FACE RECOGNITION SYSTEM: REVIEW

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Abstract: A Face Recognition System is a technology capable of identifying or verifying a person from a digital image or a video frame from a video source. In today's time it is the fastest mode of technique which is very complicated, interesting and widely used in real time applications. A huge number of face recognition algorithms have been made and developed lasts few years. This paper gives a review on a wide range of methods used for FACE RECOGNITION which includes Algorithm PCA, LDA, ICA, LBP, LDP and EBGM techniques. The challenges for FACE RECOGNITION are like illumination, pose variation, facial expression etc. The objective of this paper is to explain an introduction to the FACE RECOGNITION and it also includes an investigation on recent previous researches for obtaining well equipped and effective method for face recognition.

***Index Terms* - EBGM, Face Recognition, ICA, LBP, LDA, LDP, PCA.**

1. INTRODUCTION

Face Recognition, as the name suggests, is a method to identify and/or verify the identity of a person. Face recognition is an important part of the capability of human perception system and is a routine task for humans, while building a similar computational model of face recognition. The computational model not only contribute to theoretical insights but also to many practical applications like automated crowd surveillance, access control, design of human computer interface (HCI), content-based image database management, criminal identification and so on. The earliest work on face recognition can be traced back at least to the 1950s in psychology and to the 1960s in the engineering literature. Some of the earliest studies include work on facial expression emotions by Darwin. But research on automatic machine recognition of faces started in the 1970s and after the seminal work of Kanade. In 1995, a review paper **[1]** gave a thorough survey of face recognition technology at that time. At that time, video-based face recognition was still in a nascent stage. During the past decades, face recognition has received increased attention and has advanced technically. Many commercial systems for still face recognition are now available. Recently, significant research efforts have been focused on video-based face modelling/tracking, recognition and system integration. New databases have been created and evaluations of recognition techniques using these databases have been carried out. Now, the face recognition has become one of the most active applications of pattern recognition, image analysis and understanding. In the former process, the pre-processed image of a person is compared with face images of known individuals from a large database, the algorithms then return the recognized (and of course correct) identity. While in the later process the pre-processed image of a person is compared with one face image from a database with the claimed identity. The system then returns the verification status by measuring the similarities between the two images. An efficient face recognition system could replace current identification methods like Personal Identification Number (PIN)-codes, passwords and Identification-cards, which according to could be exposed to security attacks, but also extremely reliable methods of biometric person identification, like fingerprint analysis and retinal or iris scans. In contrast, face recognition system is more proficient, accurate and reliable than all the proposed algorithms thus far. The evolution in the field of pattern analysis and computer vision has now opened new horizons for research in commercialized face recognition systems being used by (PCA), Linear Discriminant Analysis (LDA) and the more recent 2-D PCA proffer consistent results in precise environment but have limitations when variation in several factors occur.

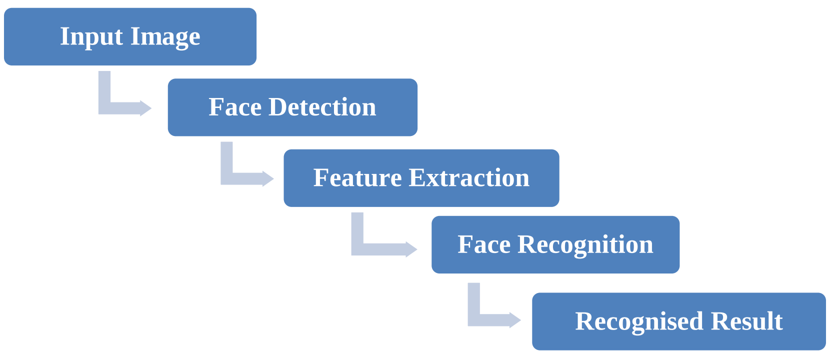

Figure 1: Face Recognition System Flow Chart

Face Recognition composed in few major steps as follows: -

(1) Face detection and processing of image (Image Acquisition)
(2) Feature Extraction
(3) Face Recognition

Brief introduction for the following steps involved in Face Recognition System.

