Streamlined Breast Cancer Identification: Self-attention CNN with Momentum Search Optimization

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Abstract. Abnormal discontinuities in the connective tissue cells of the female's feeding ducts are indicative of breast cancer. When indications of breast cancer appear in the milk ducts, a significant number of women passed away from the disease. The death rates may drop when the determination is detected earlier. It takes a lot of time for oncologists and radiologists to manually analyze mammogram pictures for breast cancer. To avoid tedious analysis and streamline the classification process, our research work proposed hybrid deep learning based Conv Neural Network with Momentum Search Optimization Approach for classifying tumors and non-tumors in mammogram images. Themammography pictures undergone image preprocessing using seam carving approach comprises phases of masking, cropping, rotating, and flipping. Following the pooling and fattening layer, the characteristics were gathered individually during the initial classification step. Additionally, the characteristics are supplied as input to the fully connected layer of the proposed CNN-MSOA model. Our experimental outcomes demonstrate that hybrid CNN-MSOA model attained 99.13% accuracy using CBIS DDSM dataset. Moreover various metrics were evaluated as mentioned in experimental part which predicts the performance of model in breast cancer diagnosis. We show the benefits of our proposed algorithm over the state-of-the-art approaches, especially in terms of accuracy, Precision, recall, F score and ROC AUC score.

Keywords: Momentum Search Optimization Algorithm (MSOA) · Stochastic Gradient Descend (SGD) · Deep Convolutional Neural Network (DCNN) · Mammogram images · Breast Cancer (BC)

1 Introduction

Among worldwide leading causes of women's death is cancer disease. Globally, BCkind of cancer makes prevalent growth among femaleNaresh et al. [1]. The effectiveness of cancer treatment greatly depends on early diagnosis. Consequently, imaging methods have been created to improve the likelihood of detecting breast cancer early on. Breast cancer is diagnosed using a variety of imaging techniques, such as mammography, ultrasound, and magnetic resonance imaging (MRI) Aiman et al. [2].

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Among these techniques, mammography, the viewing trial for diagnosing BC that is comparatively cheap, easy to use, quick, and popular because it can detect even minute changes in the breast that are not visible through manual examination thanks to the images it produces using machine and deep learning techniques. Hence the authors had chosen mammogram images for early diagnosis of Breast cancer in precise manner. Furthermore, based on graph-based clustering algorithms, machine learning techniques may enhance the evaluation of multiple-view radiological pictures Nomani et al. [3]. The interpretation of diagnostic imaging investigations has been completely transformed over the past decade by conventional techniques as machine cum deep learning sweta et al. [4]. One of the most important networks in deep based domain especially Convolutional Neural Network (CNN). Kaushal et al. [5] used Computer-Assisted diagnostic (CAD) systems on hispathological images based on extracting features including texture and dimensions. Authors of Saad Alanazi et al. [6] that use convolutional neural networks (CNN) provide faster, more robust and reliable screening than previous methods. CNNs have been a popular technique in image analysis for pattern recognition.

1.1 Problem Statement

Breast cancer is the second greatest cause of death among women around the world. Early identification through routine mammograms is the most effective way to improve breast cancer outcomes. In this study, we used two separate mammography datasets of varying sizes and created multiple neural network models to classify tumors vs. no tumors in mammogram pictures. Manually analyzing these photographs might be continuous as well asbiased. Our proposed model is intended to be used as an additional detection tool by radiologists and oncologists. This study focused on the following objectives:

- Current research work implemented mammogram images to diagnose breast lesions with deep based network framework thereby reached maximum accuracy in predicting disease diagnosis.
- To diagnose lesions, mammogram metadata are utilized here.
- To preprocess mammogram images, we applied Seam Carving algorithm enhances the resolution of images further increases in accuracy rate.
- Proposed DCNN classification model attained hopeful analysis performance with 90.56% accuracy for CBISDDSM dataset moreover combination of CNN and Momentum Search Optimization approach attained 99.13% for better optimal solution in breast cancer prediction.
- The outcomes surpass the approaches used as a benchmark.

2 Introduction

Initially the researchers found that thermography technique help to diagnose breast cancer disease. Various advanced techniques were applied for early diagnosis of breast cancer by Lakshmi Priya et al. [7]. In some investigation the radiologists detect cyst or lump or lesions on thermography images physically therefore inaccurate diagnosis as well as time-consuming. Features like texture are extracted from spatial domain on Rotational Breast Thermography fed into Support vector machine for further classification Sheeja et al. [8]. Such thermography was discontinued in medical treatment in 1978 due to low sensitivity.

