Performance study of Face Recognition systems using LBP and ICA descriptors with sparse representation - MRLSR and KNN Classifiers, respectively

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***Abstract** -In this paper an attempt has been to study and compare the results of two scenarios, i.e. 1) LBP descriptor with sparse representation (MRSLR) classifier and 2) ICA descriptor with KNN classifier, of a face recognition system, on a standard image data sets for training and testing with/without noise, occultation and different illumination facial images. The results show that the second scenario ICA + KNN exhibits better performance, compared to the first scenario LBP + MRSLR as descriptors and classifiers, respectively. The results show that the ICA + KNN scenario exhibits better performance, with a faster recognition speed and more recognition accuracy*.

Keywords - *Local Binary Pattern (LBP), Independent Component Analysis (ICA), Sparse Representation, MRLSR, KNN*

I. Introduction

Biometric Technologies can be utilized for automated identity verification performed on Finger prints, Iris, Face, Hand geometry and Voice recognition. Among these Face recognition has been proved to be more robust and requires less user interaction. This is more versatile in Biometric Identification. Face recognition is a challenging area and a lot of research is being perceived by many researchers for the last three decades. The face recognition is limited by the factors like occlusion, illumination, pose, facial expression and ageing. Different authors have used different descriptors and classifiers with different approaches, for the effective face recognition systems, to overcome the limitations [1-4].Generally Face Recognition can be classified in two groups [4,5], one is the holistic method i.e., the effectiveness of subspace based face recognition depends on utilization of subspace learning methods [6]. It gives the global feature of the observation. In this method each pixel is taken in to consideration for the processing. Thus if one pixel is varied then the entire subspace is varied. This includes the Principal Component Analysis [7, 12], Fisher Linear Discriminate Analysis (FLDA) [8] and graph embedding. These methods, due to influence of each pixel, are susceptible to occlusions and illumination [9].

The other methods are feature based local methods. These methods overcome the above drawbacks. It gives the local features of the observation. Facial recognition does best in detection of facial action. The Local Binary Pattern (LBP) [11], Gabor feature extraction, Independent Component Analysis (ICA) [13, 12] etc. are often used in this method [10]. These are invariant to linear transformation thus immune to illumination, to some extent. Feature based local methods give better object recognition than the holistic methods [9]. In the present work an attempt has been made to study the performance of a face recognition system which LBP and ICA descriptors and sparse representation and KNN classifiers. We compared FR system implemented with LBP followed by MRLSR classifier [14] and another with independent component analysis (ICA) Architecture I as implemented by the InfoMax [15] algorithm, followed by KNN classifier. The Section 1 presents the introduction to the present work and Section 2 gives the related work in Face Recognition. The proposed model of FR including the ICA and MRLSR methodologies are described in Section 3. The experimental procedure is detailed in Section 4. The results and conclusion are explained in Section 5 and 6 respectively.

II. Related work

In this section we review the work carried out by different authors using LBP and ICA descriptors and sparse representation and KNN classifiers in respective Face Recognition systems.

Heusch et al. [16] proposed a pre-processing technique based on LBP for illumination robust face authentication. Huynh et al. [17] proposed a novel efficient LBP-based descriptor, namely Gradient-LBP (G-LBP), specialized to encode the facial depth information inspired by 3DLBP. Tang et al. [18] developed a face recognition using Local Binary Pattern under expression varieties and it is widely used in ordinary facial analysis. Abdulrahman et al. [19] proposed a facial expression recognition approach, based on Gabor wavelet transform. Gabor wavelet filter is used for feature extraction in the pre-processing stage and the principal component analysis (PCA) and LBP are used to reduce the dimensionality of the feature. Shyam and Singh [20] proposed a method called augmented local binary pattern (ALBP) based on a combination of the principle of locality of uniform and non-uniform patterns and the proposed method performs better at recognizing the faces in uncontrolled environments. Jain et al. [21] represented an ensembles-based facial expression recognition system using local binary pattern which represents the local texture and global shape of face image.

