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# Mammographic Breast Image Detection using Convolution Neural Network

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***Abstract:****Ongoing years Breast Cancer is a profoundly destructive sickness in ladies' locale. It can begin from the breast and can spread over the body in a course of time. It is the second biggest infection prompting cause demise of a ladies. In this examination, we proposed a Deep learning-based design for grouping the computerized mammograms to arrange the seriousness of breast malignancy. Since it is precarious to fragment mammogram picture because of its low difference among typical and irregular tissues. Consequently, Canny edge detection is utilized to extract the underlying form of mammograms and Deep learning Convolutional Neural Network (DL-CNN) calculation is utilized to get learned with the highlights of sore explicit areas. To expand the grouping accuracy and lessen the false positives, an outstanding convolution neural network is used in the last phase of Deep Learning architecture. Test results are done by utilizing the standard benchmarking breast malignancy dataset (DDSM and BCDR) demonstrate that the proposed strategy shows huge improvement in execution over the customary strategies. The proposed structure performs well in classifying the advanced mammograms and computerized to synthesis as normal or harmful and its subclasses too.*

## I. Introduction:

Breast cancer is a harmful cell lesion that develops in the breast. If left untreated, the cancer can spread to other areas of the body form the initial stage of breast. Excluding skin cancer, breast cancer is the second most common type of cancer in women today. The incidence of breast cancer arises after 40 years. So early detection of cancer is necessary So, early detection for cancer is more important. Mammography is an initial screening diagnosis test to detect breast cancer. Mammograms are x-rays machine of the breast with low dose that have been used for screening since the 1980s. Cancers are seen as masses, areas of asymmetry tissues, calcifications, and areas of deformations. Many noncancerous conditions may also produce masses and calcifications and normal tissue can appear as areas of asymmetry tissues. Mammograms are classified into three type’s namely conventional mammogram, digital mammogram and 3D mammogram.

The Digital Mammograms are called 2D mammograms. The benefits of 2D mammograms allow detection of 2 to 7 cancers for every thousand women screened. Mammography is the recommended as the first step in breast Cancer screening for all women aged above 40 years or older and except those who are pregnant. Some women who are at the high risk may start mammographic screening by age of 30. Digital, 2-Dimensional, also known as “Full Field Digital Mammogram” (FFDM), which uses a dedicated electronic detector system to computerize and display the x-ray information. Tomosynthesis, also referred to as “3-Dimensional mammography” (3D mammography) or called as “tomo”, uses a dedicated electronic detector system to obtain multiple projection images which are “synthesized” by the computer to create thin slices of the breast.

2-D digital mammography is slightly more impressible than film mammography in dense tissue. The vast majority of hospitals facilities now use digital mammography. Digital images can be stored in a computer system database called a PACS (picture archive communication system). This allows the radiologist to quickly identify and retrieve previous diagnosis for comparison from year to year and to manipulate the images for complete examination.

Tomosynthesis or DBT (Digital Breast Tomosynthesis) creates three dimensional pictures of the breast and utilizes specially-equipped digital (x-ray) mammography machines and acquires images at multiple views and angles. Several low-dose images from different angles are taken around the breast are used to create the final 3-D picture. Hence it is relatively new, it is available only in some limited number of hospitals. A study has found that when radiologists looked at digital tomosynthesis images along with digital mammogram images, the diagnosis were more accurate and had lower false positive rates compared to radiologists who looked only at digital mammograms. A false positive rate indicates an abnormal area that looks like cancer on a mammogram, but turns out to be normal.

Unique feature for analysing not only to cancer detection but also in other fields. By the use of image processing techniques, it has become more efficient to detect cancerous tissues from an infected breast. The medical diagnosis can be effective in case of detecting early. The proposed structure of computer aided detection method is to classify 2D mammogram images and 3D tomosynthesis images using Convolutional Neural Network to detect breast cancer. The entire process is divided into four major modules. In first step, the images are pre-processed to improve the performance and it takes away any unwanted noise in the image. Hence, the region of interest is extracted from the input image. In second step, the image is segmented using a gradient edge detection and canny edge detection method. In fourth step, the features of the mammogram images will be extracted. In fourth step, cancerous and non-cancerous images are classified using the popular Convolution neural network classification algorithm.

## II. Literature Review:

**1.** Jinshan Tang (2009), proposed an overview of recent advances in the development of CAD systems and related techniques. Brief introduction to some basic concepts related to breast cancer detection and diagnosis are given. The main focus is on the key CAD techniques developed during recent years for breast cancer detection of calcifications, masses, architectural distortion, bilateral asymmetry, image enhancement, and image retrieval.

