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Mammogram Characterization using Cohesive Gray Level Feature Domain in Probabilistic Neural Network

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Abstract: Breast cancer is one of the most common causes of cancer fatality in women. Early detection and treatment are keys to preventing breast cancer from spreading. Digital mammograms are one of the most effective means for detecting possible breast abnormalities at early on stages. Digital mammograms supported with Computer Aided Diagnostic (CAD) systems help the radiologists in taking reliable decisions within short span of time. The proposed CAD system analyses and combines statistical texture features obtained from gray level correlated matrices, for the better classification of mammograms. The Probabilistic Neural Network classifier is used to analyze 256 real mammogram images acquired from different hospitals. The database contains of 136 normal and 130 abnormal i.e., in MLO or CC view. The specific dataset is carefully selected such that the abnormality is apparent in one view and subtle in other due to its complex texture. The proposed system gives 94.76% and 91.31% youden's ratio, 97.41%, 97.69% accuracies for the two different views respectively. The Youden's ratio of 94.30 and accuracy 97.14% is attained for normal - abnormal datasets discrimination. The study reveals that features extracted in unified statistical texture domain with PNN classifier proves to be a promising tool for analysis of mammograms irrespective of their appearance and views and Youden's ratio is the optimum performance measure with justness to sensitivity and specificity.

Key words: CC, gray level statistics, Mammograms, MLO, PNN, Youden's ratio.

1. INTRODUCTION

Mammography is an imaging modality using of X rays to get the inside tissue abnormalities of the breast on the film [1] and one of the best screening methods used for early detection of breast cancer for decades. Significant improvements in conservative treatment can be accomplished by early detection of cancer. Mammograms are taken in two different views Mediolateral Oblique View (MLO) and Cranio-Caudal View (CC), both are important from the aspect of radiologist. The CC view is in which the x-rays pass through the breast in a direction from the head towards the feet. The MLO view is taken diagonally across the body in a direction from the shoulder towards the opposite hip. The MLO enables the radiologist to judge whether there has been metastatic spread of cancer to the axillae. Taking two views from different angles in principle enables the radiologist to discriminate between clinically significant areas and those that are not but which might appear so in a single image.

Some of the abnormalities are such that they are perceptible in one view, and subtle in other. The radiologist may comfort to diagnose the presence of abnormality in one view and find difficult to take decision in other view. This is due to fact that certain masses in size are spread either horizontally or vertically. The database contains mammograms of abnormalities that appear apparent in one view and subtle, irregular, often with non-local differences for intensity in other view. Moreover the images are inevitably cluttered due to super imposition, the background normal structure that varies greatly between breasts and the quality of image.

2. RELATED RESEARCH

Many computer classification techniques for mammogram analysis are available. The experimental images are in either MLO view or CC view. MLO view sometimes gives better result than CC view because it covers more part and confirms the existence of auxiliary limp nodes. Further the literature survey specifies the enormous use of statistical and transforms textural features comparing to shape, artificial intelligence and other features.

A. Vadivel 1 and B. Surendiran [2] presents geometric shape and margin features for classifying mammogram mass lesions into BI-RADS shape categories: round, oval, lobular and irregular. The proposed work upholds the shape features efficiency over Haralick features. Experiments have been conducted on mammogram images from the Digital Database for Screening Mammography (DDSM) and classified using C5.0 decision tree classifier. Total of 224 DDSM mammogram masses are considered for experiment. Particle Swarm Optimized Wavelet Neural Network (PSOWNN) that produces an improvement in classification accuracy in detection of breast abnormalities in digital mammograms is proposed by [3]. The proposed

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abnormality detection algorithm is based on extracting Laws Texture Energy Measures from the mammograms and classifying the suspicious regions by applying a pattern classifier. The method is applied to real clinical database of 216 mammograms collected from mammogram screening centres. The result shows that the area under the ROC curve of the proposed algorithm is 0.96853 with a sensitivity 94.167% of and specificity of 92.105%.

