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Enhanced Crow Search Optimization Deep Convolution Network Classifier for Early Detection of Breast Cancer Detection

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Abstract

The worldwide women mainly affecting cancers diagnosed in Breast cancer through important implications for communal health. Advances in health check treatments, along with premature detection, have led to improved survival outcomes for patients. The early detection of breast cancer is primarily achieved by digital mammography, which is current standard viewing method. The conventional deep learning models is not perfect, leading to inaccuracies result and even unnecessary treatments for patients, or missed diagnoses that delay critical treatment. In order to overcome this challenge, a novel Enhanced Crow Search Optimization Deep Convolution Network Classifier (ECSODCNC) model is developed to aim of improve the breast cancer detection accuracy within minimal time as well as error rate in early stage. The proposed method comprises the five different procedures and it integrated into proposed DCNN classifier provide to accurate disease prediction. Proposed ECSODCNC utilizes DCNN which comprises of numerous layers namely input, convolutional layer, maxpooling and fully connected layer and output layer. These mammogram images are specified to input layer of the deep learning method. Next, the hidden layers are utilized to accurate computation by using mammogram images. After that, image preprocessing is designed in convolutional layer to improve the image quality using the Hamann indexive variation denoising method. The quality-enhanced mammogram images are then transferred to the max-pooling level to minimize dimensionality of the aspect maps when retaining mainly important data. In this layer, ROI segmentation and geometric features are removed and ROI are transmitting to the fully connected layer with minimum time consumption. In classification process, Canonical Concordance Correlation is performed. Enhanced Crow Search Optimization (ECSO) is also employed for the fine-tuning process of the CNN to optimize hyper parameters to improve model disease prediction performance and minimize error. Finally, the result of breast cancer classification is achieved at output layer. The performance of the proposed ECSODCNC model was experimentally analyzed based on various performance metrics. Quantitatively analyzed outcomes describe to performance of ECSODCNC model achieves the improved breast cancer detection accuracy with lesser time consumption than the different existing methods.

Keywords: Breast cancer detection (BCD), Mammographic images, convolution network classifier, Hamann Indexive variation denoising method, Canonical Concordance Correlation, Crow Search Optimization.

1.Preamble

Breast cancer is one of the most frequently diagnosed cancers affecting women global, with significant implications for public health. Early and accurate detection is crucial role in recovering survival rates and treatment results. But, the traditional convolutional neural network approaches were developed for breast cancer detection. But, the tuning hyperparameters is laborious and time-consuming. To address this issue, BFO-CNN was designed in [1] to improve the breast cancer accuracy. But, the method was unable to effectively analyze dense mammographic tissues and lacked transparency in its decision-making process, which reduced its reliability in clinical practice. To address this issue, an explainable and optimized detection framework, called Trans YOLO-GJO, was proposed in [2]. It integrates transformer-based attention mechanisms with YOLOv9 architecture, while the Golden Jackal Optimization (GJO) algorithm is obtained to optimize the model's performance. But, the computational time was not minimized. To reduce the time, Stacked Auto encoder with PSO-SAE was proposed in [3] to classifying mammogram images of breast cancer. While considering the large mammogram images with varying sizes, the PSO-SAE method did not effectively classify breast cancer within minimal time consumption. This issue overcome by, the computational method was performed in [4] to ResNet-50 neural network. However, it failed to gather large datasets for detecting cancer.

Accurate differentiation among benign and malignant breast lesions were challenging when relying on a single imaging modality. Different multimodal deep learning was examined in [5] for enhancing the classification performance by using mammography, ultrasound, and clinical data. But, it failed to perform segmentation. A DL was designed in [6] to automatic breast cancer diagnosis for applying segmentation and classification.

Nevertheless, the accuracy was not enhanced. Graphical user interface -based breast cancer prediction scheme was designed in [7] to determine the tumors as either benign or malignant with lesser time. Ensemble deep learning framework was performed in [8] for precise diagnostic decisions in the early manner. However, it failed to detect malignant images. DL method was proposed in [9] to breast cancer screening by considering the malignant images based on image segmentation. However, it failed to achieve the hyper parameters optimization. A deep convolutional generative adversarial network (DCGAN) was designed in [10] to improve breast cancer detection for hyper parameters optimization by efficiently producing mammogram images. However, it did not test additional datasets. To handle this issue, deep learning Mask R-CNN method was developed in [11] for accurately detecting and classifying breast masses at an early stage. But, the time complexity of breast cancer detection remains unresolved. For reducing the time, a CNN model was designed in [12] to identifying breast X-ray mammography descriptions into caring and cruel categories. Other than, Early identification and diagnosis of breast cancer with minimal time consumption remain challenging issues. DL and computer vision methods were performed in [13] to diagnosis breast cancer by identifying and classify breast lesions. But, the designed method was not selecting the relevant features in medical images. Hybrid classification approach was discussed in [14] to extract the spatial and temporal features with CNN. It is applied to improve the accuracy. Yet another feature extraction method such as hybrid DL was employed in [15] for accurate breast cancer identification. But it failed to perform the preprocessing with raw mammography images, thereby reducing the performance of stable classification and higher accuracy.

1.1 Research Gap

Breast cancer is a major health concern, and its early and accurate detection is essential for timely diagnosis and treatment. Existing machine learning (ML) and deep learning (DL) methods have been widely investigated for breast cancer detection; however, several limitations remain. Conventional approaches may be affected by image noise, intensity variations, complex tissue textures, limited feature representation, and classification errors. In addition, some existing methods provide limited attention to the coordinated integration of preprocessing, segmentation, feature extraction, classification, and model optimization, which can affect the overall diagnostic performance. The use of limited datasets and insufficient experimental validation can also restrict the generalizability and reliability of reported results.

Therefore, there is a need for an integrated framework that can improve image quality, accurately identify the relevant breast tissue regions, extract discriminative features, and optimize the classification process. To address these limitations, this study proposes the ECSODCNC framework, which integrates preprocessing, segmentation, feature extraction, classification, and fine-tuning within a unified breast cancer detection pipeline. The framework is designed to reduce the effects of image noise and complex tissue characteristics while improving the representation and classification of relevant features. The effectiveness of the proposed framework is subsequently evaluated using appropriate performance measures and comparative experiments.

1.2 The Novel Contributions of the ECSODCNC Technique

The major contributions of the proposed Enhanced Crow Search Optimization-based Deep Convolutional Neural Network (ECSODCNC) technique are summarized as follows:

- An ECSODCNC framework is proposed for breast cancer detection by integrating image preprocessing, ROI segmentation, feature extraction, deep convolutional neural network (DCNN)-based classification, and Enhanced Crow Search Optimization (ECSEO) for model fine-tuning within a unified framework.
- A Hamann Index Variation-based denoising framework is employed during preprocessing to reduce noise and improve the quality of the input breast images. This preprocessing stage enhances the representation of relevant image information and is evaluated using image-quality measures such as Peak Signal-to-Noise Ratio (PSNR).
- Moore Proximity-based Simple Matching segmentation is incorporated to identify and isolate the relevant region of interest (ROI) from the preprocessed breast image. This reduces the influence of irrelevant image regions and facilitates the extraction of informative characteristics for subsequent classification.
- Geometric feature extraction is employed to represent discriminative characteristics of the segmented ROI. These features are used to provide a compact representation of the relevant breast image regions and support efficient cancer classification.
- Canonical Concordance Correlation-based feature analysis is incorporated to measure the agreement between the extracted feature representations and the corresponding reference or ground-truth representations. This facilitates the identification of relevant feature relationships for breast cancer classification.
- Enhanced Crow Search Optimization (ECSEO) is employed to fine-tune the parameters/weights of the DCNN classifier. The optimization process aims to minimize classification error and improve the classification performance for multiclass breast cancer detection.

- Comprehensive experimental evaluation is conducted using appropriate performance measures and comparisons with existing deep learning approaches. The evaluation is intended to examine classification effectiveness, computational efficiency, and the contribution of the individual components of the proposed framework.

