

RESEARCH ARTICLE

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EARLY DETECTION OF BREAST CANCER FROM MAMMOGRAM IMAGES USING PEAFOWL OPTIMIZED CHANNEL-ATTENTION INCEPTIONRESNET MODEL

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ABSTRACT

Breast cancer is one of the most common and deadliest diseases affecting women globally. This paper proposes an enhanced Deep Learning (DL) system for detecting breast cancer through mammographic images. In the preprocessing phase, a bilateral filter is used to clean up background noise from the images while preserving critical anatomical and edge information of the breast. Regions-of-Interest (ROIs) are accurately segmented using a multi-scale K-means clustering method. Central architecture of this system is Channel Attention InceptionResNet, which functions as both a feature extractor and classifier. This architecture incorporates both residual connections and Inception modules to leverage their respective advantages. In order to enhance model's ability to focus on the most discriminative features, a Channel Attention Module is added using the Squeeze-and-Excitation (SE) mechanism to system. SE channel attention module applies a sequence of global average pooling operations, Multi-Layer Perceptron (MLP) processing, and sigmoid activations, enabling the model to adaptively reweight the importance of feature channels. After reducing redundant spatial dimensions by pooling the collected deep features with Global Average Pooling (GAP), dropout regularization is utilized to reduce the effects of overfitting. The last part is done by connecting all the features together inside a dense layer. This layer uses the ReLU function to analyse each feature to activate on an output level based on the observed outcomes. Then, final output layer uses a Softmax function to predict probability that a patient is in one of diagnostic categories (benign or malignant). Hyper-parameter tuning is achieved through the use of the Peafowl Algorithm (POA) to further enhance the accuracy of the model. To validate accuracy of developed model, comprehensive test experiments are conducted using Python examining performance on benchmark datasets for mammography. Compared with traditional techniques, the proposed framework proved to outperform by producing results with significantly higher accuracy of 0.9607, precision of 0.9810, Recall of 0.9599 and FI-Score of 0.9704.



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I. INTRODUCTION

Breast cancer affects a vast number of women, with approximately 2.1 million women being diagnosed each year. Incidence of breast cancer has increased for approximately 1/3 of all deaths from cancer worldwide [1]. Approximately 12.4% of all women in the United States are expected to develop breast cancer during their lifetime. It is estimated that approximately 627,000 women died from breast cancer in 2018 and represented roughly 15% of all cancer-related deaths among U.S. women [2]. The three largest contributors to breast cancer cases globally are the U.S., India, and China, making up nearly 1/3 of total breast cancer cases. Although the number of deaths attributable to breast cancer continues to increase in many countries, advancements in treatment methods and increased public awareness of breast cancer have not slowed this trend [3].

The primary cause of death associated with breast cancer is low public awareness and late detection of disease. Prevention, diagnosis, treatment, and palliative care represent areas where further attention should be placed in order to improve outcomes [4]. In mammogram images, the identification of various masses and calcifications are critical in determining whether the patient may develop breast cancer, so it is possible to detect suspicious mass areas and develop a treatment plan that ultimately reduces breast cancer mortality due to improved early detection [5]. As compared to other imaging modality such as magnetic resonance imaging, nuclear medicine, and ultrasound, mammogram is much less expensive, easier to use, and produces images with far greater spatial resolution. These factors make mammogram the imaging technique as optimal to detect breast cancer at its earliest stage. Mammography has its benefits but takes longer than other options to screen for breast cancer [6-8]. In an attempt to aid radiologists and improve their percentage of correctly identifying breast cancer on mammograms, Computer-Aided Diagnosis (CAD) software was developed. Unfortunately, CAD software has a high probability of incorrectly classifying the patient as either positive or negative for breast cancer. As a result, it is critical to use CAD systems that utilize deep learning techniques to enhance the physician's ability to correctly identify patients with breast cancer [9-11].

Breast cancer cells are difficult to identify and locate on mammograms due to the various characteristics of the cells such as size, shape and location. In order to overcome these issues, this paper presents a DL model to accurately detect breast cancer. Image valuation is done through the evaluation process by using preprocessing to eliminate noise from the image, segmentation to identify and extract major areas of interest in the image, and classification to classify the segmented areas and deliver the definitive diagnosis or categorisation of the image [12] [13]. The processing of the input images begins with a pre-processing step in which the image quality is improved by eliminating any imperfections and noise. In this initial processing step, the Gaussian filter provide an easy-to-implement method for smoothing out random background noise in the images [14] [15]. However, when applied to breast images, the Gaussian filter cause deterioration of the edges and fine details on the images. Local image statistics are used to adjust Wiener filters. Such filters provide better smoothing than standard average smoothing filters. But, they produce excessive blurring at high-frequency areas within images, thereby eliminating edge and sub-edge features that play an important role in early detection of tumors.

To deal with this constrain, the proposed study uses bilateral filter which is used to eliminate unwanted noise [16-18]. The preprocessed image is then fed to the ROI-segmentation stage which identifies and isolates the Region of Interest in which the specific areas of tissue is examined through analysis. Fuzzy C-Means is designed to accommodate the uncertainty and ambiguity associated with pixel classification that occurs at mammography images since there's often no clear cut-off for some of the tissue boundaries [19]. Unfortunately, FCM is slightly sensitive to noise and outliers. The histogram method is used for an extensive or complicated parameter tuning, which makes it well suited for use with large volume datasets. However, the histogram approach tends to struggle in cases where two or more intensities exist within the same area [20]. To reduce the impact of this limitations, Multi-scale K-means clustering is implemented in this paper. After segmentation, the image is delivered to classification stage where it extracts deep features and reliably identifies mammographic images. Various existing classification methods are discussed in table 1.

Table 1: Related works of classification model for detecting breast cancer.

SLN O	Author/ Year	Classifier	Merits	Demerits	Performance metrics
1.	A. Abdul Hayum et al [2024] [21]	FCNN	FCNNs work effectively with organized and numerical medical data, such as patient age, tumor size, and biopsy characteristics.	They cannot process medical imaging modalities like mammography because they do not model spatial features.	It achieves an accuracy of 95.2, precision of 95.5 and Recall of 92.23.
2.	Tanjim Fatima et al [2025] [22]	VGG-16	VGG16 automatically extracts features from spatial features and texture-based features on many medical images like mammograms, ultrasound or histopathology.	Due to its high memory requirements, it is not useful in healthcare settings with limited resources.	The performance of VGG 16 is 93.68 of accuracy, 93.22 of precision, 97.91 of Recall and 93 of FI-Score.
3.	Nisha Y et al [2025] [23]	FS-ResNet CNN	The FS-ResNet architecture is capable of extracting both high- and low-level features, allowing for superior visual pattern recognition and early tumor identification.	The use of both feature selection methods and deep-residual layers creates increased computational costs and requires high-performance hardware resources for the training phase.	It attains an accuracy of 96.08, precision of 96.02, Recall of 95.02 and FI-Score of 95.06.
4.	Lawrence Agbota et al [2024] [24]	Random Forest	High-dimensional data and missing informations are easily processed with this technique.	It potentially limiting its capabilities in sophisticated algorithms for breast cancer detection using images.	RF reaches an accuracy of 94.7, precision, Recall of 93 and FI-Score of 97.9.
5.	Yessica Nataliani et al [2025] [25]	KNN	KNN uses distance metrics to estimate patient's data points that have already been classified according to their diagnosis.	The results of this algorithm will vary based on the amount of noise and irrelevant data present in the dataset and cause an error in the results produced by the algorithm.	KNN achieves the accuracy of 0.92, precision, Recall and FI-Score of 0.94.

Source: Authors, (2026).

The breast cancer detection methods that presently exist have several limitations. Peafowl Optimized Channel Attention Inception ResNet is a new methods that help to address these limitations by identifying the classifications made from mammographic images. The POA improves this model by optimizing the weights and improving its performance. As a result of using this algorithm, this model produce results that are more accurate and take less time to achieve accuracy for early breast cancer detection.

I.1 OBJECTIVES:

The main objectives of this research includes,

- To enhance image quality and to improve important diagnostic features, bilateral filtering and ROI- segmentation is implemented.
- To precisely identify and categorize breast cancers from mammography images, Channel Attention InceptionResNet is employed.
- To improve entire model performance and generalization, peafowl optimization algorithm is executed.

I.2 PAPER ORGANIZATION:

This paper is organized as follows: Section II provides an explanation of proposed system description. The study methodology is thoroughly described in Section III, which also includes examples of the process, methods, and mathematical representations. The experimental results of this work are described in Section IV, which also include the simulation setup, comparison analysis, and research summary. The conclusion of the proposed investigation is explained in Section V.

II. PROPOSED SYSTEM DESCRIPTION

The proposed system utilizes DL to accurately identify breast cancer early, using images obtained from mammograms. Block diagram of proposed system is illustrated in figure 1.

