Breast Cancer Detection using Thermal Images and Deep Learning

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***Abstract* – Breast cancer is indeed a major cause of concern for women in India. There are several detection techniques currently available for breast cancer diagnosis, like mammography, magnetic resonance imaging, ultrasound, and currently Computerized Thermal Imaging is developing its way to enter this field in conjunction with mammography. Infrared imaging is found to be less harmful as compared to mammography and can give results many years prior to the detection of cancer by mammography. The purpose of the current study is to use Thermography and deep learning combination to provide new insight on how to make better predictions for breast cancer. In this work, the methodology and techniques used are based on a deep Convolutional Neural Network model to predict breast cancer from thermal images. Thermal images are pre-processed, segmented and classified using a deep neural network. The research concludes with the major finding that 95.8% accuracy of prediction is achieved for breast cancer based on the output spectrum using training data of 680 thermograms. The current approach demonstrated a significant improvement over the earlier published accuracy of 93.30% with 50 thermograms. Hence, we can summarize that the proposed deep convolutional Neural Network model is highly effective in the prediction of breast cancer.**

Keywords – CNN, Breast Cancer, AI, Deep Learning, Thermography, Mammography, CTI, ANN.

NOMENCLATURE

CNN	Convolutional neural networks
AI	Artificial Intelligence
CTI	Computerized thermal Imaging
DCNN	Deep Convolutional Neural Networks
ANN	Artificial Neural Network
MRI	Magnetic Resonance Imaging
DCIS	Ductal Carcinoma in Situ
ReLu	Rectified Linear Function
DMR-IR	Database for Research Mastology with Infrared.

I. INTRODUCTION

Breast cancer is a major health concern for women in India [1]. There are more than 18 subtypes of breast cancer but most prevalent forms of breast cancer originate in cells in the lining of milk ducts and the lobules that supply the ducts with milk. These types are known as ductal carcinomas and carcinomas. Respectively. Increasing the incidence of the disease and its diagnosis in advanced stages has led to a high mortality rate. Breast cancer detection in the early stages of its development significantly improves the chances of survival of affected females. Two common methods for diagnosis of breast cancer include mammography and histopathology. Mammography performed by a radiologist is the most widely used technique to screen women with high risk for breast cancer as it can detect breast cancer in early stages. However, frequent use of mammography may increase the risk of breast cancer in healthy females [2]. Biopsy gives confirmed results, but it involves cutting of tissue from the affected area, which is then analyzed to determine the malignancy of tissue. It is an invasive method and may sometimes cause infections and accidental injuries. Infrared thermal imaging has shown promise to overcome the limitations of the mammography and emerge as an adjunct method for breast cancer screening due to its low cost, non-invasive and non-ionizing nature. Investigators are now trying different approaches to use thermograms for breast cancer detection [3-5]. The authors of [6] considered lateral and frontal views of the breasts the region of interest (ROI) extraction from breast thermograms to discriminate between the malignant and benign cases. Authors in [7] used a classical machine learning-based approach involving discrete wavelet transform and decision tree classifiers, to distinguish the cancerous and healthy regions. On a small dataset of 50 thermograms achieved accuracy and sensitivity was 93.30%. and 86.70% respectively. Gogoi et al. [8] detected the presence of hot thermal patches by using the power-law transformation. singular value decomposition technique was used to characterize the thermal patches. Most of

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the methods presented in the literature use classical machine learning to extract the features. The traditional machine learning approach required human intervention to extract the features from the images which are fed to the neural networkto train them. Whereas deep neural networks themselves extract features from the training data and use them for classification. This speed up the classification/detection process and gives better results. In this work, a deep Convolution Neural Network (DCNN) model is developed for the detection of breast cancer from thermal images.

The rest of the paper is organized as follows: Section II provides a brief account of current breast cancer detection methods. Section III discusses the deep learning model developed for the detection of cancer from thermal images along with its performance evaluation. Section IV explainsthe system model. Finally, Section. V provides the conclusion and future directions of research.

II. Breast Cancer Diagnosis

The exact cause of breast cancer is usually unpredictable, which means that it is often difficult to answer why a woman has breast cancer while the other one doesn't have it. But through the studies, it is said that breast cancer is caused when the cell of DNA is damaged. Types of breast cancer are:

- *Ductal Carcinoma*- This is the early stage and has a high cure rate and is referred to as DCIS.
- *Invasive Carcinoma*-It is most common in terms of breast cancer and it is found in milk ducts and gradually it grows toward the surrounding tissue.
- *Invasive Lobular*-It is the small part of invasive breast cancer roughly around 10-11%, while invasive carcinoma is around 80-81%, it is found in glands.

