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# Analyses of statistical feature fusion techniques in breast cancer detection

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## ABSTRACT

Breast cancer is one of the mortal diseases amongst women with increased incidences and mortality rate in every year globally. As its symptoms are not prominently noticeable in early stage, the early detection is difficult. Over the past four decades Mammography is used for diagnosing breast diseases. Most of CAD systems use either Cranio-Caudal or Medio-Lateral Oblique mammographic views. Radiologist will look at both the view for better diagnosis. To incorporate this perception with CAD, the detection performance of various statistical feature fusion in fusing the texture features of these two mammographic views are analysed in this work. The improved performance of accuracy: 97.5%, sensitivity: 100%, specificity: 97.2%, precision: 97.1%, F1 score: 96.23%, Mathews Correlation Coefficient: 0.952% and Balanced Classification Rate: 98.74% was achieved with Local Binary Pattern features fused through Canonical Correlation Analysis.

***Keywords:*** Breast cancer, Mammogram, MLO, CC, PCA, CCA, GDA, DCA, SVM

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## 1. INTRODUCTION

Female breast cancer is a killer disease in this era and its mortality and incidence have been increased by more than 14% and 20% respectively from 2008 (Sasikala et al., 2019). It is most frequent cancer in 154 countries out of 185 countries in terms of new cases and the leading causes of cancer death in 103 countries. In 2018, 2.1 million cases i.e. 1 in 4 cases among women were newly diagnosed worldwide (Sasikala et al., 2019) and an estimate of 0.0627 million breast cancer deaths of women was occur globally (WHO, 2020).

To overcome the subjective variations in diagnosis by radiologist, Computer Aided systems for Detection (CADe) and Diagnosis (CADx) were developed. CAD through various breast imaging techniques play a significant role in breast cancer diagnosis. The General flow of a CAD system is depicted in Fig. 1.

As Mammography is able to predict the presence of tumour before it becomes visible clinically, images of various mammographic views are widely used for diagnosis. Inspection of both Cranio-Caudal (CC) and Medio-Lateral Oblique (MLO) views better discriminates the tumours (Sasikala et al., 2019). Improvement in performance with two view information was evidenced by many Retrospective and Prospective studies as it mimics the radiologist's perception in diagnosis. Fig. 2 shows the general flow of two view diagnostic system.

A quantity which measures the spatial arrangement of image intensities with respect to a pixel and its predefined neighbourhoods is known as texture (Tourassi, 1999). Since the characteristics of tumour are better represented by texture features, malignancy in tumours could be better discriminated when texture-based image analysis is used in