The ICA algorithm, as proposed by Bell and Sejnowski [15], was applied by Bartlett et al. [22, 23] to FR system. Draper et al. [24] have analysed ICA architecture I and II and PCA algorithms in FR system and found that PCA performs well but not as well as both ICA algorithms. Dagher and Nachar [25] proposed a IPCA_ICA model for FR, which achieved a higher average success rate than the Eigen face, the Fisher face, and the Fast ICA methods is both memory and calculation efficient. Zhou et al. [26] proposed a fast ICA algorithm with the fundamental difference between the traditional ICA method is that they obtained the basis images by using each person's pictures respectively, while the traditional way uses the whole training images of the database.

In recent years the sparse representation (or sparse coding) has been successfully used by many researchers in face recognition [27-29]. Wright et al. [27] considered the problem of automatically recognizing human faces from frontal views with varying expression and illumination, as well as occlusion and disguise. With the theory of sparse representation they could predict how much occlusion the recognition algorithm can handle and how to choose the training images to maximize robustness to occlusion. Yang et el. [30] proposed a robust sparse coding for face recognition and demonstrated that the RSC scheme is much more effective than the then existing state-of-the-art methods in dealing with face occlusion, corruption, lighting and expression changes, etc. Wagner et al. [31] proposed a system that uses the tools from sparse representation to align a test face image to a set of frontal training images and the system recognizes the faces under a variety of realistic conditions, efficiently and effectively. Lu et al. [32] proposed a locality Weighted Sparse Representation based Classification (WSRC) method, which uses both data locality and linearity, for a face recognition system. The WSRC can be considered as an extension of SRC. Wang et al. [33] proposed an adaptive sparse representation-based classification (ASRC) framework, where sparsity and correlation are jointly considered and the correlation structure benefits from both L^1-norm and L^2-norm. Adamo et al. [34] have studied the problem of face recognition under uncontrolled conditions and proposed a recognition system which shows very good performance with respect to L^1 norm-based sparse representation classifier (SRC), L^2 norm-based collaborative representation classifier (CRC), the LASSO-based sparse decomposition technique, and the weighted sparse representation method (WSRC), which integrates sparsity and data locality structure. Uiboupin et al. [35] proposed a new system which super resolves the image using sparse representation with the specific dictionary involving many natural and facial images followed by Hidden Markov Model and Support vector machine based face recognition. The proposed system face recognition rate is increased considerably, after applying the super resolution, by using facial and natural images dictionary.

Sohail and Bhattacharya [36] presented an automatic technique for detection and classification of the basic facial expressions from nearly frontal face images. The discrete features are identified and extracted through monitoring the changes in muscles movement (Action Units) located near about the regions of mouth, eyes and eyebrows. The extracted feature sets are used for training a K-Nearest Neighbour Classifier to classify facial expressions. Dhriti and Kaur [37] presented a fusion technique, at feature extraction level for face and fingerprint. Features of both modalities are extracted using Gabor filter and Principal Component Analysis (PCA) and the K-Nearest Neighbour classifier is used to classify different people in the database. Kamencay et al. [38] proposed a novel method for face recognition, using hybrid SPCA-KNN (SIFT-PCAKNN) approach. Kasemsumran et al. [39] Developed a two string grammar fuzzy K-nearest neighbour (FKNN) by modifying the membership value and incorporating them into the string grammar K-nearest neighbour and applied in the face recognition system.

III. PROPOSED WORK

In this paper we are comparing two methods one being the LBP descriptor for feature extraction followed by manifold regularization of local sparse representation [14] classifier, to that of the other face recognition using Independent Component Analysis (ICA) [40], followed by K Nearest Neighbour (KNN) classifier. In the first method LBP is used for feature extraction and the resultant data is used in classification. The Manifold regularization ensures that if the neighbouring coding vectors have strong correlation, then they are similar to each other. Thus manifold regularization transfers the local correlation of face patches to the local similarity of coding vectors which in turn are classified using sparse representation. In the second method, instead of regularization of subspaces in classification, we use ICA to generate spatially independent basis vectors i.e., the feature vectors are created that uniformly distribute the data samples in subspace and then the independent basis vectors are classified using KNN classifier. The architecture of the proposed model is shown in fig.1. and it consists of two feature extraction stages, followed by two classification stages respectively.