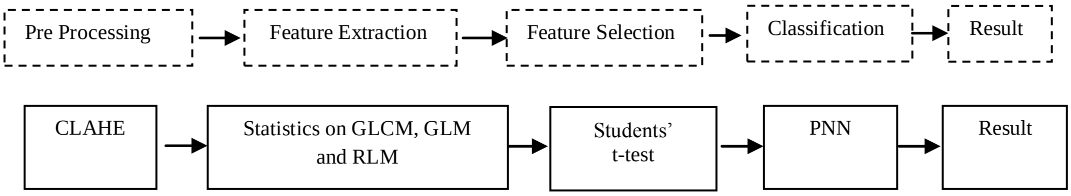

Figure 1 Flowchart of proposed method

A shape-based detection method for accurate detection of the pectoral muscle boundary is proposed by [4] in medio-lateral oblique view of mammograms. The proposed method was applied to 322 mammograms from the mini Mammographic Image Analysis Society database. A 97.2 % acceptable rate from expert radiologists and assessment results based on the false positive rate, false negative rate, and Hausdorff distance demonstrate the robustness and effectiveness of the proposed shape-based detection method. The geometry and texture characteristics are used to differentiate benign and malignant masses by [5]. It also confirmed that, not every geometry and texture features give any improvements in classification accuracy. Support vector machine (SVM)-based recursive feature elimination (SVM-RFE) procedure is added with normalized mutual information feature selection (NMIFS) retaining the advantages. A new feature selection method, the SVM-RFE with an NMIFS filter (SRN) is used on 413 ROIs of the images.

The local and discrete texture features are used by for segmentation of masses in mammograms. Co occurrence matrix and optical density transformation features are used by [6] for local textural description and photometric distribution of mammograms. Stepwise linear discriminant analysis is the algorithm to classify some adaptive square Regions of Interest (ROI) for suspicious areas in the images. A one-class classification of mammograms into benign and malignant groups is proposed by [7]. A generalization of Radon transform, the Trace transform is used for feature extraction and subsequently the features are used by classifiers. Different classifiers linear discriminant classifier, quadratic discriminant classifier, nearest mean classifier, support vector machine, and the Gaussian mixture model (GMM) were used. An accuracy of 92.48% has been obtained using GMMs comparing to others.

A mammogram enhancement technique is proposed by [8] using fast dyadic wavelet transform But it is different from other techniques as its based on lifted spline dyadic wavelets and normalized Tsallis entropy. After the mammograms are decomposed into a multiscale hierarchy of low-subband and high-subband images and then noise is suppressed using normalized Tsallis entropy of the local variance of the modulus of oriented high-subband images. The method is tested on mammogram images, taken from MIAS database, having various background tissue types and containing different abnormalities.

The watershed transform has been applied on morphologically reconstructed image to detect the suspicious mass regions [9] by. Further the results are compared with thresholding of graph based saliency map and morphological extraction from saliency. He proposed method gave 0.95 of similarity measure and 83% of ROC area. The film and full-field digital mammography (FFDM) images are used by [10] to find any considerable changes in texture features. The GLCM features are calculated achieving 96% on real images acquired of cadaver breast specimens containing simulated micro calcifications using both a GE digital mammography system and a screen-film system. Rest of the paper is divided into 3 sections, Section 3 discusses the materials and methodology used, section 4 discusses the experiments analyzed and section 5 gives the conclusion.

3. MATERIALS AND METHODS

The mammography data is taken from different hospitals of age group 35-55 from 2011 to 2014. The number of selected cancerous images are minimum due to the criteria that lesion seen in one view is hidden in other, from radiologist's diagnostics. Each case has MLO and CC views for the right and left breasts. The acquired images data set contains 120 abnormal and 136 normal mammograms. Among cancer affected images 56 are chosen as appearance of abnormality is apparent in one view and subtle in another. The dimension of the mammograms is inconvenient to further steps; hence 32×32 region has been cropped from each image so that the abnormality is covered. Matlab10 is used for the implementation of the proposed method.

