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The improvement of the efficiency of automatic annotation of medical images using Majority Voting

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ABSTRACT

Automatic annotation is actually a classification of medical images, using global and local features of images, IRMA standard code are extracted for them which consists of four data axes techniques of image providing (modality), direction, anatomy, and biological system. Recent researches show despite the fact that classification with high accuracy has been achieved good results but cannot always be optimal for all features of images. Therefore, in this paper, in order to improve the efficiency of automatic annotation system of medical images in terms of classification accuracy, the combined classifiers votes' technique (Majority Voting) and Gabor filter feature in HSV color space for images has been used. The results are promising and improved performance show the improvement of the quality of the proposed system. In fact, in addition to high speed compared with previous methods, it has been achieved good accuracy as much as 75.1 percent.

1. Introduction

Automatic annotation of medical images is an emerging technology and now still is considered as an important tool for physicians in their daily activities, which is subject of discussion for many radiologists in hospitals. Reasonable studies have been conducted in this area. Nowadays, Hospitals produce a great amount of data which, on the average, radiological groups generate multiple tera-bytes of data year. Moreover, manual annotation causes error in the label assignment, which means that part of the available knowledge is no more accessible to physicians, Guleld et al in 2002[1], and this calls individuals to be able to develop algorithms to automatically annotate medical images. [2].

Image annotation could be done manually, semi-automatically or automatically. In the manual method human being is used for annotation. The accuracy of this annotation method is high but in the long run, it is a tedious process that users mostly ask to use other alternative methods. [3]. Content based image retrieval systems (CBIR) distinguish images based on their visual feature such as color, texture, and shape.[4] But between the content features of lower level (color-texture- shape) and high level semantic features, used by human, there is a semantic gap for image description. [5]. To map bridge the semantic gap, the automatic annotation is used.

In the automatic annotation method, image annotation process is done completely by machine. The accuracy of this method is less than the other methods. In this method, images classification is done based on features extracted by using image processing techniques, machine learning algorithms, and training data. [5].

In the semi-automatic method, the users' participation is due to the quality of human modification, it has been improve in comparison with manually annotation [3]. Thomas et al [6], have produced automatic annotation system using a combination of local binary pattern features [7], SIFT and SVM Classifier. The method presented in this paper had the best results in Image CLEF 2008. Dmitrovski et al [8], developed one hierarchical system of multi- label for annotation of medical images. They have used various methods of feature extraction and their combination and combined classifiers of bagging and random forest. Muller et al [9], have generated an automatic annotation system using visual features of images and one SVM Classifier. Dzeroski et al [10], to annotate medical images, have used learning algorithms of combined machine (Boosting). This method is based on the combination of the results of weak classifiers in order to generate strong classifiers with high accuracy. The purpose of this method is to combine several classifiers with less precision in order to make the highly accurate classifiers.

In the proposed method of this paper, two steps of annotation i.e., feature extraction and classification of image are used. For the feature extraction step, improved local binary pattern has been used which is one of the most powerful and the most used local texture features; Edge Direction Histogram (EDH), SIFT descriptor and Gabor filter feature in HSV color space. For the step of images' classification, the images are classified using various machine of learning algorithms that to produce any data axis (modality, direction, anatomy, biological system) separate classification has been used.

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In this paper, the best results of employing various classifiers on different feature in four classes (modality, direction, anatomy, biological system) are investigated. To improve the performance of automatic annotation system of medical images, combination of multiple classifiers' votes in each data axis image has been used with combined classification techniques (Majority Voting) and Gabor filter feature in images.

Section 2 describes the methodology used to test the introduced data set, feature extraction methods, and combined classifiers (Majority Voting) and explains proposed architecture model. The experimental results obtained from the implementation and evaluation of the proposed method is presented in Section 3. Section 4, contains the complete results of the investigation.

2. Testing method

This section explains utilized dataset and the method of implementation of features extracted from images, using image processing techniques, combined classifiers (Majority Voting), and the proposed architectural model.

