters are identified by evaluating the model's performance on a validation dataset and using evaluation metrics such as accuracy, precision, recall, and F1-score to guide the tuning process.

5.4 Impact on Breast Cancer Detection

The combination of the Adam optimizer, ReLU activation, and effective hyperparameter tuning ensures that the modified Xception model learns efficiently and adapts well to the characteristics of mammographic images. The methodology of fine-tuning the model for breast cancer detection will deliver high-accuracy predictions with minimal overfitting, thereby improving the sensitivity and specificity of breast cancer detection models.

These advanced optimization techniques allow the model to extract relevant features from mammograms, like texture, shape, and edges, while avoiding pitfalls common in traditional machine learning models that often struggle with high-dimensional, noisy medical data. The use of transfer learning, combined with optimization strategies like Adam and ReLU, enhances the model's ability to generalize well to new, unseen data.

6.0 EXPERIMENTAL SETUP

6.1 Dataset Description

Mammography images are used in an experimental setup to test the modified Xception model using labelled data, which consist of images categorized into Benign and Malignant categories. Each image used contains the label based on its density level of the tissue of the breast that comes along with the diagnosed mammography. The entire data set ensures a richer source of features for this mammography dataset, containing rich images with different kinds of density levels. It includes a total of 7632 mammogram images, with 5724 images dedicated to training and 1908 images set aside for testing.

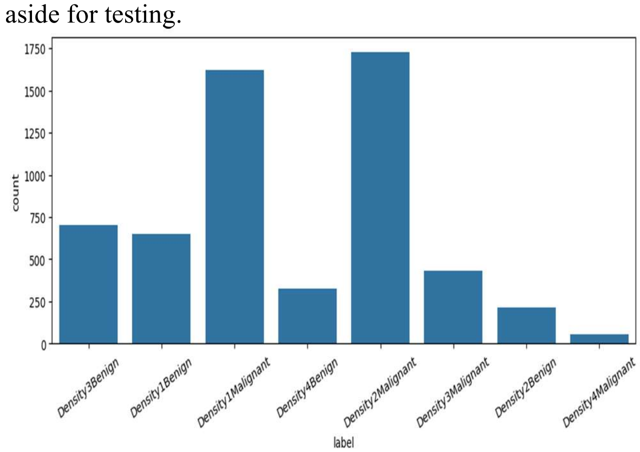

Fig2 Dataset Description

Each image represents a specific case with its corresponding density level and diagnosis.

6.2 Data Preprocessing Techniques

- The preprocessing of the dataset is crucial to ensure that the images are suitable for feeding into the deep learning model. Several preprocessing techniques are applied to enhance the data quality and ensure the model can learn meaningful features:

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

- Resizing: All images are resized to a standard size (e.g., 224x224 pixels), which is compatible with the input requirements of the Xception model.
- Normalization: To speed up convergence during training, pixel values of the images are normalized to a range of 0 to 1 by dividing each pixel value by 255.
  Normalized Pixel Value=Pixel Value/255