The proposed mammogram characterization system is depicted in Figure 1. The pattern recognition steps are given in dashed boxes whereas the particular methods selected for the proposed system are specified below.

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Contrast Limiting Adaptive Histogram Equalization (CLAHE) algorithm is used for enhancing the mammogram contrast as a required mandatory pre-processing. For feature extraction the statistics based on the gray level correlated matrices are used. The feature extraction process, makes collection of feature set which is beyond limit of usage in classification time and it bestow the way for optimal feature selection. The most distinguishing features are selected using t-test series and carried to the PNN classifier for classification.

3.1 PRE PROCESSING

The quality of mammograms is dependent on the contrast, which plays an important role in subsequent feature extraction [11]. CLAHE, a generalization of Adaptive Histogram Equalization (AHE), best fits, as it operates on small regions in the image, called tiles, rather than the entire image. It retains the brightness of the image with removal of noise amplification and usage of homogenous regions.

3.2. FEATURE EXTRACTION

The main task and requirement of classification is digging the most sustainable features, which represents the texture an image. Gray level based Statistics calculated from different correlation matrices as texture features are extracted for further analysis. Chosen gray level correlated feature domains matrices are Gap Length Matrix (GLM), Run Length Matrix (RLM) and Co occurrence Matrix (CM). Different statistical measures exist for examining the textures that considers the spatial relationship of the pixels from such matrices.

The GLM measures the gray level variations in an image, by counting the distribution of gray level gap lengths for each gray level in an image. The matrix is a 2-D array as given in Eq (1),

$$A(g, l|\theta) \tag{1}$$

where g is the gray level, l is the gap length, and θ is the given direction. For an image of M×N pixels with G gray levels from 0 to G-1, let f(i,j) be the gray level function at pixel (i,j) and L be the maximum gap length. The element of matrix A at angle θ is given by Eq. (2) and (3)

$$A(g, l|\theta) = Number\ of\ \{(i,j)\ |\ f(i,j) = f(i+x, j+y) = g, f(i+u, j+v) \neq g, u < x\ and\ v < y\} \tag{2}$$

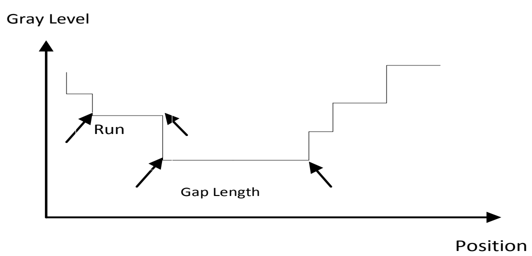
$$where\ x = (l+1)cos\theta\ \ and\ y = (l+1)s \tag{3}$$

$$0 \leq g \leq G-1, 0 \leq l \leq L\ and\ 0° \leq \theta \leq 180°$$

Table 1. Contingency Table

Mammograms	True Negative (TN)	True Positive (TP)	False Positive (FP)	False Negative (FN)	Total
Normal / Negative (N)	117	-	3	-	120
Abnormal / Positive (P)	-	121	-	4	125

The Run length gives the count of the occurrence of runs for each gray levels and length of the run at different direction. A gray level run is defined as a set of repeated pixels having the same gray level and length of the run is the number of pixels in the run. The Figure2 shows the relationship between RLM and GLM formation with gray level and position coordinates. Several texture features can be extracted from the GLM which are similar to CM and contradictory to RLM [12]. Only some of the features calculation is listed below from the extracted feature set.