The purpose of this paper is to improve the automatic annotation of medical images using combination techniques of multiple classifiers' votes and Gabor filter feature regarding system accuracy.

2.1 Data set

The Image Retrieval on Medical Application (IRMA) is a database for creating an automatic medical image provided by IRMA group from the Aachen University Hospital [11]. This set is being used in medical image annotation call of Image CLEF and it has dealt with comparison of done work each year from 2005 to 2009 [12]. In 2005, image classification work was stared with 57 classes and in 2006 it has reached 116. But from 2007 onwards, image annotation includes a 13 character IRMA code. In this paper, it has been used ImageCLEF2007 as dataset containing 10000 training image and 1000 test images.

IRMA is a 13-character code and is used to describe a class or annotation of a medical image. The schema of IRMA code has four axes, each of which has a three to four positions. To each position, a value of 0 to 9, a to z is given, in which the value of "0" indicate unspecified and determines the end of a path along the axis. These four axes are:

1-Technical axis (T, image modality) explains the method used to obtain the image.

2- Directional axis (D, body orientation) describes the direction of photographing the body organ.

3- Anatomical axis (A, body region) indicates the body organ presented in the image.

4- Biological axis (B, biological system) describes the biological system of the organ presented in the image including cardiovascular-spinal and muscular. IRMA code can be shown as follows:

Figure 1. Schema of IRMA code [8, 2].

Examples of the annotated medical images along with 13-character IRMA code have been shown in figure 2.

Figure 2. Examples of annotated images of Image CLEF 2007 [13].

For our project, Matlab 2013 software, to implement the extraction of the varieties of images features, and combined classification techniques of Majority Voting are used. Rapid Miner and Weka software have been used to measure the accuracy of the classification algorithms for automatic annotation of medical images in different data axes of the image (modality, direction, anatomy, and biological system) on the extracted data of different images' features.

2.2 Feature extraction

In the area of image classification and retrieval, images are displayed with low-level features. Because the image is a set of pixels, the first step to understand the meaning of an image, is to extract efficient visual features. Displaying the appropriate features, significantly, will improve the function of semantic learning techniques. In each image, the extractable features, using different methods, are classified into two groups, as names Global and Local. The global features are not usually sensitive to local or spatial changes of different images. Local features are more appropriate for explaining the details of the image. For example, the color histogram can be used to display or explain the extraction of the global color contents of the images. As a sample, one image can be interpreted in which 40% is blue, 37% is yellow, etc. Therefore, the image can be illustrated by both globally and based on parts of image; but there is tendency to regional segmentation [5].

In the following section, the implementation methods explained.

2.2.1- Local binary pattern

The Local Binary Pattern (LBP) is one of the best displays for texture content in images [7]. The important feature of it is being invariant to monotonous changes in gray-scale images and being calculated very fast. Therefore, they are able to select different micro patterns such as edges, dots, and constant areas. The main idea beyond LBP method is using information about the texture of a local neighborhood. At first, in this method, the radius R is defined from the local neighborhood. Then, considering an image neighbor, the light intensity of existing points in this neighborhood is being compared with the light intensity in the center of neighborhood.

Usually, in order to prevent the sensitivity of the operator towards the image rotation, neighborhood considered as circular. The Local Binary Pattern operator is created with a binary code where the local texture pattern in the neighbor's set of P pixels described. Binary code is obtained by using the gray values of the center of the neighborhood as threshold level. It is converted into a decimal number which is shown with the LBP code. Formally, a pixel is given as a central pixel in the (Xc, Yc) coordinate; as a result the LBP code is expressed as follows: [8].

$$LBP_{(P,R)}(X_c, Y_c) = \sum_{n=0}^{p-1} S(i_n, i_c)\, 2^n \quad (1)$$

In which n is the range of the neighbor P in the central pixel (Xc, Yc). Ic and In are the gray- scale values of the central pixel and neighbors to pixel. S(x), the sign function, is defined as follow: [8].

$$S(x)=\begin{cases} 1 & \text{if } x>=0 \text{ (a)} \\ 0 & \text{otherwise (b)} \end{cases} \quad (2)$$

The image along with LBP operator is traversed pixel by pixel and outputs are integrated in a discrete histogram. Figure 3 shows examples of the neighbors with different radiuses(R) and the number of different neighboring points (P).

