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Selecting the Appropriate Feature Extraction Techniques for Automatic Medical Images Classification

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ABSTRACT

In this paper, the most famous feature extractions techniques that have been utilized to represent medical x-ray images are compared. The point of this comparison is simply to select the appropriate techniques that will be used in our project - an automatic X-ray images classification's project. The experiments were evaluated using the Support Vector Machines ($SVM^{multiclass}$) classifier and on dataset containing a subset from Image CLEF 2007 – large archive medical database. The comparison results showed that BoW and LBP outperformed the other techniques with 1% and 5% error rate respectively.

Keywords: Features Extraction Techniques, GLCM, LBP, Canny Edge Detector, BoW, SVM.

INTRODUCTION

Nowadays the curve for demanding an automatically X-ray images classification approach is rising. It is depends on extract features from images using features extraction techniques. Different approaches for feature extraction have been tested at huge dataset to compare between them and select the best approach that gives the best result. The most famous features extraction techniques were selected to conduct this comparison. These techniques are Gray Level Co-occurrence Matric (GLCM), Local Binary Pattern (LBP), Canny Edge Operator and Bag of Words (BoW). Various researches are conducted to compare between these features extraction techniques [30][31][32]. These researches use Support Vector Machine (SVM) and K- Nearest Neighbour (KNN) classifiers. Support Vector Machine ($SVM^{multiclass}$) shown a better classification performance as compared with other classification techniques [12][27][28][29]. Here in this paper the $SVM^{multiclass}$ will be used to classify many different classes at the same time while the old versions of (SVM) used for binary classification. This classifier is the best in training and testing time [33] as its build N(N-1) classifiers one classifier to distinguish each pair of classes i and j.

The experiment result showed that the two features extraction techniques BoW and LBP give the best results comparing them with other features extraction techniques like GLCM and Canny edge detector. The accuracy rate for BoW and LBP is 98.5% and 94.5% respectively. Therefore, the two techniques will be used at our current automatic tool for classifying the medical images.

The paper is organized as follows. In section 2, we briefly review the steps of medical images classification process. In section 3, we compared between four techniques that we used at this paper to extract images features. The performance evaluation process will described in section 4, while the conclusion and future work are illustrated in section 5.

MEDICAL IMAGE CLASSIFICATION

The classification approach include two phases, i.e. training phase and testing phase. The chosen features – in the training phase - are extracted from all the training images, and the classifier is trained on the chosen features (extracted one) to setup a classification model. This model is then used to classify the test images into the predefined categories in the testing phase. Figure 1 illustrates the classification framework. The next subsections will explain each module of the framework.

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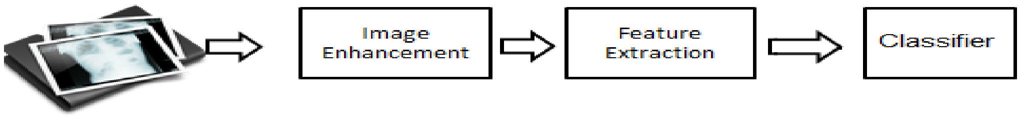


Figure1. *General Classification Framework*

Image Enhancement

The image enhancement process tries to enhance the original image by producing a more suitable image. There are many approaches for enhancing such as applying some basic gray level transformation like image negative or some processing at histogram like histogram equalization, see figure 2. In this research histogram equalization approach is used.

