Middle-East Journal of Scientific Research 25 (2): 417-426, 2017
ISSN 1990-9233

DOI: 10.5829/idosi.mejsr.2017.417.426

Breast Cancer Detection In Mammogram Images Using Deep Learning Technique

D. Selvathi and A. Aarthy Poornila

Department of ECE, Mepco Schlenk Engineering College, Sivakasi, India

Abstract: The field of medical image processing gains its importance in the need of accurate and efficient diagnosis over a short period of time. Since manual process are tedious time consuming and impractical for large data, a need for automatic processing arises which can revolutionize modern medicine. Mammography, the present "Gold Standard" for breast imaging, is the most widely used method to screen asymptomatic women for early detection of breast cancer. It gives the anatomical structure of a lesion. Though there are other imaging modalities, like CT, MRI, PET etc., available for breast cancer detection, they suffer serious disadvantages in terms of radiation exposure, in case of CT and PET and high false positives in case of MRI. The proposed system uses an unsupervised, deep learning based technique which uses Mammogram in the detection of breast cancer. The labelled data serves as the training set and the unlabelled images are classified with deep-learning nets. The deep network consists of stacked autoencoder and softmax classifier. The autoencoder has four hidden layers and a novel sparsity regularizer which incorporates both population sparsity and lifetime sparsity. The model is easy to apply and generalizes to many other scoring problems. The proposed model has achieved an accuracy of up to 98.5% in classifying dense mammogram images.

Key words: Breast cancer · Mammogram · Unsupervised Deep Learning · Autoencoder

INTRODUCTION

Cancer is one of the deadliest diseases faced by mankind. Cells in nearly any part of the body can become cancer and can spread to other areas of the body. Breast cancer starts when cells in the breast begin to grow out of control. Breast cancer is the leading cause of cancer death in women after lung cancer. Statistics show that, 1 in every 8 women is affected by breast cancer in their lifetime. As per clinical statistics, breast cancer constitutes about 12% of all new cancer cases and 25% of all cancers in women, commonly affecting women above 40 years of age. It is estimated that worldwide over 5, 08,000 women died in 2011 due to breast cancer (Global Health Estimates, WHO 2013). However, periodic clinical checkups and self-tests helps in early detection and appropriate treatment of breast cancer and thereby significantly increasing the chances of survival. Invasive detection techniques like fine needle biopsy (FNB), in case of breast cancer, causes rupture of the tumor, accelerating the spread of cancer to adjoining areas. Hence there arises the need for more robust noninvasive cancer detection system for early detection and appropriate treatment of breast cancer significantly increase the chances of survival.

Medical imaging for breast cancer can be used as non-invasive method for looking inside the body and assist the doctors in diagnosis and treatment. Md. Shafiul Islam *et al*. has explored different medical imaging techniques used in the diagnosis of breast cancer and compared their effectiveness, advantages and disadvantages for detecting early-stage breast cancer in [1], which mainly focuses on X-ray mammography, ultrasound and magnetic resonance imaging (MRI). In [2] Sachin Prasad Na and Dana Houserkovaa give an overview of the old and new modalities used in the field of breast imaging and evaluate the role of various modalities used in the screening and diagnosis of breast cancer. Though there are various imaging techniques, Mammogram is considered the gold standard for breast cancer detection. Though initial detection of breast cancer can be done using any one of the available imaging modalities, they do not give assurance that the abnormality detected is malignant. So treatment of the

Corresponding Author: D. Selvathi, Department of ECE, Mepco Schlenk Engineering College, Sivakasi, India.

patient does not start until after microscopic examination of tissue from the tumour is done to confirm its malignancy. K. Shyamala *et al*. [3] says that these procedures are associated with the risk of seeding tumor cells either into the interstitial tissue fluid from where they are carried to lymph nodes, or into the veins draining the tissue from where they enter the vasculature and may travel to lodge into any organ or tissue. There is also a risk of dragging cells along the surgical incision or needle track leading to the possibility of increasing the spread of cancer through biopsy.

Extraction of the breast profile region and the pectoral muscle is an essential pre-processing step in the process of computer-aided detection. The paper [4] by Jawad Nagi et al. has explored an automated technique for mammogram segmentation which uses morphological preprocessing and seeded region growing (SRG) algorithm in order to remove digitization noises, suppress radiopaque artifacts, separate background region from the breast profile region and remove the pectoral muscle, for accentuating the breast profile region.