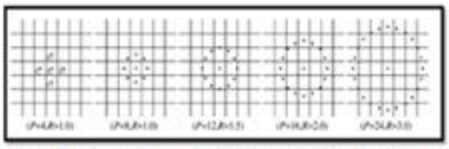


Figure 3: Examples of neighbors with different radiuses (R) and the different points of the neighbor (P). [7].

Certain of the LBP code, maintain the basic properties of the texture and they are called uniform pattern that are used to decrease the length of the texture feature vector of LBP. Sometimes more than 90% of the all patterns are observed in texture. All of these patterns have one thing in common, that is, a uniform circular structure which contains very few spatial transfers. In the experiment, the $LBP_{8,1}^{u2}$ patterns, U2 power reflects using of the uniform pattern in which the value of U, at most 2, is placed in a neighborhood of 8 sizes and a radius of 1, reduces the length of the histogram feature vector from a standard form of 256 to 59 bins. The value of U is a few of spatial transfers (0, 1 bit changes) in the pattern. The non-uniform patterns are those which have a value greater than 2 and they are grouped under one bin and one histogram. In fact for uniform pattern, a uniform measure (U) is defined which is related to a number of spatial transfer (0,1 bit changes) in the pattern. Therefore an LBP is called uniform if the binary pattern contains at most two bits transfer from 0 to 1 or vice versa, when the bit pattern is moving circularly. $LBP_{8,R}^{riu2}$ Is another uniform binary pattern that riu2 power reflects rotation invariant uniform patterns and its uniformity level is maximum 2. It decreases the length of histogram feature vector from its standard form of 256 to 10.

Binary pattern in the new and improved form is defined as follow: [7].

$$LBP_{P,R}^{riu2}=\begin{cases} \sum_{p=0}^{P-1} s(g_p-g_c) & \text{if } U(LBP_{P,R})\le 2 \\ P+1 & \text{otherwise,} \end{cases} \quad (3)$$

where

$$U(LBP_{P,R})=|s(g_{P-1}-g_c)-s(g_0-g_c)| + \sum_{p=1}^{P-1}|s(g_p-g_c)-s(g_{p-1}-g_c)|$$

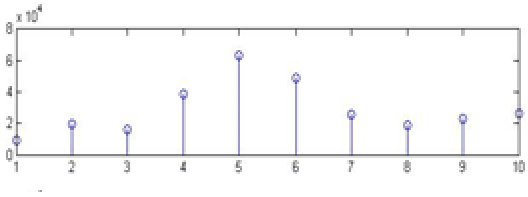
The implementation method of extraction feature of global texture LBP, that steps are as follows: [14, 8].

1)LBP algorithm is applied to the entire image with (R, P) parameters, in an experimental scale (8,1).

2)10 bins histogram is produced from global feature extraction of LBP texture in the previous step.

Radius (R) parameters and the number of neighboring sample points (P) are selected experimentally. In this paper, the experimental parameter (8, 1) is used instead of (R, P). Figure 4 shows a sample image together with the implementation of the histogram of global feature extraction of $LBP_{8,R}^{riu2}$ texture.

A). Sample image



B). Histogram of feature extraction of global feature of LBP texture on the entire image in experimental scale (8, 1) instead of (R, P).

Figure 4: A), Sample image and B), 10 bins histogram of global feature extraction of $LBP_{8,R}^{riu2}$.

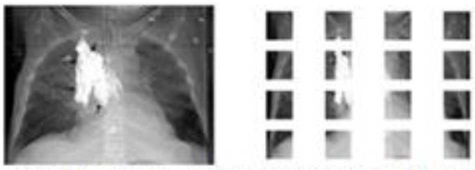
The implementation of feature extraction of LBP local texture, the steps are as follows: [14, 8].