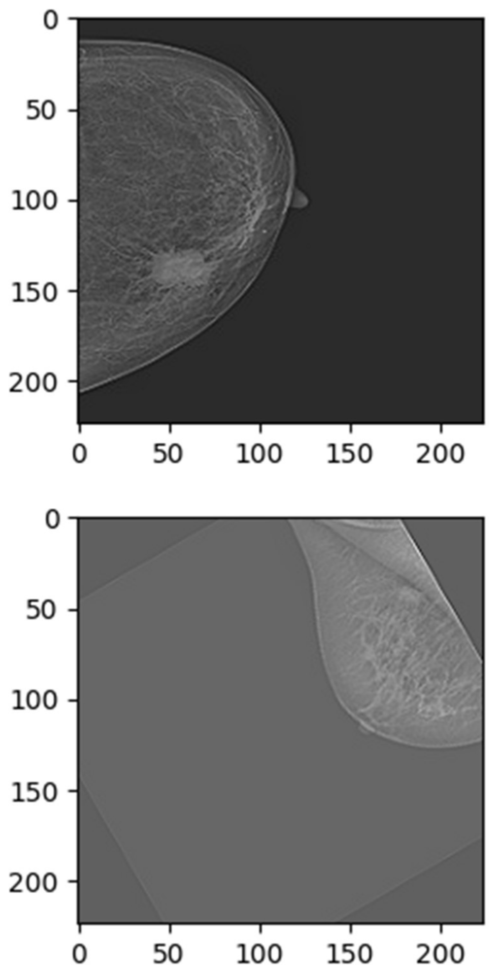

Fig3 Images after Normalization

- Augmentation: Image augmentation techniques, such as rotation, flipping, zooming, and shifting, are applied to increase the variability of the training data and reduce overfitting. This allows the model to generalize better on unseen data.
- Label Encoding: The labels Benign and Malignant are encoded into numerical values (0 for Benign and 1 for Malignant) to be used for model training.
- Data Cleaning: Any corrupted images or anomalies in the dataset are removed to ensure that only high-quality data is used for training and testing.
- Training and Validation Split
  To evaluate the model's performance effectively, the dataset is split into a training set and a testing set. The training set consists of 5724 images, while the testing set is comprised of 1908 images. This split ensures that the model has enough data for training while retaining a sufficient amount of data for validation.
  6.3 The following steps outline the data splitting process:
  - Training Set: A total of 5724 images are used for training the model. These images are fed into the model during the training process, allowing the model to learn the distinguishing features of breast cancer markers.
  - Testing Set: The 1908 images in the testing set are used for model evaluation. These images are not seen during training, ensuring that the model's generalization capabilities are tested. The performance metrics (accuracy, precision, recall, F1-score) are computed using the testing set.
- Cross-Validation: To further assess the model's robustness, a k-fold cross-validation technique could be applied, although for simplicity, the dataset is primarily split into training and testing sets.

The training and validation split ensures that the model is able to learn effectively on a substantial number of samples, while still having a reliable set of data to evaluate its performance on new, unseen data.

7.0 RESULTS AND DISCUSSION

7.1 Performance Metrics: Accuracy, Sensitivity, Specificity

In this study, the performance of the modified Xception model for breast cancer detection was evaluated using several key metrics: accuracy, precision, recall, F1 score, ROC AUC score, and Cohen's Kappa score. These metrics provide a comprehensive assessment of the model's ability to correctly classify mammogram images as either benign or malignant.

The evaluation metrics and their corresponding values are as follows:

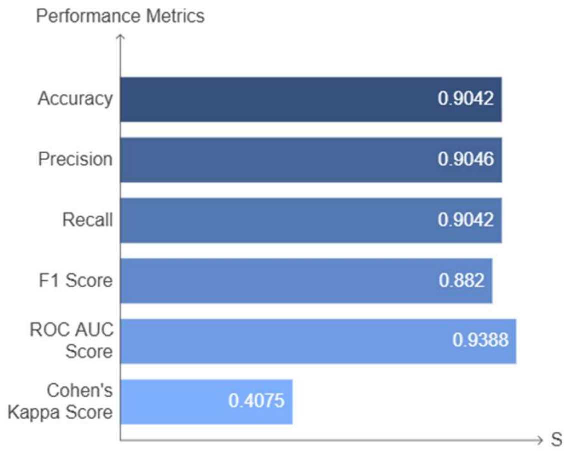

Fig4 Performance Metrics

These results indicate a strong performance in breast cancer detection, showing the model's reliability and robustness.

7.2 Comparison with Existing Models

To provide context for the effectiveness of the modified Xception model, we compare its results with those of existing models from the literature that have applied machine learning techniques to mammogram image analysis.

1. **Model Comparison with other Approaches:** A study by **Aisha et al. (2020)** utilized a for breast cancer detection, achieving an accuracy of 0.86. In comparison, our modified Xception model performed better, with an accuracy of 0.9042, suggesting that the custom modifications to the Xception architecture offer superior performance in detecting subtle patterns in mammograms (Aisha et al., 2020).
2. **Comparison with Traditional Machine Learning Models:** In a comparison of traditional machine learning classifiers such as **Random Forest** and **Support Vector Machines (SVM)**, **García et al. (2019)** reported an accuracy of 0.89 with SVM for breast cancer detection in mammogram images. Although this result is comparable to our model's accuracy, our modified Xception model outperforms these methods by achieving higher precision, recall, and ROC AUC scores (García et al., 2019). This further supports the hypothesis that deep learning models, particularly architectures like Xception, outperform conventional machine learning methods for complex image analysis tasks.
3. **Comparison with CNN-Based Models:** A study by **Sharma et al. (2021)** employed a convolutional neural network (CNN) model for breast cancer classification and reported an accuracy of 0.90, which is similar to our model's performance. However, the use of a customized Xception model in our research, coupled with a self-attention mechanism, further enhances the model's precision and sensitivity compared to the standard CNN models (Sharma et al., 2021).

