A Novel Computer Aided Diagnosis Scheme For Breast Tumor Classification

Shamsa[1], M. Nisha[2]

[1]*PG Scholar, Dept. of Computer Science and Engineering, SVS college of Engineering Coimbatore, Tamilnadu, India*
[2]*Assistant Professor, Dept. of Computer Science and Engineering, SVS college of Engineering Coimbatore, Tamilnadu, India*

Abstract - *Breast malignancy is the most widely recognized female disease in the world with an expected 1.67 million new malignant growth cases analyzed in 2012. In order to help physicians in improving the accuracy of diagnostic decisions, computer aided diagnosis (CAD) system is used in breast cancer detection and analysis nowadays. In this paper, in order to help physicians, identify the benign and malignant breast tumors in ultrasound, computer aided diagnosis scheme using multilayer perceptron is used. In this method, feature accession is applied by a feature scoring scheme that is based on Breast Imaging Reporting and Data Systems (BI-RADS) lexicon and experience of physicians. . The patterns frequently appearing in the cancerous cells with the same label can be regarded as a potential diagnostic rule. Subsequently, the diagnostic rules are utilized by the multilayer perceptron. Finally, the multilayer perceptron is performed to discover effective combinations and integrate them into a strong classifier. The proposed approach has been validated using many breast ultrasound image dataset and its performance was compared with several conventional approaches. The experimental results show that the proposed method yielded the best prediction performance, indicating a good potential in diagnosing breast tumors.*

Key Words: **Biclustering, Diagnostic rules, Computer Aided Diagnosis, Feature space, PC-CFS.**

1.INTRODUCTION

BREAST cancer is one of the most common cancer among women all over the world ranging from adolescents to adults and the second leading cause of death after lung cancer. According to the statistics of 2019, approximately 268,600 new cases of malignant breast tumors and 48,100 cases of benign cases were diagnosed among US women, and 41,760 women died from this disease. Report shows that early detection and diagnosis plays an important role in increasing the chance of survivability of breast tumor patients, reducing the mortality of over 40%.

Various imaging technologies have been of great help to early diagnosis for breast cancer. Mammography could be sed in breast cancer patients at early stages and is the most commonly used screening method. However, it has some disadvantages including low specificity and declining sensitivity in adolescent women as they have dense breasts. More specific, radiation from mammography does harm to patient's body and it increases the risk of breast cancer. Nowadays, ultrasonography has become a major alternative to mammography in hospitals. Ultrasonography has many advantages such as being non-radioactive, non-invasive, low cost and more easy in practice. Also, ultrasonography is more sensitive to dense breast tissues, as well as it has higher accuracy in differentiating malignant and benign tumors. Breast Imaging Reporting and Data System (BI-RADS); is another helpful tool commonly used in hospitals. This system was introduced to standardize the reporting of characteristics descriptions in mammography, ultrasound or MRI, thereby promoting communication among physicians. However, there is still a high misdiagnosis rate in the clinical practices because of the subjective dependence and experience variation among doctors. Hence, computer aided diagnosis (CAD) system plays a vital role in helping doctors to improve the accuracy of diagnosis of breast tumors.

1.1 Related works

Many types of CAD approaches have been proposed for breast cancer detection in recent years [10]-[12]. Some of these CAD systems utilized support vector machine (SVM) as classifier [13]-[15]. Huang et al. [16] is a software engineer who applied the SVM with 28 texture features in the ultrasound image in order to classify breast tumors as benign or malignant. His CAD system achieved a high accuracy and were of 94.3% in classification of breast tumors. A CAD system using fuzzy SVM and stepwise regression feature selection [17] was invented to automatically detect and classify tumors. The results provided a big increase in classification performance due to the integration of different features. A 3-D solid breast nodules diagnosis system was proposed in[19] by using principal component analysis as well as image retrieval. The three different practical textural features were extracted from 3-D ultrasound images such as spatial gray-level dependence matrices, gray-level difference matrix and auto-covariance matrix. Then a CAD system for classification of BI-RADS category 3 with the binary logistic regression model classifier were proposed in study [20]. Their system obtained a high sensitivity and they used morphology and texture features. Some studies used affinity propagation (AP) clustering method to differentiate breast tumors as benign or malignant [21]. Cheng et al. [22]

proposed a CAD system using both B-mode ultrasound features and color Doppler features for tumor identification.