1)Dividing each medical image into 16 blocks or sub image.

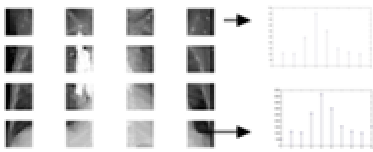
2)Calculating the 10 bins histogram of local LBP for each image block with P and R parameters in an experimental scale (8, 1).

3)Producing of the final 160bins histogram of feature vector for each medical image from the combination of the produced features histograms of each image block in the previous step.

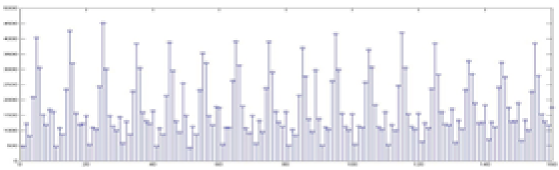
Figure 5. Shows a sample image with the implementation of feature extraction histogram of $LBP_{8,R}^{riu2}$ local texture.



A). Sample image. B). Segmentation of sample image.



C). 10 bins histogram of LBP local texture feature extraction from each image block.



D). 160 bins histogram from the combination of the feature extraction of LBP local texture from each image block.

Figure 5: Displaying the final histogram from feature extraction of $LBP_{8,R}^{riu2}$ local texture.

2.2.2 Edge Direction Histogram

Edge detection is a fundamental issue in computer and is widely studied.

It keeps important information about the shape of the objects in the scene. Human's eye is sensitive to edge feature for understanding image. One of its important features is being fixed to moving, resizing and image rotation. MPEG-7 standard is one descriptor for edge distribution in image [15].

MPEG-7 standard contains only local edge distribution in the image. This standard is important to protect the histogram size for efficient storage of metadata. Edge Direction Histogram, using image classification on the edge with the quantization of five degrees, creates the edge frequency histogram and it is used as a feature vector. Local edge feature extraction method (EHD), is used in this case:

The image space is divided into 4×4non-overlaping blocks. 16 blocks is being built and then the edge information of each block is extracted. Note that regardless of the size of the image-block, the sub-image is divided into fixed image-blocks. The size of the block fits with the resolution of the original image size. Figure 6 shows the concept of sub image and image- block.

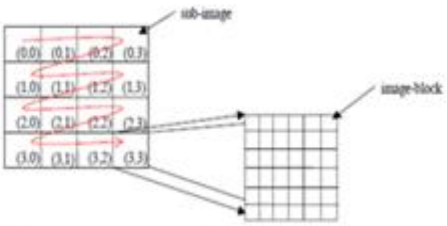


Figure 6: The concept of the sub-image and image-block [15].

The equation of 4 and 5 shows how the block size for a given image fits with the width and height of the image. [15].

$$x = \sqrt{\frac{image\_width \times image\_height}{desired\_num\_block}} \quad (4)$$

$$block\_size = \left\lfloor \frac{x}{2} \right\rfloor \times 2 \quad (5)$$

The edge extraction of each block is shown in the figure 7. Each image-block is divided into 4 blocks.

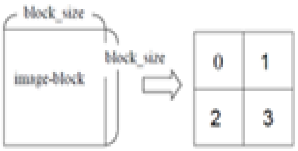


Figure 7. Sub blocks and labeling them. [15].

In order to adopt the same label like figure 8, for detecting the edge, edge filter coefficient is used. It is defined in figure 8 as follow

Figure 8: Types of filters for edge detection. [15]

Edged that do not have any direction, are extracted by non directional edge filter. Using 5 types of edges in figure 9, five edge strong points for each block/image (i, j) are obtained from equation 6. [15].

$$ver\_edge\_stg(i,j) = \sum_{k=0}^{3} \left| A_k(i,j) \times ver\_edge\_filter(k) \right| \quad (7)$$

$$hor\_edge\_stg(i,j) = \sum_{k=0}^{3} \left| A_k(i,j) \times hor\_edge\_filter(k) \right|$$

$$dia45\_edge\_stg(i,j) = \sum_{k=0}^{3} \left| A_k(i,j) \times dia45\_edge\_filter(k) \right|$$