1.3 Structure of proposed method

Organization of the manuscript is orderly: the literature review is described in section 2. ECSODCNC is exploiting in section 3 and section 4 is experimental setup and dataset description is analyzed. The analyses of ECSODCNC and existing methods with different techniques are illustrated in section 5. At last, the Section 6 describes the conclusions.

2. Literature review

Literature review is presented in this section analyzes the several research works on breast cancer detection. Feature selection denotes significant step by using interpretable models for early breast cancer recognition. But, the optimal feature selection was challenging issue. To handle this gap, the multi-criterion selection framework was utilized in [16] for discovering the most discriminative and clinically relevant features in mammography images. However, it failed to consider huge dataset with higher accuracy. In [17], the Transformer-driven multi-modal fusion and explainable DL termed Trans Fusion-BCNet was investigated into predicts the cancer. But, the accuracy was not enhanced. For dealing with this issue, multi-auto encoder framework was developed in [18] for categorize the breast cancer. CNN model was investigated in [19] to accurate and reliable breast cancer detection to enhance the patient results. However, the role of diagnostic solutions in advancing precision medicine and personalized healthcare remains insufficiently addressed. In [20], a hybrid deep neural network model was designed into classify the benign and malignant diagnoses. However, it failed to enhance the image quality. Advanced transfer DL was executed in [21] to identify BrC detection for enhancing the image quality. In [22], DL models were considered for tumors using mammogram images and classifying them into three categories. But, the segmentation issue was unaddressed with clinical mammogram images. CNN utilized to accurate image classification is designed in [23]. However, this approach has high computational cost and complexity. An enhanced transfer learning model was determined in [24] to classifying brain tumors. But, the manual mammograms were not considered for effective breast cancer classification. To address on this issue, a Novel hybrid DL method (MammoViT) was performed in [25] to capturing the both local and global relationships among the image patches. But, it did not enhance the image classification with less error. Parameterized hyper complex neural network (PHNN) was designed in [26] to carry out breast cancer classification. However, the fine-tuning step was not desirable. Multiple convolutional neural networks were developed in [27] to breast cancer classification, utilizing a broader range of potential features to achieve improved performance. But, method did not extend to clinical mammograms with different pre-processing. Also, the sensitivity was not enhanced. Novel deep learning framework was performed in [28] by combining the GAN and HDL for breast cancer detection with help of thermogram imagery. But, the ROI segmentation was not accurately performed, which impacted the time complexity of the breast cancer classification. Hybrid feature fusion method was introduced in [29] to accurately extract the RoI. But, the effectively classification of breast cancer as benign or malignant remains a challenging issue. In [30], a deep convolutional generative adversarial network was developed into improve the reliability of synthetic mammogram images. Nevertheless, more accurate forecasting techniques were not employed to enhance model accuracy in the detection process. To address these limitations, the ECSODCNC is proposed for accurate breast cancer detection with better accuracy with minimum time.

3. Proposal Methodology

A deep learning-based framework, termed Enhanced Crow Search Optimization Convolutional Neural Network (ECSODCNC), is proposed for the classification of mammographic images into normal, benign, and malignant categories. The proposed framework integrates image preprocessing, region-of-interest (ROI) segmentation, discriminative feature extraction, deep convolutional classification, and Enhanced Crow Search Optimization (ECSO)-based fine-tuning. The overall architecture of the proposed ECSODCNC framework is illustrated in Figure 1.

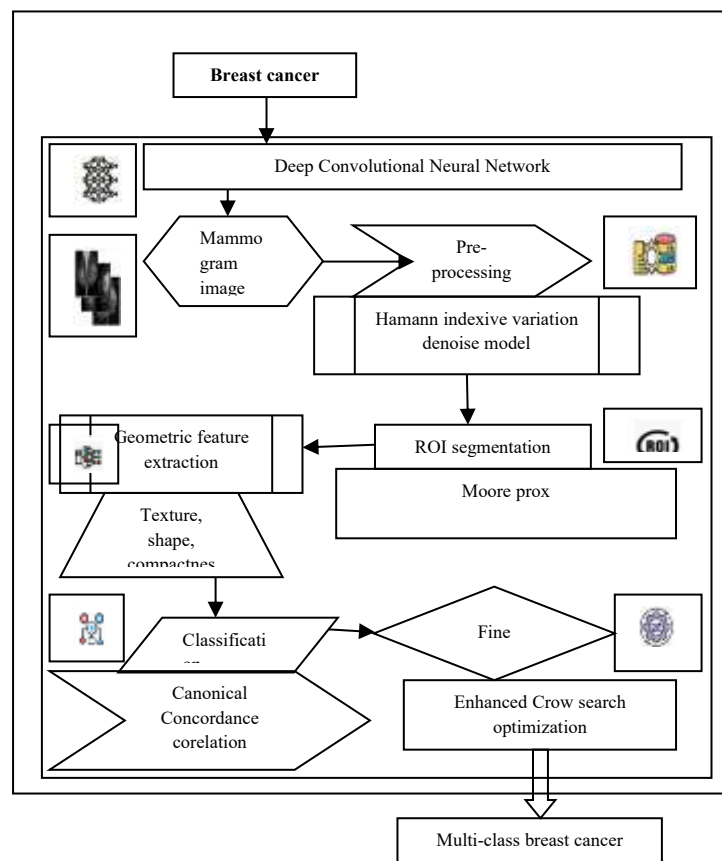


Figure 1 Architecture of proposed ECSODCNC model

Dataset Description

The essential stage of ECSODCNC is performing the image acquisition for breast cancer detection. In image acquisition process, CBIS-DDSM is taken from <https://www.kaggle.com/datasets/awsaf49/cbis-ddsm-breast-cancer-image-dataset>. Mammographic Images are gathered from CBIS-DDSM: BC Image database. It is designed to fit modern computer vision frameworks for classification, object detection, and segmentation tasks. It involves digital mammograms X-ray images of the breast to comprise patient details, lesion characteristics, and imaging parameters. The dataset contains 10239 mammograms X-ray images used for three distinct categories namely normal, Benign, Malignant. Each image is interpreted with the appropriate class label to support classification tasks. Dataset description is illustrated in Table 1.

Table 1 Dataset details

Features	Descriptions
Total images	10239 (Mammographic Images)
Number of Participants	1566
Number of studies/series	6775
Modalities	MG (Mammograpgy)
Image size	6GB (jpg format)
Dataset size	163GB (jpg format)
Class	Normal, Benign, Malignant

3.2 Enhanced Crow Search Optimization Convolution Network Classifier

CNN classifier is a deep neural network designed specifically for processing and classifying images. It extremely effective tasks in image recognition related to classification because of their ability and routinely discover and remove features from raw image data. CNN comprise the multiple layers of nodes (neurons) are namely, convolutional layer, max-pooling layer, fully connected (dense) layer.

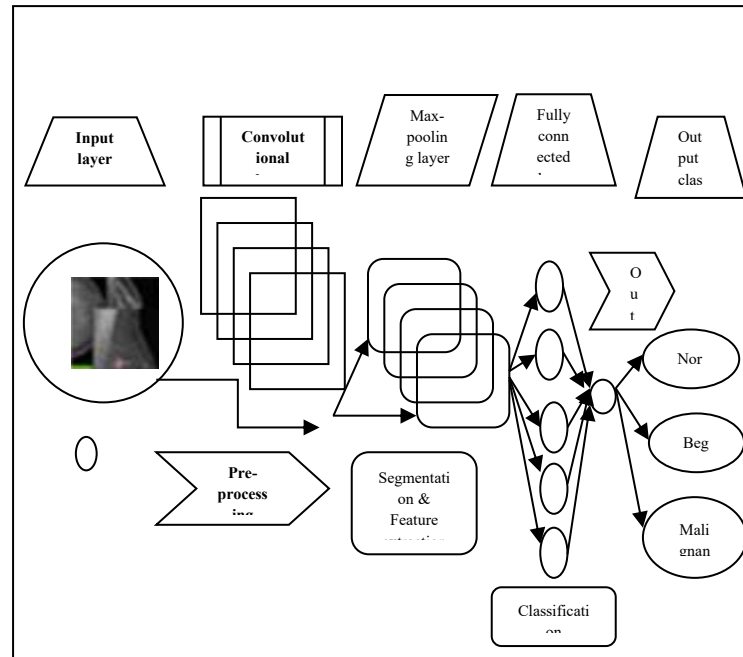


Figure 2 Schematic structure of a proposed deep Convolutional Neural Network

The structure of a deep CNN is described in Figure 2. It utilized to single layers of input and output layers, whereas hidden layers enclose multiple sub layers. Let us consider a set of input mammogram images $MI_1, MI_2, MI_3 \dots MI_n$ are given to input layer. In input layer, each neuron processes these images. The neuron in layer assigns a ' W_{ih} ' symbolize the weighted sum of input and bias ' b ' to saved value is '1'.

$$Z = \sum_{i=1}^n (MI_i * W_{ih}) + b(1)$$

In above equation, Z denoted as neuron activity. Input image is sent into the convolution layer.

