Automated pre-diagnosis of Acromegaly disease using Local Binary Patterns and its variants

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Automated Pre-Diagnosis of Acromegaly Disease Using Local Binary Patterns and Its Variants

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Abstract— **Symptoms of some disease are seen on the face area. These symptoms make typical faces by giving typical characteristics to face areas and expressions. Hippocratic face, Parkinson face, Lupus face, Leprosy face can be given as example of these faces. One of the most typical ones of these faces is Acromegaly face. Acromegaly is a disease which occurs as a result of secretion of excessive amounts of growth hormone (GH). In this work, we propose a new and effective system that can pre-diagnose of Acromegaly automatically by the way of evaluating the patients face images. For this purpose, Local Binary Patterns (LBP) and its modified models Improved Local Binary Patterns (ILBP), Center Symmetric Local Binary Patterns (CS-LBP) are applied for feature extraction of face images. Weighted Chi-square, Euclidean and Manhattan classifiers are used for the classifying to the selected sets of features. Our results showed that LBP (8,1) coupled with Manhattan classifiers resulted in highest accuracy of 97%, sensitivity of 93%, specificity of 100% compared to other feature extraction techniques and classifiers. In this way, our proposed system is more suitable for diagnosis of Acromegaly disease with higher accuracy.**

Keywords—**Weighted Chi-square, Euclidean, Feature Extraction, Manhattan.**

I. INTRODUCTION

ACROMEGALY caused by producing extremely growth hormone is a disease. A research reported that the diagnosis of Acromegaly takes an average of 7 years since onset of illness [1]. Excessive growth of body, hand, foot, jaw and nose are categorized in symptoms of Acromegaly disease. The typical face obtained by patient is the most significant symptom. The enlarged face coarsens in consequence of overgrowth of face bones, nose, ears, chin and lip. In spite of these common characteristics, the physical similarity between Acromegaly and normal face makes difficult to pre-diagnosis. The idea is that Shrek, animation hero in the film Shrek, is created with an inspiration of professional wrestler and poet, Maurice Tillet whose bones have grown extremely because of Acromegaly [2]. Photos of Tillet and Shrek are given in Fig. 1.

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Fig. 1. Tillet and Shrek

Today, accurate diagnosis of Acromegaly can be diagnosed using the result of clinical and biochemical tests and measurements. Before applying these tests, the experts use the physical appearance of patience to diagnose. As a result of this, pre-diagnosis varies depending upon the experience of the doctors and patients are subjected to lots of necessary and unnecessary tests. The experts diagnose this illness via glancing at patient's appearance. For this reason, the method makes a decision about Acromegaly using visual comparison on features of diagnosed patients and symptoms of reference books [3]. In this comparative method, the diagnosis is determined according to experiences of expert physician. Consequently, pre-diagnosis systems which are cheap, in variant of subjective diagnosis made by physician are a requirement at present.

In this study, an automated pre-diagnosis of Acromegaly system utilizing face images has been proposed and evaluated. There are only a few studies about this subject in the literature. Harald J. Schneider et al. studied about Acromegaly recognition using automated face classification [4]. In their work, similarity analysis based on Gabor and geometric functions was performed on the frontal pose and one side pose of face images of patients classified with regard to grade of Acromegaly. Ralph E. Miller et al. transforms face images to three dimension space from two dimension space, and they tried to diagnose Acromegaly with binary classification [5]. Down syndrome, a disease made its diagnosis from face images such as Acromegaly, was recognized with original LBP operator by Burcin et al. [8]. They performed face feature extraction with LBP operator and classified with Euclidean distance and Changed Manhattan distance. A few studies have been occurred about other syndromes beside Down syndrome [6, 7].

The rest of the paper is organized as follows: Section 2 explains our database and pre-processing. Section 3 gives information about methods used for feature extraction LBP, ILBP, CSLBP. Section 4 gives various classifiers. Section 5 of the paper presents the results and analysis of the proposed method and finally, the paper concludes in Section 6.

II. DATABASE AND PRE-PROCESSING

Due to the lack of a database used in the literature of patients with Acromegaly, the training and test images used in the study was obtained from open image sources on the

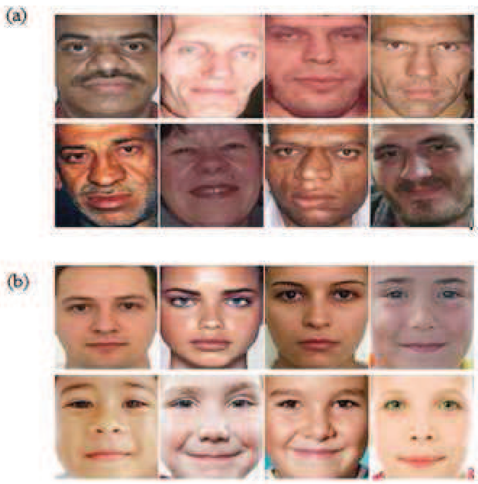

Fig. 2. (a) Acromegaly faces (b) Normal faces.

