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Diagnosis of Breast Cancer from Mammographic Image using Artificial Neural Networks

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Abstract
Among women breast cancer is one of the common leading causes of cancer. In this paper we present the recent work done in diagnosing breast cancer from mammographic image using Artificial Neural Network.
Keywords: *Artificial Neural Network, mammographic image, benign, malignant.*

1. Introduction

Among women breast cancer is one of the common leading causes of cancer. Every year half a million women are dying of breast cancer [1]. For most women increase age is considered as the major factor for causing breast cancer. If tumor is detected early, when it is small then chance of survival also increases. Detecting the tumor in the early stage, raise the survival rate of breast cancer patient. To detect the tumor by radiologist in early stage screening mammograms is considered as the best tool.

A mammogram is low radiation X-ray. Mammograms have two types; one is screening mammograms: this mammogram is taken for patient who doesn’t have symptoms of breast cancer. Screening mammograms detects the disease early before it is spread to other parts of the body. The other mammogram is diagnostic mammograms: this mammogram is taken for patients having symptoms of breast cancer. Diagnostic mammogram also helps doctors to locate the presence of abnormalities.

With the availability of digital mammograms, abnormalities in the breast cell can be easily seen with more clarity as per the requirement of the radiologist such as: magnification, orientation, brightness and contrast. Digital mammography is an electronic X-ray which we can stored in computer and access whenever required. Determining the stages of the cancer from mammogram by radiologist is time consuming and inefficient. Using digital mammography and Computer-Aided Detection (CAD) radiologist can automatically identify the tumor present in the mammogram that can be correlated with malignancy. As the result of increasing improvement in ML and growth in computer vision with more advance automated learning system commonly known as Deep Learning CAD system has been constantly improving the diagnostic capabilities.

Some of the important steps of image processing in CAD include enhancement, segmentation, feature extraction, feature classification, and an evaluation for the classifier. For accurately identifying breast cancer, in the image processing step feature extraction is considered an imperative step. Various CAD model has been created so far using Artificial Neural Network (ANN) to develop an advanced automated CAD system that gives high accuracy and reduce the waiting time. Most frequently used ANN techniques include BPNN [1,2,3,4,5,7,11,15], RBF [10,11] network, SVM [10,14], PNN [6,8,10], KNN [10], TSK [10], CNN [9,14,18,19,20] etc.

This paper presents the recent work done in diagnosing breast cancer from mammographic image using ANN. This paper also provides the reader the growth in breast cancer detection using CAD with advanced computer vision and the challenges faced. We present the recent studies that have addressed these challenges and finally provide some insights and discussions on the current open problems.

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2. Artificial Neural Network

ANN mimic the limited understanding of working system of human neurons. It makes the computer system learn from data and make decisions just like the human neurons. ANN structure has input and output nodes like human neural network. In each layer the nodes are not connected whereas nodes in various layers are interconnected. Each interconnected node is link with a weight that determines the importance of the connecting node. A simple ANN have three layers one input layer, one hidden layer and one output layer which are interconnected with each other as shown in Figure 1.

Artificial neurons were first invented by McCulloch and Pitts in 1943 and in 1958 Frank Rosenblatt developed the practical perceptron model [16]. Different ANN model includes multilayer feedforward network (FFN), Hopfield network, Radial Basis Function (RBF), Kohonen's Self Organizing Neural network, Recurrent Neural Network, Convolutional Neural Network (CNN) etc. Among them multilayer's FFN are the most extensively studied and used network.

ANN can be used to find patterns and discover trends that are overly complicated to be noticed by either humans or computer techniques. A skilled neural network can be thought of as an expert in the class of data it has been given to analyze. It has wide application and has been applied in many areas: such as engineering, sciences, medical, agriculture etc. Figure 1 show a three-layer neural network. The input layer has n input nodes, the hidden layer has m nodes and the output layer has p nodes, weights between the input layer and hidden layer are denoted by w_{ij} where $i = 1,2,..n$ and $j = 1,2,...m$. Backpropagation neural network (BPNN) is commonly used neural network algorithm. The input nodes collect input information and pass to the next hidden nodes which is process using activation function. Some of the activation functions are listed in Table 1. The output from the hidden nodes provides as input to the next layer and process using activation function and gives the output. In backpopagation neural network loss function is calculated from the output layer and backpropagated to adjust weight and minimize loss function.