○ Image Preprocessing Using Hamann Index Variation Denoising (Covolution layer)

The input mammogram image is first passed to the hidden layer, where a pre-processing step is performed to improve its quality by minimum noise and unwanted artifacts. In this stage, Hamann Indexive Variation Denoising is determined for preprocessing the input image and effective edge-preserving filter concurrently preserving edges while smoothing the noise. Let assume the input image $MI_1, MI_2, MI_3 \dots MI_n$. The numeral images in both mammogram images are known as $Q_1, Q_2, Q_3 \dots Q_m$. The denoising method choose the window with volume of $k * k$ for arranging the images,

Q_1	Q_2	Q_3
Q_4	Q_5	Q_6
Q_7	Q_8	Q_9

Figure 3 $k * k$ Filtering window

In above Figure 3, pixels $Q_1, Q_2, Q_3 \dots Q_m$ are structured in row and columns. Afterward, pixels are sorted into ascending order. Then, the Hamann Indexive function is utilized to measure the variation in intensity between

pixels within the filtering window and surrounding pixels. Based on these variations, noisy pixels are recognized for more processing. The formula for the variation around the pixels is derived as follows,

$$HI = 1 - \left[\frac{2 |Q_j \Delta Q_k|}{m} \right] (2)$$

Where, HI denotes a Hamann index variation, Q_j indicates a pixel, Q_k is a neighboring images in filtering window, ' m ' is denotes the total number of pixels in image, $Q_j \Delta Q_k$ is a variation between two pixels. The index function gives an outcome as of 0 to 1. As, index functions test is 1 indicates variability among data points. Otherwise, the pixels through additional deviation considered as noisy as well as smoothed through applying standard value of additional neighboring pixels in the filtering window,

$$Q_s = \sum_{j=1}^m \frac{Q_j}{m} (3)$$

Where, Q_s is denotes the smoothed image pixels, m indicates sum number of pixels. Accordingly, the noisy pixels are extracted and it evened by the average value. As a result, quality enhanced mammogram images are obtained for accurate cancer detection.

• ROI Segmentation Using Moore Proximity-Based Simple Matching (Max pooling layer)

The quality-enhanced mammogram images are then transferred to the max-pooling level to minimize dimensionality of aspect maps as retaining important data. It is a second hidden layer of CNN which is down sampling technique to reduce the spatial dimensions of an input volume. In this layer, ROI segmentation and geometric features are removed by effective cancer detection with lesser time consumption.

ROI segmentation is a process utilized with breast cancer detection to divide the explicit weak region within a mammogram image. It is typically a subset of full image to include the essential information for analysis, helping to lesser computational complexity and develop the accuracy of model by focusing only on the significant features. Moore proximity simple matching technique is employed for ROI segmentation. The Moore proximity is a concept used to define the adjacent pixels surrounding a central pixel in a grid. It includes all 8 neighboring pixels that contact the central pixel, whether horizontally, vertically, or diagonally.

In the image segmentation, Moore proximity simple matching based segmentation utilizes this concept to evaluate and group pixels based on their connectivity and similarity. The 8-connected neighborhood ensures that not only directly adjacent pixels but also diagonally adjacent pixels are considered.

	$Q_{x-1,y+}$	$Q_{x,y+1}$	$Q_{x+1,y+}$	
	$Q_{x-1,y}$	$Q_{x,y}$	$Q_{x+1,y}$	
	$Q_{x-1,y-}$	$Q_{x,y}$	$Q_{x+1,y-}$	

Figure 4 Moore proximity simple matching based segmentation

Figure 4 illustrates Moore proximity simple matching based segmentation based pixel connectivity. Initially, early point is manifest through a middle pixel positioned ($Q_{x,y}$). For a pixel located at center position, Moore neighborhood consists of 8 neighborhood connectivity as

$$MC_8 = [(Q_{x-1,y-})(Q_{x-1,y})(Q_{x-1,y+})(Q_{x,y+1})(Q_{x,y-1})(Q_{x+1,y+1})(Q_{x+1,y})(Q_{x+1,y-1})] (4)$$

Where, MNC_8 denotes a Moore neighborhood with 8 neighborhood connectivity between the pixels 'Q'. The connectivity or similarities between the pixels are identified through Sokal-Michener's simple matching coefficient.

$$SMC = 1 - \frac{|Q_{x,y} \Delta Q_{x,y(n)}|}{m} (5)$$

$Q_{x,y}$ denotes center pixel, $Q_{x,y(n)}$ denotes a neighboring pixel located in the 8 different directions around center pixels, $|Q_{x,y} \Delta Q_{x,y(n)}|$ represents the variation between two pixels, m is a number of pixels. The matching coefficient gives the output as of 0 to 1. Coefficient value of 1 represents that the pixel intensities are considered similar, facilitating the connection of neighboring or adjacent pixels. Subsequently, these segmented regions are extracted for accurate cancer detection, where the infected or abnormal regions are extracted from the input image.

- **Feature Extraction from the Segmented ROI**

Followed by, various features are extracted from images for identifying and diagnosing cancerous regions. The features are texture, shape, compactness and smoothness.

- **Texture Feature**

Texture features are important in image analysis for extracting and quantifying patterns, structures, and variations during intensity pixels. It is mainly helpful in checkup pixels for tumors are detecting and characterizing in mammogram pixel. The correlation of pixel intensity with mean and standard deviation is determined to extract the feature based on spatial patterns or structures.

$$Tx = \sum_i \sum_j \frac{1}{d^2} [(Q_i - \mu_i)(Q_j - \mu_j)] \quad (6)$$

Where, Tx refers to a texture, pixel Q_i and its neighboring pixels Q_j , μ_i and μ_j denotes a mean and the deviation 'd'.

- **Shape feature**

A shape feature includes an area and perimeter of the lesion is essential in image analysis for describing and quantifying the geometric properties of regions within an image. These features are particularly useful when distinguishing between different types of lesions and tumors, as shape often varies considerably with benign and malignant cases. In order to calculate the boundary of a lesion, the Euclidean distance function is applied between neighboring pixels along the contour. This distance is calculated using equation (7).

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \quad (7)$$

From (7), 'd' represents the distance between two adjacent points lying on the lesion's boundary, the coordinates (x_1, y_1) , (x_2, y_2) correspond to successive boundary pixels in image. The point (x_1, y_1) is the origin (center) point of the shape (0,0) and point (x_2, y_2) indicates outer point of shape in the given image. By summing these pixel-to-pixel distances as the boundary is traced around the entire shape, the total perimeter of the lesion is obtained. The ROI region by summing up all pixels are formulated as,

$$a_{ROI} = \sum_i \sum_j Q_{ij} \quad (8)$$

Where, a_{ROI} denotes the region of the ROI, Q_{ij} is a number of all images within ROI. The perimeter is considered by including the different boundary pixels and it denoted as length of derived ROI boundary. The perimeter is calculated as,

$$p_{ROI} = \sum_i \sum_j Q_{ij}(B) \quad (9)$$

Where, p_{ROI} denotes perimeter, $Q_{ij}(B)$ denotes boundary pixels. Compactness feature is a measure of tumor shape. It is useful metric for characterizing the smoothness of a tumor region in image analysis.

