Journal of Image Processing and Artificial Intelligence
Volume 2 Issue 1

Performance Analysis of Face Recognition using Feed Forward Neural Network and PCA

Manpreet Kaur, Ajay Kumar Singh
Department of Computer Science & Engineering, CET-Mody University of Science & Technology, Lakshmangarh, Sikar, India
E-mail: manpreet0kaur0@gmail.com, ajay.kr.singh07@gmail.com

Abstract

*In this paper, a face recognition system for personal identification and verification using Principal Component Analysis (PCA) with Neural Networks (NN) is proposed. The dimensionality of face images is reduced by the PCA and the recognition is done by the NN for efficient and robust face recognition. In this also focuses on the face database with different sources of variations, especially pose, expression. In this method of face identification covariance matrix of training and testing samples is prepared, which is further utilized for finding the eigenvalues and eigenvectors. These components are utilized for training of the face identification model. The algorithm has been tested on 165 grayscale images (15*11 classes). Face will be categorized as known or unknown face after matching with the present YALE face database. Experimental results in this paper showed that an accuracy of 96.4% was achieved.*

Keywords: *Face recognition system, principal component analysis (PCA), covariance matrix, eigen values, eigen vector, neural network*

INTRODUCTION

Face recognition is an integral part of biometric technology which is used in security system, passports, online banking, access control, information security, human computer interaction, driver licenses etc. Face recognition is a process of automatically identifying or verifying a person from a digital image or a video frame from a video source. We use the face recognition for understanding of human behavior and emotions of the human. Face recognition system classify a face as either known or unknown comparing with stored face images [1–3]. A basic face recognition system may follow a Face Detection System whose function is to identify a face in a given image and ignore all the other background details. After the face image is extracted it is given as input to the Face Recognition System, which first extracts basic features of a face that distinguishes one from the other and then classifiers are used to match images with those stored in the database to identify a person [4, 5].

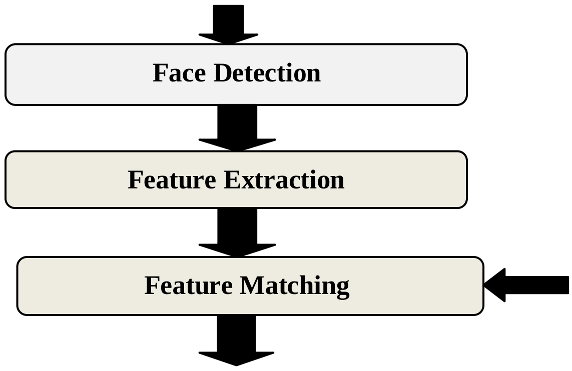
Face recognition system mainly used for feature extraction, data reduction and recognition or classification of human face images. Find the features of the faces like pose, expression using feature extraction and make easily for the other face images [6, 7]. Using the data reduction we reduce the dimension of the features but also important information is not destroyed. It holds the basic information. Face recognition using eigen faces has been shown to be accurate and fast. When Neural Network (NN) technique is combine with Principal Component Analysis (PCA) non-linear face images can be recognized easily [8–10]. The various methods for face detection can be grouped into four categories: knowledge-based methods, feature invariant approaches, template matching methods and appearance based methods. Knowledge-based methods are rule based methods. These methods try to capture human knowledge of faces, and translate them into a set of rules. The feature invariant approach finds some invariant features for face recognition. The idea is to overcome the limits of our instinctive knowledge of faces. The template matching methods compare input images with stored patterns of faces or features.

The Appearance-based methods rely on techniques from statistical or probabilistic analysis and machine learning to find the relevant characteristics of face images. In general, appearance-based methods had been showing superior performance to the others.

FACE RECOGNITION SYSTEM

Face recognition system is a complex image-processing problem in real world applications with complex effects of illumination, occlusion and imaging condition on the live images. These images have some known properties like; same resolution, including same facial feature components, and similar eye alignment. Recognition applications uses standard images and detection algorithms detect the faces and extract face images which include eyes, eyebrows, nose and mouth [10, 11].