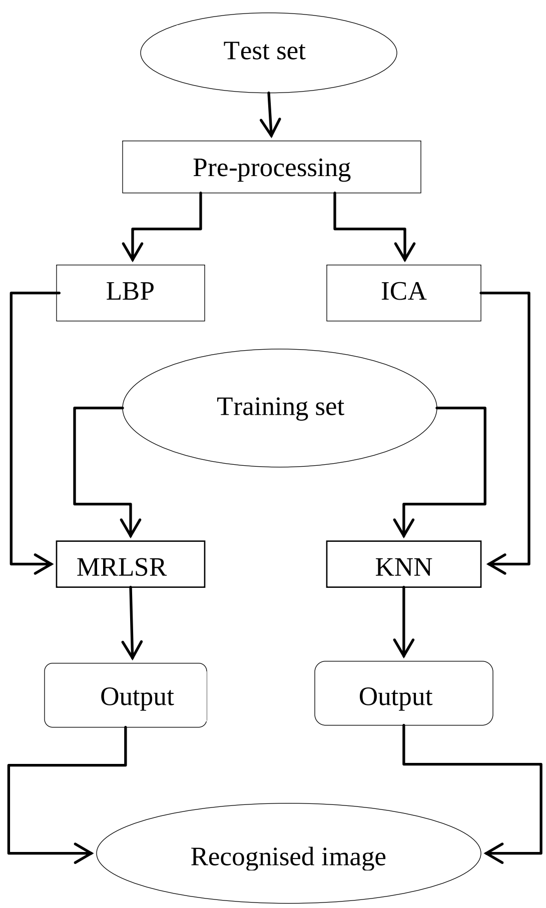

Fig. 1. Architeture of the proposed model

In the first method the test set subspace vector projection is projected on to the training set MRLSR, this is classified to obtain the best match. In the second method the vector projection is applied in the feature extraction stage such that the data obtained as the output in the feature extraction stage is fed to the K Nearest Neighbour classifier. The architecture of LBP descriptor and the KNN classifier, used in the present study, are explained in the literature [11] and [41] respectively. The independent component analysis and Manifold regularized local sparse representation (MRLSR) that are used in the FR systems are discussed in the following sections.

A. *Independent Component Analysis (ICA)*

ICA is related to the blind source separation (BSS) problem, where the goal is to decompose the observed signal into a linear combination of independent signals. ICA decreases the dependencies of input on econ order and higher order statics, there by generating compressed data. Let **S** be the vector of unknown source signals, **X** be the vector of observed mixtures and **A** is the unknown mixing matrix, then the mixing model is written as: **X=AS.**

It is assumed that the source signals are independent of each other and the mixing matrix **A** is invertible. Based on these assumptions and the observed mixtures, ICA algorithm try to find the mixing matrix **A** or the separating matrix ***W*** such that **U** = ***W*X** = **WAS** is an estimation of the independent source signal.

The Algorithm for ICA

1) *Centering (sub mean to create zero mean signal)*

The basis vectors are computed from a set of training images **I.** As a first step, the average image in **I** is computed and subtracted from the training images and a set of data samples are created as: $i_1, i_2, \ldots, i_n \in \mathbf{I} - \bar{\mathbf{I}}$

These data samples are then arranged in a matrix **X**, with one column per sample image.

$$\mathbf{X} = \left[\begin{bmatrix} \vdots \\ i_1 \\ \vdots \end{bmatrix} \cdots \begin{bmatrix} \vdots \\ i_n \\ \vdots \end{bmatrix} \right]$$

$\mathbf{XX^T}$ is the sample covariance matrix for the training images, and the principal components of the covariance matrix are computed by solving:

$$\mathbf{R^T(XX^T)\,R = D}$$

Where **D** is the diagonal matrix of Eigen values and **R** is the matrix of orthonormal eigen vectors. Geometrically, **R** is a rotation matrix that rotates the original coordinate system onto the Eigen vectors, where the Eigen vector associated with the largest Eigen value is the axis of maximum variance, the Eigen vector associated with the second largest Eigen value is the orthogonal axis with the second largest variance etc.