Training in ANN is the technique of adjusting the weight using training datasets that connect between different neurons in different layers. The learned neural network is then used and tested on the testing data set to perform the realistic output solution. Different network architecture of ANN can be created by adding more layers in the hidden layers. An ANN that has more than three hidden layers is called deep neural network which develop deep learning. ANN that is three layer or deep neural network information flows from one layer to another like human neurons.

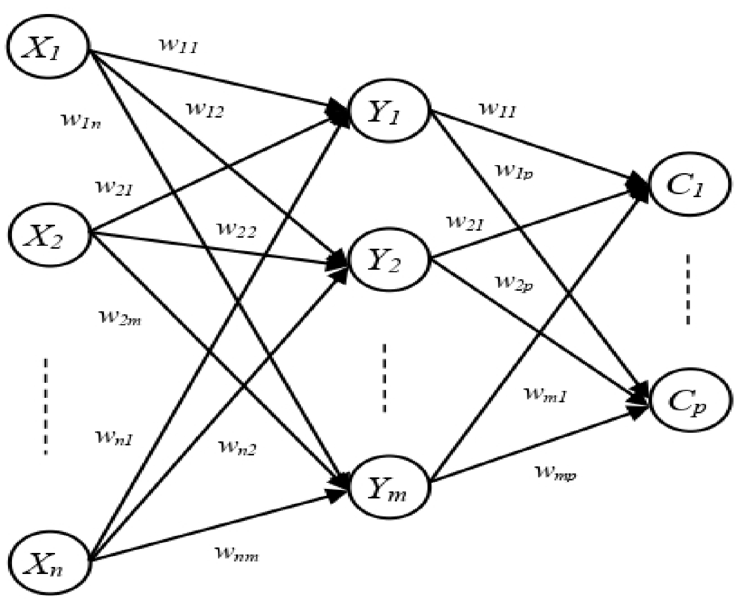

Fig. 1 Neural Network

Table 1: Activation Function for BPNN

Name	***Function***
Sigmoid	$\frac{1}{1+e^{-x}}$
Tanh	$\boldsymbol{tanh(x)}$
Relu	Max(0,x)
Softmax	$\frac{e^{x_i}}{\sum e^{x}}$

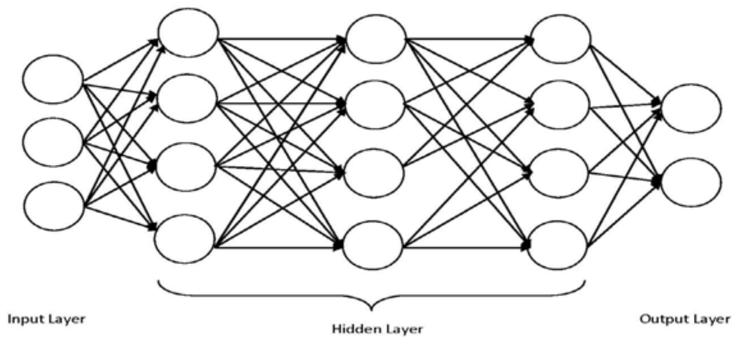

Fig. 2 A Deep Neural Network

Regular ANN doesn't scale well to full images. CNN are mostly used for classification of image datasets as they used kernels to automatically generate features from the image. For CNN the neuron is organized in 3 dimensions as compared to regular NN. The architecture of a CNN includes an Input layer, convolution, pooling and fully connected layer. Input neurons accept input as matrix of pixel values, convolution receives feature values by applying filters in input image, provide special variance, which simply means that the system will be capable of recognizing an object even when its appearance varies in some way, in a fully connected layer, the output to the last convolution is flatten and connect fully to the next layer for classification. Figure 3 shows a CNN with two Convolution layer two pooling layer and two fully connected layers.

3. ANN for Breast Cancer Detection

Breast cancer starts when the cancer cells inside the breast grow out of control. Breast cancer tumor can be notice from the mammogram or it can be felt as a lump. The tumor is said to be malignant (cancerous), if it can invade other tissue. Dutch's researchers perform an AI based breast cancer detecting system like radiologist [17]. They collected 29,000 reading which is broken down into 9 datasets, each containing digital mammograms read by 101 radiologists [17]. They train and tested the AI on more than 9,000 cancerous mammograms and 180,000 non-cancerous mammograms. Experiment results shows that AI outperform radiologists with area under the curve (ROC) of the AI as 0.84 as compared to 0.814 achieved by radiologist. It achieves a higher sensitivity than 55 of 95 radiologist, but the researchers found that AI performance is lower than that of the best radiologist. One of the possible take away from their research is the possible positive effect of an AI algorithm in region with less experienced radiologists, the author argued.