Detection of the malignant tissues is done by detecting tissues which represent higher intensity values compared to background information and other regions of the breast. However, in case of some normal dense tissues having similar intensities to tumor region, it is necessary to detect tumor region excluding those regions successfully. Anuj Kumar Singh and Bhupendra Gupta proposed a method consisting of two main steps: detection and segmentation in [5]. In the detection phase, an averaging filter and thresholding operation is applied on original input image which outputs malignant region area. To find the malignant tissues, a rectangular window is created around the outputted region area and Max-Mean and Least-Variance technique are applied. In segmentation phase, a tumor patch is found using morphological closing operation and image gradient technique to find the region boundary. Mellisa Pratiwi et al. proposed a mammogram classification technique using Radial Basis Function Neural Network (RBFNN) based on Gray-level Co-occurrence Matrix (GLCM) texture based features. The computational experiments showed that RBFNN is better than Back-propagation Neural Network (BPNN) in performing breast cancer classification. For normal and abnormal classification, the result showed that RBFNN's accuracy was 93.98%, which was 14% higher than BPNN, while the accuracy of benign and malignant classification was 94.29% which was 2% higher than BPNN [6].

Artificial intelligence may be the new face of medical diagnostics. Deep learning aids in breast exams and help patients avoid unnecessary biopsies. A lot of research has been devoted to selecting and handcrafting features that encode the important factors of variation in the input data. However, it can be time-consuming and tedious to mathematically describe human intuition and domain-specific knowledge.

Jürgen Schmidhuber, in [7], distinguished shallow and deep learners by the depth of their credit assignment paths, which are chains of possibly learnable, causal links between actions and effects. Supervised learning, unsupervised learning, reinforcement learning, evolutionary computation and indirect search for short programs encoding deep and large networks are reviewed in this paper. Martin Langkvist , Lars Karlsson and Amy Loutfi, give a review of the recent developments in deep learning and unsupervised feature learning for time-series problems in [8]. Li Deng and Dong Yu provide an overview of general deep learning methodology and its applications to a variety of signal and information processing tasks in [9]. The application areas that have been transformed by the successful use of deep learning technology are discussed. Yanming Guo et al. give an overview of various deep learning approaches and their recent developments, discuss their applications in diverse vision tasks and summarize the future trends and challenges in designing and training deep neural networks [10].

Autoencoders play a fundamental role in unsupervised learning and in deep architectures for transfer learning and other tasks. Pierre Baldi in [11] presents a general mathematical framework for the study of both linear and non-linear autoencoders. The framework sheds light on the different kinds of autoencoders, their learning complexity, their horizontal and vertical composability in deep architectures, their critical points and their fundamental connections to clustering, Hebbian learning and information theory.

Mammographic risk scoring is automated by computing breast cancer risk by extracting a set of features from mammograms in [12] by Kersten Petersen *et al*. The learned features are used as the input to a simple classifier. Two different tasks can be addressed: (i) breast density segmentation and (ii) scoring of mammographic texture. Maxine Tan et al. have predicted near-term breast cancer risk based on quantitative assessment of bilateral mammographic image feature variations in a series of negative full-field digital mammography (FFDM) images in [13]. Mammographic density, structural similarity and texture based image features are computed. The absolute subtraction value between the left and right breasts was selected to represent each feature which is used in SVM.

The objective of this work is to develop automated system for unsupervised detection of breast cancer that explores human intelligence based deep learning techniques for achieving error free detection and risk scoring of breast cancer.

Proposed System: The proposed system uses human intelligence based unsupervised deep learning technique for detecting breast cancer using multiple imaging modalities. The various stages of the proposed system are shown in Fig. 1.

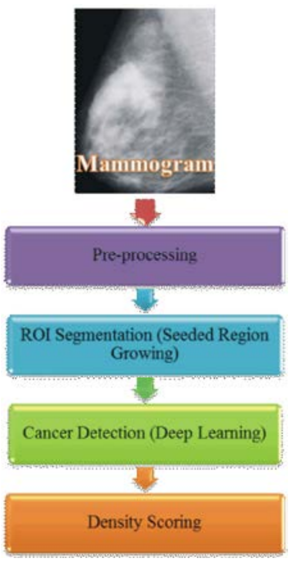

Fig. 1: Flow chart of Proposed System

Input Imaging Modalities: Several medical imaging modalities can be used as primary inputs to the medical image processing. The selection of the imaging modality for a targeted clinical study requires medical insights specific to organs under study. The proposed system uses Mammogram. Traditional mammograms use X-rays to generate information about the anatomical structure of a lesion.

Pre-Processing: Pre-processing is a common name for operations with images at the lowest level of abstraction i.e. both input and output are intensity images. Image pre-processing may have dramatic positive effects on the quality of feature extraction and the results of image analysis. The aim of pre-processing is an improvement of the image data that suppresses unwanted distortions or enhances some image features important for further processing. Fig. 2 shows the various pre-processing stages.

