Volume 1 Issue 1 August-2024 ISSN (online) 3049-0324

A COMPARATIVE STUDY OF PCA AND LDA HUMAN FACE RECOGNITION

Megha Shah

Assistant Professor
Department of I.T. Engineering
LDRP Institute of Technology & Research,
KSV University, Gandhinagar – 382015, Gujarat, India
megha_ce@ldrp.ac.in

Abstract - In this research, we investigate face recognition with the Principal Component Analysis (PCA) technique and with Linear Discriminant Analysis (LDA) with Euclidean distance as the classifier. Many authors have used the Olivetti Research Laboratory (ORL) database and FERET face databases for these methods. Face recognition software employs memory to identify a given face image, usually via a training set that simulates a face recognizer's memory. Although some studies have contrasted different techniques, a thorough examination of the subject is still absent. We intend to address this gap by examining the most widely used approaches and procedures and compiling the results of their numerical appraisals.

Key Words: Principal Component Analysis (PCA) and Eigenface, Fisher faces, Dimension Reduction, Face Recognition, Olivetti Research Laboratories.

1. INTRODUCTION

For the beyond 30 years, face recognition studies have been ongoing. numerous laptop scientists as well as researchers from diverse psychophysical technological know-how fields have tested it. while engineers exploring system reputation of human faces address the computational aspects of face recognition, psychologists and neuroscientists commonly cognizance on the human belief facet of the sector.

Applications for face recognition are mostly found in the domains of biometrics, security and surveillance systems, law enforcement, and access control. Biometrics are the better approach to automatically verify records or the identify of individuals using their physiological or behavioral characteristics [1]. Biometric technologies include [2]:

- Facial Recognition
- Fingerprint
- Hand Geometry
- Iris data Identification
- speech and voice Recognition field
- Hand gesture Recognition
- Handwritten text classification

Facial recognition technology is crucial for private and secure access control. Unlike other biometric systems, facial recognition does not require human intervention, making it highly significant. Facial recognition algorithms aim to address concerns related to identification and verification **[3].** During verification, the system compares a face image with a claimed identity to accept or reject the claim. Likewise, during identification, the system is trained with a test image and a database of known individuals to determine the person's identity in the test image.

The following is a statement of the facial recognition problem: Using a database of stored faces, recognize one or more people in a situation from still photos or video **[4].** The primary issue at hand is one of classification. The primary function of facial recognition systems is to categorize freshly arrived test photos into one of the classes and train the systemusing photographs of known individuals

1.1 Challenges to face recognition

This topic is very easy for a human, other hand limited Memory can be a main problem, whereas the problems in Machine recognition is manifold. Main possible challenges for a machine face recognition system are mainly:

1) ***Change in facial expression*****:** Even a tiny variation in a person's expression can have a big impact on a facial recognition system. Examples of these expressions include laughing, sobbing, and closing one's eyes.

2) ***Illumination change:*** The success of face recognition is significantly impacted by the direction in which the subject of the image is lighted. According to a study on the effects of illumination on face recognition, face recognition is difficult when the face is lit from the bottom up **[5].**

3) ***Aging:*** Pictures acquired at intervals ranging from five minutes to five years significantly alter the accuracy of the System.

4) ***Rotation:*** As seen in figure 1, the system's performance is impacted by the person's head rotating either clockwise or counterclockwise (even if the image remains frontal withregard to the camera).

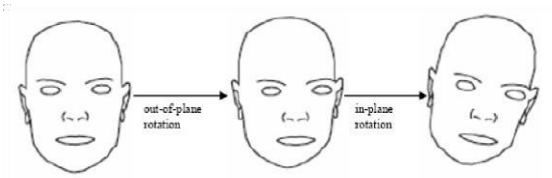


Fig.1. For in-plane and out-of-plane rotation

5) ***Image size:*** If the original class of the image was 100x100, it can be difficult to categorize a test image that is 20x20.

6) ***Frontal vs. Profile:*** The accuracy of the system varies depending on the angle at which the subject of the shot wascaptured in relation to the camera.

