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Image Classification for Breast Cancer Using a Modified Convolution Neural Network Architecture

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Abstract— The most common type of cancer that results in death is breast cancer. In the world, millions of people struggle with this disease. Breast cancer can affect men and women but women are more affected. For awareness, it is necessary to understand the sign and symptoms of breast cancer. The most common sign is an abnormal lump in the breast. But there may be many reasons of develop abnormal lumps. Computer-Aided Diagnosis (CAD) is extensively used in pathological image analysis to help pathologists enhance diagnosis efficiency, accuracy, and consistency. Recent studies have looked into deep learning methodologies to improve the effectiveness of pathological CAD.

Keywords- Machine Learning, Image Classification, Breast Cancer, CNN, Deep Learning, Artificial Intelligence.

I. INTRODUCTION

Breast cancer is one of the most often diagnosed cancers in women. There are millions of people throughout the world who are afflicted with this disease. It can be increasing the survival rate through early detection and prevention. The American Cancer Society estimates that more than 1.8 million new cancer cases will need to be diagnosed in 2020, with 30% of females having breast cancer [1].

For awareness, it is necessary to understand the sign and symptoms of breast cancer. The most common sign is abnormal lumps in the breast. But there are many reasons of develop abnormal lumps. For prevention without delay consult to doctor. The main challenge ng task for detection is the diagnosis because of the complex structure of the breast. Mammograms are utilized in the traditional CAD approach for cancer detection. The performance of the CAD method is still not reliable for the frequently used clinical procedure. To increase the performance of CAD systems by exploiting new technology like machine learning and deep learning. Nowadays, CNN (Convolution Neural Network) method is used to the improving performance using extract the features from mammograms [25]. In cancer classification, the deep learning technique is useful for extracting the features from the complex dataset and classifying them into invasive and non-invasive tumors. We cannot replace the clinical procedure with machine learning models. The artificial Intelligence based model only can assist doctors. As a result, machine learning models may be used in the area of medicine to minimize diagnosis costs and predict illness outcomes. CNN method is an improved technique of deep learning. To apply a CNN model to a problem, to train the model over a lengthy period, a vast amount of data is necessary. However, data of a relatively modest magnitude is accessible in the medical sector.

Machine learning algorithms have overtaken CAD systems for diagnosing ailments and managing patients in a variety of healthcare applications [13]. In contrast, traditional machine learning algorithms need a time-consuming human feature extraction stage. It also needs topic expertise as well as the support of a radiologist. Deep learning (DL) models, on the other hand, may extract features from an input dataset and generate an adaptive learning process depending on the goal output [14]. The DL techniques significantly accelerate data processing and pattern extraction activities, enabling for the reuse of approaches Various studies have been conducted to look at breast cancer images from various angles [15]. Convolutional neural networks (CNNs), machine learning

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(ML), and deep learning (DL) are currently popular approaches. Deep CNN for feature extraction is not the only application of CNN in medical imaging research. A second area where CNN can help medical research is synthetic visual rendering.

Machine learning includes transfer learning technology which allows pre-trained models to be utilized directly as feature extraction preprocessing and then blended into whole new models. CNN model requires a large amount of data the train a model so the transfer learning technique resolves this issue [29]. For example, it is feasible to employ a model that has been trained to perform a certain task, such as tumor classification. The advantage of transfer learning is it requires minimum training time and provides better performance.

II. LITERATURE SURVEY

In 2017, Shuyue Guan and Murray Loew [2] presented a CNN (Convolution Neural Network) model that was based on a transfer learning approach for breast cancer diagnosis. In this paper, the author takes the mammograms from the MIAS and DDSM databases and apply three method- 1. Trained the model using CNN 2. Apply pre-trained VGG-16 model 3. The third model updated the weight using backpropagation in the last layer of the VGG-16 model. The result shows that applying transfer learning in CNN achieved better accuracy for detect breast cancer.

Gelan Ayana and Kokeb Dese [3] discuss a work that uses transfer learning with ultrasound pictures to identify and diagnose breast cancer. The author encounters several obstacles when using transfer learning, such as selecting an architecture and determining the number of layers required for fine-tuning in addition to the pre-trained model's number of layers. Vijayerajeswari and colleagues (2019) suggested a methodology for early diagnosis of breast cancer based on the Hough transform and the Support vector machine [4]. This approach is used to extract features. This model was evaluated on 95 mammography images and obtained 94% accuracy.