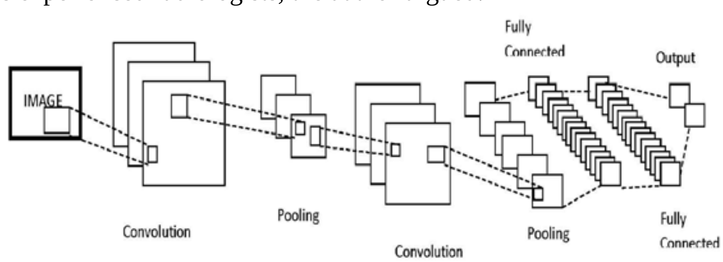

Fig. 3 CNN

Current advancement in ANN and advance in computer vision narrows down the breach between computers and human experts in detecting breast cancer in digital mammograms [17]. Several classification algorithms based on ANN algorithms has been proposed to improve the automatic classification of breast cancer. Some of the classification algorithms used are Probabilistic Neural network (PNN), Radial Basis Function (RBF), Backpropagation Neural Network, Deep Learning, Convolution Neural Network (CNN). ANN model using leave one out cross validation is used for classification of mammographic image taken from the Digital Database for Screening Mammography (DDSM) into Normal, Benign and cancers in [7]. Here texture characterization is applied on the mammographic image using Haralick’s descriptors. The performance accuracy of the classifier for the leave-one out cross validation and test set is found to be 84.72%. ANN model and texture feature extraction using Gray Level Co-occurrence Matrix (GLCM) along 0° is used for classifying mini-MIAS dataset containing 322 mammograms of which 270 images are benign and 52 images are malignant in [12]. The proposed system consists of four stages: acquisition of image, feature extraction from image, selection of optimal features, and classification of the mammogram image as benign and malignant. Using GLCM along 0°, 10 features are extracted which further filter into 6 features using rank features and then train the ANN. The ANN consists of three layers: input, hidden and output layer. The result on validation dataset shows accuracy of 100% and an overall accuracy of 99.4%.

A neural network model Extreme Learning Machine Neural Networks (ELM ANN) for classification of Breast Cancer Wisconsin Dataset is proposed in [13]. ELM ANN train the network model with small norm weight giving low training error rate that gives better generalization model and attain global minima. The proposed method used k-fold cross-validation with $k = 5$. The performance of the classifier is evaluated using accuracy, specificity and sensitivity. The proposed method is compared with BP ANN. From the experimental results ELM ANN has better performances with accuracy of 0.964 as compared to BP ANN with accuracy of 0.921. The experiment found that ELM ANN has less specificity of 0.97 as compared to 0.98 for BP ANN.

In [6] the authors proposed a method for classifying Breast cancer mammographic images into normal, benign and malignant using Probabilistic Neural Network (PNN). The proposed method involves image enhancement using Adaptive median filter and Balance Contrast Enhancement, segmentation using Thresholding and Fuzzy C-Means, Feature extraction using Discrete Wavelet Transform and classification using PNN. Experiments were conducted on 75 images and the proposed methods achieve accuracy of 90%.

A feature extraction method from digital mammogram using Digital Image Processing, Knowledge Discovery Database and Artificial Intelligence (AI) is proposed by [8], to diagnose Breast Cancer using GRANN. The proposed methodology extract features from the image and used as input to GRANN for training the model. Feature extraction is done using Digital Image Processing that produces a Bio Marker for detecting breast cancer. The image feature is used to classify the mammogram as benign and malignant. The network is train by keeping smoothing factor of e1-4 and the training accuracy of the network model gives 95.83%. The performance of the classifier model is calculated using accuracy, sensitivity, specificity and precision. This CAD using AI is created to diagnose Mexican breast cancer patients. The authors conclude that the proposed method will reduce the waiting time and reduce human and technical error in diagnosing breast cancer.

