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Research paper

Performance Evaluation of Optimized Artificial Neural Network Classifier for Mammography

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Abstract

This paper works on the detection of the breast cancer at initial stage, by utilizing the mammogram images. The contrast of the mammogram image has been enhanced by pre-processing using histogram equalization. The extracted grey level co-occurrence matrix (GLCM) features have been reduced to the significant subset of features. Then, an ANN classifier has been used to classify the image as malignant or benign. The improvement in sensitivity, specificity, accuracy and f-measure signifies effectiveness of the work.

Keywords*: Mammogram, Computer Aided Diagnosis, Artificial Neural Network*

1. Introduction

Breast Cancer is the second most common reasons of the deaths happening due to cancer in women. It has been reported that about 12% (1 in 8) women have invasive breast cancer during their lifetime in the US [1]. India constitutes approximately six percent of hazards of the total deaths occurring due to breast cancer. One out of every 22 women in India is suffering from cancer of breast [2]. Breast cancer risk may be reduced if breast cancer diagnosis is done regularly after every 4-6 weeks and appropriate treatment of cancer is done if detected. Early detection of benign and malignant cases becomes very important as the cancer can be treated in its initial stages if detected [3]. Although cases of breast cancer are increasing over the past many years, but breast cancer mortality rate has declined amongst women of all ages. By incorporating proper diagnosis the mortality rate due to breast cancer has been reduced [4]. Ultrasound imaging, MRI imaging and advanced Mammography are used for imaging of breast [5]. Mammography is most broadly utilized for recognition of breast cancer [6]. It is exceptionally troublesome for the Radiologists to effectively read the mammogram in view of low differentiation [7] prompting distortion of the outcomes. Twofold perusing of mammogram is taken to decrease the extent of missed diseases, in spite of the fact that it is tedious and immoderate. Selection of a CAD framework could decrease the specialists' workload and enhance the recognition rate [8-9]. Image registration strategies are exceptionally useful for breast cancer analysis [10]. Different techniques, such as, wavelets [7] and statistical strategies [11] utilized Feature Extraction to identify breast malignancy. A few Researchers utilized element choice extraction strategies for ANN based bosom tumour analysis [12-16].

2. Proposed Methodology

The process of classification needs the pre-processing and few other steps for the optimized performance. The pre-processing of the image has been done using the histogram equalization. A systematic method has been followed for achieving the objectives of the study and has been shown in figure

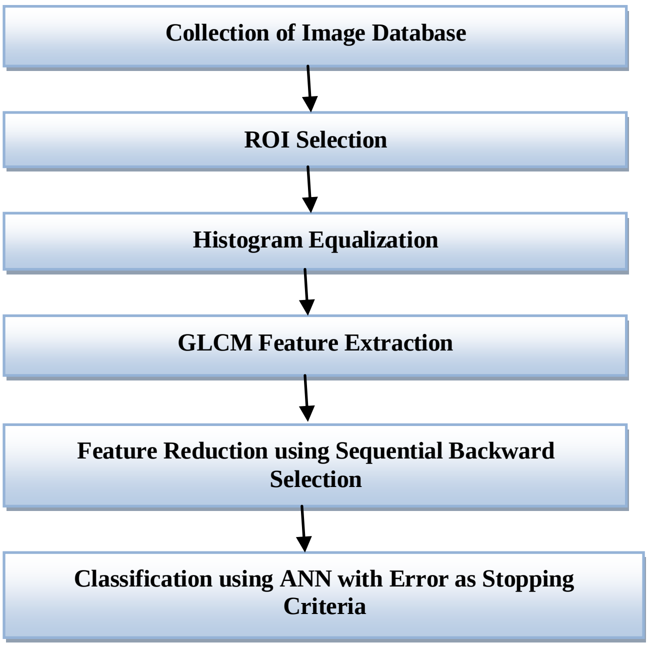


Fig 1: Flow chart of the OANN Classifier

From this pre-processed image, the GLCM features are extracted by using grey level co-occurrence matrix. The extracted features may include the insignificant information so the sequential backward selection (SBS) is applied to select the subset of significant features. Then the optimized ANN classification using error as stopping criteria is applied to classify the image based on the selected subset of features. The whole process is applied to Region of Interest only. The detail of each step involved in the methodology been described under the following subheads:

- Input Image database Collection
- Region of Interest (ROI) Selection
- Image Enhancement by Histogram Equalization
- GLCM Feature Extraction
- Feature Selection by Sequential Backward Selection Algorithm
- Implementation and Performance Comparison

The detail of each step involved in the methodology is described as under:

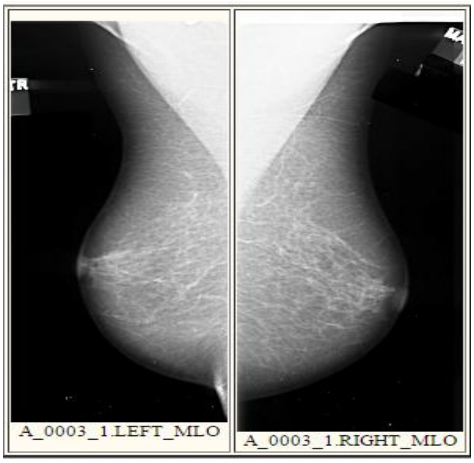


Fig 2: Sample Mammogram

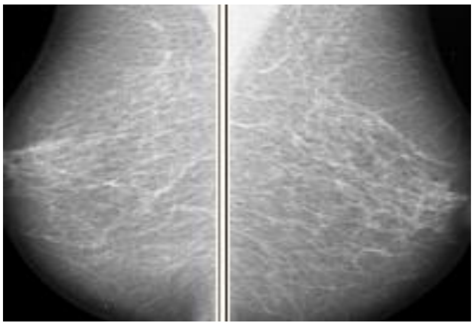


Fig 3: Selection of ROI

2.1 Input Image Database Collection

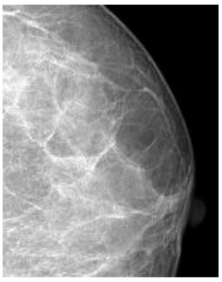
The execution examination has been done with two standard datasets named as MIAS and DDSM. The MIAS dataset is given by Mammographic Image Analysis Society which is an association of UK exploration assembles. The dataset utilizes 322 digitized movies. The DDSM dataset is acronym for Digital Database for Screening Mammography. DDSM dataset is collectively given by exertion between the University of South Florida Computer Science and Engineering Department and Massachusetts General Hospital, Sandia National Laboratories. A sample mammogram has been shown in figure 2.

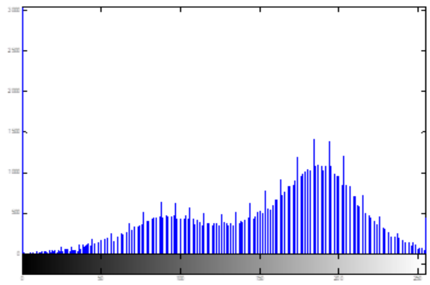
2.2 Selection of Region of Interest (ROI)

Initially images of digital mammograms may be clipped of to remove dark regions which are not the part of the area of interest as a part of preprocessing. Figure 3 shows the ROI selection on mammogram image. Therefore regions outside the breast are rejected so that they may be excluded to take part in later stages so that just the zone of interest is left for further processing.