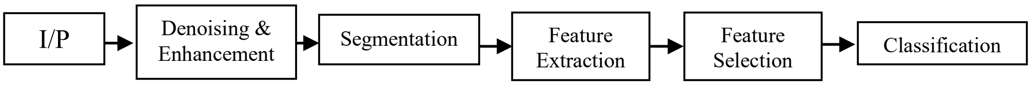


**Fig. 1.** General flow of a CAD system

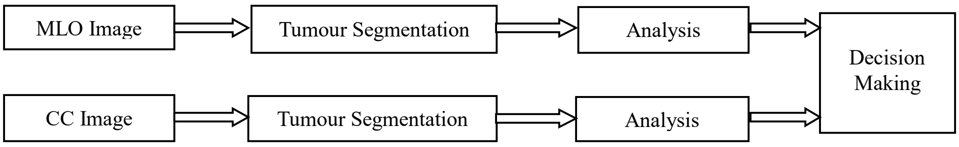


**Fig. 2.** General flow of two view diagnostic system

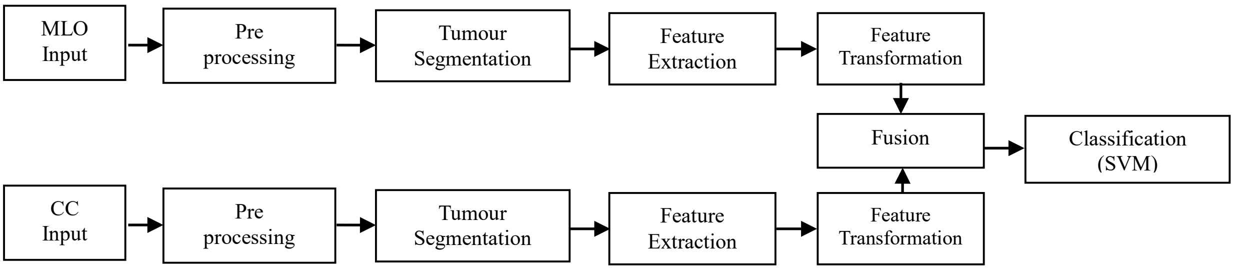


**Fig. 3.** Detection by fusion of two view textures through statistical transformation

diagnostics (Sasikala and Ezhilarasi, 2018; Sasikala et al., 2018; Sasikala and Ezhilarasi, 2016).

The main focus of this work is to analyse the performance of various feature statistical feature transformation techniques in fusing the texture features from MLO and CC view images for breast cancer detection.

## 2. MATERIALS AND METHODS

Detection system involving the combination of LBP features of the two views using statistical feature transformation techniques were developed and their performance were analysed for different texture features. The system flow is illustrated in Fig. 3.

In this two view system, the pre-processing, tumour segmentation and feature extraction are performed for MLO and CC view mammograms separately. Then, features extracted from the two views are fused through one of the proposed statistical feature transformation technique to form a new prominent feature set and classified by SVM classifier. From the classifier results, seven performance metrics defined in Sasikala and Ezhilarasi (2016) are computed. The performance metrics for different features with different fusion techniques are computed for analyses.

### 2.1 Datasets

The public datasets INbreast and DDSM are used for the development and testing of the algorithm (Moreira et al., 2012; Heath et al., 1998). In DDSM, the MLO and CC mammograms of 323 benign and 323 malignant cases were used to develop a tumour detection using fusion of two view mammographic features through statistical feature transformation technique. The Individual view images are denoised, enhanced (Sasikala and Ezhilarasi, 2018) and individually segmented using Fuzzy Level Set Algorithm (FLSA) for separating the tumour (Sasikala et al., 2019). In FLSA, level set evolution is automatically initiated from the result of fuzzy c means clustering.

### 2.2 Feature Extraction

Extraction of appropriate feature is essential for classification. Five texture features: Gray Level Run Length Matrix (GLRLM), Gray Level Co-Occurrence Matrix (GLCM), Gray Level Difference Matrix (GLDM), LAWs texture energy measure and Local Binary Pattern (LBP) were extracted to do the performance analyses.

GLRLM computes the number of gray level runs of various lengths across a given direction. For an image, matrices of different run-length may be computed in different directions. The GLCM describes the co-occurring gray-scale values and calculates spatial inter-pixel relationships with different distance of separation and angle. GLDM computes texture features from the probability distribution function of gray level difference between two nearby pixels. The Law's mask is applied on image; the result is used to compute texture energy measures (Sasikala and Ezhilarasi, 2016).

A binary label will be formed for each pixel in an image by thresholding the 16 x 16 neighbourhoods of that pixel with the centre value and converting the result as a binary number. To measure these texture descriptors, histograms of LBP output values are calculated (Sasikala et al., 2019).

### 2.3 Feature Extraction

Fusion of features creates a novel discriminant feature set as merger of more than one features of different modalities or domains after eliminating redundant information. Feature selection is the important step in feature level fusion

(Mangai et al., 2010).

Improved detection performance through combination of the texture features of MLO and CC view was addressed in Sasikala and Ezhilarasi (2018); Sasikala et al. (2018); Sasikala and Ezhilarasi (2016). A detailed review of two view detection methods was given in Sasikala et al. (2019). Four different statistical transformation methods are used to reduce the feature dimension and perform the feature fusion: Principal Component Analysis (PCA), Generalized Discriminant Analysis (GDA), Discriminant Correlation Analysis (DCA) and Canonical Correlation Analysis (CCA).