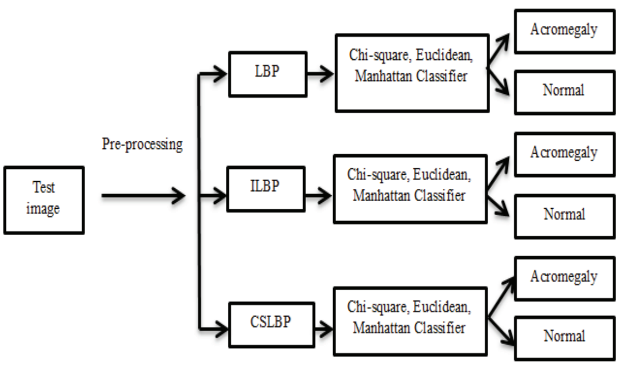

Fig. 3. Proposed system

internet. We used color face images with size of 100×100 pixels. In the pre-processing stage, all images are converted to gray levels. Fig. 2 is shown example of Acromegaly and normal faces from our database.

As you can see in Fig. 2, Acromegaly faces have a big similarity ratio with normal faces. This makes pre-diagnosis issue more complicated.

III. Feature Extraction

The proposed system is illustrated in Fig. 3. LBP, ILBP and CS-LBP are used for feature extraction from the pre-processed faces. These features are utilized to train and evaluate the performance of classifiers. The classifier output will be two classes (Acromegaly/Normal).

In this section, feature extraction techniques are described.

A. Local Binary Patterns

Local Binary Patterns (LBP), introduced by Timo Ojala, is simple on theory, very powerful and invariant of the gray levels texture analysis method. It has proven that LBP operator is very successful texture descriptor in many computer vision applications [9, 10]. One of the most important features of LBP is that invariant of the changes in the intensity of the light source. The original LBP operator labels for every pixel of the image, by evaluating the binary differences of the 3x3-neighbourhood g_n (n=0, 1, ... ,7) of each pixel with the center pixel g_c. If g_n is greater than or equal to g_c, the binary result of the pixel is set to 1 otherwise

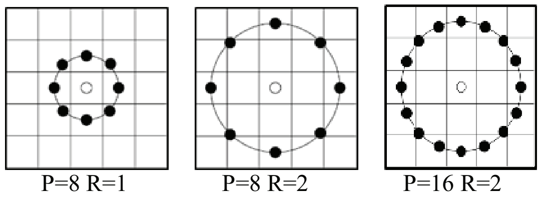

Fig. 4. Various LBP operators

set to 0. All the results are combined to get 8 bit value. The decimal value of this binary code is the LBP feature. Every pixel of the image is labeled with equation (1).

$$LBP_{P,R}(x_c, y_c) = \sum_{n=0}^{P-1} s(g_n - g_c) * 2^n \tag{1}$$

where,

$$s(m) = \begin{cases} 1, & if \quad m \geq 0 \\ 0, & otherwise \end{cases} \tag{2}$$

Where $LBP_{P,R}(x_c,y_c)$ is the decimal label of point (x_c,y_c), g_c is the gray level of central point (x_c,y_c), g_n represents one of its P neighbors, R is radius and $s(t)$ is step function. In the original LBP operator, 8 neighbors (P=8) that are equally spaced on a circle of radius 1 (R=1) are used to obtain LBP labels. Various LBP operators can be defined according to the neighbors (see Fig. 4). The output of the LBP operator is a P-bit with 2^P distinct values for the binary pattern. For instance, it is obtained 2^8 distinct value while P=8. In the study LBP (8,1), (8,2), (16,2) operators have been used.

Later, a histogram of the decimal label is calculated and can be used as a texture feature. This histogram of the LBP image shows how often these 256 different patterns (P=8) occur in a given texture. It has been shown that certain patterns contain more information than the others [13]. It is possible to use only a subset of the 2^P binary patterns to describe the texture of the images. Ojala et al. named these patterns as uniform patterns [13]. A LBP pattern is called as uniform if the binary pattern consists of at most two bitwise transitions from 0 to 1 or vice versa. For example, if the bit pattern 11111111(no transition) or 00111110 (two transitions) are uniform whereas 10101010 (eight transition) are not uniform. The uniform patterns decrease the number of LBP pattern from 2^P to (P-1)*P+1. For this reason LBP histogram has 58 instead of 256 bins for P=8.

