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An Efficient Neural Network Based System for Diagnosis of Breast Cancer

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Abstract-Breast Cancer is one of the fatal diseases causing more number of deaths in women. Constant efforts are being made to develop more efficient techniques for early and accurate diagnosis of breast cancer. Classical methods required cytopathologists or oncologists to examine the breast lesions for detection and classification of various stages of the cancer. Such manual attempts have proven to be time consuming and inefficient in many cases. Hence there is a need for efficient methods that diagnoses the cancerous cells without human involvement with high accuracies. This paper proposes an automated technique using artificial neural networks as decision making tools in the field of breast cancer. The features extracted from biopsy slide images are used to train the neural network. Both supervised and unsupervised methods of neural networks are tested to develop the most efficient alternative for breast cancer diagnosis. Self-organization map (SOM) method under unsupervised techniques is used to classify the WDBC dataset into benign and malignant. Under supervised method, a variant of back propagation algorithm, scaled conjugate gradient is investigated for the same. The generalization capability of the network is improved using the Bayesian regularization technique.

Index Terms - Artificial Neural Network, Breast cancer diagnosis, SOM, LVQ, Back propagation, Generalization, Bayesian regularization.

1. INTRODUCTION

Cancer detection and diagnosis is one of the most important areas of research in medical field. Neural networks have been used for same by many researchers [1]-[5] for different classes of cancer. Different algorithms of neural networks have been used for cancer detection [6]-[8], [10]-[12].

Breast cancer is the second most common disease that affects women, next to skin cancer. According to recent statistics, about 1 in 8 women in US develop breast cancer over the course of her life [11]. However, it is curable at initial stages and hence early detection can reduce the mortality rate. Conventionally, Breast cancer detection and classification is performed by a clinician or a pathologist by observing stained biopsy images under the microscope. However, this is time consuming and can lead to erroneous results [7]. This paper proposes a novel approach for automated cancer detection using Artificial Neural Networks (ANN).

Artificial Neural Networks:

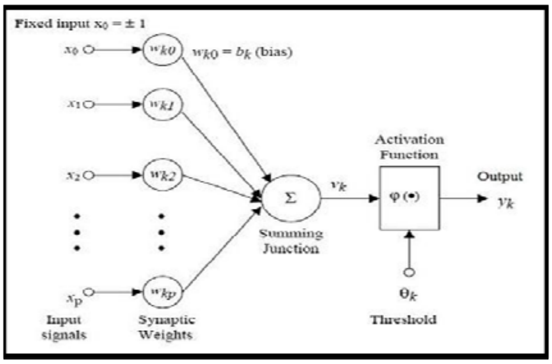

Fig. 1: Components of ANN

Artificial neural networks are computational systems whose concept is derived from biological neural networks. An ANN consists of a collection of processing elements that are highly interconnected and transform a set of inputs to a set of desired outputs. The result of transformation is determined by the characteristics of the elements and the weights associated with the interconnections among them. Fig. 1 shows the components of ANN.

The various tasks performed by ANN are pattern classification [9], fault detection [13], [14], speech analysis, processing of inaccurate or incomplete inputs, optimization problems, data compression etc. Neural networks have the advantages of adaptive learning, self-organisation, and real time operation. It involves no assumptions. In this paper, the capability of unsupervised techniques and supervised techniques for classification of well-known WDBC Dataset is investigated. It consists of biopsy images of breast tissues. The performances of both the techniques are compared.

Generalization is the most important characteristic of ANN. It means that the neural network based system should be efficient and generalized enough to diagnose new unseen cases of breast cancer which was not present in training data. Therefore the proposed work also focuses on improving the generalization property of the designed network. The network is trained using a variant of Back propagation that uses Bayesian regularization technique. This technique has provided a better accuracy compared to the simple back propagation technique used by Ref [5] and Ref [12]. Moreover, unsupervised methods are also analysed in this paper which is not explored in the literature.

Following sections in the paper include the existing methods, unsupervised methods, Variants of Back propagation algorithm, the proposed method and results of proposed method.

2. EXISTING METHODS

ANN tools have shown to be valuable in reducing the workloads on clinicians by detecting artefact and providing decision support. Table I provides information about different neural network algorithms studied by various researchers to detect and classify case of Breast cancer, Brain cancer, Skin cancer etc. The methods mentioned in the table have not given enough importance to generalization aspect of neural network. The proposed method in this paper uses the Bayesian regularization variant of back propagation algorithm (BR technique).