- **Compactness Feature**

The compactness is mathematically computed as follows,

$$CO = \frac{p_{ROI}^2}{a_{ROI}} \quad (10)$$

Where, CO denotes a compactness, a_{ROI} denotes an area of the ROI, p_{ROI} denotes a perimeter. For a perfect circle, compactness CO equals 1. This is because, for a circle, the ratio of its area to the square of its perimeter is maximal. For irregular shapes, compactness is less than 1. Shapes with high irregularity have a lower compactness value.

- **Smoothness Feature**

Smoothness is a feature aids to recognize consistency of pixel intensity values within a ROI. It gives an indication of how much variation there is in the pixel intensities to determine whether a region is smooth or rough. The smoothness is mathematically computed as follows,

$$S = \frac{1}{1 + \sigma^2} \quad (11)$$

$$\sigma^2 = \frac{1}{m} \sum_{j=1}^m (Q_j - \mu)^2 \quad (12)$$

$$\mu = \frac{1}{m} \sum_{j=1}^m Q_j \quad (13)$$

Where, S denotes a smoothness, σ indicates a standard deviation, μ is a mean, m specified as a number of pixels, Q_j denotes a pixels in the ROI region.

- **Deep Convolutional Neural Network Classification (Fully connected layer)**

This layer removes the feature for detecting the breast cancer. It also called as a dense layer is a core component of neural networks where both neurons are related to both neurons in earlier and next layers. It learn the features removed from the preceding layer. In fully connected layer, feature learning process is executed by analyzing the extracted feature with testing features (ground truth). The Canonical Concordance Correlation is employed to consider the similarity between removed features via ground truth features. It is formulated as,

$$CCC = 2 * \frac{\rho Tr_{EF} T_{eF}}{Tr_{EF}^2 + T_{eF}^2 + (\mu_{Tr_{EF}} - \mu_{T_{eF}})^2} \quad (14)$$

$$\rho = \frac{Cov(Tr_{EF}, Te_F)}{Tr_{EF}Te_F} \quad (15)$$

Where, 'CCC' denotes Canonical Concordance Correlation coefficient between the features set, Tr_{EF}^2 is specified as a square of standard deviation of extracted features ' Tr_{EF} ', Te_F^2 is a square of the standard deviation of testing features ' Te_F ', $Cov(Tr_{EF}, Te_F)$ denotes the a covariance between the extracted features and testing features, $\mu_{Tr_{EF}}$ symbolized as mean of extracted features, μ_{Te_F} denotes a mean of testing features. The correlative index provides the output ranges value between 0 and 1. The similarity value is transferred into the activation function of softmax is employed to give the multiple classification results like as normal, benign, and malignant cases.

$$Y = F(H * W_{ho}) \quad (16)$$

Where Y is a classification outcome, F specified as softmax activation function, H denotes output of preceding layer, W_{ho} simplified as weight between hidden and output layer.

$$F = \frac{\exp(TI_c)}{\sum \exp(TI_c)} \quad (17)$$

Where, $\exp(TI)$ denotes an exponential of the correlation results for the c^{th} class, $\sum \exp(TI_c)$ denotes a sum of the exponentials of the correlation results for the c^{th} class. After the mammogram images are classified as normal, benign, or malignant, the results obtained from the fully connected layer.

• Enhanced Crow Search Optimization-Based Fine-Tuning

Although the CNN can learn discriminative representations through gradient-based training, its performance depends on suitable parameter values and training configurations. Therefore, Enhanced Crow Search Optimization (ECSO) is employed to fine-tune the CNN.

Enhanced Crow Search Optimization (ECSO) algorithm is a bio-inspired optimization technique that is based on the natural food-searching and hiding behavior of crows. It is used to optimize the model parameters, leading to improved classification performance and more accurate breast cancer detection. It is based on the way crows hide food, remember the locations of their hidden food, and observe or follow other crows to determine better food sources. On the contrary to existing Crow Search Algorithm methods, ECSO incorporates several enhancement strategies to improve overall performance. These improvements help achieve faster convergence, produce higher-quality solutions, and maintain a better balanced with exploration and exploitation, with minimum likelihood of getting trapped in local optima. As a result, ECSO is an effective optimization technique for solving complex, nonlinear, and high-dimensional optimization problems across various engineering and scientific applications. When applied to fine-tuning CNN, ECSO helps to optimize hyperparameters to improve model accuracy and minimize error. For each outcome, ERR is calculated based on squared dissimilarity between actual and predicted output.

$$ERR = [Y_a - Y_p]^2 \quad (18)$$

The 'ERR' is error rate, Y_a denotes actual categorization output, Y_p refers to forecasted categorization output. In the fine-tuning stage, backpropagation algorithm updates the model weights by gradient descent to reduce the prediction errors. It enhances the learning capability of the model and improves its prediction accuracy.

$$W_{t+1} = W_t - \eta \left[\frac{\partial ERR}{\partial W_t} \right] \quad (19)$$

Where, W_{t+1} is a updated weight, W_t denotes the current weight, η specified as learning rate ($\eta < 1$), $\frac{\partial ERR}{\partial W_t}$ symbolized a partial derivative of the error 'Err' with respect to current weight ' W_t '. Initially, the population of the Crows (i.e. weights ' W_k ') initialized in search space.

$$W_k = W_1, W_2, W_3, \dots, W_k \quad (20)$$

Where, $W_k = W_1, W_2, W_3, \dots, W_k$ is a weights between the layers. Afterward, fitness is computed depend on the gradient descent function.

$$f(x) = \arg \min ERR \quad (21)$$

Where, $f(x)$ is denotes the fitness function, $\arg \min$ is the argument of minimal function which is a gradient descent function to discover lesser error, ERR is the error rate. From the fitness value, the individual crow is selected based on their fitness. Then, position of individual crow is reorganized as,

$$X_{CS}^{t+1} = X_{CS}^t + R * Fl * (X_{CS}^{best} - X_{CS}^t) \quad (22)$$

Where X_{CS}^{t+1} updated position of Crow 'C' is, X_{CS}^t denotes the old position of crow, R specifies a random number $\in [0, 1]$, Fl is a the flight length for great influence on searching capability. The smaller value of Fl directs to local search, as the large value of Fl directs to global search, X_{CS}^{best} denotes the best position of the crow. After that, the possibility position of crow is established reliable with the fitness.

$$Y = \begin{cases} ff(X_{CS}^{t+1}) > ff(X_{CS}^t), & \text{Select } X_{CS}^{t+1} \text{ as best solution} \\ \text{otherwise,} & \text{Select } X_{CS}^t \text{ as best solution} \end{cases} \quad (23)$$

Where, Y is the possibility of verification outcomes. If fitness of the updated positions ' $ff(X_c^{t+1})$ ' is better than fitness of old position ' $ff(X_c^t)$ ', the updated position is measured the optimal solution. Otherwise, the old position ' X_c^t ' is reserved as optimal solution. It continues until the highest number of iterations is reached. At last, the optimal solution (i.e., weight) is chosen for reducing the error. It aids to enhance the breast cancer detection accuracy at the output layer.