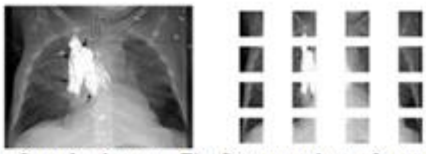
$$dia135\_edge\_stg(i,j) = \sum_{k=0}^{3} \left| A_k(i,j) \times dia135\_edge\_filter(k) \right|$$

$$nond\_edge\_stg(i,j) = \sum_{k=0}^{3} \left| A_k(i,j) \times nond\_edge\_filter(k) \right|$$

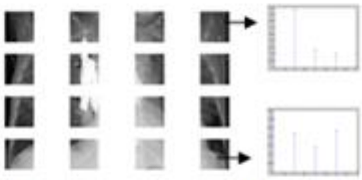
the maximum amount among 5 strong points, obtained from equation 6, is greater than the threshold edge in equation 7, the block/ image is considered with its corresponding edge. [15].

$$\max\{ver\_edge\_stg(i,j), hor\_edge\_stg(i,j), dia45\_edge\_stg(i,j), dia135\_edge\_stg(i,j), nond\_edge\_stg(i,j)\} > Th_{edge} \quad (8)$$

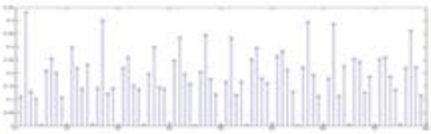
Figure 9 shows a sample image along with implementation of feature extraction histogram (EOH), (since there are 16 blocks and 5 types of edge in image, totally 16 × 5 = 80 bins histogram are required.)



A). Sample image. B). Segmentation of sample image.



C). 5 bins histogram of local feature extraction (EOH) of each image block.



D). 80 bins histogram of local feature extraction combination (EOH), from each image block.

Figure 9: Displaying the final histogram from local feature extraction (EOH).

2.2.3 SIFT descriptor

One tools for image local feature description is Scale Invariant Feature Transform (SIFT). It is insensitive to the rotation conversions and image stretch and has good accuracy in object recognition, face recognition, etc. [16].

This descriptor works on the basis of extracted feature points on the images. Extraction of key points of image is a good representative for describing that object. But the number of extracted key points in images are high that requires more calculations. This problem in images with higher complexity is more apparent. The purpose of this paper is to decrease the number of feature points, using K-means algorithms clustering technique that improves the accuracy of classification and the efficiency of computational time. [8].

In this study, a modified version of descriptor SIFT (ModSIFT) is used. In this version, SIFT rotation-invariance, not related to medical image classification, is removed and key points extraction are considered in one octave.

Local feature extraction method (ModSIFT) of image, is considered in this case: [8,2].

1) Extracting of 30 key points randomly from each medical image of the standard dataset training group using SIFT improved algorithm.

2) Clustering of extracted key points in the previous step using the K-Means to 500 clusters.

3) Producing a representative for each cluster in step 2 called Visual-Words.

4) Determining the state of belonging of extracted feature points of test image set generated in the previous step.

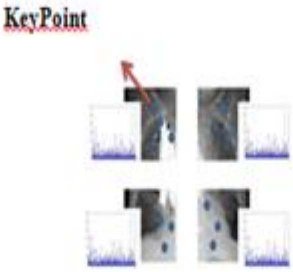
(In the phase of testing new image, at first it is divided into 2 × 2 spaces and, for each blocks, 1500 key points are extracted. Then it becomes clear that each feature point belongs to which cluster. And instead of its feature vector, its (visual-word) is taken into consideration).

5) 500 bins histogram from feature extraction of improved SIFT of each block of image.

