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Implementation and Study of Performance Analyses of Various Classifiers on Mammograms

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***Abstract*— In present research, designing and analysis of the performance of classifiers for breast cancer is done. In digital mammography, data mining techniques are used to detect and characterize abnormalities in images and clinical reports. In the existing approaches, the mammogram image classification is done in either clinical data or statistical features of an image using neural networks and Support Vector Machine (SVM) classifier. Present work address the issue by assigning different labels to automatically separating mass tissue from normal breast tissue given a region of interest in a digitized mammogram is investigated. It is the critical stage in developing a robust automated classification system because the classification depends on the accurate assessment of the tumour-normal tissue border as well as information gathered from the tumour area. Since the ultimate goal is robust classification, the qualities of the tissue segmentation are assessed by its impact on the overall classification performance. Computer Aided Diagnosis (CAD) technology helps in identifying lesions and assists the radiologist makes his final decision. A CAD system had been previously developed to perform the following tasks: (a) pre-processing, (b) segmentation and (c) feature extraction of mammogram images. The main focus of this work was two-fold: (a) to analyze these features, select the most important features among them and study their impact on classification accuracy and (b) to implement and compare Neural Networks (NNs),Support Vector Machines (SVMs) and KNN(K-Nearest Neighbour) Classifier's. And also evaluate their performances with these features. From obtained results it is shows that KNN classifier gives the better accuracy compared to NN and SVM classifiers. From the obtained results, the superiority of the proposed approach in terms of accuracy is justified.**

Index terms* — Neural Networks (NNs), Support Vector Machines (SVMs), KNN (K-Nearest Neighbour), Computer Aided Diagnosis (CAD)

I. INTRODUCTION

Breast cancer (BC) is the second foremost cause of cancer deaths among women in United States and it is the foremost cause of cancer deaths among women in the 40 – 55 age groups. According to American College of Radiology (ACR) statistics, one out of nine women will widen breast cancer through her lifetime. Mammography is an efficient tool for early detection because in many cases it can detect abnormalities such as masses, calcifications, and other suspicious anomalies up to two years before they are palpable.

There are important distinctions between detection and classification of suspected abnormalities when considering computer applications. The detection process always precedes classification and may be implemented by some automated method or by a radiologist through predictable methods, as in the normal mammography procedure. Once there is a detected abnormality, by whatever means, it must be classified, which may be achieved by human assessment, pathology analysis, with automatic methods, or some grouping of the three.

The Mammograms are digitized in the attainment phase while the abnormality is placed in the second phase called detection. The next three phases: segmentation, feature extraction and classification cover the main processing steps of the automated mass classification system that is under development here at this competence. This paper is proposed to evaluate the performance of all main Features Extracted by means of combining the clinical and image features for clustering and classification in mammogram images. Initially, mammogram dataset is divided into training and test set. For the training and test sets, pre-processing techniques like noise removal and background removal are done to the images for computing classification accuracy and precision. The statistical features are extracted from the ROI and the clinical data are obtained from the dataset. The feature set is clustered using KNN SVM and ANN methods followed by classification to classify the image as benign or malignant

II.STATE OF ART

Arianna Mencattini and Marcello Salmeri [1], automatic mammogram analysis is important in early breast cancer detection. In this paper, it presents a multi-resolution approach to automated classification of mammograms using Gabor filters. Specifically, Gabo filters of different frequencies and orientations have been used to extract textual patterns of mammograms. For increasing classification efficiency and reduce feature space, statistic t-test and its pvalues for feature selection and weighting are proposed. Experimental results prove that Gabor filters are able to extract textual patterns of mammograms, Statistical-based feature selections and weighting can be used to further reduce the feature space without degrading the classification performance.

Rinker Panchal and Brijesh Verma [2], the significance of combining grey-level based image features and BI-RADS lesion descriptors along with patient age and a subtlety value (radiologists' interpretation) for the reliable classification of calcification and mass type breast abnormalities into malignant and benign classes. Three sets of experiments with grey-level based image features, BI-RADS features and shared features were conducted on DDSM benchmark database. The classification rate 91% on mass dataset and 74% on calcification dataset was obtained when both types of features combined together.