Most of the given proposed systems mainly used various kinds of textural features that were extracted from region of interest (ROI) of BUS images to train their classifiers. However,there exist some drawbacks in those methods. Primarily, the BUS image often contains intrinsic artifact called speckle which may cause low signal/noise ratio (SNR),blurry boundaries as well as poor quality. Hence, the preprocessing for noise reduction is an unavoidable part in traditional CAD systems. Secondly, the difference in types or settings of accession instruments causes large variation in cell shapes, sizes and locations, thereby making the extracted characteristics unstable. Presently, most of the CAD systems have been developed to automate feature acquisition and classification through those difficult procedures, however it results in unavoidable risk of higher number of false positives and may lead to painful biopsies. In image processing and pattern classification [27], [28], feature extraction and selection plays an important role. Thus, there is no any fully automated CAD approach that has been widely applied in medical practices so far. This encourages us to develop a novel CAD approach using multilayer perceptron for the classification of tumors.

Many studies have confirmed that ultra sonographic features based on the BI-RADS lexicon provides great effectiveness in classifying breast tumors as benign or malignant[29]-[31]. Moreover, physicians would like to use some high level feature such as BI-RADS lexicon when detecting and diagnosing breast tumors. Inspired by this fact, the physicians directly score the BI-RADS features and then the scores are used by the multilayer perceptron. This idea of integrating the human's judgment forms a human-in the-loop CAD architecture. Because of the human, the CAD would be more easily understandable and hence more acceptable by physicians. In this paper, we train the multilayer perceptron for the classification of breast tumors.

1.2 The Proposed Framework

Prior to the introduction of the technical side, let us describe about the two examples of breast cancers as illustrated in Fig. 1. According to WHO classification of breast cancer [36], breast carcinoma fall into 15 categories, including ductal carcinoma in situ (DCIS), invasive breast carcinoma as given in Fig. 1(a), specific subtypes of invasive breast carcinoma, such as intra-ductal papillary carcinoma as shown in Fig.1 (b), mesenchymal tumor, etc.

When diagnosing various types of breast cancers, every category of tumors shows specific image characteristics in BUS images. BI-RADS lexion helps physicians to analyze the tumors as it covers all these characteristics. For instance, as illustrated in Fig. 1(a), a 29 year old woman with invasive ductal cancer has a breast lesion with an angular and speculated margin. In contrast, for a case of intra-ductal papillary tumor illustrated in Fig. 1 (b), a circumscribed margin of the lesion can be seen as well as it has no microcalcification. In another word, only a specific subset of BI-RADS features could be used to diagnose a specific type of breast cancer. As a result, traditional clustering techniques using features to provide a classification cannot be used any more.

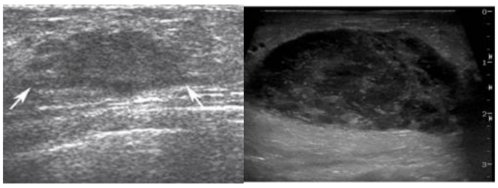

Fig-1: An example of two different breast tumors.(a) A BUS image of a tumour of a 29 year old demonstrates an irregular shape ,indistinct, angular, microloblated. (b) A 75 year old women has a complex cystic and solid mass with an oval shape.

Similarly, we propose a novel CAD framework incorporating Multilayer perceptron in neural network. Apart from the typical CAD framework, we develop an operator-participating feature rating scheme and extraction method with the use of BI-RADS lexicon and experience of physicians. According to medical reports (Fig. 1),those tumorous lesions in the same category just show the same character on some specific feature subset. Besides, physicians usually make the diagnosis of breast tumors according to particular patterns that represents some kind of feature combination. Therefore, perceptron based neural networks has been proposed to discover the diagnostic rules hidden in the dataset of feature scores in this paper. Here, we innovatively train the multilayer perceptron to utilize those features to classify tumors as benign or malignant. The interesting features of the proposed method is that it uses a user-participated and unsupervised way, and hence good understanding of the final model.

2. DATA PREPARATION

In data preparation, we first introduce the concept of the proposed BI-RADS feature scoring scheme, which makes the proposed system a user-participated CAD system. Then, the detailed description of information about the dataset is given. Finally, the procedure of feature scoring and training is described.

2.1 The BI-RADS feature scoring scheme

In real medical cases, the physicians usually analyse and classify a breast carcinoma according to BI-RADS descriptors on the basis of doctor's experience. The BI-RADS lexicon provides various useful feature descriptors, e.g. shape, orientation, mass, posterior acoustic characteristic, calcification, margin, echo pattern associated findings as well as special cases. In this proposed system, we have included 25 features to represent the characteristics of tumors based on the BI-RADS lexicon and the recommendation of experienced physicians. In order to describe how to provide each feature the right score, we have developed a reference table with the guidance of physicians and the BI-RADS lexicon.

