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Advancement on Breast Cancer Detection Using Medio-Lateral-Oblique (Mlo) and Cranio-Caudal (CC) Features

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Abstract:
The purpose of this paper is to diagnose accurately the breast cancer for which a a computer aided diagnostic system (CAD) is being proposed. In this paper two types of views are used to enhance diagnostic efficiency, such as cranio-caudal (CC) and medio-lateral-oblique (MLO). This paper involves segmentation, feature extraction and classification of images. Adaptive K means clustering method is used in segmentation to segment the two views from a mammogram image. The combination of conventional k-means clustering method and Gabor filter is employed in the feature extraction stage to extract the features of CC and MLO views. Finally, Knn classifier is used to classify the mammogram image into four ways, such as CC-Normal, CC-Malignant, MLO-Normal and MLO-malignant.

***Keywords**— Segmentation, Adaptive K-means clustering, Feature extraction, conventional K-means clustering, Gabor filter, Classification, Knn classifier*

I. INTRODUCTION

In recent years, cancer is considered as a factor for causing death. According to WHO, the number will reach 12 million in the year of 2030. The breast cancer is the common cancer for women worldwide and approximately 2.1 million women are affecting. It is estimated that 627,000 women died due to breast cancer in the year 2018. Breast research is conducted by mammography usin g low-dose x-rays. For radiologists, this method is easily accessible and effective for breast cancer detection. From this study, a total of four images are obtained in which two images refer to the right breast and the other two correspond to the left breast of the medio-lateral oblique(MLO) and cranio-caudal(CC) projections. The visualization of breast tissue is improved by image acquisition method and it also increases the chances of identifying symptoms that describe the occurrence of non-palpable lesions such calcification, nodules, signs of bilateral asymmetry and distortion of architecture (Rangayyan et al., 2007)

The false positive is reduced by these two views like overlapping of dense tissue shows like mass. Radiological analysis combines the challenging requirements of human vision and intelligence, such as geometry, texture and morphological location of lesions in breast image, combined knowledge of two views, variations of two breasts, and the search for changes between previous and current mammograms where appropriate. The detection of lesions in two view mammogram provides better results than one view given by clinical studies (Linsman, 1987, Thurfjell, 1994 and Blanks et al, 1999). The sensitivity of mammography screening is improved in the case of double reading by a radiologist is also shown by clinical studies (Anderson et al., 1994 and Thurfjell et al., 1994).

But this double reading technique is more complicated, as time consuming increases as a result of reading a vast number of mammographic images (Mencattini et al., 2010). The computerized method such as computer aided diagnosis (CAD) method is introduced as a second option for radiologist to visualize the mammographic image. The mammographic image is applied to this method to analyze or detect the mammographic image as normal or abnormal, such as mass, microcalcification or some distortion. This method reduces the error rate and increases the detection rate accuracy (Chan et al., 1990, Kegelmeyer et al., 1994 and Warren et al., 2000). The mass detection from MLO and CC view information was detected using CAD system is developed by (Zheng et al., 2006). In this approach false positive rate is reduced as 23.7% and obtain sensitivity accuracy as 74.4%.

In the year of 2007, Qian et al., proposed a multiview CAD system to identify the mass on breast image. This system comprises of region segmentation where mass regions are segmented. Next by segmentation stage, extraction of features and classification of mass is obtained. In classification stage, neural network with Kalman filtering is used for the detection of mass on the breast image. In this approach false positive is reduced and detection rate is increased

The spatial correspondence between CC and MLO view of breast image is proposed by Kita et al., 2001. The mass detection using CAD system for two views is developed by Paquerault et al. Using CC and MLO to view information, th dual system technique is employed to detect the mass. In this approach 13 morphological features are extracted from CC and MLO view information and the classification of the breast image is based on the linear discriminant analysis classifier (Wei et al., 2009).

The multiview mammographic analysis is used for the detection of cancerous lesions in the breast image using Bayesian network. From this study analyzed that Bayesian network framework provides significant improvement compared to the single view method (Velikova et al., 2009).