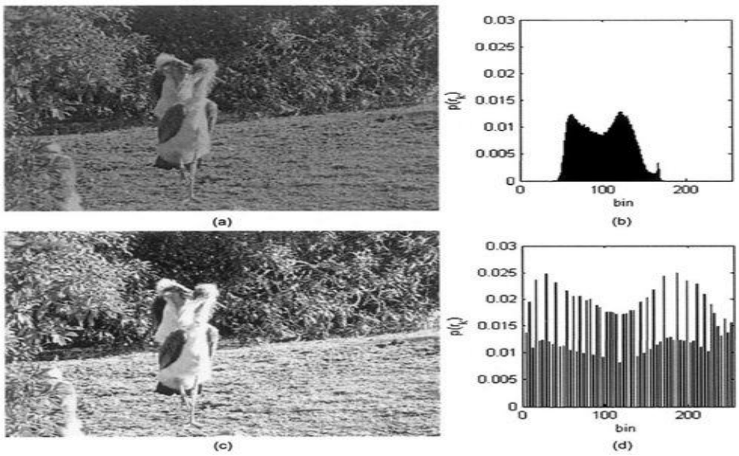


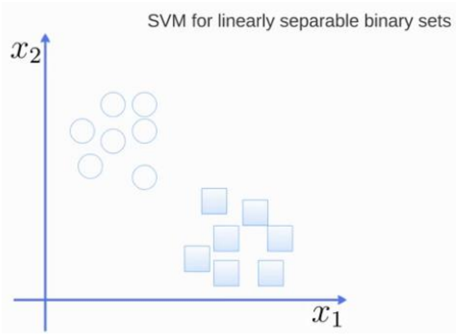
Figure2. *(a) Original image (b) its histogram (c) image after using histogram equalization (d) histogram after using histogram equalization*

Feature Extraction

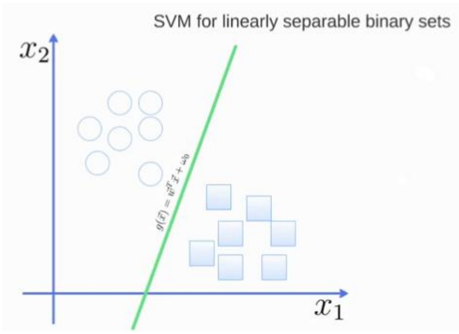
Feature extraction is the second component of image classification module. Since this component produces a significant impact on the results of classification, it plays an important role in the performance of any image classification. Feature extraction is a type of dimensionality reduction that efficiently represents interesting parts of an image as a compact feature vector. This approach is useful when image sizes are large and a reduced feature representation is required to quickly complete tasks such as image matching and retrieval.

Classifier

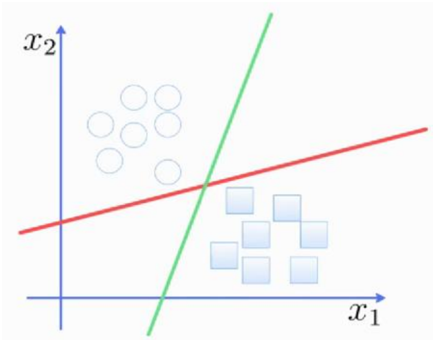
The extracted features from the training dataset are fed into classifier. Based on empirical results and several classification applications in same domain –medical x-ray images classification- Multiclass Support Vector Machine ($SVM^{multiclass}$) shown a better classification performance as compared with other classification techniques [12][27][28][29] and it is differ from SVM as $SVM^{multiclass}$ classifies many different classes at the same time while the old versions used for binary classification (two classes).(All-vs-All) also called (one-vs-one or all-pairs) approach will be used. Its build N(N-1) classifiers, one classifier to distinguish each pair of classes i and j. At figure 3, the goal is to design a hyperplane that classifies all training vectors -circles and squares- in two classes as shown in (3.a). Suppose we have the green one as shown in (3.b). May be two or more different hyperplanes which can classify correctly all the vectors in this sets as in (3.c). The best choice will be the hyperplane that leaves the maximum margin from both classes as in (3.d). We used the multi-class approach for this project which is an extension of the binary support vector machine but for more than two categories. It aims to find the best hyperplane separating relevant and irrelevant features vectors maximizing the size of margin. This optimum hyperplane has the maximum margin towards the sample objects. The greater the margin, the less the possibility that any feature vector will be misclassified.



