Detection of Breast Thermograms using Ensemble Classifiers

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***Abstract*—Mortality rate of breast cancer can be reduced by detecting breast cancer in its early stage. Breast thermography plays an important role in early detection of breast cancer, as it can detect tumors when the physiological changes start in the breast prior to structural changes. Computer Aided Detection (CAD) systems improve the diagnostic accuracy by providing a detailed analysis of images, which are not visible to the naked eye. The performance of CAD systems depends on many factors. One of the important factors is the classifier used for classification of breast thermograms. In this paper, we made a comparison of classifier performances using two ensemble classifiers namely Ensemble Bagged Trees and AdaBoost. Spatial and spectral features are used for classification. Ensemble Bagged Trees classifier performed better than AdaBoost in terms of accuracy of classification, but training time required is higher than AdaBoost classifier. An accuracy of 87%, sensitivity of 83% and specificity of 90.6% is obtained using Ensemble Bagged Trees classifier.**

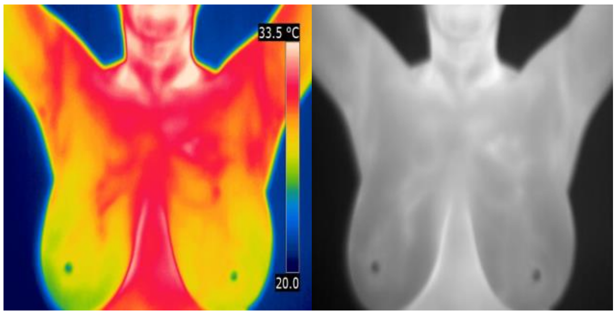
***Index Terms*—AdaBoost; Breast Cancer; Ensemble Bagged Trees; Thermogram Images; Spectral Features; Spatial Features; Wavelet Transform.**

I. INTRODUCTION

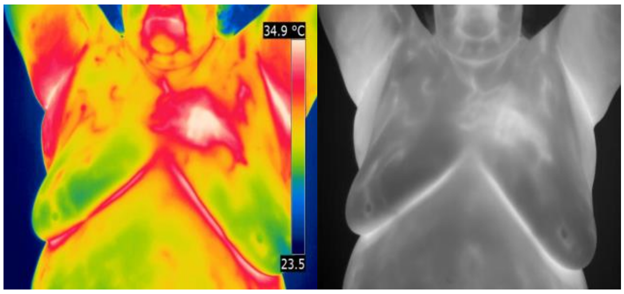
Breast thermography is a developing medical imaging tool used for early detection of breast cancer. It is a non-invasive, low-cost screening test and can be utilized for women of all ages, concretely women having dense breast, where mammography is less efficacious [1-7]. When coalesced with other types of examinations, breast thermography may increase the possibilities of screening and could be a potent adjunct imaging implement for breast cancer detection.

Cancerous parts show higher temperature in comparison to normal tissue due to the higher metabolic activity and angiogenesis surrounding the cancerous tissue, which results in asymmetry between breasts [8-11]. Figure 1 shows breast thermogram images of normal and abnormal breast [12]. Images shown on the left side are pseudocolor thermogram images and that shown in the right side are respective grayscale images. Temperature distributions in the right and left breast are symmetric as shown in Figure 1(a), and asymmetric as in Figure 1(b), since the patient was suffering by infiltrating ductal carcinoma in the union of upper quadrants in left breast [12-13]. Radiologists search for such abnormalities and analyze subjectively.

Development of CAD systems for breast cancer detection using breast thermograms can increase the accuracy of detection by the detailed image analysis, which is not possible to be detected by the naked eye. CAD system can serve as a second opinion in decision making [14-17]. The overall performance of the CAD system for breast thermography depends on various factors such as the accuracy of input data, segmentation of Region of Interest (ROI), extracted features and classifier used.



(a)



(b)

Figure 1: Examples of breast thermogram images (a) normal breast (b) abnormal breast.

II. RELATED WORK

Classifier plays an important role in the classification of breast thermogram images. Supervised classification techniques are applied for classification of breast thermogram images than unsupervised techniques. Moreover, the used supervised classifiers for classification of breast thermogram images includes neural networks [6, 18-20], Support Vector Machines (SVM) [20-23], Naive Bayes classifier [22,24] and Fuzzy classifier [25-26].

Among unsupervised techniques, the most common one used is clustering algorithms like the k-nearest neighbor [22, 27]. Some of the researchers proposed various types of hybrid classifiers [28-30] for the detection of breast thermograms. Schaefer et al. [25] used a fuzzy classifier and obtained an accuracy of 80%.