Kwok [6] used four separate state-of-the-art pre-trained algorithms based on histological pictures to classify breast cancer (VGG19, InceptionV3, InceptionV4, and ResNetV2). To improve prediction accuracy, several data augmentation procedures are used. The ResNetV2 and According to the evaluation data, inception models attained the highest degree of precision. The models scored 91 percent and 79 percent accuracy for binary and multi-class classification challenges, respectively. Vang et al. [7] suggested an ensemble strategy for a multi-class breast cancer classification task using the InceptionV3 model. To arrive at the final forecast, the model employed the gradient boosting mechanism, the representative democratic approach, and additional logistic regression models. Nawaz et al. [5] used a fine-tuned AlexNet model to classify breast cancer. Patch-wise and image-wise training were used to train the model on the dataset (512512 pixels). The model was accurate 75.73 percent of the time and 81.25 percent of the time on the dataset. Sarmiento and Fondón [9] used feature vectors to create a model. Color, texture, nucleus, and form were the qualities extracted from each image. To categorize images, the researchers utilized the SVM model with 10-fold cross-validation and a quadratic kernel.

The model's total accuracy, however, was just 79.2 percent. Kijsipongse et al. [8] proposed a distributed deep-learning voluntary computing infrastructure that expands GPU clusters. In this platform, owners of computer devices allow users to use the idle processing capabilities on their machines to increase the GPU's capacity. Desell [11] proposed a novel method for large-scale CNN evolution that relied on volunteer computing. For two months, 120,000 CNNs were taught and tested on 4,500 voluntary computers. The researchers achieved an accuracy of 98.32 percent using the MNIST dataset. The findings appear to be superior to those achieved using the traditional back-propagation method for CNN training. Liang et al. [10] devised a diagnostic technique for detecting breast and thyroid abnormalities in ultrasound pictures using a deep-learning algorithm. The authors used a hybrid approach, using classifiers based on the various feature extraction methods. The methodologies chosen depend on the picture segmentation results. The CNN-based technique with picture classification yields the best segmentation results among the models. Wang et al. [12] suggested a breast cancer classification strategy based on CNN. To improve feature extraction in ABUS imaging, the system used the InceptionV3 pre-trained model. The model provides a viable way to acquire Multiview features. Using fivefold cross-validation, the approach yielded a 0.9468 area under a curve (AUC).

III. BACKGROUND

A. Data Augmentation

Data Augmentation refers to a variety of strategies for creating a subset of the learning samples that develop more effective Deep Learning models. To improve Deep Learning performance, a multitude of ways is referred to as data augmentation. for increasing the volume and size of training datasets. To avoid biased prediction results, data augmentation was used. For each photograph in the collection, augmented images with applicable masks such as rotation, reflection, shifting, and scaling were created [27]. Augmentation is a powerful technique for adding differences to existing photographs to grow an image collection. This generates one-of-a-kind and inventive images from a big image collection using a range of conditions. This improves model performance by increasing generalization and decreasing overfitting. As a

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result, augmentation generates a large range of images from a small set of photographs for image classification, detection, or segmentation.

They might be used to make models. Data Augmentation combats overfitting by addressing the problem at its source: the training dataset. This allows augmentations to pull more data from the primary dataset. These augmentations artificially expand the size of the training dataset through data distortion or oversampling [26]. Existing images are altered with data-distorting advancements while their labels are preserved. A few examples of augmentations include geometric and color changes, random erasure, adaptive training, and neural style transfer. Using oversampling augmentations, synthetic samples are produced and added to the training dataset.

To show data augmentations, basic alterations such as horizontal flipping, color space augmentations, and random cropping were initially used. Many previously reported models that cause problems with image classification are conveyed by these alterations. Among the developments are geometric modifications, color space transformations, kernel filters, image mixing, random erasure, feature space augmentation, adversarial training, GAN-based augmentation, neural style transfer, and meta-learning approaches.