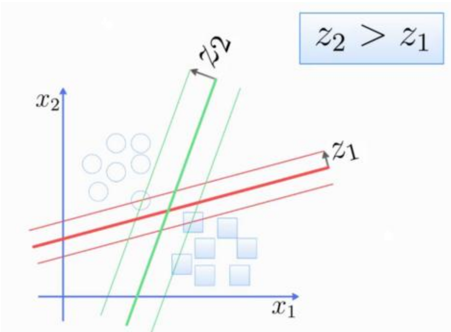
(3.a)



(3.b)



(3.c)



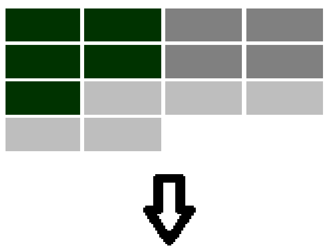
(3.d)

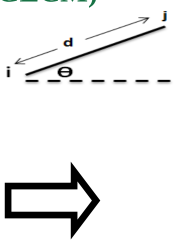
Figure3. *Support Vector Machine*

EXPLANATION OF EXTRACTION FEATURES TECHNIQUES

Classification in x-ray medical images is very difficult, subject to high variability and composed of different smaller structures. There are enormous extracted features and from the results we obtain a few observations that specify the correct class respond to image features. So the challenge in this field - medical one- is to find the relevant features that specify the class of the x-ray image. Therefore, a group of the most feature extraction techniques GLCM, LBP, Canny and BoW will be discussed in this section.

Gray Level Co-Occurrence Matrix (GLCM)





0	0	1	1
0	0	1	1
0	2	2	2
2	2	3	3

	0	1	2	3
0	4	2	1	0
1	2	4	0	0
2	1	0	6	1
3	0	0	1	2

Figure4. *Original Image & Co-occurrence Matrix*

GLCM [9] contain information about the positions of pixels having similar gray level values. The GLCM is a tabulation of how often different combinations of pixel brightness values (grey levels) occur in an image. At figure 4 a simple "test image" for working out examples, the values are image grey levels and its co-occurrence matrix. Each element at GLCM matrix represents the probability of joint occurrence of intensity level i and j at a certain distance d and angle ϴ.

Local Binary Pattern (LBP)

LBP [10] is a type of visual descriptor used for classification in computer vision. LBP is the particular case of the Texture Spectrum model proposed in 1990.LBP was first described in 1994. The LBP feature vector, in its simplest form, is created in the following manner first divide the examined window into cells (e.g. 16x16 pixels for each cell. Second for each pixel in a cell, compare the pixel to each of its 8 neighbours (on its left-top, left-middle, left-bottom, right-top, etc.). Follow the pixels along a circle, i.e. clockwise or counter-clockwise. Third where the centre pixel's value is greater than the neighbour's value, write "0". Otherwise, write "1". This gives an 8-digit binary number (which is usually converted to decimal for convenience). Fourth compute the histogram, over the cell, of the frequency of each "number" occurring (i.e., each combination of which pixels are smaller and which are greater than the centre). This histogram can be seen as a 256-dimensional feature vector. Fifth optionally normalize the histogram. Finally concatenate (normalized) histograms of all cells. This gives a feature vector for the entire window. Figure 5 illustrate these steps.

