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Performance Analysis of LBP& CLBP Based Texture Classification

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ABSTRACT: Texture analysis is important in many applications of computer image analysis for classification or segmentation of images. These applications are based on local spatial variations of intensity or color. For the successful classification or segmentation we require an efficient description of image texture. As the texture classification is being the major problem in texture analysis, in this paper we have proposed an analysis of texture classification characteristics with local binary pattern (LBP) and an associated completed LBP (CLBP) based on conventional LBP. It is proposed that, image features will be extracted from database image using LBP & CLBP descriptor.

KEYWORDS: local binary pattern (LBP),Texture descriptors, feature extraction, texture classification, texture analysis.

I. INTRODUCTION

Texture is a fundamental and important characteristic of the appearance of virtually all natural surfaces. Texture classification is gaining more attention during the past decades, due to its value in understanding the working of texture recognition process in humans, in the field of computervision and pattern recognition. Typical applications of texture classification are medical image analysis and understanding, object recognition, remote sensing, industrial inspection, and document classification. The texture classification problem is generally divided into the two parts. The extraction of powerful texture features is more important for successful texture classification so, most research in texture classification focuses on the feature extraction part.

Among many local texture descriptors, Local Binary Pattern (LBP) has emerged as one of the most prominent and has attracted increasing attention in the field of image processing and computer vision due to its outstanding advantages. Ease of implementation, no need for pre-training and low computational complexity makes LBP a preferred choice for many applications.

The LBP method has been successfully applied to many diverse areas of image processing like dynamic texture recognition, remote sensing, fingerprint matching, visual inspection, image retrieval, biomedical image analysis, face image analysis, motion analysis, edge detection, and environment modeling. Completed LBP (CLBP) is with improved rotation invariance, lower dimensionality & satisfactory discriminative power. Along with the original LBP, CLBP approach combines the information on center pixel, signed differences & magnitude of differences.

Many important applications of texture classification includes industrial and biomedical surface inspection, for example for defects and disease, ground classification as well as segmentation of satellite or aerial imagery, segmentation of textured regions in document analysis, and content-based access to image databases.

II. RELATED WORK

In [1], the authors have proposed a simple, efficient and robust multi-resolution approach to texture classification called binary rotation invariant and noise tolerant (BRINT). The proposed approach is very fast to build and very compact with robustness to illumination variations, rotation changes, and noise.

A local binary descriptor based on the conventional local binary pattern (LBP) approach, preserves the advantageous characteristics of uniform LBP in which points are sampled in a circular neighborhood, with number of

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bins in a single-scale LBP histogram kept constant and small, so that arbitrarily large circular neighborhoods can be sampled and compactly encoded over a number of scales.

The paper [2] presents a simple and very powerful approach for texture classification which is suitable for large texture database applications. At the feature extraction stage, a small set of random features is extracted from local image patches. Learning and classification are carried out in a compressed domain.

The proposed unconventional random feature extraction is simple; their approach of feature extraction methods involves careful design and complex steps. Experiments are done on each of the CUReT, the Brodatz, and the MSRC databases. This approach leads to significant improvements in classification accuracy with reduced feature dimensionality.

It is presented in [3] that texture features are obtained by generating an estimated global map, which represents the measured intensity similarity between any given image pixel and its surrounding neighbors within a certain window.

The estimated dominant neighborhood similarity is robust to noise and referred to as image dominant neighborhood structure. The global rotation-invariant features are extracted from the generated image dominant neighborhood structure. Features obtained from the local binary patterns (LBPs) are extracted for additional local texture features to the generated features from the dominant neighborhood structure.

The experimental results show that proposed method is robust to noise and can achieve significant classification accuracy in comparison to the LBP method. In addition, the method classification accuracy is comparable to the two recent LBP extensions: dominant LBP and completed LBP.

The paper [4] is based on investigation of material classification from single images obtained under unknown viewpoint and illumination is obtained. They have shown that materials can be classified using the joint distribution of intensity values over extremely compact neighborhoods as small as 3 _ 3 pixels square and classification is done using filter banks with large support. The developed novel texton based representation is well suited to modeling this joint neighborhood distribution for Markov random fields.

The representations are learned from training images and then used to classify novel images (with unknown viewpoint and lighting) into texture classes. Three such representations are proposed and their performance is compared to that of filter banks.