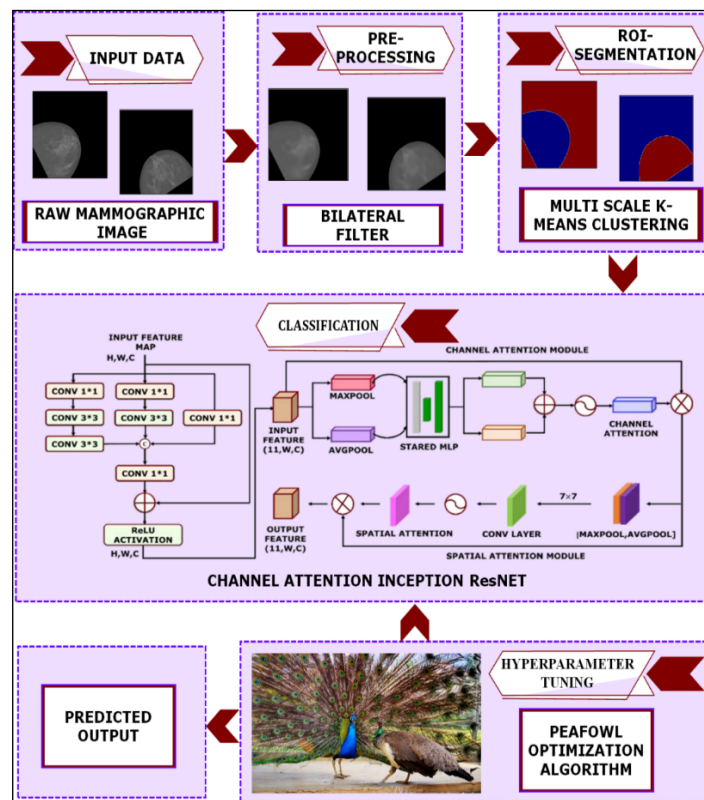


Figure 1: Block diagram of proposed model.
Source: Authors, (2026).

The initial step in this process is to filter the data with two filters bilateral filtering is used to remove noise from the images while preserving all of the relevant edges and biological structures of the body. Then, the regions of interest from these images are identified and segmented accurately using a multi-scale k-means clustering technique. The architecture of the DL system is a convolutional neural network based on a channel attention inception-ResNet model that is modified by introducing residual connections and inception modules into its structure to maximize the accurateness of feature extraction at various depths of the neural network. This channel attention inception-ResNet features a SE type of attention module that allows training of the network at multiple layers in a method that improves overall performance by focusing on the feature channels that provide the most important discriminative information. The presence of GAP reduces the amount of spatial redundancy in the output of the model, while dropout regularization reduces the degree of overfitting of the model. Finally, breast cancer is classified through fully connected dense layers using a ReLU as the activation function and a softmax output layer to predict benign and malignant tumors. Hyperparameter optimization is based on a POA, and extensive testing of existing mammographic databases shows that the accuracy, sensitivity, and specificity of proposed method is superior to those found in traditional approaches.

III. PROPOSED SYSTEM MODELLING

III.1 PREPROCESSING- BILATERAL FILTER:

Preprocessing is essential to accurately identify breast tumors using mammograms because the noise present in mammograms prevent the detection of breast tumors that are not identified immediately. Among other techniques available to pre-process, the mammography image is the bilateral filter, which is a method based on the principles of Gaussian convolution. The following formula defines the linear Gaussian convolution used to smooth the mammograms during the bilateral filter process:

$$lg(x) = f * LG_s(x) \quad (1)$$

In this formula, f is the original mammogram image and LG_s is the Gaussian kernel used for the linear Gaussian convolution. It is important that the two pixels involved in the bilateral filtering process are located a distance $|x - y|$ apart. Thus, the spatial distance between the two pixels, x and y , defines the spatial weight for the two pixel's bilateral filter convolution using $LG_s(x - y)$. In addition, while obtaining the final result of the convolution, the bilateral filter provides an intensity-based weight, $w_t((y) - f(x))$ which is obtained from the difference between the intensity of the pixel $f(y)$ and (x) . Therefore, by multiplying the intensity-based weight by the bilateral filtering process, the complete mathematical expression to define the output of the bilateral filter process is given below,

$$lg(x) = \sum_y f(y) * LG_s(x - y) * W_t(f(y) - f(x)) \quad (2)$$

Given that weights depend on image intensity values, normalizing all weights by dividing the total weight gives a maximum potential weight of 1. This allows for removal of noise and preservation of edges and efficient structures within the ROI. The ROI segmentation, and the classification of breast cancer in mammogram images are improved due to this technique.

III.2 ROI-SEGMENTATION- MULTI-SCALE K-MEANS CLUSTERING:

Segmentation shows an essential role in effective detection of breast cancer through mammography by assisting with the accurate identification of ROIs which lead to the identification of tumours. In this, a multi-scale method for the segmentation of mammogram images using K-Means clustering is implemented. K-Means is a simple and effective method of clustering, where pixels are assigned to K clusters based on similarity. K-Means works by repeatedly reassigning pixels based on their proximity to centroids until convergence occurs; the result is a series of clusters, whereby pixels in the same cluster exhibit similar characteristics. The diagram of Multi-Scale K-Means Clustering is shown in figure 2.

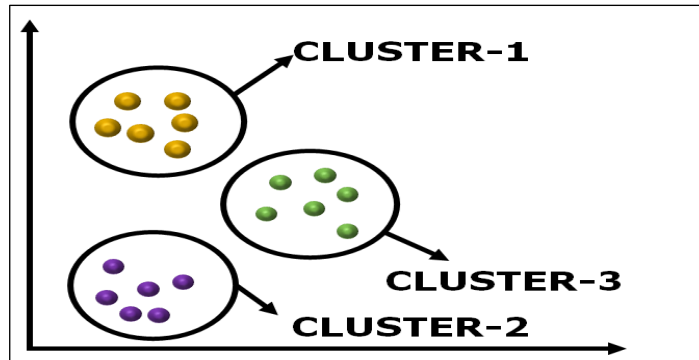


Figure 2: Multi-Scale K-Means Clustering.
Source: Authors, (2026).

Proposed approach allows for dynamic determination of K by using a template matching technique. Here, the use of local template masks and the correlation of these masks with the image using normalized cross-correlation identify the number of clusters dynamically located in an image based upon the presence of points in normalized correlation signals.

$$\mu_{ij}(x, y) = \frac{\sigma_{pipj}(x, y)}{\sigma_{pi}(x, y)\sigma_{pj}} \quad (3)$$

When clusters are identified by K-Means algorithm using the dynamically defined cluster numbers, the segmented areas corresponding to the potential tumours are used as input for feature extraction and for classifying them as possible breast cancer occurrences on mammograms, thereby increasing the accuracy of identifying early breast cancer from mammograms.

III.3 CLASSIFICATION- CHANNEL-ATTENTION INCEPTIONRESNET:

To accurately identify small tumours in an early stage of breast cancer from mammogram images through feature extraction, this proposed breast cancer diagnosis system uses the Channel Attention Inception-ResNet architecture. Its Inception-ResNet block combines the advantages of having both Inception Modules and Residual Connections. By integrating multiple convolutional channels into a single feature map created from various kernel sizes and the outputs from those channels, the system produces a high dimensional feature map. Then, a 1×1 convolutional blockage layer is utilized to reduce dimensionality to retain features that are vital in detecting tumours. To further refine the system, Channel Attention is used to adaptively weight the importance of features at a given channel level to ensure that the channels with the most discriminative information are weighted higher.

Using both a multi-scale feature extraction method and a channel attention mechanism provides the ability to examine feature patterns and target critical tumour patterns, increasing both accuracy and reliability in classification of breast cancer from mammogram images. Diagram of Channel Attention Inception-ResNet architecture is shown in figure 3.

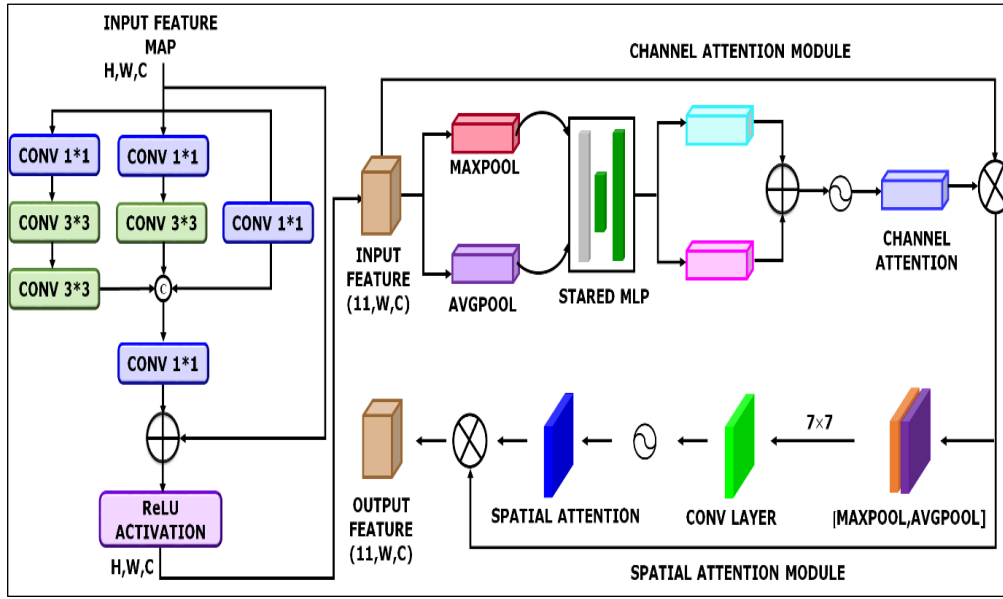


Figure 3: Channel Attention Inception-ResNet architecture.