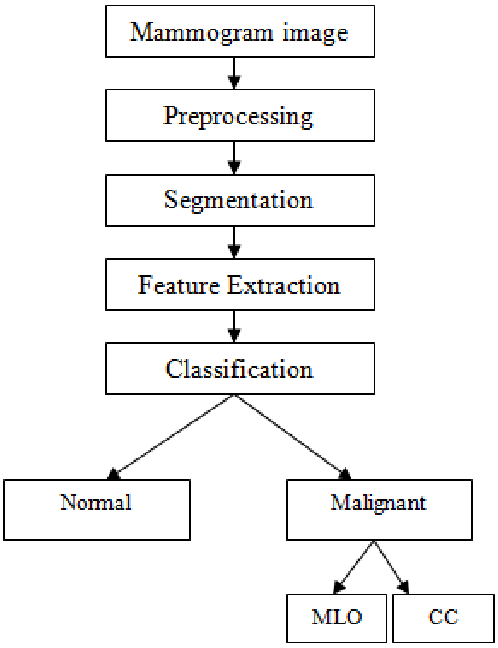
The information of MLO and CC is extracted and classified using wavelet transforms and support vector machine for the detection of mammogram lesions on breast image. The accuracy of this approach is 81% (Rogério et al., 2012).

The computer aided diagnosis method is used for detection of breast cancer into benign and malignant using linear binary pattern (LBP) and Support Vector Machine (SVM) classifier. In this study, they used MLO and CC mammographic view information for the detection purpose. The features from MLO and CC information are extracted using LBP technique and given into SVM classifier to classify the breast image. From this analysis, it was analyzed that the combination of information from the MLO and CC view provides a better result compared with information from a single view (Sasikala et al., 2018). The accuracy of the detection rate for DDSM and INBrest databases is 6.245% and 6.395%.

The remainder of the paper is sorted out as pursues. Section 2 explains the framework we were proposing. Analysis of the experimental results is given in section 3. The conclusion and direction of future work is given in Section 4.

II. Proposed Methodology

The proposed methodology is illustrated in figure 1. The mammogram images are collected from hospital. The obtained images are given to preprocessing followed by segmentation and feature extraction process is happening. The adaptive k means segmentation is subjected to segment the suspicious regions from mammogram region. The segmented regions are given to the feature extraction stage where KMC-GF method is evolved. The process of KMC-GF is consist of two steps; first k-means clustering method is applied on a segmented region to cluster the region; the second Gabor filter is employed in the cluster region to extract the features. Finally, KNN classifier is employed for classification to classify the mammogram region as benign and malignant



A. Adaptive K Means Segmentation

The adaptive k means clustering algorithm begins from the selection of k inputs from the given database. The clusters are formed from the selected K elements and select it randomly. The properties of clusters are formed from the properties of each K element which is constituted by the element. The distance between the given element and the clusters are computed based on above algorithm. The distance should be account depends on the properties is an important one which is also normalized. Hence the obtained is not dominated or ignored by any properties. The Euclidean distance is used in most cases and is given as:

$$\sqrt{(E_{11}-E_{12})^2+(E_{12}-E_{22})^2+\cdots+(E_{1n}-E_{2n})^2}$$

The obtained distance function is to be modified for the reason of the dropped square root function. In this process different weights are required for properties during comparison. The distance of each cluster to another cluster is calculated and store as a triangular matrix.

The distance is calculated for each unclustered element from each cluster. There are three cases are given as below for this element.

•If the distance is zero, then assign respective element to that cluster and start the process with that element itself.

•If the distance is less than the minimum distance, then assign the element to its closest cluster. Due to this, the representation of the cluster or centroid may change. The centroid is recalculated by taking the average value of properties of all elements in the cluster. Also recalculate the minimum distance and affected cluster distance from every other cluster.

•The last case is occurring when the minimum distance is less than the distance of the element from the nearest cluster. In this case, two clusters and are merged. Also, cluster is destroyed by removal of all elements from the cluster. Finally, new cluster is created by the addition of new elements into the empty cluster. At last, the two closest clusters are identified by recalculation of distance between all clusters.