The subsequent level after a face detection system is a face reputation system. its miles assumed in this work that all the pixel used within the machine's training or testing are images of faces. although it is outdoor the purview of this is to clear up the assignment of precisely locating the face, preprocessing must be used to ensure that each face becomes oriented inside the identical course in each image.

2. PCA OR PRINICPAL COMPONENT ANAYLSIS

2.1 Evaluation

Turk and Pentland's PCA approach **[6]** is one of the primaries strategies used inside the literature is founded on the expansion of Karhunen-Loeve. Their studies are stimulated by way of the Sirowich and Kirby's earlier work **[7]**. Its base is the application of predominant aspect searchto the observe of human faces. Whilst handled as two- dimensional information, the facial photographs are projected onto the eigenface area to be classified. This consists of eigenvectors techniques acquired from the versions within the face images. Eigenface identity receives its name derived from the German word's personalor precise that means prefix "eigen" The Eigenface facial recognition technique is believed to be the unique face recognition approach.

Main aspect evaluation (PCA) is a broadly used the approach in sign processing and statistical pattern recognition for function extraction and information reduction. since the pattern regularly carries redundant information, a maximum of its intrinsic information content material may be preserved at the same time as the redundant facts are removed via mapping the sample to a characteristic vector. Those retrieved traits are critical for differentiating enter styles. Another call for PCA is the Eigenface method.

2.2 Eigenface Method

Foremost factor evaluation (PCA) is a broadly used methodin signal processing and statistical sample reputation for function extraction and information discount. Since the pattern regularly includes redundant records, most of its intrinsic data content material may be preserved even as theredundant information is eliminated with the aid of mapping the pattern to a feature vector. those retrieved traits are important for differentiating input patterns.

everyother call for PCA is the Eigenface method.

Once the facial images are transformed from vectors and they will cluster together at a specific point in the image space because of their shared structure, which includes a mouth, nose, and eye, as well as a correlation between theirrelative positions. The primary starting point for the Eigenface study is this correlation.

By removing the variance caused by non-facial images, or focusing only on the variation resulting from the variation between the face photos, the Eigenface approach attempts to discover a reduced dimensional space for the illustration of the face photographs. Eigenface technique aims to identify a low-dimensional space for representing the face photos by removing non- facial images' variance and focusing solely on the variationamong the face images.

Using the eigenface method at the education pix yields the eigenface space. later on, the eigenface space is projected using the schooling photographs. subsequent, the check photo is projected into this new area and the gap of the projected test image to the schooling images is used to categories the take a look at image. within the popular eigenface procedure suggested with the aid of Turk and Pentland [6], Euclidean distance is used for the type of testsnap shots.

In mathematical terms:

$$\textit{Image}\ \ I: (Nx \times Ny) \text{ pixels} \qquad (1)$$

The image matrix I of size (Nx x Ny) pixels is converted to the image vector Γ of size (P x 1) where P = (Nx x Ny);that is, by adding each column consecutively, the image matrix is formed."

$$\textit{Training Set}\ \Gamma = [\Gamma_1 \Gamma_2 \ldots \Gamma_{mt]} \qquad (2)$$

The training set for picture vectors has a size of (P x Mt), where Mt is the total number of trainingimages.

Mean Face

$$\Psi = \frac{1}{M} \sum_{i=1}^{M_t} \Gamma_i \qquad (3)$$

is the arithmetic average of the training image vectors ateach pixel point and its size is (P x1).

Mean subtracted image $$\Phi = \Gamma - \Psi \qquad (4)$$

is the difference of the training image from the meanimage (size P x 1).

Difference Matrix $$A = [\ \Phi_1\ \Phi_2\ \ldots\ \Phi_{Mt]} \qquad (5)$$

is the matrix of the entire mean subtracted train base image vectors and its size is (P x Mt).

Covariance Matrix

$$X = A \cdot A^T = \frac{1}{M_t} \sum_{i=1}^{M_t} \Phi_i \Phi_i^{\ \Gamma} \qquad (6)$$

is the covariance matrix of the training image vectors of size (P x P). Finding the covariance matrix' eigen vectorsis a crucial aspect of the Eigenface approach. The variance matrix for a face image with size (Nx x Ny) pixels is (P x P), where P = (Nx x Ny). This covariance matrix's enormous dimension, which results in computational complexity, makes it extremely difficult towork with.