From the gap length matrix

Gray Level Fluctuation,

$$GLF = \frac{\sum_{g=0}^{G} \left(\sum_{l=0}^{L} A(g,l\,|\,\theta)\right)^2}{\sum_{g=0}^{G-1} \left(\sum_{l=0}^{L} A(g,l|\theta)\right)} \tag{4}$$

Short Gap Emphasis,

$$SGE = \frac{\sum_{g=0}^{G-1} \left(\sum_{l=0}^{L} \frac{A(g.l|\theta)}{l^2}\right)}{\sum_{g=0}^{G-1} \left(\sum_{l=0}^{L} A(g.l|\theta)\right)} \tag{5}$$

Long Gap Emphasis,

$$LGE = \frac{\sum_{g=0}^{G-1} \left(\sum_{l=0}^{L} l^2\ A(g.l|\theta)\right)}{\sum_{g=0}^{G-1} \left(\sum_{l=0}^{L} A(g.l|\theta)\right)} \tag{6}$$

Similarly two of the Run-Length Features derived by Galloway [13] from the run-length matrix are shown in Eq. (7) and Eq.(8) The RLM is a two-dimensional matrix where each element is the number of runs with pixels of gray level 'i' and run-length 'j', in the direction θ.

Short Run Emphasis (SRE),

$$SRE = \frac{1}{n^r} \sum_{i=1}^{M} \sum_{j=1}^{N} \frac{p(i,j)}{j^2} \tag{7}$$

and Long Run Emphasis (LRE)

$$LRE = \frac{1}{n^r} \sum_{i=1}^{M} \sum_{j=1}^{N} P(i,j) * j^2 \tag{8}$$

The correlation matrix has been proved to be a popular and most used statistical method in textural feature

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extraction. The correlation matrix is defined over an image for the distribution of co-occurring values at a given offset. The CM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image. Fourteen textural features measured from the probability matrix are explored by Haralick [14], like Energy, Auto correlation, and the Inverse Difference Moment. Eq. (9) gives the calculation of the Energy or uniformity or angular second moment feature,
Energy,

$$E = \sum_{i,j=0}^{N-1} \left(P_{ij}\right)^2 \qquad (9)$$

Where Pij is the element (i,j) in the CM and N the number of gray levels in the image.

3.3. FEATURE SELECTION

Feature extraction yields different dimensionality characteristics set, which is in need of optimal minimum feature selection, reducing time and space requirements. Single statistical domain gives a limited number of features, representing the relationship of real pixel values, whereas the multi statistical domain represents an image with matrix of features. Through the feature vector combination a large dimension feature vectors set is obtained and only the features which have most discerning ability have to chosen to be fed to the classifier. Student t-test series is used in feature selection [15] for gray level based statistics. Student t-test series, computes the probability if other subsets perform substantially better and gives a set of features. It finds whether the two sets of data are significantly different from each other, by a statistic which follows a Student's t-distribution if the null hypothesis is supported.

3.4. CLASSIFICATION

The probabilistic neural network PNN [16] is based on Bayesian classification and probability density estimation function (PDF). The classifier framework is given in Figure 3, depicting the intuitive layers, the images after input layer are feature extracted through pattern layer representing images. The summation layer rounds the features and fed to decision layer. The PDF approximates the probability density of the underlying pattern's distribution using the Equation [10].

$$p_i(x) = \frac{1}{(2\pi)^{n/2}\,\sigma^n}\,\frac{1}{N}\sum_{i=1}^{N_i} \exp\left[\frac{(x-x_{ij})^T (x-x_{ij})}{2\sigma^2}\right] \qquad (10)$$

where σ is the smoothing parameter, and x_{ij} is a training pattern belonging to class c, N_i denotes the total number of samples in class c.. The maximum likelihood of sample x being classified into c as per Baye's decision rule is given in Eq. (12)

$$C(x) = \text{argmax}\ \{p_i(x)\}, \quad i = 1,2,\ldots,c \qquad (11)$$

where C(x) denotes the approximated class of the test sample x.

4. RESULTS AND DISCUSSION

The mammograms are contrast enhanced to improve the quality and then textural features are extracted. The principal features are selected from each matrix through paired t test series, normalized and fed to the PNN classifier. The overall performance of the features is combined for precise classification and the classifier's performance is cross validated by using leave-one-out method. The leave-one-out tests one pattern leaving others and the process is recurring until all patterns of database crosses testing phase.