The paper [5] presents a theoretically very simple, efficient, multi-resolution approach to gray-scale and rotation invariant texture classification based on local binary patterns. The method is based on recognizing that certain local binary patterns, termed uniform are fundamental properties of local image texture and their occurrence histogram is proven to be a very powerful texture feature.

The focus of paper [6] is on the image processing aspects and in particular using texture information for browsing and retrieval of large image data. They have proposed the use of Gabor wavelet features for texture analysis and give comprehensive experimental evaluation. The Gabor features provides the best pattern retrieval accuracy as compared with other multi-resolution texture features using the Brodatz texture database.

III. LOCAL BINARY PATTERN (LBP)

Local Binary Pattern (LBP) is most popular due to its computational simplicity and good performance. The original LBP method, characterizes the spatial structure of a local image texture by thresholding neighborhood with the value of the center pixel and considering only the sign information to form a local binary pattern. In the original LBP method, a local image texture is thresholded in a 3 × 3 square neighborhood with the value of the center pixel (xc) and considering only the sign information to form a local binary pattern.

Given a pixel xcin the image, the LBP pattern is computed by comparing itsvalue with those of its p neighboring pixelswhich are evenly distributed in an angle with radius r.

$$x_{r,p} = [x_{r,p,0,\dots\dots,} xr,p,p-1]^T$$

So, the LBP operator takes the following form:

$$\sum_{n=0}^{p-1} s(x_{r,p,n} - x_c)2^n \ , \ s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases}$$

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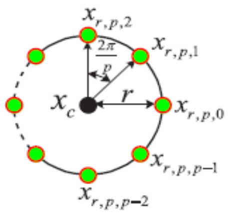
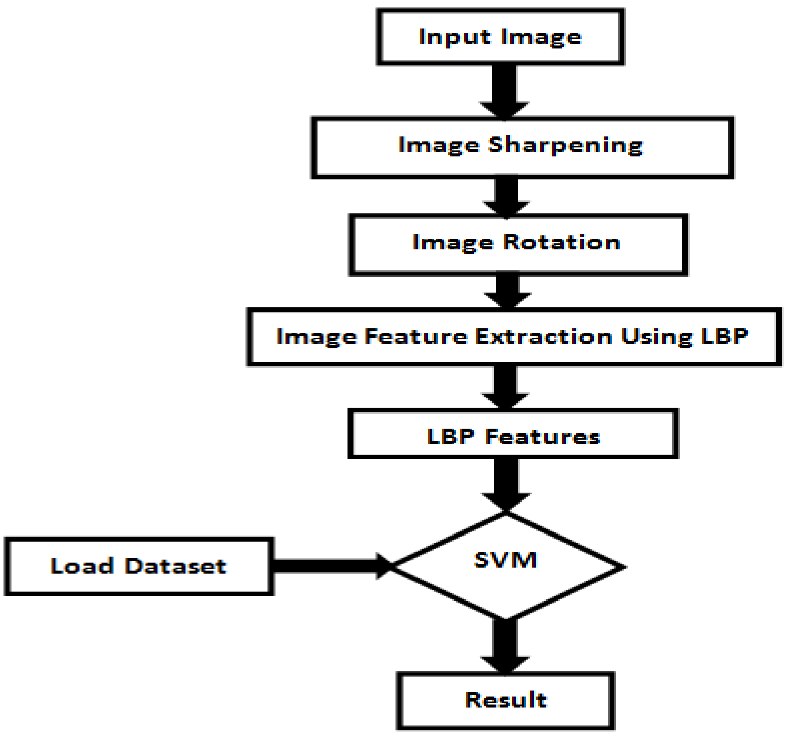


Fig.1: The *(r, p)* neighborhood type used to derive a LBP like operator: central pixel and its *p* circularly and evenly spaced neighbors on circle of radius *r*.

IV. FLOW CHART OF LOCAL BINARY PATTERN (LBP)

For proposed analysis we have trained the SVM classifier for 90 texture images which are of from 10 different texture samples rotated at different angles. The input image is then preprocessed with image sharpening and provided with rotation at angles of 0^o,30^o,45^o,90^o. The texture features of the preprocessed image are extracted using LBP method to get the LBP feature vector in the form of histogram. This histogram is given to the SVM classifier for texture classification.