A classification model based on Convolutional Neural Network (CNN) has been proposed in [9]. The proposed model has two forms: 1st form uses 2D-DWT to decompose into four sub bands and 2nd form use discrete curvelet transform (DCT). The CNN is train using a soft max layer and an SVM layer. The proposed model is use for classifying large dataset. The dataset used is IRMA. The proposed model uses 10-fold cross validation for classifying the mammographic image into three classes normal, benign and malignant. The validation of the proposed model is calculated using classification accuracy, Positive Predictive Value (PPV), Negative Predictive Value (NPV), sensitivity, specificity, Matthews Correlation Coefficient (MCC), and Receiver Operating Characteristic (ROC). The performance of the model CNN-DW on the validation dataset is 83.14% and test dataset is 81.18% using softmax layer. The average performance of CNN-DW using SVM layer is 81.23% in ten cross validation. For the model CNN-CT the performance on the validation dataset is 84.57% and on the test dataset is 82.54% using softmax layer. The average performance of CNN-CT using SVM layer is 83.11% in ten cross validation. The author concludes that breast cancer detection using feature learn from the dataset as input to CNN perform better in breast cancer detection.

In [10] the author proposed a new technique for breast cancer classification as normal benign mass and malignant mass using geometric feature extraction and classification algorithm. The proposed method determine the boundary of the masses and classify the image using classification algorithm such as the radial basis function (RBF), probabilistic neural network (PNN), and multi-layer perceptron (MLP) as well as the Takagi-Sugeno-Kang (TSK) fuzzy classification, the binary statistic classifier, the k-nearest neighbors (KNN) clustering algorithm and support vector machine (SVM). The dataset used in this paper is digital database for screening mammography (DDSM). The performance of the proposed method is evaluated using accuracy, sensitivity and specificity. The proposed method generates 19 features for each image which serve as an input vector to the RBF, PNN, MLP, TSK, KNN clustering algorithm and SVM. Experimental results show that SVM algorithm gives the best result with accuracy: 97%±4.36, sensitivity: 100%±0 and specificity: 96%±5.81. The authors conclude that using a greater number of simple features extracted from the mammographic image and classifying using many classification algorithms predict the masses more accurately.

In [11] the author proposed a method for classifying a breast cancer mammographic data obtained from Near East University Hospital into cancerous and non-cancerous. The proposed method used discrete Haar wavelet for enhancing the mammographic and then fed into BPNN and RBF network. Discrete Haar wavelets are evaluated on the mammograms which results in four different mammogram images: approximate, horizontally detailed, vertically detailed, diagonally detailed images. The resultant images are then summed and construct a new image using inverse wavelet. This new image is than fed into BPNN and RBF networks. The dataset contains taken for this experiment contain 176 mammogram images which is divide into two sets, 115 training dataset and 61 testing datasets. The result of the experiment shows an accuracy of 59.0 % with an error rate of 0.01352 for BPNN and 70.4 % with an error rate of 0.0220 for RBF networks.

In [15] the author presented a study for detecting breast cancer as benign or malignant using BPNN on dataset retrieved from 11,850 screened cases from Shahid Motahhari breast clinic between 2004 and 2012. The BPNN is trained and tested using 10-fold cross validation. The performance is evaluated using accuracy, sensitivity and specificity. The AUC of the BPNN, is 0.955 with sensitivity and specificity as 0.82 and 0.90. The authors state the limitation as the retrospective of the proposed method on the registered data which limit the external validity of the result obtained.

In [14] the authors proposed a new methodology for classification of breast cancer mammogram using Deep Neural Network and two segmentation techniques. The segmentation techniques used are determination of region of interest (ROI) manually and technique of threshold and region based. The approach used Alexnet Deep convolution Neural Network (DCNN) for feature extraction and classification of the dataset as benign and malignant is done by connecting SVM to DCNN. The dataset used is DDSM and CBIS-DDSM. The classification performance is evaluated using confusion matrix, accuracy, receiver-operating characteristic curve (ROC), precision, and F1 score. The network architecture consists of five stages of CNN and the last fully connected layer is connected to SVM. The proposed method is trained using 5-cross validation. The experimental result of DCNN using ROI segmentation method on DDSM gives accuracy of 71.01% whereas with SVM it gives accuracy of 79% and88% AUC. The experimental result of DCNN using technique of threshold and region-based segmentation method on DDSM gives accuracy of 69.2% whereas with SVM it gives accuracy of 80.9% and 88% AUC. The experimental result of DCNN on CBIS-DDSM gives improved accuracy of 73.6% whereas with SVM it gives highest accuracy of 87.2% and 94% AUC.

