

# Face Recognition using LBP-LCP Coefficient Vectors with SVM Classifier

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**Abstract** – Face recognition applications are continuously gaining demands because of their requirements in person authentication, access control and surveillance systems. The researchers are continuously working for making the system more accurate and faster. As a part of that research this paper presents an in depth analysis of face recognition system based on Local Binary Pattern (LBP), Local Configuration Pattern (LCP) features with Support Vector Machine (SVM) as classifier. Finally the both techniques with their three variants named uniform, rotation invariant and uniform, rotation invariant are implemented and comprehensively analyzed for their efficiency we also compared these feature extraction method with their variants.

**Keywords** – Face Recognition, Support Vector Machine (SVM), Local Binary Pattern (LBP), Local Configuration Pattern (LCP).

## I. INTRODUCTION

Continuously increasing security demands are forcing the scientists and researchers to develop robust and advanced security systems. Although presently many type of systems are in progress one of them is biometric security which has already proven its effectiveness and considered as most secured and applicable system. This system is particularly preferred or adapted because of its proven natural uniqueness and eliminates the need of carrying additional devices like cards, remote etc. the biometric security systems refers to the identification of humans by their characteristics or traits. Presently the Biometric systems are largely used for identification and access control. There are many human characteristics which can be used for biometric identification such that finger print, palm, iris and face etc. amongst them the face is relatively advantageous because of it can be detected from much more distance without need of special sensors or scanning devices this provides easy observation and capability to identify individuals in group of persons.

There are several methods are proposed so far for the face recognition system using different feature extraction techniques or different training approaches or different classification approaches to improve the efficiency of the system. The rest of the paper is arranged as the second section presents a short review of the work done so far, the third section presents the details of technical terms used in the algorithm, the fourth section presents proposed algorithm followed by analysis and conclusion in next chapters.

## II. RELATED WORK

This section presents some of the most relevant literatures available. IgnasKukenys and Brendan McCane

[2] describe a component-based face detector using support vector machine classifiers. The authors presented current results and outline plans for future work required to achieve sufficient speed and accuracy to use SVM classifiers in an online face recognition system. Their proposal utilizes straightforward approach in implementing SVM classifier with a Gaussian kernel that detects eyes in grayscale images, a first step towards a component-based face detector. Details on design of an iterative bootstrapping process are provided, and training parameter values are analyzed to give best results. Jixiong Wang et al [11] presented a detailed report on using support vector machine (SVM) and application of different kernel functions (Linear kernel, Polynomial kernel, Radial basis kernel, and sigmoid kernel), multiclass classification methods and parameter optimization. YimoGuo et al [1] proposed FSC-based learning (FBL)-LBP descriptor for representing the image structure. TimoOjala et al [4] presented generalizations to the gray scale and rotation invariant texture classification method based on local binary patterns (LBP). They derive a generalized presentation that allows for realizing a gray scale and rotation invariant LBP operator for any quantization of the angular space and for any spatial resolution, and presented a method for combining multiple operators for multi-resolution analysis. The application of LBP for facial expression recognition is proposed in [6] in their proposal, the textures are modeled with volume local binary patterns (VLBP), which are an extension of the LBP operator widely used in ordinary texture analysis, combining motion and appearance. TimoAho et al [7] proposed Local Binary Pattern Histogram Fourier features (LBP-HF) unlike most other histogram based invariant texture descriptors which normalize rotation locally, the proposed invariants are constructed globally for the whole region to be described. In addition to being rotation invariant, the LBP-HF features retain the highly discriminative nature of LBP histograms. Antony Lam and Christian R. Shelton [9] presented a support vector machine (SVM) based system that learns the relations between corresponding local regions of the face in different poses as well as a simple SVM based system for automatic alignment of faces in differing poses. A global versus component based approach for face recognition with Support Vector Machines is presented by Bernd Heisele et al [10]. In the component system they first locate facial components, extract them and combine them into a single feature vector which is classified by a Support Vector Machine (SVM).

## III. LBP ESTIMATION

Local binary patterns (LBP) is a type of feature 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. It has since been found to be a powerful feature for texture classification.

LBP's are usually extracted in a circularly symmetric neighborhood by comparing each image pixel with its neighborhood.

