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Combined Feature Extraction on Medical X-ray Images

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Abstract: **Medical images form an essential source of information for various important processes such as diagnosis of diseases, surgical planning, medical reference, research and training. Therefore, effective and meaningful search and classification of these images are vital. In this paper, the approaches of content- based image retrieval (CBIR) using low level features such as shape and texture are investigated in order to create a framework that classify medical X-ray image automatically. Gray level Co-occurrence Matrix, Canny Edge Operator, Local Binary Pattern and pixel level information of the images in this work act as image based feature representations which are adopted in our method. The state-of-the-art machine learning method, Support Vector Machine (SVM) is used for classification. In addition, the performance of image classification offered by combining the promising features stated above is investigated. Experimental results using 116 different classes of 11,000 X-ray images showed 90.7% classification accuracy.**

Keywords: Image Classification, X-ray Images, SVM

I. INTRODUCTION

Over the last decade, storage of non text based data in database has become an increasingly important trend in information management. Image in particular, has been gaining popularity due to the rapid development of digital and information technologies. There is an increasing trend towards the digitization of medical imagery. Medical image databases are key component in future diagnosis. As it shows a wealth of information, it also creates a problem in terms of retrieving the data. As a result, there is an increased demand for effective management of image data.

Content based image retrieval enables the elimination of the difficulties that exist in traditional text based query for large image database. The aim of a CBIR system is to retrieve information that is relevant to the user's query like text based search engine. The number of digitally produced medical image is increasing quickly. The radiology department of the university Hospital of Geneva alone produced 12000 images per day in 2002 and it is still rising [1].

In medical domain information system, the goal is to provide information at the right time and place to the right person for improving the quality and efficiency of the medical process. Visual features were categorized into primitive features such as color or shape, logical features such as the identity of the object shown and abstract attribute such as the significance of the sense depicted. In clinical decision making process it may be beneficial and important to find other images of the same modality, the same anatomic region of the same disease [1]. Beside diagnostics, teaching and research specially are expected to improve through the use of visual access methods as visually interesting images can be chosen and can actually be found in the existing large repositories [1].

II. RELATED WORK

The research area of medical image classification has been very active for the past decade. This is due to rapid growth of computerized medical imagery using picture archiving and communication systems in hospitals which generate a critical need for efficient search engines called CBIR. A successful categorization of images would greatly enhance the performance of any CBIR system. Automatic image categorization is mapping images into pre-defined classes and it involves some basic principles [2] such as representation where feature of the image are extracted and generalization which is training and evaluating the classifier. As it mentioned above, the classification task begins with extracting appropriate features of the image which is one of the most important factors in design process of such system [3]. Moreover, feature extraction step affects all other subsequent processes. Generally there are three types of visual information which can be extracted from images such as pixel, global and local information.

The most direct and simplest form of image feature is pixel value, it will be extracted from both query and database images, compared with each other for retrieval purposes. Pixel value provides good results for simple images with few objects such as medical images [4]. Most of the CBIR systems are using global image features. They provide overall idea of an image. Normally color, shape and texture feature represent the global information of the image. However, as most medical images are gray level images, the related CBIR systems only deal with shape and textures for feature extraction process. Texture is an important feature of an image which provides the

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information about the spatial variation in pixel intensities. Texture features refers to visual patterns of the image and it is characterized by the spatial distribution of grey levels in a neighborhood.

One of the approaches used to describe texture is statistical techniques. This approach characterizes textures by using the statistical properties of the grey levels of the pixels containing a surface image. These properties can be computed by the wavelet transformation of the surface as well as the gray level co-occurrence matrix of the surface. Gray Level Co-occurrence Matrix (GLCM) is the most popular texture analysis method introduced by Haralick et al. [6]. GLCM provides a matrix of joint probability density of the gray levels of two pixels.

Majority of medical images of different modalities can be distinguished by their texture characteristics [5]. Texture has been one of the most important characteristics which have been used to classify and recognize objects for image retrieval in many other published papers. [7] [8] [9] [10].