B. CNN (Convolution Neural Network)

In computer vision, NLP (Natural Language Processing), and other fields, deep learning is a prominent approach. Convolutional Neural Networks (ConvNets or CNNs) are a form of Neural Network that has been demonstrated to be exceptionally good at image recognition and classification. ConvNet is capable of detecting faces, objects, and traffic signs, as well as powering robot and self-driving car vision.

A CNN, like any other multilayer neural network, consists of one or maybe more convolutional layers (sometimes with an oversampling step), followed by one or more fully connected layers. A CNN's architecture is built to make use of the layered nature of an input picture (or other 2D input such as a speech signal). Translation invariant features are generated via local connections and linked weights, which are then pooled [28]. Because CNNs have fewer parameters, they are also better to handle than fully connected networks with the same number of hidden units [18]. The CNN classifier has the advantage of automatically extracting the important properties of the input image. The characteristics are shift and form distortions of the input characters invariant to a degree. This inconsistency arises as a result of CNN's usage of the weight-sharing technique on a single feature map.

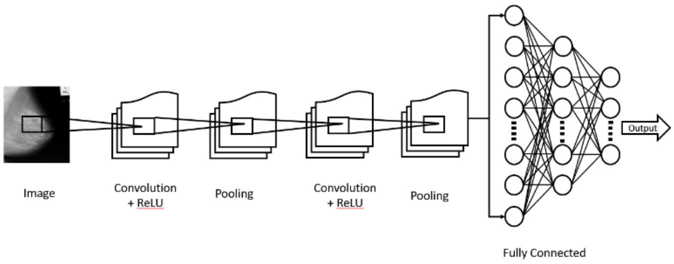

Figure 1. CNN Architecture with Relu

CNN has the benefit of requiring fewer neurons and hyperparameters. Several fundamental CNN computer vision architectures have been developed and used to difficult visual imaging challenges with success. Pretrained models such as VGG16 and ResNet50 were used to create the proposed models in this paper. We'll go through these groundbreaking CNN designs in the next part.

figure 1 explains the CNN architecture. Every input image passes testing and training of CNN models through the fully connected, convolutional, and pooling layers. A SoftMax activation function was then used to the pictures into categories using probabilistic values between 0 and 1.

B.1 VGG 16

VGG16 is made up of 16 layers, whereas VGG19 is made up of 19 layers. A series of VGGs is identical in the last three completely linked levels. In all, there are five convolutional layers, followed by a MaxPool. The five sets of convolutional layers differ in that they comprise an increasing number of cascaded convolutional layers. VGGNet's convolution layers have two to four convolution operations each. The convolution kernel has a step size of 1 and is 3 * 3, whereas the pooling kernel has a step size of 2 and is 2 * 2. The decrease in the size of the convolution kernel while increasing the number of convolution layers is the most visible enhancement to VGGNet.

On the one hand, combining numerous convolution layers with tiny convolution kernels rather than a bigger convolution layer with convolution kernels reduces parameters and, according to the author, results in more non-linear mapping, which improves Fit expression ability.

B.2 RseNet 50

ResNet, or residual neural network, is a deep network approach for avoiding gradient dispersion and accuracy loss by incorporating residual learning into a standard convolutional neural network. As you get further, you may manage both accuracy and speed. The residual module will dramatically reduce the parameter value in the module, allowing the network's parameters to respond more quickly to the loss of reverse conduction, while the basic module will remain

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unchanged [18]. It does not eliminate the problem of insufficient backhaul loss, but it does lower the parameters. In terms of backhaul loss, it amplifies the effect while simultaneously generating a regularization effect.

Backpropagation occurs when a network outputs a value and then compares it to the real value to calculate an error loss. At the same time, the parameter is adjusted by changing the loss. The initial loss and gradient determine the returning loss. Because the goal is to alter the parameter, the issue is that if the intensity of changing the parameter is too low, the parameter's value can be reduced, resulting in a loss of intensity of changing the substantially greater parameter. As a result, the residual module's most essential duty is to change the way forward and backward information is transmitted, greatly increasing network optimization.

Second, because the forward process provides branching for identity mapping, the back-propagation process has more simple channels for gradient conduction, and the gradient can be communicated to the preceding module after only one relu .