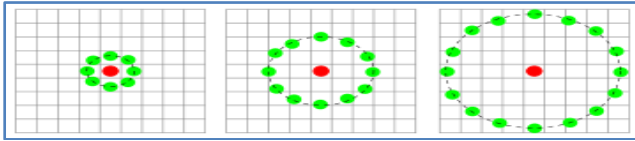


Fig.1. LBP Calculation for three different neighbors

The LBP feature vector, in its simplest form, is created in the following manner:

- Divide the examined window into cells (e.g. 16x16 pixels for each cell).
- For each pixel in a cell, compare the pixel to each of its 8 neighbors (on its left-top, left-middle, left-bottom, right-top, etc.). Follow the pixels along a circle, i.e. clockwise or counter-clockwise.
- Where the center pixel's value is greater than the neighbor's value, write "1". Otherwise, write "0". This gives an 8-digit binary number (which is usually converted to decimal for convenience).
- 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 center).
- Optionally normalize the histogram.

Concatenate (normalized) histograms of all cells. This gives the feature vector for the win. The LBP feature vector, in its simplest form, is created in the following manner

#### IV. LCP ESTIMATION

LCP feature decomposes the information architecture of images into two levels, as shown in Figure 2 [3]:

1. Local structural information
2. Microscopic configuration information

For local structural information, LBP is utilized while a microscopic configuration information involves image configuration and pixel-wise interaction relationships

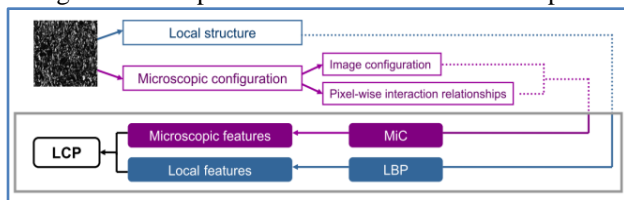


Fig.2. LCP Estimation Structure.

A microscopic configuration model (MiC) is developed to obtain microscopic features which reflect textural properties.

Modeling of microscopic configuration. To model the image configuration with respect to each pattern, we estimate optimal weights, associating with intensities of neighboring pixels, to linearly reconstruct the central pixel intensity. The detailed explanation of LBP and LCP is presented by YimoGuo et al [3].

#### V. SUPPORT VECTOR MACHINE (SVM)

Support Vector Machines (SVMs) have developed from Statistical Learning Theory [6]. They have been widely applied to fields such as character, handwriting digit and text recognition, and more recently to satellite image classification. SVMs, like ASVM and other nonparametric classifiers have a reputation for being robust. SVMs function by nonlinearly projecting the training data in the input space to a feature space of higher dimension by use of a kernel function. This results in a linearly separable dataset that can be separated by a linear classifier. This process enables the classification of datasets which are usually nonlinearly separable in the input space. The functions used to project the data from input space to feature space are called kernels (or kernel machines), examples of which include polynomial, Gaussian (more commonly referred to as radial basis functions) and quadratic functions. By their nature SVMs are intrinsically binary classifiers however there are strategies by which they can be adapted to multiclass tasks. But in our case we do not need multiclass classification

##### 5.1 SVM Classification

Let  $x_i \in R^m$  be a feature vector or a set of input variables and let  $y_i \in \{+1, -1\}$  be a corresponding class label, where  $m$  is the dimension of the feature vector. In linearly separable cases a separating hyper-plane satisfies

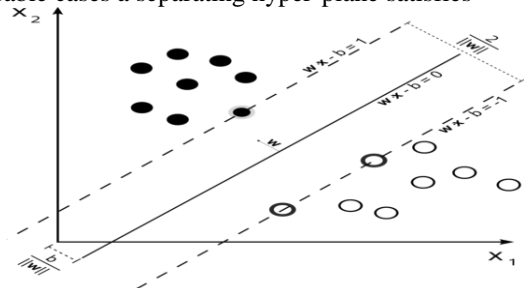


Fig.3. Maximum-margin hyper-plane and margins for an SVM trained with samples from two classes. Samples on the margin are called the support vectors.

$$y_i(\langle w, x_i \rangle + b) \geq 1, i = 1 \dots n, \dots (1)$$

Where the hyper-plane is denoted by a vector of weights  $w$  and a bias term  $b$ . The optimal separating hyper-plane, when classes have equal loss-functions, maximizes the margin between the hyper-plane and the closest samples of classes. The margin is given by

$$d(w, b) = \min_{x_i, y_i=1} \frac{|\langle w, x_i \rangle + b|}{\|w\|} + \min_{x_i, y_i=-1} \frac{|\langle w, x_i \rangle + b|}{\|w\|} = \frac{2}{\|w\|} \dots (2)$$