The above three processes are repeated until all the elements have the clustered.

B. K –Means Clustering-Gabor Filter Feature Extraction Method (Kmc-Gf)

The extraction of useful features is a difficult task in computer aided system because sometime the obtained feature vector reduces the classification performance. Therefore, the extraction of features is an important step in breast cancer identification and classification. The breast features such as geometry and internal luminance structure are an important factor to differentiate the breast cancer into malignant and benign. The characteristics of

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luminance and geometry are represented by texture and shape features. Combining clustering and Gabor Filters is used in this work to extract the features from the mammogram image. The objective of the feature extraction technique is:

•The texture features are obtained through the Gabor filter.
•The shape features are obtained through clustering techniques.
The shape characteristics of mammogram image are obtained through k-means clustering technique. It is an unsupervised clustering where it minimizes the squared error between the data point and cluster center (MacQueen, 1967). The texture characteristics are obtained through Gabor filter technique. It is a multi resolution and multiscales filters and has an excellent property of spatial frequency localization (Daugman, 1985, Hamamoto, 1998, Jain, 1997), selection of orientation, spectral bandwidth and spatial extent. Through the above properties it easily evaluates the internal structure of mammogram image. Hence the texture information is extracted from specific regions, tissue and internal structure of the mammogram image through Gabor Filter techniques. The combination of k means clustering with Gabor filter (KMC-GF) provides the important characteristics of mammogram image.

K-means clustering:
The clustering algorithm k-means provides the shape characteristics of the mammogram image. It was introduced by MacQueen. It generates a specific number of disjoint and flat clusters [21, 22]. First, k objects are randomly chosen in which initial cluster center is represented. The next step is to use Euclidean distant to take each point belonging to a given data set and compare it with the nearest center based on the object's closeness with the cluster center. The new k cluster center is recalculated after distribution of all objects in giving set. Repeat the above process until no change is made in the center of k cluster. The squared error function between the cluster center and data point is minimized using below equation:

$$K(v) = \sum_{i=1}^{c} \sum_{j=1}^{c_i} \left(\|d_i - v_j\| \right)^2$$

Where,

- Euclidean distance of data points and cluster center
- number of data points
- number of cluster center

The following step defines the K-means algorithm:
Step1: The given dataset is partially set to k by random.
Step 2: The below steps are found for each data point in the given dataset
Calculate the distance of data point to each cluster.
If the data point or sample from the mammogram region is closer or nearer to its own cluster, then left it otherwise moves to its closest cluster.
Step 3: The above step is repeated for all data points. In this step the clusters are stable and the clustering process is finished.
Step 4: The final cluster point is affected due to the choice of the initial partition. It provides inter cluster and intra-cluster distances and cohesion.
Step 5: The obtained k values are given in Gabor filter for the extraction of features from mammogram image.

Gabor filters:
The 2-D Gabor Filters are used in computer vision and image processing because of their usefulness to efficiently represent the images. Essentially, 2-D Gabor filters are in the spatial domain centered at (0,0) and are given as

$$G(a, b, v_a, v_b, \sigma_a, \sigma_b, \theta) = \frac{1}{\sqrt{\pi \sigma_a \sigma_b}} e^{-\frac{1}{2}} \left[\left(\frac{M_1}{\sigma_a} \right) \right]$$

where,
- defines the spatial frequency
- defines the standard deviation
- represent the orientation

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The elliptical Gaussian envelope with an aspect ratio of 1.5-2.0 is present in the simple and complex cells of primary visual cortex are revealed by physiological findings. The Gaussian envelope has the direction of propagation of the plane wave along the short axis of the elliptical Gaussian envelope (Daugman, 1985; Lee, 1996). The above findings recommend the following relation:

In the above equation

Substitute the above relation into Gabor filter equation () and it's given us:

$$G(a,b,\omega,\sigma,r,\theta) = \frac{1}{\sqrt{\pi r \sigma}} e^{-\frac{1}{2}\left[\left(\frac{M_1}{\sigma}\right)^2 + \left(\frac{M_2}{\sigma}\right)^2\right]} e^{1\omega M_1}$$

In the above equation

The below equation simply represent the Gabor filter at centered. It is computed as convolution:

$$C = \sum_a \sum_b I(a,b) G(a' - a, b' - b, \omega, \sigma, r, \theta)$$

Finally, take the mean and standard deviation for all obtained Gabor values.