Another major image feature is the shape of the object. The shape information is determined by the histogram of the edge direction. Edge typically occurs in the boundary between two different regions in an image and has significant local change in intensity. The edge information in an image is obtained by using canny edge detection [11]. There are many shape representation techniques found in the literature such as Fourier descriptors [12], polygonal approximation [13], invariant moments [14], etc.

Local image information also can be obtained by dividing images into small patches. Local image describes image in more details as compared to global features [16]. LBP is a gray scale invariant local texture descriptor with low computational complexity. It labels image pixel by thresholding neighborhood of each pixel with center value and considering the results as a binary number.[17]

III. METHODOLOGY

Automatic image classification is an active research area in field of pattern recognition. In this work, supervised learning approach is used in order to classify images. Classification process is in two steps of training and testing phases. In training phase, the selected features are extracted from all the training images, and classifier is training on these extracted features to create a model. This model will be used to classify the test images after their features are extracted.

Figure 1 shows the overall process of the proposed method. There are 3 main components in this process which are very important for image classification.

Image Enhancement: upon reading an image from database, it scaled down to 100x100 based on empirical results to determine the optimum size of an image pixels resolution. Then histogram equalization as one of the image enhancement techniques is applied to improve the quality of the image such as removing noises and increasing the contrast of the image.

This contrast adjustment provides better gray intensities distributed on the histogram. The method is useful in images with backgrounds and foregrounds that are both bright or both dark. In particular, the method can lead to better views of bone structure in x-ray images.

Feature Extraction: The second component is feature extraction which plays an important role in the performance of any image classification because it can produce significant impact on the results of classification.

Numerous low-level features such as color, texture shape are described in existing literature review. Since medical X-ray images are used in this domain which is mostly gray level images, it is not necessary to extract color feature of the image. In this work, the feature extraction is divided into two sections; first section is where texture, shape and pixel information of the images are extracted; and another one is where each image is segmented into four non overlapping sub-images and LBP are extracted from each image. These two sections are explained in details below:

Texture: texture accommodates important information about the structural arrangement of the surface. Gray-Level Co-occurrence Matrix (GLCM) is one of the well-known statistical tools for extracting texture information of the image is used in this work. It provides information about position of pixels having similar gray level values. GLCM extracts contrast, energy, homogeneity and entropy features of the image at four different directions ($\theta \in \{0°, 90°, 45°, \text{and } 135°\}$).

Shape: Another major image feature is the shape of the object. The shape information is determined by the histogram of the edge direction. Edge typically occurs in the boundary between two different regions in an image and has significant local change in intensity. It provides geometrical information of an object in image which does not change regardless of any changes in location, scale and orientation of the objects in image. In this work, canny edge detector [11] is used to generate edge histogram.

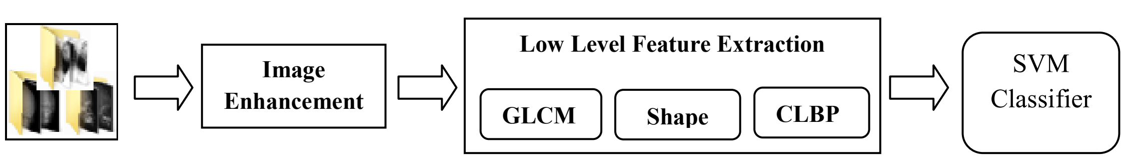


Fig. 1: Block Diagram of the Proposed Method

It is considered to be an optimal edge detector due to its good detection, good localization as well as minimal response.

Additionally, pixel information for each image is also added to feature vector which is obtained by resizing an image to 15x15 pixels.