Fig. 2: Pre-processing Steps

Mammogram usually suffers from digitization noises such as straight lines. Radiopaque artifacts such as wedges and labels are also present in the mammograms. The presence of pectoral muscle in mammograms biases detection procedures, which recommends removing the pectoral muscle during mammogram pre-processing. Extraction of the breast profile region and the pectoral muscle is an essential pre-processing step in the process of computer-aided detection. Primarily it allows the search for abnormalities to be limited to the region of the breast tissue without undue influence from the background of the mammogram.

Digitization Noise Removal: Digitization noises such as straight lines present in the majority of acquired mammogram images are filtered using a two-dimensional (2D) Median Filtering approach in a 3-by-3 window. Each output pixel contains the median value in the 3-by-3 neighborhood around the corresponding pixel in the input images. The edges of the images however, are replaced by zeros (total absence or black color).

Artifact Suppression and Background Removal: Radiopaque artifacts such as wedges and labels in the mammograms images are removed using thresholding and morphological operations. Through manual inspection of the all mammogram images acquired, a global threshold with a value of $T = 18$ (normalized value, $T_{norm}= 0.0706$) is found to be the most suitable threshold for transforming the grayscale images into binary [0, 1] format. After the grayscale mammogram images are converted into binary, morphological operations such as dilation, erosion, opening and closing are performed on the binary images. The algorithm used for suppression of artifacts, labels and wedges is given as follows:

- All objects present in the binary image (thresholded using, T = 18) are labelled. The binary objects consist of the radiopaque artifacts and the breast profile region.
- The 'Area' (actual number of pixels in the region) of all objects (regions) is calculated.
- From all of the binary objects in the mammogram image, the largest object¯breast profile, in each image is selected, using the object with the largest Area (calculated in Step 2). This process morphologically opens a binary image and removes all objects in the binary image, except the largest object (breast profile). This operation uses an 8-connected neighbourhood.
- Next, a morphological operation to reduce distortion and remove isolated pixels (individual 1's surrounded by 0's) is applied to the binary images.
- Another morphological operation is applied the binary images to smoothen visible noise using an algorithm that checks all pixels in a binary image and sets a pixel to 1 if five or more pixels in its 3-by-3 neighbourhood are 1's, otherwise, it sets the pixel to 0.
- The binary images are eroded using a flat, disk-shaped morphological structuring element. The radius of the structuring element object used is R = 5.
- Next, the binary images are dilated using the same structuring element object in Step 6. Morphological dilation is performed.
- The holes in the binary images are filled using an algorithm that fills all holes in the binary images, where a hole is defined as a set of background pixels that cannot be reached by filling in the background from the edge of the image.
- The resulting binary image obtained from Step 8 is multiplied with the original mammogram image to form the final grayscale image. During artifact, wedge and label suppression the breast profile region is also segmented from the background.

ROI Segmentation: A region of interest (often abbreviated ROI), is a selected subset of samples within a dataset identified for a particular purpose. An ROI is a portion of an image that has to be filtered in order to perform some other operation on it. An ROI can be defined by creating a binary mask, which is a binary image that is the same size as the image to be processed. The steps involved in ROI segmentation are given in Fig. 3.

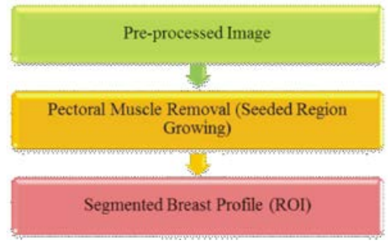

Fig. 3: ROI Segmentation Steps

Region growing is a simple region-based image segmentation method. It is also classified as a pixel-based image segmentation method since it involves the selection of initial seed points. This approach to segmentation examines neighboring pixels of initial seed points and determines whether the pixel neighbors should be added to the region.

