Breast Cancer Detection in Mammograms using Convolutional Neural Network

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Abstract—Breast cancer is among world's second most occur-ring cancer in all types of cancer. Most common cancer among women worldwide is breast cancer. There is always need of advancement when it comes to medical imaging. Early detection of cancer followed by the proper treatment can reduce the risk of deaths. Machine learning can help medical professionals to diagnose the disease with more accuracy. Where deep learning or neural networks is one of the techniques which can be used for the classification of normal and abnormal breast detection.

CNN can be used for this detection. Mammograms-MIAS dataset is used for this purpose, having 322 mammograms in which almost 189 images are of normal and 133 are of abnormal breasts. Promising experimental results have been obtained which depict the efficacy of deep learning for breast cancer detection in mammogram images and further encourage the use of deep learning based modern feature extraction and classification methods in various medical imaging applications especially in breast cancer detection.

It is an ongoing research and further developments are being made by optimizing the CNN architecture and also employing pre-trained networks which will hopefully lead to higher accuracy measures. Proper segmentation is mandatory for efficient feature extraction and classification.

I. Introduction

Cancer is a disease caused by the changes occurred in cells spread uncontrollably. Mostly cancer cells forms a lump or mass which is called tumor and named after the part of body in which it originates. Breast cancer usually produces no pain at its early stage when it is easily treated, that's why screening is important for early detection. Most lumps are found to be non cancerous (benign). 80% breast cancers are invasive and usually breast cancer is referred to single disease but there are up to 21 histological sub-categories. An estimate was calculated by American cancer society for the year 2017 approximately 252,710 new cases will be diagnosed of invasive cancer among women and 2470 new cases in men[1]. Incidence and death rates for breast cancer increases with age. During 2010-14 the average age at the time of breast cancer is 62. In Asia, Pakistan has the highest rate of breast cancer. Approximately 90,000 cases are reported annually causing a death rate of 40,000[2]. Breast cancer has over 90% chances of being cured completely among all other cancer types. Because cancer doesn't cause pain at early stage, it doesn't get attention until the health conditions are severe. Average age among Pakistani women reporting cancer is 40s.

The survival rate of patients is the percentage estimate of the patients who will survive for a given period of time after the diagnosis, for the expectancy of a normal life. Survival rate varies by the stage at which cancer is detected. According to most recent data the survival rate for the breast cancer diagnosed among women are[1]:

- 91% at 5 years after diagnosis.
- 86% after 10 years.
- 80% after 15 years.

Women and men with first degree relative (parent, child or sibling) having a history of breast cancer are most prone to the disease.

Mammography is a procedure which is low dose x-ray through which we can visualize breast's internal structure. Different signal processing techniques such as ultrasound imaging, microwave imaging, wavelet transform which is the time-frequency representation of a signal using small waveform called wavelet and curvelet transform which is derived from wavelet transform are used for breast cancer detection, its degree of localization varies with scale and produce images on different scales[3]. Other techniques like fuzzy logic and neuro-fuzzy system are also used for feature extraction for breast cancer to differentiate between abnormal and normal categories[3].

Deep learning is a machine learning technique in which a computer model performs classification tasks directly learning from text, images or sound. Models are trained on a large number of datasets and CNN architectures containing many layers. In medical imaging deep learning is used to detect cancer cells automatically. Training a deep convolution network from start is difficult because it needs large amount of data for training. One way is to fine tune an existing per-trained network. Deep learning is used in various medical fields such as bioinformatics, early diagnosis of Alzheimer's disease and molecular imaging etc.

Molecular imaging is a new field that combines patient-specific and disease-specific molecular information with conventional anatomical imaging readouts[4]. A new method was proposed which was capable of analyzing multiple classes in one setting which worked on minimum prior domain knowledge and required less labeled samples for training[5].

II. Previous Work

CNN's applications can be traced in medical imaging since 1990s when calcifications were detected in digital mammography. "Transferability" is one of the important aspects of CNN, embedded in pre-trained CNN. Recent research shows that transfer learning in the field of medical imaging can be categorized into two groups. First, to use pre-trained networks for feature extraction from a specific layer of the network

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and those features are used to train a new pattern classifier. Second, where the rest of the pre-trained network is used as same except the fully connected layers that are replaced with a new logistic layer.