The Eigenface technique, on the other hand, determines the (Mt x Mt) matrix's eigenvectors using the number of face pictures (Mt), and then uses those eigenvectors to obtain the (P x P) matrix.

Initially, a matrix Y is defined as,

$$Y = A^T \cdot A = \frac{1}{M_t} \sum_{i=1}^{M_t} \Gamma^T_i \Gamma_i$$

Volume 1 Issue 1 August-2024 ISSN (online) 3049-0324

(7)

that is a size of (Mt x Mt).
Then, the eigenvectors v_i and the eigenvalues μ_i of Y are obtained,

$$\mathbf{Y} \cdot \boldsymbol{v}_i = \boldsymbol{\mu}_i \cdot \boldsymbol{v}_i \tag{8}$$

$$\mathrm{A}^{\mathrm{T}} \cdot \mathrm{A} \cdot v_i = \mu_i \cdot v_i \tag{9}$$

Both sides are left multiplied by A,

$$\mathrm{A} \cdot \mathrm{A}^{\mathrm{T}} \cdot \mathrm{A} \cdot v_i = \mathrm{A} \cdot \mu_i \cdot v_i \tag{10}$$

The necessary matrix arrangements are made,

$$\mathrm{A} \cdot \mathrm{A}^{\mathrm{T}} \cdot \mathrm{A} \cdot v_i = \mu_i \cdot \mathrm{A} \cdot v_i$$

(as μ_i is a scalar, this arrangement can be done)

$$\mathrm{X} \cdot \mathrm{A} \cdot v_i = \mu_i \cdot \mathrm{A} \cdot v_i \tag{11}$$

Now group $\mathrm{A} \cdot v_i$ and call a variable $\upsilon_i = \mathrm{A} \cdot v_i$. It iseasy to see that

$$v_i = \mathrm{A} \cdot v_i \tag{12}$$

is one of the eigenvectors of $\mathrm{X} = \mathrm{A} \cdot \mathrm{A}^{\mathrm{T}}$ and its sizeis (P x 1).

it's miles viable to obtain the eigenvectors of X by means of using the eigenvectors of Y. To boom computational efficiency, a matrix of length (Mt x Mt) is applied as opposed to a bigger matrix of size (P x P) (i.e. [{Nx x Ny} x {Nx x Ny}]). In figure 2, some pattern photos are shown, even as discern 3 presentations the suggest photograph of the photographs from the ORL database. moreover, figure 4 shows some of the function eigenfaces acquired from this database the use of the carried-out gadget. it's far really worth noting that the eigenfaces are definitely represented as (P x 1) vectors for computations, and for visualization functions, they may be rearranged as (Nx x the big apple) matrices

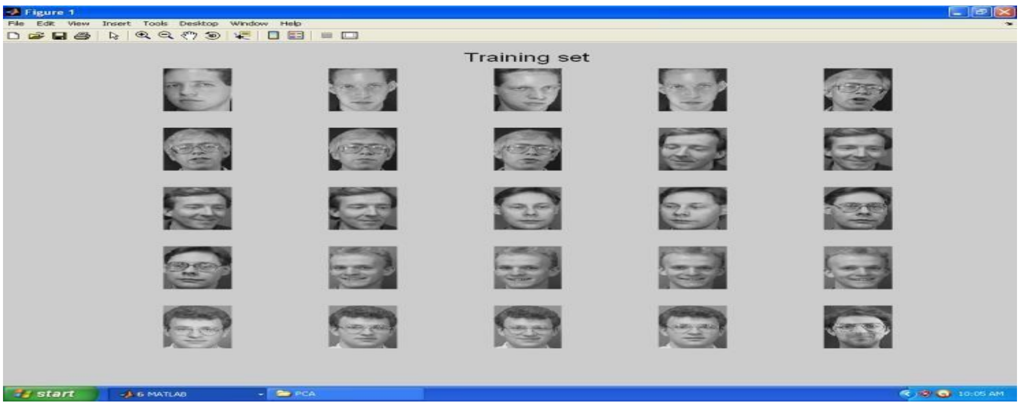


Fig 2. Sample face images from the ORL face database.