3. DETECTION OF BREAST CANCER

Breast cancer is the disease whose prevention is still uncertain and the only way to help patients survive is by early detection of the breast cancer. This paper makes an attempt to detect the breast cancer using both unsupervised and supervised learning techniques of ANNs with higher accuracies.

Wisconsin diagnostic breast cancer dataset:

The proposed work classifies the well renowned Wisconsin Breast Cancer Database (WDBC) which is available in UCI repository. It consists of 569 Fine Needle Aspirate biopsy samples of human breast tissues. There are 32 attributes computed for each cell sample. The 10 most important features namely radius, perimeter, texture, area, smoothness, compactness, concavity, concave points, symmetry and fractal dimension have been used as the only inputs to the network as these are sufficient to obtain good results. This also makes the network less complex and more concise.

An effort is made to explore various supervised and unsupervised techniques for detection of breast cancer. A comparative analysis is carried out to bring out the best detection method.

4. UNSUPERVISED LEARNING METHODS

4.1 Unsupervised techniques

The unsupervised learning methods are those in which, the neural networks are trained only with input data. The network can recognize various patterns and features of the input data. These abilities are not obtained from an external supervision; instead, a significant amount of learning is accomplished through a process that proceeds unsupervised. Such a method can be used to perform tasks such as clustering, vector quantization, pattern recognition etc. The classification of the training samples is performed based on certain inherent similarities in the given set of input data. The measurement of distance is one of the key steps in the unsupervised learning process, as it is through these distance measurements that patterns and correlations are discovered. Some of the unsupervised learning techniques are namely Self Organizing Maps (SOM), Self Organizing Feature Maps (SOFM), Counter Propagation Networks (CPN), Adaptive Resonance Theory (ART) and Linear Vector Quantization (LVQ). Two of these unsupervised techniques: SOM and LVQ are used in this paper to perform the classification of WDBC dataset.

4.2 SOM Algorithm

The Self Organizing Maps (SOM) combines a competitive learning principle with a topological structuring of nodes such that adjacent nodes tend to have similar weight vectors. The learning algorithm of SOM ensures that most highly activated node and its neighboring nodes move towards a sample presented to the network. The SOM network learns to classify input vectors according to how they are grouped in the input space. Thus, SOM learns both the distribution and topology of the input vectors they are trained on. The SOM network is used for both clustering of the given inputs and to reduce the dimensionality of the given dataset.

TABLE 1 EXISTING METHODS OF NEURAL NETWORK ALGORITHMS FOR CANCER DIAGNOSIS

S. No	Authors	Technique	Algorithms	Results
1	Sulochana Wadhwani, A.K Wadhwani, Monika Saraswat [1]	Artificial Neural Network	Back propagation Algorithm	Classification of Breast cancer into malignant or benign with the accuracies of 94.11% and 100%
2	Pankaj Sapra, Rupinderpal Singh, Shivani Khurana [2]	Computer Aided Detection System and Probabilistic Neural Network	Competitive Learning Algorithm	Detection of Brain Tumor, obtained 100% accuracy.
3	Yongjun WU, Na Wang, Hongsheng ZHANG, Lijuan Qin, Zhen YAN, Yiming WU [4]	Artificial Neural Network	Back propagation Algorithm	Diagnosis of lung cancer. Provides accuracy of 96.6%.
4	Ayoub Arafi, Youssef Safi, Rkia Fajr and Abdelaziz Bouroumi [5]	Image processing and Artificial Neural Network	Multilayer Perceptron Training Algorithm	Classification of mammographic images of breast cancer. Accuracy obtained is 95.49%.
5	Seema Singh, Sunita Saini, Mandeep Singh [6]	Artificial Neural Network	Adaptive Resonance Theory	Detection of cancer using ART. Obtained accuracy 82.64%.
6	Ali Raad, Ali Kalakech, Mohammad Ayache [12]	Artificial Neural Network	Back propagation Algorithm	Breast cancer detection and classification using ANN. provided an accuracy of 94%
7	Yuehui Chen, Yan Wang, Bo Yang [8]	Artificial neural network	Hierarchical Radial Basis Function	Breast cancer detection using hierarchical RBF with the accuracy of 97.09%.

4.3 SOM Network for classification of WDBC dataset

A 3 layer SOM network is used in this paper to classify the WDBC dataset; they are input layer, hidden layer and output layer. The input layer consists of 10 nodes each corresponding to 10 main features of the dataset that are used as inputs. SOM network consists of 2 nodes in the hidden layer with a hexagonal topology where, each node identifies single class of breast cancer, that is, Benign and Malignant. The output of hidden layer is mapped onto the output layer containing 2 nodes.