The histogram H can be defined as,

$$H(i) = \sum_{x,y} f(LBP_{P,R}(x,y) = i), \quad i \in [0, (P-1) * P + 1] \tag{3}$$

where,

$$f(A) = \begin{cases} if\ A = true, & 1 \\ else, & 0 \end{cases} \tag{4}$$

LBP histogram over local regions provides more efficient description for recognition. For this purpose, we used spatial LBP histograms and divided the face image into m small regions R_0, R_1, ... , R_m. Every region has calculated its histogram with equation (3) and concatenated into a single, spatially enhanced feature histogram. We used 100*100 size of face image and divided it into 10*10 sub-regions. Fig. 5 shows an example face for this.

Fig. 5. (a) Normal image (b) Gray level image (c) Divided image.

B. Improved Local Binary Patterns

Jin et al pointed out that original LBP could miss the local structure information under some circumstances [11]. Therefore, the mean value of the patch was taken as a threshold instead of the gray level of the central point to obtain all the patterns in a small patch such as 3*3. For instance, LBP (8, 1) operator can only get 256 (2^8) of all 511 patterns (2^9 - 1), as all zeros and all ones are the same) for a 3x3 neighborhood, as the central pixel is not considered. In order to obtain the complete information, they proposed an Improved LBP (ILBP) which compares all the pixels (including central pixel) with the mean of all the pixels in the kernel (as shown in Fig. 7). Later ILBP was extended to the neighborhoods of any sizes instead of the original 3x3. The definition of ILBP is given as follows:

$$ILBP_{P,R}=\sum_{i=0}^{P-1} r(g_i-m)*2^i+r(g_c-m)*2^P \tag{5}$$

where,

$$r(x)=\begin{cases}1, & if\ x>0\\ 0, & otherwise\end{cases} \qquad m=\frac{1}{P+1}\left(\sum_{i=0}^{P-1} g_i+g_c\right) \tag{6}$$

Where m is the mean of the center pixel and its P neighbors.

C. Center Symmetric Local Binary Patterns

CS-LBP, another modified version of LBP, is compact descriptor. It is difficult to use the original LBP as a region descriptor. Because LBP operator produces rather long histograms. Therefore, Heikkilä proposed the CS-LBP descriptor for region description [12]. CS-LBP also reduces the computational complexity when compared with basic LBP [12]. For instance, CS-LBP (8, 1) operator can only get 16 (2^4) patterns, while LBP (8, 1) produces 256 (2^8) patterns for a 3x3 neighborhood. In CS-LBP method, instead of comparing the gray level value of each pixel with the center pixel, the center symmetric pairs of pixels are compared (Fig. 8). CS-LBP is closely related to gradient operator. It considers the gray level differences between pairs of opposite pixels in a neighborhood.

Binary Pattern

LBP =	CS-LBP =
$s(g_0-g_c)2^0$ +	$s(g_0-g_4)2^0$ +
$s(g_1-g_c)2^1$ +	$s(g_1-g_5)2^1$ +
$s(g_2-g_c)2^2$ +	$s(g_2-g_6)2^2$ +
$s(g_3-g_c)2^3$ +	$s(g_3-g_7)2^3$ +
$s(g_4-g_c)2^4$ +	
$s(g_5-g_c)2^5$ +	
$s(g_6-g_c)2^6$ +	
$s(g_7-g_c)2^7$	

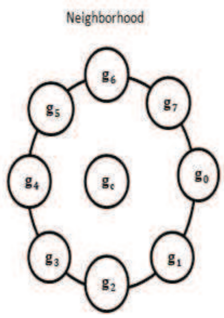

Fig. 6. LBP and CS-LBP features for a neighborhood of 8 pixels

The definition of CS-LBP is given as follows:

$$CSLBP_{P,R,T}(x_c\,,y_c)=\sum_{i=0}^{(P/2)-1} s\left(g_i-g_{i+P/2}\right)*2^i \tag{7}$$

where,

$$s(x)=\begin{cases}1, & if\ x>T\\ 0, & otherwise\end{cases} \tag{8}$$

Where g_i and $g_{i+P/2}$ correspond to the gray level of center symmetric pairs of pixels P equally spaced on a circle of radius R. The value of the threshold T is 1% of the pixel value range in our experiments. Since the region data lies between 0 and 255, T is set to 25.6. The radius is set to 1 and the size of the neighborhood is 8.