C. Knn Classifier

The KNN algorithm is the simplest method to resolve the classification problem which provides competitive outcomes. The KNN classifiers have an ability to overcome the scalability problem compare and its structure imposes the lower computational burden compare to Support Vector Machine (SVM) and Artificial Neural Network (ANN) algorithm (Bishop, 2006). Moreover, it provides faster speed in train and testing stages compared to SVM and ANN algorithm. Implementing the Knn algorithm is easy due to the simple Euclidean distance used to measure the similarity between the training and testing samples.

According to Leif (Leif, 1883), Knn classifier is a non-parametric method and it was developed by Fix and Hodges in 1951. Until 1960, this method isn't gaining more popularity because of its more computing power, even though it is applicable in pattern recognition and classification (Jiawei, 2006). Knn classifier is learnt by comparing a specific test sample with a set of training samples that are similar to it. The classification is based on the class of their closest neighbors. The letter "K" from Knn classifier indicates the number of neighbors taken into account to determine the class (Jiawei, 2006).

III. Result and Discussion

The performance metrics of the proposed framework are estimated from the confusion matrix. Totally140 images collected from hospital. The collected 140 images are divided into testing and training purpose. Each breast image contains two views of images are Medio-Lateral Oblique (MLO) and Cranio Caudal (CC) view images. The performance metrics are calculated for both views. The following terms are used in performance metrics are:

TP (True Positive): The classifiers correctly classify the abnormal region as abnormal.

FP (False Positive): The classifiers incorrectly classify the normal region as abnormal.

TN (True Negative): The classifiers correctly classify the normal region as normal.

FN (False Negative): The classifiers incorrectly classify the abnormal region as normal.

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

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

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

$$\text{Prediction Error} = \frac{\text{FP} + \text{FN}}{\text{FP} + \text{FN} + \text{TP} + \text{TN}}$$

$$Precision = \frac{TP}{TP + FP}$$

$$False\ Positive\ Rate = \frac{FP}{FP + TN}$$

$$False\ Negative\ Rate = \frac{FN}{FN + TP}$$

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$$Negative\ likelihood = \frac{1 - sensitivity}{specificity} \qquad AUC = \frac{sensitivity + Specificity}{2}$$

$$Younden's\ index = Sensiivity - (1 - Specificity)$$

Measure	KMC-GF				GLCM			
	CC-M	CC-N	MLO-M	MLO-N	CC-M	CC-N	MLO-M	MLO-N
Sensitivity	8.38	98.79	88.39	96.85	78.37	98.58	86.85	92.25
Specificity	82.75	81.09	76.72	93.56	78.20	78.19	72.48	89.77
Accuracy	82.56	87.96	81.51	95.15	78.26	86.38	78.29	90.06
Prediction error	17.1	12.01	18.1	4.5	21.70	14.02	21.70	9
Precision	82.82	76.76	72.72	93.93	78.25	73.60	68.18	89.28
False positive rate	17.25	18.91	23.28	6.44	21.8	21.8	27.52	10.23
False negative rate	17.62	1.28	11.61	3.15	21.63	1.42	13.15	7.75
Positive likelihood	4.75	5.22	3.79	15.03	3.59	4.51	3.15	9.01
Negative likelihood	21.29	1.57	15.13	6.88	27.65	1.81	18.62	8.6
AUC	82.44	89.90	82.55	95.20	78.28	88.38	79.66	91.01
Youden's index	163.13	179.88	165.11	190.41	156.57	176.77	159.33	182.03