Hence several articles were surveyed on mammogram, ultrasound images for breast cancer diagnosis based on segmentation, Computer Aided detection, and classification of tumor, non-tumor using machine and deep learning techniques. Especially CNN plays an important role in diagnosing breast cancer disease earlier. Some of the pre-trained models of CNN namely AlexNet model was used Titoriya et al. [9] and ResNet-50 model introduced by Qasem Abu Al-Haija et al. [10] for train 7909 histopathology images and BreakHis dataset, Rajkumar Pattanaik et al. [11] applied DenseNet121 + ELM model for breast cancer disease classification on mammogram images with 159.77 min, EfficientNet model developed where compound scaling involved to append more layers to extract the features from cancer images, applied multi-fractal dimension method.

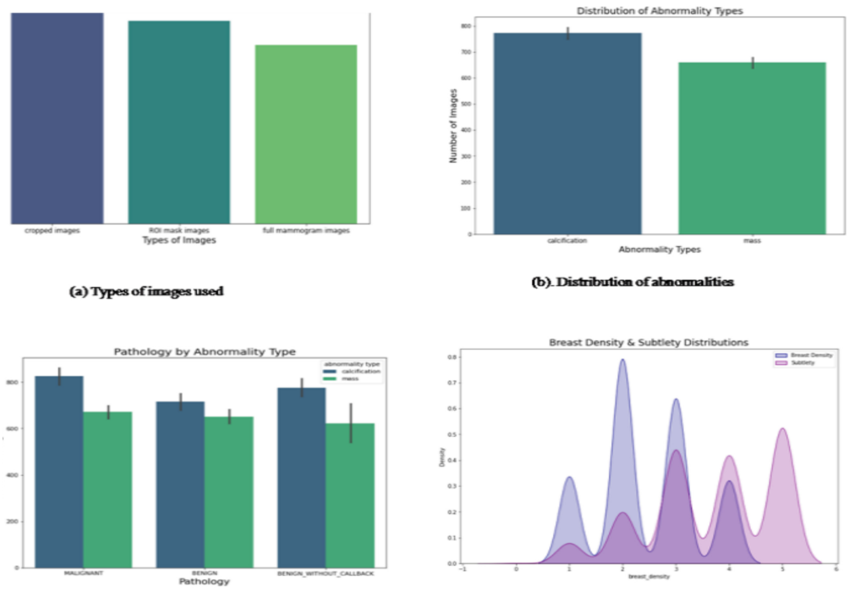
3 Research Methodology

In this section, the authors discussed overall workflow implemented for disease diagnosis with two-class categorization as class 0 (No tumor) and class 1 (Tumor). Furthermore, images are pre-processed in which seam carving algorithm used, features are extracted, images are trained using various CNN models with SGD and Adam optimizers, deep CNN and CNN-MSOA model, such models are validated during validation phase for BC disease diagnosis. Finally, evaluation has done among proposed algorithms based on performance metrics by that way model performance also evaluated.

3.1 Dataset Description

Mammogram images have gathered from open source kaggle dataset. The link for dataset used in this research work is https://www.kaggle.com/skooch/ddsm-mammography. The images were pre-processed and converted to 299 x 299 pixels through extorting the Regions of Interest and were stored as tfrecords files for TensorFlow in a Kaggle Challenge. 55,890 training scenarios total from 5 tfrecords entries contained within the dataset; 14% BC positive while another 86% Negative. In order to offer information, the positive (CBISDDSM) images used in Parita et al. [13] had their ROIs eliminated via filters and a tiny bit of padding. The photos were then enlarged to 299x299 after each ROI was arbitrarily cropped repeatedly into 598x598 images comprising randomized flips and rotations. Figure 1 (a) plots the statistical distribution of the various photos that were used, including the cropped, ROI mask, and full mammography images. Moreover, the distribution abnormalities of mass and calcification images are plotted in Fig. 1 (b) thereby accurate diagnosis can be aided by knowing its features and consequences.