IV. Classification

After feature extraction with LBP, ILBP and CSLBP, extracted features for each class were averaged. Thus, a single feature vector for each class was obtained. In the classification phase, the distance between the LBP, ILBP and CSLBP histograms of test image and the mean histograms of Acromegaly and normal classes are computed, and the image is classified according to the minimum distance. Weighted Chi-square, Euclidean and Manhattan distance between the mean histograms of Acromegaly and normal classes and the test feature value is calculated as equation (9), (10), (11).

$$Weighted\ Chi-square\ (x,y)=w\frac{(x-y)^2}{x+y}=\sum_{i,j} w_{i,j}\frac{\left(x_{i,j}-y_{i,j}\right)^2}{x_{i,j}+y_{i,j}} \tag{9}$$

$$Euclidean(x,y)=\sqrt{(x-y)^2}=\sqrt{\sum_{i=1}^{k}(x_i-y_i)^2} \tag{10}$$

$$Manhattan\ (x,y)=|x-y\,|=\sum_{i=1}^{k}|x_i-y_i| \tag{11}$$

Where i,j is the $i.$ bin of the histogram of $j.$ region, $w_{i,j}$ is the weight of $j.$ region, x and y respectively shows the feature vector of test image and the mean feature vector of Acromegaly and normal classes.

V. Experimental Results And Analysis

In this work, our database consists of totally 74 face images. 40 face images of them are used in training process and also the performance of the study is tested 34 face images. With this, there are the 20 Acromegaly face images and 20 normal face images in the training set. These good samples are enough to train even though their number is not too many. The experimental results obtained with C# software. Afterwards, three feature extraction techniques were used independently to identify best representation of features. For this purpose, we extracted facial features for each sample with LBP (8, 1), (8, 2) (16, 2), ILBP (8,1) and CS-LBP (8,1). Later, average of the LBP features for each set, Acromegaly and Normal, are received and feature vectors of these sets have been obtained. The distance between the LBP histogram of test image and the mean histograms of sets are computed and the image is classified with various classifier such as weighted Chi-square, Euclidean and Manhattan classifiers. In

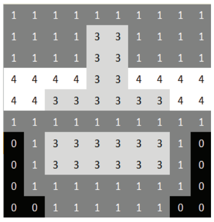

Fig. 7. The proposed weighted matrix

TABLE I
WEIGHTED CHI-SQUARE, EUCLIDEAN AND MANHATTAN CLASSIFIERS USING LBP (8,1) FOR ACROMEGALY AND NORMAL FACE SAMPLES.

	Acromegaly	Normal
Weighted Chi-square Classifier	**89**	92
Euclidean Classifier	**148**	159
Manhattan Classifier	**6140**	6371
	Acromegaly	Normal
Weighted Chi-square Classifier	90	**85**
Euclidean Classifier	196	**178**
Manhattan Classifier	6622	**6035**

TABLE II
WEIGHTED CHI-SQUARE, EUCLIDEAN AND MANHATTAN CLASSIFIERS USING LBP (8,1) FOR ACROMEGALY FACE SAMPLE.

	Acromegaly	Normal
Weighted Chi-square Classifier	**94**	97
Euclidean Classifier	**172**	182
Manhattan Classifier	**6913**	7222

the classification with weighted Chi-square, we proposed a weighted matrix (w, in equation (9)) for Acromegaly face. Due to the fact that Acromegaly patients have overgrowth of face bones, nose, chin and lip, these regions are emphasized with higher coefficients compared to other regions. Our proposed weighted matrix for Acromegaly faces is shown in Fig. 7.

Table I and Table II shows the results of weighted Chi-square, Euclidean and Manhattan classifiers using LBP (8,1) for Acromegaly and normal face samples.

As seen in Table I, all classifiers for given test samples (first Acromegaly, second normal) produced accurate results.

Although Acromegaly face in Table II is very similar to normal face, our system classifies this image into Acromegaly class.

TABLE III
THE ACCURACY OF THE FEATURE EXTRACTION TECHNICS ACCORDING TO THE CLASSIFIER

	Weighted Chi-square Classifier	Euclidean Classifier	Manhattan Classifier
LBP(8,1)	82	94	97
LBP(8,2)	85	91	91
LBP(16,2)	73	91	76
ILBP(8,1)	85	85	94
CSLBP(8,1)	85	82	79

TABLE IV
TPF, 1-FPF, PPV, NPV OF ALL THE CLASSIFIERS USING LBP (8, 1) COMPONENTS AS INPUT FEATURES.