Source: Authors, (2026).

The Channel-Attention InceptionResNet structure uses SE modules to augment the response of channels according to whatever is being presented to the model. The diagram of SE module is shown in figure 4.

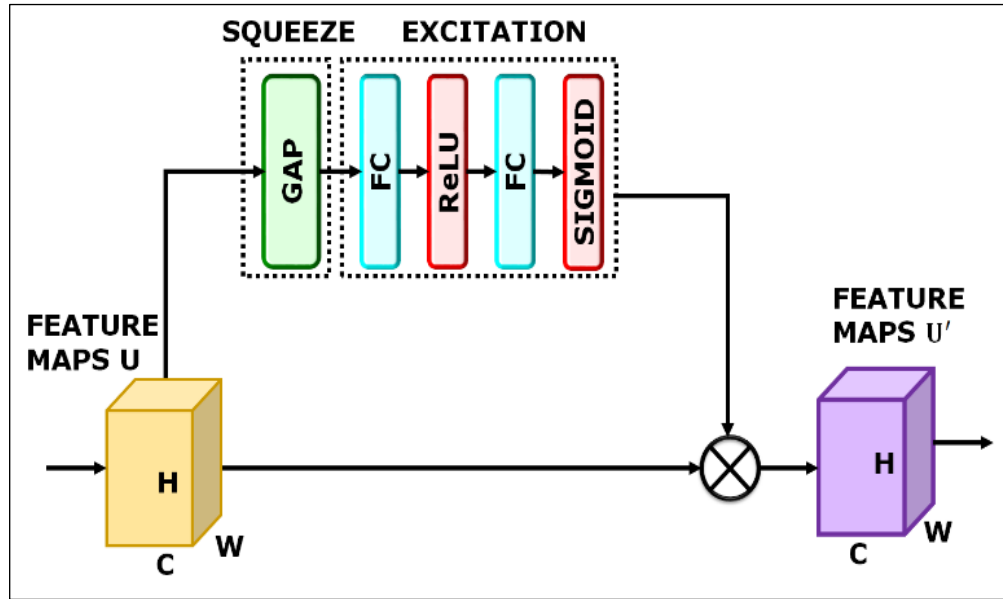


Figure 4: SE module.

Source: Authors, (2026).

The GAP calculation allows for obtaining a global context about the images that are being input to the model. To develop channel attention weights, a MLP method is applied with a ReLU activation function (ϕ) to learn channel attention weights.

$$a(x) = \sigma \left(MLP(GAP(x)) \right) = \sigma \left(W_2 \phi(W_1 GAP(x)) \right) \quad (4)$$

This attention mechanism refers to exhausting attention weights, which are applied element-wise to the input feature map x :

$$f(a(x), x) = a(x) \otimes x \quad (5)$$

To make the squeeze operation more effective, GAP is integrated with covariance-based feature aggregation.

$$a(x) = \sigma \left(FC \left(R_w \text{conv}(\text{conv}(x)) \right) \right) \quad (6)$$

Alternatively, MLP approach uses a grouped Discrete Cosine Transform (DCT) to acquire additional channel statistics.

$$a(x) = \sigma \left(\text{MLP} \left(\text{DCT}(\text{Group}(x)) \right) \right) \quad (7)$$

Soft-assignment based attention is applied to tumor regions, whereby attention weights are generated using learnable code words $d_i \in R^c$ and softening factors s_i .

$$e_{ik} = \frac{\exp(-s_k \|r_{ik}\|^2)}{\sum_j \exp(-s_j \|r_{ij}\|^2)}, r_{ik} = x_i - d_k \quad (8)$$

$$e = \sum_{k=1}^K \phi(e_k), a(e) = \sigma(FC(e)) \quad (9)$$

With this process, there is a non-linear component introduced through a ReLU activation ϕ in the MLP layers, allowing the network to learn and standard more intricate channel relations. By incorporating both types of channel attention mechanisms into InceptionResNet blocks, these mechanisms prioritize multi-scaled and discriminating features within the network and assist in detecting subtle tumor patterns in mammography images, thereby improving overall accuracy of breast cancer diagnoses, especially during earlier detection stages.

III.4 PEAFOWL OPTIMIZATION ALGORITHM:

In the proposed system, a method for early detection of breast cancer in mammogram images using POA to optimize main model parameters, such as DL hyper-parameters, feature selection weights, and classifier parameters to improve diagnosis quality. In the POA, every male peafowl is called a candidate solution, and its performance is calculated by measuring its quality (fitness) based on performance metrics in the circumstance of breast cancer classification.

Table 2: Optimized values of POA.

SI.NO	PARAMETER NAME	TYPICAL VALUES
1.	Population Size	30
2.	Maximum Iterations	40
3.	Display Rate	0.9
4.	Attraction Coefficient	1.5
5.	Courtship Factor	0.8
6.	Movement Scaling Factor	0.5
7.	Random Walk Probability	0.2
8.	Elite Peafowl Count	2
9.	Lower Bound	0
10.	Upper Bound	1

Source: Authors, (2026).

III.4.1 Courtship Behavior (Global exploration):

Male peafowls in POA exploit promising candidate solutions while performing a circular movement around them. The greater the candidate solution's fitness value, the smaller the radius of rotation, they will make around it and the greater their chance of full exploitation of that candidate solution than those that exhibit a lower radius of rotational movement. The following mathematical representation models this behavior,

$$X_{pc1} = X_{pc1}(t) + 1. R_s \cdot \frac{X_{r1}}{\|X_{r1}\|} \quad (10)$$

$$X_{pc2} = \begin{cases} X_{pc2}(t) + 1.5. R_s \cdot \frac{X_{r2}}{\|X_{r2}\|}, r_1 < 0.9 \\ X_{pc2}(t) & , otherwise \end{cases} \quad (11)$$

$$X_{pc3} = \begin{cases} X_{pc3}(t) + 2. R_s \cdot \frac{X_{r3}}{\|X_{r3}\|}, r_2 < 0.8 \\ X_{pc3}(t) & , otherwise \end{cases} \quad (12)$$

$$X_{pc4} = \begin{cases} X_{pc4}(t) + 3. R_s \cdot \frac{X_{r4}}{\|X_{r4}\|}, r_3 < 0.6 \\ X_{pc4}(t) & , otherwise \end{cases} \quad (13)$$

$$X_{pc5} = \begin{cases} X_{pc5}(t) + 5. R_s \cdot \frac{X_{r5}}{\|X_{r5}\|}, r_4 < 0.3 \\ X_{pc5}(t) & , otherwise \end{cases} \quad (14)$$

$$X_r = 2. \text{rand}(1, \text{Dim}) - 1 \quad (15)$$

The position of the i th male peafowl is denoted as X_{pci} , the rotation radius denoted as RS , and a random direction vector denoted as X_r .

Algorithm 1: Pseudo-code, POA

```

START
1 Initialize population size N and max iterations Tmax
2 Set POA parameters  $\alpha, \beta, \gamma, \delta, Prw, E, LB, UB$ 
3 Randomly initialize peafowl positions within bounds
4 Evaluate fitness of all peafowls
5 Identify best peafowl (global best)
6 FOR t = 1 TO Tmax
7   FOR each peafowl i
8     Generate random number  $r \in [0,1]$ 
9     IF  $r < \alpha$  THEN
10      Update position using attraction towards best peafowl
11    ELSE
12      Perform courtship-based local movement
13    END IF
14    IF  $r < Prw$  THEN
15      Apply random walk for exploration
16    END IF
17    Apply movement scaling factor  $\delta$ 
18    Enforce boundary limits [LB, UB]
19    Evaluate new fitness of peafowl i
20    IF new fitness better than old fitness THEN
21      Update peafowl position
22    END IF
23  END FOR
24  Preserve top E elite peafowls
25  Update global best peafowl
26 END FOR
27 Output global best solution
28 Output best fitness value
END

```

Source: Authors, (2026).