A. State of the art - breast cancer diagnosisprocedures

There are various ways by which diagnosis of breast cancer can be done and it include mammography, magnetic resonance imaging, histopathology, thermography, ultrasound-

- *Mammography*–It uses X-Ray image of the breast. Breast tomosynthesis is used to capture images of the breast from different angles and reconstruct them in a three-dimensional figure[9].
- *MRI* – It uses magnets, radio waves to produce images of structure within the breast. It is used as a supplement tool for screening with the mammogram [10].
- *Histopathology*–It uses the study of tissues having diseases with biopsy [11].
- *Thermography*- Thermography is used to record the temperature changes of a body with the help of infrared cameras. Thermography can detect tumors up to 1.28cm while mammography can detect up to 1.66cm [12].
- *Biopsy*-Biopsy is performed to get a clearer view. The removed area of skin tissue is then further analyzed for the correct detection of cancer.

B. Limitations of existing Procedures

The diagnosis methods discussed above contains various limitations such as:

- While undergoing mammography, there are chances of developing cancer from radiation exposure and have a true-false ratio ranging between 5-15% [13].
- MRI exam can malfunction the implanted devices. Kidney assessment must be carefully done during MRI before proving the injection of gadolinium for people having Nephrogenic systemic fibrosis [14].
- Biopsy sometime causes bleeding, infections and sometimes there are accidental injuries. It also removes tissues of the patient's breast causing bruising swelling of that region [15].

III. Deep Learning Model

Deep Learning is also referred to as structured learning or hierarchal learning based on the representation of data like machine learning. Various architectures of deep learning involve deep neural network, belief network and recruitment network which are been used in areas like computing, audio recognition, language processing, machine translation i.e., converting machine language into computer language.The word deep has its useful meaning as it refers to various steps through which data is processed to get specific output.

A neural network is a circuit or network of neurons where it is based on the working of human brains. As various neurons are associated with the brain and help to carry on various functions of body parts, similarly artificial neural network is used for artificial intelligence. Its architecture consists of the leftmost layer which is referred to as a data collector, centered as a secret layer and a single data distributor. The hidden layer or middle layer is simply a layer that is neither input or an output layer. The hidden layer can be either single or multiple. Deep Neural Networks have at least more than one hidden layer. Deep Convolutional Neural Networks (DCNN)is used to analyze for a specific region of an image rather than analyzing the whole image and hence, are more useful for image recognition. In CNN complexity of computation of an image can be done easily as compared to that with neural networks. To train large data if we increase the hidden and input layer then the problem of overfitting may arise and to avoid this situation, we use the convolution network. Overfitting arises when we use a large data set and a network is not able to learn efficiently. CNN architecture is divided into three parts i.e., height, width, and depth while the architecture of the neural network consists of neurons. It consists of convolution, pooling, and fully connected layers.

Figure1shows a typical vision algorithm pipeline, which consists of four stages: pre-processing the image, identifying regions of interest (ROI), object recognition, leading to decision making. The pre-processing step is usually dependent on the details of the input, especially the camera system.The input layers contain a digital thermogram. With the help of the scalar product between the input layer and weights, the convolution layer will determine the output. The use of a rectified linear function (ReLu) is to apply the activation function. Relu function is used between the layers so that their performances can be enhanced. It gives the output in the form of the dimensional vector which comprises of probabilities of each class of the images. Hence, with the help of SoftMax function, it provides the output.

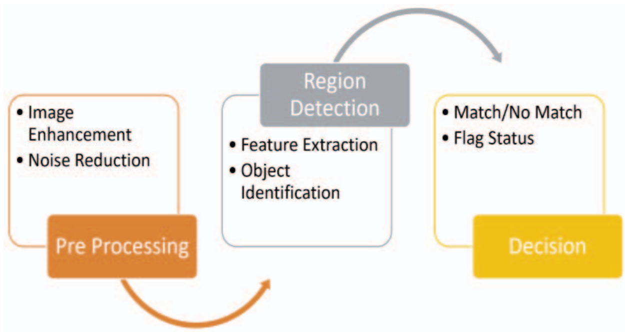

Fig. 1. Breast Thermogram classification using DNN

IV. Proposed Model

In this work images of the breast thermogram image database of the Visual Lab group of Federal Fluminense University, Brazil are used [2]. Images were taken by FLIR SC-620 camera, with resolution640 x 480 pixels. The reason behind using this model is that they are easily implemented in MATLAB. Obtained images are converted into the GREY scale which then pre-processed, segmented and then further classified using a neural network. Figure 2 shows some segmented grayscale images fed to the network.