(1) Image Acquisition or Face Detection: - First of all the Image can be static image or image sequences must contain more information than a still static image. 2-D monochrome (grey scale) facial image sequence are the most popular type of pictures used for Artificial Expression Recognition. There are 4 methods by which a face can be detected easily Knowledge Based, Feature Invariant, Template Matching, Appearance Based.

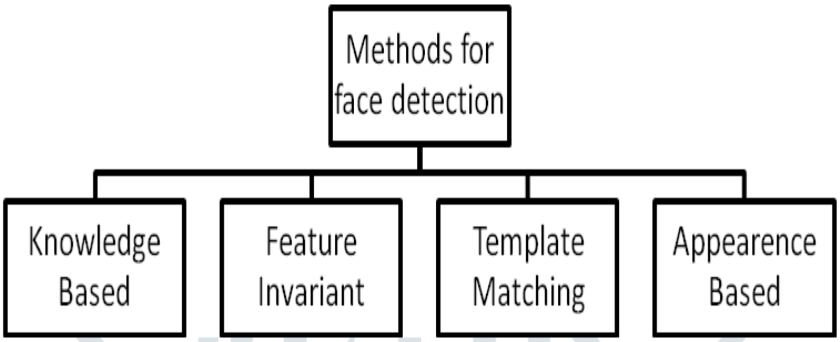

Figure 2: Methods of face detection

(2) Feature Extraction-It converts Pixel Data into a higher-level representation. It reduces the dimensionality of Input Space. It can be done by following the Feature Extraction Techniques. This includes Principal Component Analysis [PCA]Independent Component Analysis, Linear Discriminant Analysis [LDA], ICA, Linear Binary Pattern [LBP] and etc.

Feature Extraction is majorly classified into two parts, which are Global Features and Local Features.

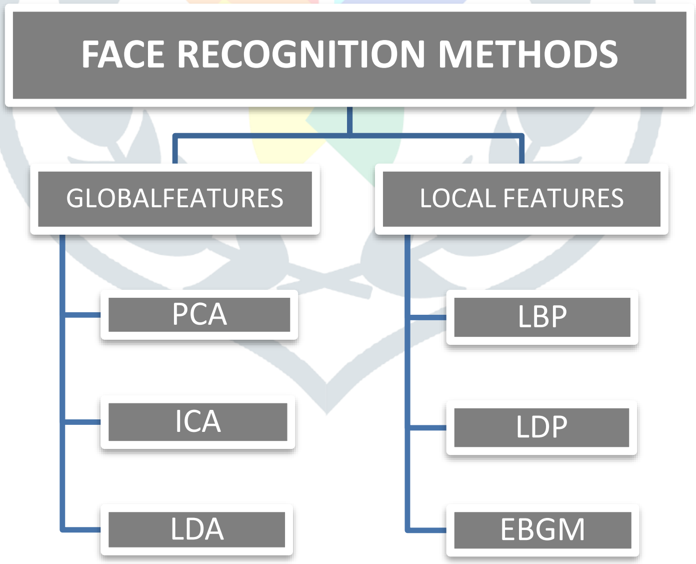

Figure 3: Feature Extraction Methods

2. GLOBAL FEATURES

2.1. PRINCIPAL COMPONENT ANALYSIS (PCA)

PCA is a Karhumen-Loeve transformation. PCA is a recognized linear dimensionality reduction method which determines a set of mutually orthogonal basis functions and uses the leading eigenvectors of the sample covariance matrix to characterize the lower dimensional space. Then Moghaddam et al **[2]** suggested Bayesian PCA method. In this system, the Eigenface Method based on simple subspace-restricted norms are extended to use a probabilistic measure of similarity. Chung et al. **[3]** in his paper suggested another combined approach for recognition using PCA and Gabor Filters.