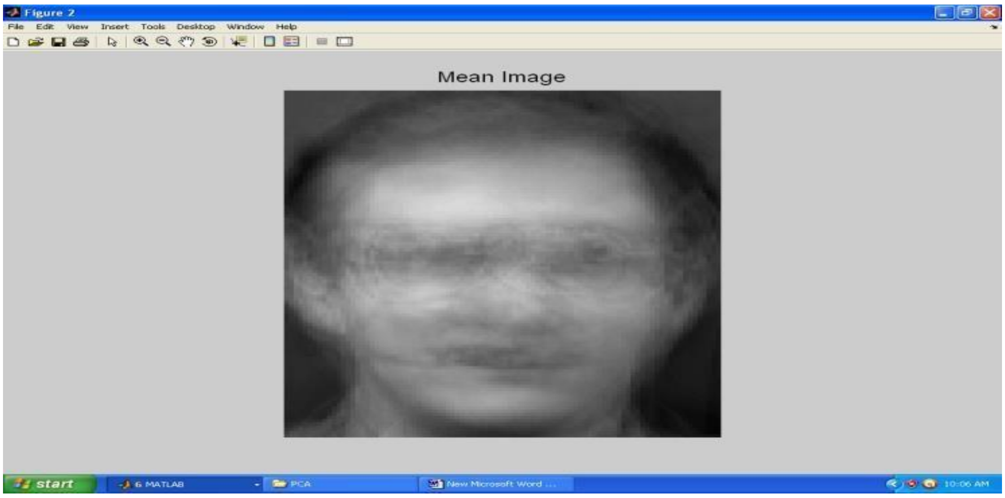


Fig 3. Mean face obtained from ORL database.

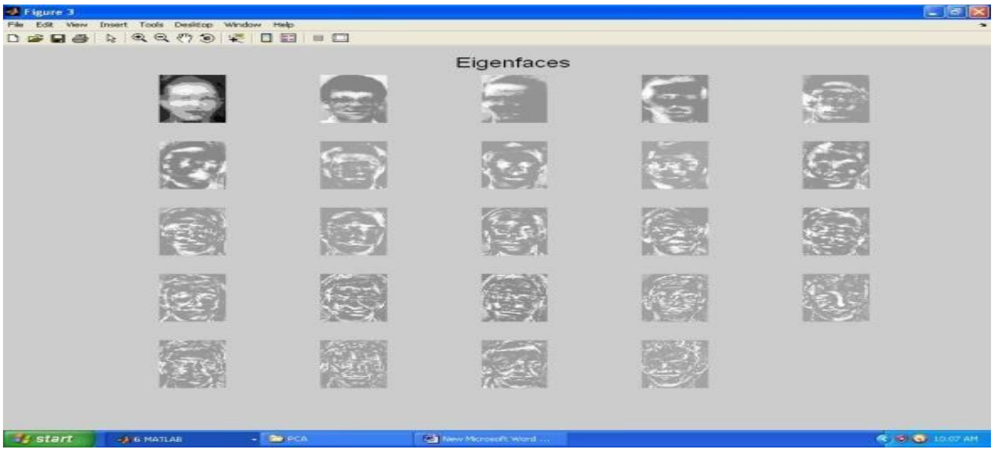


Fig 4. Eigenfaces obtained from ORL database.

within the subsequent step, the education pics are projected into the eigenface space and for this reason the weight of each eigenvector to symbolize the picture in theeigenface area is calculated. This weight is clearly the dotproduct of each photo with every of the eigenvectors.

Projection $$\omega_k = V_k^T \cdot \Phi = V_k^T \cdot (\Gamma - \Psi) \quad (13)$$

Weight Matrix $$\Omega = [\omega_1 \omega_2 \ldots \omega_{M'}]^T \quad (14)$$

is the projection of a training image on each of the eigenvectors where k = 1, 2, …, M′ where M'<<M_t.

is the representation of the training image in theeigenface space and its size is (M′ x 1).