Algorithm 1: Enhanced Crow Search Optimization Convolution Network Classifier	
Input: Number of mammogram images $MI_1, MI_2, MI_3 \dots MI_n$	
Output: Increase the breast cancer detection accuracy	
Begin 1. Number of mammogram images $MI_1, MI_2, MI_3 \dots MI_n$ at the input layer 2. For each image MI_i –[convolutional layer] 3. Extract the number of pixels in filtering window 4. Measure Hamann index variation using (2) 5. If $(HI = 1)$ then 6. Pixel is identified as noisy 7. else 8. Pixel is identified as normal 9. End if 10. End for 11. For each noisy pixels 12. Smoothen the images using (3) 13. End for 14. Perform ROI segmentation using (5) –[maxpooling layer] 15. Extract the significant features using (6)(7)(8)(9) (10) (11) 16. For each extracted feature ' F_E ' –[fully connected layer] 17. Measure the Canonical Concordance correlation using (14) (15) 18. End for 19. Apply softmax activation function using (16) 20. Obtain multiple classification results 21. For each classification result ' Y ' 22. Measure error rate using (18) 23. Initialize the populations of crows (i.e. weights) using (20) 24. for each weight 25. Calculate the fitness using (21) 26. if (arg min ERR) then 27. Select optimal solution or weight 28. Else 29. Not select optimal solution or weight 30. End if 31. End for 32. Update the positions using (22) 33. Replace current best solution 34. Return optimal weight 35. Obtain the final classification results with minimum error at the output layer End	

4. Experimental setup

Result of ECSODCNC and conventional BFO-CNN [1] and TransYOLO-GJO [2] is implemented in MATLAB using CBIS-DDSM: Breast Cancer Image Dataset. This dataset includes 2,620 scanned film mammography revision, consisting of normal, benign, and malignant cases, both with recognized pathology data. The large scale of this database, combined with its validated ground truth, makes DDSM an exclusive resource for breast cancer detection and diagnosis. It contains 10,239 mammogram pixels for cancer detection. For experimental evaluation, the number of Mammogram Images is progressively varied between 1,000 and 10,000 samples to analyze the impact of dataset size on model accuracy and effectiveness.

Table 2 Hardware and Software Configurations

Name	Description
Dataset name	CBIS-DDSM: Breast Cancer Image Dataset
Number of Mammogram images	1000-10000 images
Operating system	WINDOWS 10 and above
Software	MATLAB
RAM	8GB
Hard drive capacity	1TB
Processor	Intel® Core™ i3 Processor

5. Performance analysis

The analysis of ECSODCNC and existing methods are analyzed with different metrics.

5.1 Metrics description

PSNR: It is measured as reconstructed mammogram image by comparing to original image and expressed in decibels (dB). PSNR is calculated by MSE among unique and preprocessed image.

$$\text{PSNR} = 10 * \log_{10} \left[\frac{MQ^2}{MSE} \right] (24)$$

$$MSE = [\text{Original}_{\text{size}} - PP_{\text{size}}]^2 (25)$$

Where 'MQ²' refers to highest possible pixel value (255), PP_{size} is a preprocessed image size, Original_{size} symbolized as original image size.

Intersection over Union (IoU): it is estimate metric applied in breast cancer detection to calculate the overlap between the predicted positive samples and actual positive samples. A higher IoU provides better accuracy

$$\text{IoU} = \frac{\text{TRP}}{\text{TRP} + \text{FLP} + \text{FLN}} * 100 (26)$$

Where, 'TRP' denotes true positive, 'FLP' indicates false Negative, FLN indicates false positive.

Breast Cancer Detection Accuracy '**BCDA**': It is defined as breast images effectively categorized from total number of input images. It is formulated as,

$$\text{BCDA} = \left(\frac{\text{TRP} + \text{TRN}}{\text{TRP} + \text{TRN} + \text{FLP} + \text{FLN}} \right) * 100 (27)$$

Where, TRP is a true positives rate, the true negative is identified as TRN, FLP is a false positive, FLN denotes false negative. It is measured in percentage (%).

Sensitivity 'Se': it also known as recall is utilized to appraise result of categorization method, particularly in breast cancer detection, where identifying all positive cases is malignant.

$$\text{Se} = \frac{\text{TRP}}{\text{TRP} + \text{FLN}} (28)$$

Where, TRP specified as an images are effectively detected as normal, benign or malignant, FLN is a normal images wrongly detected as malignant.

Breast Cancer Detection Time 'BDT': It is ratio of amount of time taken by algorithm for detecting the breast cancer detection from given input mammogram images. It is calculated as,

$$\text{BDT} = \sum_{i=1}^n MI_i * TM [\text{BCD}] (29)$$

Where, TM denotes a time, BCD is a breast cancer detection, the single mammogram is denoted as image 'MI_i'. The overall time of breast cancer detection is calculated in milliseconds (ms).

5.2 Results and Discussion

This section presents the evaluation metrics utilized to measure the performance of proposed technique and compares its results with those of different existing methods.

Table 3 Peak Signal to Noise Ratio

Mammogram Image Size (MB)	Peak signal to noise ratio (dB)		
	Proposed ECSODCNC	Existing BFO-CNN [1]	Existing TransYOL O-GJO [2]

1.23	72.56	64.04	67.30
1.39	69.04	64.60	65.85
1.56	71.22	65.20	67.46
1.70	74.15	66.54	68.85
1.44	73.32	67.30	68.76
1.16	70.06	59.83	64.60
1.71	75.06	66.19	67.30
2.25	74.15	65.85	66.99
2.50	73.48	66.12	68.13
2.85	66.54	60.61	62.11

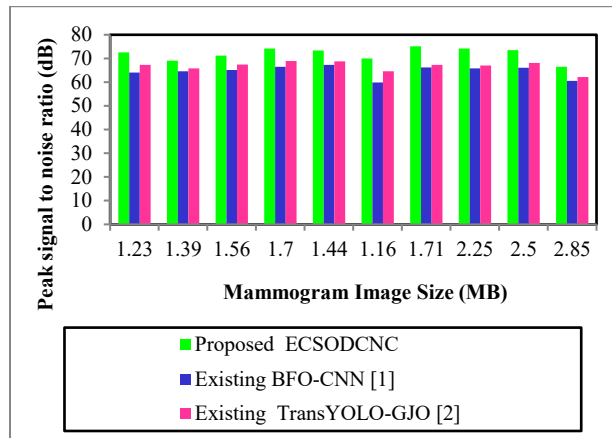


Figure 5 Performance analysis of Peak signal to noise ratio

In Table 3 and Figure 5, illustrate the performance analysis of PSNR versus size of mammogram images. Three methods, namely ECSODCNC and existing BFO-CNN [1] and TransYOLO-GJO [2] are utilized to evaluate peak signal to noise ratio. The x axis is the size of input image, while the y axis represents PSNR. Results of ECSODCNC model achieve higher PSNR and minimal MSE compared to other two existing methods. To achieve this improved performance, ECSODCNC model utilizes Hamann indexive variation denoising method. Image preprocessing is performed to improve the image quality by extract the noisy pixels. This helps to enhance PSNR by minimize error. PSNR is enhanced using ECSODCNC by 11% and 8% compared to [1] and [2].

Table 4 Intersection over Union

Number of mammogram images	Intersection over Union (%)		
	Proposed ECSODCNC	Existing BFO-CNN [1]	Existing TransYOLO-GJO [2]
1000	96.62	91.25	93.37
2000	96.58	91.24	93.32
3000	96.61	91.36	93.25
4000	96.55	91.56	93.65
5000	96.41	91.44	93.41
6000	96.36	91.34	93.63
7000	96.74	91.63	93.55
8000	96.63	91.05	93.44
9000	96.42	91.63	93.28
10000	96.23	91.55	93.12

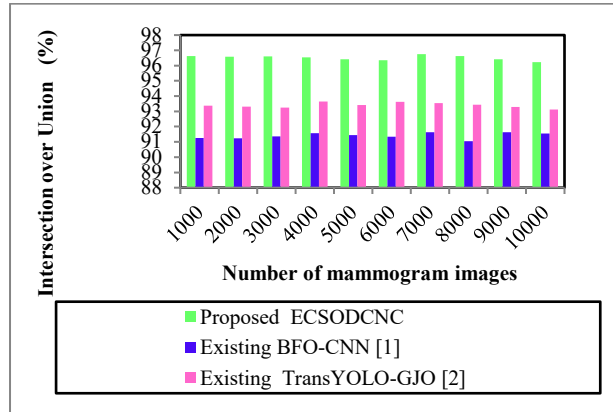


Figure 6 Performance analysis of Intersection over Union

Table 4 and Figure 6 illustrate a performance analysis of IoU regarding the number of mammogram images, ranging from 1000 to 10000. The assessment entails three deep learning methods namely proposed ECSODCNC and conventional BFO-CNN [1] and TransYOLO-GJO [2]. In the graph, the x-axis represents the number of mammogram images, while the y-axis illustrates the corresponding IoU values for each deep learning method. The results evidently reveal that the ECSODCNC model consistently attains superior IoU scores when compared to the other two approaches. For example, when considering with 1000 images, ECSODCNC model attained an IoU of 96.62%, outperforming [1] and [2], which recorded IoU values of 91.25% and 93.37% respectively. Across multiple ten experiments and varying number of sizes, ECSODCNC model consistently outperformed the other two existing methods, showing an average improvement of 6% and 3% in IoU compared to [1] and [2] respectively. This enhanced performance is mainly attained due to the integration of the canonical concordance correlation within the ECSODCNC model. Furthermore, applying robust classification, thus improving IoU performance.