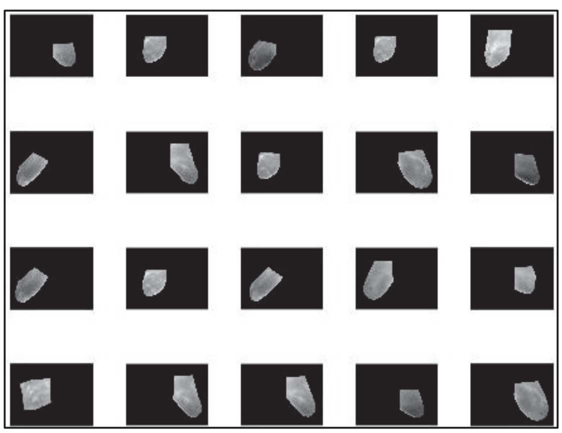

Fig. 2. Sample segmented grayscale images from dataset

Following are the overall processes of the system.

A. Pre-processing

The images are normalized and resized to ensure that all images are of same size. Preprocessing and further implementation of Deep neural network is done using MATLAB 2018a deep learning and computer vision toolbox.

B. Deep Neural Network-

Segmented and resized gray images are divided into training set and validation sets. The developed Deep Convolutional neural network is created by stacking a sequenceof layers. namely: Image Input layer, Convolutional Layers, Normalization layers, Max- Pooling Layers, Fully Connected Layers, Non-Linear activation layers (ReLU,Softmax). From Figure 3, it may be observed that deep neural network uses input images as raw data and progressively extracts higher level features.

C. Image Input Layer

Image Input Layeris the input layer to the network. Since database containsgrayscale images. the channel size is 1 and input image size is 480x640x1.

D. Convolutional Layer

Convolutional Layer is the core building block of the deep neural network. It contains a set of filters which operate on the input image to compute activation maps. The layeroutput is obtained by stacking the activation maps along the depth dimension. Structure of convolution layer is defined by three parameters,first argument specifies the size of filter, and second argument determines the feature maps. Function of‘Padding’in this layer is to ensure that the output size is the same as the input size.

E. Batch Normalization Layer

Normalizationlayer ensures easier convergence of optimization algorithm by normalizing the gradients and activations propagating through the neural network.

F. ReLU Layer

ReLU Layerapplies rectified linear unit (ReLU) activation function on a input, without changing its spatial or depth information.

G. Max Pooling Layer

This follows the Convolutional layer and it performs down-sampling operation. Most dominant features of previous feature map are retained after max-pooling operation and redundant information is removed resulting in reduced feature map.

H. DropoutLayer

It eithers drop out individual nodes out of the net with probability *1-p* or keep them with probability *p*, so that a reduced network is left. It helps neural network to learn more robust features that are useful in conjunction with many different random subsets of the other neurons. Number of iterations required to converge are doubled roughly but, training time for each epoch is less.

I. Fully Connected Layer

It integrates all the information learned by preceding layers across the network to classify the given image. The output from the previous max-Pooling or Convolutional Layer is first flattened and subsequently fed to the Fully Connected layer.

J. SoftMax Layer

It uses SoftMax function that converts the output offully connected layer into a range of 0 to 1, which can then be interpreted as classification probabilities.

K. Classification Layer

This is the last layer in the network. This layer uses the classification probabilities generated by the SoftMaxlayer for each input to assign the input to one of the mutually exclusive classes.After training, classification of the validation set is performed by the trained network. With our DNN we got the accuracy of 95.8%.

V. Result

Simulations were performed on Intel Core i5-8250U Processor (1.60GHz), 8 GB RAM with single GPU.Figure5 presents the result, showing developed system output dashboard with validation accuracy.Table I shows the count of "Healthy" and "Problem" images in the dataset. "Healthy" represent the normal thermogram and "Problem" represents thermograms with region likely to have cancerous growth. Since the number of images are less in the dataset hence augmentation on the fly was used to increase data. The augmented images generated through random rotation, X translation and Y translation are directly fed to the network. Confusion matrix in two class classification problem or a table of confusion has two rows and two columns.