"When an image is provided to the system for testing, it is converted into the Eigenface space. The system then compares the test image with all the images in the training set to determine the minimum Euclidean distance. The image in the training set with the smallest distance is identified as the equivalent image. To calculate the Euclidean distance, the following formula is used."

KSV E - Journal Engineering, Management, Science and Humanities

Volume 1 Issue 1 August-2024 ISSN (online) 3049-0324

$$\delta_i = \left\|\Omega_T - \Omega_{\Psi i}\right\| = \sqrt{\sum_{k=1}^{Mt}(\Omega_{Tk} - \Omega_{\Psi ik})^2} \qquad (15)$$

is the Euclidean distance between projections. The whole approach of PCA faceidentification is shown graphically in figure 5.

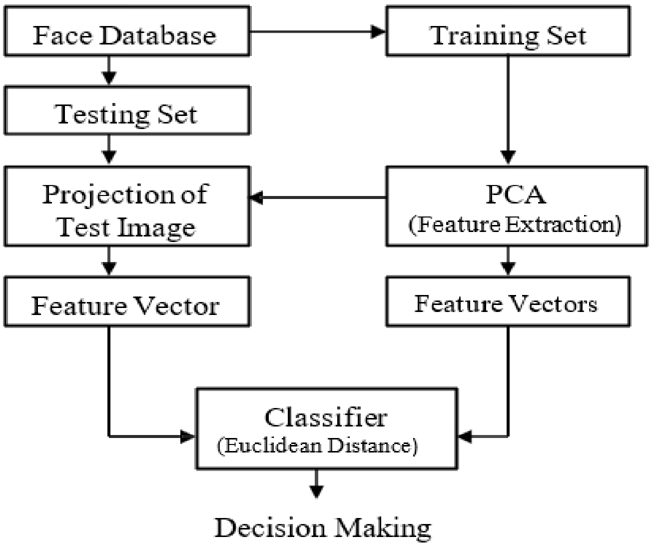


Fig 5. PCA Method For Face Recognition.

3. LINEAR DISCRIMINANT ANALYSIS (LDA)

3.1 Introduction

The Fisher faces technique, also called Linear Discriminant evaluation, addresses the restrictions in Eigenfaces method by using imposing Fisher's linear discriminant criterion. In this criterion aims to maximize the ratio of the element of the among-class of all scatter matrix of the projected samples to the determinant of the inside-class scatter matrix of the projected samples, thereby enhancing the effectiveness of the method. Pictures of the equal class are grouped collectively even as pics of different classes are separated by Fisher discriminant. N2 dimensional space is used to challenge photographs into C dimensional space, wherein C is the wide variety of picture instructions. think about, for illustration purposes, sets of two-dimensional factors projected onto a single line. The factors may be blended (discern 2.1a) or break up (figure 2.1b) based totally on the direction of the road. the line that high-quality divides the points is determined via Fisher discriminants. The projected check image is in comparison to each projectededucation photograph which will pick an input take a lookat photograph. The test photo is then determined to be thenearest schooling photograph.

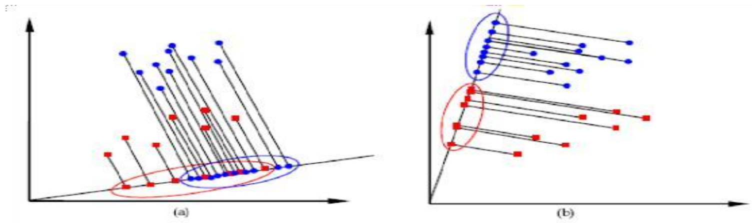


Fig 2.1 (a) Points mixed when projected onto a line. (b) Points separated when projected onto another line

The Fisher faces method, additionally known as Linear Discriminant evaluation, addresses the boundaries of the Eigenfaces technique through imposing Fisher's linear discriminant criterion. This criterion goals to maximize the ratio of the element of the between-elegance scatter matrix of the projected samples to the determinant of the within-magnificence scatter matrix of the projected samples, thereby enhancing the effectiveness of the technique.

images of the equal magnificence are grouped together at the same time as pix of various training are separated by way of Fisher discriminant. N2 dimensional area is used to assignment pictures into C dimensional space, where C is the range of picture lessons. take into consideration, for example functions, units of 2-dimensional points projected onto a unmarried line. The factors can be blended (parent 2.1a) or cut up (figure 2.1b) primarily based at the route of the road. the road that first-class divides the factors is located thru Fisher discriminants. The projected check photo is in comparison to each projected education photograph witha view to pick an enter test photograph. The check imageis then decided to be the closest education photograph.