Completed Local Binary Pattern: each image are segmented into four 50x50 non-overlapping sub-images and completed local binary pattern (CLBP) as feature are extracted from each sub-image[17]. CLBP consists of two components: the sign and the magnitudes; and their operators are CLBP-sign(CLBP_S) and CLBP-magnitudes (CLBP_M). CLBP_S is equivalent to traditional LBP. LBP is computed by comparing a given pixel in the image with its neighbours using:

$$LBP_{P,R} = \sum_{P=0}^{P-1} S(g_P - g_c)2^P, \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \quad (1)$$

where g_c is the gray value of the central pixel, g_p is the value of its neighbors, P is the total number of involved neighbours and R is the radius of the neighborhood. In a consistent format with CLBP_S, CLBP_M is defined as follow:

$$CLBP_{M_{P,R}} = \sum_{P=0}^{P-1} t(m_p, c)2^P, t(x, c) = \begin{cases} 1, x \geq c \\ 0, x < c \end{cases} \quad (2)$$

where c is a threshold to be determined adaptively. Both CLBP_S and CLBP_M produce binary strings so that they can be used for pattern recognition. The feature vector attained from each sub-image is 118; then CLBP histogram extracted from each region are concatenated with each other to obtain a more local description of the image.

The third component is classifier where it gets the extracted feature vector as an input to create a model. Based on empirical results and several classification applications in same domain, Support Vector Machine (SVM) has shown a better generalization performance compare with other classification techniques.

Support Vector Machine: support vector machine have shown their capacities in pattern recognition and a better performance in many domains compared with other machine learning techniques. Support vector machine is very attractive for image classification as its aim to find the best hyperplane separating relevant and irrelevant vectors maximizing the size of margin. This optimum hyperplane has the maximum margin towards the sample objects, that is, the greater the margin, the less the possibility that any feature vector will be misclassified.

The hyperplane decision function can be written as:

$$f(x) = sign(\sum_{i=1}^{n} \propto_i y_i x_i \cdot x + b) \quad (3)$$

where the coefficients $\propto_i$ and b are calculated by quadratic programming problem.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

In this section, the effectiveness and efficiency of the proposed algorithm will be evaluated. This experiment was conducted on ImageCLEF 2007 database; there are 116 categories which differ from each other either on account of image modality, examined region, body orientation and biological system examined. 20% of 11,000 training images are taken as test images to ensure that each class has representation in testing data and the remaining 80% are taken as training images.

The total classification accuracy obtained on the entire 116 classes is 90.7 % .Table 1 shows the classification result for this model.

Table 1. Classification result on 116 classes

No. of Classes	Accuracy % (Acc)
70	Acc ≥ 80
14	60 ≤ Acc < 80
16	40 ≤ Acc < 60
8	10 ≤Acc < 40
8	Acc < 10

This database consist 9 main human body regions where each region has its own sub regions, which represented as a separate class in database. Numbers of images in every class are not distributed uniformly in this database.

The main scope of this work is to get high recognition rate from each class involved in this experiment. As presented in table 1, after the classification on the entire 116 classes, there are 60% of the classes fall in a category whose classification accuracy is higher than 80% which is label it as “good region” and 16% of the classes are below 40%. Even though the total accuracy obtained is 90.7% which is a good result compare with similar works and smaller number of classes [5], yet to be a satisfactory result to meet the objective. This is due to the influence of the unbalanced dataset. Almost all large categories have recognition rates of above 85% whereas images from small classes are frequently misclassified. This shows that a very good performance on the major classes hide a lack of accuracy in less predominant classes. This is a drawback on the recognition rate when it goes to class specific level where correctness rate of all classes evaluated separately. This shortcoming would also lead to fail the proper annotation of x-ray images. Other major challenges in medical X-ray image classification are high intra-class variability and inter-class similarity between some classes. Drill down analysis has been applied on those body regions suffering from the mentioned shortcoming as explained below.

Table 2 shows the number of classes per body region as well as the percentage of the classes to be appeared in good region ("G") categories.

As table 2 depicts, there are 33 classes under "Arm" body region, and it contains 6 main sub body regions. Table 3 shows the class confusion matrix of the 6 sub body region of "Arm".