Performance Measures

Different evaluation measures exist to assess the classifier performance which also shows the dominance of features used for classification. The base table for calculations of fitness measures is given in Table 1.

Where N gives the total number of normal mammograms or negative count,
P gives the total number of mammograms with abnormality or positive count,
TN is number of actual normal mammograms and grouped as normal
FP is the number of actual normal mammograms and grouped as abnormal.
TP is the number of actual abnormal mammograms and grouped as abnormal.
FN is the number of actual abnormal mammograms and grouped as normal
Among performance measures, Accuracy is the most used fitness criteria calculated as follows

$$Accuracy = \frac{(TP + FN)}{(P + N)} \qquad (12)$$

It is clearly based on true classification power i.e., true negative and true positive; leaving the failure i.e., false positive and false negative. Including Mathew's Correlation coefficient (MCC), F-Ratio , likelihood and Youden's index are the measures giving equal prominence for true as well as false classification ability.
For the current experimental analysis, the binary classification performance of the classifier is found using Youden's J statistic also called as Youden's index [17]. The statistics detain the performance of the classifier by including sensitivity and specificity calculations. Along Youden's index, the Sensitivity and Specificity are considered as performance measures and calculated using Equations (13), (14) and (15) respectively,

$$Sensitivity = \frac{TP}{(TP + FN)} \qquad (13)$$

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which presents the ability of the classifier for correct identification of those patients with disease.

$$Specificity = \frac{TN}{(FP + TN)} \qquad (14)$$

It shows the classification ability for recognition of patients without the disease or normal patients and Youden's index,

$$J = \text{Sensitivity} + \text{specificity} - 1 \qquad (15)$$

is a single statistic that gives equal weight to sensitivity and specificity.

Table 2 Performance analysis on Feature Domains

Texture Domain	Matrices	Features Extracted	Youden's index J (%)	Accuracy (%)
Statistical	Gap Length	Low Level Gap Emphasis Gap Level Fluctuation	84.50	92.24
	Run Length	Gray Level Non Uniformity Short Gray Level Run Emphasis	87.73	93.88
	Co Occurrence	Autocorrelation Entropy, Energy Cluster Prominence and Homogeneity	91.00	95.51
Combination			94.30	97.14

The performance of the classifier in gray level based domain for discrimination from normal to abnormal are experimented and the results are tabulated as shown in Table 2. As per the statistics result, Gap Length domain is not much least significant comparing to other texture features i.e., correlation and run length matrices. But the gap length domain is much concentrated on measuring the distribution of gray level gap lengths for all the gray levels in an image.

The run length feature, paradoxical to gap length shows considerable performance. It gives the non uniformity measure with Run Emphasis. The co occurrence matrix based Haralick features as exemplified from literature survey gives peak classification accuracy comparatively to others. The different gray level matrices with significant correlation take the role of counterpart in feature domain for successful classification. The feature set combination unite the Gap length supporting size and non homogeneity, Run Length to analyze whether there is a predominance of relatively long run lengths in relation to the short runs or vice-versa and Co occurrence to evaluate adjacency of pixels. Thus the feature set obtained from combining statistical calculations on GLM, RLM and CM result in an improvement for classification and analysis. The classification efficiency is depicted in Receiver Operating Characteristic (ROC) curve, given in Figure 4 which yields an accuracy of 97.14%.

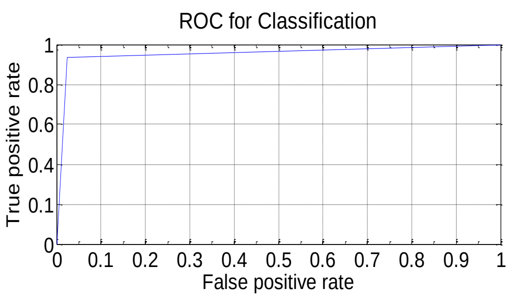

Figure 4 ROC curve

The ROC curve shows the relationship between sensitivity and specificity higher the sensitivity, the lower the specificity and vice versa, which are dependent on the cut-off value above or below which, the test is positive. The sensitivity measure 97.50% in the current experiment is equivalent to specificity 96.80% giving equal partition.