Nicandro et al. [21] extracted various features based on temperature data and classified using a Bayesian network classifier. The average accuracy of 74.7% was obtained using Naive Bayes, Hill Climber and Repeated Hill Climber

Bayesian classifiers. Moreover, they used SVM with various kernel functions to detect normal and abnormal breasts using statistical and GLCM features. They analyzed the precision of classifier utilizing four types of scenarios. Each scenario had a different number of images for training and testing. For statistical features, quadratic and linear kernel procured a precision of 85% and 80% for GLCM predicated features utilizing quadratic and polynomial kernels.

Milosevic et al. [27] extracted the Gray Level Co-occurrence Matrix (GLCM) features and used SVM, Naive Bayes, and k- nearest neighbor classifiers. Fivefold cross-validation and receiver operating characteristics were used for assessing the performance of classifiers. Whereby, [28] classified breast thermogram images using a hybrid multiplier classifier system.

The design of multiple classifier systems was predicated on hybridization of three computationally astute techniques namely neural network or SVM as base classifiers, neural fuser to coalesce the individual classifiers and Fuzzy measure for abstracting the redundant classifier from the ensemble. An average of 81.3% sensitivity, 90.6% specificity, and 88.7% accuracy was obtained in their work. [20] has computed higher order spectral features based on entropy measures. Feedforward Artificial Neural Networks (ANN) and SVM classifiers were used for classifying the images as normal or abnormal thermograms.

Pramanik et al. [6] computed Initial Feature Point Image (IFI) for each segmented breast thermogram image by applying Discrete Wavelet Transform (DWT). Statistical features were extracted from the IFI. ANN was used for classification. Kapoor et al. [6] extracted bio-statistical features and obtained an accuracy of 80% using ANN. Fifty samples were used for training and 10 samples for testing. Joanna et al. [20] collected temperature data from 16 sensors placed on the surfaces of each breast and were given as inputs to the classifiers.

Probabilistic Neural Network, ANN, Fuzzy, SVM and Gaussian mixture Model were used for classification. These classifiers were able to procure approximately 80% average accuracy in classification. [31] proposed a combinatorial model using ANN and Genetic Algorithm for detection of breast thermograms. They extracted various statistical features. Results revealed that thermal pattern and kurtosis were important parameters in breast cancer diagnosis. Their model attained 50% sensitivity, 75% specificity, and 70% accuracy.

Rodrigues et al. [23] extracted statistical moments, GLCM and RLM based features. Various SVM kernels were used for classification. Prabha et al. [9] extracted second-order features of co-occurrence matrix such as energy, entropy, contrast, and difference of variance from denoised and raw images. Furthermore, features from denoised images were found to be very effective in discriminating abnormalities present in breast tissues.

III. PROPOSED METHODOLOGY

The ensemble of classifiers is a set of classifiers whose individual decisions are coalesced to relegate incipient data. If training data is not providing adequate information for culling a single best classifier then coalescence is the best compromise. This paper discusses the performance of Ensemble classifiers in classifying breast thermograms into normal or abnormal. Statistical features are extracted from the spatial domain by computing histogram, GLCM [7], Run Length Matrix (RLM) and Neighborhood Gray Tone Difference Matrix (NGTDM) [32]. Also, spectral features are extracted by computing local energy features of Wavelet subbands [33].

Selection of an appropriate set of features is very important to improve classifier performance and to reduce the computational complexity of the CAD system. Significant feature sets are selected by performing a statistical t-test, Sequential Forward Selection (SFS), Sequential Floating Forward Selection (SFFS), Random Subset Feature Selection (RSFS) and Genetic Algorithm (GA). Significant features selected by various feature selection methods are fed to Ensemble classifiers to classify normal and abnormal breast.

A. Ensemble Classifiers

Ensemble classifiers are more accurate than individual classifiers for some feature data points. This could be due to the insufficient information of training data [34]. Two types of ensemble classifiers namely Bagging, and Boosting is used in this work. Bagging is a type of ensemble learning proposed by [35]. In this method, a set of models are generated by training them individually. Each training set is selected by randomly sampling the feature data. Such a training set is called a bootstrap replicate of the original training set and the technique is called bootstrap aggregation.

The predictions of all these models are combined to produce the final prediction using averaging [36, 37]. In this approach, we used decision trees as the classification model and the results of these weak learners are combined using bootstrap aggregation. Normally, individual decision tree tends to overfit. Moreover, the Bootstrap-aggregated (bagged) decision trees cumulate the results of many decision trees, which reduces the effects of overfitting and ameliorates generalization. This method runs particularly well on algorithms, where the output classifier undergoes major changes in response to small changes in the training set.