Their method consists of two phases. Initially to extract facial features he uses Gabor Filter and then use PCA to classify the facial features optimally. Some of the recent PCA-based algorithms discussed as follow: Kernel PCA approaches **[4]** delivers generalizations which take higher order correlations into consideration. This method handles the non-linearity in face recognition and achieve lower error rates. Symmetrical PCA **[5]** in which PCA is combined with even/odd decomposition principle. This approach uses the different energy ratios and sensitivities of even/odd symmetrical principal components for feature selection. Two-dimensional PCA involves framing of a 2-dimensional matrix instead of 1 D vector. Adaptively weighted sub pattern PCA **[6]** involves the division of the original whole image pattern into sub patterns and then the features are obtained from them. The sorting is done by adaptively computing the contributions of each part. Weighted modular PCA **[7]** methods involve partitioning the whole face into different modules or subregions like mouth, nose, eyes and forehead and then the weighted sum of errors of all these regions is found to get the final decision.

2.2. INDEPENDENT COMPONENT ANALYSIS (ICA)

Independent component analysis (ICA) is a method for finding underlying factors or components from multivariate (multidimensional) statistical data. There is need to implement face recognition system using ICA for facial images having face orientations and different illumination conditions, which will give better results as compared with existing systems **[8].** What distinguishes ICA from other methods is that, it looks for component that are both statistically independent and non-gaussian. The ICA is similar to blind source separation problem that boils down to finding a linear representation in which the components are statistically independent. Comparison of face recognition using PCA and ICA on FERET database with different classifiers **[9]** were discussed and found that the ICA had better recognition rate as compared with PCA with statistically independent basis images and also with statistically independent coefficients. Face recognition using ICA with large rotation angles with poses and variations in illumination conditions was proposed in **[10]**. A novel subspace method called sequential row column independent component analysis for face recognition is proposed in **[11].**

In ICA each face image is transformed into a vector before calculating the independent components. RC_ICA reduces face recognition error and dimensionality of recognition subspace becomes smaller. A novel technique for face recognition combined the independent component analysis (ICA) model with the optical correlation technique was proposed in **[12]**. This approach relied on the performances of a strongly discriminating optical correlation method along with the robustness of the ICA model. Independent component analysis (ICA) model had sparked interest in searching for a linear transformation to express a set of random variables as linear combinations of statistically independent source variables. ICA provided a more powerful data representation than PCA as its goal was that of providing an independent rather than uncorrelated image decomposition and representation. A fast-incremental principal non-Gaussian directions analysis algorithm called IPCA_ICA was proposed in **[13].** This algorithm computes the principal components of a sequence of image vectors incrementally without estimating the covariance matrix and at the same time transform these principal components to the independent directions that maximize the non-Guassianity of the source. IPCA_ICA is very efficient in the calculation of the first basis vectors. PCA_ICA achieves higher average success rate than Eigenface, the Fisher face and Fast ICA methods.

2.3. LINEAR DISCRIMINANT ANALYSIS (LDA)

The linear discriminant analysis (LDA) is a powerful method for face recognition. It yields an effective representation that linearly transforms the original data space into a low-dimensional feature space where the data is well separated. However, the within-class scatter matrix (SW) becomes singular in face recognition and the classical LDA cannot be solved which is the under sampled problem of LDA (also known as small sample size problem). A subspace analysis method for face recognition called kernel discriminant locality preserving projections was proposed in **[14]** based on the analysis of LDA, LPP and kernel function. A non-linear subspace which can not only preserves the local facial manifold structure but also emphasizes discriminant information. Combined with maximum margin criterion (MMC) a new method called maximizing margin and discriminant locality preserving projections (MMDLPP) was proposed in **[15]** to find the subspace that best discriminates different face change and preserving the intrinsic relations of the local neighbourhood in the same face class according to prior class label information.