The training of the network takes place in 2 phases: Ordering phase and Tuning phase. The ordering phase last for a given number of steps, which in this case is 100. The neighbourhood distance decreases upto to the tuning distance value. During this time the network nodes organize themselves in the input space with the hexagonal topology. The Tuning phase lasts for the rest of the training. The neighbourhood size decreases below 1 so that only the winning neuron learns for each example. Network was tested to find whether there is enough dissimilarity between malignant and benign cases with respect to distance factor of various cells of breast tissue biopsy images.

The SOM technique is not found to be efficient enough as 88 out of 569 samples were found to be misclassified.

4.4 LVQ Network

A Learning Vector Quantizer (LVQ) is an application for classification tasks. It shows how an unsupervised learning mechanism can be made use of to solve supervised learning tasks in which, class membership is known for every training pattern. Each node in an LVQ is associated with an arbitrarily chosen class label. The number of nodes chosen for each class is proportional to the number of training patterns that belong to that class, making an assumption that each cluster has roughly the same number of patterns.

4.5 LVQ Network for the classification of WDBC dataset

The LVQ network consists of 4 layers: the input layer, 2 hidden layers and a single output layer. The input contains 10 nodes each corresponding 10 main features of the WDBC dataset. 2 hidden layers are present in the LVQ network namely competitive layer and linear layer. Each node in competitive layer identifies a different class from the inputs given to the network. The linear layer consists of nodes equal to that of resulting classes. Each node in the linear layer identifies the class to which competitive layer node output belongs to. Since LVQ method is used to perform a supervised task, the target classes to be obtained by the network are fed along with the inputs. After these initial adjustments, the network training begins. The network is trained by the method of random incremental training where, the inputs are presented in a random order to the network. The learning rate of the network was fixed to 0.01.

LVQ method seems to work inefficiently for the nonlinearly separable classes of benign and malignant cases.

Both the methods presented a very low accurate performance. Therefore, supervised techniques were used for the classification of the same database, which presented in the next section. Supervised learning techniques are capable of feeding doctor’s expertise of diagnosis of several cancer samples to a neural network system.

5. Supervised Learning Techniques

Supervised learning technique is one of the two types of learning techniques under artificial neural networks. It is the one in which the network is trained by providing it with input and matching output patterns. These input-output pairs can be provided by an external teacher (expert doctor in this case). Basically this input-output pairs is training data provided to ANN to build network for generalization. Once a neural network is trained with enough cases of breast cancer samples, it will be

It is a type of machine learning algorithm that uses a known dataset (called the training dataset) to make predictions. The training dataset includes input data and response values. From it, the supervised learning algorithm seeks to build a model that can make predictions of the response values for a new dataset. A test dataset is often used to validate the model. Using larger training datasets often yield models with higher predictive power that can generalize well for new datasets.

Some of the neural network algorithms which come under supervised learning technique are: Back propagation algorithm, Counter propagation algorithm, Radial Basis Function etc.

5.1 Back propagation Algorithm

Back propagation, an abbreviation for “backward propagation of errors”, is a common method of training artificial neural networks. It is a supervised learning algorithm for multilayer feed forward neural network. Since it is a supervised learning algorithm, both input and target output vectors are provided for training the network. The error data at the output layer is calculated using network output and target output. Then the error is back propagated to intermediate layers, allowing incoming weights to these layers to be updated. This algorithm is based on the error-correction learning rule.

Basically, the error back-propagation process consists of two passes through the different layers of the network: a forward pass and a backward pass. In the forward pass, input vector is applied to the network, and its effect propagates through the network, layer by layer. Finally, a set of outputs is produced as the actual response of the network. During the forward pass the synaptic weights of network are all fixed. During the backward pass, on the other hand, the synaptic weights are all adjusted in accordance with the error-correction rule. The actual response of the network is subtracted from a desired target response to produce an error signal. This error signal is then propagated backward through the network, against direction of synaptic connections - hence the name “error back-propagation”. The synaptic weights are adjusted so as to make the actual response of the network move closer the desired response.