The optimal separating hyper-plane can now be solved by maximizing (2) subject to (1). The solution can be found using the method of Lagrange multipliers. The objective is now to minimize the Lagrangian

$$L_p(w, b, a) = \frac{1}{2} \|w\|^2 - \sum_{i=1}^l \alpha_i y_i (\langle w, x_i \rangle + b) + \sum_{i=1}^l \alpha_i \dots (3)$$

and requires that the partial derivatives of  $w$  and  $b$  be zero. In (3),  $\alpha_i$  is nonnegative Lagrange multipliers. Partial

derivatives propagate to constraint  $sw = \sum_i \alpha_i y_i x_i$  and  $\sum_i \alpha_i y_i = 0$ . Substituting  $w$  in to (3) gives the dual form

$$L_d(w, b, a) = \sum_{i=1}^l \alpha_i - \frac{1}{2} \sum_{i,j=1}^l \alpha_i \alpha_j y_i y_j \langle x_i, x_j \rangle \dots (4)$$

which is not anymore an explicit function of  $w$  or  $b$ . The optimal hyper-plane can be found by maximizing (4) subject to  $\sum_i \alpha_i y_i = 0$  and all Lagrange multipliers are nonnegative. However, in most real world situations classes are not linearly separable and it is not possible to find a linear hyperplane that would satisfy (1) for all  $i = 1, \dots, n$ . In these cases a classification problem can be made linearly separable by using a nonlinear mapping into the feature space where classes are linearly separable. The condition for perfect classification can now be written as  $y_i (\langle w, \phi(x_j) \rangle + b) \geq 1, i = 1, \dots, n, \dots (5)$

where  $\phi$  is the mapping into the feature space. Note that the feature mapping may change the dimension of the feature vector. The problem now is how to find a suitable mapping  $\phi$  to the space where classes are linearly separable. It turns out that it is not required to know the mapping explicitly as can be seen by writing (5) in the dual form

$$y_i \left( \sum_{j=1}^l \alpha_j y_j \langle \phi(x_j), \phi(x_i) \rangle \right) + b \geq 1, i = 1, \dots, n \dots (6)$$

and replacing the inner product in (6) with a suitable kernel function  $k(x_j, x_i) = \langle \phi(x_j), \phi(x_i) \rangle$ . This form arises from the same procedure as was done in the linearly separable case that is, writing the Lagrangian of (6), solving partial derivatives, and substituting them back into the Lagrangian. Using a kernel trick, we can remove the explicit calculation of the mapping  $\phi$  and need to only solve the Lagrangian (5) in dual form, where the SVM product  $(x_j, x_i)$  has been transposed with the kernel function in nonlinearly separable cases. In the solution of the Lagrangian, all data points with nonzero (and nonnegative) Lagrange multipliers are called support vectors (SV).

Often the hyper plane that separates the training data perfectly won't. The slack variable is adjusted by the regularization constant  $C$ , which determines the tradeoff between complexity and the generalization properties of the classifier. This limits the Lagrange multipliers in the dual objective function (5) to the range  $0 \leq \alpha_i \leq C$ . Any function that is derived from mappings to the feature space satisfies the conditions for the kernel function.

The choice of a Kernel depends on the problem at hand because it depends on what we are trying to model. The SVM gives the following advantages over neural networks or other AI methods (link for more details <http://www.svms.org>).

SVM training always finds a global minimum, and their simple geometric interpretation provides fertile ground for further investigation.

Most often Gaussian kernels are used, when the resulted SVM corresponds to an RBF network with Gaussian radial basis functions. As the SVM approach "automatically" solves the network complexity problem, the size of the hidden layer is obtained as the result of the QP procedure. Hidden neurons and support vectors correspond to each other, so the center problems of the RBF network is also solved, as the support vectors serve as the basis function centers.