D.Cascio and F.Fauci [3], developed a new approach to model and classify breast parenchymal tissue. Given a mammogram, first, it will find out the distribution of the different tissue densities in an unsupervised manner, and second, it will use this tissue distribution to perform the classification. It has achieved by using a classifier based on local descriptors and Probabilistic Latent Semantic Analysis (PLSA), a generative model from the statistical text literature.

Sukhwinder Singh and Vinod Kumar [4], mammography is the most effective procedure for an early diagnosis of the breast cancer. An algorithm for detecting masses in mammographic images has been presented. The database consists of 3762 digital images acquired in several hospitals belonging to the MAGIC-5 collaboration (Medical Applications on a Grid Infrastructure Connection). A decrease of the whole image's area under investigation is achieved through a segmentation process, by way of a ROI Hunter algorithm, without loss of important information. In the subsequent classification step, feature extraction plays a essential role: some features give geometrical information, other ones present shape parameters. Xiaoming Liu and Jinshan Tang [5], it uses dataset of 57 breast mass mammographic images, each with 22 features computed for investigation. The extracted features are related to edge-sharpness, shape, texture. The innovation of this paper is the adaptation and application of genetic programming (GP). To refine the pool of features available to the GP classifier, it has used five feature-selection methods, including three statistical procedures Student's t-test, Kolmogorov-Smirnov Test, Kullback- Leibler Divergence. Both training and test accuracies obtained were above 99.5% for training and typically above 98% for testing.

Heng-Da Cheng [6], it presents a SVM based computer-aided diagnosis (CAD) system for the characterization of clustered micro calcifications in digitized mammograms. First, the region of interest (ROI) in mammogram is enhanced using morphological enhancement (MORPHEN) method. Second, pixels in potential micro calcification regions are segmented out by using edge detection and morphological operations. Third, a feature depends upon shape, texture and statistical properties are extracting from each region. Finally, these features are given as input to a SVM based classifier for identifying the clusters as either benign or malignant. The SVM with RBF kernel gave Az = 0.9803 with 97% accuracy and the SVM with polynomial kernel gave Az = 0.9541 with 95% accuracy.

Ted C. Wang and Nicolaos [7], it presents a novel methodology for the classification of suspicious areas in digital mammograms. The method is based on the fusion of clustered sub classes with various intelligent classifiers. A number of classifiers have been included into the proposed methodology and evaluated on the well known benchmark digital database of screening mammography (DDSM). The results in the form of overall classification accuracies, TP, TN, FP and FN have been analysed, compared and presented. The results of all four tested classifiers with clustered sub classes on the DDSM benchmark. Database shows that the proposed method can significantly improve the accuracy and reduce the false positive rate.

Matthew A. Kupinski and Maryellen L. Giger [8], it performs the assessment of a CAD for the tumoral masses classification in mammograms by the uncertainty propagation during the system. Carrying on the work of the authors with reference to the metrological characterization of the developed CAD, we authorize the features extraction, features selection, classification steps in this paper. In particular, appropriate metrics such as the Receiving Operating Curve (ROC) and the Area under ROC (AUC) are widely used in order to provide a quantitative evaluation of the performance. Finally, it implements a Monte Carlo simulation in order to provide the confidence interval for some coverage probabilities for all involved parameters. The method is tested on mammographic images containing both malignant and benign breast masses.

Olivier Chapelle and Patrick Haffner [9], Masses will be represented as primary indications of breast cancer in mammograms, and it is essential to classify them as benign or malignant. Benign and malignant masses be different in geometry and texture characteristics. On the other hand, not every geometry and texture feature are extracted contributes to the development of classification accuracy; thus, to choose the best features from a set is vital.

III.METHODOLOGY

The focus of this work was to study the suitability of using the NN, SVM and KNN algorithms in the detection of MCs in mammograms, study their impact on classification accuracy. Support Vector Machines (SVM), Neural Networks (NN) and K-Nearest Neighbour (KNN) are the mathematical structures, or models, that underlie learning. They are all machine learning techniques that study patterns based on training data, fit the models to this training data and predict or classify unseen data.