2) *Dimensionality Reduction*

Typically, only the **N** is the designed subspace dimensionality. The matching of images in the subspace of **N** Eigen vectors is done by compression. It is computationally more efficient to compare images in subspace with significantly reduced dimensions, for example, image vectors with 65,536 pixels ie. (256X256) might be projected into a subspace with only 100-300 dimensions.

3) Whitening (Eigen value decomposition)

The whitening transform can be determined as $\mathbf{D}^{-\frac{1}{2}}\mathbf{R}^{\mathbf{T}}$. Applying whitening to the observed mixture, however, results in the source signal only up to an orthogonal transformation. ICA then transforms the whitening data into a set of statistically independent signals, when

$$f_u(u) = \prod_i f_{u_i}(u_i),$$

Where f_u is the pdf of u (here u is uniformly distributed). Unfortunately there is no matrix **W** that fully satisfies the independent condition, and there is no closed form expression to find **W**. Instead, there are several algorithms that iteratively approximate **W,** so as to indirectly maximize independence.

Since it is difficult to maximize the independence condition directly, all common ICA algorithms recast the problem to iteratively optimize a smooth function, whose global optima occurs when the output vectors **u** are independent. Info max is one of the method that is used in this paper, it relies on the observation that independence is maximized when the entropy **H(u)** is maximized, where

$$\mathbf{H}(u) \equiv -\int f_u(u)\,\mathbf{log}\,f_u(u)\,d u.$$

B. Sparse Representation

Sparse representation has many applications and is popular for its adaptability to both local as well as global feature classification. The sparse representation is used in face recognition by wright et al [27]. The test image is sparsely represented over all the training set and the classification result is obtained such that there is minimum representation error to which the test image is similar in class. Sparse representation is the representation of the data in the form of dictionary of signals. Here the trivial template represented by identity occlusion dictionary results in high computational cost, this can be overcome by introduction of Gabor features [6] resulting in compression of occlusion dictionary. The speed of the sparse representation can be increased by elimination of identity occlusion dictionary which intern increases recognition rate, when face image is occluded by disguise.

Let $X=[X^1 ; X^2 ; X^3 ; \ldots ; X^C]$ be the set of training images, in which X^i represent images of class I, and C is the number of classes. In sparse representation based face recognition, the testing image Y is sparsely coded on X via L^2 minimization, given by

$$\widehat{\alpha_b} = \mathrm{argmin}_{\alpha_b} \frac{1}{2}\|y_b - x_b\alpha_b\|_2^2 + \gamma_b\,\|\alpha_b\|_1 \ , \qquad (1)$$

Where γ_b is weighting constant, which gives tradeoff between the reconstruction error and the sparsity of the coding vector α. The objective of recognition is then to find the smallest reconstruction error of all classes, given by

$$\mathrm{IDENTITY}(y) = \arg\min_i \left\|y - X^i\widehat{\alpha_b}^{\,i}\right\|_2^2 \qquad (2)$$

Where $\widehat{\alpha_b} = [\hat{\alpha}^1;\ \hat{\alpha}^2;\ \ldots;\ \hat{\alpha}^C]$, and $\hat{\alpha}^i$ is the coding vector associated with the i-th class.

Manifold regularized local sparse representation

In this method manifold regularization is to ensure that the neighbouring coding vectors are similar if they have strong correlation. That is, manifold regularization is proposed to transfer the local correlation of face patches to the local similarity of coding vectors.