The input patterns are represented by a vector and are submitted to the ANN through the input layer that simply redistributes them to the following hidden layer. Each neuron of the following layer receives the weighted signals (signal multiplied by a weight) and generates an output signal to the following layer. This process is repeated until the output layer is reached, where the neurons will generate the output of the ANN for the given input vector. With the output of the ANN obtained, the weight adjustment of the connections will begin in the direction from output layer to input layer. The weight adjustments are realized in order to minimize the error function for a certain pattern.

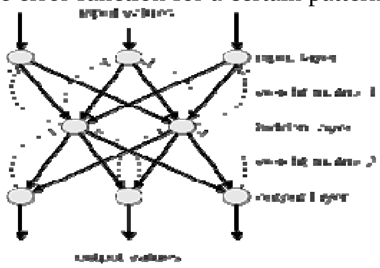

Fig 2: Back Propagation Network

5.2 Scaled Conjugate Gradient (SCG)

The designed network was initially trained with scaled conjugate gradient method. This method is one of the variants of Back propagation algorithm. The performance of the network is evaluated based on the mean square error obtained at every iteration. The SCG technique uses the second order derivatives of the goal function to minimize the mean square error.

For the 20 test samples presented, the network successfully classified all the samples to their respective classes without any misclassification. Hence an accuracy of 100% is achieved.

When the same network was trained with 100 test samples containing both benign and malignant classes, the network provided a classification with a low accuracy as compared to its performance for 20 test data. Hence an improvement in the generalizing capability of the network was required. This is done with help of Bayesian regularization.

5.3. Bayesian Regularization (BR)

During the training phase of neural network, the major problem which is encountered in general is over-fitting of the data. Over-fitting means memorization of the data by neural network. One of the methods to overcome this problem is to have a larger network that provides an adequate fit. But, as the size of the network changes with the size of the problem, it cannot be determined in priori. There are two methods which can be used in order to improvise the generalization of neural network. They are early stopping and regularization.

In early stopping technique, the whole data is divided into training set, validation set and test set randomly. When the network begins to overfit the data during training phase, the error on the validation set starts increasing. At this point, the training is stopped and the weights and biases at the minimum of the validation error is returned.

Regularization technique involves the modification of performance function by choosing the performance ratio parameter manually. Using this modified performance function, it is possible to make the network to have smaller weights and biases which forces the network response to be smoother.

The above techniques which are used to improvise the generalization of neural network involve manual modifications which can be again erratic. This creates a need to have an automated approach for improvising the generalization of neural network. BR technique serves the purpose. In this technique, the weights and biases are assumed to be random variables with specified distributions. The performance function is modified by adding a term that contains mean of sum of squares of network weights and biases. Using this technique, the response of the network will be comparatively smoother which indicates that the network is able to generalize when new inputs are presented to it.

5.4 ANN implementation using Bayesian Regularization

In this paper, a Multi-layer Feed Forward network using Back Propagation algorithm is used to classify the WDBC dataset. The network structure consists of 4 layers: an input layer with 10 neurons, 2 hidden layers with 5 neurons in each layer and an output layer with 1 neuron. 10 features of the WDBC data set are applied as inputs to the network. The numbers of hidden layers were determined experimentally. The output neuron classifies the input samples into 2 classes of breast cancer, that is, Benign as 0 and Malignant as 1. The ANN was implemented in MATLAB software version R2012b.

In the learning phase, the network is trained using the supervised back propagation algorithm with Bayesian Regularization. The training is carried out for 2000 epochs so that the network converges at an optimum point. Once the network is trained, it is tested with 100 test samples. Also, the network performance is evaluated by obtaining confusion plots.

6. DISCUSSION OF RESULTS

Firstly, two unsupervised techniques namely, SOM and LVQ were used for the classification of WDBC dataset. Once the training of the SOM network was complete, the performance of the network was evaluated using the SOM sample hits plot. The SOM Sample hits plot, shows a SOM layer with each neuron showing the number of input vectors that it classifies. Fig. 3 shows the sample hits plot for the training of SOM network.

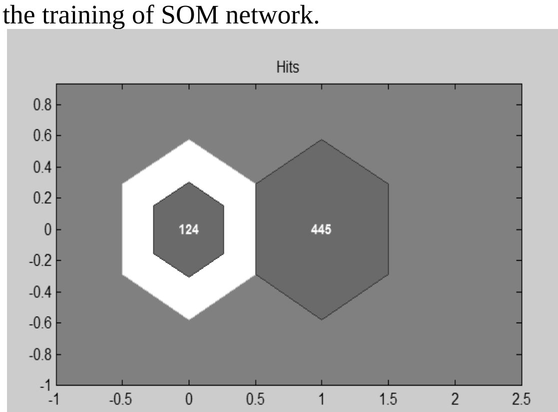

Fig 3: Sample hits plot for the SOM network

It can be observed from the plot that, the output nodes hold values of 124 and 445 corresponding to malignant and benign classes respectively. But the given input data set contains 357 and 212 cases of benign and malignant classes respectively. Therefore 88 samples have been misclassified, thus giving a low accuracy of classification.