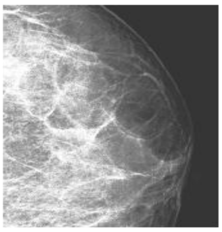
2.3 Image Enhancement by Histogram Equalization

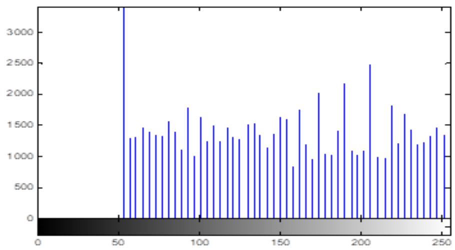
Histogram Equalization or Enhancement may be used for Image Enhancement of Mammogram images. Histogram evening out is utilized to modify the contrast of the picture utilizing the Image histogram by expanding dynamic range of the grey scale [17].
The image enhancement by Histogram Equalization and corresponding histogram of the mammogram is shown in figure 4





(**a**)





(**b**)

Fig 4: a) Original Image and Its Histogram **b)** Enhanced Image and Its Histogram

2.4 Feature Extraction

Grey Level Co-occurrence Matrix (GLCM) features have been utilized as input to the ANN classifier.
can be accessed through back-end web technology and the data contained within those sheets can be displayed at the webpage

2.5 Feature Reduction by Sequential Backward Selection Algorithm

Sequential Backward Selection Algorithm is utilized for the reduction of the extracted features. It is a top down method of selection which starts with the full set containing all the features and repeatedly removes or deletes a single feature which is the least significant feature in the full set. The algorithm has been shown in figure 5. The features have been reduced to significant features by using the following steps:

Suppose $\mathrm{D} = \{\mathrm{d_i}; 1 \leq \mathrm{i} \leq \mathrm{n}\}$
where n is the number of features in a dataset. The selected feature subset having f number of features is $\mathrm{S_f} = \{\mathrm{x_j}; 1 \leq \mathrm{j} \leq \mathrm{f}, \mathrm{x_j} \in \mathrm{D}\}$. The value of the objective function $(\mathrm{d_i}) 1 \leq i \leq n$; only if the ith feature is selected will be known as R (d_i) of the feature.

The relevance of any feature $R_{k-1}(x_j); j = 1,2,3 \ldots f$ in the set S_f is given by $R_{k-1}(x_j) = OF(S_f) - OF(S_f - x_j)$ while the relevance $R_{k+1}(d_i)$ of the feature d_i from the set D-S_f

$$D - S_f = \{d_i; i = 1,2,3, \ldots . n - f, d_i \in D, d_i \neq x_p for all x_p \in S_f$$

is given by $R_{k+1}(d_i) = OF(S_f + d_i) - OF(S_f)$.

The least significant feature in S_f can be given as $R_{k-1}(x_j) = \min_{1 \leq i \leq k} R_{k-1}(x_i)$

$$\Rightarrow \quad OF(S_f - x_j) = \max_{1 \leq i \leq k} OF(S_f - x_i).$$

Similarly for the feature $d_i \in D - S_f$, the relevancy

$$R_{k+1}(d_j) = \min_{1 \leq i \leq n-f} R_{k+1}(d_i)$$

$$\Rightarrow \quad OF(S_f + d_j) = \min_{1 \leq i \leq n-f} OF(S_f + d_i).$$

The SBS algorithm for any Dataset D having n features can be given as:

1. f=0;
2. Initiate $S_f = D$
3. Remove Least relevant feature from S_f i.e.

$x_j = \max_{1 \leq i \leq f} OF(S_f - x_i)$.

4. Update

$S_{f+1} = S_f - x_j;\ f = f + 1$

Repeat step 3 & 4 until stopping criteria achieved.

2.5 Diagnosis/Classification

After extracting and selecting, the GLCM features are used as inputs to train, test and validate an ANN based Diagnosis System. The whole process is implemented using the MATLAB and corresponding results are discussed in next section.