Table 2: Body regions & number of classes per body region

Body Region	**No. of Classes Per body region**	**No. of classes appeared in "G" region**
abdomen	5	2
Chest	9	8
Breast	4	3
Leg	36	21
Arm	33	15
Cranium	12	8
Spine	16	12
Pelvis	1	1

The overall success rate is 82%. Note that each sub body region containing different number of classes which differ from one another in terms of imaging direction and biological system examined. Table 4 represents the number of classes per sub-body region of "Arm" as well as those with accuracy of more than 80%.

Table 3: confusion matrix on sub-body region of "Arm"

	forearm	Shoulder	Upper arm	Radio carpal joint	Hand	elbow	Other region	Classification (%)
Forearm	17			8	1	1	5	53%
shoulder		46	1				3	92%
Upper arm			6				1	86%
Radio carpal joint	5			30			4	77%
hand		1		1	179		5	96%
elbow				1	1	34	3	87%

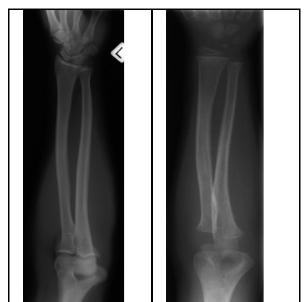
As it can be seen in table 3, although the recognition rate for "forearm" sub-body region was 53%, but with further investigation on each sub-body region separately, it is shown that none of 8 classes involved in "forearm" region are obtaining the classification accuracy higher than 80%. This represents that they were misclassified within the sub-region itself. And the same thing goes on the rest of the sub-body regions.

Table 4: number of classes per each sub-body regions

	Number of classes	**Number of classes with accuracy of above 80%**
Forearm	8	0
shoulder	6	4
Upper arm	3	1
Radio carpal joint	4	3
hand	8	4
elbow	4	3

Further investigation on misclassified images and related classes shows that most of them are suffering from high inter-class similarities and intra-class variabilities. Although some categories differ in IRMA code, but images have a similar appearance. For instance, figure 2 illustrates 2 sample images; each belongs to two distinct classes under the category of "forearm".

Both images are coded identically ((a): 1121-120-437-700) and ((b): 1121-120-438-700), and based on the IRMA code for anatomy, " 43* " refers to forearm. Some other similar cases such as finger vs. toe, upper arm vs. upper leg or different projection of the cervical spine were also revealed by inspecting the confusion matrix.



(a) (b)

Fig. 2: inter-class similarities

Figure 3 shows high intra class variability. According to the IRMA code given for this class, these images are labeled as "X-Ray, Plain Radiography, Analog, Overview image, coronal, anteroposterior (AP, coronal), upper extremity (arm), hand, carpal bones, musculoskeletal system".

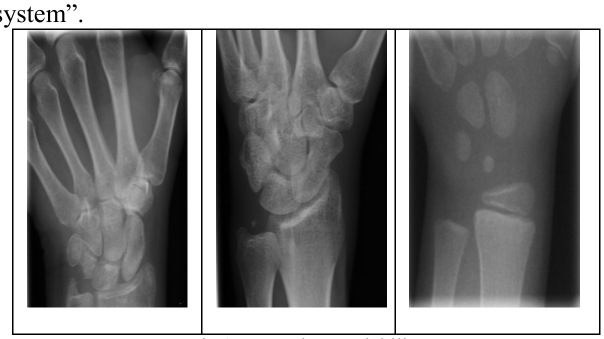


Fig 3. Intra-class variability

Lehmann in [5] used combined classifier on 81 categories of similar data, yet obtaining the error rate of 15% due to above mentioned reasons. This shortcoming will be analyzed in details in future and some sort of filtering and merged classifier will be used to rectify this problem.

V. CONCLUSION

The use of image categorization is demonstrated to be useful in improving the precision of image retrieval systems. This work presents a method for automatic X-ray image classification. The proposed approach combines extracted information from X-ray images based on texture, shape and local binary pattern as well as pixel information of the image. Support Vector Machine is used for classification purpose, Total accuracy of 90.7% obtained on entire 116 classes.