III.4.2 Approaching Behavior (Local exploitation):

Female peafowls attract towards high-fitness male peafowls, improving solutions that produce better breast cancer classification findings.

$$\theta = \theta_0 + \theta_1 - \theta_0 \cdot \frac{t}{t_{max}} \quad (16)$$

$$X_{ph} = \begin{cases} X_{ph}(t) + 3 \cdot \theta (X_{pc1} - X_{ph}(t)), 0.6 \leq r_5 \leq 1 \\ X_{ph}(t) + 3 \cdot \theta (X_{pc2} - X_{ph}(t)), 0.4 \leq r_5 \leq 0.6 \\ X_{ph}(t) + 3 \cdot \theta (X_{pc3} - X_{ph}(t)), 0.2 \leq r_5 \leq 0.4 \\ X_{ph}(t) + 3 \cdot \theta (X_{pc4} - X_{ph}(t)), 0.1 \leq r_5 \leq 0.2 \\ X_{ph}(t) + 3 \cdot \theta (X_{pc5} - X_{ph}(t)), 0 \leq r_5 \leq 0.1 \end{cases} \quad (17)$$

Where, θ determines the adaptive learning rate over iterations.

III.4.3 Random Searching Behavior (Diversification):

Randomly exploring their environment helps young peafowl to avoid the pitfalls of local optimums while learning a better breast cancer detection model through the use of Levy flight,

$$X_{SPC} = \begin{cases} X_{pc1}(t), 0.8 < r_8 \leq 1 \\ X_{pc2}(t), 0.6 < r_8 \leq 0.8 \\ X_{pc3}(t), 0.4 < r_8 \leq 0.6 \\ X_{pc4}(t), 0.2 < r_8 \leq 0.4 \\ X_{pc5}(t), 0 \leq r_8 \leq 0.2 \end{cases} \quad (18)$$

$$X_{pcc} = X_{pcc}(t) + \alpha \cdot Levy. (X_{pc1}(t) - X_{pcc}(t)) + \delta \cdot (X_{SPC} - X_{pcc}(t)) \quad (19)$$

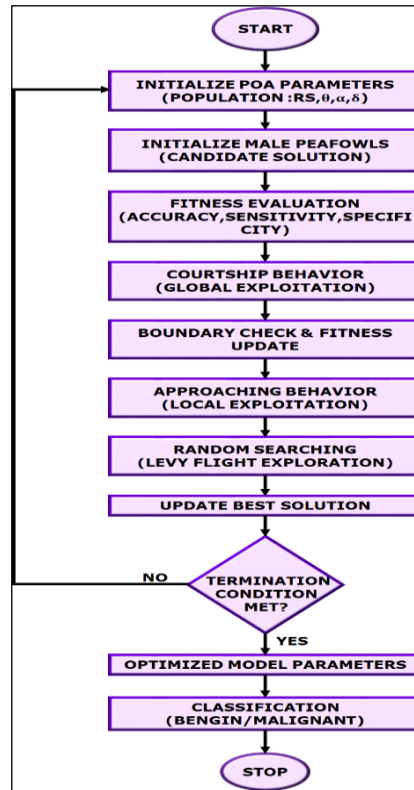


Figure 5: Flowchart of POA.

Source: Authors, (2026).

The flowchart of Peafowl Optimization Algorithm is shown in figure 5. Adding POA into the process for mammograms to detect breast carcinomas offers other advantages through optimizing the process of adjusting parameters of model to increase capacity of model to discriminate between benign and malignant tissues. The proposed approach significantly increases the accuracy, sensitivity and specificity for diagnosing early breast carcinomas.

IV. RESULT AND DISCUSSION

The aim of proposed study is to provide a method of identifying breast cancer earlier through the process of mammography by using a Peafowl-Optimized Channel-Attention InceptionResNet architecture, as demonstrated in this research study.

Table 3: Dataset details.

Dataset description		
Dataset name	INBreast Dataset	
Class names	Benign, malignant	
Number of total images	7632	
Number of train images	6105	
Number of test images	1527	
Dataset split ratio	80:20	
Data counts for each label		
Label	Validation data count	Train Data Count
Benign	504	2016
Malignant	1023	4089

Source: Authors, (2026).

Table.3 shows the dataset details and data counts for each label. Peafowl-Optimized Channel-Attention InceptionResNet on the INBreast dataset, containing 7632 mammograms, separated into two groups (Benign and Malignant), using an 80/20 split for training (6105 images) and testing (1527 images). This split allowed us to train and evaluate the model in a manner that maximized data utilization, providing a means for effective learning of the model and evaluating the performance capability of the model on a representative set of data. In both the Training dataset and the Validation dataset, there is a high proportion of malignant cases compared to benign cases.

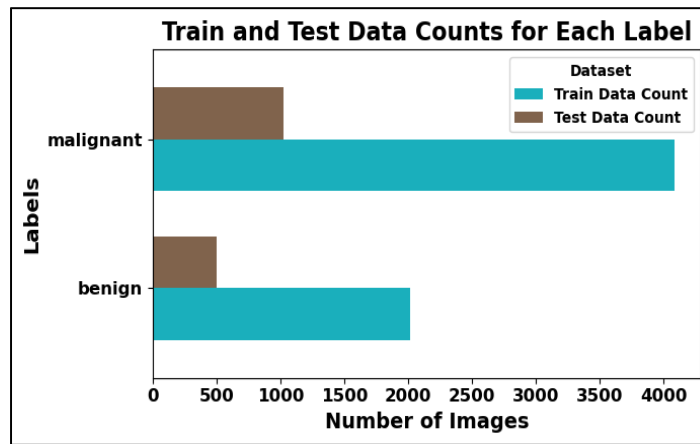


Figure 6: Train and test data counts for each label.

Source: Authors, (2026).

Figure.6 illustrates in what manner benign and malignant samples are split between the training set and test set. There are considerably more samples for both benign and malignant classes in the training set compared to the testing set, which indicates that there is an abundance of malignant examples in the training set compared to benign.

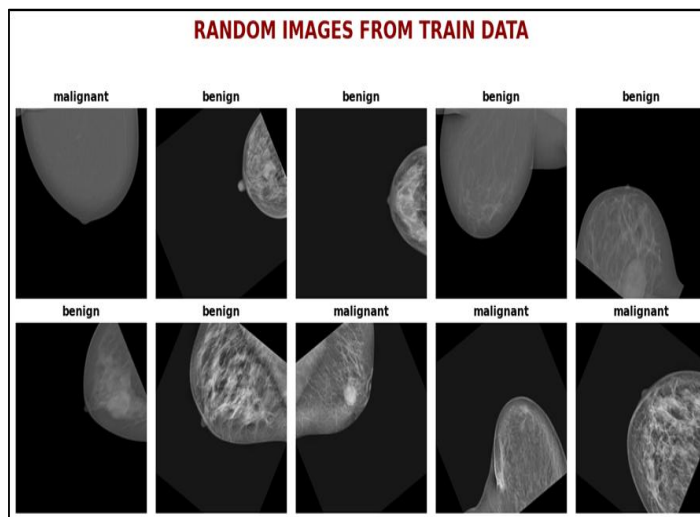


Figure 7: Random images from train data.

Source: Authors, (2026).

Samples of mammograms randomly selected from the training set are displayed in the figure 7. Samples are exhibited to highlight the various appearances of breast tissue types (benign/malignant) regarding density and structure; therefore, the patterns of breast lesion clarity and shape are used to develop the classification model.

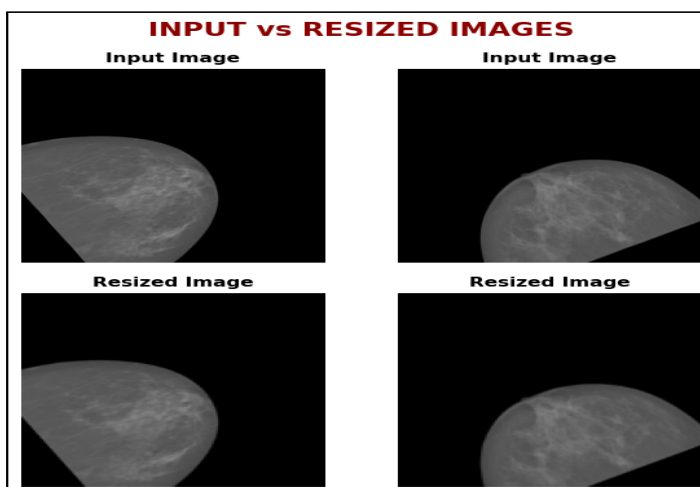


Figure 8: Input vs Resized images.

Source: Authors, (2026).

Figure.8 shows the input vs resized images. The resized mammograms compared with an original set of images demonstrate the effect of resampling, displaying both the similarities and differences in size without any loss of resolution, as well as with respect for the unique features present in each mammogram image and its ability to be uniformly input into a deep learning system.