In [18] the author proposed a breast cancer detection method using Convolution Neural Network (BCDCNN) for classifying a mammogram image collected from mini-MIAS database as malignant, benign, or normal. The training dataset is subsample using image transformation such as rotation 90, 180, 270 degrees adding horizontal reflected version for each rotation. The CNN classifier is trained using the training dataset and tested on 322 mammogram images. The proposed model shows an improved accuracy of 0.75 to 0.8585 for mass only and 0.608974 to 0.8271 for all argument.

In [19] the author proposed a network model to classify breast cancer mammographic data as benign or malignant using preprocessing step and CNN. The dataset is collected from Health Cooperative. Preprocessing in done on the mammograms using contour let transform to enhance features in image. In the proposed model the authors used 3 CNN layers with filters 30, 50 and 40. Three pooling layers are used in the network whose size is 2 x 2 with stride of 2 and four fully connected layers each of 105, 25, 7 and 2 neurons with RelU activation function. The network model was trained for 4000 iterations and achieved an accuracy of 100% on the testing dataset. The author suggests future work with larger dataset.

In [20] the author proposed a quantum convolutional neural network (QCNN) for classification of breast cancer mammography data in Wisconsin breast cancer database from Kaggle, which are MRI images using deep learning and quantum framework. The proposed model learns from the label data and minimizes loss function. The network model learns from the label data by training the network of ten qubits. The proposed model is tested at the IBM quantum experience platform for effectiveness on quantum simulator. From the experimental result CNN achieve an accuracy of 98.6%, with sensitivity and specificity of 97.5% and 99.4%. Whereas the proposed model QCNN achieve an accuracy of 98.9%, with sensitivity and specificity of 97.7% and 99.6%. Thus, QCNN perform slightly better than CNN in terms of accuracy, sensitivity and specificity.

In [21] the authors proposed new method based on Deep Neural Network with Support Value (DNNS) for classification of breast cancer data as benign or malignant. The proposed method consists of three stages: 1st stage preprocessing using Gaussian noise, 2nd stage feature extraction and the third stage segmentation using Histo-sigmoid based fuzzy clustering. The dataset is taken from M. G Cancer Hospital & Research Institute, Visakhapatnam. Rotation of 90◦, 180◦, and 270◦ has been carried out in the training and testing dataset. The performance of DNNS is evaluated using Accuracy, Sensitivity, Precision, Recall, F-measure, Rank sum. The performance of the proposed model DNNS have accuracy of 97.21, 97.9 precision and 97.01 recall which is found to perform better as compared to Naive Bayes classifier, SVM classifier, Bi-clustering and Ada boost techniques, RCNN classifier, Bidirectional Recurrent Neural Networks (HA-BiRNN).

In [22] the author uses machine learning and deeplearning (ML-DL) method detecting breast cancer as malignant or benign. The method aims at detecting early breast cancer from a large dataset collected from Maccabi Health Services and Assuta Medical Centers. The experimental result shows that the proposed model achieve a sensitivity of 75% and specificity of 88%–95% which is within the acceptable range of radiologist.

Table 2: ANN Algorithm used for detecting Breast Cancer

Reference	***Model Used***	***Performance***
Y. A. Hamad, K. Simonov and M. B. Naeem	PNN	90% accuracy
M. Pérez, M. E. Benalcázar, E. Tusa, W. Rivas and A. Conci	ANN based on BPNN	accuracy using leave-one out cross validation and test set is 84.72%
J.M.O. Rodriguez, C.G. Mendez, M.R.M. Blanco, S.C. Tapia, M.M. Lucio, R.J. Martinez, L.O.S. Sánchez, M.L. Fierro, I.G. Veloz, J.C.M. Galvan and J.A.B. Garcia.	GRANN	training accuracy of the network model gives 95.83%.
M.M. Jadoon, Q. Zhang, I.U. Haq, S. Butt and A. Jadoon,	1st model CNN-DW that uses 2D-DWT to decompose into four subbands and 2nd Model CNN-CT that uses discrete curvelet transform (DCT).	Average performance is 81.23% for CNN-DW and 83.11% for CNN-CT.
N. Safdarian and M.R Hedyehzadeh,	RBF, PNN, MLP, TSK, KNN, SVM	SVM perform better with accuracy 97%±4.36, sensitivity: 100%±0 and specificity: 96%±5.81.
S. Kaymaka, A. Helwana and D. Uzuna	RBF, BPNN	Accuracy of 59.0 % with an error rate of 0.01352 for BPNN and 70.4 % with an error rate of 0.0220 for RBF networks.
N. Tariq	ANN and texture feature extraction using Gray Level Co-occurrence Matrix (GLCM) along 0°	On validation dataset shows accuracy of 100% and an overall accuracy of 99.4%
C.P. Utomo, A. Kardiana and R. Yuliwulandari	ELM ANN	accuracy of 0.964 has specificity of 0.97.
D.A. Ragab, M. Sharkas, S. Marshall and J. Ren,	DCNN with SVM	accuracy of 87.2% and 94% AUC.