Table 5 Breast cancer detection accuracy

Number of mammogram images	Breast cancer detection accuracy (%)		
	Proposed ECSODCNC	Existing BFO-CNN [1]	Existing TransYOLO-GJO [2]
1000	97	92	94
2000	97.23	92.52	94.63
3000	97.52	92.63	94.55
4000	97.63	92.41	94.75
5000	97.52	92.66	94.32
6000	97.45	92.44	94.42
7000	96.88	92.32	94.26
8000	97.56	92.32	94.41
9000	97.11	92.05	94.36
10000	97.08	92.32	94.74

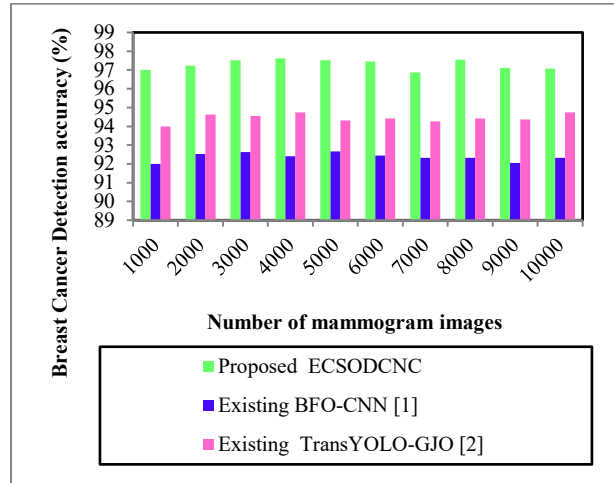


Figure 7 Performance analysis of Breast cancer detection accuracy

Table 5 and Figure 7 demonstrate breast cancer detection accuracy using three methods. As depicted in Figure 7, the horizontal axis represents number of mammogram images, while the vertical axis specified as results of accuracy. For considering 1000 images for accuracy calculation, the ECSODCNC, existing models [1] and [2] achieved an accuracy of 97%, 92% and 94%. Contrary to existing methods, performance of ECSODCNC of accuracy is improved. This improvement is achieved due to application of CNN where Canonical Concordance Correlation is applied for measuring the similarity between the extracted features from the ROI and ground truth features in fully connected layer. Normal, benign and malignant images classified. In addition, Enhanced Crow Search Optimization (ECSO) is employed for the fine-tuning process to optimize hyperparameters and improve prediction performance. Accuracy of the ECSODCNC model improved considerably by 5% and 3% compared to [1] and [2].

Table 6 Sensitivity

Number of mammogram images	Sensitivity (%)		
	Proposed ECSODCNC	Existing BFO-CNN [1]	Existing TransYOLO-GJO [2]
1000	98.85	96.53	97.68
2000	98.75	96.22	97.65
3000	98.52	96.05	97.05
4000	98.63	96.11	97.21
5000	98.77	96.41	97.18
6000	98.63	96.32	97.32
7000	98.41	96.05	97.25
8000	98.32	96.41	97.12
9000	98.05	96.21	97.08
10000	98.33	96.32	97.06

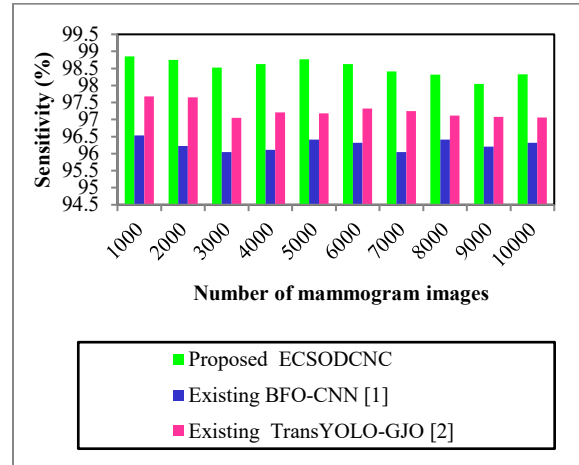


Figure 8 Performance analysis of Sensitivity

Table 6 and Figure 8 show sensitivity. Results of ECSODCNC achieved improved sensitivity performance compared to the other two existing techniques. By considering 1000 images, the recall achieved by the ECSODCNC, [1] and [2] was found to be 97.7%, 95.4% and 96.53%. This improved performance is achieved by ECSO to update weights, minimize error rate in multi-class classification results with better TP and minimal FN. ECSODCNC of sensitivity enhanced by 2% and 1% than [1], [2].

Table 7 Breast cancer detection time

Number of mammogram images	Breast cancer detection time (sec)		
	Proposed ECSODCNC	Existing BFO-CNN [1]	Existing TransYOLO-GJO [2]
1000	63	86	74
2000	68.3	89.6	78.3
3000	72.2	92.5	85.6
4000	75.8	95.7	88.6
5000	80.3	98.4	92.4
6000	83.5	105.2	96.3
7000	88.4	109.6	101.4
8000	92.2	120.3	112.2
9000	96.3	125.3	118.5
10000	102.4	130.6	123.2

Table 7 and Figure 9 illustrate breast cancer detection time. However, the ECSODCNC model minimizes time compared to existing techniques. For the experiment with 1000 images, the time consumption for breast cancer detection using ECSODCNC, existing [1] and [2] was found to be 63ms, 86ms and 74ms. This improvement is achieved through automatic ROI segmentation and feature extraction. ECSODCNC model utilizes Moore proximity and simple matching-based segmentation. From the ROI, various features are extracted to enable accurate breast cancer detection, thereby minimizing time.

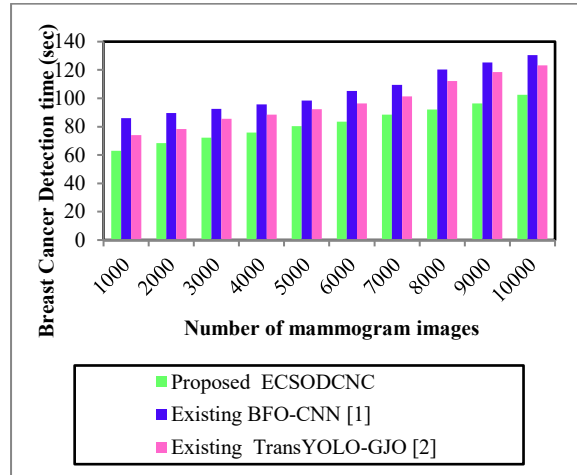


Figure 9 Performance analysis of Breast cancer detection time

Results of breast cancer detection time of the ECSODCNC model is minimized by 22% and 15% compared to [1] and [2].

5.3 Performance analysis of ROC and AUC

In order to estimate the predictive performance of breast cancer detection, researchers utilize Receiver Operating Characteristic (ROC) analysis. This evaluation method plots the True Positive Rate (Sensitivity) against the False Positive Rate (1 – Specificity) at diverse threshold values to calculate the classification performance of the model. Area under the ROC Curve (AUC) is evaluated for classification. Higher AUC scores indicate a more precise, robust, and reliable detection model.