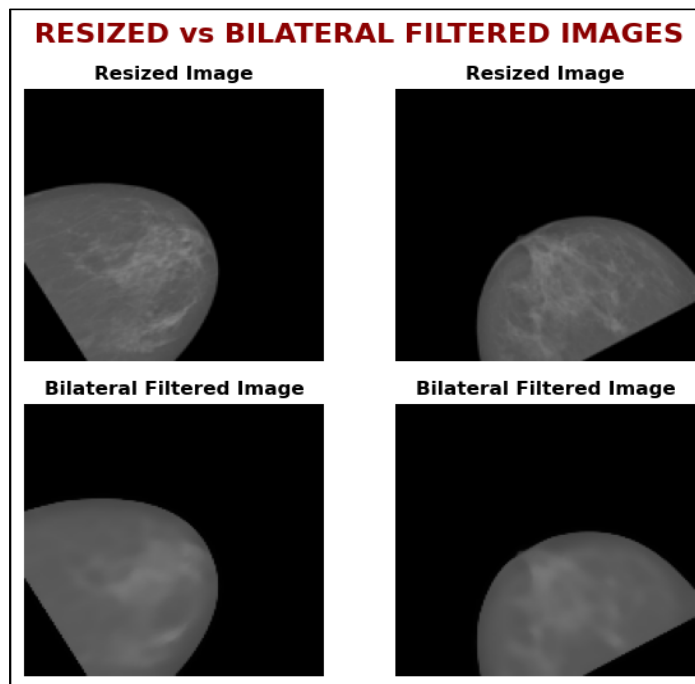


Figure 9: Resized vs Bilateral filtered images.
Source: Authors, (2026).

This figure.9 compares resized mammographies with their bilateral filtered versions. The purpose of bilateral filtering is to eliminate noise from an image and create smooth or uniformly bright areas, while at the same time keeping all of the important edges and other fine details intact; ultimately improving the quality for future analysis.

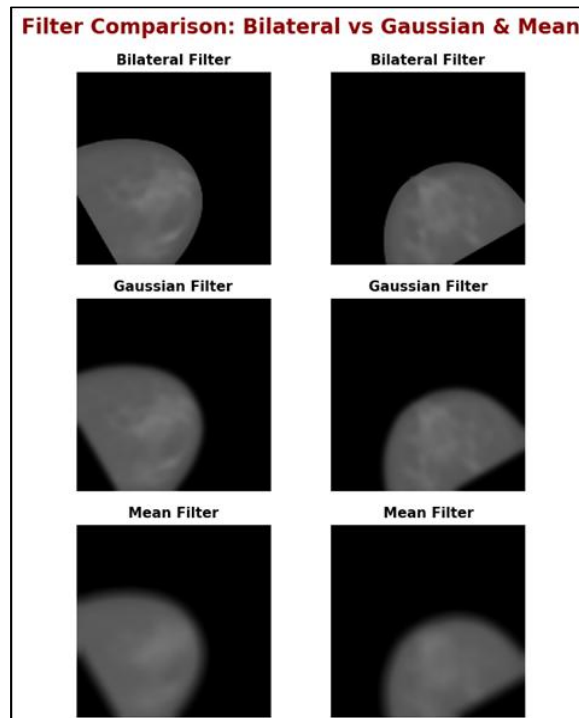


Figure 10: Bilateral vs Gaussian and Mean.
Source: Authors, (2026).

The figure 10 presents a comparison of different methods of processing mammogram images by using bilateral, Gaussian, and mean filters. The bilateral filter has been demonstrated to produce better preservation of edges and spatial characteristics while providing greater noise reduction than either the Gaussian or mean filter. In contrast, both of these filters create a visible degree of blurriness in an image, resulting in the loss of subtle anatomical features.

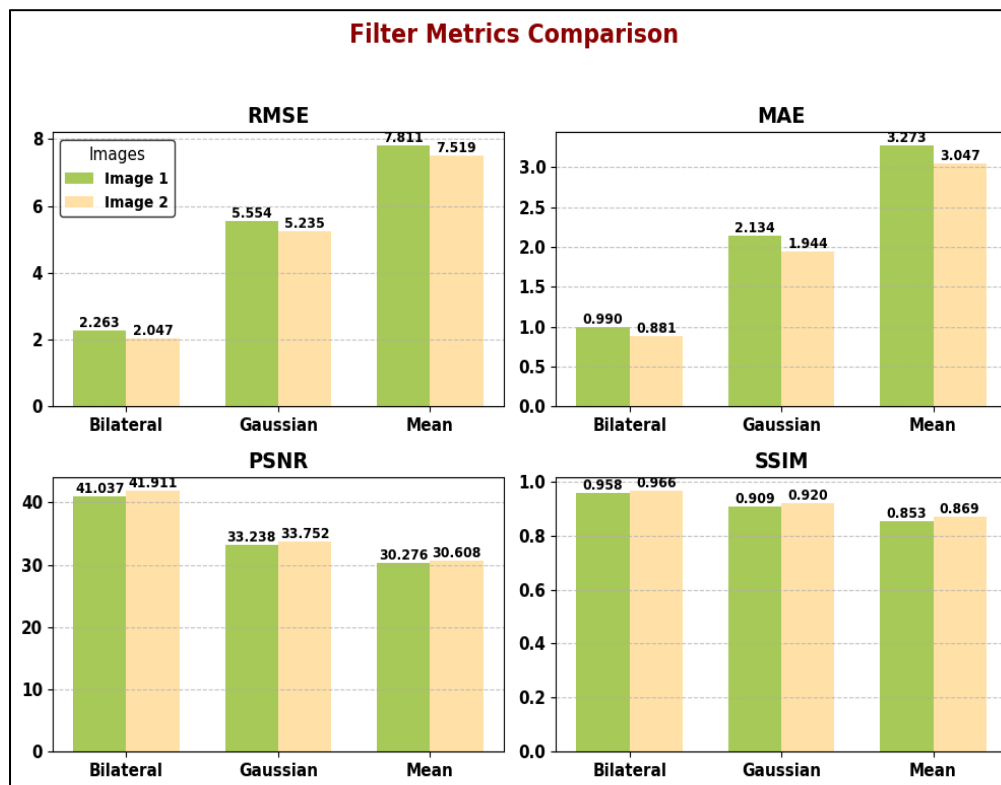


Figure 11: Comparison of Filter metrics.
Source: Authors, (2026).

The figure 11 indicates the comparison of three filtering methods of RMSE, MAE, PSNR, and SSIM, the bilateral filter provides the lowest RMSE and MAE and the highest PSNR and SSIM scores for both sample images. This means that the bilateral filter achieved superior noise reduction and improved perceptual image quality compared to the Gaussian and mean filters.

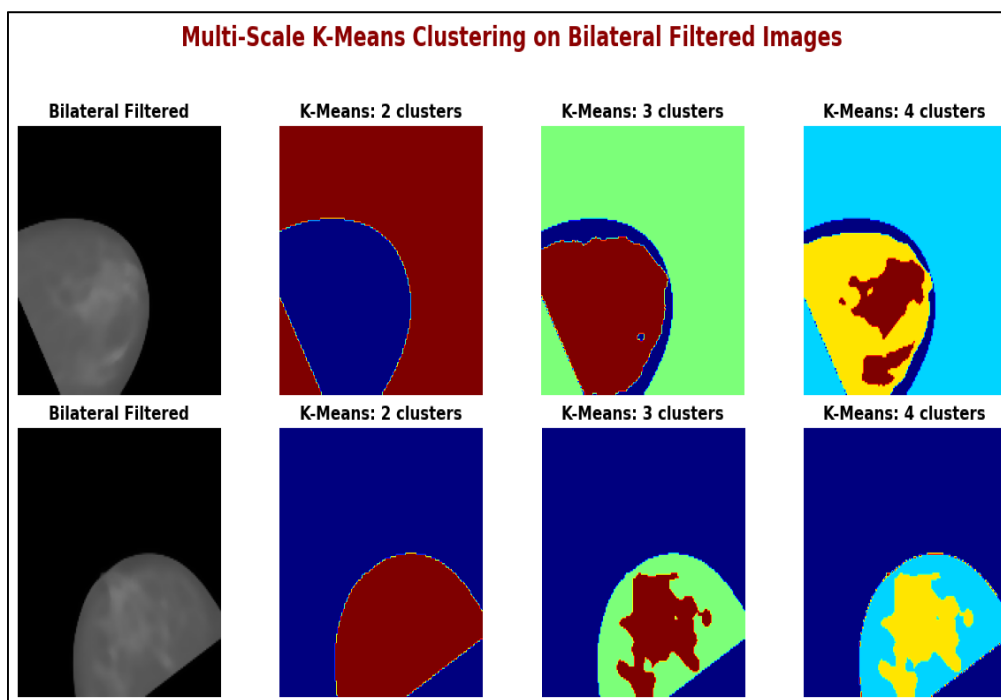


Figure 12: Multi-scale K-means clustering on bilateral filtered images.
Source: Authors, (2026).