The algorithm applied for pectoral muscle segmentation using Seeded Region Growing (SRG) is illustrated in the following steps:

- The breast orientation in each mammogram image needs to be determined prior to performing Seeded Region Growing (SRG). In order to determine the breast profile orientation (left or right) using an automated procedure, the binary image is used. The binary image is cropped left to right and then cropped top to bottom, such that the breast profile touches all four borders (left, right, top and bottom) of the image. Then the sum of the first and last 5 columns of the binary values in the cropped binary images is calculated. The breast profiles are classified using a simple if-else logic, such that, if $sum_{first} > sum_{last}$ then t he breast is right orientated else it is left-orientated.
- Contrast enhancement is performed on the breast-profile images. The limits to contrast stretch an image are found and the values in an intensity image are mapped to newer values.
- After the breast orientation in determined in Step 1 and the breast profile contrast is enhanced in Step 2, the pectoral muscle is segmented using the Seeded Region Growing (SRG) technique. In order to implement automated SRG a seed needs to be placed

inside the pectoral muscle of the grayscale mammogram image. Using results obtained from Step 1, if the breast profile is right-orientated a seed is placed inside the first 5th column and 5th row of the mammogram image, while if the breast profile is right-orientated a seed is placed inside the last 5th column and 5th row. The following four steps (a to d) are applied in the SRG process:

- The region is iteratively grown by comparing all unallocated neighboring pixels to the region.
- The difference between the pixel of interests' intensity value and the region's mean used as a measure of similarity.
- The pixel with the smallest difference measure is allocated to the respective region.
- The process stops when the intensity difference between the region mean and the new pixel become larger than the threshold value (maximum intensity distance). Based on inspection of all acquired mammogram images a SRG threshold value of T = 32 is identified as the optimum threshold satisfying all mammogram images to reliably segment the pectoral muscle from the breast profile. After SRG is complete, a binary image of the segmented pectoral muscle is obtained.
- The binary images are eroded and dilated using a flat, disk-shaped morphological structuring element with radius of R = 3.
- The resulting binary image obtained in Step 6 is multiplied with the pre-processed grayscale image. This step produces the final grayscale mammogram image with the segmented pectoral muscle.

Cancer Detection by Deep Learning Technique: Deep nonlinear models have been proven to generate descriptors that are extremely effective in object recognition and localization in natural images. Inspired by the human brain, these architectures first learn simple concepts (or features) and then compose them to more complex ones in deeper layers. Most of these models are trained by iteratively encoding features (forward propagation) and updating the learned weights to improve the optimization (backward propagation). The features can also be learned in an unsupervised way, e.g., using Restricted Boltzmann Machines or autoencoders.

The features are typically learned in a greedy, layer-wise fashion, before a classifier is trained to predict the labels from the feature responses of the top most layers. The division into multiple optimization problems has several advantages. Large amounts of unlabeled data can be exploited for training the features. The features are learned faster and more stable, as each layer is optimized by small encoder-decoder architecture instead of a complex deep network. These deep models can incorporate transformations and classifiers that are optimized independently from the features. In this work a sparse autoencoder is employed for learning the features in an unsupervised way.

The cancer detection using deep learning include the following implementation steps: input generation, construction of deep network, training the network and testing the network. The steps in cancer detection are shown in Fig. 4.

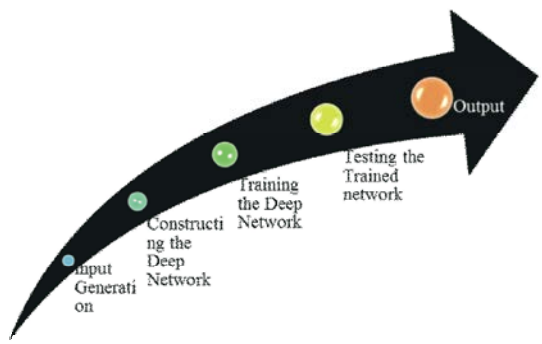

Fig. 4: Steps in Cancer detection using deep learning

Input Generation: The patch size in terms of number of pixels is restricted to 100x100 in order to keep the number of trainable weights and bias terms limited. The patches extracted from Mammogram are shown in Fig. 5. The training patches were sampled across the whole dataset. For density scoring 10% of the patches were sampled from the background and the pectoral muscle, 45% from the fatty breast tissue and 45% from the dense breast tissue.

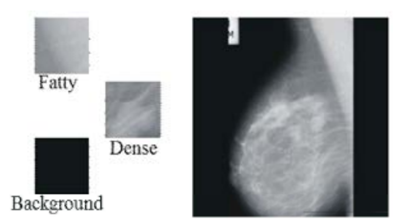

Fig. 5: Patch Extraction for Mammogram

Constructing the Deep network: The deep network is constructed by stacking an unsupervised autoencoder and a supervised softmax classifier.

The autoencoder has 4 hidden layers with sparsity parameter ρ=0.01 and weighting term of sparsity regularizer λ=1. During the training phase, the autoencoder learns a hypothesis function.

$$h:X\text{->}Y \tag{3.1}$$

where X is the input and Y is the target. During the testing phase, the autoencoder applies this hypothesis function h to the input X. The Fig. 6 shows the deep network that is constructed by stacking autoencoder and softmax classifier.