Table 8 RoC-AUC Curve comparison for breast cancer detection

False positive rate or 1-specificity	True positive rate or Sensitivity		
	Proposed ECSODCNC	Existing BFO-CNN [1]	Existing TransYOLO-GJO [2]
0	0	0	0
0.1	0.552	0.325	0.413
0.2	0.643	0.466	0.537
0.3	0.718	0.575	0.625
0.4	0.789	0.658	0.726
0.5	0.882	0.734	0.789
0.6	0.925	0.801	0.861
0.7	0.956	0.885	0.927
0.8	0.967	0.904	0.938
0.9	0.973	0.913	0.942
1	0.987	0.925	0.951

Table 8 and Figure 10 present relative performance outcomes of ROC and AUC for five approaches namely ECSODCNC and existing parallel BFO-CNN [1] and Trans YOLO-GJO [2] using a dataset comprising 1000 images. As exposed in the figure, the proposed ECSODCNC consistently achieves higher TPR values compared to both [1] and [2].

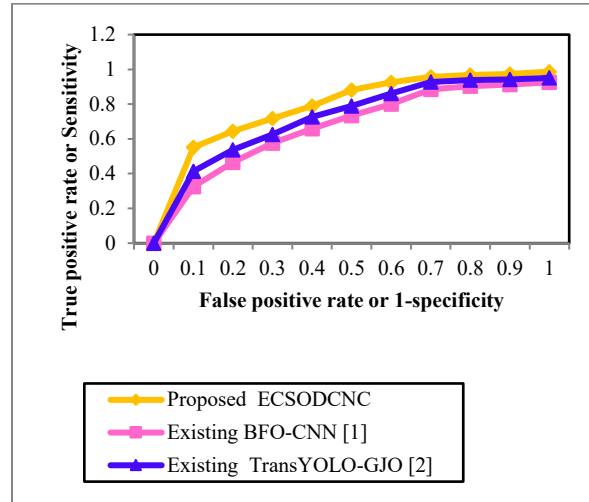


Figure 10 graphical chart of RoC-AUC Curve

The diagonal dashed line in the graph represents the baseline for reference. The calculated AUC values are 0.790 for the proposed ECSODCNC, 0.546 for [1] and 0.723 for [2]. Although all three models demonstrate a reasonable level of classification ability, the proposed ECSODCNC attains the highest AUC score, indicating superior discriminative performance in breast cancer detection over the existing methods.

Ablation Analysis

To investigate the contribution of the individual components of ECSODCNC, an ablation study should be conducted. The complete framework should be compared with progressively simplified configurations by removing one major component at a time.

Model/ Merits	PSN R	Accur acy	Sensit ivity	Io U	Detec tion time
CNN only	66	97	95	94	101
CNN + Hamann denoising		97.34	96.7	94. 8	117
CNN + Hamann + Moore segmenta tion	67.5	98	97.10	95. 6	119
CNN + Hamann + Moore + feature analysis	69.6 8	98.5	97.82	96. 2	124
Full ECSODC NC + ECSO	79.7 2	98.9	98	97	129

The ablation results should be used to determine whether each component provides a measurable contribution to the overall framework. In particular, the comparison between the CNN-only configuration and the complete ECSODCNC model can demonstrate the combined effect of preprocessing, ROI segmentation, feature analysis, and ECSO-based fine-tuning

6. Conclusion

The proposed ECSODCNC model designed for breast cancer detection using mammogram images. It performs the image denoising to enhance the image quality with higher peak signal to noise ratio. Followed by, Moore proximity and simple matching-based segmentation is performed to reduce the time consumption of cancer detection. The proposed ECSODCNC model extracts the feature and analyzes the training and testing feature vector using canonical concordance correlation. This process helps to develop the accuracy of the cancer detection. The fine tuning process minimizes the error rate of cancer detection with aid of ECSO in multi-class classification results. A thorough performance assessment is conducted using numerous key metrics, including PSNR, accuracy, sensitivity, IoU, and detection time across a range of mammogram images samples. The experimental assessment demonstrates that the proposed ECSODCNC model achieves superior classification performance by improving overall accuracy by 97% while considerably decreasing detection time by 47ms compared with conventional deep learning methods.

Conflict of Interest

The authors declare that they have no conflict of interest.

Funding Statement

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Data Availability Statement

CBIS-DDSM:Breast Cancer Image Dataset is available within the article.

The dataset was gathered from <https://www.kaggle.com/datasets/awsaf49/cbis-ddsm-breast-cancer-image-dataset>

References

- [1] D. Banumathy, D. Karthikeyan, G. Mohanraj & R. Sarathkumar, "Deep learning-based bacterial foraging optimization algorithm to improve digital mammography-based breast cancer detection", Scientific Reports, Springer, Volume 15, 2025, Pages 1-18. DOI:10.1038/s41598-025-97301-y
- [2] Ahed Abugabah, Prashant Kumar Shukla, Piyush Kumar Shukla & Abhishek Dwivedi, "Enhancing breast cancer detection in mammographic imaging using explainable clinical decision support system and framework", Discover Artificial Intelligence, Springer, 2026, Pages 1-28. <https://doi.org/10.1007/s44163-025-00681-3>
- [3] S. Manimurugan, P. Karthikeyan, MajedAborokbah, C. Narmatha, SubramaniamGanesan, "Breast cancer diagnosis model using stacked autoencoder with particle swarm optimization", Ain Shams Engineering Journal, Elsevier, Volume 15, Issue 6, 2024, Pages 1-12. <https://doi.org/10.1016/j.asej.2024.102734>
- [4] Hameedur Rahman, Tanvir Fatima NaikBukht, Rozilawati Ahmad, Ahmad Almadhor, and Abdul RehmanJaved, "Efficient Breast Cancer Diagnosis from Complex Mammographic Images Using Deep Convolutional Neural Network", Computational Intelligence and Neuroscience, Hindawi, Volume 2023, March 2023, Pages 1-11. <https://doi.org/10.1155/2023/7717712>
- [5] Samaneh Rashedi, Amir Rashedi, Bentolhoda, Otroshi Shahreza, Maryam Tabatabaeian, Iraj Abedi, "Multimodal deep learning frameworks for breast cancer detection using ultrasound, mammography, and clinical data", Informatics in Medicine Unlocked, Elsevier, Volume 63, 2026, Pages 1-13. <https://doi.org/10.1016/j.imu.2026.101761>
- [6] Ahed Abugabah, "A deep learning framework for automated breast cancer diagnosis using intelligent segmentation and classification", Healthcare Analytics, Elsevier, Volume 8, 2025, Pages 1-13. <https://doi.org/10.1016/j.health.2025.100414>
- [7] Dr. G. Jothi, Dr. S. Nivetha, Dr. H Hannah Inbarani, "AI-Driven Decision Support System for Early Breast Cancer Detection", International Journal on Science and Technology (IJSAT), Volume 17, Issue 2, 2026, Pages 1-11.
- [8] Divyakant T. Meva, Kalpesh Popat, Hirenkumar Kukadiya& Nikisha Jariwala, "Deep learning-based breast cancer detection with customized ensemble attention", Scientific Reports, Springer, Volume 16, Issue 1, 2026, Pages 1-16. doi: 10.1038/s41598-026-50563-6