The proposed method was compared with PCA as well as locality preserving projections (LPP) ORL, YALE, YALEB face database and authors had shown that it provides a better representation of class information and achieved better recognition accuracy. Illumination adaptive linear discriminant analysis (IALDA) was proposed in **[16]** to solve illumination variation problems in face recognition. The recognition accuracy of the suggested method (IALDA), far higher than that of PCA method and LDA method. The recognition accuracy of the suggested method was lower than that the Logarithmic Total Variation (LTV) algorithm. However, The LTV algorithm has high time complexity. Therefore, the LTV method is not practically applicable. At the same time, this also indicates that the proposed IALDA method is robust for illumination variations. David Monzo et. al. **[17]** compared several approaches to extract facial landmarks and studied their influence on face recognition problems. In order to obtain fair comparisons, they used the same number of facial landmarks and the same type of descriptors (HOG descriptors) for each approach. The comparative results were obtained using FERET and FRGC datasets and shown that better recognition rates were obtained when landmarks are located at real facial fiducial points. In this work, comparison was done using Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA) and Orthogonal Linear Discriminant Analysis (OLDA) **[18].** OLDA is one of the many variations of LDA which aims to tackle the problem of under sampling. The key idea of OLDA, the discriminant vectors are orthogonal to each other. In [18] Ye provides an efficient way of computing OLDA.

3. LOCAL FEATURES

3.1. LINEAR BINARY PATTERN (LBP)

LBP was introduced by Ojala et al. **[19]** in 1996, is described as an ordered set of binary comparisons of pixel intensities between the centre pixel and its surrounding pixels. It is used for extracting unique and useful features from pre-processed images and is the most efficient and newest approach for face recognition. With LBP it is possible to describe the texture and shape of a digital image. Each pixel of an image is labelled with an LBP code which is obtained by converting the binary code into decimal one. First it will divide the image to several small blocks from which the features are extracted. Then it will start calculating the LBP histograms for each block from the obtained features. After that it will combine all LBP histograms for that image to obtain one concatenated vector. Images can then be compared by measuring the similarity (distance) between their histograms. Several studies and research work **[20]** indicate that face recognition using the LBP method provides very good results with different facial expressions, different lightening conditions, image rotation and aging of persons. Speed and discrimination performance of an LBP system is also magnificent.

The computation procedure of LBP is simple yet efficient: pixels of an image is labelled by thresholding the neighbourhood of the pixel *locally* compared to the pixel itself to a *binary* number. Specially, its feature vector is built by comparing the pixel with each of its neighbouring pixels, and it interpolates values bilinearly at non-integer coordinates. We could use notation (P; R) to signify LBP parameters, which stands for extracting P sampling points on a circle of radius of R. The LBP operator uses a

$$\text{LBP Kernel} - (2R + 1) * (2R + 1) \qquad \text{(i)}$$

Kernel equation (i) to summarize the local image structure. At a given centre, (X_C, Y_C), it takes the (2R +1) * (2R + 1) neighbouring pixels surrounding of the centre pixel. However, R is often assigned to 1, which results in 8 neighbouring pixels excluding the centre itself. If the centre pixel's value is greater than the neighbour's value, mark it with ``1"; mark it with ``0" otherwise. An 8-digit binary number surface depicting local texture pattern. The pattern is then transformed into a decimal number by multiplying each digit by powers of two and sum. Given an image I and denoting i_c as the grey level of the pixel c of the image I, the LBP operator on this pixel is defined in equation (ii) as:

$$\text{LBP}_{(P,\,R)} = \sum_{p=1}^{p=1} s(i_p - i_c)2^{p}, \text{ with } s(x)=\begin{cases} 1 \ \ if\ x \geq 0; \\ 0\ otherwise; \end{cases} \qquad \text{(ii)}$$