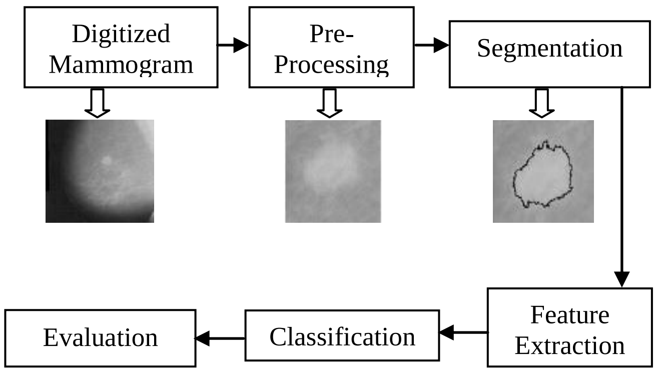

Figure 1. Architecture and Designing of classification System

Step1: Reading input images from MIAS database.
Step2: Resized all images into same size to all images (image dimensions).
Step3: Converted resized images to grayscale images
Step4: Performed filtering operation to grayscale images for reducing noise.
Step5: Sharpened the image
Step6: Remove the unwanted information from the mammogram image by using FCM and extract the various features from segmented region.
Step7: Those feature vectors are given as input to the various classifiers corresponding output vectors.
Step9: Test using selected dataset and classify the classes based on the classifier's output.
Step10: Evaluate the performance of the implanted system using accuracy and confusion matrix.

A.Pre-Processing:

This module involves noise reduction, and intensity adjustment. Image enhancement is typically performed by noise reduction or contrast enhancement. Increase in contrast is very important in mammograms, in particular for dense breasts. Contrast between the malignant tissue and the normal dense tissue may be present in the but may not be perceptible to the human eye. Conventional image processing techniques may not work well on mammographic images because of the large variation in feature size and shape. There are two possible approaches to enhancing mammographic features. One is to suppress background noise and the other is to increase the contrast of suspicious areas. Noises due to intrinsic characteristics of imaging device and from imaging process will impact detection sensitivity of CAD. Several types of filters have been reported.Non- linear filtering has proven more robust than linear filtering in preserving details of the image during noise reduction. Median and selective median filterings locally adapt to the image gray scale using empirically derived threshold criteria. Selective median filtering is generally based on restricting the set of pixels within the selected window to those pixels with a difference in gray level not greater than an empirically derived threshold.

***B.Enhancement and Segmentation*:**

Following noise suppression, image enhancement is performed to improve digital image quality. Segmentation is used to identify suspicious areas from the whole image. The fuzzy C-means (FCM) algorithm was used for soft segmentation based on fuzzy set theory. It allows for fuzzy pixel classification based on iterative approximation of local minima to global objective functions. This has two advantages over other segmentation approaches, namely it is unsupervised and is robust to missing and noisy data. This algorithm helps differentiate small size suspicious regions. Segmentation is used to identify suspicious areas from the whole image. Mammographic lesions are extremely difficult to identify because their radiographic and morphological characteristics resemble those of normal breast tissue. As a mammogram is a projection image, lesions do not appear as isolated densities but are overlaid over parenchymal tissue patterns. Once the features are compute for each ROI, they are use as inputs to a supervised neural network with momentum. The output neurons provide the probability that the ROI is pathological or not. Results are gives in terms of ROC and FROC curves: the area under the ROC curve was found to be AZ = 0.862 and we get a 2.8 FP/Image at a sensitivity of 82%. This software is included in the CAD station actually working in the hospitals belonging to theMAGIC-5 Collaboration.

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C. Feature extraction:

Feature extraction and selection is an important part of supervised classification. The number of features selected for breast cancer detection reported in literature varies with the CAD approach employed. It is desirable to use an optimum number of features since a large number of features would increase computational needs, making it complicated to define accurate decision boundaries in a large dimensional space. Features in different domains (morphological, spatial, texture etc.) are extracted. In this process, the most important characteristics of the ROI are studied. Among the most important characteristics reported by radiologists are given below

(a) **Area**: some benign calcifications have larger size compared to malignant calcifications.