2.Zhang X, Zhang Y, Han EY, Jacobs N, Han Q, Wang X, Liu J (2018), proposed an approach of digital mammogram and digital tomosynthesis classification based on Convolution Neural Network (CNNs). Different models of CNNs were built to classify both the 2-D mammograms and 3-D tomosynthesis, and every classifier was assessed with respect to truth-values and follow-up confirmed by expert radiologists. The outcomes demonstrated that CNN-based models had developed and optimized efficient transfer learning and data augmentation with good potential for automatic breast cancer detection based on the mammograms and tomosynthesis data.

3.Gustavo Carneiro, Jacinto Nascimento, and Andrew P. Bradley (2017), describe an automated method for the analysis of unregistered cranio-caudal (CC) and mediolateral oblique (MLO) mammography views in order to measure the patient's risk of developing breast cancer. The main focus behind this methodology lies in the use of deep learning models for the problem of classifying unregistered mammogram images and respective segmentation maps of breast lesions. This is an integrated methodology that can classify a whole mammographic exam, containing the CC and MLO views and the segmentation maps.

4.Karthikeyan Ganesan, U. Rajendra Acharya, Chua Kuang Chua, Choo Min Lim, and K. Thomas Abraham (2014), presents a one-class classification pipeline for the classification of breast cancer images into benign and malignant classes. Because of the sporadic distribution of abnormal mammograms, the two-class classification problem is reduced to a one-class outlier identification problem. Trace transform has been used to extract the features. Most popular Classifiers such as the linear discriminant classifier, quadratic discriminant classifier, nearest mean classifier, support vector machine, and the Gaussian mixture model (GMM) were used.

5.Xu J, Xiang L, Liu Q, Gilmore H, Wu J, Tang J, Madabhushi A. (2016), proposed a Stacked Sparse Autoencoder (SSAE), an instance of a deep learning strategy, is used for nuclei detection on histopathological images of breast cancer. The SSAE learns high-level features from the pixel intensities alone and identifies the features of nuclei. A sliding window operation is applied to each image in order to represent image patches through high-level features obtained via the auto-encoder, which are then fed to a classifier that categorizes each image patch as nuclear or non-nuclear.

6.Brijesh Verma and John Zakos (2001), presents a system based on fuzzy-neural network and feature extraction techniques for detecting microcalcifications in digital mammograms and a neural network is used to classify it into benign/malignant cancer tissues.

7.Dhungel N. Carneiro G. and Bradley A.P. (2016), proposed a deep learning method to automatically learns features directly on the optimization of breast mass classification from mammograms. The approach lies in the two-step training process that involves a pre-training, followed by a fine-tuning stage that learns the breast mass classifier. The proposed classifier is integrated into a fully automated breast mass detection and segmentation, which produces best results.

8.Fuyong Xing, YuanpuXie and Lin Yang (2016), developed a learning-based structure for automatic nucleus segmentation. The proposed algorithm is tested on three large-scale histopathology image datasets using different tissues in convolutional neural network

9.Gennaro, G., et al., (2010), To compare the performance of digital breast tomosynthesis (DBT) with that of full-field digital mammography (FFDM) in a diagnostic population. Clinical performance of DBT compared with that of FFDM was evaluated in terms of the difference between areas under ROC curves (AUCs) for BIRADS scores.

10.Hong B. W. and Sohn B. S. (2009), is used to segment the region of interest using a region-based image segmentation technique using active contours with signed pressure force (SPF) function. A Gaussian kernel is used to regularize the level set function and removes expensive reinitialization. The proposed segmentation algorithm has applied to different images in order to display the accuracy, effectiveness, and robustness of the algorithm.

11.Maurice Samulski and Nico Karssemeijer (2011), propose a new optimizing case-based detection performance for learning Multiview CAD systems. The method develops a single-view lesion detection system and a correspondence classifier. This method is applied to the cause of detecting severe masses and architectural distortions.

12.Shen-Chuan Tai, Zih-Siou Chen, and Wei-Ting Tsai (2014), uses local and discrete texture features for mammographic mass detection. This algorithm segments some adaptive square regions of interest (ROIs) for affected areas. This study also used two feature extraction methods based on co-occurrence matrix and optical density transformation and finally uses linear discriminant analysis to classify abnormal regions by selecting, rating and achieving satisfactory performance.