TABLE I. Data Labels

Data Labels		
S. No.	***Label***	***Count***
1	Healthy	521
2	Problem	160

TABLE II. Simulation Parameters

Simulation Parameters		
S. No.	***Parameter***	***Value***
1	Input Sample Size	640x480
2	Batch Size	2
	Batch Normalization 'batchnorm_1' 'batchnorm_2'	 8 Channels 32 Channels
3	Weight Initialization Algorithm	Gloret
4	Learning Rate	.01
5	Pooling 'maxpool_1 'maxpool_2	2x2
6	Stride	2
7	Optimization Algorithm	Stochastic Gradient Descent (SGD)

Thermal images captured by the dynamic protocol were used in this work where, after the cooling of the breasts by air stream, 20 sequential images with intervals of 15 seconds between them were taken during the process of returning the patient's body to thermal equilibrium with the environment.After pre-processing the images, training classification of the validation set is performed by the trained neural network. As shown in Figure 4, with the implementation of the proposed model, 95.84%accuracy isobtained.Figure5 shows the confusion matrix with the values, numbers of false positives (FP), false negatives (FN), true positives (TP) and true negatives (TN).

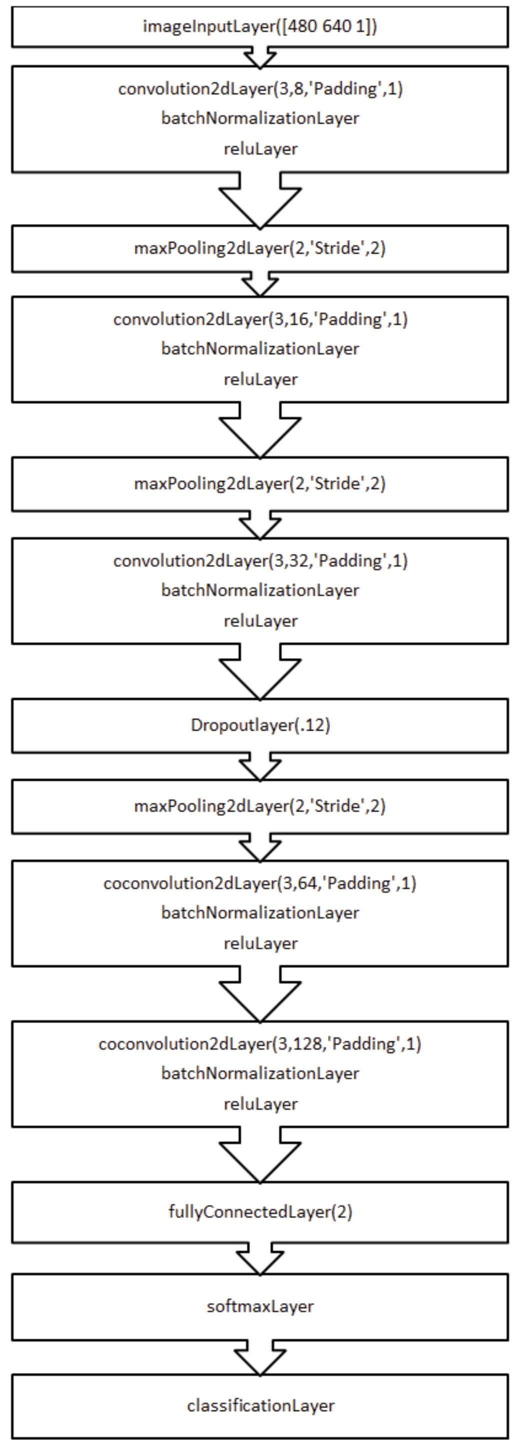

Fig. 3. Network architecture

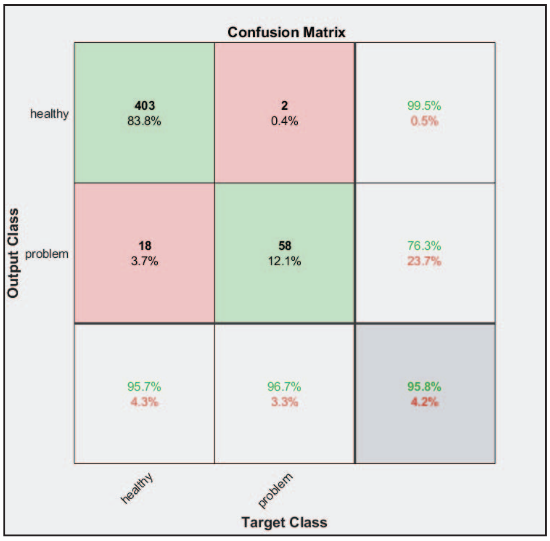

Fig. 4. Confusion Matrix