Assuming that the input image is divided into B=m Xn blocks, we denote the block index set by *B*={1,2,...,B}.For the b-th block, we consider a 3X3 neighbouring block centred on this block as its neighbourhood. The neighbouring coding vectors of α_b within this local window are $\{\alpha_{b_1}, \alpha_{b_2}, \ldots, \alpha_{b_8}\}$, Where $b_1, b_2, \ldots, b_8$ are the coordinates of the blocks arranged from the top-left to bottom right. Note that the block itself is not its neighbourhood. The same as Laplacian Eigen maps [7], the weighted difference is utilized to interpret local similarity between α_b and its neighbouring coding vectors.

$$E(b) = \sum_{i=1}^{8} w_{bb_i} \left\|\alpha_b - \alpha_{b_i}\right\|_2^2 , \qquad (3)$$

Where w_{bb_i} is the weight (or similarity) between two blocks. In this paper, the weight w_{bb_i} is obtained by calculating the Canonical Correlation Analysis (CCA) of two corresponding blocks, i.e.,X_b and X_{b_i} .With above definitions, the total difference, which is defined by the summation of all blocks, is

$$E(\Lambda) = \frac{1}{2}\sum_{b=1}^{B} E(b) = \frac{1}{2}\sum_{b=1}^{B}\sum_{i=1}^{8} w_{bb_i}\left\|\alpha_b - \alpha_{b_i}\right\|_2^2 = \mathrm{tr}(\Lambda L \Lambda^T) , \qquad (4)$$

in which matrix Λ contains all representation coding vectors, namely, $V = [\alpha_1 ; \alpha_2 ; \ldots ; \alpha_B] \epsilon \mathbb{R}^{dxB}$ where d is the number of pixels in each block; and tr(.) is the matrix trace operation.

The MRLSR Model

The manifold regularization on all coding vectors is proposed in Eqn.(4) combined with Eqn.(1) , the MRLSR model is defined as

$$F(\Lambda) = \sum_{b=1}^{B}\left(\frac{1}{2}\|y_b - x_b\alpha_b\|_2^2 + \gamma_b\,\|\alpha_b\|_1\right) + \frac{\lambda}{2}\mathrm{tr}(\Lambda L \Lambda^T), \qquad (5)$$

Where λ is a weighting constant. As illustrated in Eqn.(5), the first term is composed of B L^1 regularised SR models, which means that the first term of F(Λ) term convex. Moreover, the Laplacian matrix L is semi-definite, which indicates that the second order term of F(Λ) is also convex. Accordingly, we can obtain that the objective function of F(Λ) is convex. The core idea behind our MRLSR model is to ensure all coding vectors hold the following two properties: individual sparsity and local similarity**.** Based on the two properties, the coding vectors are group sparse.

IV. EXPERIMENTAL PROCEEDURE

Present systems, as reported in the literature, including the sparse representation perform well under controlled environment but tend to suffer when variations in different factors are present. Manifold Regularized Local Sparse Representation (MRLSR) model address such difficulties. To increase the robustness of the FR system with highest recognition rate, the MRLSR model can be further improved by incorporating other outliers to enhance its group sparsity. We present a new model for face recognition by effectively combining some of the previously published approaches. Local Binary Pattern (LBP) is used for feature extraction and the resultant data is used in classification. Manifold regularization ensures that if the neighbouring coding vectors have strong correlation then they are similar to each other. Thus manifold regularization transfers the local correlation of face patches to the local similarity of coding vectors which in turn are classified using sparse representation. The ICA method is used for feature extraction from face images. ICA source vectors are independent and not necessarily orthogonal and they will be closer to natural features of images, and thus more suitable for face recognition. The experiments were performed in MATLAB environment. To evaluate the performance of the proposed face recognition system, the ORL (Olivetti Research Laboratory) face database is used.

The Algorithm of the proposed system:

Model (1):

In the model (1) the LBP is used for feature extraction then the output is classified using the MRLSR, thus the output is used to find the accuracy, sensitivity, specificity and rate of finding the best match.

1. Acquire a set of training images.
2. Calculate the Eigen faces from the training set, keeping only the best *M* images with the highest eigenvalues. These *M* images define the "face space". As new faces are experienced, the Eigen faces can be updated.
3. Calculate the corresponding distribution in *M*-dimensional weight space for each known individual (training image), by projecting their face images onto the face space.