M. Sepandi, M. Taghdir, A. Rezaianzadeh and S. Rahimikazerooni	BPNN	AUC is 0.955 with sensitivity and specificity as 0.82 and 0.90.
Y. J. Tan, K. S. Sim and F. F. Ting	CNN	accuracy of 0.75 to 0.8585 for mass only and 0.608974 to 0.8271 for all argument.
N. Pirouzbakht, J. Mejıa, E. Computacion,	CNN	100% of accuracy.
A. Bisarya, W.E. Maouaki, S. Mukhopadhyay, N. Mishra, S. Kumar, B.K. Behera, P.K. Panigrahi and Debashis de	quantum CNN (QCNN),	accuracy of 98.9%, a sensitivity of 97.7% and a specificity of 99.6%.
A.R. Vakaa, B. Sonia, and S. Reddy K.	Deep Neural Network with Support Value (DNNS).	accuracy of 97.21, precision of 97.9 and recall of 97.01

Table 1: Margin specifications

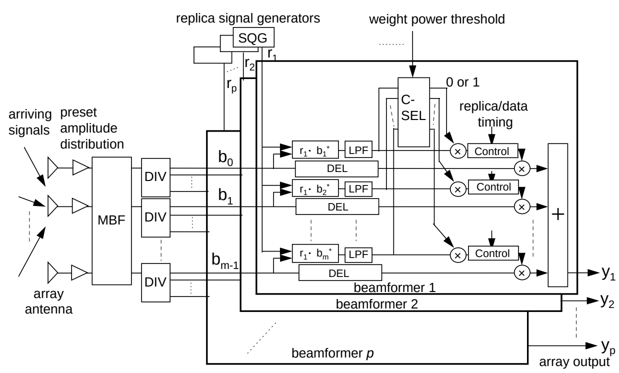

Fig. 1 Proposed beam former.

4. Discussion

Features extraction plays a main role in detecting the breast cancer mammogram image as cancerous or non-cancerous, using the ANN algorithms and different features extraction techniques [12][6][8][9][10] improves the accuracy of the classifier. As can be seen from table 2, ANN with optimal features extraction in mini-MIAS dataset having 270 benign and 52 malignant, achieves an accuracy of 99.4% [12]. In [6] feature extraction using discrete wavelet transform and PNN on 75 images achieve an accuracy of 90%. In [8] feature extraction with GRANN achieve an accuracy of 95.83% on training datasets. In [9] the author concluded that detection of breast cancer using feature and the performance of the classifier CNN-CT using SVM has better accuracy. In [10] the authors found that SVM with features extraction give better accuracy of 97%±4.36 and it is found that if more feature is used from the mammogram image with the classifier gives better accuracy. We found that feature extraction using SVM increase the sensitivity to 100%±0 and specificity: 96%±5.81 [10] and 94% AUC with DCNN [14].

The performance of the classifier can be increased by rotating the images. In [18] CNN with rotation of degrees 90, 150 and 270 improves its accuracy. Using DNN with support value (DNNS) and rotation with feature extracted from image as input to the model DNNS gives an accuracy of 97.21 % as compared to other classifier. CNN perform better in accuracy for classifying the mammographic images into malignant and benign. In [19] CNN gives an accuracy of 100% and in [20] QCNN perform better than CNN with accuracy of 98.9%.

5. Conclusions

Several ANN classification algorithms have been used for detecting breast cancer and it has been found that the performance in terms of accuracy is high as compared to other classifier. The accuracy of the model also depends on the dataset, the feature extraction steps and image segmentation. To create a model that give good accuracy one must find an appropriate segmentation method, feature extraction technique and choose a neural network algorithm. From the study we see that a good feature extraction technique with SVM network gives good performance in detecting breast cancer.

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