The performance of the LVQ network was studied using the confusion plots which confirmed its inefficiency.

It can be inferred that both the unsupervised techniques studied did not meet the expected results for a critical scenario of cancer detection. Hence in this paper, supervised techniques were explored for the classification of the same database.

First among them was Scaled conjugate gradient method. The network training provided the best results for 18 nodes in the hidden layer, when trained with learning rate of 0.02. To evaluate the training performance of the network, the dataset is divided into training, test and validation sets by an appropriate ratio. Confusion plots were plotted using MATLAB for the training carried out using Scaled Conjugate gradient method shown in Fig. 4.

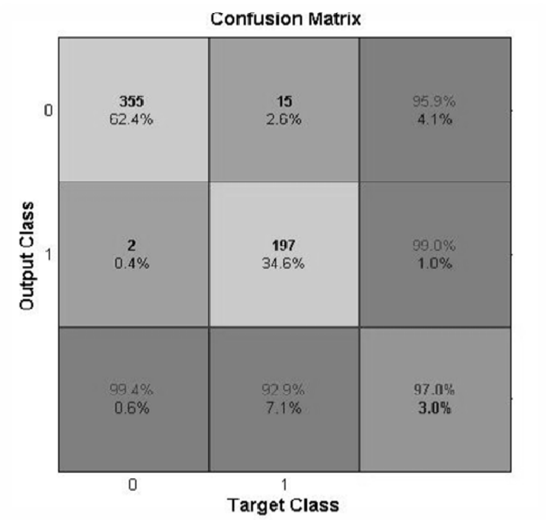

Fig 4: confusion plot for training using SCG method

It can be seen that, out 569 samples 19 have been misclassified, thus giving a high accuracy of 97.47%. Table II provides Sensitivity, Specificity and Accuracy and other parameters measured for the network training.

TABLE 2
PERFORMANCE PARAMETERS FOR SCG METHOD

S.No	Performance parameters	Performance %
1	True Positive rate	95.95
2	False Positive rate	4.05
3	True Negative rate	98.99
4	False Negative rate	1.02
5	Sensitivity	98.95
6	Specificity	96.09
7	Accuracy	97.47

Figure 5 shows the confusion plot for the testing phase of the network. The network designed was presented with 20 test input samples containing 11 benign and 9 malignant cases. A high accuracy of 100% was obtained. The network rightly classified all the test input samples. Since the network was presented with very few samples for testing, the number of test samples was increased to 100 which contained both Benign and Malignant classes. It was observed that for 100 test samples, the efficiency of the network came down. This result suggested that the network was not able to generalize the classification for new and more samples. That is, the network could not deliver the same efficiency for more test samples.

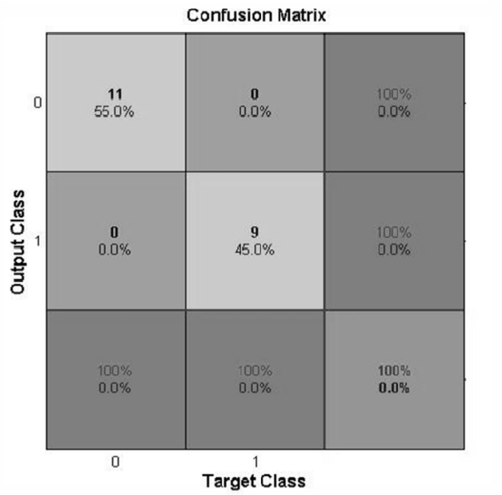

Fig 5: confusion plot for testing using SCG method

Therefore a method that could provide a good generalization capability was required to achieve high classification accuracy for more number of test samples. For this purpose the Bayesian Regularization based back propagation algorithm (BRBPA) technique was explored for the classification of the same database.