Autoencoder: In the unsupervised part, features are learned using autoencoders. A variant of the autoencoder that enables to learn a sparse overcomplete representation is proposed. A feature representation is called overcomplete if it is larger than the input. Sparsity forces most of the entries to be zero, leaving only a small number of non-zero entries to represent the input signal. Sparse overcomplete representations provide simple interpretations, are cost-efficient and robust to noise.

A novel sparsity regularizer that combines population sparsity and lifetime sparsity is used. Population sparsity limits the number of active (non-zero) units per example and lifetime sparsity limits the number of examples for which a specific unit is active. While population sparsity enforces a compact encoding per example, lifetime sparsity leads to example-specific features.

Softmax Classifier: Softmax Classifier is a two layer neural network, consisting of a pre-trained convolutional layer (Supervised layer). Softmax classifier outputs probabilities rather than margins. Probabilities are much easier for us as humans to interpret, so that is a particularly nice quality of Softmax classifiers. The regularization term is appended to the loss function and is used to control the weight matrix W. By controlling W classification accuracy can be increased.

The three class labels for density scoring are background, fatty and dense. In case of texture scoring the class labels are cancer and control. The Fig. 7 shows the classes in density scoring and texture scoring.

Training the Deep Network: Neural networks with multiple hidden layers can be useful for solving classification problems with complex data, such as images. Each layer can learn features at a different level of abstraction. However, training neural networks with multiple hidden layers can be difficult in practice.

One way to effectively train a neural network with multiple layers is by training one layer at a time. This can be achieved by training a special type of network known as an autoencoder for each desired hidden layer.

First the hidden layers are trained individually in an unsupervised fashion using autoencoders. Then a final softmax layer is trained and then the layers are joined together to form a deep network, which is trained one final time in a supervised fashion. Fig. 8 depicts the deep network trained with multiscale data.

Testing The Trained Network: If the training is perfect, the network outputs and the targets would be exactly equal. If the network is not sufficiently accurate, the network can be initialized and the trained again. Each time a feedforward network is initialized; the network parameters are different and might produce different solutions.

As a second approach, the number of hidden neurons can be increased above 20. Larger numbers of neurons in the hidden layer give the network more flexibility because the network has more parameters it can optimize. The layer size has to be increased gradually. If the hidden layer is made too large, it can cause the problem to be under-characterized and the network must optimize more parameters than there are data vectors to constrain these parameters.

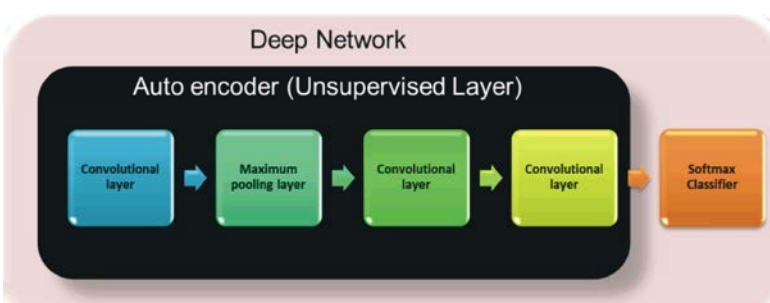

Fig. 6: Deep network

Fig. 7: Softmax Classifier Classes

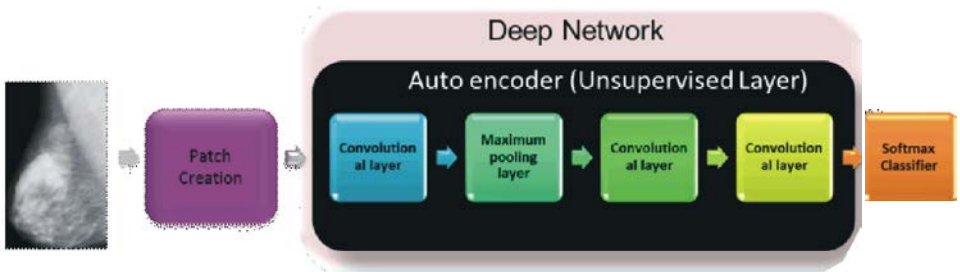

Fig. 8: Training the Deep Network

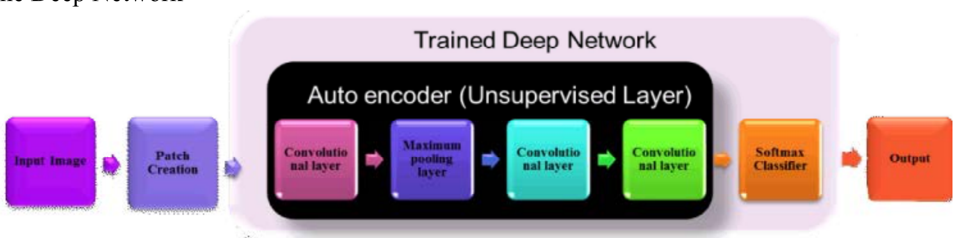

Fig. 9: Deep Network Testing

A third option is to try a different training function.