Having initialized the system, the following steps are used to recognize new face images:

1. Given an image to be recognized, calculate a set of weights of the *M* Eigen faces by projecting the it onto each of the Eigen faces.
2. Determine if the image is a face at all by checking to see if the image is sufficiently close to the face space.
3. If it is a face, classify the weight pattern as Eigen a known person or as unknown.
4. (Optional) Update the Eigen faces and/or weight patterns.
5. (Optional) Calculate the characteristic weight pattern of the new face image, and incorporate into the known faces.

Model (2):

In this model the experiments were performed by implementing the feature extraction technique by using Independent Component Analysis (ICA) and this technique decomposes a complex dataset into independent sub-parts. And the Extracted feature is used for classification by using the KNN algorithm.

The face recognition algorithm using ICA architecture is given below:

1. The 2-D facial images of size N*N in the training set are represented as column vectors of size N^2*1. Suppose we have M images represented as $X_1, X_2, \ldots, X_M$. The average face image (m) is calculated as:

$$m = \frac{1}{M}\sum_{i=1}^{M} X_i$$

2. Subtract mean from each image vector to obtain mean centered images Φ_I

$$\Phi_i = X_i - m$$

Matrix A is constructed as the set of all these mean centred images

$$A = [\Phi_1, \Phi_2, \ldots, \Phi_M]$$

$$C' = A^T A$$

3. The Eigenvectors and corresponding eigenvalues are computed by using

$$A^T A V_i = \lambda_i V_i$$

4. Multiply the above equation by A both sides

$$AA^T A V_i = A(\lambda_i V_i)$$

$$AA^T (AV_i) = \lambda i(AV_i)$$

Eigenvectors corresponding to AA^T can be easily calculated now with reduced dimensionality where AV_i is the eigenvector, denoted by U_i and λ_i is the eigenvalue. U_i represents facial images which look ghostly and are called Eigen faces. These Eigen faces seems to accentuate different features of face.

Dimensionality of these Eigen faces is equal to the dimensionality of original face image.
From the Eigen faces of M-training images, best K faces are selected with largest eigenvalues and which therefore accounts for the most variance between the set of face images (K<M).

5. Each face image in the training set is now be projected onto its face space using

$$\omega^{K} = U^{T}(X_K - m) \qquad K=1, 2, \ldots, M$$

where (X_K– m) represents the mean-centered image. Hence projection of each image can be obtained using above equation, as ω^1 for first image, $\omega^2$for second image and so on. Each weight vector is of dimension K.

For each training set, we have calculated and stored associated weight vectors [40].

V. RESULTS

The typical input and output facial images of the proposed system with model (1) and model (2), at different stages, are shown in the following figures: 2-6. The images in the face data base are pre-processed to achieve noise free, average face shape and pose adjustment which will result in reduction of computational cost and increase in recognition rate.

a) Input image

b) Noise pixels

c) Pose adjustment and quality improvement

Fig. 2 Pre-processing: (a) Input facial image for FR system, (b) Noise pixels, (c) output of pre-processing stage which is used for feature extraction in the subsequent stages

Fig 3 LBP output

Fig 4 MRLSR output

Fig 5 Eigen Face

Fig 6 ICA output

The accuracy of the system can be computed using statistical parameters like precision (P) and recall (R). Precision of positive predictive value denotes the percentage of selected items that are correct. Recall or true positive rate is the percentage of correct items that are selected. The accuracy, sensitivity and specificity are given by the equations below

$$\text{Accuracy} = (\mathbf{t_p+t_n})/(\mathbf{t_p + t_n + f_p + f_n}) \quad (6)$$

$$\text{Sensitivity}=\mathbf{t_p/(t_p+f_n)} \quad (7)$$

$$\text{Specificity}=\mathbf{t_n/(f_n+t_n)} \quad (8)$$

where $\mathbf{t_p}$ stands for true positive, $\mathbf{t_n}$ stands for true negative, $\mathbf{f_p}$ stands for false positive and $\mathbf{f_n}$ stands for true negative.