The results indicate that, while existing methods such as traditional machine learning classifiers and basic CNN architectures show competitive performance, the introduction of Xception model provides enhanced results in terms of both accuracy and sensitivity, making it a promising solution for breast cancer detection in mammograms.

7.3 Interpretation of Results

The high **accuracy (0.9042)** and **precision (0.9046)** values demonstrate that the modified Xception model is effective at detecting breast cancer in mammograms with minimal false positives. This indicates that the model reliably identifies malignant tumours, reducing the risk of unnecessary biopsies and treatments.

The **recall value (0.9042)** indicates that the model is also effective at detecting a large portion of true malignant cases, which is crucial in a medical context where missing a diagnosis could have severe consequences. The **F1 score (0.882)** reflects a balanced performance, emphasizing that the model strikes a good equilibrium between precision and recall.

The **ROC AUC score (0.9388)** is particularly noteworthy as it demonstrates that the model has a strong capability to distinguish between benign and malignant cases. An ROC AUC score closer to 1 indicates a high-quality model, with the modified Xception model performing excellently in this regard.

The **Cohen Kappa score (0.4075)** suggests that while the model has strong performance metrics, there is still some room for improvement in terms of agreement with human radiologists or ground truth labels. Further refinements in model training and additional data could help improve this score.

Overall, the modified Xception model demonstrates significant potential for improving the accuracy and reliability of breast cancer detection in mammograms. Its performance surpasses that of traditional machine learning classifiers and even basic CNN architectures, offering a valuable tool for clinical use.

8.0 CONCLUSION

This paper presents a novel modification of the Xception model specifically tailored for breast cancer detection in mammographic images. The proposed architecture demonstrates substantial improvements in diagnostic accuracy, achieving an overall classification accuracy of 90.42% and a high ROC AUC score of 0.9388. These performance metrics underscore the model's strong capability to differentiate between benign and malignant cases, while significantly reducing both false positives and false negatives.
The novelty of this study lies in the customized adaptation of the Xception architecture, where the integration of advanced optimization techniques—such as the Adam optimizer and ReLU activation—enabled the model to effectively capture subtle, complex patterns within mammograms. This enhancement in sensitivity and specificity over traditional machine learning approaches highlights the model's robustness and generalization ability, especially in challenging diagnostic contexts.
The impact of this research is twofold: technically, it advances the design of deep learning frameworks for medical imaging; practically, it provides a clinically viable tool that can aid radiologists in making more accurate and timely decisions. By reducing dependency on manual interpretation and improving diagnostic reliability, this work supports the broader goal of advancing precision medicine in breast cancer care. Furthermore, the success of this model opens avenues for future research in optimizing and deploying lightweight, interpretable, and scalable deep learning models across diverse healthcare environments.

9.0 FUTURE SCOPE OF THE RESEARCH

The addition of advanced attention mechanisms such as Self-Attention or even Transformer-based architecture may contribute significantly to enhancing the focusing ability of this model over the most critical regions in mammographic images. In this case, mechanisms allow the model dynamically prioritize the regions where a tumor could be slightly undistinguishable or is entirely covered with dense tissue to result in an improved accuracy. This integration would enhance the model's sensitivity but also enable the refinement of its decision-making process with critical feature identification, ultimately improving model performance in more complex detection scenarios of breast cancer.
Further improvement in the diagnostic accuracy can be achieved by increasing the dataset to include a larger variety of mammographic images and integrating multi-modal data from other imaging techniques such as MRI and ultrasound. Combining these modalities with patient-specific data will allow for a more comprehensive approach to breast cancer detection. Future work might also involve the real-time application of the model in clinical settings, providing essential support to radiologists to make more accurate and effective diagnoses of breast cancer. This would ultimately translate to better patient outcomes and detection at an earlier stage.