TABLE 1: COMPARISON OF PERFORMANCE METRICS BETWEEN FEATURES USING KNN CLASSIFIER

The performance metrics for the proposed framework are given in Table 1. The sensitivity, specificity and accuracy indicate the classifier's recognition rate. The performance metrics are evaluated using TP, TN, FP and FN parameter for CC-N, CC-M, MLO-N and MLO-M cases. The above four cases are obtained using two features are KMC-GF and GLCM features with KNN classifier. The parameter TP is 82.855, 76.92%, 72.54%, and 93.33% and for TN is 82.27%, 99%, 90.47%, and 96.96% and for FP is 17.17%, 23.07%, 27.45%, and 66.66% and for FN is 17.72%, .9%, 9.5% and.3% respectively for CC-M, CC-N, MLO-M and MLO-N cases using KCM-GF features with KNN classifier.

In the case of GLCM features, the parameter TP is 72.5%, 69.92%%, 69.54%, and 83.43% and for TN is 72.27%, 89.90%, 85.47%, and 87.79% and for FP is 20.14%, 25.07%, 32.45%, and 10% and for FN is 20%, 1%, 10.52% and 7% respectively for CC-M, CC-N, MLO-M and MLO-N cases with KNN classifierThe sensitivity, specificity and accuracy obtained for KMC-GF features are 96.85%, 93.56% and 95.15% of MLO-N cases, whereas for GLCM features are 92.25%, 89.77% and 90.06% for the same case. The KMC-GF features and GLCM both gives the texture features, but KMC-GF provides better recognition rate compared to GLCM features. The reason behind the better recognition rate of

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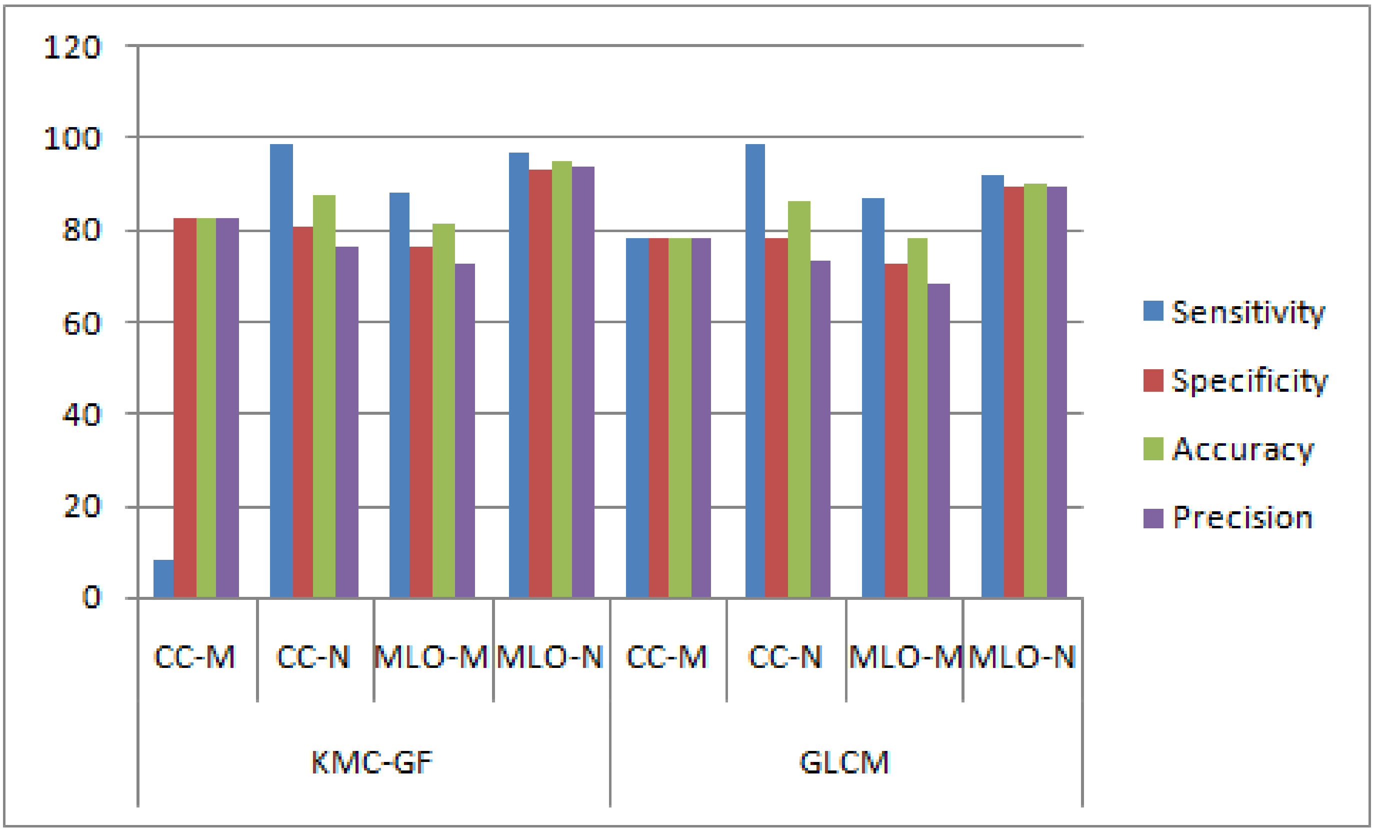
KMC-GF features compared to GLCM feature is able to give better orientation and multi-resolution filter. Same as Accuracy, the precision error calculates the correct and incorrect classifications. The predictive power of the knn classifier with given features is reviewed by metric precision. A low precision value such as 68.18% indicates a large number of false positive given by MLO-M using GLCM features compared to other cases.