The experimental results are shown in Table 1 and 2 for model 1 and Table 3 and 4 for model 2 respectively. From this study, it is observed that integration of LBP and MRLSR gives better results compared with the state-of-the-art algorithm [14]. This is in conformity, that the LBP operator is simpler and faster than the illumination normalization process [16]. ICA and KNN model 2 gives better performance with recognition accuracy as shown in table 5, compared to model 1.

Table 1: Statistical parameters for the System with LBP and MRSLR

Class	**Precision**	**Recall**	**Accuracy**
Class 1	0.9589	0.9333	0.9259
Class 2	0.9558	0.9285	0.9183
Class 3	0.9689	0.9765	0.9596
Class 4	0.9837	0.9604	0.9554
Class 5	0.9670	0.9670	0.9478
Class 6	0.9456	0.9508	0.9249
Class 7	0.9677	0.9605	0.9425

Table 2: LBP + MRSLR System Performance

Class	**Sensitivity**	**Specificity**
Class 1	0.9333	0.9090
Class 2	0.9285	0.8928
Class 3	0.9765	0.9124
Class 4	0.9604	0.9345
Class 5	0.9670	0.8750
Class 6	0.9508	0.8571
Class 7	0.9605	0.8695

Table 3: Statistical parameters for the System with ICA and KNN

Class	**Precision**	**Recall**	**Accuracy**
Class 1	0.9615	0.9638	0.9615
Class 2	0.9523	0.9638	0.9523
Class 3	0.9596	0.9661	0.9596
Class 4	0.9590	0.9646	0.9590
Class 5	0.9649	0.9782	0.9649
Class 6	0.9458	0.9646	0.9458
Class 7	0.9507	0.9708	0.9507

Table 4: ICA + KNN System Performance

Class	**Sensitivity**	**Specificity**
Class 1	0.9638	0.9523
Class 2	0.9638	0.9090
Class 3	0.9661	0.9345
Class 4	0.9646	0.9345
Class 5	0.9782	0.9090
Class 6	0.9646	0.8695
Class 7	0.9708	0.8695

Table 5: Performance Evaluation of the system

FR Method	***LBP+MRLSR***	***ICA+KNN***
ACCURACY	90	96.154
SENSITIVITY	91	96.386
SPECIFICITY	89	95.238
TIME	8.1	8.0

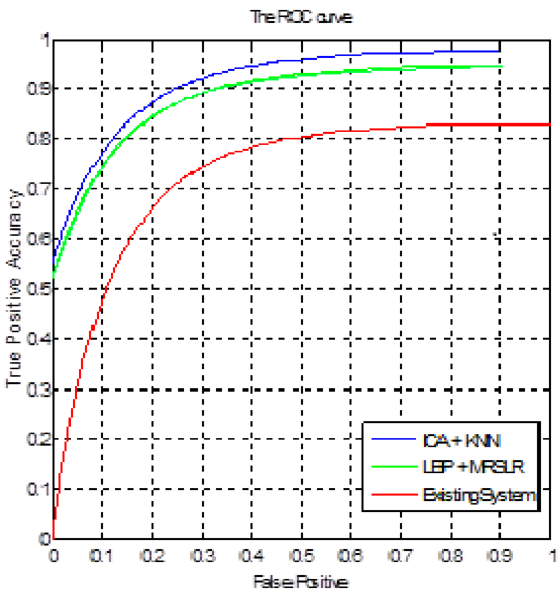

Figure 7: Curve ROC of the proposed system

The performance of the proposed model is also confirmed by the Receiver Operating Characteristic (ROC) curve. The ROC is used to show the evaluation of discrimination of the classifier's ability and the performance of classifier. The ROC graph describes False Positive Accuracy (FP) and True Positive Accuracy (TP), and is shown in fig. 7 for model 1 and 2 of our results and that of the MRSLR algorithm as reported in [14].

VI. CONCLUSION

From these experiments the following conclusions are drawn:

1. Both the model (1) and model (2) are performing well on all kinds of data sets which include lighting variation, occlusion and facial expressions of a face recognition system.
2. The model 2 has a faster recognition speed and more recognition accuracy.

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