PCA reduces the feature dimensionality by determining orthogonal linear combinations called principal components with largest variance (Sasikala and Ezhilarasi, 2018) and retaining only the first several principal components containing most of the information and discarding the remaining components without much loss of information.

GDA, a nonlinear extension of Linear Discriminant Analysis (LDA) can minimize the within-class scatter and maximize the between-class scatter. It reduces the dimensionality by minimizing the intra-class inertia and maximizing the inter-class inertia in a mapped feature space (Baudat and Anouar, 2000).

DCA integrates the class information in correlation analysis of the feature sets. It maximizes the pair-wise correlations among the two feature sets and eliminating the between-class correlations simultaneously. Incorporating the class structure into the correlation analysis helps to highlight the differences between classes and imultaneously aximize the pair-wise correlations between features across he two data sets (Haghighat et al., 2016).

In feature fusion using CCA, the mutual relations between two feature sets a and b are examined and two new sets $A = w_a^T a$ and $B = w_b^T b$ are formed based on cross correlation between the input feature sets in such a way that discriminant information between two features are maximized. Maximization is done by maximizing cross correlation and minimizing auto correlation between the feature vectors at the same time (Sasikala and Ezhilarasi, 2018).

### 2.4 Classification

After feature fusion, the Support Vector Machine (SVM) is employed to categorize the tumours as benign or malignant, which creates a separating hyper plane by maximizing the margins between two classes. Non-linear mapping of input into a higher dimensional space through Radial Bias Function (RBF) kernel is performed to boost the classification performance (4).

## 3. RESULTS AND DISCUSSIONS

The various stages of pre-processing of an image from the two datasets are illustrated in Fig. 4 and Fig. 5. Table 1 to Table 5 show the performance of the four statistical feature fusion techniques in breast cancer detection using GLCM, GLDM, GLRLM, LAWs and LBP texture features for DDSM dataset.

a. Original image b. Preprocessed c. Level set evolution d. Segmented mass

**Fig. 4.** Stages of pre-processing (DDSM)

a. Original image b. Preprocessed c. Level set evolution d. Segmented mass

**Fig. 5.** Stages of pre-processing (INbreast)

**Table 1.** Performance of GLCM with statistical feature fusion

| | ACC(%) | SEN(%) | SPC(%) | PRE(%) | F1 | MCC | BCR(%) |
|---|---|---|---|---|---|---|---|
| PCA | 77.4 | **86.7** | 68.1 | 73.1 | 79.32 | 0.595 | 76.84 |
| GDA | 56.2 | 52 | 60.4 | 56.8 | 54.3 | 0.597 | 56.03 |
| DCA | 70 | 69.3 | 70.6 | 70.2 | 69.75 | 0.399 | 69.95 |
| CCA | 79.7 | 81.7 | 77.7 | 78.6 | 80.12 | 0.838 | 79.68 |

**Table 2.** Performance of GLDM with statistical feature fusion

| | ACC(%) | SEN(%) | SPC(%) | PRE(%) | F1 | MCC | BCR(%) |
|---|---|---|---|---|---|---|---|
| PCA | 91.2 | **92.6** | 89.8 | 90.1 | 91.33 | 0.824 | 91.19 |
| GDA | 53.4 | 29.4 | 77.4 | 56.5 | 38.68 | 0.078 | 47.7 |
| DCA | 73.2 | 81.7 | 64.7 | 69.8 | 75.28 | 0.470 | 72.7 |
| CCA | 91.5 | 91 | 92 | 91.9 | 91.45 | 0.837 | 91.5 |

**Table 3.** Performance of GLRLM with statistical feature fusion

| | ACC(%) | SEN(%) | SPC(%) | PRE(%) | F1 | MCC | BCR(%) |
|---|---|---|---|---|---|---|---|
| PCA | 66.3 | 72.8 | 59.8 | 64.4 | 68.34 | 0.328 | 65.98 |
| GDA | 56.8 | 52.3 | 61.3 | 57.5 | 54.78 | 0.137 | 56.62 |
| DCA | 52.8 | 96.9 | 8.7 | 51.5 | 67.26 | 0.118 | 29.04 |
| CCA | 69 | 67.5 | 70.6 | 69.6 | 68.53 | 0.477 | 69.03 |

