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CLASSIFICATION OF MEDICAL X-RAY IMAGES FOR AUTOMATED ANNOTATION

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ABSTRACT

Of late, the amount of digital X-ray images that are produced in hospitals is increasing rapidly. Efficient storing, processing and classifying X-ray images have thus become an important research topic. Due to the increase in medical digital images, there is a rising need of managing this data properly and accessing them accurately. To overcome the difficulties of manual classification, the automated method is preferable and hence proposed in this work, wherein an effort has been made to automatically classify X-rays at the macro level (coarse level) using SVM classifier with six classes of X-ray images being taken, viz., chest, foot, spine, neck, head, and palm. Each class consists of 30 images collected from IRMA database. Initially, pre-processing is performed by using the M3 filter and its region-of-interest is found by applying connected component labeling (CCL) and both the shape and texture features were extracted. The fusion of shape and texture features gave a better performance of 96.56%.

Keywords: *Medical X-ray image classification, Gray level Co-occurrence matrix, Principle Component Analysis, Discrete Cosine Transformation, Zernike moments and Support Vector Machine.*

1. INTRODUCTION

Due to the immense need for effective and accurate medical image retrieval , new trends for image retrieval using automatic image classification and annotation has been investigated for the past few years. It is believed that the quantity of such medical system can be improved by a successful classification of images, so that the irrelevant images can be filtered out. Currently the medical images are annotated manually by doctors and medical experts. As manual annotation is a time consuming and a tedious work, automated annotation is most-acclaimed so as to overcome its aforesaid practical difficulties and hence this technique is proposed. In this work, an effort has been made to automatically search and classify the X-ray images in to six classes namely chest, spine, foot palm, head and neck. Each class consists of 30 images and it is collected from IRMA image dataset representing different ages, genders, views, positions and pathologists, wherein the image quality varies significantly. This paper is organised as follows; section 2 gives an outlay of the available literature, proposed methodology is mentioned in Section 3, Section 4 presents pre-processing, feature extraction and classification, and the experimental results are described in Section 5, followed by the conclusion in Section

2. EXISTING WORKS

The variety of learning methods are described to support medical tasks, wherein [1] presents novel multiple keywords annotation for medical images, keyword-based medical image retrieval, and relevance feedback method for image retrieval for enhancing image retrieval performance. A technique for Retrieving vertebra pairs that exhibit a specified disc space narrowing (DSN) and inter-vertebral disc shape is described in [2]. DSN is characterized using spatial and geometrical features between two adjacent vertebrae. The author in [3] proposed a classification-based multi-class multi-label semantic model and the corresponding learning procedure to address the problem of automatic image annotation using J48 decision tree classifier and show its application to medical image retrieval. A novel method is proposed in [4] for image retrieval based on texture feature extraction using Vector Quantization (VQ). In this Linde-Buzo-Gray(LBG) and Kekre's proportionate Error algorithms for texture feature extraction. The work in [5] describes different features extraction techniques to represent X-ray images. They are categorized into two groups; (i) Low-Level image

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representation such as Gray Level Co-occurrence matrix (GLCM), Canny Edge Operator, Local Binary Pattern (LBP), pixel value, and (ii)Local patch-based image representation such as Bag of Words (BOW). Medical Image Annotation and Retrieval System (MIARS) suggested in [6] not only provides automatic annotation, but also e-training, research, and diagnostics, the system utilizes three trained classifiers and goal of these classifiers is to provide multi-level automatic annotation. Image analysis techniques are used for evaluating disc space narrowing of cervical vertebrae interfaces from X-ray images. Four scale-invariant, distance transform-based features are presented for characterizing the spacing between adjacent vertebrae is presented in [7].

3. PROPOSED WORK

The medical X-ray images are pre-processed so as to avoid noises by using median filter and they are segmented by applying CCl. The shape and texture features are extracted by ZM, GLCM, PCA & DCT. The extracted features are classified by SVM classifier. The process flow is depicted in Fig. 3.1.

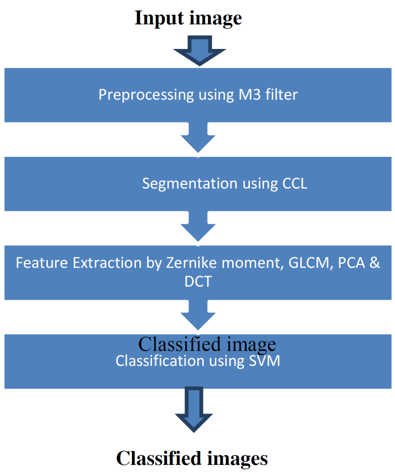

Fig. 3.1 Block Diagram of proposed system

4.1 Pre-processing

Image enhancement technique is applied to improve the image quality it provides better grey intensities distribution. In this work, median filter is applied to enhance the image, wherein segmentation process is done to find the region of interest (ROI). The ROI is found by segmenting the biggest region in the image. Connected Component Labelling (CCL) is applied for this purpose. CCL scans an image and groups its pixels into components based on pixel connectivity.