Classical learning systems like neural networks suffer from their theoretical weakness, e.g. back-propagation usually converges only to locally optimal solutions. Here SVMs can provide a significant improvement. The absence of local minima from the above algorithms marks a major departure from traditional systems such as neural networks. SVMs have been developed in the reverse order to the development of neural networks (SVMs). SVMs evolved from the sound theory to the implementation and experiments, while the SVMs followed more heuristic path, from applications and extensive experimentation to the theory

$$y_i (\langle w, \phi(x_j) \rangle + b) \geq 1, i = 1, \dots, n, \dots (7)$$

## VI. PROPOSED ALGORITHM

The proposed algorithm can be described in following steps.

1. Firstly divide the image into NxN blocks
2. Now select any of the variants from uniform, rotation invariant and uniform rotation invariant depending upon the variants to be used.
3. Take the LBP or LCP of the image depending upon the technique to be used.
4. Like above step these vectors are created for all classes of faces.
5. These vectors are used to train the  $N*(N-1)/2$  (N number of classes) SVM classifiers as we used one against one method.
6. For detection purpose the input image vectors are calculated in same way as during training and then it is applied on each classifier.
7. Finally the decision is made on the basis of majority of class returned by  $N*(N-1)/2$  vectors.

## VII. SIMULATION RESULT

We used the ORL database for testing of our algorithm. The ORL database contains 40 different faces with 10 samples of each face. The accuracy of the algorithm is tested for different number of faces, samples and vector length.

The comparison of the different variants of LBP and LCP method with SVM. For all test results the total 10 faces with 10 samples each are used although the training samples are from 5 to 10.

Table 1: LBP-U, SVM Results

Samples	Training Time (sec.)	Matching Time (sec.)	TPR	TNR	FPR	FNR	Accuracy	Precision	Recall	F-Measure
5	0.3203	0.0213	0.57	0.9522	0.0478	0.43	0.914	0.9189	0.57	0.6484
6	0.1634	0.0216	0.67	0.9633	0.0367	0.33	0.934	0.9233	0.67	0.7348
7	0.1948	0.0209	0.76	0.9733	0.0267	0.24	0.952	0.9294	0.76	0.8062
8	0.1891	0.0211	0.84	0.9822	0.0178	0.16	0.968	0.9385	0.84	0.8673
9	0.1977	0.0229	0.93	0.9922	0.0078	0.07	0.986	0.9588	0.93	0.9372
10	0.1973	0.0225	1	1	0	0	1	1	1	1

Table 2: LBP-RI, SVM Results

Samples	Training Time (sec.)	Matching Time (sec.)	TPR	TNR	FPR	FNR	Accuracy	Precision	Recall	F-Measure
5	0.1577	0.0206	0.55	0.95	0.05	0.45	0.91	0.9182	0.55	0.6308
6	0.1625	0.0209	0.66	0.9622	0.0378	0.34	0.932	0.9227	0.66	0.7267
7	0.1719	0.0208	0.74	0.9711	0.0289	0.26	0.948	0.9278	0.74	0.7912
8	0.2083	0.0215	0.83	0.9811	0.0189	0.17	0.966	0.937	0.83	0.8599
9	0.207	0.0225	0.91	0.99	0.01	0.09	0.982	0.9526	0.91	0.9216
10	0.2254	0.0218	1	1	0	0	1	1	1	1

Table 3: LBP-URI, SVM Results

Samples	Training Time (sec.)	Matching Time (sec.)	TPR	TNR	FPR	FNR	Accuracy	Precision	Recall	F-Measure
5	0.2102	0.0254	0.8	0.9778	0.0222	0.2	0.96	0.864	0.8	0.8025
6	0.2185	0.0193	0.82	0.98	0.02	0.18	0.964	0.8556	0.82	0.8192
7	0.2555	0.0205	0.86	0.9844	0.0156	0.14	0.972	0.8751	0.86	0.8586
8	0.2688	0.0212	0.93	0.9922	0.0078	0.07	0.986	0.9376	0.93	0.93
9	0.2675	0.0217	0.97	0.9967	0.0033	0.03	0.994	0.9718	0.97	0.9699
10	0.3084	0.0219	1	1	0	0	1	1	1	1