V. COMPLETELOCAL BINARY PATTERN (CLBP)

Completed Local Binary Patterns (CLBP) consists of three LBP-like descriptors: CLBP_C, CLBP_S and CLBP_M which include information on the center pixel, signed differences, and magnitudes of differences, respectively. The CLBP_S descriptor is same as the original LBP descriptor while CLBP_C thresholds the central pixel against the global means gray value of the whole image.

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CLBP_M performs a binary comparison between the absolute value of the difference between the central pixel and its neighbors and a global threshold to generate anLBP-like code. The sign component preserves the information of local difference. The magnitude component contributes additional discriminant information. Also, the intensity valueof the center pixel itself can also contribute useful information. The original image is presented as its center gray level (C) and the local difference. So, CLBP_C, CLBP_S and CLBP_M, can be codedthe C, S, and M features, respectively.

The CLBP_C, CLBP_S, and CLBP_M codes together form the CLBP feature map of the original image. A CLBP histogram can be built, and some classifier as Support Vector Machine can be used for texture classification. The CLBP_S operator is the same as the original LBP operator. Instead of the binary 1 and -1 values, the M components are of continuous values and they cannot be directly coded as that of S. we define the following CLBP_M operator as:

$$CLBP\_M_{P,R} = \sum_{p=0}^{P-1} t(mp, c)2$$

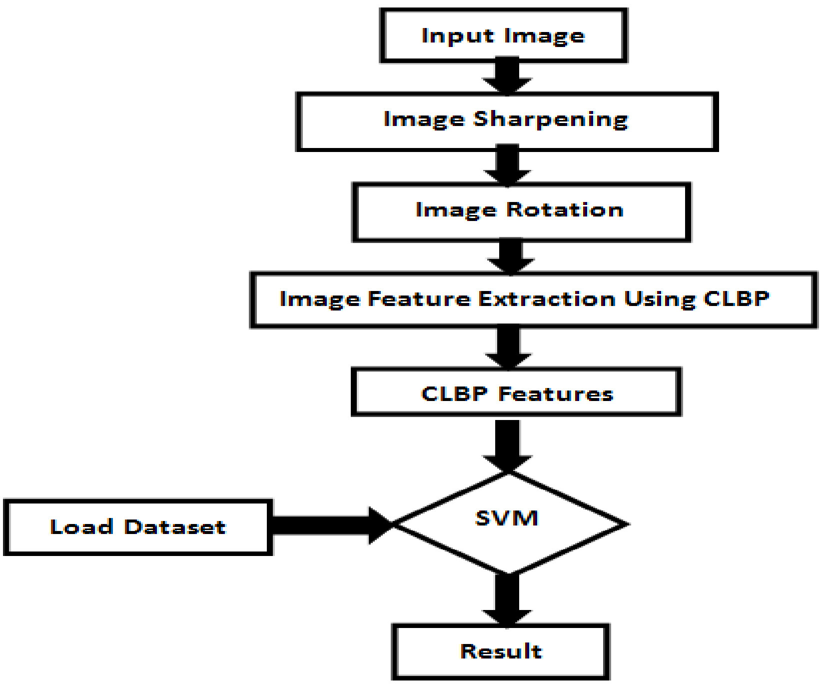
Where c is a threshold that is to be determined adaptively, we set it as the mean value of *mp*from the whole image. Both CLBP_S and CLBP_M produce binary strings so as to use themconveniently together for pattern classification. The center pixel, which expresses the image local gray level, also has discriminant information. To make it consistent with CLBP_S and CLBP_M, we code it as,

$$CLBP\_C_{P,R} = t(gc, c_1)$$

Where c1 is set as the average gray level of the whole image, the three operators, CLBP_S, CLBP_M, and CLBP_C, could be combined in two ways, jointly or hybrid.

VI. FLOW CHART OF COMPLETE LOCAL BINARY PATTERN (CLBP)

For proposed analysis we have trained the SVM classifier for 90 texture images which are of from 10 different texture samples rotated at different angles. The input image is then preprocessed with image sharpening and provided with rotation at angles of 0°,30°,45°,90°. The texture features of the preprocessed image are extracted using LBP method to get the LBP feature vector in the form of histogram. This histogram is given to the SVM classifier for texture classification.