Different techniques with classifiers are proposed like SVM, wavelet transforms, fusion of cosine transform and descriptive CNN are used for feature extraction for this dataset[6]. Different comparisons have been done using this dataset either by comparing 2 or 3 images or using different classifiers for feature extraction.

SVM classifier was used with DSIFT, features classification was done for two classes (normal and abnormal) and three classes (normal, benign and malignant)[6]. Mammogram patches were used to produce augmented dataset where contrast enhancement was applied on the dataset. One of the methods used was 2D-DWT (Discrete wavelet transform) which decomposed the enhanced mammogram into four sub-bands and the second method used was DCT (Discrete curvelet transform) where classification was done using SVM layer and softmax layer to train CNN[6]. Database used in this paper was IRMA and average accuracy achieved was upto 81.83% for DCT and 83.74% for CT[6].

Wavelet transform, time-domain signal is passed through different high-pass and low-pass filters and breaks into scaled and shifted version of the initial wavelet by filtering out either low or high frequency components of the signal, where the curvelet transform identifies the skinny ridges with a precise orientation and verifies the multi-dimensional features at wedges[3].

Fuzzy logic shows some attributes of human reasoning processes like hypothesis and logic reasoning, it also helps in processes where there is no proper mathematical representation done[3]. But creating a fuzzy system model is very difficult because it needs precise tuning and simulation[3]. Neuro fuzzy logic is a combination of intelligent systems which helps in logical reasoning using fuzzy sets using if-then rules[3]. Multi-scale curvelet provides better results for the detection of masses which showed a classification accuracy rate of 98.59%[3].

Other methods like C-mean clustering has been used and suggested that along with genetic algorithm it gives better results for segmentation efficiency of affected region's extraction and detection[7]. Breast cancer detection and diagnosis on 3D breast ultrasound images was done to differentiate between fatty and non-fatty tissues, watershed transform was used for region classification[8]. Early detection of breast cancer is also done by breast thermographs using K-means clustering, where the hot region is segmented out (cancer area), color analysis of breast thermograms is proposed[9]. A paper also suggested the extraction of tumor region based on size from breast ultrasound[10]. First, segmentation was done to separate tumor from the background tissues, multiple characteristics were extracted from the segmented tumor region, adaptive thresholding, regression classifiers were constructed for the statistical analysis[10].

A research was done on interval and screen detected breast cancer in which 32 different image features were examined using an alternative dense area identification method which was carried out by a set of logistic regression models[11]. Dyadic wavelet transform is another technique which was used for the enhancement and denoising of the mammographic images[12]. This method was a suitable approach to enhance the small features like micro-calcification and low contrast features such as masses[12]. Self transfer learning for object localization was proposed where the dataset DDSM and MIAS were used for the classification and localization which used a weighted loss as an objective function to prevent localizer from falling in a bad local optimum[13].

A review paper suggested techniques like effective statistical texture detection algorithm (ESTD) and texture analysis for feature extraction in mammography images[14]. Principal component analysis and classifiers like self adaptive resource allocation network were mentioned for the classification of breast cancer[14].

III. Dataset

CNN requires large amount of data for training to achieve high accuracy. Due to less availability of large dataset, training and testing was done from the most available dataset on internet. Dataset used for this research is Mammograms MIAS[15]. 322 total images were used for this purpose. Actual size of the images was 1024-by-1024. In which approximately 133 images were of abnormal and 189 of normal class. Abnormal images included asymmetry in which one of the breasts has increased density mass, 21 images were included of this abnormality. Architectural distortion was second type of abnormality where abnormal arrangement of tissues appears on the breasts, 22 images were included. Calcification is another type where small calcium deposits are developed in breasts, 24 images were of this type. Circumscribed masses are irregular shaped masses in breasts which can be malignant, 24 images were included. 24 images were included of spiculated masses which is a mass with poorly defined margin or edges. Miscellaneous class included 18 images where there was no confirmation of malignancy. Training was done by randomly dividing the dataset in 70% for train and 30% for testing done automatically by CNN. Images were already in gray scale.