IV. ACTIVATION FUNCTION

Activation functions influence the output of a neural network. These functions are allocated to every neuron in the network and decide whether the neuron should be active or not based on the value of the information provided by each neuron to the model's forecast. The activation function also assists in normalizing the output of every neuron to a range of 1 to 0 or -1 to 1.

In the input layer of a neural network, inputs are supplied to neurons. Each neuron provides output by multiplying the input number by its weight, which is subsequently sent to the next layer [24]. The activation model is a mathematical "gate" that links the input and output of the present neuron.

*A. **Rectified linear unit activation function (ReLU) Function***

The highest possible value is returned by the ReLU function. It's important to note that this isn't entirely interval-derivable, but we can utilize sub-gradients as shown in the diagram. Despite its simplicity, ReLU is a remarkable breakthrough in recent years. The ReLU (Rectified Linear Unit) function is a prominent activation function right now [19]. When compared to the sigmoid and tanh functions, it provides the following advantages and disadvantages:

Advantages:

1) There is no gradient saturation problem when the input is positive.

2) The calculation time is much lowered. The ReLU function's only connection is a linear one. It is substantially quicker than sigmoid and tanh in both directions. (The exponent must be determined using Sigmod and tanh, which is time-consuming.)

Disadvantages:

1) ReLU is fully inactive when the input is negative, which implies that if a negative value is supplied, ReLU will die. It is not difficult in the forward propagation process in this way. Some parts are sensitive, while others are not. However, if you provide a negative integer in the backpropagation process, the gradient will be absolutely zero, which is the same problem as with the sigmoid and tanh functions.

2) We discover that the ReLU function's output is either 0 or a positive value, indicating that it is not a 0-centric function.

$$\mathrm{ReLU}(x)=\max(x,0)$$

where $\mathrm{ReLU}(x) \in (0, x)$, and $x \in [-\infty, +\infty]$

B. Sigmoid Function

In the early stages of deep learning, the Sigmoid function was the most commonly employed activation function. It's an easy-to-deduce smoothing function.

The output of the sigmoid function is in the open interval, as can be seen (0,1). We can think about probability, but we shouldn't approach it as such in the literal sense [20]. The sigmoid function gained popularity once more. It's comparable to the rate at which a neuron fires. It is the sensitive region of the neuron in the center of the slope. It is the inhibitory portion of the neuron on the sides where the slope is mild.

The function itself has certain defects-

1. The function's gradient gets very small, virtually 0 when the input is little removed from the coordinate origin. To calculate the difference of each weight w in the backpropagation of neural networks, we all employ the chain rule of differential. The divergence on this chain is extremely minimal when backpropagation travels through the sigmoid function. Furthermore, it may pass via many sigmoid functions, causing the weight w to have minimal influence on the loss function, which is incompatible with weight optimization. This Gradient saturation and gradient dispersion refer to the same issue.
2. The output of the function is not centered on 0, reducing the weight update's efficiency.
3. The sigmoid function is used to change the value of a variable.

The function formula and chart are as follows

$$\sigma(x)= 1/ 1+e^{-x}$$

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where σ(x)∈ (0,1), and x∈ [−∞, +∞].

C. Transfer Learning

Transfer learning (TL) is an optimization algorithms approach for solving new prediction/classification tasks utilizing a previously trained network [21]. To address the new learning difficulties, the learning parameters of the used pre-trained network with randomly started weights must be fine-tuned. Learning and training with TL are often faster than learning and training the network from scratch. It aims to ensure the transmission of all vital information. It has grown in prominence as a result of the fact that it reduces training time and uses significantly less data to improve performance [23].

Pre-trained models are commonly employed in computer vision to demonstrate transfer learning. To address a scenario comparable to the one at hand, A large dataset was used to train a pre-trained model [22]. In transfer learning, to train, CNNs are employed a large number of pre-trained models. By removing the classifier and integrating only a few classification layers, and also retraining the convolution base layers, we repurposed the pretrained CNN versions VGG16, DenseNet201, InceptionV3, and Xception for our dataset.

V. RESEARCH METHODOLOGY

A. Dataset

In this paper, the MIAS dataset is used for training a model. The MIAS dataset contains 326 mammography images which are divided into three tissue types (fatty, fatty-glandular, and dense-glandular). Normal images are 207, abnormal images are 119, benign images are 68, and malignant images are 51. All of the photos in this dataset are 1024 by 1024 pixels in size and are stored in portable gray map (PGM) format.