Table 1 illustrates the detailed information of the feature descriptors and the corresponding scoring scheme. As represented in Table 1, the score assignment of features is shown on different pattern according to the medical reports and empirical rules of physicians. The scores range from 0 to 5; if the score is high, then more it is inclined to be malignant. With respect to the shown reference table, the physicians assign each feature in BUS images with a corresponding score according to the different clinical observations.

As shown in Fig. 2, in order demonstrate how our scoring scheme works, we have collected two typical examples. Fig. 2(a) is a BUS image of benign instance while Fig. 2(b) is an example for malignant instance. Their scores of all 25 BI-RADS features from an experienced physician are listed in the corresponding Table 2. According to the BUS images and medical observations, the benign tumor usually tends to be oval in shape, parallel in lesion orientation, with circumscribed and distinct border, and are not spiculated nor angular margin; while typical malignant carcinoma is commonly irregular in shape,as well as non-parallel in orientation, without circumscribed or indistinct border and with spiculated or angular margin. Also, vascularity, hypoechoic echo pattern, microcalcification in mass and duct extension usually appears in malignancy. However, these features rarely appear in benign diagnosis.

Id	Feature	0	1	2	3	4	5
1	Shape	Oval	Round	Irregular			
2	Orientation	Parallel	Not parallel				
3	Margin Integrality	Circumscribed	Not circumscribed				
4	Margin ambiguity	Distinct	Indistinct				
5	Angular	Absent	Present				
6	Microlobulated	Absent	Present				
7	Spiculated	Absent	Present				
8	Echo Pattern	Anechoic	Hyperechoic	Isoechoic	Heterogeneos	Complex cystic and soild	Hypoechoic
9	Posterior Feature	Enhancement	None	Combined Pattern	Shadowing		
10	Calcification in mass	Absent	Coarse Calcification	Scattered microcalcification	Clustered microcalcification	Both coarse and microcalcification	
11	Architectural Distortion	Absent	Present				
12	Ducts changes	Normal	Cystic extension	Object found in ducts			
13	Skin thickening	Absent	Present				
14	Skin retraction	Absent	Present				
15	Edema	Absent	Present				
16	Vascularity	Absent	Vessel in rim	Internal Vasclarity			
17	Elasticity	Soft	Intermediate	Hard			
18	Cyst type	Absent	Sample cyst	Clustered microcysts	Complicated cyst		
19	Mass in or on skin	Absent	Present				
20	Foreign body including implants	Absent	Present				
21	Lymph nodes-intramammary	Absent	Present				
22	Lymph nodes-axillary	Absent	Reactive	Metastatic			
23	Postsurgical fluid collection	Absent	Present				
24	Postsurgical fluid collection	Unoperated	Absent	Present			
25	Fat necrosis	Absent	Present				

Table -1: The feature descriptors and corresponding rating scheme.

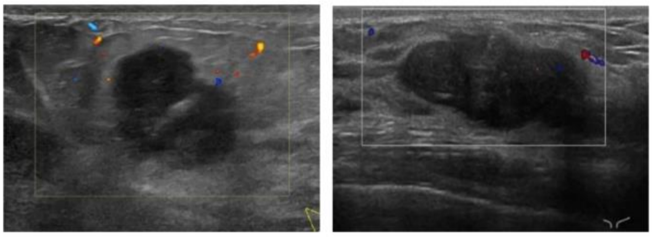

Fig-2: An example of two different breast tumors.(a) Benign instance (b)Malignant instance.

label \ feature id	1	2	3	4	5	6	7	8	9	10	11	12	13
benign	0	0	0	0	0	0	0	5	1	0	0	0	0
malignant	2	1	1	1	1	1	1	5	1	2	1	0	0

label \ feature id	14	15	16	17	18	19	20	21	22	23	24	25
benign	0	0	0	0	0	0	0	0	0	0	0	0
malignant	0	0	1	0	0	0	0	0	2	0	1	0

Table -2: The feature scores for the given benign and malignant breast instances.

2.2 The Description of Materials

The BUS datasets were gathered through the long-term cooperation with the specialists from various clinical centres. Three doctors with more than 15-year experiences and five interns have participated in the data collection. Finally, a large dataset of breast tumors have been captured from various female patients including patients with benign as well as malignant tumors. All these cases of breast carcinoma were validated by biopsy and the result was benign in some cases and malignant in other. If we consider the size of the tumor, the malignant tumors were seen with a diameter of 2.57±1.47 cm and were bigger than the benign tumors with diameter of 1.95±1.19 cm. During the feature acquisition technique, the physicians were blinded to the final diagnosis results for avoiding the confusion of score assignment of selected features.