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REFERENCES

[1] H. Hengen, S. Spoor, M. Pandit. "Analysis of Blood and Bone Marrow Smears using Digital Image Processing Techniques." *SPIE Medical Imaging*, San Diego, Vol. 4684, Feb.2002, pp. 624-635.

[2] Jain AK, Duin RPW, Mao J. "Statistical pattern recognition—a review".*IEEE Trans Pattern Anal Machine Intell* 2000;22(1):4–36.

[3] Muller H, Michoux N, Bandon D, Geissbuhler A. "A review of content-based image retrieval systems in medical applications – clinical benefit and future direction." *Int J Med Inform.* 2004;73:1–23

[4] Keysers, D., Gollan, C., and Ney, H., "Classification of medical images using non-linear distortion models." *In Bildverarbeitung fur die Medizin*, Berlin, Germany.2004

[5] Lehmann TM, G¨uld MO, Deselaers T, Keysers D, Schubert H, Spitzer K. "Automatic categorization of medical images for content-based retrieval and data mining." *Comput Med Imaging Graph* 2005;29:143

[6] Haralick, R.M., Shanmugam.K., and Dinstein, I., "Textural features for image classification*", IEEE Trans. System*, 3, 1973: 610-621.

[7] H. Pourghasem, H. Ghasemian, " content-based medical image classification using a new hierarchical merging scheme", *Computerized Medical Imaging and Graphics* 32 (2008) 651–661

[8] A. Mueen, M. Sapian Baba, R. Zainuddin, "multilevel feature extraction and X-ray image classification," *journal of applied science*, 2007, 1224-1229

[9] H. Greenspan, A.T. Pinhas, "medical image categorization and retrieval for PACS using GMM-KL Framework", *IEEE transaction on Information Technology in Biomedicine,* 2007, Vol.11, No. 2

[10] M. mahmudur Rahman, B. C. Desai, P. Bhattacharya, "Medical Image Retrieval with probabilistic multi-class support vector machine classifiers and adaptive similarity fusion", *Computerized Medical Imaging and Graphics*,2007, 95-108

[11] Canny, J., "A computational approach to edge detection." *IEEE Trans. Pattern Analysis and Machine Intelligence,* 8(6),1986, pp. 679-698.

[12] T. D. Bui, G. Y. Chen, and L. Feng, "An orthonormal-shell-Fourier descriptor for rapid matching of patterns in image database," *Int. J. Pattern Recognit. Artif. Intell.*, vol. 15, no. 8, pp. 1213–1229, 2001.

[13] Z. Ping, Y. Sheng, S. Deschenes, and H. Arsenault, "Fourier–Mellin descriptor and interpolated feature space trajectories for 3-D object recognition," *Opt. Eng.*, vol. 39, no. 5, pp. 1260–1266, 2000.

[14] L. J. Latecki and R. Lak¨amper, "Shape description and search for similar objects in image databases," in *State-of-the-Art in Content-Based Image and Video Retrieval, Computational Imaging and Vision*, R. C. Veltkamp, H. Burkhardt, and H. P. Kriegel, Eds. Norwell, MA: Kluwer, 2001, vol. 22, pp. 69–96.

[15] M. K. Hu, "Visual pattern recognition by moment invariants," *IRE Trans. Inf. Theory*, vol. 8, no. 2, pp. 179–187, Feb. 1962

[16] Datta, R., Joshi, D., Li, J., and Wang, J.Z.," Image Retrieval: Ideas, Influences, and Trends of the New Age". *ACM Computing Surveys*, vol. 40(2), 2008, pp.1-60.

[17] Z. Guo, L. Zhang and D. Zhang, "A Completed Modeling of Local Binary Pattern Operator for Texture Classification," *IEEE Trans. on Image Processing*, vol. 19, no. 6, pp. 1657-1663, June 2010