Finally, additional training data can be used. Providing additional data for the network is more likely to produce a network that generalizes well to new data. The Fig. 9 depicts the testing of data using the trained deep network.

RESULTS AND DISCUSSIONS

There are many different publicly available Mammographic databases. The methodology described in this work is tested using the mini-MIAS Mammographic Database.

Database: The Mammographic images from MIAS Mini Mammographic Database were used in the unsupervised deep learning based cancer detection. The Mammographic Image Analysis Society (MIAS) is an organisation of UK research groups interested in the understanding of mammograms and has generated a database of digital mammograms. Films taken from the UK National Breast Screening Programme have been digitised. The database contains 322 digitised films. It also includes radiologist's "truth"-markings on the locations of any abnormalities that may be present. The database has been padded or clipped so that all the images are 1024x1024. Mammographic images are available via the Pilot European Image Processing Archive (PEIPA) at the University of Essex. A sample of these images are shown in Fig. 10.

Pre-Processing: The results obtained at various pre-processing stages of mammogram are discussed in the following sections.

Digitization Noise Removal: A 2D Median filtering with 3x3 neighborhood window is used to remove the digitization noises present in the input image shown in Fig. 11(a). The resultant image after removal of digitization lines is given in Fig. 11 (b).

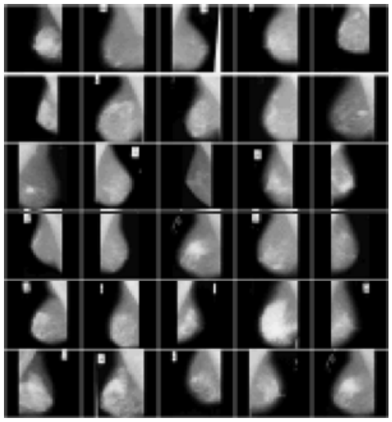

Fig. 10: Sample images from MIAS database

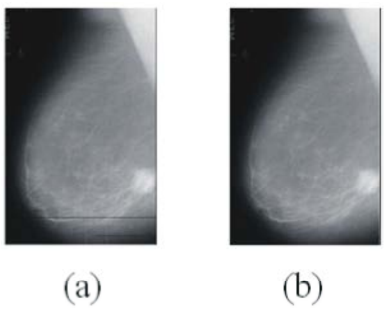

Fig. 11: (a) Original image (b) Filtered image after noise removal

Artifact Suppression and Background Separation: Radiopaque artifacts such as wedges and labels in the mammograms images are shown in Fig. 12(a). This can be removed using thresholding and morphological operations. Through manual inspection of the all mammogram images acquired, a global threshold with a value of T = 18 (normalized value, Tnorm= 0.0706) is found to be the most suitable. The thresholded image is shown in Fig. 12(b).

From all of the binary objects in the mammogram image, the largest object¯breast profile, in each image is selected, using the object with the largest area. The binary image is morphologically opened and all objects in the binary image, except the largest object (breast profile) are removed. This operation uses an 8-connected neighbourhood.

The resulting binary image is shown in Fig. 12(c). This image is multiplied with the original mammogram image to form the final grayscale image shown in Fig. 12(d).

ROI Segmentation: The Seeded Region Growing (SRG) algorithm is applied for pectoral muscle segmentation. The breast orientation in each mammogram image is determined prior to performing Seeded Region Growing (SRG). If the breast profile is right-orientated a seed is placed inside the first 5th column and 5th row of the mammogram image, while if the breast profile is right-orientated a seed is placed inside the last 5th column and 5th row. SRG threshold value of T = 32 is identified as the optimum threshold satisfying all mammogram images to reliably segment the pectoral muscle from the breast profile.

The region is iteratively grown by comparing all unallocated neighboring pixels to the region. The resultant binary image is shown in Fig. 13(b). The resulting binary image is multiplied with the pre-processed grayscale image (Fig. 13(a)). This step produces the final grayscale mammogram image with the segmented pectoral muscle shown in Fig. 13(c).

Patch Creation: It is computationally prohibitive to map entire images to label masks. Downsampling the image is also infeasible, as many structures of interest occur at a fine scale. So, a compact representation can be learned for local neighbors (or patches) from the image. Thus images are separated into patches of size 100x100 as shown in Fig. 14.