TABLE I
SPECIFICATIONS OF MIAS DATASET AND ITS DIVISION INTO TRAIN AND TEST SET IN THE PROPOSED SYSTEM

		Class	
		Normal	**Abnormal**
Images	**Training Samples (70%)**	132	93
	Test Samples (30%)	57	40

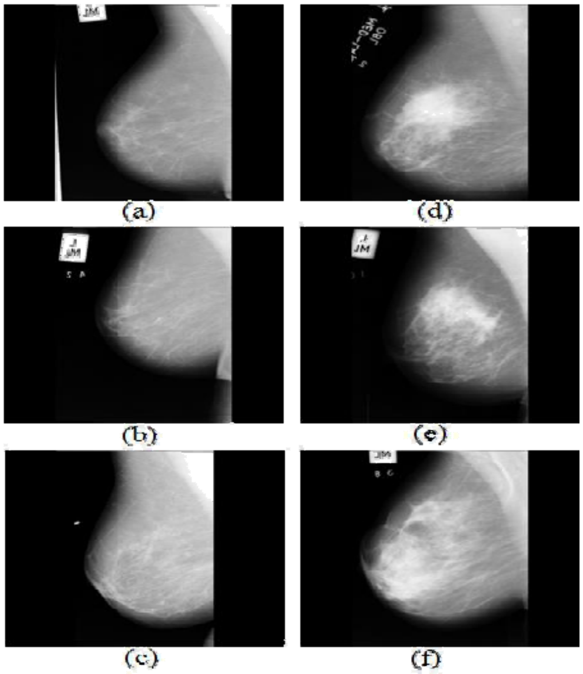


Fig. 1. Sample images from MIAS mammograms dataset. (a-c) Normal images, (d) Asymmetry, (e) Calcification, (f) Spiculated mass.

IV. Methodology

Training was done on 70% of the dataset from Mammograms MIAS from a total of 322 images. Fig. 2 shows the methodology followed for the proposed system.

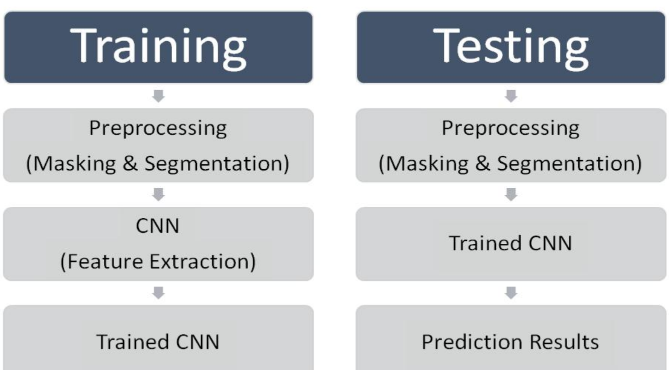


Fig. 2. Conceptual level block diagram of the training and testing procedures in the proposed system

For training SGDM stochastic gradient descent momentum is used. Optimum results were obtained by tuning the parameters like base learning rate, mini batch and max epochs. Some parameters used are given in the table II.

In this paper we trained the CNN from scratch for our application. Network layers in a CNN works as a detection filter for the presence of specific patterns or features present in an image. First layers of a CNN detect large features which can be interpreted easily. Next layers detect smaller features that are more abstract. Last layer is able to make very detailed classification by merging all the features detected by the previous layers.

TABLE II
Training Parameters used for CNN.

Sr.no	Parameters	Values
1	Minimum batch size	5
2	Maximum Epochs	50
3	Initial learn rate	0.01
4	Learn rate drop factor	0.2
5	Learn rate drop period	0.5

DCNN contains 7 layers with weights as shown in Fig. 3, the first four layers are convolutional layers and the remaining 3 are fully connected layers. The inputs of the DCNN are gray scale images. Each neuron computes a dot product of weights to the local region which is connected to the input volume. We have used 4, 16 and 80 number of filters of size (2, 3, 5), padding of size (3, 2, 1) along all edges of the input layer. Filter size [3 3] specifies filters of height 3 and width 3. Each filter is slided across the width and height of the input.

Two pooling layers are used which performs down sampling to minimize the computation and enhance the robustness. Pooling layers with filter size of 2 by 2 pixels which outputs the maximum value of 4 inputs in each local region.