Figure 5 shows the classification accuracy for nine feature combination sets of normal and abnormal classes with equivalent dimensions.

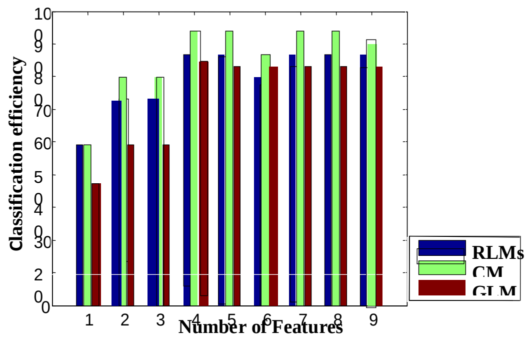

Figure 5 Effect of Feature size on classification

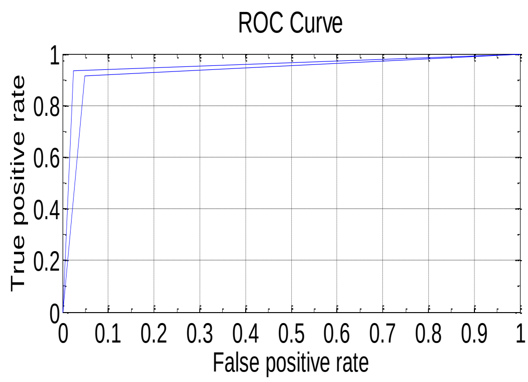

Figure 6 Comparisons of Apparent and Subtle Datasets

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Different data set sizes are obtained, by keeping the size of one set fixed and varying another. The classifier efficiency fluctuates as dataset size is kept varying, for certain datasets the accuracy of classifier remains consistent and equal, depending on their combination. As the datasets are changed i.e., certain mammograms are removed and added which much and more strengthens the dataset, hence the classifier has been tested for possible datasets combination.

The unpaired test feature selection method is used for prominent feature selection, concentrates for data selection with feature distribution to offer more class separability and bring a decision state among the sample sets. Hence, it changes the accurateness of statistical features set in combination. On calculation of absolute mean difference and a 95% confidence interval for the mean difference the t-test evaluate the means of the two classes and it determines whether the data has come from the same class or not. The Table 3 shows the eminent statistics, of GLCM features Energy and Autocorrelation for their membership is optimal feature set. The mean, standard deviations are also tabulated for distinguished classes.

Table 3 student's t-test statistics

GLCM Features	Normal Mean ± sd	Abnormal Mean ± sd	Mean Difference ± 95% CI	P
Energy	0.220 ± 0.032	0.155 ± 0.038	0.065 ± 0.015	P<0.0001
Autocorrelation	0.644 ± 0.101	0.602 ± 0.120	0.042± 0.048	P<0.0001

Table 4 Performance analysis on different datasets

Samples	TN	TP	FN	FP	Sensi.	Speci.	J (%)	Accuracy (%)
Normal -Apparent	59	53	2	1	96.36	98.33	94.70	97.39
Normal- Subtle	58	52	2	2	96.36	96.67	93.03	96.49
Normal –Abnormal	121	117	3	4	97.50	96.00	93.50	97.14

Table 4 gives the figures of TP, FN, TN, FP of the data sets used and the classification accuracy of the proposed system in terms of sensitivity, specificity and youden's index value, for leave-1-out cross validation. The performance of the classifier in discriminating normal – subtle, normal - apparent and from normal to abnormal are experimented and the results are tabulated. It is clear that the proposed method works well for the set of images where the abnormality is apparent whereas for the dataset where the abnormality is subtle. On observation, the classifier based on hybrid feature space gives non-uniform percentage results 94.70 and 93.03 for two different datasets irrespective of visual information. The accuracies of the classification are depicted in Figure 6, giving 97.39 % for normal-apparent and 96.52% for normal-subtle sub datasets.