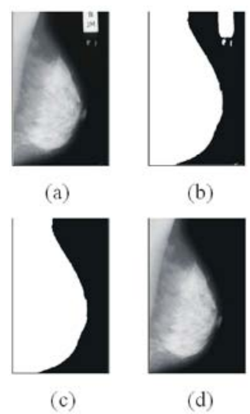

Fig. 12: Suppression of artifacts, wedges and labels from a mammogram (a) Original image (b) Thresholded image using T = 18 (c) Largest area (object) selected from thresholded image (b) (d) Mammogram image with radiopaque artifacts suppressed

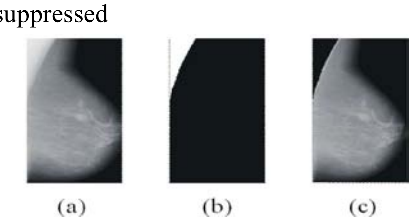

Fig. 13: (a) Preprocessed Image (b) Segmented Pectoral Muscle (c) After Pectoral Muscle Removal

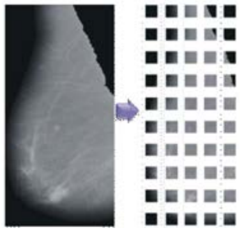

Fig. 14: Mammogram separated into 100x100 patches

Performance of the Deep Network: The performance metrics used for evaluating the performance of the deep network are listed below.

Confusion Matrix: A confusion matrix is a specific table layout that allows visualization of the performance of an algorithm. Each column of the matrix represents the instances in a predicted class while each row represents the instances in an actual class (or vice versa). The name stems from the fact that it makes it easy to see if the system is confusing two classes (i.e. commonly mislabelling one as another). Fig. 15 shows the confusion plot for the Mammogram.

Performance Measures: Accuracy and misclassification rate can be calculated from the confusion matrices.

Accuracy: Accuracy is the ratio of correct classifications to the total number of inputs.

$$Accuracy = \frac{(TP+TN)}{TOTAL} \quad (4.1)$$

where, TP – True Positive and TN – True Negative

Misclassification Rate: Misclassification Rate is the ratio of wrong classifications to the total number of inputs.

$$Misclassification\ Rate = \frac{(FP+FN)}{TOTAL} \quad (4.2)$$

where, FP –False Positive and FN – False Negative.

Fig. 16 shows the accuracy and misclassification chart for mammogram using deep learning technique.

Density Scoring: After training the deep network, this trained network is used in predicting the density score of Mammogram. The input image is first divided into patches and the density of each patch is predicted. The Figure 17 shows the density scoring results for a Mammogram.