4.2. Feature Extraction

In this work, shapes and textures are extracted by using GLCM, ZM, DCT & PCA and ZM & GLCM [8-10].

4.2.1. Shape Feature Extraction

Shape is an important property in the medical image processing domain. X-ray images with similar shapes may belong to the same category. Zernike moments have been reported to be a good descriptor for shape description. Therefore, this study uses the Zernike moments for describing the medical X-ray images because of the following two properties:

(1) The Zernike basis function satisfies the orthogonal property, implying that the contribution of each moment coefficient to the underlying image is unique and independent, i.e. no redundant information overlap between the moments;

(2) Calculation of the Zernike moments does not require knowledge of the precise boundary of an object. This makes Zernike moments suitable for representing X-ray images with obscure boundaries.

The shape features of the images are as follows:

- Normal

$\varphi 1 = \mu 20 + \mu 02$

- Rotation

$\varphi 2 = (\mu 20 + \mu 02)^2 + (4\mu 11)^2$

- Inversion

$\varphi 3 = (\mu 30 + 3\mu 12)^2 + (3\mu 21 - \mu 03)$

4.2.2. Texture Feature Extraction

Co-occurrence matrix is one of the most traditional techniques for encoding texture information. Texture is one of the most important defining characteristic of an image. It describes spatial relationships among grey-levels in an image. A cell defined by the position (i, j) in this matrix registers the probability at which two pixels of grey levels i and j occur in two relative positions. A set of co-occurrence probabilities (such as, energy, entropy, contrast) has been proposed to characterize textured regions.

In our work we are using the Grey Level Co-occurrence Matrix (GLCM) for extracting five important texture features reported in the literature [12] viz,

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$$Contrast = \sum_{n=0}^{Ng-1} n^2 \left\{ \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} p(i,j) \right\}, |i,j|$$

$$Entropy = \sum_i \sum_j P_{d^2(i,j)} \log P_d(i,j)$$

$$Correlation = \sum_i \sum_i (i-\mu_x)(j-\mu_y) p_d(i,j)/\sigma_x \sigma_y$$

$$Homogenity = \frac{\sum_i \sum_j P_d(i,j)}{1+(i-j)^2}$$

Where, p_d the probability matrix obtained through GLCM; μ_x and μ_y are the means and σ_x and σ_y are standard deviations of $P_{d(x)}$ and $P_{d(y)}$ respectively.

4.2.3 Feature Extraction Using DCT & PCA

Like other transforms, the Discrete Cosine Transform (DCT) attempts to de-correlate the image data. After de-correlation each transform coefficient can be encoded independently without losing compression efficiency [6].

The most common DCT definition of a 1-D sequence of length N is

$$C(u) = \alpha(u) \sum_{x=0}^{N-1} f(x) \cos\left[\frac{\pi(2x+1)u}{2N}\right]$$

for u = 0,1,2, . . . , N – 1. Similarly, the inverse transformation is defined as

$$f(x) = \sum_{x=0}^{N-1} \alpha(u) C(u) \cos\left[\frac{\pi(2x+1)u}{2N}\right]$$

for u = 0,1,2, . . . , N – 1.

In both equations (1) and (2) α(u) is defined as

$$\alpha(u) = \begin{cases} \sqrt{\frac{1}{N}}, & for\ u = 0 \\ \sqrt{\frac{2}{N}}, & for\ u \neq 0 \end{cases}$$

It is clear from (1) that

$$C(u=0) = \sqrt{\frac{1}{N}} \sum_{x=1}^{N-1} f(x)$$

for u = 0,

Thus, the first transform coefficient is the average value of the sample sequence. In literature, this value is referred as the DC coefficients. All other transform coefficients are called the AC coefficients.

The 2-D DCT is a direct extension of the 1-D case and is given by

$$C(u,v) = \alpha(u)\alpha(v) \sum_{x=0}^{N-1} \sum_{x=0}^{N-1} f(x,y) \cos\left[\frac{\pi(2x+1)u}{2N}\right] \cos\left[\frac{\pi(2y+1)v}{2N}\right]$$

for u,v = 0,1,2,…,N −1 and α(u) and α(v) are defined in (3).