**Table 4.** Performance of LAWS with statistical feature fusion

| | ACC(%) | SEN(%) | SPC(%) | PRE(%) | F1 | MCC | BCR(%) |
|---|---|---|---|---|---|---|---|
| PCA | 74.5 | 79.9 | 69 | 72.1 | 71.65 | 0.424 | 77.15 |
| GDA | 58.8 | 40.9 | 76.8 | 63.8 | 66.61 | 0.190 | 49.04 |
| DCA | 72.3 | 81.4 | 63.2 | 68.8 | 67.44 | 0.453 | 76.72 |
| CCA | 95.8 | 94.4 | 95 | 95.3 | 96.49 | 0.917 | 95.1 |

**Table 5.** Performance of LBP with statistical feature fusion

| | ACC(%) | SEN(%) | SPC(%) | PRE(%) | F1 | MCC | BCR(%) |
|---|---|---|---|---|---|---|---|
| PCA | 96.1 | 98.1 | 94.1 | 94.3 | 95.09 | 0.929 | 97.09 |
| GDA | 94.4 | 96.3 | 92.6 | 92.8 | 93.49 | 0.889 | 95.35 |
| DCA | 69 | 69 | 69 | 69 | 69 | 0.381 | 69 |
| CCA | **97.5** | **100** | **97.2** | **97.1** | **96.23** | **0.952** | **98.74** |

**Table 6.** Performance of LBP with statistical feature fusion for INbreast dataset

| | ACC | SEN | SPC | PRE | F1 | MCC | BCR |
|---|---|---|---|---|---|---|---|
| PCA | 73.1 | 70.2 | 75.4 | 70.2 | 70.2 | 0.46 | 72.75 |
| GDA | 87.5 | 72.3 | **100** | **100** | 83.92 | 0.77 | 85.03 |
| DCA | 80.8 | 76.6 | 84.2 | 80 | 78.26 | 0.61 | 80.31 |
| CCA | **93.3** | **93.6** | 93 | 91.7 | **92.64** | **0.86** | **93.3** |

From the Tables 1 through 5, it is found that LBP produces better results than other features. For GLCM and GLDM, if sensitivity is high, the specificity is low or vice versa. But in case of LAWS and LBP, both sensitivity and specificity values are high. The performance of GLRLM is very low with respect to all parameters except sensitivity. LBP produces better performance with all four fusion techniques. Since LBP produces better results than other features, it is also applied to INbreast database to detect breast cancer using various statistical feature transformations. The performance metrics estimated for the INbreast dataset using LBP feature with serial fusion through statistical feature transformation algorithms is given in Table 6 and found that the fusion through CCA technique shows better results. The results show that the performance of the detection using LBP with CCA feature transformation is comparatively much better than other methods for both the datasets.

Fusion of information at both the feature input level and classifier output level was performed. Two view CAD systems using several linear discriminant analysis (LDA) models through fusion of Haralick's texture features were developed and their performances were compared against ROC areas (Az) of their corresponding single-view baseline systems. A significantly better performance was obtained than single view classifiers with the average or product classifier configurations. Also, a strong relationship was found between the performance of the feature input level classifiers and the correlation between corresponding features from the different views (Gupta et al., 2006).

Using breast's symmetry properties, a geometric transformation was computed through CC and MLO views and tested using 112 pairs of pathological images. It reduces false positives up to 70% (Magro et al., 2008). A hybrid feature fusion using LBP feature of two view mammograms followed by optimization through firefly algorithm also resulted an improvement in detection performance (Sasikala et al., 2020). Fusion using Deep learning based Convolution Neural Network (CNN) on three imaging modalities resulted an accuracy improvement of 90% (Antropova et al., 2017). Many literatures addressed the use of two views; detailed reviews of those are given in Sasikala et al. (2019) as discussed below.