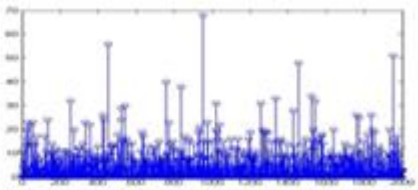
6) Creating the final 2000bins histogram from the combination of improved SIFT feature extraction of each block of the image.

Figure 10. One sample image along with the implementation of ModSIFT local feature extraction histogram.

A). Sample image.



B). Creating 500 bins histogram for each block test image.



C). Creating 2000 bins histogram from SIFT local feature extraction combination for each test image bock.

Figure 10: Displaying final histogram from ModSIFT local feature extraction.

2.2.4 Gabor Filter

One of the important and strong characteristics of feature extraction of texture Spectral is Gabor Filter. This characteristic in addition to texture feature extraction can be used in the HSV color space and color features can be extracted from it. This feature due to doing less computation for complexity in distance domain, is strong. This filter has improved localization properties in two areas of spatial and frequency and is appropriate for texture and color classification. This feature has high accuracy in image recognition and color analysis. 2D Gabor function is defined as follow: [17].

$$G(x,y)=\frac{1}{2\pi\delta_x\delta_y}\exp\{-\frac{1}{2}[(\frac{x}{\delta_x})^2+(\frac{y}{\delta_y})^2]+j(ux+vy)\} \quad (8)$$

2D Gabor function is a complex function its computation is relatively difficult. In this paper, the real part of the function in equation 8 is used as filter. The form of this filter is as follow: [17].

$$H(x,y,\phi,f)=\exp\{-\frac{1}{2}[\frac{x_\phi^2}{\delta_x^2}+\frac{y_\phi^2}{\delta_y^2}]\}\cos(2\pi f x_\phi)$$

$$x_\phi = x\cos\phi + y\sin\phi,\; y_\phi = -x\sin\phi + y\cos\phi \quad (9)$$

φ is the direction of filter and F is the frequency. δ_x and δ_y are Gaussian envelope function along X and Y axis. Selecting these parameters is very important in feature extraction. Image feature extraction technique (Gabor Filter), is considered as follow:

1)Image conversion of RGB color space to HVS color space

2)Gabor filter feature extraction from each medical dataset image. (In this stage, at first, a bank of Gabor filter is created on images in different frequencies and directions. And number of filters for each image is extracted).

Table 1, shows the bank creation of Gabor filter in different frequencies and directions.

Table 1. Bank creation of Gabor filter in different direction and frequencies [17].

The number of filters	**The number of direction**	**The number of frequency**
4×7=28	7	**4**
3×4=12	4	**3**

Gabor filter, usually, is formed in 4 frequencies and in different direction of 0 to 180 degrees. Then, the extraction of two means parameters and standard deviation will be done on each of the filtered image.

3) Creating histogram of Gabor filter feature extraction, from each image of second step.

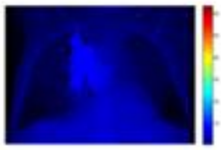
Table 2 shows the length of feature vector from Gabor filter feature extraction.

Table 2. The length of feature vector from Gabor filter feature extraction. [17].

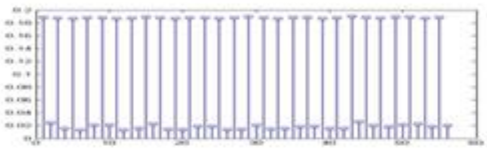
The length of feature vector	**The number of filter**	**The number of direction**	**The number of frequency**
4×7×2=56	4×7=28	7	4

Figure 11. Shows an image sample with the histogram implementation of Gabor Filter feature extraction.

A). Sample image in RGB color space



B). Sample image in HSV color space



C). Creating 56bins histogram from Gabor filter feature extraction, each image with the frequency number of 4 and direction number of 7.

Figure 11: Displaying 56bins histogram from Gabor filter feature extraction with the frequency number of 4 and the direction number of 7.

2.3 advanced techniques of learning (the combination of multiple classifiers).