Discrete Cosine transforms is applied to the segmented region to extract coefficients which are used as features for classification. In an image, most of the energy will be concentrated in the lower frequencies, so if the image is transformed into its frequency components and the higher frequency coefficients are discarded, the amount of data needed to describe the image can be reduced. DCT's energy compaction efficiency is so great that can reduce the amount of data needed to describe the image without sacrificing too much image quality.

4.2.4. Feature Reduction Using PCA

The feature vector is created by applying PCA to obtain the most relevant 30 coefficients. PCA transforms a number of (possibly) correlated variables into a (smaller) number of uncorrelated variables called *principal components based on the* mathematical procedure.[5] The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible. The most relevant 30 DCT coefficients are obtained by using PCA from a large number of coefficients which are irrelevant and redundant.

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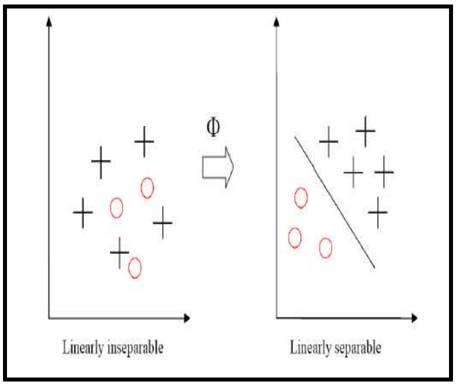
4.3Classification

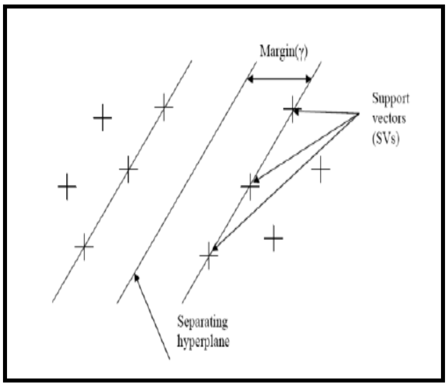
Classification is a technique to detect the dissimilar texture regions of the image based on its features. It can be used to classify the feature sets of the image that characterized as different regions. In this study [11, 13], SVM algorithm is used for classifying the images so that different regions of the texture image have been identified in order to increase the performance. Classification is a method of identification of the different texture regions based on the corresponding features. SVM has been shown to provide better generalization performance for many classification applications than that of others.

4.3.1. Support Vector Machine (SVM)

SVM is used to find the optimal hyper plane by minimizing an upper bound of the generalization error through maximizing the distance, margin, between the separating hyper plane and the data. SVM maps the input space to a high dimensional feature space. By this mapping, more flexible classifications are obtained. A separating hyper plane is found which maximizes the margin between itself and the nearest training points. All the training samples that lie on the hyperplane constitute the support vectors. These support vectors are used to classify the X-ray images into any of the six classes of X-rays namely chest, foot, palm, head, neck and spine during testing. The Fig 4.1 (a) and (b) show the principle of SVM.



(A)



(B)

Fig. 4.1 (a) and (b) Principle of SVM

4.3.2. Performance Measures

Supervised machine learning has several ways of evaluating the performance of learning algorithms and the classifiers they produce. Measures of the quality of classification are built from a confusion matrix which records correctly and incorrectly recognized examples for each class. The various performance measures which are used to assess the classifiers performance are sensitivity, specificity and accuracy. Performance analysis of the proposed methodology can be ascertained by using the following performance indices as given below;

Precision = TP/(TP+FP)

Recall =TP/(TP+FN)

Accuracy = (TP+TN)/(TP+TN+FP+FN)

5. EXPERIMENTAL RESULTS

Initially the X-ray images are pre-processed and segmented using CCL. Then the features are extracted by applying GLCM, ZM, combination of DCT & PCA and GLCM & ZM. The extracted features are fed into the SVM classifier which gives an accuracy of 96.56%. Fig. 5.1 shows the pre-processed and segmented X-ray image and the results of the classified images using SVM classifier are shown in Fig. 5.2. The performance measures for the classified X-ray images are shown in Table 5.1