The classifier result for Normal-Apparent dataset is has high specificity comparing to Normal-Subtle. The subtle mammograms could be the result of density of breast tissues. Sensitivity of both the feature sets is constant, supporting equally to normal mammograms.

The Table 5 illustrates the behaviour of the PNN classifier, when the test sample sizes are fluctuated. On experimentation the size of normal class is kept constant and the size of abnormal class is varied gradually and results are noted, in the same way the size of abnormal class is kept constant and the size of normal class is varied.

The classification rate changes abruptly when the sample sets are changing by keeping the size of one class fixed and by varying the size of the other class and then vice versa, The paramount classification results are obtained only when the difference among the size of paired sets is minimal.

The spread value or the estimation of probability function in PDF has significant impact on classification accuracy as shown in Figure 7. The choice of sigma or the spread value in the PDF has a fair impact on the classification accuracy. The value of sigma (Eq. 11) is varied from 0.1 to 1, and the results are shown in Figure 4 in terms of accuracy. At the value nearest to zero of spread value the classifier performance is similar to that of nearest neighbour classifier, considering the neighbourhood values. Experimentally it is shown that the proposed system achieves best classification rate at 0.4 with gradual increase from 0.1 and then there is deterioration in accuracy.

5. CONCLUSION

The proposed work analyses the mammograms with gray level features domain in classification of normal and cancerous using PNN classifier. Through the experiments it can be deduced that statistical features gives a robust set of discriminative features which are dependent on gray level neighbourhood relation in a mammogram. The proposed system extracts, analyses and unites the features in order that the combined features compensates the drawbacks of each other, giving more precise classification of 97.14%.

The system aids radiologist in taking fair decision even for the mammograms with hidden abnormality at earlier

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stages. By experimental analysis on normal - Apparent and normal – Subtle abnormalities classification in different views, it is found that the classifier gives almost uniform results for both. The system gives 94.70% and 93.03% of Youden's index for both the datasets and proves that the CAD system in invariant of the visual appearance of the abnormality. Through the experiments it is found that the PNN classifier with PDF kernel works excellently in the hybrid feature domain. Experiments show that the features set grade, balance in test sample size dataset and the value of probability density in PNN are the optimal smoothing parameters for the proposed classification system. Future work concentrates on grading the low frequency gray level values in comparison with high level frequency gray level values.

Table 5 Performance analysis leave-M-out Cross validation

Samples size M	TN	TP	FN	FP	Sensitivity	Specificity	J	Accuracy
M=1	116	120	4	5	96.67	96.00	92.67	96.33
M=2	114	120	6	5	95.00	96.00	91.00	95.51
M=3	116	119	4	6	96.67	95.20	91.87	95.92
M=4	111	105	9	20	92.50	84.00	76.50	88.16
M=6	114	118	6	7	95.00	94.40	89.40	94.69
M=8	109	101	11	24	90.83	80.80	71.63	85.71
M=10	98	98	22	27	81.67	78.40	60.07	80.00

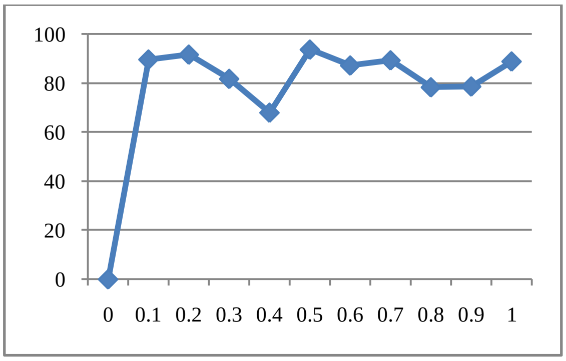

Figure 7 Spread Function Vs Accuracy

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