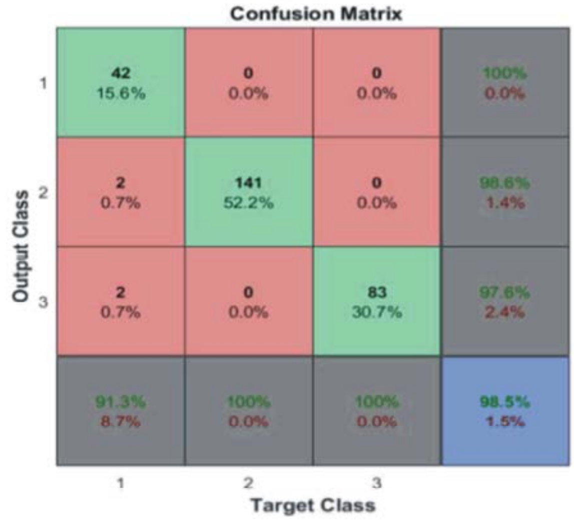

Fig. 15: Confusion plot for Mammogram

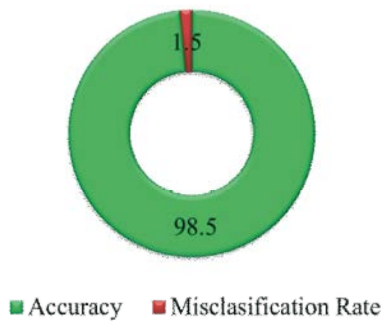

Fig. 16: Performance Chart

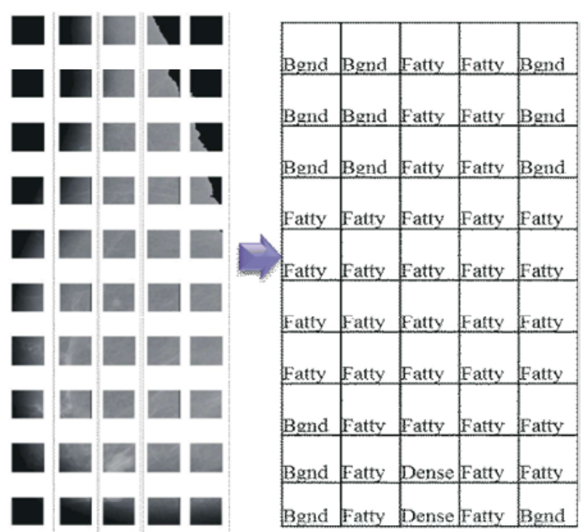

Fig. 17: Density Scoring for Mammogram

Thus, from the results, it is clear that the dense tissue represents cancer in detection using Mammogram.

CONCLUSION

In the proposed work, an unsupervised deep learning technique is used in breast cancer detection from Mammogram images. The mammographic images used in this work are obtained from publicly available database Mini MIAS. The mammograms are first pre-processed to remove digitization noise, radio opaque artifacts, background and pectoral muscle which reduce the effectiveness of the deep network in detecting the cancer. The proposed model has achieved an accuracy of up to 98.5% in classifying dense mammogram images. The use of unsupervised deep learning techniques helps to identify smaller masses more accurately pinpoint their locations,. This helps in providing earlier treatment for women with breast cancer and spares other women the pain and anxiety of undergoing a biopsy.

REFERENCES

1. Md. Shafiul Islam, Naima Kaabouch and Wen Chen Hu, 2013. “A survey of medical imaging techniques used for breast cancer detection”, IEEE, Electro/Information Technology (EIT), IEEE International Conference, pp: 1-5.
2. Sachin Prasad N. and Dana Houserkova, 2007. “The role of various modalities in breast imaging”, Biomed Pap Med Fac Univ Palacky Olomouc Czech Repub, pp: 209-218.
3. Shyamala, K., H.C. Girish and Sanjay Murgod, 2014. “Risk of tumor cell seeding through biopsy and aspiration cytology”, Journal of International Society of Preventive & Community Dentistry, pp: 5-11.
4. Jawad Nagi, Sameem Abdul Kareem, Farrukh Nagi, Syed Khaleel Ahmed, 2010. “Automated Breast Profile Segmentation for ROI Detection Using Digital Mammograms”, IEEE EMBS Conference on Biomedical Engineering & Sciences.
5. Anuj Kumar Singh and Bhupendra, 2015. “A Novel Approach for Breast Cancer Detection and Segmentation in a Mammogram”, Gupta Eleventh International Multi-Conference on Information Processing-2015 (IMCIP-2015).
6. Mellisa Pratiwia, Alexandera, Jeklin Harefaa, Sakka Nandaa, 2015. “Mammograms Classification using Gray-level Co-occurrence Matrix and Radial Basis Function Neural Network”, IEEE, International Conference on Computer Science and Computational Intelligence (ICCSCI 2015).
7. Jürgen Schmidhuber, 2015. “Deep learning in neural networks: An overview”, Elsevier, Neural Networks 61: 85-117.
8. Martin Langkvist, Lars Karlsson and Amy Loutfi, 2014. “A review of unsupervised feature learning and deep learning for time-series modelling”, Elsevier, Pattern Recognition Letters, 42: 11-24.
9. Li, Deng and Dong Yu, 2014. "Deep Learning: Methods and Applications", Foundations and Trends® in Signal Processing, 7(3-4): 197-387.
10. Yanming Guo, Yu Liu, Ard Oerlemans, Songyang Lao, Song Wu and Michael S. Lew, 2016. “Deep learning for visual understanding: A review”, Elsevier, Neurocomputing, pp: 27-48.
11. Pierre Baldi, 2012. “Autoencoders, Unsupervised Learning and Deep Architectures”, JMLR: Workshop and Conference Proceedings, pp: 37-50.
12. Michiel Kallenberg, Kersten Petersen, Mads Nielsen andrew Y. Ng, Pengfei Diao, Christian Igel, Celine M. Vachon, Katharina Holland, Rikke Rass Winkel, Nico Karssemeijer and Martin Lillholm, 2016. “Unsupervised Deep Learning Applied to Breast Density Segmentation and Mammographic Risk Scoring”, IEEE Transactions On Medical Imaging, 35(5).
13. Maxine Tan, Bin Zheng, Joseph K. Leader and David Gur, 2016. “Association Between Changes in Mammographic Image Features and Risk for Near-Term Breast Cancer Development”, IEEE Transactions on Medical Imaging, 35(7).