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VII. SUPPORT VECTOR MACHINE(SVM) CLASSIFIER

Classifying data is a common task in machine learning. Support vector machines (SVM) are supervised learningmodels with associated learning algorithms that analyze thedata used for classification analysis. For given a set of training examples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, which makes it a non-probabilistic binarylinear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall.

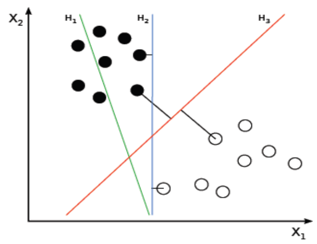

Fig 2. maximum-margin hyper-plane

There are many hyper-planes that might classify the data. One reasonable choice as the best hyper-plane is the one that represents the largest separation, or margin, between the two classes. So we choose the hyper-plane so that the distance from it to the nearest data point on each side is maximized. If such a hyper-plane exists, it is known as the maximum-margin hyper-planeand the linear classifier it defines is known as a maximum margin classifier.

VIII. PROPOSED WORK

The proposed work is as follows:

1. As shown in fig.1 extraction of image from the database.
2. Pre-processing and Image Feature extraction using Local Binary Pattern (LBP)
3. Training of SVM Classifier by LBP feature vector in the form of histogram.
4. Selection of any random input image and its pre-processing.
5. Image Feature extraction using Local Binary Pattern (LBP)
6. Based on the training SVM and depending on optimal marginal distance, classification of the input image as one of its classes.
7. Same procedure repeated for Completed Local Binary Pattern (CLBP)

Performance is analyzed by determination of classification accuracies of both LBP and CLBP in the form of graph.

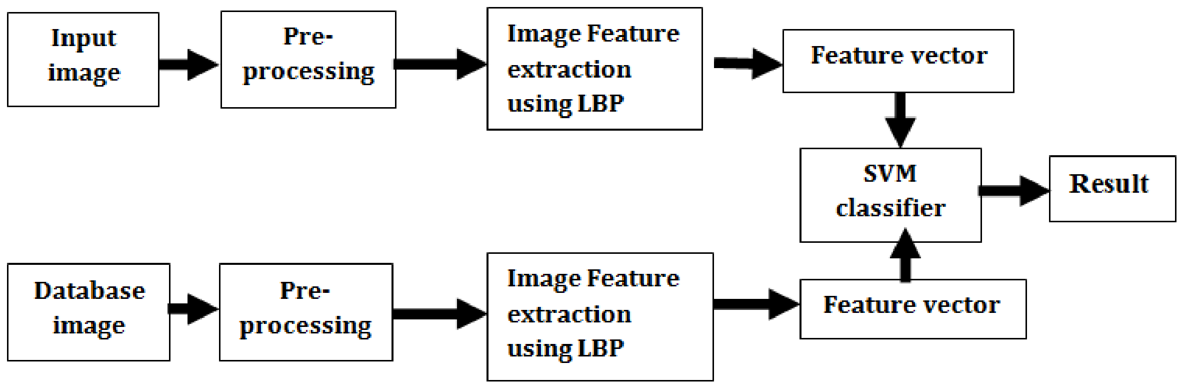

Fig.3.Block diagram of proposed system for Image classification using LBP

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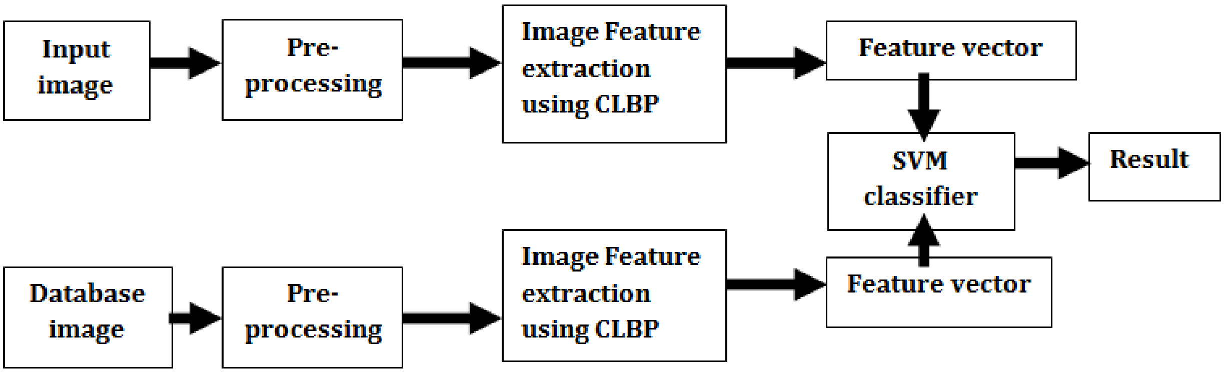