2.3 The Feature Selection and Data Preparation

In order to evaluate the discriminative skills of those BI-RADS primarily based features, we use the variance to carry out feature selection. The result showed that the pores and skin retraction, elasticity, mass in or on pores and skin, foreign body which includes implants, lymph nodes intramammary, postsurgical fluid series and fat necrosis have the variances decrease than 0.1, implying that there is little difference among benign and malignant instructions in those 7 features. Therefore, the remaining 18 features given in Table 4 were chosen as our new feature set. According to the final biopsy results, we use -1 to denote the benign tumor and +1 for malignancy. Then the feature information of all tumors can be constructed as a data matrix with the rows representing breast tumors and the columns representing the final diagnostic result and the 18 features. Due to different score range on each feature, the min-max standard method was applied to normalize the data in the matrix (from the 2th to the 19th column).

3. METHODS

In this section, we present the working of Multilayer perceptron in neural network. We start by explaining how a multilayer perceptron works to classify tumors from the datasets generated. Fig. 3 shows the workflow of the proposed approach.

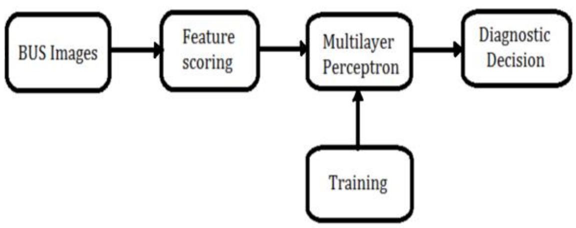

Fig-3: An example of two different breast tumors.(a) Benign instance

3.1 Multilayer Perceptron

Algorithm of deep learning multilayer perceptron can be easily understood with the help of a perceptron in a single layer. Multiply with weights (Here features) and add Bias. Then update the weight when an error is found in classification or miss-classified. The Weight update equation is given below

*weight = weight + learning_rate * (expected - predicted) * x*

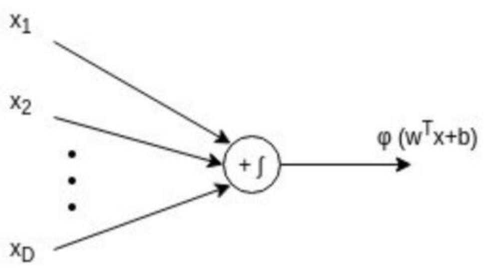

Fig-4: An example of single layer perceptron.

In Multilayer perceptron, there are more than one linear layer (combinations of neurons). Let s consider a simple example of a three-layer network, the first layer constitutes the input layer and last will be the output layer and middle layer will be known as the hidden layer. We input data into the input layer and take the output from the output layer. Based on the complexity of the task in our model, the number of hidden layers could be increased.

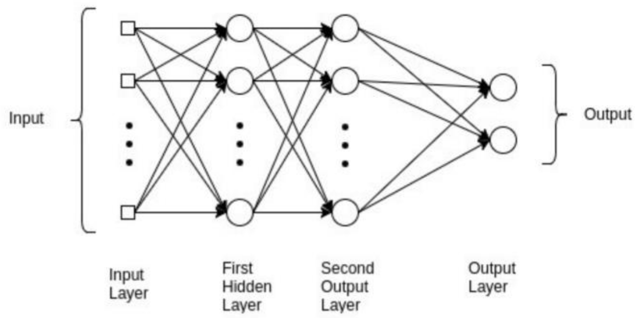

Fig-5: An example of multilayer perceptron.

Multilayer perceptron or Feed Forward Network, is the most classic neural network model. It aims to approximate some function f (). Given, for example, a classifier y = f ∗ (x) that maps an input x to an output class y, the Multilayer Perceptron finds the best approximation to that classifier by defining a mapping. The mapping can be defined as y = f(x; θ) and learning the best parameters θ for it. MLP networks consists of many functions that are chained together. The mapping of a network with three functions or layers would form f(x) = f (3)(f (2)(f (1)(x))). Each layer is composed of units that perform a definite transformation of a linear sum of inputs. Each layer is given as y = f(WxT + b). Here f is the activation function (covered below), W is the set of parameter, or weights, in the layer, x is the input vector (output of the previous layer), and b is the bias vector. The layers of an MLP is composed of several fully connected layers because each unit in a layer is connected to all the units in the previous layer. The parameters of each unit in a fully connected layer, are independent of the rest of the units in the layer, that means each unit possess a unique set of weights.