The AdaBoost algorithm is based on a set of positive and negative data points and activates a set of weak classifiers to generate a binary classification function that maximizes the margin between positive and negative data points. Classifiers are constructed on "weighted versions of the training set, which are independent of previous classification results in AdaBoost". Initially, all objects have equal weights, and the first classifier was designed on this data set. Later, weights were changed according to classifier performance. Misclassified data points get higher weights, and the next classifier was trained on the re-weighted training set and classified. Hence, a sequence of training sets and classifiers is obtained, which is then combined by a weighted majority voting to get the final decision [34].

IV. RESULTS AND DISCUSSIONS

Classifier performance of ensemble classifiers is compared using spatial and spectral features.

A. Classifier Performance on Spatial Features

Table 1 presents the classifier performance of ensemble bagged and boosted classifiers for various combinations of feature selection methods using spatial features. Performance is evaluated using k-fold cross-validation with k=5. As shown in Table 1, Ensemble Bagged Trees performs better than AdaBoost classifier. A number of learners used for

Ensemble Bagged Trees classifier are 30. Ensemble Bagged Trees classifier attained a maximum of 71% accuracy, 62.5% sensitivity and 78.8% specificity using RSFS.

Training time required for each classifier is shown in the last column of Table 1 for Intel Core i3 processor with 4 GB RAM. Ensemble Bagged Trees classifier acquired more training time compared to AdaBoost. The classifier performance of AdaBoost with decision trees training was poor with thirty learners and twenty splitters. From the experiments, it is found that there is no change in the performance of AdaBoost classifier for increase or decrease in the number of learners and splitters.

Table 1
Classifier performance in detection of breast cancer using spatial features

Classifier	Feature Selector	Performance (%)			Training time in seconds
		Accuracy	Sensitivity	Specificity	
Ensemble Bagged Trees	None	69	66.6	71.2	4.0138
	t	66	58.3	73	3.6953
	SFS	67	54.2	78.8	3.3364
	SFFS	69	66.7	71.2	3.3465
	RSFS	71	62.5	78.8	3.869
	GA	70	52	86.5	3.5578
AdaBoost	None	52	20.8	80.8	2.2325
	t	52	20.8	80.8	0.8266
	SFS	56	45.8	65.4	1.6172
	SFFS	52	15	86.5	0.7029
	RSFS	52	20.8	80.8	1.2080
	GA	55	22.9	84.6	1.4838

Performances of classifiers are also compared using Receiver Operating Characteristic (ROC) curves. It is a plot of the true positive rate versus false positive rate. ROC of Ensemble Bagged Trees classifier considering all features is shown in Figure 2. The marker on the plot displays the performance of the classifier. As shown in Figure 2, if all spatial features are used for classification then only 67% of the observations are correctly assigned to the positive class and 29% of the observations are incorrectly assigned. The Area under Curve (AUC) is a measure of the overall quality of the classifier. Larger AUC values indicate better classifier performance. An AUC value of 0.75 is obtained by Bagged Trees classifier for all spatial features.