Fig.4.Block diagram of system for Image classification using CLBP

VIII. EXPERIMENTAL RESULTS

The proposed analysis of LBP &CLBP-based texture classification has been evaluated against a benchmark texture image database, namely the Brodatz album. The experimental dataset included a total of 90 gray-scale images. The images are from 10 different texture classes. The source images were rotated to obtain 7 different rotation angles of 0°, 30°, 60°, 90°, 120°, 150°, and 200°. The dataset included 9 images for each rotation angle of a texture class.

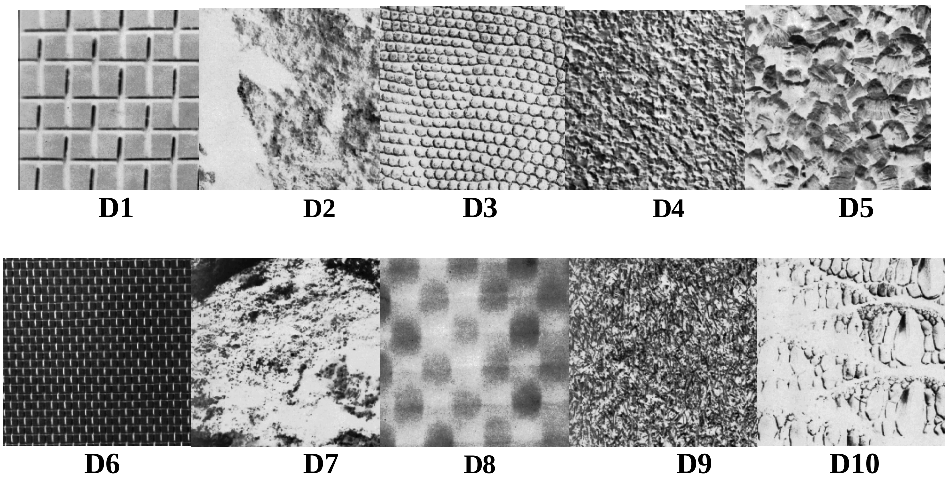

Figure 5: Sample images of 10 texture classes used for experiment.

In our experiment, half of the images in each class were used to train the classifier and the remaining images were used as the testing sets. Therefore, both the training and the testing dataset included 90 texture images of different rotation angles as 0^0, 30^0,60^0,90^0,120^0,$150^0$and 200^0. We have compared the proposed method in terms of classification rate with widely-used local texture operators, namely Local Binary Pattern (LBP), Complete Local Binary Pattern Sign (CLBP_S), Complete Local Binary Pattern Magnitude (CLBP_M) and Complete Local Binary Pattern Center (CLBP_C). Support vector machine was used for the classification task. Results obtained from the experiments are shown in Table 1.

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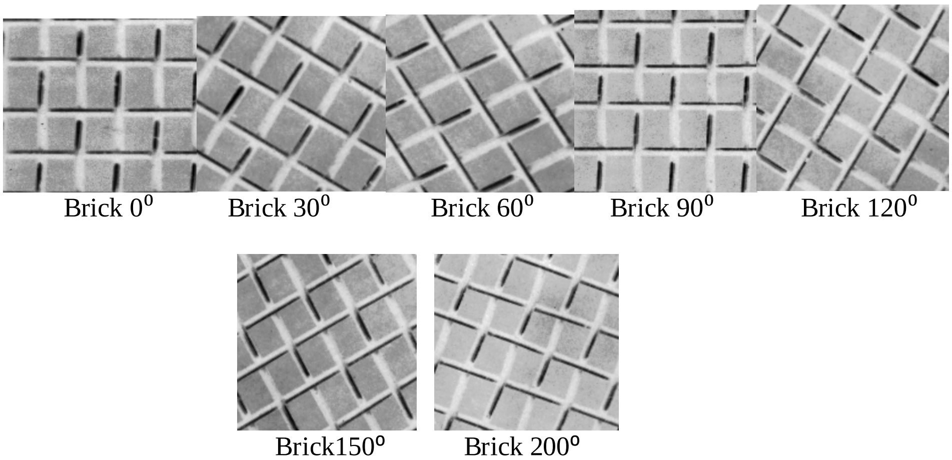

Figure 6: Sample images of a texture class digitized at different rotation angles.