(b) **Orientation**: malignant calcifications often have shapes that are oriented to the nipple

(c) **Mean**: The mean gives the average intensity value of an image. Mammographic images that contain microcalcifications have a higher mean than those of normal images.

$$M=\frac{1}{mn}\sum_{p=1}^{m}\sum_{q=1}^{n} i(p,q) \quad (1)$$

Where ‘p, q’ indicates rows and columns of the image and i (p, q) is the cell denoted by row and column of the image.

(e)Standard Deviation: It refers to the distribution of values in a mammographic image around the mean.

$$S\_D=\sqrt{(M)^2} \quad (2)$$

(g)Entropy: It is a statistical measure of randomness that can be used to characterize the texture of the input image.

$$EN = -\mathrm{sum}(q.*\log2(q)) \quad (3)$$

Where p contains the histogram counts returned from imhist. By default, entropy used two bins for logical arrays and 256 bins for uint8 and uint16 or double arrays. It can be a multidimensional image. If it have other than two dimensions, the entropy function treat it as a multidimensional grayscale image and not as an RGB image.

(h) Contrast: It is a measure of the level to which an object is discernible from its background. It represents the local variations present in an image, calculated the intensity contrast between a pixel and its neighbour. It is calculated from the image as per the following equation.

$$CT = \sum_{p,q=0}^{n-1}(p - q^2 i(p,q) \quad (4)$$

Where n represents the number of pixels in the image and i (p, q) is the cell denoted by row and column of the image.

(g)Uniformity: It measures the uniformity of intensity in the histogram

$$UN=\sum_{p,q=1}^{m-1,n-1} i^2\,(p,q) \quad (5)$$

(h)Smoothness: It finds the relative smoothness of the intensity in a region.

$$S=1-\frac{1}{(1+SD)^2} \quad (6)$$

***D.Classification*:**

Classification using NN, KNN and SVM algorithms are studied and evaluated. The focus of this work was to study the suitability of using the NN, SVM and KNN algorithms in the detection of classes in mammograms and study their impact on classification accuracy. SVM, KNN and NN are the mathematical structures, or models, that underlie learning. They are both machine learning techniques that learn patterns based on training data, fit the models to this training data and predict or classify future data. The active development of NNs research started in 1970s and that of SVMs started in 1980s. Currently, both techniques are used widely even though SVMs show superior performance in various problems compared to NNs. The applications of SVMs are expected to increase even though NNs are more widely known.

IV.CLASSIFICATION ALGORITHMS

Support Vector Machines (SVM), Neural Networks (NN) and K-Nearest Neighbour (KNN) are the mathematical structures, or models, that underlie learning. They are all machine learning techniques that learn patterns based on training data, fit the models to this training data and predict or classify unseen (or future) data.

***A. Neural Networks*:**

The ANN is an information processing system inspired by the biological nervous system. It is composed of a large number of highly interconnected processing elements called neurons. An artificial neuron is a device with many inputs and one output. The neuron contains two modes of operation, the training mode and the testing mode. In the training mode, the neuron can be trained to fire (or not) for a particular set of input patterns. In the testing mode, when a pattern is presented at the input the firing rule decides whether to fire the neuron or not. These neurons form the nodes of the NN. Each node is assigned a threshold and each interconnection between the nodes is assigned a weight that represents the strength between the neurons. The simplest NN has a set of inputs and one output. Fig (2) shows a 1-level NN also called a Perceptron.

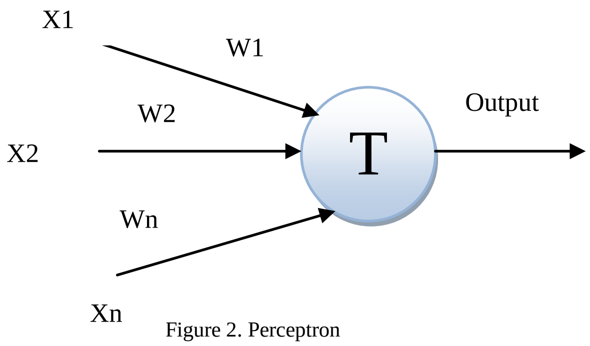

Figure 2. Perceptron

In the above figure, *x* refers to the inputs, *w* the weights, *y* the output and *T* the threshold of the node. The strength of signals a node receives is calculated as the weighted sum of inputs

$$w_1x_1 + w_2x_2 + \cdots w_nx_n \quad (7)$$

If this value overcomes the threshold T of the node, then the signal is transmitted to other connected nodes. The value of the output of the node is decided by the activation function *f*, which decides whether the perceptron should fire or not. Thus, the output y is given as

$$y = f(w_1x_1 + w_2x_2 + \cdots w_nx_n - T) \quad (8)$$

The SBP (Standard Back Propagation) is the most popular NN training algorithm. Other examples of training algorithms are the conjugate gradient descent, Quasi-Newton, quick propagation etc.