For each image, the histogram is computed showing the frequency of each occurring number. For LBP codes with 8 neighbours, the histogram should have 2^8= 256 bins, thus the range of LBP is from 0 to 255. An important property of the LBP operator is its *invariance to monotonic photometric change* caused probably by illumination variations. Though LBP could be directly used in face recognition, there are approaches to form a robust feature based on LBP. Feature fusion is one particular example: images blocks are often used and histograms over cells are fused. Other notifying and used extension are the *uniform pattern* **[21].**

$$\text{LBP}_{P,R} = \begin{cases} \sum_{p=1}^{p=1} s(i_p - i_c) & if\ U(LBP_{P,R}) \leq 2; \\ P+1 & otherwise \end{cases}, \qquad \text{(iii)}$$

Where, U is a uniform measure defined as the number of spatial transitions (or bitwise 0/1 or 1/0 changes) in the binary pattern.

According to this formula, LBPs with U value up to 2 are defined as *uniform patterns* and their labels are accumulated respectively (there are 58 of them), while non-uniform patterns are grouped into a single bin in the histogram. This idea originated from the fact that certain binary patterns occur more commonly in texture images than others. LBPs assign separate bins for every uniform pattern in a histogram, while all non-uniform patterns are assigned to a single bin. With uniform patterns, the length of the histogram with 8 neighbours reduce from 256 to 59, and the code is robust to noise. Uniform LBP is widely used in face recognition **[22]-[29].**

3.2. LOCAL DIRECTIONAL PATTERN (LDP)

The proposed Local Directional Pattern (LDP) is an eight-bit binary code assigned to each pixel of an input image. This pattern is calculated by comparing the relative edge response value of a pixel in different directions. For this purpose, we calculate eight directional edge response value of a particular pixel using Kirsch masks in eight different orientations (M_0~M_7) cantered on its own position. These masks are shown in the fig. 4. Applying eight masks, we obtain eight edge response value m0, m1, …, m7, each representing the edge significance in its respective direction. The response values are not equally important in all directions. The presence of corner or edge show high response values in particular directions.

$$\begin{array}{cccc}
\begin{bmatrix}-3 & -3 & 5\\ -3 & 0 & 5\\ -3 & -3 & 5\end{bmatrix} & \begin{bmatrix}-3 & 5 & 5\\ -3 & 0 & 5\\ -3 & -3 & -3\end{bmatrix} & \begin{bmatrix}5 & 5 & 5\\ -3 & 0 & -3\\ -3 & -3 & -3\end{bmatrix} & \begin{bmatrix}5 & 5 & -3\\ 5 & 0 & -3\\ -3 & -3 & -3\end{bmatrix}\\
\text{East } (M_0) & \text{North East } (M_1) & \text{North } (M_2) & \text{North West } (M_3)\\
\begin{bmatrix}5 & -3 & -3\\ 5 & 0 & -3\\ 5 & -3 & -3\end{bmatrix} & \begin{bmatrix}-3 & -3 & -3\\ 5 & 0 & -3\\ 5 & 5 & -3\end{bmatrix} & \begin{bmatrix}-3 & -3 & -3\\ -3 & 0 & -3\\ 5 & 5 & 5\end{bmatrix} & \begin{bmatrix}-3 & -3 & -3\\ -3 & 0 & 5\\ -3 & 5 & 5\end{bmatrix}\\
\text{West } (M_4) & \text{South West } (M_5) & \text{South } (M_6) & \text{South East } (M_7)
\end{array}$$

Figure 4: Kirsch edge response masks in eight directions

We are interested to know the *k* most prominent directions in order to generate the LDP. Hence, we find the8 top *k* values |*mj*| and set them to 1. The other (*8-k*) bit of 8- bit LDP pattern is set to 0.