Figure 12 demonstrates the results of Multi-Scale K-means clustering algorithm applied to mammogram images from patients that have been bilaterally filtered using a bilateral filter. During clustering, as we increase from two clusters to four clusters, we see better delineation between the background area, breast region, and internal tissue patterns, and better separation of those areas as we increase the number of cluster counts to four.

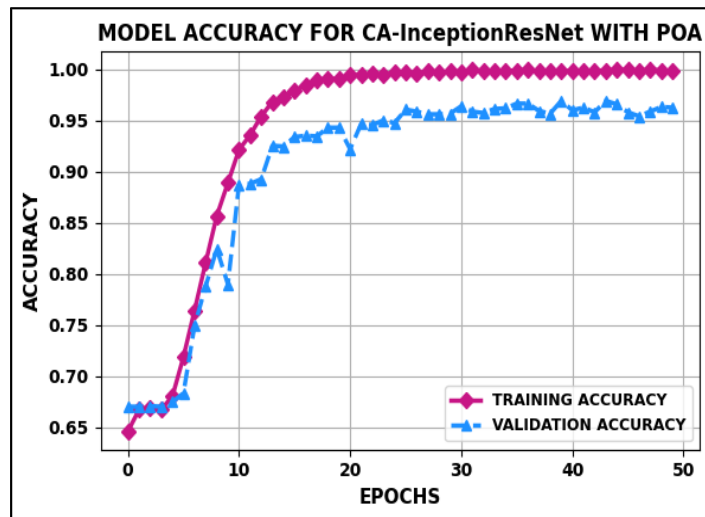


Figure 13: Model accuracy for CA-InceptionResNet with POA.
Source: Authors, (2026).

Training and validation accuracy of CA-InceptionResNet model with POA over the epochs are depicted in figure 13. The accuracy during training consistently increases at an extreme rate, reaching approximately 100%. Conversely, validation accuracy remained stable at 96% to 97%. Therefore, the rapid convergence of the model demonstrates efficient learning, high classification performance and generalization, but with very low levels of overfitting.

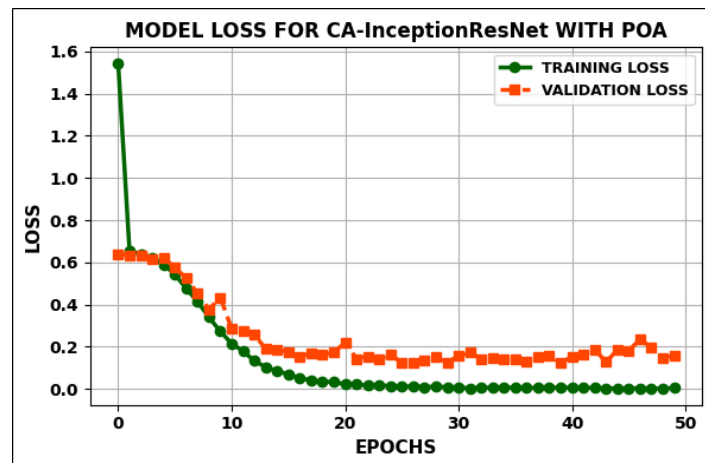


Figure 14: Model loss for CA-InceptionResNet with POA.
Source: Authors, (2026).

Figure 14 depicts a model loss for CA-InceptionResNet with POA. Training loss impacts rapidly decrease and stabilize to near zero after just a few epochs; this represents fast and effective learning. As for the validation loss, it decreases over time with some fluctuation around a low value during later training epochs, which indicates good generalization and very little overfitting.

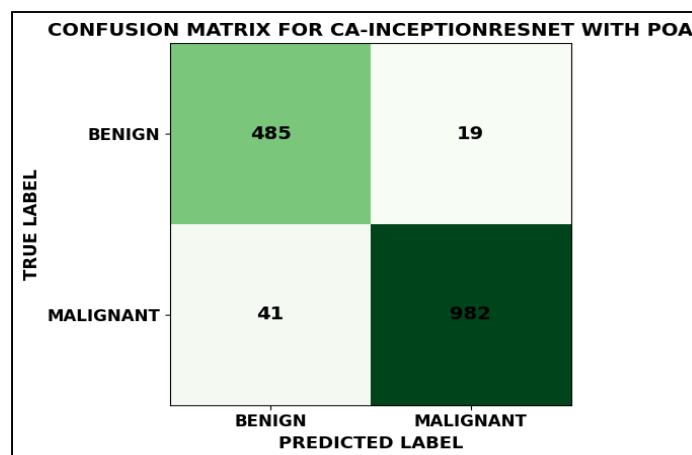


Figure 15: Confusion matrix for CA-InceptionResNet with POA.
Source: Authors, (2026).

Figure 15 illustrates the confusion matrix for CA-InceptionResNet with POA. Confusion matrix provides evidence of good classification performance, with vast majority of both benign (485) and malignant (982) cases correctly classified. There were very few instances of misclassification; therefore, there is a strong level of accuracy and a high ability to successfully differentiate between both classes.

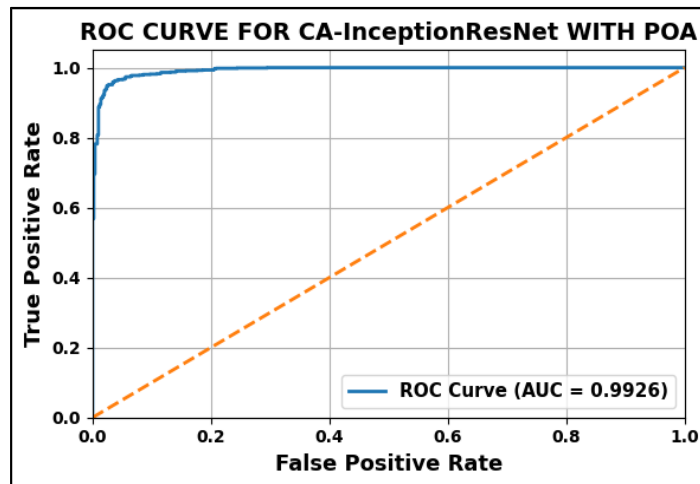


Figure 16: ROC curve for CA-InceptionResNet with POA.
Source: Authors, (2026).

Figure 16 shows the ROC curve for CA-InceptionResNet with POA. With the curve showing a broad path to the upper left of the ROC space where there are very high true positives with only small numbers of false positives, the AUC equals 0.9926, which indicates outstanding overall classification performance.

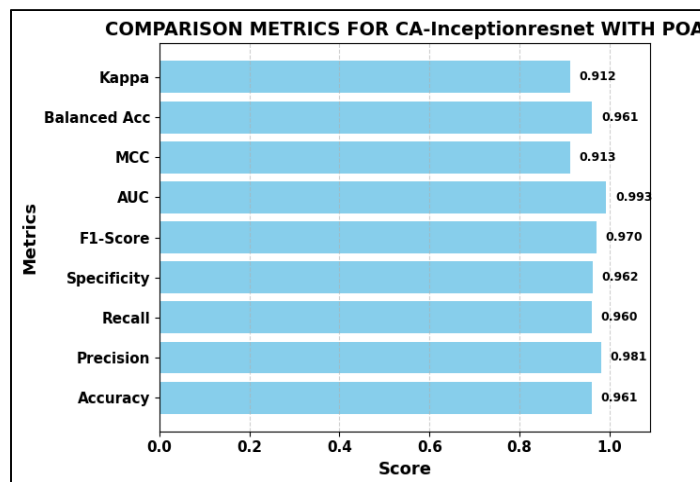


Figure 17: Comparison metrics for CA-InceptionResNet with POA.
Source: Authors, (2026).

In figure 17, the CA Inception-ResNet with the POA Model performed very well, exceeding or equaling the other Metrics overall. The accuracy, balanced accuracy, recall, and specificity are close to 0.96 with precision at 0.98; the F1-Score is equal to approximately 0.97, while the AUC has the highest value of 0.993; MCC/Kappa equals greater than 0.91 which shows excellent and balanced classification performance.

Table 4: Classification metrics for CA-InceptionResNet with POA.

Performance metrics	Values
Accuracy	0.9607
Precision	0.9810
Recall	0.9599
Specificity	0.9623
F1-Score	0.9704
AUC Score	0.9926
MCC	0.9126
Balanced Accuracy	0.9611
Kappa Score	0.9121

Source: Authors, (2026).