Most recent literature [20] shows that DT and fuzzy classifiers yielded a highest average accuracy of 93.30%. Compared to this accuracy of 95.84% obtained in current work is significantly higher. Hence the proposed deep learning system can be used for an automatic classification of normal and abnormal breast thermograms which can aid the radiologists in their diagnosis.

VI. Conclusion and Future Scope

In this paper we have used deep learning methodology to detect cancerous region in sample thermogram. Visual lab-IR dataset was split into training, validation and testing datasets. A deep learning model developed for detection of cancer from thermal images along with its performance evaluation. Research concludes with the accuracy of 95.8%, of detection based on output spectrum and identified training data of 680 thermograms. This is significant improvement over published accuracy of 93.30% with 50 thermograms [20].On further refinement sensitivity and specificity obtained are 99.50% and 76.3% respectively.The model can be further improved by increasing the number of input samples using data augmentation.

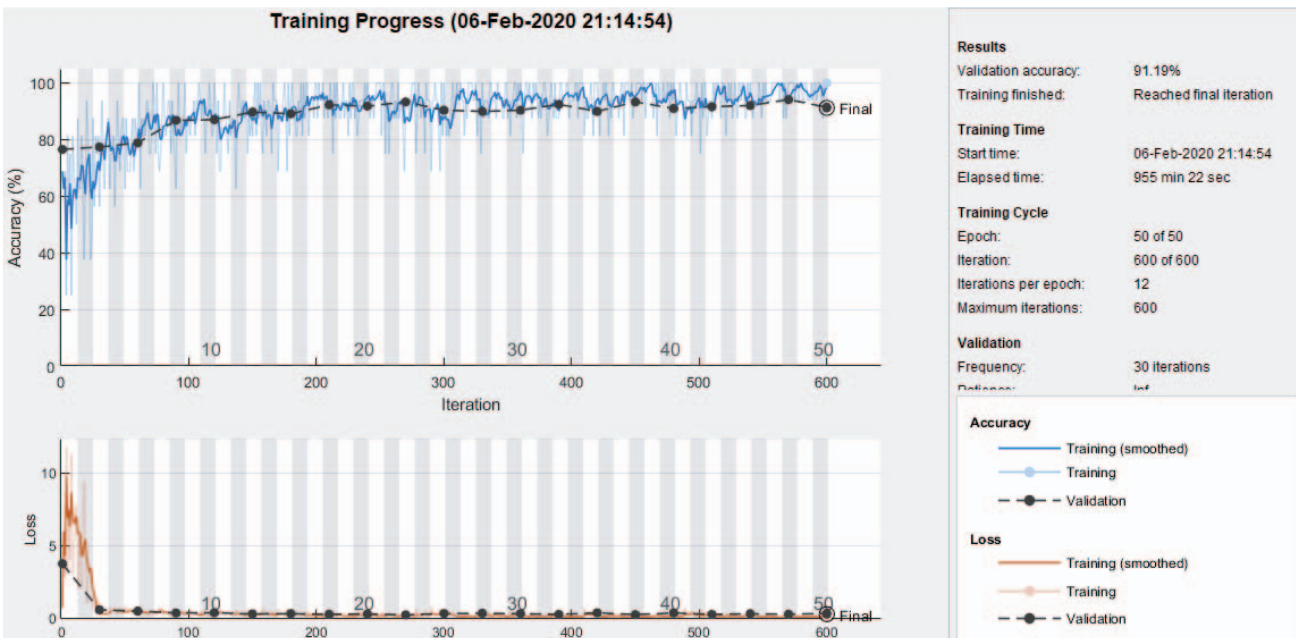

Fig. 5. Output/results of developed system dashboard with validation accuracy

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