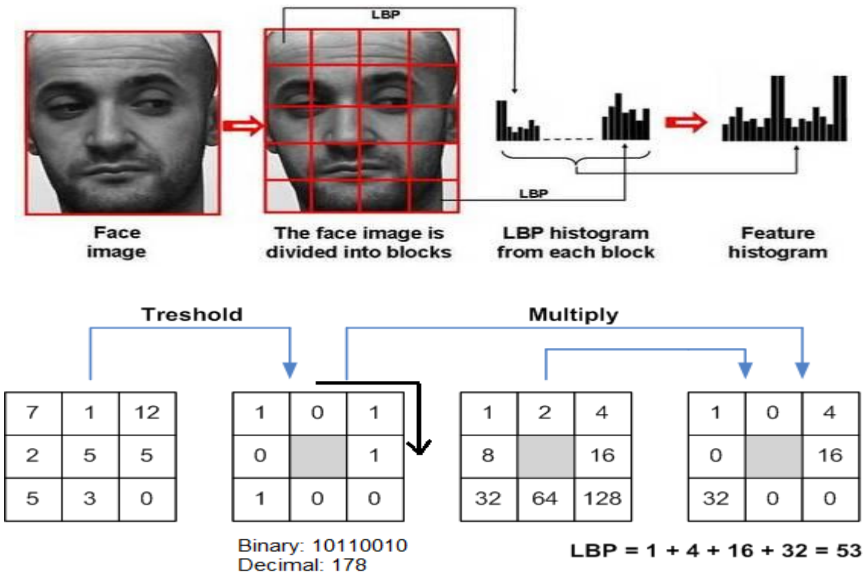


Figure5. *Creation of Local Binary Pattern*

Canny Edge Detector

The Canny edge detector [11] was developed by John F. Canny in 1986. A multi-stage algorithm is used to detect a wide range of edges in images. Canny depends on find gradients (edges) where gray scale intensity changes the most. The Process of Canny edge detection algorithm consists of 5 steps. In the first step the Gaussian filter is applied to smooth the image in order to remove the noise. In the second step the intensity gradients of the image is determined. In the third step, apply non-maximum suppression to get rid of spurious response to edge detection. Double threshold is applied to determine potential edges in the fourth step. Finally, track edge by hysteresis: Finalize the detection of edges by suppressing all the other edges that are weak and not connected to strong edges. Figure 6 illustrate the image before and after applying candy edge detector algorithm.

Figure6. *Some x-ray images before and after applying canny edge detector*

Bag of Words (BoW)

Another technique that we used to extract features is Bag of Words which treats image features as words so it is a vector of occurrence counts of a vocabulary of local image features and to represent an image, it usually includes three steps feature extraction, visual vocabulary, and codebook generation (Image representation) see figure 7. [22-23].

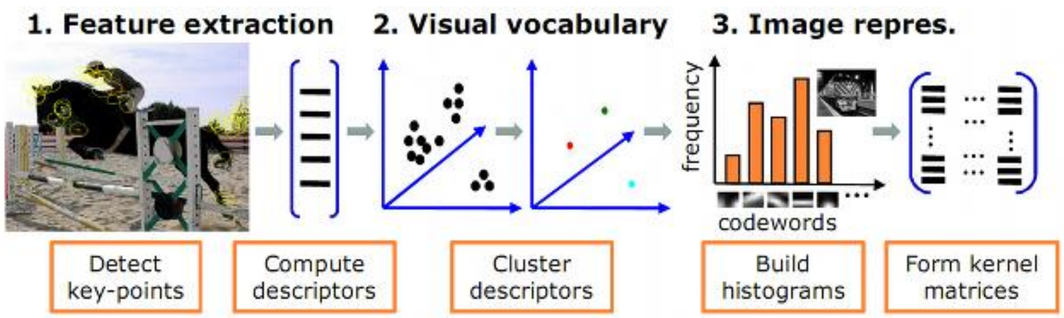


Figure7. *Bag of Words steps*

In this work, a comparison of these four techniques is conducted and each extracted feature vector from every technique can after that be processed using the Support vector machine to classify the images.

PERFORMANCE EVALUATION

Platform Specification

The Image Processing Toolbox at MATLAB R2015a is used for extracting image features, and applying multi class Support Vector Machine (SVM ^{multiclass}). In addition to, the Visual Studio 2013 will be the interface of introduced system, besides SQL server 2014 management studio is used to store the results of experiments. Subsets – 1000 x-ray medical images - of imageCLEF 2007 is used as a dataset for our experiment. This datasets is recorded randomly at the Department of Diagnostic Radiology of the RWTH Aachen (Lehman et al, 2003) University. The estimated number of these images is 11000 images, which are classified manually by experts into 193 different classes.