The classification rate of proposed LBP and CLBP feature description methods can be influenced by adjusting two parameters as the number of selected neighbors *P* and the radius *R* of the local neighborhood. So, proposed system evaluates the performance of LBP and CLBP method for different parameter values to find the optimal parameter setting. It can be observed that, CLBP provides the highest classification rate of 56.73% for the parameter setting (*P*, *R*) = (8, 1). The highest classification rate obtained for different texture operators using the optimal parameter settings is shown in table 1.

From the experimental results, it is seen that the texture feature representation based on complete local binary pattern is more robust and provides higher classification rate than LBP method for texture feature representation. It is evident that the superiority of the CLBP encoding is due to the utilization of the magnitude of the difference between the center and the neighbor gray values which are combined with the basic LBP pattern. It can be considered as a compensation for the texture information which was discarded by the LBP operator. So, this method provides an effective and efficient approach to rotation invariant texture classification which is more discriminative than the original LBP operator.

For 10 different texture samples mentioned in fig 4, the classification accuracies have been calculated. Fig. 6 shows the graphical representation of obtained % accuracies.

	LBP	CLBP_S	CLBP_M	CLBP_C
sample 1	53.57	53.57	75	75
sample 2	39.28	39.28	57.14	57.14
sample 3	57.15	57.15	46.43	46.43
sample 4	32.14	32.14	39.29	39.29
sample 5	42.86	42.86	67.86	67.86
sample 6	35.72	35.72	39.26	39.26
sample 7	71.42	71.42	71.43	71.43
sample 8	46.42	46.42	67.86	67.86
sample 9	64.28	64.28	42.86	42.86
sample 10	57.15	57.15	60.72	60.72

Table 1.classificaton % of each sample image

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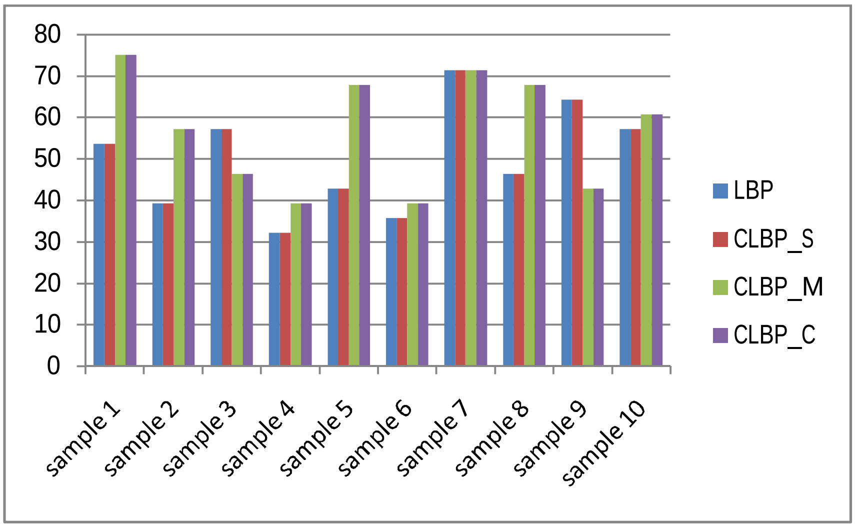

Fig.7Graphical representation of obtained % accuracies

IX. CONCLUSION

This paper describes the analysis of texture classification accuracies of LBP and CLBP. The proposed CLBP method utilizes an encoding scheme which combines the magnitude information of the difference between two gray values with the original LBP pattern and provides increased robustness in many situations where LBP fails to generate consistent codes. Experimental results show that, the CLBP operator provides an effective and efficient approach for representing texture information with high discriminative ability, which is computationally efficient and robust against rotation effects.

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