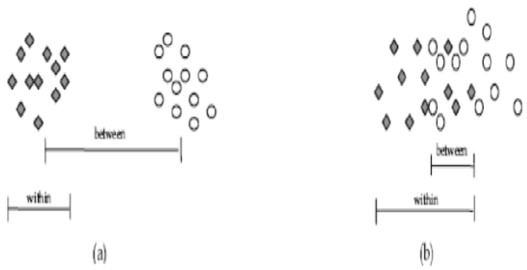


Fig 2.2 (a) Good class separation. (b) Bad classseparation

The within-class scatter matrix *Sw and* the between-class scatter matrix *Sb* are defi

$$S_w = \sum_{j=1}^{C} \sum_{i=1}^{N_j} (\Gamma_i^j - \mu_j)(\Gamma_i^j - \mu_j)^T \qquad (16)$$

Where the i[th] sample of class j, μ j is is the mean of class *j*, *C* is the number of classes, Nj is thenumber of samples in class *j*.

$$S_b = \sum_{j=1}^{C} (\mu_j - \mu)(\mu_j - \mu)^T \qquad (17)$$

Where μ represents the mean of all classes. Thesubspace for LDA is spanned by a set of vectors *W* = [*W1*, *W2*, ..., *Wd*], satisfying

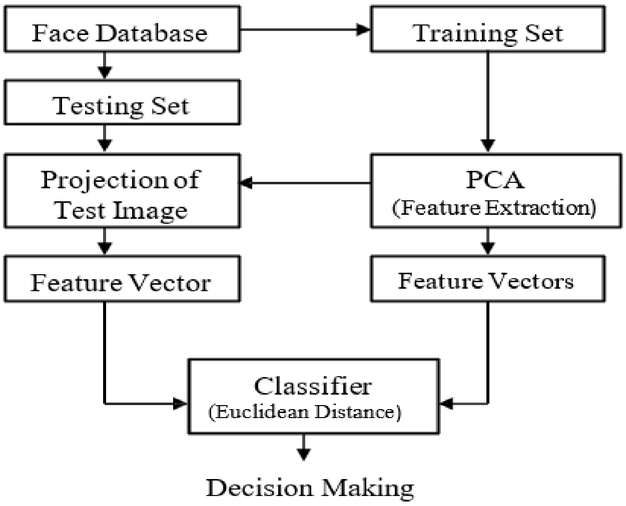
$$W = \arg\max = \left| \frac{W^T S_b W}{W^T S_w W} \right| \qquad (18)$$

The between magnificence scatter matrix illustrates how instructions are divided from one another, and the within class scatter matrix indicates how face photos are dispersedclosely inner training. Face images have to be as lightly dispersed during instructions as viable and as broadly spaced between training as possible whilst projected onto the discriminant vectors W. positioned differently, these discriminant vectors in Equation (18) maximize the numerator and reduce the denominator. Therefore, W may be constructed using Sw-1 Sb's eigenvectors. PCA attemptsto generalize the enter facts to extract the capabilities, LDAtries to discriminate the input facts with the aid of size discount. discern 2.4 shows the testing section of the LDA method.

4. RESULTS AND COMPARISON

KSV E - Journal Engineering, Management, Science and Humanities

Volume 1 Issue 1 August-2024 ISSN (online) 3049-0324



4.1 Comparison of both the approaches

The performances of the systems are leisurely by variable the number of faces of every subject in the training and test faces. Table 1 shows the success rates using different training and test images for PCA approach and the success rates using same number of test and training images for PCA using neural network by seeing the success rate we can conclude that PCA- NN performs better compare to PCA using euclidean distance that is shown graphically in figure 9.