RESULTS

The gray level co-occurrence matrix (GLCM), Local binary pattern (LBP), canny edge detector and bag of words (BoW) are applied with multiclass support vector machine classifier for six classes' dataset: cranium class, chest class, upper extremity (arm) hand class, upper extremity (arm) radiocarpal joint class, upper extremity (arm) hand forearm class and lower extremity (leg) class. Figure 8 illustrates the results of this experiment, it shown the average performance for each technique being used with the previous classes.

Our experiments results showed that Bag of Words (BoW) technique gives the high results as it gave approximately 98.5% corrected medical images for all classes. At the same level came LBP nearly the same as BoW as it give 94.5% corrected results. GLCM came at the third level with 71% of successfully. And finally, canny technique give 25.5% corrected results.

Figure8. *General results from the four techniques.*

Figure 9 shows the percentage of successfully for the four techniques at every test class which used at the classification process. For the Cranium class, BoW, LBP and GLCM techniques give nearly the same results, it successfully to assign the images to these classes with 100% of successfully for BoW and LBP and with 97.5 of successfully for GLCM. While in the same class, the Canny techniques assign the images with only 50% of successfully, In addition to, with Chest class the BoW, GLCM and LBP techniques give results between 83 % and 98% of successfully, while Canny fails to assign any image. Also canny technique fails in Hand Forearm class and gives the lowest results compared with other techniques for the remainder classes. And for the rest classes hand, radiocarpal joint, hand forearm and leg, Bow and LBP techniques maintains levels at the top with (85% – 100%) while the range of percentage of successfully for GLCM techniques between (45% - 70%) and Canny technique between (0% - 55%).

Also, we observed that the technique that gives accurate results is BoW but it takes from 8 minutes to 20 minutes to assign each image to its class. Unlike LBP, GLCM and Canny as they take less than one minute (from 1 second to 10 seconds) to assign an image to its class.

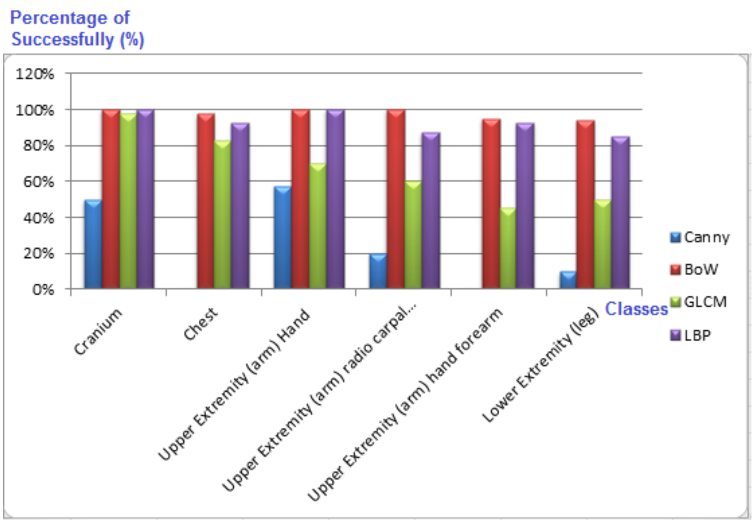


Figure9. *Classification result for every test classes that have been used at the classification process*

CONCLUSION AND FUTURE WORK

The classification is performed well with BoW, LBP and GLCM techniques but had poor results with canny technique. For example canny edge detector gives the worst result at chest class and upper extremity (arm) hand forearm class as the error rate was 100%.

For the classification that needs accurate data we can use BoW technique to extract image features and for one that need speed we can use LBP or GLCM technique with condones the error rate that reaches to 5% for LBP and 29%for GLCM.

Some limitations of this study included: different image classes are very similar or overlapping "content". For example, during the classification process, the classifier faced confusion between "forearm images" and "hand images".

For our project automatic medical image classification tool that are under construction we can merge the classes that cause confusion for multiclass support vector machine classifier such as "forearm images" and "hand images". In addition to, we can get high precision in results by using BoW technique that gives accurate data with 1% error rate and for the data that needs speed in processing like we can use LBP technique that takes approximately 5 seconds average time to assign image to its class.

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