## III. Proposed System :

This section describes thetechniques used for detection of region of interest and classification in mammogram images to detect cancer. It consists of three important stages such as segmentation and deep learning classification. In first phase deep learning is used to pre-process the mammogram image thenThresholding, edge-based method and region detection method comes under segmentation phase. The second phase uses Convolutional neural networkfor classification process to diagnosis the cancerous or non-cancerous tissues. All these Procedure are put together in order to solve a problem of computer aided diagnosis of breast cancer detection technique.

CNN can able to learn its features in supervised way. Deep learning is mainly used to train the model because it takes the raw pixels and transformed into set of features. Thus, feature extraction process is not required.Mammographic images of breast are given as the input and segmented using gradient edge detection algorithm to detect the region of lesion in the breastthen it is classified using convolutional neural network classifier to improve the accuracy and reduce the false positive rate. The flowchart of the breast cancer classification is shown as follows in the Fig.1.

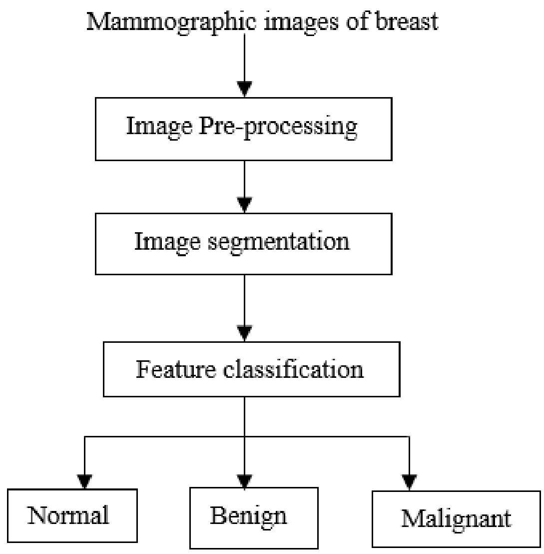



**Fig. 1. Classification of Breast cancer**

Segmentation procedure is done using the edge-based detection methods. The edge-based detection method is classified into two types namely Grey histogram and gradient-based detection. This method uses gradient based detection with two derivatives namely first order derivative operator and second order derivative operator for image segmentation.

## IV. Methods :

### A. Edge Based Segmentation

An edge is stated as the boundary in middle of regions with different gray level properties. Neighbouring intensity changes in an image is referred to as edges.

**Gradient Based Method**: Gradient edge detection method detects the edges by looking for the maximum and minimum in the first derivative of the image.If there is a little noise inimage, then gradient based method works well. Gradient based operators are Roberts, Prewitt, Sobel, Laplacian of Gaussian (LOG), Zero-cross and Canny operators etc. From this technique, it is that Sobel operator gives better result when compared to other operators.

**Sobel Operator:** The Sobel operator consists of a pair of 3x3 convolution masks. Conversely, it is modification of Prewittoperator by altering the centre coefficient to 2.

| | | |
|---|---|---|
| -1 | -2 | -1 |
| 0 | 0 | 0 |
| 1 | 2 | 1 |

| | | |
|---|---|---|
| -1 | -0 | 1 |
| -2 | 0 | 2 |
| -1 | 2 | 1 |

**Canny edge operator**: The Canny edge detector is a multi-stage edge detection algorithm. It is an edge detection operator that is employed in the detection of wide range of edges for the given images. It is a detection technique that helps to extract the useful structural information from different vision objects which also reduces the amount of data that need to be processed.

Canny edge detection algorithm is accompanied by four filters that detect the horizontal, vertical and diagonal edges in the blurred images. An edge in an image may be any point of variety of directions corresponding to the given image. The edge detectionsobel operator is used to return the value of the first derivative in the horizontal direction ($G_x$) and the vertical direction ($G_y$). From which edge gradient and direction can be can be calculated by the following edge detection algorithm formula in the image segmentation.

$$G = \sqrt{G_x{}^2 + G_y{}^2} \qquad \text{--------------(1)}$$

$$\theta = \text{atan2}(G_y, G_x) \qquad \text{--------------(2)}$$

**TABLE I EDGE DETECTION TECHNIQUES**

| Edge Detection Technique | Comparison of Techniques | |
|---|---|---|
| | Merits | Demerits |
| Sobel | Smoothing edge | Noise effect |
| Canny | Wide range of edges | Difficult to select a generic threshold |

Classification procedure is done using the Convolutional Neural Network. It is one of the machine learning algorithms to perform image classification to recognize objects, faces, scenes etc. They learn directly from the images without any feature extraction. CNN composed of many input layers, output layer and many hidden layers as well.