Matching between MLO and CC region correspondence through four features was used to distinguish pathology (True Positive (TP) / False Positive (FP)) labels and found that 82.4% of tested 412 malignant cases were correctly linked in both views for TP detections.

To discriminate normal and cancerous patients, information from multiple views were analyzed through Bayesian method was suggested. Multi-view information and temporal information were integrated for further improving decision-making. A set of 1063 two view screening images with 383 cancerous cases was used to evaluate model. A normality score was measured from supervised learning output to express the suspiciousness. The view probabilities of suspiciousness are combined by the averaging scheme to determine the probability of overall suspiciousness. The Area Under receiver operating Characteristics (AUC) for MLO and CC examinations was found to be 0.863 and 0.871.

A multi-view CAD was developed using 2 contour features and 5 shape features and averaging the individual view scores to get final classifier's score. The accuracy, true negative rate and true positive rate were found to be 95.27%, 95.46% & 95.27% respectively. For further improving performance, multi-agent algorithm was introduced for fusion and accuracy, sensitivity & specificity were obtained as 93.98%, 97.37% & 91.27% respectively.

Texture features were extracted using different transform from two views and fused after determining the relevant features through Singular Value Decomposition (SVD) with Analysis of Variance (ANOVA). A better performance of AUC: 0.831, sensitivity: 77.08%, specificity: 89.17% and accuracy: 83.13% was obtained with the SVM classifiers using the Daubechies wavelet.

Boosting algorithm with view information was proposed to reduce FPs and applied on 192 DDSM cases. AUC was improved from 0.7479 to 0.7123 with the classifier ensemble method instead of using feature-level fusion with single SVM classifier.

A comparative study was done for the classification of masses in mammograms by fusing two view wavelet coefficients using SVD with ANOVA and Principal Component Analysis (PCA). The SVD with ANOVA better classifies were benign from malignant with AUC = 0.83 and normal from benign with AUC = 0.78, whereas normal and malignant images were better discriminated by PCA with AUC = 0.85 (Sasikala et al., 2019).

Two view images were compared to detect suspicious area and Extreme Learning Machine (ELM) was used to classify them after extracting geometry and textural features from each single view. A simple Bayes method was used to get the final grade of tumour.

Masses were detected automatically by applying adaptive region growing method with active contour based on narrowband. GLCM and CLBP texture features were computed and classified by SVM. The detection sensitivities of 82.4% with 5.3 false positives per image (FPsI) and 78.2% with 1.48 FPsI were achieved with and without active contour refinement.

A risk examination system was developed using density features and 3 different texture feature groups from two views and tested. From each individual view, 3 asymmetry scores and 91 features were computed and classified separately. Finally, classification using combined dual view scores and asymmetry scores was done which provides highest AUC of 0.753 ± 0.039.

Fusion of single view features and contrastive double view features using feature selection based on genetic algorithm with ELM classifier was suggested to imitate radiologist's diagnostic procedure and tested using 222 pairs of Mammograms.

## 4. CONCLUSIONS AND FUTURE WORK

Since the tumour region seen in view may not be visible in another view, it is a possible to get additional details if both the views are examined compared to the information obtained from individual views. Texture features better discriminates the presence of malignancy. Hence, texture features from both the views are combined for diagnosing breast tumours. Statistical feature transformations are very much useful for dimensionality reduction. Thus, Serial fusion of two view mammographic texture features using four different statistical feature transformation techniques were implemented using MATLAB and their performances were compared.

LBP is robust against illumination changes and very fast to compute. It has a low computational complexity as it does not involve too many parameters. CCA transform provides better feature set by improving the cross correlation and reducing the autocorrelation between the input features to be fused. Serial fusion of two view LBP features through CCA improves the detection performance. Since, the specificity and sensitivity are improved; the false negatives and false positive are reduced. Thus, this system will help doctors for better detect of breast tumours.

In future, the proposed could be implemented in appropriate Digital Signal Processor to develop a portable hardware so that it could be embedded with already used Mammographic system. Also, instead of SVM, Deep learning algorithms could be applied for further improving detection performance.

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