B. Preprocessing

Random horizontal flipping, resizing cropping, and rotation are all used in Data Augmentation to get more photos. Image pre-processing may have an impact on how the final data processing findings are interpreted.

C. Proposed Method

The MIAS breast cancer data set was used in this study. We scaled these images to 224X 224 because they were accessible in various sizes and qualities. We used image augmentation because the amount of data was reduced at this scale. We proposed CNN base models for this study and then incorporated transfer learning models like VGG19 and ResNet50. For additional refinement, dense and average pooling layers were added to the original architectures, and the updated architectures were tested on a breast cancer image data set explained in Figure 2. To enhance the size of the data set, data augmentation was used.

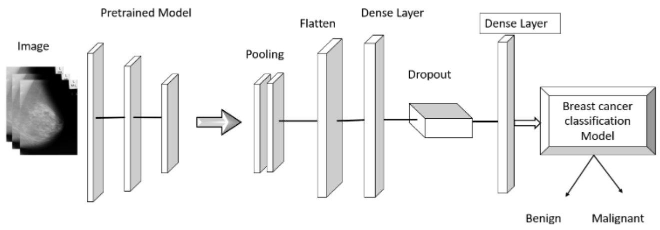

Figure 2 Proposed Model Architecture (MCNN)

D. Performance Evolution Criteria

The testing approach was decided to be data augmentation with 90-degree rotates and horizontal flips. The findings are assessed using

specificity, accuracy, sensitivity, precision, F1-score, and recall. False negatives (FN), true negatives (TN), true positives (TP), and false positives (FP) are all affected by these factors (FP).

The cross-validation approach was created to improve database efficiency, performance validity, and outcome verification. Many measures, including accuracy, sensitivity, specificity, precision, recall, and F1-score, as well as the area under the receiver operating characteristic (ROC) curve, also known as the area under the curve, are utilized to evaluate the classification performance of our suggested technique (AUC).

These features are employed as quantitative elements in comparisons of the proposed technique to state-of-the-art algorithms. The values that were measured are as follows.

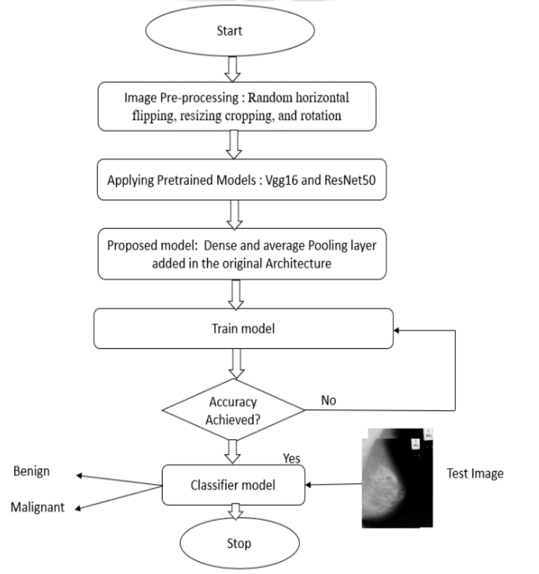

Figure 3 Flow diagram of Proposed Model

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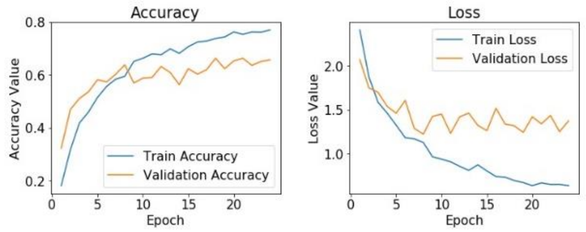
Figure 3 describes the step-by-step flow of the model. The quantity of Since this size of data is reduced, we used image augmentation in step 1 of figure 3. We created a head model and added the information for this paper to models for pretransfer learning like VGG19,To get results on the accuracy, precision, recall, and loss and accuracy graphs, use ResNet50 and add a dense layer.