SoftmaxLayer is mostly used in the final layer of a CNN based classifier. Learning rate defines the changes of weights on each epoch e.g. larger learning rate determines larger weight changes on each epoch and the network learns quicker and vice versa. We have used learning rate of 0.01.

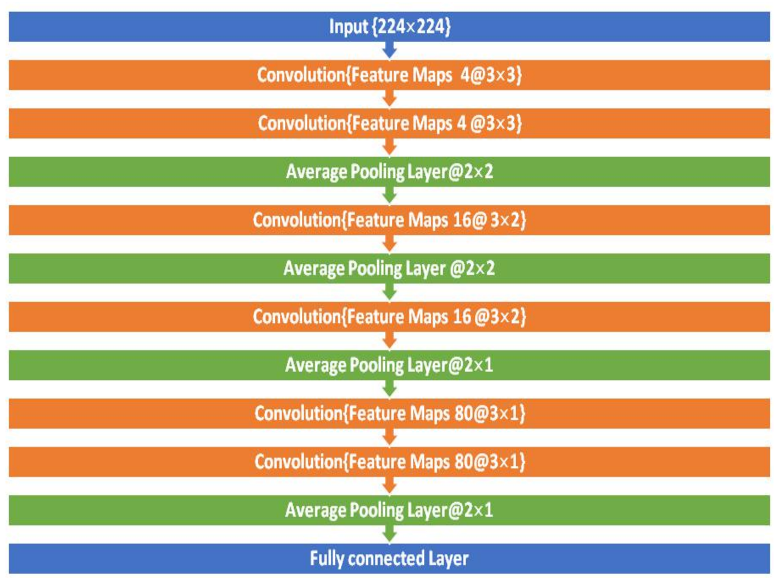


Fig. 3. Architecture of CNN in the proposed system

A. Training and Testing the CNN using original data

Original data was of size 1024-by-1024. We performed Training by first dividing the dataset into 2 classes as normal and abnormal, where 150 and 100 images respectively were used for training and remaining were used for testing.

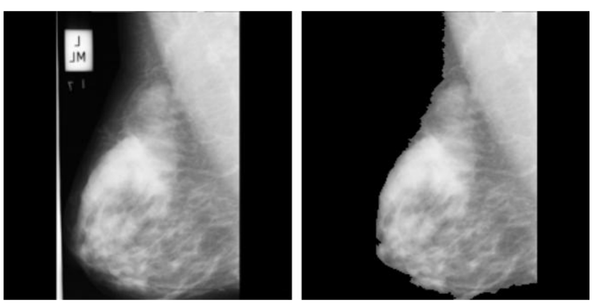
Filters were used of different sizes (2, 3, 5). Also, we tried splitting each training and testing dataset automatically and manually by 70:30 ratio and we got different results. The data trained randomly yield better results as compared to without randomizing it automatically. Proposed method is good and it has introduced deep learning for breast cancer detection. Satisfactory results have been obtained as shown in Fig. 6. It is an ongoing research and further developments are underway by optimizing the CNN architecture and also employing pre-trained networks which will probably lead to higher accuracy.

B. Training and Testing the CNN using pre-processed data

Dataset was pre-processed where the images were of size 1024-by-1024 were resized to 224-by-224. Noise was removed by applying morphological operations like binarization and masking to extract the Region of Interests (ROIs). Morphological operations are used for describing and extracting image component regions.

Dataset was further divided into 7 sub-classes, 6 among them included different types of abnormalities and 1 class containing normal images. The classes were named according to abnormalities like architectural distortion, asymmetry, calcification, spiculated masses, circumscribed masses and miscellaneous (images which were neither recognized as benign or malignant).

Here we trained and tested the pre-processed dataset with same 3 filter sizes (2, 3, 5) where we also tested the data with and without randomizing it. Satisfactory results were achieved on all filter sizes as shown in Fig. 7.



(a) (b)

Fig. 4. Morphological operations used on data. (a)An example raw image from the MIAS dataset (b) Result of ROI segmentation using morphological closing operation and masking.

Segmentation process was carried out by giving raw images as the input on which morphological closing was applied. Morphological closing did the erosion of dilation by a structuring element, which performs the noise removal. Opening helps in removal of small objects while the closing eliminates small holes. Connected components CC detected connected regions in the binary images. Among all those extracted connected regions, largest connected area was selected for masking. Masking was applied at the end to set the background pixel values as zero as shown in Fig. 4. Fig. 5 shows the segmentation steps for pre-processing.