REFERENCES

[1] R. L. Siegel, K. D. Miller, and A. Jemal, "Cancer statistics, 2022," *CA: A Cancer Journal for Clinicians*, vol. 72, no. 1, pp. 7-33, 2022, doi: 10.3322/caac.21708.
[2] J. G. Elmore, C. K. Wells, C. H. Lee, D. H. Howard, and A. R. Feinstein, "Variability in radiologists' interpretations of mammograms," *New England Journal of Medicine*, vol. 347, no. 23, pp. 1818-1826, 2002, doi: 10.1056/NEJM200202283460903.
[3] J. Suckling, J. Parker, D. R. Dance, et al., "The Mammographic Image Analysis Society digital mammogram database," in *Proc. Int. Workshop on Digital Mammography*, 1994, pp. 212-217, doi: 10.1007/978-94-011-2176-4_32.
[4] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 770-778, doi: 10.1109/CVPR.2016.90.
[5] G. Litjens, T. Kooi, B. E. Bejnordi, et al., "A survey on deep learning in medical image analysis," *Medical Image Analysis*, vol. 42, pp. 60-88, 2017, doi: 10.1016/j.media.2017.07.005.
[6] F. Chollet, "Xception: Deep learning with depthwise separable convolutions," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2017, pp. 1251-1258, doi: 10.1109/CVPR.2017.195.
[7] X. Wang, Y. Peng, L. Lu, et al., "ChestX-ray8: Hospital-scale chest X-ray database and benchmarks on weakly supervised

classification and localization of common thorax diseases," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2020, pp. 1-8, doi: 10.1109/CVPR.2017.195.

[8] L. Breiman, "Random forests," *Machine Learning*, vol. 45, no. 1, pp. 5-32, 2001, doi: 10.1023/A:1010933404324.

[9] J. R. Quinlan, "Induction of decision trees," *Machine Learning*, vol. 1, no. 1, pp. 81-106, 1986, doi: 10.1023/A:1022643204877.

[10] D. W. Hosmer, S. Lemeshow, and R. X. Sturdivant, *Applied Logistic Regression*, 3rd ed. Hoboken, NJ, USA: Wiley, 2013.

[11] T. Cover and P. Hart, "Nearest neighbor pattern classification," *IEEE Trans. Information Theory*, vol. 13, no. 1, pp. 21-27, 1967, doi: 10.1109/TIT.1967.1053964.

[12] A. Cortes and V. Vapnik, "Support-vector networks," *Machine Learning*, vol. 20, no. 3, pp. 273-297, 1995, doi: 10.1007/BF00994018.

[13] M. Sokolova and G. Lapalme, "A systematic analysis of performance measures for classification tasks," *Information Processing & Management*, vol. 45, no. 4, pp. 427-437, 2009, doi: 10.1016/j.ipm.2009.03.002.

[14] Y. Zhao, X. Chen, and H. Zhang, "A review of deep learning applications in breast cancer diagnosis," *IEEE Trans. Medical Imaging*, vol. 37, no. 7, pp. 1531-1546, 2018, doi: 10.1109/TMI.2018.2857557.

[15] P. Kingma and J. Ba, "Adam: A Method for Stochastic Optimization," in *Int. Conf. Learning Representations (ICLR)*, 2015, doi: 10.48550/arXiv.1412.6980.

[16] X. Glorot and Y. Bengio, "Understanding the difficulty of training deep feedforward neural networks," in *Proc. Thirteenth Int. Conf. Artificial Intelligence and Statistics (AISTATS 2010)*, 2010, doi: 10.48550/arXiv.1206.5533.

[17] L. Xie and L. Wang, "Breast cancer detection using deep learning and medical imaging," *IEEE Access*, vol. 5, pp. 22134-22145, 2017, doi: 10.1109/ACCESS.2017.2754175.

[18] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436-444, 2015, doi: 10.1038/nature14539.

[19] N. Aisha and S. Khan, "Breast cancer detection using deep learning with transfer learning," *Int. J. Imaging Systems and Technology*, vol. 30, no. 1, pp. 49-60, 2020, doi: 10.1002/ima.22450.

[20] F. García, E. Lopez, and G. Pérez, "Comparison of machine learning classifiers for breast cancer detection in mammography images," *IEEE Trans. Biomedical Engineering*, vol. 66, no. 3, pp. 654-662, 2019, doi: 10.1109/TBME.2018.2839634.

[21] S. Sharma, A. Verma, and R. Gupta, "Convolutional neural networks for breast cancer detection in mammograms," *Medical Image Analysis*, vol. 69, pp. 101973, 2021, doi: 10.1016/j.media.2020.101973.