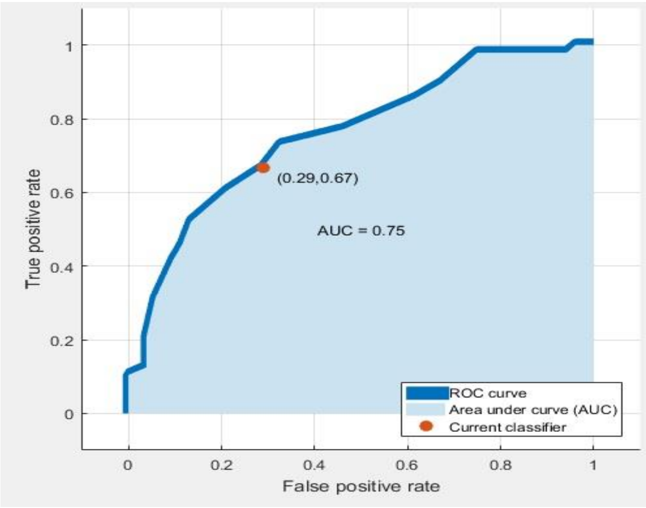


Figure 2: ROC of Ensemble Bagged Trees with all spatial features

B. *Classifier Performance on Spectral Features*

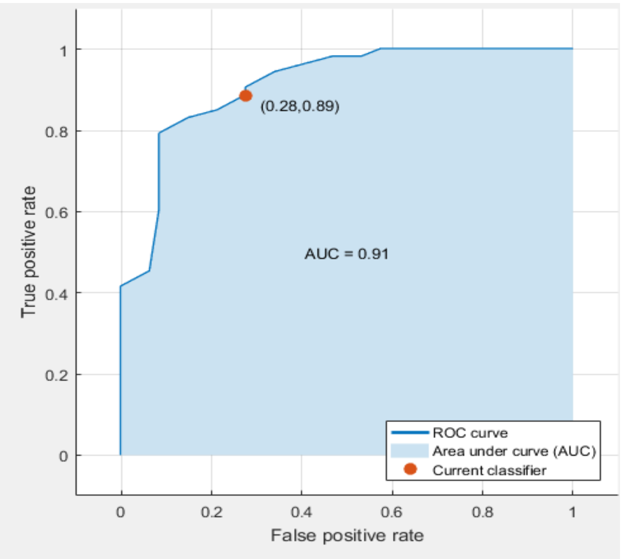
Various Wavelet sub-band local energy features are extracted from segmented breast thermograms [7, 33]. The significant subset of local energy features of wavelet sub-bands was selected by statistical t-test, RSFS, SFS, SFFS and GA methods. 144 local energy features of wavelet sub-bands of six wavelets were fed to various feature selectors. Best selected subsets are fed to classifiers and the results are shown in Table 2 using k fold cross-validation with k=5. Features selected by RSFS attained higher accuracy in comparison with the other feature selectors.

We have obtained maximum accuracy of 87% using Bagged Trees with the RSFS method. Also, classification accuracy is high for spectral features than spatial features. Training time required for each classifier is shown in the last column of Table 2 for Intel Core i3 with 4 GB RAM.

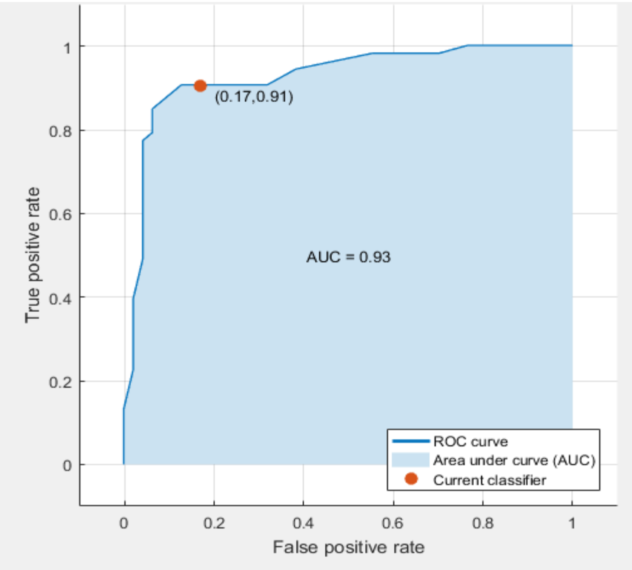
Table 2
Classifier performance in detection of breast cancer using spectral features

Classifier	Feature Selector	Performance (%)			Training time in seconds
		Accuracy	Sensitivity	Specificity	
Ensemble Bagged Trees	None	81	72.3	88.7	3.801
	t	83	79.2	86.5	3.5936
	SFS	71	70.8	71.2	3.4011
	SFFS	77	70.2	83	3.6824
	RSFS	87	83	90.6	3.4017
	GA	79	79.2	78.8	3.4679
AdaBoost	None	70	45.8	92.3	1.2580
	t	62	31.25	90.4	1.1044
	SFS	65	58.3	71.2	1.9670
	SFFS	63	31.3	92.3	1.4806
	RSFS	70	62.5	76.9	4.7502
	GA	63	50	75	1.1453

ROC curves of Ensemble Bagged Trees for all and selected features using RSFS method are shown in Figure 3. Ensemble Bagged Trees with features selected by RSFS method performed better with an AUC value of 0.93. 91% of the abnormal cases are correctly identified and classified into positive class. Only 17% of the observations are incorrectly assigned to the positive class. The RSFS method selected combination of 33 features from a total of 144 spectral features.



(a)



(b)

Figure 3: ROC Ensemble Bagged Trees a) For all spectral features and b) Selected spectral features by an RSFS method

V. CONCLUSION

Accuracy and speed of classification are two important parameters in the selection of classification algorithms. Performance of two different ensemble classifiers namely Bagged Trees and AdaBoost classifiers were compared for classification of breast thermograms using spatial and spectral features. Ensemble Bagged Trees classifier performed better than AdaBoost classifier in terms of accuracy of classification, whereas in terms of training time AdaBoost classifier performed better than Ensemble Bagged Trees classifier. Also, Classifier accuracy was better for spectral features compared to spatial features.

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