The pathology of images are performed to detect whether the images are benign considered as Class 0 (No Tumor), malignant denoted as Class 1 (Tumor) and Benign without callback are shown as Fig. 1 (c). Such multi-class labels are Class 0 if BC not found, Class 1 if benign calcification, Class 2 benign mass, Class 3 malignant calcification and Class 4 malignant mass. To predict the ratio of glandular and fibrous tissue to fatty tissue in the breast, density of breast feature was analyzed. Additionally, "subtlety distribution" describes the range of challenges associated with identifying and interpreting anomalies in breast imaging shown in Fig. 1 (d).



(a) Types of images used

(b). Distribution of abnormalities

(c) Pathological representation on images

(d) Histogram on breast density and Subtlety

Fig. 1. Representation of mammogram image dataset

3.2 DDSM Data Preprocessing

In several image processing applications, scaling images is a standard technique. In order to achieve a specific size, the image is uniformly resized. Image retargeting aims to resize an image while preserving its key characteristics that can be identified either upward or bottom-up has increased prominently nowadays. In this regard, BC images are resized using seam carving method while maintaining crucial information as calcification and mass producing visually appealing downsized images. The author utilized python programming language for uploading BC images which are resized with easiness indicating flexibility and effectiveness of seam carving in processing images. We propose an automatic seam carving algorithm where masking, cropping, rotating and flipping the images for image enlarging to replace the manual method leads to more time-consuming in prediction.

Data pre-processing techniques like masking, cropping, and rotation that help increase the precision and effectiveness of image interpretation in the identification of breast cancer. These procedures are frequently used to improve the identification and characterization of breast lesions in mammogram images. The seam carving method comprises three phases namely a) Masking b) Cropping c) Rotation and flipping Masking refers the process of using a binary mask to isolate particular areas of interest (ROI) within breast mammogram image. This procedure reduces noise and enhances the clarity of the region under investigation by helping to focus on certain areas while discarding unimportant aspects. Figure 2 depicts the identification of lesion in mammogram image such particular area marked with red color square box.

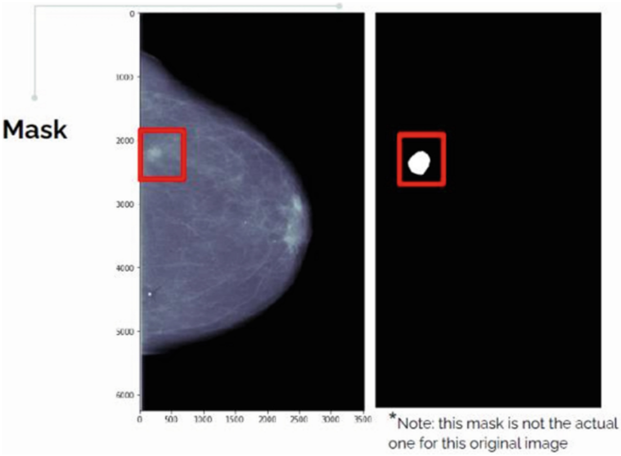


Fig. 2. Identification of lesion in mammogram

Cropping is the technique of reducing the size of the image by deleting any irrelevant portions and keeping only the area of interest. In this work, each Region of Interest was randomly cropped 3 times into 598x598. By reducing the size of theimage, this technique improves concentration on the area of interest and increases the efficiency of processing and storage. Figure 3 shows the chosen Region of Interest where lesion is found. which is detected as tumor.

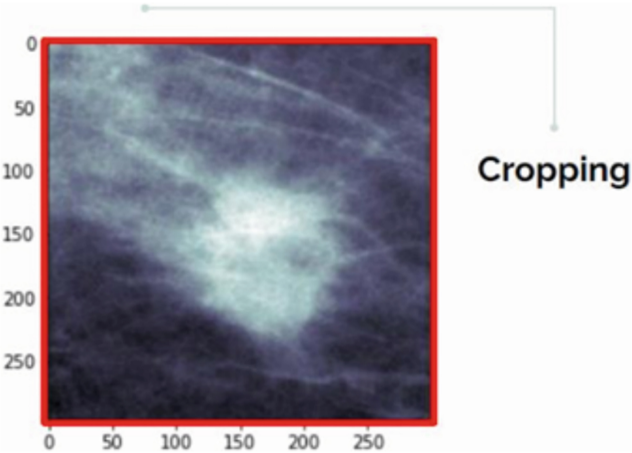


Fig. 3. Lesion ROI marked via cropping

In rotation and flipping phase, the perspective of calcifications modified to produce typical perspectives that may be sent via automated systems, used for long-term comparison, and reliable diagnosis. Images were then randomly flipped and rotated hence images were resized down to 299 × 299. Rotation of images appropriate in enhance the visual of certain features, such as angle of calcified tissue. The representation of rotating and flipping of breast images indicates how the images are resized to focus on certain feature which predicts the angle of tumor shown in Fig. 4. Consequently, we applied deep learning CNN which train the images using several layers to evaluate images correctly.