- [9] Muhammad Yaqub, Feng Jinchao, NazishAijaz, Shahzad Ahmed, AtifMehmood, Hao Jiang & Lan He, "Intelligent breast cancer diagnosis with two-stage using mammogram images", Scientific Reports, Volume 14, 2024, Pages 1-17.<https://doi.org/10.1038/s41598-024-65926-0>
- [10] Dilawar Shah, Mohammad AsmatUllah Khan, and Mohammad Abrar, "Reliable Breast Cancer Diagnosis with Deep Learning: DCGANDriven Mammogram Synthesis and Validity Assessment", Applied Computational Intelligence and Soft Computing, Hindawi, Volume 2024, Issue 1, February 2024, Pages 1-13. <https://doi.org/10.1155/2024/1122109>
- [11] Muhammad Anas, IhtishamUlHaq, GhassanHusnain, Syed Ali FarazJaffery, "Advancing Breast Cancer Detection: Enhancing YOLOv5 Network for Accurate Classification in Mammogram Images", IEEE Access, Volume 12, 2024, Pages 16474 – 16488. DOI: 10.1109/ACCESS.2024.3358686
- [12] Zhaoqi Liu, Jidong Peng, XiumeiGuo, Shaoqiong Chen, Liansheng Liu, "Breast cancer classification method based on improved VGG16 using mammography images", Journal of Radiation Research and Applied Sciences, Elsevier, Volume 17, Issue 2, 2024, Pages 1-6. <https://doi.org/10.1016/j.jrras.2024.100885>
- [13] Jawad Ahmad, SheerazAkram, ArfanJaffar, Zulfiqar Ali, Sohail, Masood Bhatti, Awais Ahmad, Shafiq Ur Rehman, "Deep learning empowered breast cancerdiagnosis: Advancements in detection andclassification", PLoS ONE, Volume 19, Issue 7, 2024, Pages 1-24. <https://doi.org/10.1371/journal.pone.0304757>
- [14] S. Vijayalakshmi, Binay Kumar Pandey, Digvijay Pandey & Mesfin Esayas Lelisho, "Innovative deep learning classifiers for breast cancer detection through hybrid feature extraction techniques", Scientific Reports, Springer, Volume 15, Issue 1, 2025, Pages 1-16. DOI: 10.1038/s41598-025-06669-4
- [15] M. Pradeepa, B. Sharmila & M. Nirmala, "A hybrid deep learning model EfficientNet with GRU for breast cancer detection from histopathology images", Scientific Reports, Springer, Volume 15, Issue 1, 2025, Pages 1-24. DOI: 10.1038/s41598-025-00930-6
- [16] Amira J. Zaylaa, Lama N. Yassine and Silva Kourtian, "A Multi-Criterion Selection of Hybrid Features in Mammographic Imaging for Early Computer-Assisted Sensing and Detection of Breast Cancer", Sensors, MDPI, Volume 26, Issue 12, 2026, Pages 1- 12 3874. <https://doi.org/10.3390/s26123874>
- [17] Ahmed Kateb Jumaah Al-Nussairi, Saleem Malik, Yasser Taha Alzubaidi, S Gopal Krishna Patro, Kasim Sakran Abass, Iman Basheti, Mohammad Khishe , "TransFusion-BCNet: A transformer-driven multi-modal fusion and explainable deep learning framework for breast cancer diagnosis", Intelligence-Based Medicine, Elsevier, Volume 13, 2026, Pages 1-26. <https://doi.org/10.1016/j.ibmed.2026.100346>
- [18] Long Jun Yan, Lei Wu, Meng Xia, Lan He, "A hybrid deep learning model for mammographic breast cancer detection: Multi-autoencoder and attention mechanisms", Journal of Radiation Research and Applied Sciences, Elsevier, Volume 18, Issue 3, 2026, Pages 1-17. <https://doi.org/10.1016/j.jrras.2025.101578>
- [19] Mahesh T R, Arastu Thakur, Muskan Gupta, Deepak Kumar Sinha, KritikaKumari Mishra, Vinoth Kumar Venkatesan& Suresh Guluwadi, "Transformative Breast Cancer Diagnosis using CNNs with Optimized ReduceLRonPlateau and Early Stopping Enhancements", International Journal of Computational Intelligence Systems, Springer, Volume 17, 2024, pages 1-18. <https://doi.org/10.1007/s44196-023-00397-1>
- [20] Rengarajan Karthiga, Kumaravelu Narasimhan, Ravikumar Chinthaginjala, Rajesh Anbazhagan, Manikandan Chinnusamy, Giovanni Pau, Kumar Satish, Rengarajan Amirtharajan, Mohamed Abbas, "A novel exploratory hybrid deep neural network to predict breast cancer for mammography based on wavelet features", Multimedia Tools and Applications, Springer, Volume 83, 2024, Pages 65441–65467. <https://doi.org/10.1007/s11042-023-18012-y>
- [21] Tareg M. Al Mansour, Mohammed Sallah, Roxana Rusu-Both, Ghada A. Khouqeer, Tamer Medhat, Ahmed Elgarayhi, Elmetwally M. Abdelrazek, "Enhanced detection of female breast cancer from digital mammography employing transfer deep learning neural networks", Journal of Radiation Research and Applied Sciences, Elsevier, Volume 18, Issue 2, 2025, Pages 1-13.<https://doi.org/10.1016/j.jrras.2025.101392>
- [22] S. R. SannasiChakravarthy, N. Bharanidharan, V. VinothKumar, T. R. Mahesh, Mohammed S. Alqahtani and Suresh Guluwadi, "Deep transfer learning with fuzzy ensemble approach for the early detection

- of breast cancer”, BMC Medical Imaging, Springer, Volume 24, 2024, Pages 1-15. <https://doi.org/10.1186/s12880-024-01267-8>
- [23] Khadija Aguerchi, Younes Jabrane, Maryam Habba and Amir Hajjam El Hassani, “A CNN Hyperparameters Optimization Based on Particle Swarm Optimization for Mammography Breast Cancer Classification”, journal of Imaging, Volume 10, Issue 2, 2024, Pages 1-17. <https://doi.org/10.3390/jimaging10020030>
- [24] Sannasi Chakravarthy, Bharanidharan Nagarajan, V. Vinoth Kumar, T. R. Mahesh, R. Sivakami & Jonnakuti Rajkumar Annand, “Breast Tumor Classification with Enhanced Transfer Learning Features and Selection Using Chaotic Map-Based Optimization”, International Journal of Computational Intelligence Systems, Springer, Volume 17, 2024, Pages 1-18. <https://doi.org/10.1007/s44196-024-00409-8>
- [25] Abdullah G. M. Al Mansour, Faisal Alshomrani, Abdullah Alfahaid and Abdulaziz T. M. Almutairi, “MammoViT: A Custom Vision Transformer Architecture for Accurate BIRADS Classification in Mammogram Analysis”, Diagnostics, MDPI, 2025, Volume 15, Issue 3, Pages 120. 285; <https://doi.org/10.3390/diagnostics15030285>
- [26] Eleonora Lopez, Filippo Betello, Federico Carmignani, Eleonora Grassucci, Danilo Comminiello, “Attention-map augmentation for hypercomplex breast cancer classification”, Pattern Recognition Letters, Elsevier, Volume 182, 2024, Pages 140-146. <https://doi.org/10.1016/j.patrec.2024.04.014>
- [27] Sannasi Chakravarthy, N. Bharanidharan, Surbhi Bhatia Khan, V. Vinoth Kumar, T. R. Mahesh, Ahlam Almusharraf & Eid Albalawi, “Multi-class Breast Cancer Classification Using CNN Features Hybridization”, International Journal of Computational Intelligence Systems, Springer, Volume 17, 2024, Pages 1-19. <https://doi.org/10.1007/s44196-024-00593-7>
- [28] Preethi Veerlapalli & Sushama Rani Dutta, “A hybrid GAN-based deep learning framework for thermogram-based breast cancer detection”, Scientific Reports, Springer, Volume 15, Issue 1, 2025, Pages 1-33. DOI: 10.1038/s41598-025-04676-z
- [29] Anum Shaukat, Saima Farhan, Rabia Javed, Salma Idris, Faten S. Alamri, Anees Ara & Tanzila Saba, “HyFusion-X: hybrid deep and traditional feature fusion with ensemble classifiers for breast cancer detection using mammogram and ultrasound images”, Scientific Reports, Springer, Volume 15, Issue 1, 2025, Pages 1-29. DOI: 10.1038/s41598-025-22262-1
- [30] Dilawar Shah, Mohammad Asmat Ullah Khan, Mohammad Abrar, Farhan Amin, Bader Fahad Alkhamees and Hussain Als Salman, “Enhancing the Quality and Authenticity of Synthetic Mammogram Images for Improved Breast Cancer Detection”, IEEE Access, Volume 12, 2024, Pages 12189 – 12198. DOI: 10.1109/ACCESS.2024.3354826