$$C\,[f\,(x, y)] = (C_i=1) \qquad \text{if } 0\leq i \leq 7 \text{ and } m_{i\ \geq \Psi}$$

$$\text{Where } \Psi = k^{th}(M) \qquad M=\{m_0,m_1\ldots\ldots\ldots m_7\}$$

The LDP code produces more stable pattern in presence of noise. The Extracted face feature is utilized during the face recognition process. The objective is to compare the LDP encoded feature vector from one person with all other candidate's feature vector with a Chi-Square dissimilarity measure. The selected candidate with lowest measured value indicates a match is found. From face physiology knowledge it is evident that some portion of face e.g. eye, eye-brow, mouth, nose etc have more discrimination capacity. Therefore, a weighted chi-square measure is used which provides different weight in different face block region.

$$\chi^2_w(SLH^1, SLH^2) = \sum_{i,j} w_i \frac{\left(SLH^1_{i,j} - SLH^2_{i,j}\right)^2}{\left(SLH^1_{i,j} + SLH^2_{i,j}\right)}$$

Weighted Chisquare dissimilarity measure between two spatially encoded LDP histograms SLH1 and SLH2 is defined in where indices *i* refer to the region number, *j* indicates bin no. of that region & w_i is the weight of region *i*.

3.3. ELASTIC BUNCH GRAPH MATCHING (EBGM)

The EBGM technique obtains a bunch of jets from the key points in the face image which is used for the training of the system. By joining bunch of jets, a graph is obtained which is known as a graph node. Later a bunch graph, which is a collection of facial images, is obtained which in turn compared with the probe image provided for the identification. During the process of matching an image to the bunch graph, the jets extracted from the facial features of the test image are compared to all jets in the corresponding bunch attached to the bunch graph and the best matching one is selected. **[31]**

A bunch graph contains different faces with different features or properties to generate a model graph. The nodes joining the model graph are placed over the probe image and jets are extracted from the fiducial points. The jets so extracted are used for comparing the model graph with the test image. In the final step, a match is obtained between the probe image and the model graph using a similarity function. **[33]** The basic steps followed in EBGM algorithm are: the image is kept to the normalized form using the pre-processing steps, then the landmark locations are localized, after that a face graph for each image is created in the gallery images, and in the final step a distance measure is obtained between the face graph obtained and the given test images. As studied in the review of literature, the EBGM approach is independent of variation in lighting, pose, and expression. Facial features at the key position in the image are used for identification instead of the whole face image due to the fact that the facial features are insensitive to lighting variation. **[31]** As studied, the PCA technique seems to be computationally efficient but it has many disadvantages which are; PCA's performance deteriorates when the lighting, face position, and expression change significantly especially in case of images from a live video.**[30]** Regardless of the above discussed advantages and disadvantages of PCA; EBGM is independent of the variation in lighting, face position, and expression.**[31]** The only major drawback of the EBGM technique is that the process is time consuming. **[32]**

4. COMPARATIVE ANALYSIS

In this analysis we are analysing the different face recognition method which are explained above. The table contains the recognition rate of different face method which are using different databases like AR-Faces, FERET, JAFFE, & YALE.

Table 1: Comparison Table of Face Recognition Methods

FACE METHOD	DATABASE	RECOGNITION RATE
PCA	YALE	97
LDA	AR-Faces	88
ICA	FERET	89
LBP	JAFFE	80
LBP	YALE	76.5
LDP	JAFFE	89
LDP	YALE	87
LTP	JAFFE	89
LTP	YALE	87
LDTP	JAFFE	96
LDTP	YALE	90.5
EBGM	-	90

We can easily find the difference in the Local Feature and Global feature for extraction from table and the graph of the above table. In somehow the dominant method for face extraction is local feature extraction which divide particular face in different block then comparing with the faces. Whereas Global methods like PCA, ICA, LDA are the methods which works globally over the faces. PCA is most common and widely used algorithm in research field for face recognition and it is the base of all the algorithms. But now with advancement of the recognition methods we are moving towards the Local feature extraction methods.