In recognition pattern and learning machine, recently, combinations of a number of classifiers are active in research area. It can be called ensemble or modular classifiers. The aim of modular classification, is obtaining highly accurate classifiers by combining the result of weak classifiers [10]. The performance of this type of combined classifiers, most probably, is better than the one of the best single classifier used in isolation.

In this paper, in order to improve the efficiency of medical automatic annotation system, Majority Voting classifiers technique has been used which is described below.[18].

2.3.1 Majority Voting

It is a general method for improving the function of each algorithm in learning classification. In this method, the binary output of separate classifiers K is combined. Then a class with the highest number of votes is selected as the final decision of classification. In general, the final decision of classification is made of the majority of K+1/2 reached votes. Figure 12, shows the general architecture of modular classifiers.

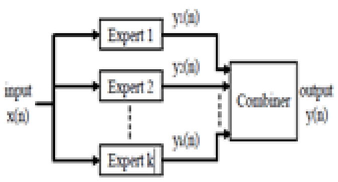


Figure 12: General architecture of modular classifiers.[19].

2.4 The pattern of proposed architectural model

In order to improve the automatic system of medical images' annotation, the result of multiple classifiers in each image data axis (Modality, Direction, Anatomy, Biological system), with lower accuracy, are being combined with combined classifiers techniques of Majority Voting, then one class, with most votes in each data axis, is being considered as the class relating to that axis. The ultimate aim of this paper is to produce IRMA 13-characters code in order to improve the annotation of test images. Figure 13, shows proposed architectural model.

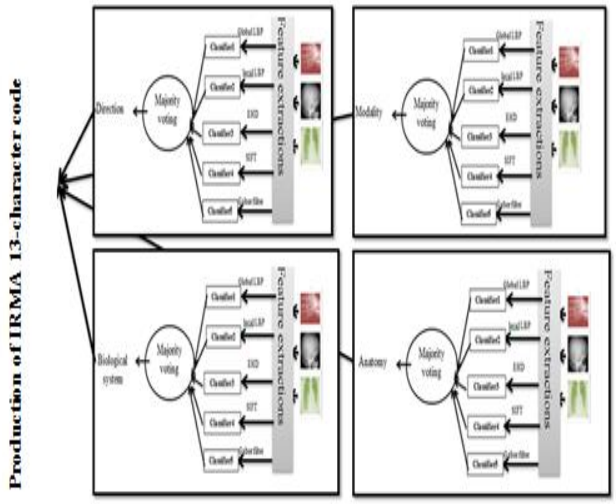


Figure 13. The pattern of proposed architectural model.

3. Results and Evaluation

The overall recognition rate is a common method and is widely used to measure evaluation. It is a fraction of tested images that estimates IRMA 13-character code correctly. [8].

$$accuracy = \frac{correctly\ annoteted\ images}{total\ tested\ images} \quad (10)$$

In this method of evaluation, at first, classifiers are trained with training images. Then, using the tested images, the accuracy of classification is tested based on different measured features. In order to improve the efficiency of annotation system, the results of multiple classifiers' votes with weaker accuracy are combined together in each data axis image (Modality, Direction, Anatomy, Biological system). They are compared with the real test data and the final precision of system is measured.

Tables 3, 4, 5, and 6, show the result of classification (Modality, Direction, Anatomy, Biological system) using different feature of images on separate classifiers.

Table 3. Results of the classification of modality axis using different features of image.

Features	Classifier	Prameters	%Accuracy modality
EHD	SVM	RBF Kernel, gamma=3	98/80
Local$LBP_{8,R}^{riu2}$	KNN	K=1	97/40
ModSIFT	SMO		94/40
Global$LBP_{8,R}^{riu2}$	Bagging/Weka		90
Gabor Filter	KNN	K=10	87/20
Gabor Filter	AdaBoost	Iteration=100	84/90

Table 4: Results of the classification of direction axis using different features of image.