The SBP algorithm is stated as follows

(a)Create a feed-forward network with ni inputs, no outputs and nh hidden units.

(b)Initialize all the weights to random values (say between -0.05 and 0.05)

(c) Until convergence do for each training sample *(x, y)*, do

(a) Compute the output *ou* of every unit for instance *x*

(b) For each output unit *k* calculate

$$\delta_k = o_k(1 - o_k)(t_k - o_k) \quad (9)$$

(c) For each hidden unit *h* calculate

$$\delta_k = o_k(1 - o_k) \sum_{k=\text{downstream}\ (h)} w_{kh}\,\delta_k \quad (10)$$

(d) Update each network weight w_{ij} as

$$w_{ji} \leftarrow w_{ji} + \Delta w_{ji}$$

Where $\Delta w_{ji} = \eta\delta_j x_{ji}$, thus the weights of the network are updated until the convergence criterion is met.

Once the features are compute for each ROI, they are use as inputs to a supervised neural network with momentum. The output neurons provide the probability that the ROI is pathological or not. Results are gives in terms of ROC and FROC curves: the area under the ROC curve was found to be AZ = 0.862 and we get a 2.8 FP/Image at a sensitivity of 82%. This software is included in the CAD station actually working in the hospitals belonging to theMAGIC-5 Collaboration.

***B.Support Vector Machines*:**

The formulation of SVM embodies the Structural Risk Minimization (SRM) principle, as opposed to Empirical Risk Minimization (ERM) commonly employed with other statistical methods.SRM minimizes the upper bound on the generalization error, as against ERM which minimizes the error on the training data. Thus, SVMs are known to generalize better.

A linear learning machine learns a linear classifier or hyper plane from the training data

$$h(x) = wx + b, w\epsilon R^n, b\epsilon R \quad (11)$$

Thus the hyperplane divides the data so that that all the points with the same label lie on the same side of the hyper plane. This amounts to finding *w* and *b* so that

$$y_i(wx_i + b) > 0 \quad (12)$$

It is possible to rescale w and b so that

$$y_i(wx_i + b) \geq 0 \quad (13)$$

***C.K-Nearest Neighbour (KNN)*:**

In KNN classifier suppose if we have C classes each has N samples, then the distance between test sample and each is calculated. The test data belongs to the class with which the distance is minimum. The most familiar point to distance measure is ‘cityblock’. If we consider two points in the XY-plane, the ‘cityblock distance’ is calculated as the sum of distance in X and the distance in Y, which is similar to the way we move in a city where we have to move around the buildings instead of going straight through. The cityblock distance between two points, X and Y, with ‘n’ dimensions is calculated as:

$\sum|x_i - y_i|$, where X= $[x_1, x_2, x_3, .. x_n]$ and Y= $[y_1, y_2, y_{3,....}y_n]$ (14)

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V.RESULT AND DISCUSSION

The results of various experiments conducted on the training and testing images. The 'Classification' and 'Evaluation' stages were the main focal point of this work. Classification was performed using the NN, SVM and KNN algorithms. Total images taken from the MiniMammographic database of MAIS (Mammographic Image Analysis Society) for this work. This database consists of 322 images, out of 322 images 208 are normal, 63 are benign and 51 are malignant. By using these images, different numbers of training and testing results were achieved for various classifiers. MATLAB R2012b has been used for this experiment. In that 322 images 300 images are used for training and 22 images used for testing.