After learning the features using many layers, the architecture CNN shifts to classification phase. Thus, it gives a high accuracy on medical image classification and lessen the false positive rates.

**B. CNN Architecture**

Convolution Neural Network is named because of its Convolutional layers present in their engineering. Convolutional layers are fundamentally utilized for recognizing highlights of a picture. In every single development of the piece on the picture, CNN learns the element of a picture. Every neuron in Convolutional layer is utilized to acquire the highlights of the nearby structure of a picture. To get the comparative highlights for the info picture channels, loads of every neuron are shared between the hubs in the Convolutional layers.

A Deep Convolutional Neural Network is prepared by nourishing it contribution to the first layer and giving it a chance to compute and extract the features and lastly yield the output. After computing the output result, the error is determined and this mistake is spread in reverse through the net by backpropagation. At each progression in the model, parameters are tuned to limit the error. This procedure proceeds with the information and improves the demonstrate as the procedure goes on. Preparing and Training the CNN is an iterative process that includes various layers and the info is passed to these layers and parameter is refreshed in each layer until the show joins.There are three critical layers which are utilized to assemble Convolutional Neural Network design: Convolutional layer, fully connected layer and pooling layer. For the most part, a completely CNN design is developing by putting a few of these layers in a steady progression. A general case of CNN design with two components organize is appeared as follows.

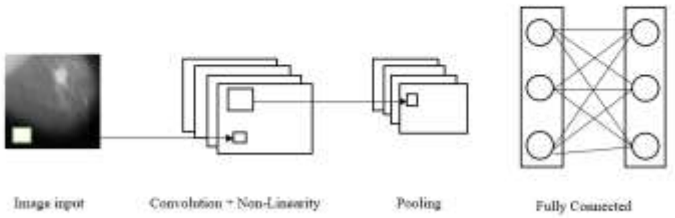



**Fig. 2. Example of CNN Architecture**

In our paper, we have utilized CNN engineering with a few varieties in parameter that has given the best outcome which contains the accompanying layers.

## V. Discussions:

**Input layer**: In this layer, a picture is given as an info and produces yield which is utilized to encourage the Convolutional layers. In our model, input is of (32 X 32 or 64 X 64 pixels) is taken into thought and the quantity of channel of picture is 3 for grey scale.

**Convolutional layers**: In this layer, input picture is convolved with a lot of learnable channels, which produces a component map relating to each picture in the yield picture. In our model, there are six Convolutional layers. For initial three layers size of the bits is of 5 X 5 and cushioning is set to zero and the walk is set to two and for next three layers, we have kept the extent of bit to be 3 X 3.

**ReLU layers**: This layer is otherwise called Rectified Linear Unit. This is an activation function which initiates the neurons over a certain limit esteem. Give the allowed contribution to esteem is y, the ReLU layers registers the neurons yield as y if $f(y) > 0$ and 0 if $f(y) < = 0$.

**Pooling Layers**: Pooling layer is essentially used to diminish the span of a picture keeping the abnormal state highlights of a picture. This layer is in charge of down testing the spatial element of the information picture. We can make them pool layer after each Convolutional layer. Every one of the pooling layers is set to utilize 3 X 3 open field spatial degree) with a walk of 2. In the initial three pooling layer, at the most pooling capacity is connected to the picture to get the most extreme pixel esteem in a window. For other three pooling layer, we have utilized normal pooling.

**Fully Connected Layer or inner product layer**: In this layer neurons are completely associated with each other and creating the outcome. Here info is essentially treated as a vector and produce aoutput as a single solitary vector. In our model, we have utilized two internal item layers. The last layer is a completely associated layer where a softmax layer is used to arrange the info picture. Complete number of classes utilized for our situation is two, one for benign and other for malignant.

## VI. Findings And Results :

In order to measure the performance of the proposed algorithm, mammograms were selected from the mammography digital database of the University of South Florida and breast cancer digital repository. The experiment was composed of for parts. The first part was the object detection and measurement of threshold is calculated using binary gradient mask. Since the gradient mask shows the high contrast image, in the second part dilated gradient mask delineate the outline of the region of interest. The third part shows the segmented object with smoothened image. The fourth part shows the outlined image of the segmented object.