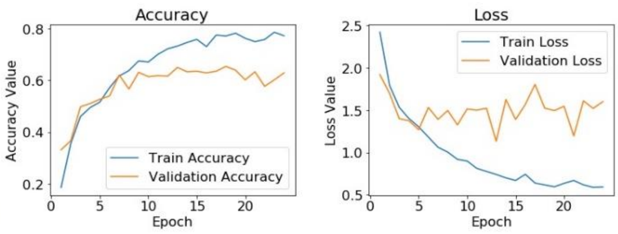
VI. EXPERIMENT RESULT

Several experiments examining the proposed model's performance on the MIAS dataset are described in this section. The accuracy, precision, sensitivity, specificity, and AUC of three DL models (VGG 19, ResNet50, and ResNet152) are compared using Transfer learning. "Benign," "Malignant," and "Normal" were used to categorize the data. The training and testing assignments were then divided into 80 percent and 20 percent, respectively. The suggested models' efficiency was assessed using evaluation metrics for three classes, as given in Table 1.

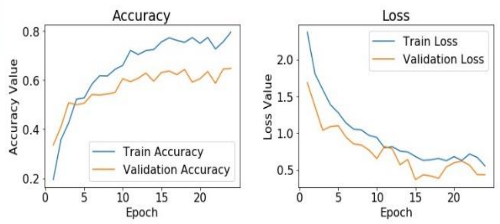
Model	**Proposed Model Result**					
	Accuracy (%)	***Sensitivity (%)***	***Specificity (%)***	***Precision (%)***	***Recall***	***F1 score***
VGG 19	0.9531	0.94	0.96	0.94	0.94	0.94
ResNet 50	0.9782	0.97	0.94	0.95	0.97	0.97
Modified-ResNet 50	0.92	0.96	0.97	0.94	0.96	0.96
Modified VGG 19	0.9722	0.95	0.96	0.95	0.95	0.94



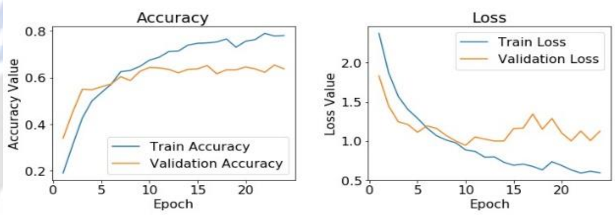
a Training and validation accuracy of VGG-19



b Training and validation accuracy of ResNet50



c Training and validation accuracy of Mod VGG-19



d Training and validation accuracy of Mod ResNet 50

Figure 4 Accuracy and loss graphs of different models: (a) VGG19, (b) ResNet 50 (c) Modified-VGG-19, and (d) Modified ResNet 50.

Figure 5 compares the accuracy of modified deep learning architectures to those of the original deep learning architectures F1-score, recall, and precision. The figures below demonstrate that the modified proposed architectures outperformed the original architectures.

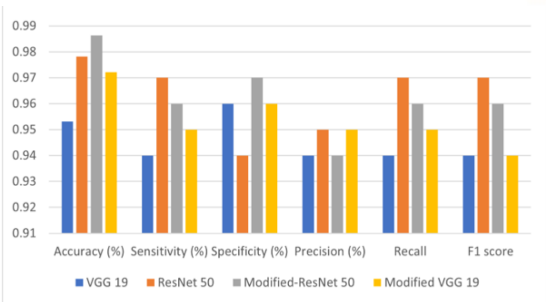


Figure 5 Accuracy comparison of different CNN Models

VII CONCLUSION

This research looks into breast cancer classification. Two pre-trained models (VGG19 and ResNet50) were modified in this paper. For additional refinement, dense and average pooling layers were added to the original architectures, and the updated architectures were evaluated on a MIAS data set. To enhance the amount of data collection, data augmentation was used. The accuracy of Modified-VGG19 and ModifiedResNet50 was 0.9722 percent and 0.9863 percent, respectively, whereas the accuracy of VGG19 and ResNet 50 was 0.9531 percent and 0.9782 percent, respectively. According to the findings, modified pre-trained models outperformed their original counterparts. Other types of deep learning techniques for breast cancer detection will be examined and enhanced in the future. The proposed framework could be used to diagnose abnormal images in a variety of medical applications.

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