Features	Classifier	Parameters	%Accuracy direction
EHD	SVM	RBF Kernel, gamma=3	84/50
Local $LBP_{8,R}^{riu2}$	KNN	K=1	67/40
ModSIFT	SVM	Polynomial Kernel, degree=2, gamma=1.5	64/50
Gabor Filter	Bagging	**Iterations=10**	42/70
Global $LBP_{8,R}^{riu2}$	Random Tree		42

Table 5. Results of the classification of anatomical axis using different features of image.

Features	Classifier	Parameters	%Accuracy anatomy
EHD	SVM	RBF Kernel, gamma=2	86/20
EHD	SVM	RBF Kernel, gamma=1.5	86
EHD	SVM	Polynomial Kernel, degree=2, gamma=1.5	83/70
EHD	KNN	K=1	83/40
EHD	SVM	Polynomial Kernel, degree=3,gamma=1.5	80/40

Table 6. Results of the classification of biological system axis using different features of image.

Features	Classifier	Parameters	%Accuracy Biological system
$LBP_{8,R}^{riu2}$ Local	KNN	K=1	96/50
Local $LBP_{8,R}^{riu2}$	SVM	Polynomial Kernel, degree=3, gamma=1.5	95/30
ModSIFT	SVM	Polynomial Kernel, , degree=2 gamma=1.5	92/40
Global $LBP_{8,R}^{riu2}$	SVM	Polynomial Kernel, degree=3, gamma=1.5	89/30
Gabor Filter	KNN	K=10	87

Table 7, shows the best results from measurement of classification algorithms' accuracy on each data axis image (Modality, Direction, Anatomy, Biological system).

Table 7. The best results from the accuracy measurement of classification accuracy on each data axis image.

IRMA Axis Code	Classifiers	Parameters	%Accuracy
Modality	SVM	RBF Kernel, gamma=3	98/80
Direction	SVM	RBF Kernel, gamma=3	84/50
Anatomy	SVM	RBF Kernel, gamma=2	86/20
Biological system	KNN	K=1	96/50

In order to measure the real accuracy of system, the estimation of test data label, from classifiers ' result, with the highest accuracy on each image data axis (Modality, Direction, Anatomy, Biological system), table 7, are combined together and are compared with real test data. %748 is the real accuracy of this system. Therefore, in order to improve the accuracy of annotation system, the results of each data axis (Modality, Direction, Anatomy, Biological system) in tables 3, 4, 5, and 6 are combined using Majority Voting technique, and in each data axis, a class with the most votes is selected. The result of the combination of multiple classifiers of mentioned tables is compared with the real test data and the final accuracy of system is measured. The final accuracy of system is measured %751.

Table 8. the comparison of proposed model with two architectural models of reference method.

Features	Classifiers	The Final Accuracy of System	Methods
EHD	SVM	68/37	[8]
LBP+EHD	PCT	58/98	[8]
LBP+EHD+SIFT	PCT	64/89	[8]
Visual Methods	SVM	69/6	[9]
Global LBP, Local LBP, EHD, ModSIFT Gabor Filter	**SVM, KNN Bagging, AdaBoost, Random Tree.** → Majority Voting	**۷۵/۱**	**Proposed Method**

Conclusions

To annotate medical images, the aim is to produce 4 data axes including Modality, Direction, Anatomy, Biological system. In this paper, due to the discrete nature of different axis of medical images' annotation, discrete features and classifiers of each axis are used.

In modality axis, two features of EHD, on SVM classifier and local $LBP_{8,R}^{riu2}$ feature on KNN classifier had the best results, whereas, in anatomy and direction axes, EHD feature on SVM classifier had the best result and in biological system axis, $LBP_{8,R}^{riu2}$ Local feature on SVM and KNN classifiers had the best result.

SVM classifier improved results compared to other classifiers, is its less sensitivity to noise. In this method, in addition to high speed, appropriate accuracy is achieved.

As the results show in above tables, using high accurate features and classification for combined method, don't improve the results. Because their answers are close to each other. Therefore, although it's possible that the accuracy of one system is low, its combination with higher classifiers improves the results of combined classifiers.

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