	TPF Sensitivity	Specificity 1-FPF	PPV	NPV
Weighted Chi-square Classifier	70	94	92	76
Euclidean Classifier	86	100	100	90
Manhattan Classifier	93	100	100	95

TABLE V
TPF, 1-FPF, PPV, NPV OF ALL THE CLASSIFIERS USING LBP (8, 2) COMPONENTS AS INPUT FEATURES.

	TPF Sensitivity	Specificity 1-FPF	PPV	NPV
Weighted Chi-square Classifier	75	94	92	81
Euclidean Classifier	81	100	100	86
Manhattan Classifier	81	100	100	86

With this, we are calculated performance measures such as Sensitivity, Specificity, Accuracy, Negative Predictive Value (NPV) and Positive Predictive Value (PPV) on testing data to measure the accuracy of recognition test. The number of True Positives (TP), False Negatives (FN), True Negatives (TN) and False Positives (FP) obtained using each classifier is calculated. TP be the number of Acromegaly cases correctly identified as they are, FP be the number of normal cases incorrectly identified as Acromegaly, TN be the number of normal cases identified as normal and FN be the number of Acromegaly cases incorrectly identified as normal. Sensitivity measures the ratio of actual positives which are correctly identified and specificity measures the of ratio negatives which are correctly identified. Accuracy is the proportion of the number of correctly classified samples to the total number of samples. PPV and NPV is the proportion of patients with positive and negative results who are correctly diagnosed. TPF=1 and FPF=0 for an ideal test. Sensitivity, Specificity, Accuracy, PPV and NPV are given as following:

$$Sensivity = TPF = \frac{TP}{TP+FN} \tag{12}$$

$$Specificity = 1 - FPF = \frac{TN}{TN+FP} \tag{13}$$

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{14}$$

$$PPV = \frac{TP}{TP+FP} \tag{15}$$

$$NPV = \frac{TN}{TN+FN} \tag{16}$$

TABLE VI
TPF, 1-FPF, PPV, NPV OF ALL THE CLASSIFIERS
USING LBP (16, 2) COMPONENTS AS INPUT FEATURES.

	TPF Sensitivity	Specificity 1-FPF	PPV	NPV
Weighted Chi-square Classifier	62	83	77	71
Euclidean Classifier	81	100	100	86
Manhattan Classifier	62	100	100	62

TABLE VII
TPF, 1-FPF, PPV, NPV OF ALL THE CLASSIFIERS
USING ILBP (8, 1) COMPONENTS AS INPUT FEATURES.

	TPF Sensitivity	Specificity 1-FPF	PPV	NPV
Weighted Chi-square Classifier	72	100	100	76
Euclidean Classifier	72	100	100	76
Manhattan Classifier	86	100	100	90

TABLE VIII
TPF, 1-FPF, PPV, NPV OF ALL THE CLASSIFIERS
USING CS-LBP (8, 1) COMPONENTS AS INPUT FEATURES.

	TPF Sensitivity	Specificity 1-FPF	PPV	NPV
Weighted Chi-square Classifier	75	94	92	81
Euclidean Classifier	71	94	92	76
Manhattan Classifier	66	94	92	81

The main contribution of this study is that of a new system to yield highest possible accuracy in classification. Table III shows the accuracy of the feature extraction technics, LBP(8,1), LBP(8,2), LBP(16,2), ILBP(8,1) and CSLBP(8,1).

We obtained the highest accuracy of 97% for LBP (8,1) and Manhattan combination.

Table IV, Table V, Table VI, Table VII and Table VIII shows the performance of the classifier according to the feature extraction techniques.

We have performed exhaustive experiments in Table III and shown that LBP (8, 1) features provide highest accuracy (97%) with Manhattan Classifier to discriminate Acromegaly and normal faces. With this, as shown in Table IV, Table V, Table VI, Table VII and Table VIII the best performance of classification sensitivity of 93% specificity 100%, PPV of 100% and NPV of 95% have been obtained with Manhattan Classifier and LBP (8,1) combination.

VI. CONCLUSION

We performed an effective and successful system, automatically pre-diagnosis of Acromegaly. Consequently, the proposed method offers good diagnostic accuracy and automation invariant of pose, illumination, facial expression and gender. Considering of our method's performance, it is a suitable candidate for testing in a clinical environment.

In future work, the system database can be expanded and the developed system can be applied for pre-diagnosis of different visual diseases.

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