Table 4: LCP-U, SVM Results

Samples	Training Time (sec.)	Matching Time (sec.)	TPR	TNR	FPR	FNR	Accuracy	Precision	Recall	F-Measure
5	0.3127	0.0198	0.56	0.9511	0.0489	0.44	0.912	0.8574	0.56	0.6167
6	0.179	0.0202	0.65	0.9611	0.0389	0.35	0.93	0.8702	0.65	0.6987
7	0.168	0.0195	0.75	0.9722	0.0278	0.25	0.95	0.837	0.75	0.7651
8	0.196	0.02	0.84	0.9822	0.0178	0.16	0.968	0.9217	0.84	0.861
9	0.2034	0.0203	0.91	0.99	0.01	0.09	0.982	0.9526	0.91	0.9216
10	0.1979	0.0209	1	1	0	0	1	1	1	1

Table 5: LCP-RI, SVM Results

Samples	Training Time (sec.)	Matching Time (sec.)	TPR	TNR	FPR	FNR	Accuracy	Precision	Recall	F-Measure
5	0.17	0.0188	0.56	0.9511	0.0489	0.44	0.912	0.9022	0.56	0.6359
6	0.1656	0.0193	0.66	0.9622	0.0378	0.34	0.932	0.9227	0.66	0.7267
7	0.1803	0.019	0.76	0.9733	0.0267	0.24	0.952	0.9192	0.76	0.8026
8	0.1991	0.0204	0.82	0.98	0.02	0.18	0.964	0.9357	0.82	0.8526
9	0.1975	0.0209	0.91	0.99	0.01	0.09	0.982	0.9526	0.91	0.9216
10	0.2071	0.0213	1	1	0	0	1	1	1	1

Table 6: LCP-URI, SVM Results

Samples	Training Time (sec.)	Matching Time (sec.)	TPR	TNR	FPR	FNR	Accuracy	Precision	Recall	F-Measure
5	0.157	0.0193	0.56	0.9511	0.0489	0.44	0.912	0.9022	0.56	0.6359
6	0.1756	0.0195	0.65	0.9611	0.0389	0.35	0.93	0.9222	0.65	0.7187
7	0.1697	0.0205	0.74	0.9711	0.0289	0.26	0.948	0.9278	0.74	0.7912
8	0.1874	0.0198	0.83	0.9811	0.0189	0.17	0.966	0.937	0.83	0.8599
9	0.205	0.0204	0.93	0.9922	0.0078	0.07	0.986	0.9588	0.93	0.9372
10	0.216	0.0209	1	1	0	0	1	1	1	1

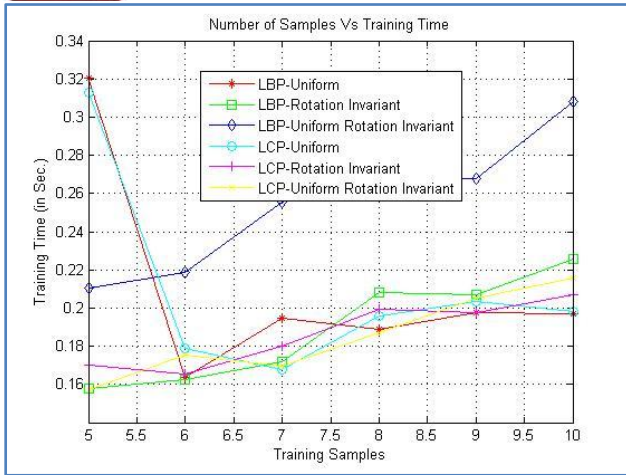


Fig.4. Comparison of training time for all variants of LBP and LCP techniques the graph shows that the LBP-URI takes the highest time while the LCP-URI takes the lowest time

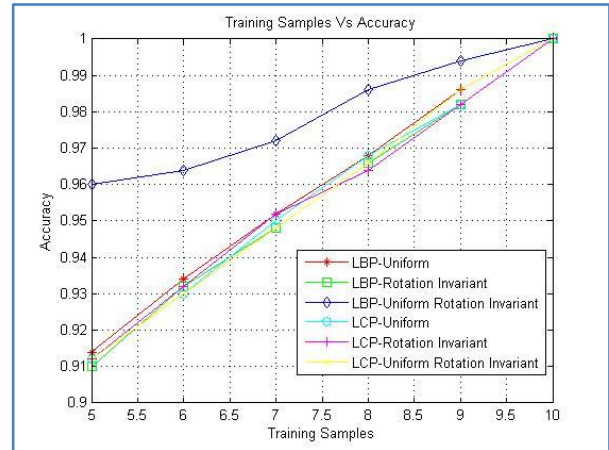


Fig.7. Comparison of Detection Accuracy for all variants of LBP and LCP techniques the graph shows that the LBP-URI gives maximum accuracy.