Total Number of Images	Number of Training Images	Number of Test Images	PCA Success Rate (%)	LDA Success Rate (%)
400	25	25	68	71
400	50	50	79	82
400	75	75	85	88
400	100	100	93	96

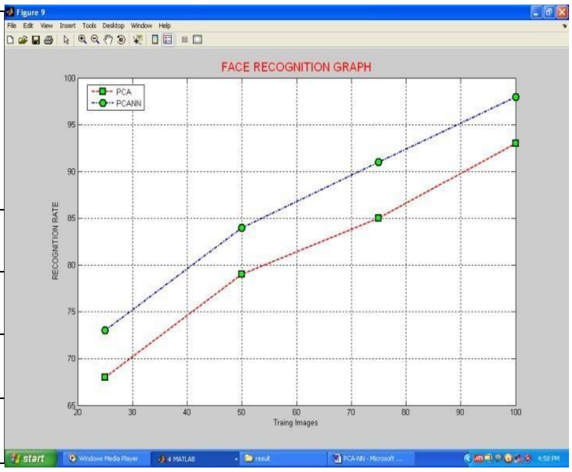


Table 1. The success rates for PCA and PCA-NNapproaches.

5. CONCLUSION

Face recognition techniques are provided on this paper: the first uses Euclidean distance as a classifier and is based totally on PCA, at the same time as the second makes use of Euclidean distance as a classifier and is primarily based on LDA. Whilst compared to conventional PCA facial reputation systems that rent classifiers based totally on Euclidean distance, the second method, LDA, well-known shows better reputation quotes. In each instance, we have got made use of the ORL Face Database. For training and checking out, PCA and LDA are carried out to the facial picture records. the second one technique, LDA, yields the first-class popularity charge amongst various combos of training and test pictures.

6. REFERENCES

1. *Huang, C. J. Harris, and M. S. Nixon, "Human Gait Recognition in Canonical Space using Temporal Templates", IEE Proc.-Vis. Image Signal Process, Vol. 146, No. 2, April 1999.*

2. *Huang, "Detection Strategies for Face Recognition Using Learning and Evolution", PhD. Thesis, George Mason University, May 1998.*

3. *S.A. Rizvi, P.J. Phillips, and H. Moon, "A verification protocol and statistical performance analysis for face recognition algorithms", pp. 833-838, IEEE Proc. Conf. Computer Vision and Pattern Recognition (CVPR), Santa Barbara, June 1998.*

4. *R. Chellappa, C. L. Wilson and S. Sirohey, "Human and Machine Recognition of Faces: A Survey", Proceedings of the IEEE, Vol. 83, No. 5, May 1995.*

5. *W. Zhao, R. Chellappa, A. Rosenfeld, and P.J. Phillips, "Face Recognition: A literature Survey", Technical Report, Univ. of Maryland, 2000.*

6. *M. A. Turk, and A. P. Pentland, "Face Recognition using Eigenfaces", pp. 586-591, IEEE, 1991.*

7. *L. Sirovich, and M. Kirby, "Low-dimensional Procedure for the Characterization of Human Faces", pp. 519-524, Journal of the Optical Society of America, Vol. 4, No. 3, March 1987.*

8. *Olivetti & Oracle Research Laboratory, The Olivetti & Oracle Research Laboratory Face Database of Faces.*

9. *J. J. Weng and D. L. Swets, "Face Recognition", in A.K. Jain, R. Bolle, Biometrics: Personal Identification in Networked Society, Kluwer Academic Press, 1999.*

10. *V. Bruce, "Identification of Human Faces", pp. 615-619, Image Processing and Its Applications, Conference Publication No. 465, IEEE, 1999.*

11. *PCA and LDA based Neural Networks for Human Face Recognition Alaa Eleyan and Hasan Demirel Eastern Mediterranean University Northern Cyprus.*

12. *P. Temdee, D. Khawparisuth, and K. Chamnongthai, Face Recognition by Using Fractal Encoding and Backpropagation Neural Network", pp. 159-161, 5th International Symposium on Signal Processing and its Applications, ISSPA '99, Australia, August 1999.*