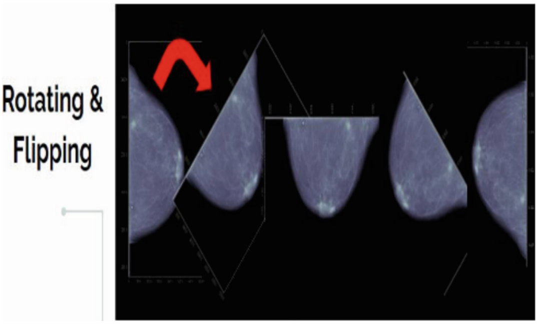


Fig. 4. Representation of rotation and flipping

Starting with the original breast cancer image's seam carving functioning, our optimal image resizing algorithm is applied. We immediately scale the current image to the required size when every seam is eliminated, then calculate the approximate distance to the original image. The outcome that remains is the scaled image that has the smallest distance. When the output resolution is significantly lower than the input resolution, combining seam cutting with scaling can preserve the original image's overall visual impression along with its features. By maximizing the image distance function, the enlarged image's excellence is guaranteed.

3.3 Feature Extraction Phase

Feature extraction is a critical component of image processing because it allows quantitative data (features) within healthcare images that are not visible through perception to be extracted using the right statistical algorithms. Various aspects, including statistical, textural, appearance, and form features, can be retrieved from the photos for this purpose. The present investigation involved the extraction of Matrix co-occurrence along with run length features from every ROI sample. These features are commonly employed in texture analysis.

4 Proposed Architecture

In order to extract the features for each model, we bypass the final fully connected (FC) layer and extract the features from the last layer before it because the final FC layer's output has already been trained for 1000 classes of the CBIS-DDSM dataset. Table 2 shows the number of features extracted for each CNN model utilized in this paper, as well as the layer that comes before the final FC layer. The workflow of our proposed architecture is depicted in Fig. 5.