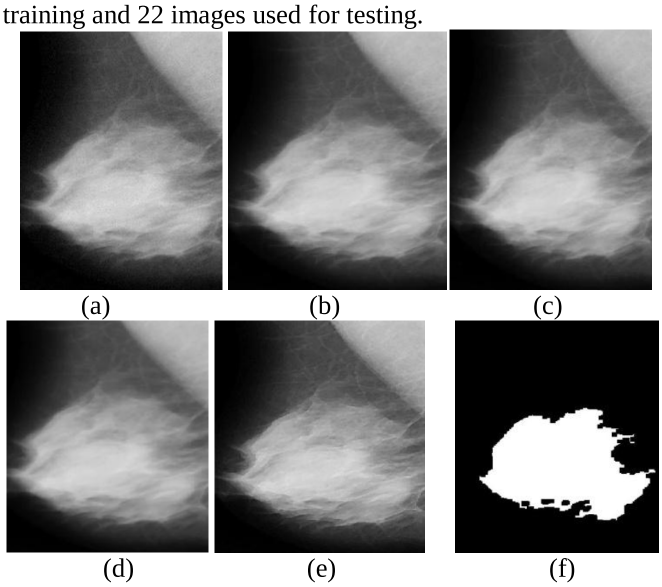

Figure 3. (a) Input image (b) Resized output (c) Gray scale Image (d) Denoised Image (e) Sharpened Image (f) Region (Segmented Region)

The results are presented as follows:
1) Detailed statistical analysis of input features.
2) Use the most considerable features with the NN, SVM and KNN to classify normal, Benign, Malignant and compare their performances.
3) Classification results for different types of training and testing methods without feature selection.

Extracted Features from the Cancered region are summarized in table 1.

Features	Normal	Benign	Malignant
Intensity	0.753641	0.701045	0.69229
Std_variance	0.83205	0.078612	0.058183
variance	0.006923	0.00618	0.003385
area	13617	14535	32202
Centroid_X	106.6106	106.9866	138.4625
Centroid_Y	174.7246	186.804	155.5674
Orientation(^{o})	-86.542	-23.6925	79.87267
uniformity	0.574898	0.497644	0.48265
Entropy_Val	6.351712	6.249053	5.795322
Contrast(gain)	0.004996	0.004189	0.002528
smoothness	0.076814	0.072882	0.054984

Confusion matrix for multi classifier is summarized in table 2.

	0	1	2
0	T00	F01	F02
1	F10	T11	F12
2	F20	F21	T22

Accuracy: Ratio of total number of predictions that was correct

$$A = \frac{\mathrm{T00} + \mathrm{T11} + \mathrm{T22}}{\mathrm{T00} + \mathrm{F01} + \mathrm{F02} + \mathrm{F10} + \mathrm{T11} + \mathrm{F12} + \mathrm{F20} + \mathrm{F21} + \mathrm{T22}}$$

Where
T00, T11, T22 = number of correct predictions that an instance is 0, 1, 2
F01, F02, F10, F12, F20, F21= number of incorrect predictions that an instance is 0, 1, 2
Accuracy for NN, SVM, and KNN were achieved for both training and testing cases were summarized in table 3.

Classifiers / Accuracy (%)	NN	SVM	KNN
Training	65	75.66	93.66
Testing	65.5	86.36	95.45

From the above results, the superiority of the proposed approach in terms of accuracy is justified. In Table (1), 10 features are extracted from ROI (cancer region) and from that cancer region features will be calculated. Features are Orientation (degrees), Centroid (coordinates), Contrast (gain), Smoothness, Intensity (pixels), Variance (pixels), Standard deviation (pixels), Area, Entropy and Uniformity.

VI.CONCLUSION

The present work was to find out if it is possible, by classifying screening mammograms according to the likelihood of malignancy, to divide the recalled women to a group in which there is high suspicion of malignancy, most having breast cancers, and a group with more obscure findings. In this work, SVM, NN and KNN classify algorithms are used. The classifiers had been trained through these techniques, to test on every mammogram whether the detected output was a normal or Benign or Malignant. All features were originally used to represent three classes. Obtained results Table (3) from the various classifiers and compared. From the results it is shows that KNN classifier gives better efficiency when compared to SVM and NN classifiers. Not much work has been done on classification system and none of the methods report 100% recognition rate.

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