The network is trained to converge at an optimum point. To evaluate the network performance at the end of the training, the dataset is divided into training and test sets by an appropriate ratio. In general, the dataset is divided into a third set which is used for validation. Bayesian Regularization based technique performs regularization instead of validation checks. Figure 6 shows the performance of the network at the end of training phase. It is the graph obtained by plotting the number of epochs taken versus the mean squared error. It can be observed that, the training graph initially undergoes some variations which vanish at the end of the training. That is, as the training proceeds, the network responds very smoothly to the input samples applied to converge at an optimal point. An accuracy of 97.51% has been obtained. Table III shows the Specificity, Sensitivity, Accuracy and other measures obtained for the learning phase.

100 instances were randomly chosen as the test samples and were presented as inputs to test the network. A high classification accuracy of 100% was obtained. Also, the network performance is further evaluated by plotting confusion plots. Figure 7 and Figure 8 shows the confusion plots obtained for train and test phases respectively. High accuracies of 97.9% and 100% were obtained for train and

test phases respectively. Table III provides a comparison of results obtained using the proposed method with the results mentioned in Ref [5] and Ref [12]. For the same number of test samples, the proposed method provides the highest accuracy compared to the other two methods which uses basic version of back propagation algorithm. Though the network is trained with more number of input samples, the over-fitting problem that generally occurs is avoided by BRBPA.

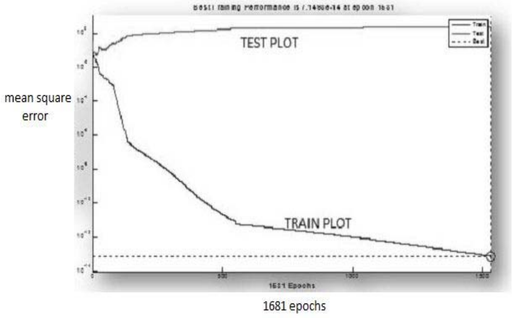

Fig. 6: Training performance plot

TABLE 3 PERFORMANCE PARAMETERS FOR BR TECHNIQUE

S.No	Performance Parameters	Performance %
1	True Positive rate	99.15
2	False Positive rate	0.85
3	True Negative rate	95.87
4	False Negative rate	4.13
5	Sensitivity	96.00
6	Specificity	99.12
7	Accuracy	97.51

Fig 7: Confusion plot for training using BR method

Fig. 8: Confusion plot for testing using BR method.

TABLE 4 COMPARITIVE ANALYSIS WITH EXISTING METHODS

S.No	Parameters	ALI RAAD et al. [12]	AYOUB ARAFI et al.[5]	Proposed Method
1	Train Samples	278	222	569
2	Test Samples	100	100	100
3	Test Data Accuracy	94%	95.49%	100%

TABLE 5 COMPARITIVE ANALYSIS OF UNSUPERVISED AND SUPERVISED TECHNIQUES

S.No	TECHNIQUE	METHODS	ACCURACY
1	UNSUPERVISED	SOM	84.45%
2		LVQ	65%
3	SUPERVISED	SCG	97.47%
4		BR	100%

7. CONCLUSION

This paper proposes a novel method for automated detection of breast cancer using Artificial Neural networks. Breast cancer is curable when detected in early stages. The proposed method provides a faster diagnosis of Breast cancer into Benign or Malignant stage, with accurate results. Unsupervised methods namely, SOM and LVQ techniques were designed for the classification of WDBC dataset. Both the techniques did not meet the expected results for a critical scenario of cancer diagnosis. Hence supervised techniques were explored for the classification of same database.

The designed 10-(5-5)-1 neural network is trained using two variants of Back propagation algorithm, namely scaled conjugate gradient (SCG) and Bayesian regularization (BR). The SCG method was used to train 10-(18)-1 network for which it provided the accuracy of 100% for 20 test samples. However, the generalizing capability of the network for more test samples reduced. The generalization capability of the network is improved using the Bayesian Regularization technique for a new network structure 10-(5-5)-1. The network successfully classifies the 569 cases of breast cancer present in WDBC dataset. The accuracy obtained is as high as 97.51%, with sensitivity and specificity of 96% and 99.12% respectively. The well generalized network provides 100% accuracy for a test data with 100 samples. Hence, the proposed work can be used as a decision support system to assist clinicians in cancer detection.

The proposed work used extracted features of biopsy slides available in WDBC database. The work can be extended to diagnose biopsy slides directly. Various image processing techniques can be used to extract features like radius, area, perimeter etc. of the cancerous cells. These extracted features can be used as inputs to the network for classification. The network can be implemented on DSP or FPGA to evaluate time constraints of the method.

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