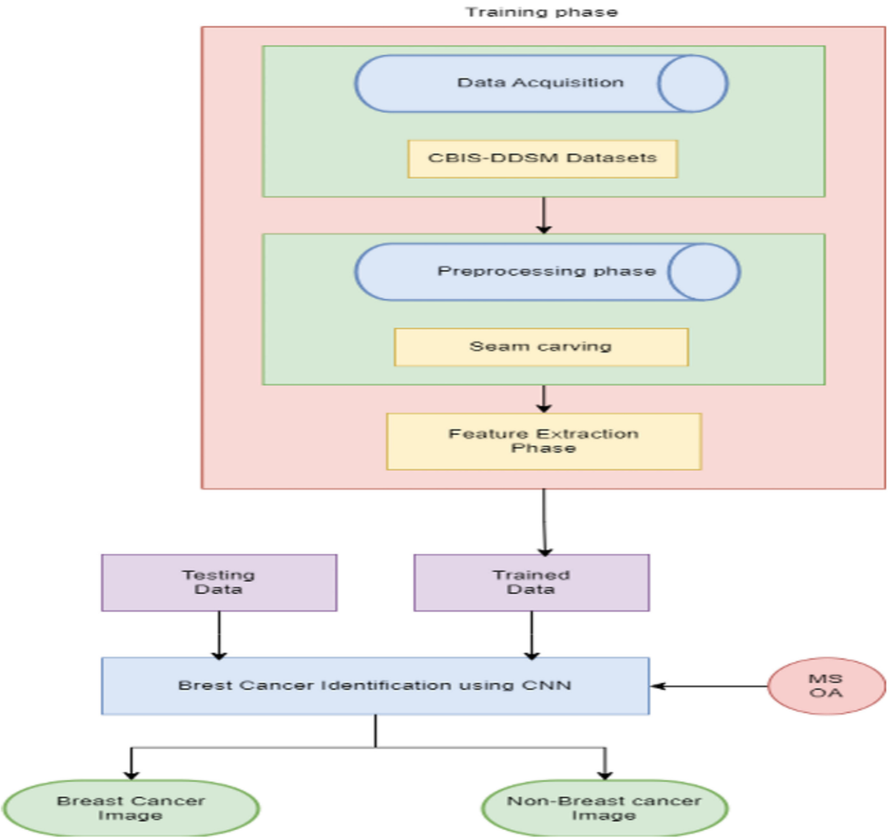


Fig. 5. Framework for proposed BC detection

5 Training the Model

The initial step for training process is to define the model, after which the Fit Generator method is used. Several batches are within the dataset. Each batch comprises one or more data components. The total number of training elements in a given batch is indicated by the batch size. To determine the best outcomes, an optimization algorithm iterates the training instances a set number of times. The optimization algorithms employed in this investigation are Adam optimizer and Momentum Search Optimization algorithm. Algorithms for optimization perform both forward and backward. A specific one that run across the entire Breast Cancer dataset is called an epoch.

6 Breast Cancer Detection with Hybrid Model

We propose hybrid model comprises CNN along with MSOA (momentum search optimization algorithm) optimizes the criteria for cancer diagnosis by generating a randomly distributed population. Algorithm for MSOA shown as below:

Algorithm1:
Start MSOA
INPUT: $\mathrm{N, n, T, X_{min}, X_{max}}$
Initialize MSOA population $\mathrm{x_i (i = 1,2,3, \ldots . n)}$
For iteration 1:T
Compute the fitness function of each search agent
Update Best (t) and worst (t)

$$\mathrm{Best}(t) = \min_{\mathrm{i=}} = 1,2,..\mathrm{m}$$

$$\mathrm{mit}_i(t) \qquad \mathrm{fit}_{\,i}(t).$$

$$\mathrm{Worst}(t) = \max_{\mathrm{i=}} = 1,2,\ldots\mathrm{m}$$

Evaluate the mass for all bodies

$$m_i(t) = \frac{\mathrm{fit}_{\,i}(t) - \mathrm{worst}\ (t)}{\mathrm{best}\ (t) - \mathrm{worst}\ (t)}$$

Update Momentum M
Calculate Mass for all bodies $m_i^{(d)}(t)$
Compute best and worst body using $B_i^{(d)}(t)$ and

$$W_i^{(d)}(t)$$

Update the mass with speed for external bodies
Compute image new position ($\mathrm{X_{min}, X_{max}}$) following collisions so as to maximize the weight parameter.
Accumulate the best solution
END iteration
OUTPUT: Return the best fitness value
END MSOA

7 Model Evaluation

We propose hybrid model comprises CNN along with MSOA (momentum search optimization algorithm) optimizes the criteria for cancer diagnosis by generating a randomly distributed population. Algorithm for MSOA shown as below:

Model evaluation has done through metrics which are evaluated based on True Positive, False Positive, True Negative and False Negative.

Accuracy-Accuracy is defined as correctly identified image samples from total number of images in dataset.

In another way, accuracy identify correct prediction that model has achieved from the total predictions using Eq. (1).

$$\text{Accuracy} = \frac{\text{Number of Correct prediciton}}{\text{Total mammogram images}} \quad (1)$$

Cross Entropy (Loss)-Loss function measurements indicate how effectively the network is functioning as expected. The definition of the cross-entropy (CE) loss or log-loss is the classifier's accuracy indicator using Eq. (2).

$$\text{Cross Entropy} = -\sum_{i}^{n} a_i \log p_i \quad (2)$$

Here, ai indicates the actual value whereas pi represents the predicted value; n represents number of classes in images namely Class 0 and Class 1.

8 Experimental Outcomes

The comparison among various models such as CNN1, CNN2, deep CNN and integration of both CNN with Momentum Search optimization approach using CBIS-DDSM dataset presented. Among those models, CNN with MSOA frequently scores better in terms of F1-Score, ROC AUC score, precision, recall, and accuracy. Its architecture, which enables it to gather pertinent information and make precise predictions on CBIS-DDSM dataset, is responsible for its outstanding outcome. Amongst various models, CNN with MSOA approach turns out to be the most successful option for correctly categorizing healthcare images in breast cancer dataset. The images are trained via Conv layer, max pooling, drop out, flatten and dense layer with 40 epochs, batch size 64 for CNN model 1 using SGD optimizer, and for CNN model 2 using Adam optimizer 50 epochs along with batch size 64. Moreover, the images are trained with 50 epochs with 0.2 losses, batch size 64 for Deep CNN model.