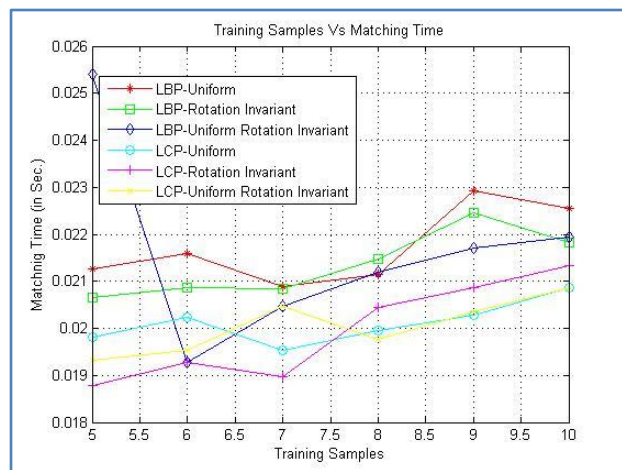


Fig.5. Comparison of matching time for all variants of LBP and LCP techniques the graph shows that the LCP-URI takes the lowest time while the LBP-U takes the highest time.

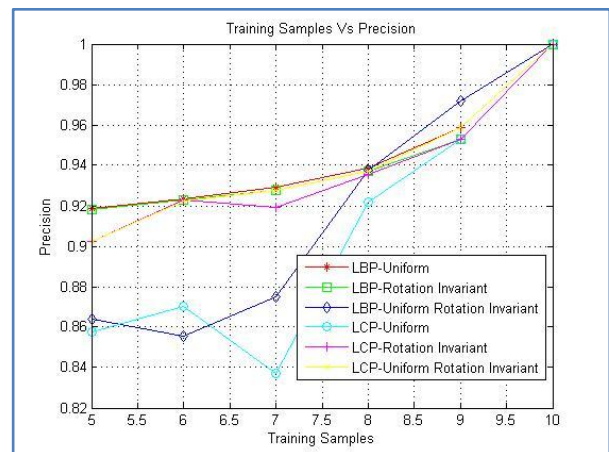


Fig.8. Comparison of Precision for all variants of LBP and LCP techniques the graph shows that the LCP-URI gives best Precision.

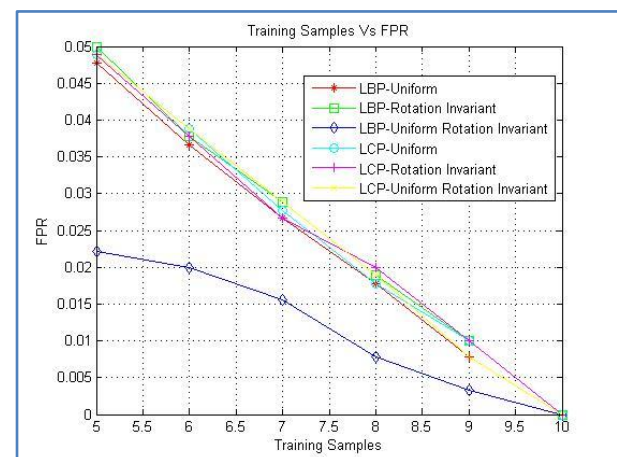


Fig.6. Comparison of False Positive Rate for all variants of LBP and LCP techniques the graph shows that the LBP-URI gives minimum FPR.

## VIII. CONCLUSION

This paper presents a LBP, LCP approaches for feature extraction and during the classification phase, the Support Vector Machine (SVM) is tested for robust decision in the presence of wide facial variations. The experiments that we have conducted on the ORL database indicated that the LCP-SVM method performs better than LBP-SVM when compared for detection precision, training time and detection time but when compared for detection accuracy and FPR the LBP-SVM out performs the LCP-SVM. In this paper we have developed, tested and compared all three variants of LBP-LCP in future we can also compare them with using different kernel functions and learning technique.

## ACKNOWLEDGMENT

First and foremost, I would like to express my profound for given me an opportunity to under go as Thesis work on Face Recognition using LBP - LCP Coefficient Vectors with SVM Classifier. This is part of my M.Tech.

I am Thanks to Mr. Krishnkant Pathak helped me choosing this very relevant topic and guided me throughout the study.

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