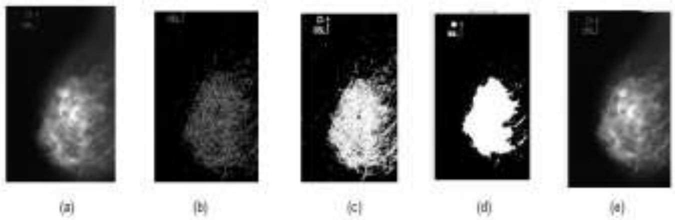



**Fig. 3. (a) mammogram image (input image) (b) object detection (c) dilated region of interest image (d) segmented region of interest (e) outlined image.**

Classification of the mammogram images is done using Convolutional Neural Network that classifies into its subclasses as well. Thus, it produces an accurate result with less false positive images.

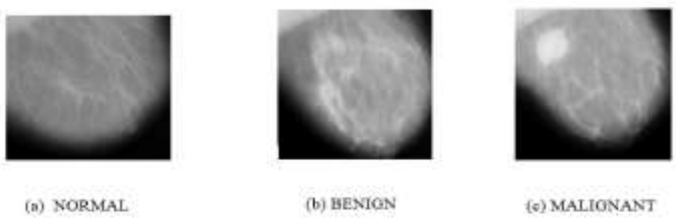
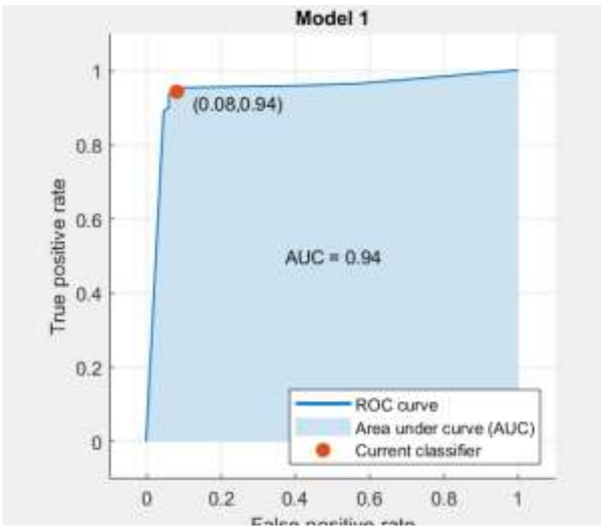



**Fig. 4. (a) Normal class 1 image. (b) Benign class 2 image. (c) Malignant class 3 image.**

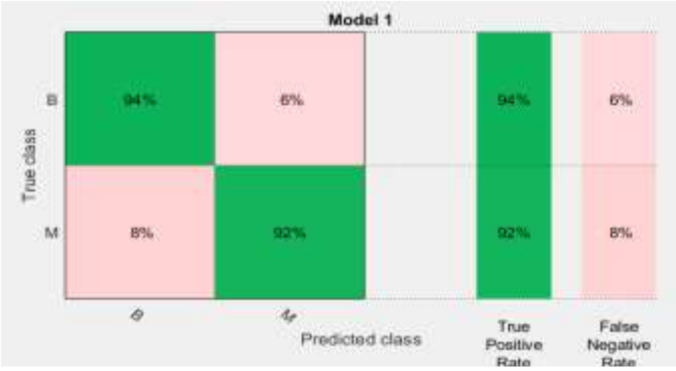
Performance metric is used to evaluate the performance of the classification architecture by the use of ROC curve and Confusion matrix.




(a) ROC curve analysis for breast dataset

Accuracy and misclassification rate can be calculated by the confusion matrix. Accuracy is the ratio of total number of classifications to their inputs.
Accuracy = (TP + TN) / TOTAL -------(3)
Where TP – True positive and TN – True Negative in the classification analysis
Misclassification rate is the ratio of wrong classifications to the total number of inputs.

Misclassification rate = (FP + FN) / TOTAL-------(4) Where FP – False Positive and FN – False Negative in the confusion matrix analysis.




(b) Confusion matrix of the breast dataset

## VII. Conclusion

The study shows the efficacy of mammograms over other diagnostic techniques and also examined various segmentation and classification methods used for breast cancer detection. The judgment on the benign and malignant status of digital mammogram images in 2D and 3D is subjective and may vary from specialist to expert. CAD systems largely help to make an automated biomedical image decision and allow a second opinion for both patients and doctors. A conventional image classifier uses hand-made local image classification features. In the classification of mammogram images, the proposed work achieved 94 percent. The latest state-of - the-art CNN model, however, mainly uses global information using kernel-based working techniques to extract global features from the classification images. Using this CNN model, this paper has classified a set of images of breast cancer (DDSM and BCDR image data set) into benign and malignant classes.

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