The proposed work comparison of various models along with various metrics like Accuracy, precision, Recall, F1-score and ROC AUC score are analyzed in Table 1.

Table 1. ParameterfindingsforBC diagnosis using deepcnn

Model	Accuracy	Precision	Recall	F1-Score	ROCAUC Score:	Binary CrossEntropy
CNN1-CBIS-DDSM	0.8692	0.8635	0.8445	0.7940	0.9115	0.38
CNN2-BIS-DDSM	0.8712	0.8977	0.8502	0.8252	0.9243	0.38
DCNN-CBISDSM	0.9056	0.9046	0.9056	0.8851	0.9526	0.2
CNN-SOA-CBIS-DDSM	0.9913	0.9288	0.9313	0.9241	0.9632	0.1

9 Comparison with State-Of-Art Models

It is clear from the results shown in Table 2 that the CNNMSOA performs at the utmost level. Thus, in order to compare the proposed strategy with the current techniques, we used CNN-MSOA as the benchmark. As a consequence, we used CBIS and DDSM datasets to compare our suggested model to other approaches for the goals of this subsection. Similar to Naresh et al. [1] finding accuracy and loss not only providing greater performance but our results also achieved 99% with additional metrics comprises precision, f1 core, ROC-AUC and recall. Additionally, our proposed method used CNN-MSOA optimization algorithm for providing better optimal solution in Breast cancer disease prediction. The findings are shown in Fig. 5.

Table 2. Comparison on Proposed MSOA With Existing Approaches

Author	Dataset used	Methodology	Accuracy
Naresh et al. [1]	Wisconsin Breast Dataset	CNN	99
Nomani et al. [3]	BC images	PSO-CNN	98.4
Sweta et al. [4]	BreaKHis 400X	Machine learning	85
Manali et al. [11]	DDSM	Decision fusion based CNN	98
PROPOSED MODELS	CBIS-DDSM	CNN Model 1	86.9
	CBIS-DDSM	CNN Model 2	87.1
	CBIS-DDSM	Deep CNN	90.5
	CBIS-DDSM	CNN MOSA	99.13

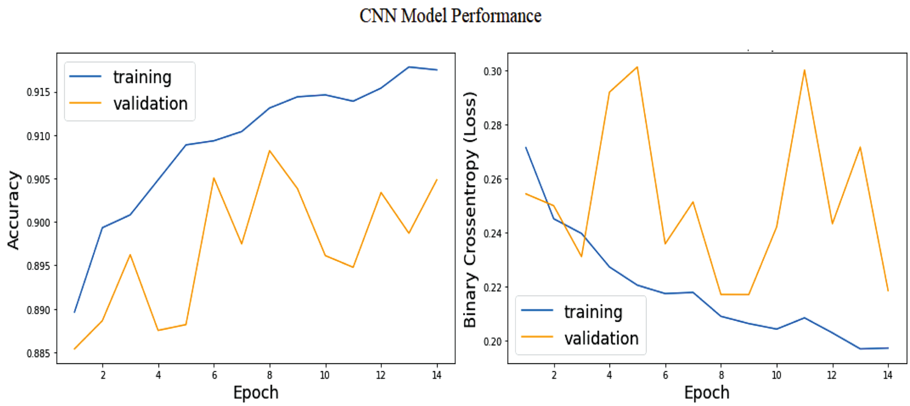


Fig. 6. Evaluation on model performance with accuracy and loss

10 Conclusion

In summary, the authors created modern technique to facilitate the exact diagnosis of breast cancer in mammography images. Our proposed method includes pre-processing the data using seam carving technique, extracting features from mammography images for the purpose of diagnosing diseases, and then utilizing deep learning-based CNN model 1, CNN model 2, deep CNN on two datasets using Adam optimizer,Convolutional Neural Network with MSOA to train the models. The outcomes produced for various datasets show how successful our suggested approach is CNN with MSOA approach. The authors looked into hybrid optimization techniques like Momentum Search Optimization and CNN with Adam to determine an optimal solution for an early detection of breast cancer. Additionally, CBIS and CBIS-DDSM datasets were utilized in the execution of this work.

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