In table 4, the outcomes of the model exhibit a superior and balanced performance across all metrics, achieving an accuracy of 96.07% with high performance on both Precision (98.10%) and Recall (95.99%). In addition, the F1-score of 97.04% and the AUC of 0.9926 indicate strong classification capability. The MCC and Kappa scores (0.91) indicate a strong agreement and consistent reliability across all classes. Figure.18 presents performance of CA, InceptionResNet model where the training accuracy goes up to roughly 95% and validation accuracy remains close to 90%. Meanwhile, the training and validation loss curves show slight overfitting. The confusion matrix indicates that 456 benign instances have been correctly classified and 922 malignant cases have been correctly identified. However, it also points out that 48 benign cases have been misclassified as malignant and 53 malignant cases have been misclassified as benign, representing diagnostic errors. The ROC curve gives an AUC of 0.9500 which is a strong but not an ideal classification performance. On the other hand, the proposed POA based CA, InceptionResNet model produces better results with an accuracy of 0.9607, precision of 0.9810, recall of 0.9599, and F1, score of 0.9704, outperforms by the baseline model in all the metrics.

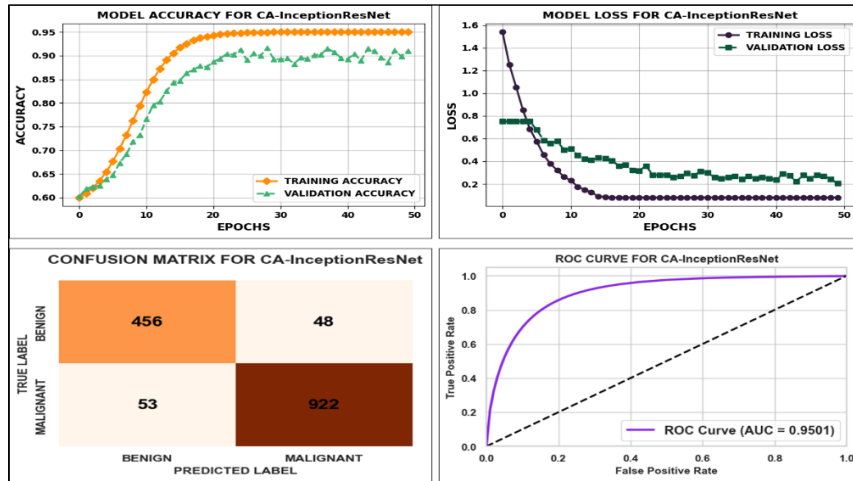


Figure 18: CA-InceptionResNet model.

Source: Authors, (2026).

Table 5: Classification metrics for CA-InceptionResNet.

Performance metrics	Values
Accuracy	0.9023
Precision	0.9150
Recall	0.9035
Specificity	0.9010
F1-Score	0.9092
AUC Score	0.9500
MCC	0.8100
Balanced Accuracy	0.9023
Kappa Score	0.8050

Source: Authors, (2026).

Table 5 and Figure.19 represents the classification metrics of the CA-InceptionResNet model which, although it performs well, is less effective than the proposed POA based CA-InceptionResNet model. The CA InceptionResNet model achieves an accuracy of 0.9023, precision of 0.9150, recall of 0.9035, specificity of 0.9010, F1, score of 0.9092, and an AUC score of 0.9500 supported by a Matthews Correlation Coefficient (MCC) of 0.8100, balanced accuracy of 0.9023, and Kappa score of 0.8050. It establish the model's robustness across various evaluation dimensions. However, the CA-InceptionResNet model, energized by Peafowl Optimization, outperforms leading to a higher diagnostic precision, feature prioritization, and generalization capability.

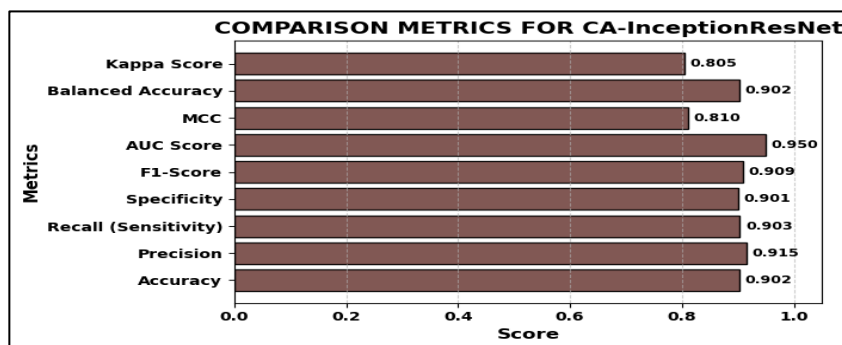


Figure 19: Comparison metrics of CA-InceptionResNet.

Source: Authors, (2026).

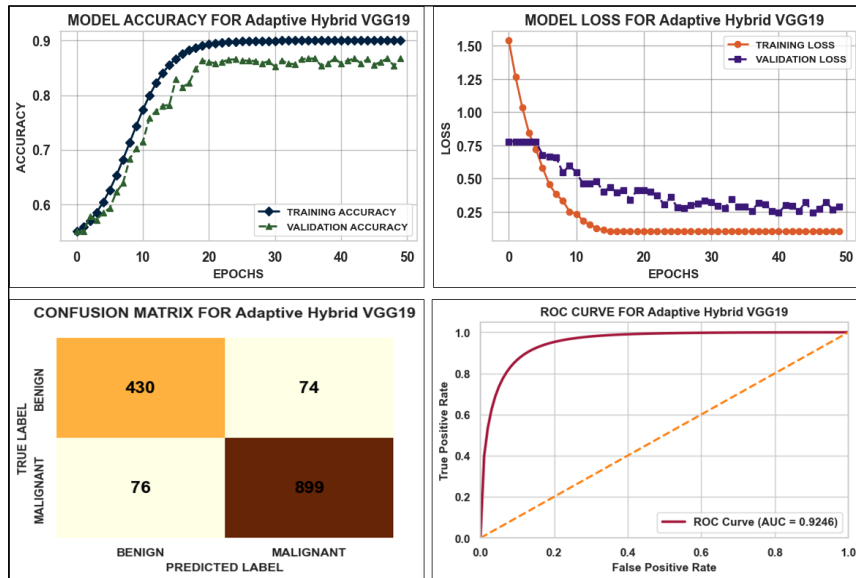


Figure 20: Adaptive hybrid VGG19.
Source: Authors, (2026).

Figure.20 displays the efficiency of the adaptive hybrid VGG19 model, with training accuracy goes over 90%, while validation accuracy remains steady at about 86%, indicating a moderate level of generalization. The training loss goes down to less than 0.25, however, validation loss is still kept at a higher value of about 0.4, thus pointing to overfitting. The confusion matrix shows that 430 benign and 899 malignant cases have been correctly classified, whereas 74 benign and 76 malignant cases have been misclassified. The ROC curve produces an AUC of 0.92 which is indicative of a good, yet not optimal, discriminative capability. On the other hand, the proposed POA based CA-InceptionResNet mode attains better metrics accuracy of 0.8656, precision of 0.8800, recall of 0.8675, and F1, score of 0.8736 thus, a significantly increased diagnostic precision and reliability is exhibited.

Table 6: Classification metrics for Adaptive hybrid VGG19.

Performance metrics	Values
Accuracy	0.8656
Precision	0.8800
Recall	0.8675
Specificity	0.8630
F1-Score	0.8736
AUC Score	0.9200
MCC	0.7400
Balanced Accuracy	0.8653
Kappa Score	0.7350

Source: Authors, (2026).

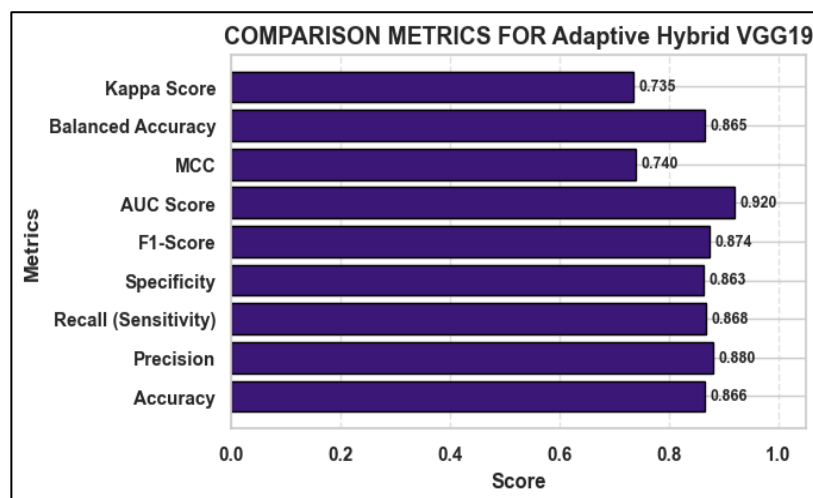


Figure 21: Comparison metrics of Adaptive hybrid VGG19.
Source: Authors, (2026).