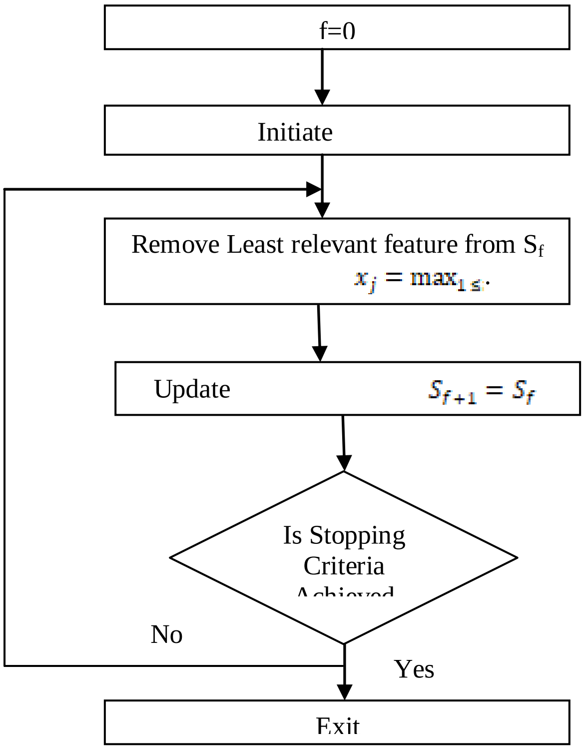


Fig 5: Sequential Backward Selection Algorithm

3. Performance Parameters

The process of classification needs Following are the performance parameters for evaluating the performance of different Classifiers.

i) Accuracy

Accuracy (Ac) is the proportion of the total number of predictions that were correct. It may be defined as ratio of sum of true positive and true negative to all the testing data.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (1)$$

Where TP, TN, FP and FN are true positive, true negative, false positive and false negative respectively. Accuracy may also be defined as a pointer to demonstrate the precision of the classifier for chose subset of elements. It can be given as:

$$Accuracy = \frac{1}{N} \sum_{i=1}^{N} Match(T_i, O_i) \qquad (2)$$

Where Match is function which gives 1 if the target value T_i and output O_i is matched otherwise 0, N is the number of instance.

Sensitivity and Specificity

Sensitivity and specificity are used as statistical parameters for the performance evaluation of a classifier. Sensitivity (Se) and specificity (Sp) portray how well a classifier separates the positive and negative classes. The affectability is a normal of accurately arranged positive components for every class while the affectability is normal of effectively ordered negative components for every class.

Sensitivity

Sensitivity may be defined as a measure of the proportion of correctly identified positives i.e. positives that are correctly identified as such (e.g., the percentage of malignant correctly identified malignant). It is also termed as true positive rate, recall, or probability of detection in some fields. Sensitivity is generally expressed as

$$Se = \frac{1}{c}\sum_{i=1}^{c}\frac{TP_i}{TP_i + FN_i} \tag{3}$$

Where TP is true positive and FN is false negative respectively, c is the number of classes in any particular dataset. A perfect classifier would have 100% sensitivity (e.g., all malignant are identified as malignant).

Specificity

Specificity measures the proportion of correctly identified negatives i.e. negatives that are correctly identified as such (e.g., the percentage of benign correctly identified benign). It is also termed as the true negative rate.

Thus specificity quantifies the avoiding of false positives. The specificity may be expressed as

$$Sp = \frac{1}{c}\sum_{i=1}^{c}\frac{TN_i}{FP_i + TN_i} \tag{4}$$

Where *TN* is true negative and *FP* is false positive, c is the number of classes in any particular dataset. A perfect classifier would have 100% specificity (e.g., no benign are identified as malignant).

F-Measure

A measure that combines precision and recall is the harmonic mean of precision and recall, the traditional F-measure or balanced F-score.

4. Results and Discussions

The calculation has been actualized utilizing the MATLAB. The algorithm has been compared with SVM and ANN based classification. Various parameters like accuracy, specificity, sensitivity and f-measure are analyzed on real dataset. The ANN, SVM and proposed classifier has also been tested on a mammogram data containing 42 digital mammogram Images. The mammogram images comprise of 30 genuine and 12 cancerous images. The performance of the OANN classifier has been compared with existing techniques such as ANN and SVM. The comparison of classification accuracy of different classifiers on real data has been shown in table1. The graphical representation of classification accuracy has been shown in figure 6.