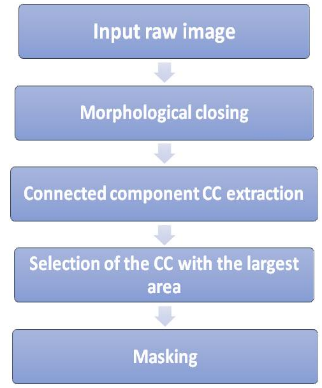


Fig. 5. Segmentation steps for pre-processing.

C. Platform Specifications

Matlab 2017a was used for implementation purpose. NVIDIA Graphic card with 12 GB memory and computing capability of 3.5 was used. For training, NVIDIA GPU was used instead of CPU.

V. Results

Satisfactory results have been obtained using the CNN based proposed breast cancer detection method. The dataset was sub-divided into 7 classes in total in which the abnormal classes were further sub-divided into 6 more classes. Training and testing was done through two methods, in first method the dataset was divided into two classes named normal and abnormal. While the second method included further sub-division of the abnormal classes, that included six types of abnormalities found in breasts such as asymmetry, calcification, spiculated masses, circumscribed masses, architectural distortion and miscellaneous. Miscellaneous contained those images where there was lack of surety that either the images were benign or malignant. CNN was trained and tested on the dataset where total abnormal class images were 133 and normal images were 189. Training and testing was done on original as well as pre-processed data. Pre-processing is done to get better performance and faster learning of neural networks. Accuracy of the raw images obtained by using different filter sizes in CNNs is shown in Fig. 6 in which original data set was used without pre-processing while in Fig. 7 the images were first pre-processed using morphological operations to remove the noise from Region of Interest as shown in Fig. 4. Pre-processed data yielded better results than original images. Accuracy is determined when the model parameters are learned and fixed and no further learning takes place. An overall accuracy of 65% was obtained on the MIAS dataset as shown in Fig. 7[15].

VI. Conclusion

This study implemented the Convolution neural networks on mammograms for detection of normal and abnormal mammograms. This deep learning technique is used on mammograms MIAS dataset by extracting features from sub-divided

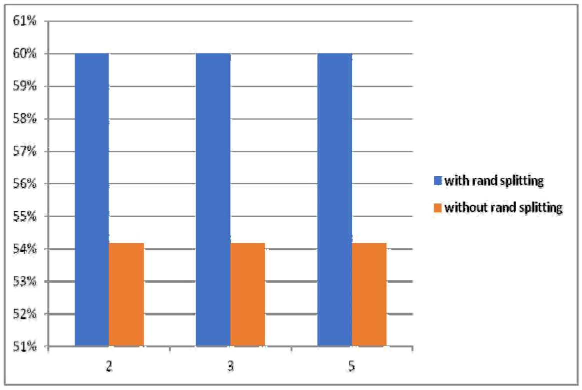


Fig. 6. Accuracy obtained by the CNNs with different convolutional filter sizes on the raw images from MIAS dataset.

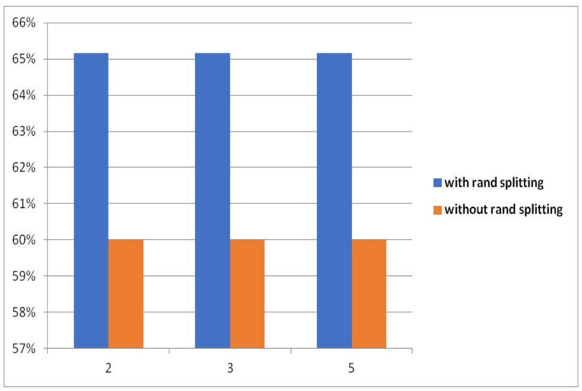


Fig. 7. Accuracy obtained by the CNNs with different convolutional filter sizes on pre-processed images from MIAS dataset.

abnormal classes to the normal class. Different filter sizes and pre-processing techniques were used on the original data to remove noise factors which can lower the accuracy of the overall network. It was also noted that proper segmentation is mandatory for efficient feature extraction and classification. Masking and segmentation based on morphological operations significantly improved the classification results.

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