Figure 21 displays the comparison metrics of the Adaptive Hybrid VGG19 model that indicates classification performance of moderate level, but it is still less powerful than the POA based CA-InceptionResNet model. The model yields an accuracy of 0.8656, precision of 0.8800, recall of 0.8675, and specificity of 0.8630 which express the balanced but restricted diagnostic ability of the instrument. As shown in Table 6, the instrument also attains an F1, score of 0.8736, AUC score of 0.9200, MCC of 0.7400, balanced accuracy of 0.8653, and Kappa score of 0.7350 that corroborate its capacity across the standard metrics. Yet, the adaptive hybrid VGG19 does not over perform the proposed breast cancer detection model.

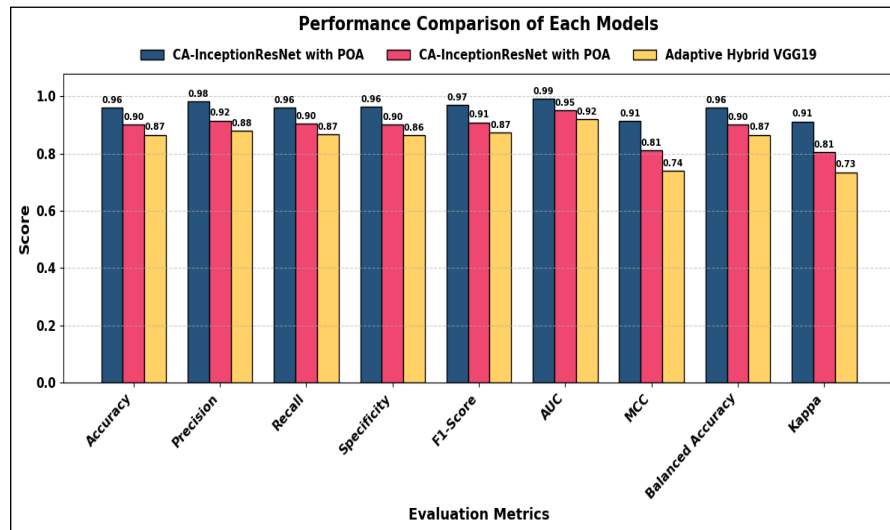


Figure 22: Performance comparison of each module.
Source: Authors, (2026).

Figure 22. compares visually the classification effectiveness of three models, i.e., the POA based CA-InceptionResNet, CA-InceptionResNet and adaptive hybrid VGG19, across nine main evaluation metrics. The POA based CA-InceptionResNet model is always the best of the three, reaching the highest scores in all categories: accuracy (0.96), precision (0.98), recall (0.95), specificity (0.96), F1, score (0.97), AUC (0.99), MCC (0.91), balanced accuracy (0.96), and Kappa score (0.91). On the other hand, the baseline CA, InceptionResNet model exhibits a moderate performance, whereas the Adaptive Hybrid VGG19 model has its performance metrics lower. Such a comparative analysis makes it evident that the proposed breast cancer prediction framework is the most precise, well, generalized as well as reliable in the

Table 7: Comparative analysis of accuracy for various methods.

Model	Accuracy
KNN [25]	0.92
VGG-16 [22]	0.936
Random Forest [24]	0.947
FCNN [21]	0.95
Proposed	0.9607

Source: Authors, (2026).

In table 7, the proposed model produces the highest level of accuracy (0.9607) when compared to traditional machine learning techniques (KNN=0.92 and Random Forest=0.947) as well as to deep learning models (VGG-16=0.936 and FCNN=0.95).

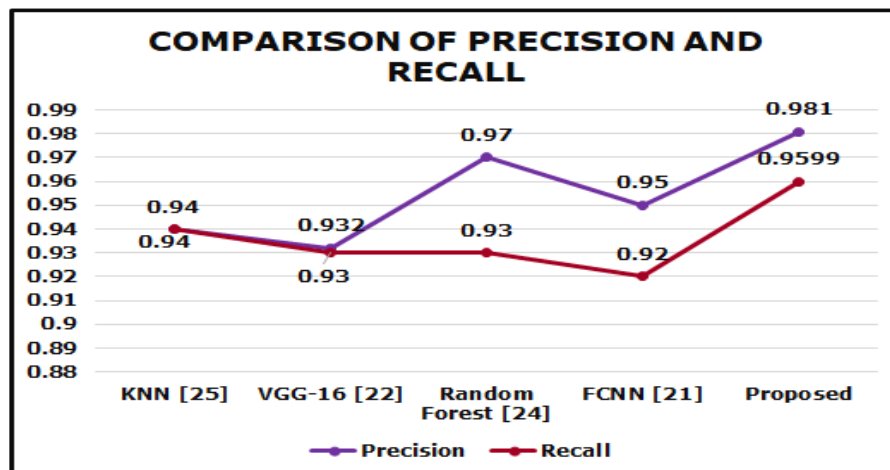


Figure 23: Comparative analysis of precision and recall for various methods.
Source: Authors, (2026).

In figure 23, the proposed model exceeds all baseline models on every evaluation metric assessed, with maximum Precision and Recall of 0.9810 and 0.9599. Traditional machine learning techniques (KNN and RF) and DL models (VGG-16 and FCNN) delivered lower precision-recall outcomes.

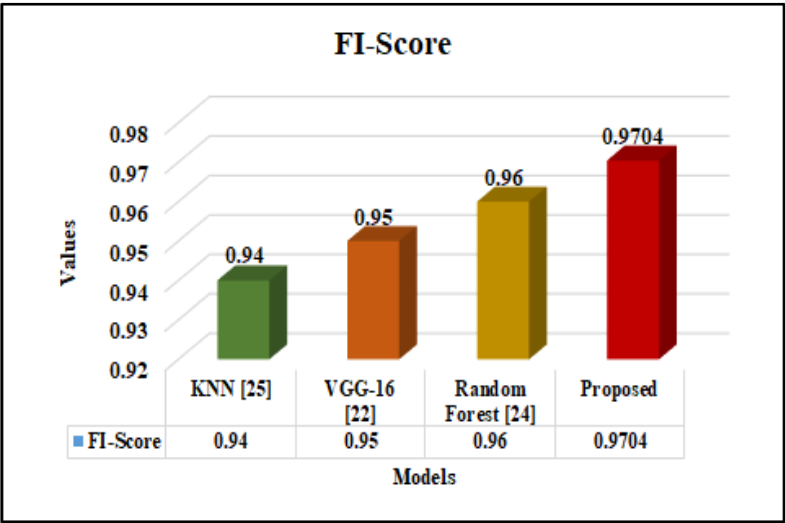


Figure 24: Comparison of FI-Score for various methods.
Source: Authors, (2026).

The comparison of the F1 scores provides an overview of the increased performance of the different models tested in figure 24. The KNN classifier has an F1 score of 0.94. VGG-16 performed better than KNN with an F 1 score of 0.95. Random Forest classifier also showed an increase in performance with the highest F1 score of 0.96 among the three classifiers tested. Finally, the newly proposed model outperformed all of the previously tested classifiers with the highest overall F1 score of 0.9704, thus, confirming the models superior performance in achieving an optimal balance between precision and recall for classification task.

V. CONCLUSION

Using mammograms, this work has developed a DL system to detect breast cancer earlier. This new system is designed to be better than previous breast cancer screening systems at appropriately diagnosing patients. To reduce image noise while maintaining important anatomical features, the system uses a bilateral filter during its preprocessing step. During preprocessing, ROIs are segmented accurately using multi-scale K-means clustering techniques. The main structure of the channel-attenuated InceptionResnet architecture is that it combines Inception and residual connections, with the addition of a SE attention mechanism, so that the most discriminative features are emphasized prior to classification. Model uses GAP and Dropout regularization to decrease overfitting and uses a final dense layer and a Softmax output layer to classify the final results as either benign or malignant. The hyper-parameter optimization method, called the POA, was implemented to enhance system performance. This system has undergone extensive testing against benchmark datasets, and results show that the proposed model outperforms prior breast cancer detection systems and is more accurate than traditional methods used currently for diagnosing cancer and demonstrating greater accuracy of 0.9607, precision of 0.9810, Recall of 0.9599 and FI-Score of 0.9704. These results indicate possible role of DL technologies in improving the early detection of breast cancer, thus providing a valuable resource to support clinical decision making for patient care.

VI. AUTHOR’S CONTRIBUTION

- Conceptualization:** M Shobha, N Ashok Kumar.
- Methodology:** M Shobha, N Ashok Kumar.
- Investigation:** M Shobha, N Ashok Kumar.
- Discussion of results:** M Shobha, N Ashok Kumar.
- Writing – Original Draft:** M Shobha, N Ashok Kumar.
- Writing – Review and Editing:** M Shobha, N Ashok Kumar.
- Resources:** M Shobha, N Ashok Kumar.
- Supervision:** M Shobha, N Ashok Kumar.
- Approval of the final text:** M Shobha, N Ashok Kumar.

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