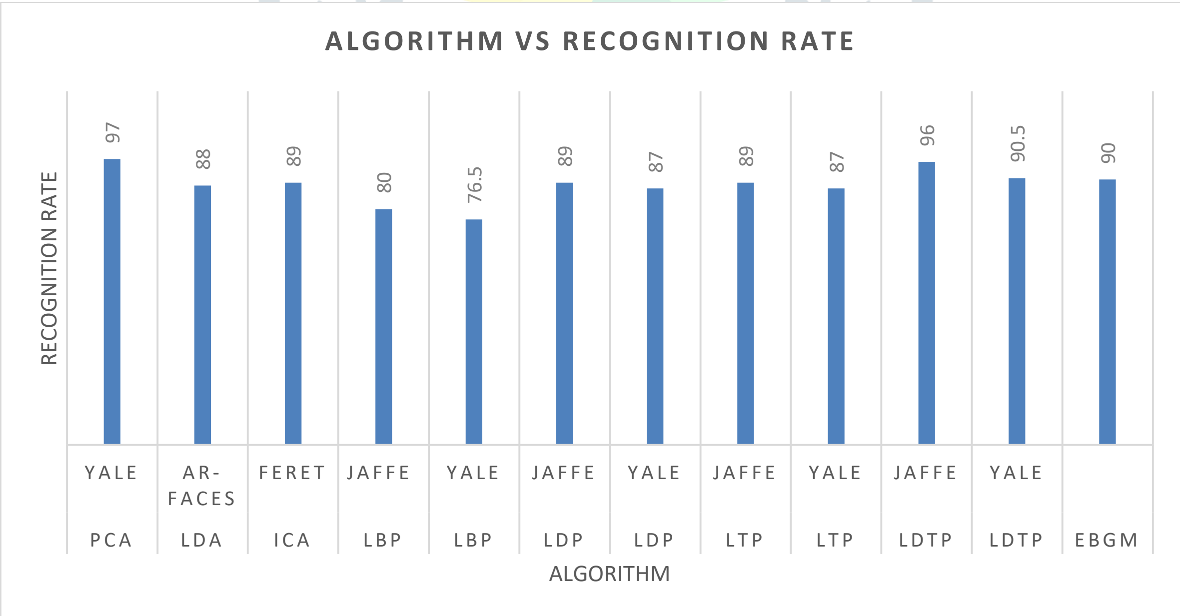

Figure 5: Algorithm Vs Recognition Rate

5. FUTURE SCOPE

In present scenario the face recognition is most on demand technology. As we want to monitor and keep eyes on everyone which is not possible by human. So, the demand is aggressively increasing for face recognition. In nowadays the work over the increasing the recognition rate of the algorithms. The Hybrid model is being used as mixing the any two Global feature and Local feature extraction method like PCA+ICA. Over all of this the researcher are also trying to be perfect in facial expression recognition which will recognise the state of mood and basic emotions like anger, neutral, disgust, fear, happy, sad and surprise. Still more advances need to be done in the technology regarding the sensitivity of the face images to environmental conditions like illumination, occlusion, time-delays, pose orientations, facial expressions. In nowadays, research work on 3 D face recognition and face recognition in videos is also pacing parallel. However, the error rates of current face recognition systems are still too high for many of the applications. So, the researchers still trying to get accurate face recognitions.

6. CONCLUSION

Nowadays, Face Recognition System is requirement of present and future generation. In this paper we have discussed the Global and Local methods of feature extraction. In Global Methods PCA, LDA, & ICA feature extraction methods are thoroughly explained. And in Global Methods LBP, LDP, & EBGM is also explained. In last in this paper also include the various advancements in this field and what are the futuristic goals going to be occurred in future in this field. In this face recognition system steps are also elaborated. A comparison table is also included in paper of different face extraction methods with their recognition rate along with different databases like AR-Faces, JAFFE and YALE. And a graph plotted between the Algorithm Vs. Recognition rate.

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