Here a supervised classification system is used, where each input vector is associated with a label(or ground truth) which defines its class (or class label) is given with the data. The output of the network provides a class score (or prediction), for each input. The loss function is defined to measure the performance of the classifier. If the predicted class does not correspond to the true class then the loss will be high and low otherwise. The problem of overfitting and underfitting may occur sometimes at the time of training the model. As a result our model performs very well on training data but not on testing data. An optimization procedure using loss function and an optimizer is required in order to train the network,. This procedure will find the values for the set of features, W that minimizes the loss function.

A popular step is to initialize the weights to random values and refine them iteratively to get a lower loss. This refinement is done by means of transferring on the direction described through the gradient of the loss function. And it is vital to set a learning fee defining the amount wherein the algorithm is transferring in every iteration.

Activation function:

In order to describe the input-output relations in a non-linear way, an activation function also known non- linearity is used. This provides the model with power to be more flexible in describing arbitrary relations. Some of the other popular activation functions include Sigmoid, Relu, and TanH.

3.2 Training the model

Training of the dataset are crucial for a multilayer perceptron to provide accurate output. While training we specify the outcomes that should be obtained for a given input. In training procedure, we provide many tumorous breast ultrasound images and train them. The three major steps used in training the model are

1. Forward pass
2. Calculate error or loss
3. Backward pass

4. EXPERIMENTS AND RESULTS

In this study, the following two experiments were designed and performed. First, the performance comparison was performed on the proposed CAD system with the cross validation. Second, we analyzed the working of multilayer perceptron to discover the clinical findings potentially related to benign and malignant tumors.

4.1 Performance Comparison

In this experiment, various breast tumor instances including various benign cases and malignant cases were used. The SVM [16], neural network (NN) [23], fuzzy SVM [17], based methods and experts evaluation were as compared with the proposed scheme. Sensitivity, accuracy and specificity are all popular metrics for performance measuring in the discipline of binary class problems. The accuracy is the proportion of correct classification in all instances. The sensitivity is the proportion of positives (malignant instances) that are correctly identified and the specificity is the proportion of negatives (benign instances) that are correctly identified.

The 10-fold cross validation scheme become performed to evaluate the performance of the proposed method. The entire dataset is randomly partitioned into 10 mutually one-of-a-kind subsets of same size. For each fold, a single subset is retained for trying out. This method changed into repeated for 10 runs and then every subsample become used only once because the checking out data. The very last overall performance become evaluated by means of averaging the consequences of 10 folds.

Method	Classifier	Accuracy	Sensitivity	specificity
[16]	SVM	94.4%	94. 3%	94.4%
[17]	Fuzzy SVM	94.25%	91. 67%	96.08%
[23]	Fuzzy cerebral mode	92.31%	93.55%	91.18%
Experts	Judgement by experience	85.62%	93.08%	72.97%
[30]	Biclstering + Adaboost	95. 75%	96.26%	95.12%
Proposed	Multilayer Perceptron	97.5%	97.08%	96.15%

Table -3: Comparison results among different systems.

5. CONCLUSIONS

In this paper, a novel CAD gadget using multilayer perceptron is proposed for classifying benign and malignant breast tumors with people judgment on the BI-RADS lexicon based features. We have verified its suitable overall performance in a big dataset with diverse tumor instances relative to the small datasets using in traditional methods. It is an innovative try to undertake operator-based totally feature scoring scheme instead of the tactics of picture de-noising, picture segmentation and characteristic extraction in traditional CAD systems. Each of those traditional techniques remains a challenging hassle in the fields of image processing and pc vision especially in ultrasound images, and really impacts the final class output. In contrast, we introduce the revel in of physicians during the feature extraction, that is easily ideal to doctors in actual utility and improve the robustness of our gadget.

In addition, we have reconfirmed that a few functions (i.e. Margin integrality, margin ambiguity, micro lobulated and calcification in mass) have played vital roles in distinguishing the breast tumors. The resultant analysis shows that a tumor with incorporated and distinct margin is an powerful benign symptom similarly to the symptom of without micro lobulated and calcification in mass. Likewise, ultrasonic discovery of uncompleted, vague and micro lobulated border with calcification in mass regularly indicates a vast malignant case. The use of multilayer perceptron has improved the accuracy in classifying tumors. One of our destiny studies will be centered on the use of our three-D ultrasound machine [50][51] to provide additional interpretable functions and integrate them into the modern CAD system for extra diagnostic guidelines and higher type performance.

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