Table 1: Classification Accuracy of SVM, ANN and optimized ANN Classifier

CLASSIFIER	ACCURACY
SVM	70
ANN CLASSIFIER	92.1
ANN CLASSIFIER WITH SBS	94.1

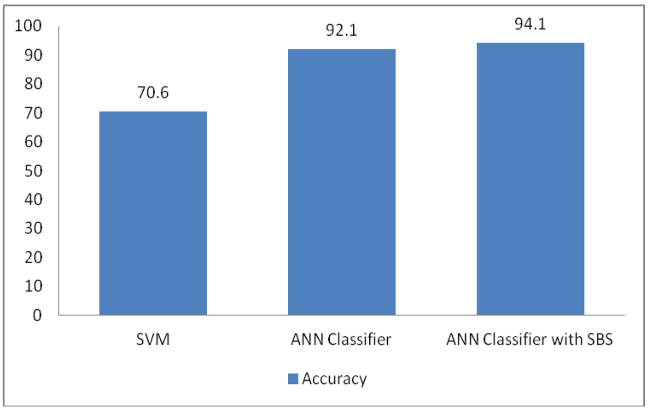


Fig 6: Comparison of accuracy, Sensitivity, Specificity and F-measure on testing data

The graphical representation of classification accuracy has been shown in figure 2. The graph clearly indicates that the OANN classifier has achieved highest accuracy of 94.1 % followed by ANN classifier and SVM. The performance of the classifier has also been tested on the basis of sensitivity, specificity and F1 Score. The sensitivity, specificity and F1 Score of SVM, ANN and optimized ANN Classifier has been shown in Table 2 and corresponding graph has been shown in figure 7.

Table 2: Sensitivity, Specificity and F1 Score of SVM, ANN and optimized ANN Classifier

CLASSIFIER	SENSITIVITY	SPECIFICITY	F1 SCORE
SVM	0.44	0.44	0.33
ANN	0.25	0.25	0.70
ANN WITH SBS	0.81	0.93	0.90

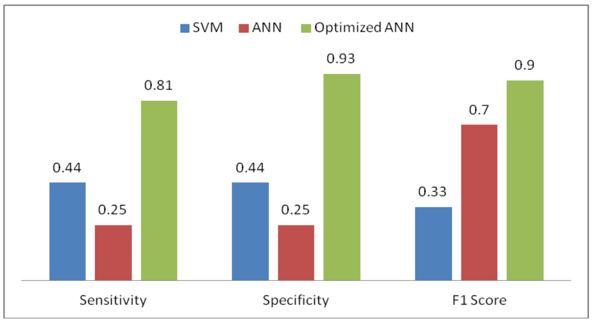


Fig 7: Sensitivity, Specificity and F1 Score of SVM, ANN and optimized ANN Classifier

The graphical representation shows that the Sensitivity, Specificity and F1 score of ANN classifier with SBS are highest with a value of 0.81, 0.93 and 0.90 respectively.

So, it has been observed that Optimized ANN classifier has the highest classification accuracy of 94.1 %. The proposed classifier also have highest sensitivity of 0.81, highest specificity of 0.93 and highest F1 score of 0.90. So all the performances measures i.e. accuracy, sensitivity, specificity and F1 score have shown a significant improvement as compared to other classifiers.

5. Conclusion

This paper presents sequential backward selection (SBS) based ANN classifier to classify breast malignancy. The technique performs the pre-processing, feature extraction, feature reduction as well as the classification. The results of the technique are compared with SVM and ANN based classification techniques using accuracy, sensitivity, specificity and f-measure as the parameters on real datasets. The graphical as well as the tabular comparison shows that the given methodology separates the positive and negative classes better (analyzed using accuracy, specificity, sensitivity and F1 score) as compared to other existing techniques In future the significant feature selection process can be optimized by using meta-heuristic feature selection technique.

The status of the railway crossings and the underpasses is being recorded successfully. The data is being stored in the database from where it is being transmitted to the web page and the mobile app. This data can be accesses by the police at the police station and also by the common people on the app. Hence, now people will be notified beforehand if there is any situation of traffic congestion or traffic jam on the way.

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