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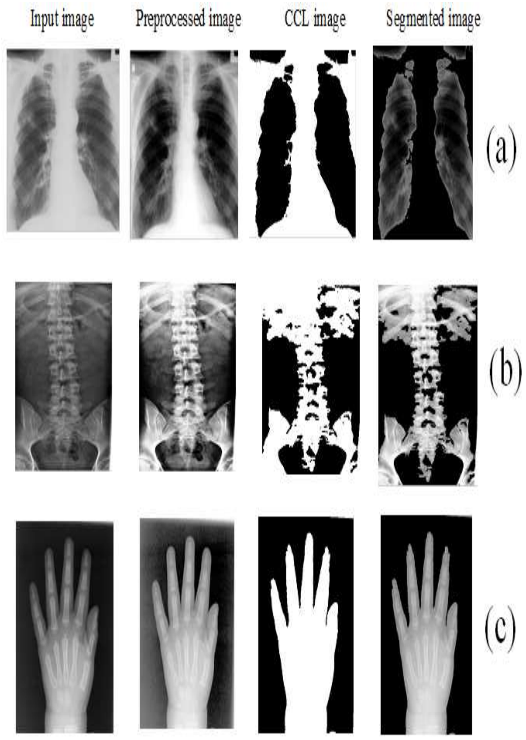

Fig. 5.1. (a) represents chest X-rays, Fig. 5.1 (b) represents spine X-rays and Fig 5.1 (c) represents palm X-rays.

Table 4.1 The performance measures for GLCM with SVM.

X-ray Image	Accuracy (%)	Sensitivity (%)	Specificity (%)
Chest	92.01	75	97
Foot	91	65	99
Palm	90.02	70	100
Skull	93.33	85	95
Neck	88	45	100
Spine	90.55	50	82
Overall Performance	**90.81**	**65**	**95.5**

Table 4.2 The performance measures for ZM with SVM.

X-ray Image	Accuracy (%)	Sensitivity (%)	Specificity (%)
Chest	96.66	87.5	98.64
Foot	93.33	99.09	84.28
Palm	91.66	93.11	91.41
Neck	89.44	82.35	90.18
Head	90.55	70.96	94.63
Spine	92.32	100	93.16
Overall Performance	**92.32**	**88.83**	**92.05**

Table 4.3 The performance measures for DCT and PCA with SVM.

X-ray Image	Accuracy (%)	Sensitivity (%)	Specificity (%)
Head	**96.60**	**90.00**	**95.00**
Foot	93.33	90.00	95.00
Palm	93.33	90.00	95.00
Chest	96.20	90.00	94.10
Palm	93.33	90.00	95.00
Spine	92.60	90.00	93.00
Overall Performance	**94.23**	**90.00**	**94.51**

Table 4.4 The performance measures for combination of ZM and GLCM with SVM.

X-ray Image	Accuracy (%)	Sensitivity (%)	Specificity (%)
Chest	98	91	100
Foot	99	99.09	94.28
Palm	97.06	99	92.41
Neck	94.44	88.35	91.18
Head	97.02	75.96	94.63
Spine	93.88	100	93.16
Overall Performance	**96.56**	**92.23**	**94.27**

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Table 4.5 Performance measures of the overall percentage of classified X-ray images

S. No.	Features extracted	Classifier	Sensitivity %	Specificity	Accuracy
1.	GLCM	SVM	65	95.50	90.81
2.	ZM	SVM	88.83	92.05	92.32
3.	DCT & PCA	SVM	90	94.51	94.23
4.	GLCM & ZM	SVM	92.23	94.27	96.56

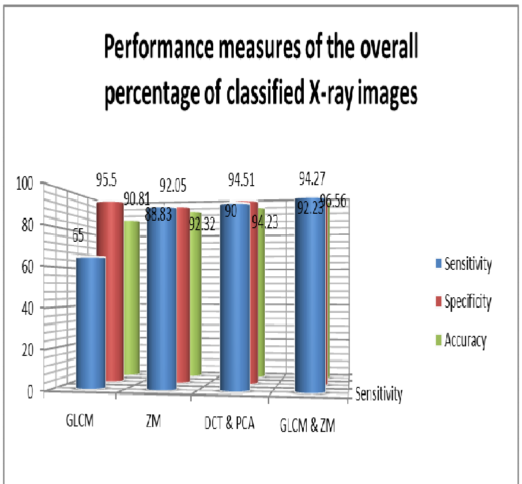

Fig. 5.1 Performance measures of the overall percentage of classified X-ray images

6. CONCLUDING REMARKS

In this work, the feature database of six different classes of X-ray images namely chest, skull, spine, foot, pelvic and palm have been created by extracting both shape and texture features. The texture and shape features have then been investigated by GLCM, ZM, DCT & PCA and GLCM & ZM, which are being classified using SVM classifier to categorize the X-ray images into any of the six classes. It has been found that the combination of GLCM and ZM with SVM is said to be more accurate, producing the accuracy of 96.56% when it is compared with other techniques, thereby making this combination as the efficient and more viable method for classifying the X-ray images.

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