The false positive rate are acquired as 10.23 and 21.8 for MLO-N and CC-M cases, respectively, for GLCM features, but in the case of KMC-GF features it is reduced to 6.44 and 17.25. Similarly, minimum false negative rates of 1.28 and 1.42 are obtained with KMC-GF and GLCM features for CC-N cases from given images, respectively. The ability of prediction of positive and negative classes on confusion matrix is assessed by positive likelihood and negative likelihood. The good performance in positive and negative classes is recognized by higher positive likelihood and lower negative likelihood. The positive likelihood was improved from 9.01 to 15.03 for MLO-N cases and from 4.51 to 5.22 for CC-N cases when KMC-GF feature was used. The negative likelihood is reduced to 8.6 to 6.88 for MLO-N cases and 27.65 to 21.29 for CC-M cases for giving images using KNN classifier.

The area under the receiver operating characteristic curve was used by classifier to assess the imbalance data and also it is more reliable than accuracy. The AUC of 95.24 for MLO-N cases using KCM-GF features ad 90.01 for the same case using GLCM features.

The avoidance of failure in proposed system is evaluated using a Youden's index. The higher value of Youdens index represents the better results. In table I normal cases of MLO and CC provides better results.

Figure 2: KNN Classifier performance between KCM-GF feature extraction for CC-M, CC-N, MLO-M and MLO-N cases and GLCM features for all cases



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Thus, table 1 and Figure 2 show that the KNN classifier performance with KCM-GF feature extraction for CC-M, CC-N, MLO-M and MLO-N cases provide better performance compared to GLCM features for all cases.

IV. Conclusion

The use of double view provides a better result compared to a single view. In this paper, MLO and CC view mammogram images are employed for breast cancer detection. The Adaptive K-means segmentation method is used for segmentation of suspicious region. The KMC-GF feature extraction method is employed in this work. The advantage of KMC-GF method is extracting the fine texture features from the clustered region and provides the shape, orientation features. Compared to GLCM features, KMC-GF feature gives a good result for early detection of breast cancer. Finally, KNN classifier is used to classify the view of mammogram images into normal and malignant. Hence, this method could be used for breast cancer diagnosis in the medical field and also give low false positive. The principal advantage of this approach is to reduce the radiologists' workload.

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