Input Image



DB DB Face Identification

Fig. 1: *Basic Flow of Face Recognition.*

Figure 1 show basic flow of face recognition system. The first step for face recognition system is to acquire an image from a database. Second step is face detection from the acquired image. As a third step, face recognition that takes the face images from output of detection part. Final step is person identity as a result of recognition part.

PRINCIPAL COMPONENT ANALYSIS

The PCA method was first developed in the in the 1901 by the Karl Pearson. For the recognition of the faces we use the principal component analysis. This technique is used to reduce the dimensionality of the images and extract the features. PCA calculates the eigenvectors of the covariance matrix these calculated eigenvectors are referred to as eigen faces. The use of eigen faces and the eigenvectors is called as the principal component analysis [11]. There are five steps involved in the system developed by Turk and Pentland. Next, when a face is encountered it calculates an eigen faces for it. By comparing it with known faces and using some statistical analysis it can be determined whether the image presented is a face or not a face at all [12, 13].

Algorithm for PCA Module

The first step is to obtain a set S with M face images. Each image is converted into a vector of size N and the training set is formed with M faces is given by

$$S = \{\Gamma_1, \Gamma_2, \Gamma_3, \dots\dots\dots, \Gamma_M\} \quad (1)$$

Training Set

A Training set is formed by combining different face images. The images of all the different individuals were collected in a set called the training set.

Pre-Processing

The input image to this module is resized using the inbuilt resize function available in MATLAB. We have resized the image to 64*64 pixels. Eigen value and Eigen vector are extracted to achieve principal component analysis [14, 15, 16–24].

Then obtain the mean of training faces as

$$\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n \qquad (2)$$

And it is subtracted from the original face as

$$\Phi_i = \Gamma_i - \Psi \qquad (3)$$

Where i=1….M, Γ_i input image and Ψ is the mean image

The co- variance matrix is formed by

$$C = \frac{1}{M}\sum_{n=1}^{M}\Phi_n\Phi_n^T \qquad (4)$$

$$= AA^T$$

Where the matrix A is given by

$$A = \{\Phi_1, \Phi_2, \Phi_3, \ldots\ldots\ldots, \Phi_n\}$$

Using the covariance matrix we calculate the eigen value (λ_k) and eigenvector (μ_k)

$$\lambda_k = \frac{1}{M}\sum_{n=1}^{M}(\mu_k^T\Phi_n)^2 \qquad (5)$$

Then the new face image is converted into its eigen faces components and calculates the resulting weights form the weight vectors.

$$w_k = \mu_k^T(\Gamma - \Psi) \qquad (6)$$

Where w = weight, μ = eigenvector, Γ = new input image, Ψ = mean face

Then the weight vector Ω^T is given by,

$$\Omega^T = [w_1, w_2, w_3, \ldots\ldots\ldots, w_M] \qquad (7)$$

The Euclidian distance between two points' x_i & x_j is given by

$$d(x_i, x_j) = \sqrt{\sum_{r=1}^{n}(ar(x_i) - ar(x_j))^2} \qquad (8)$$

The face is known if the Euclidean distance is minimum and the face is unknown if the Euclidean distance is maximum.

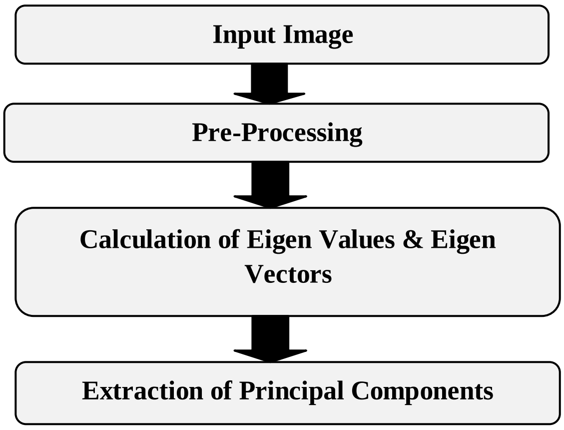


Fig. 2: *Flow Diagram of PCA Module.*

NEURAL NETWORKS

The general Neural Network approach contains following steps:

- Neural Network Creation.
- Configuration.
- Training.
- Simulation.

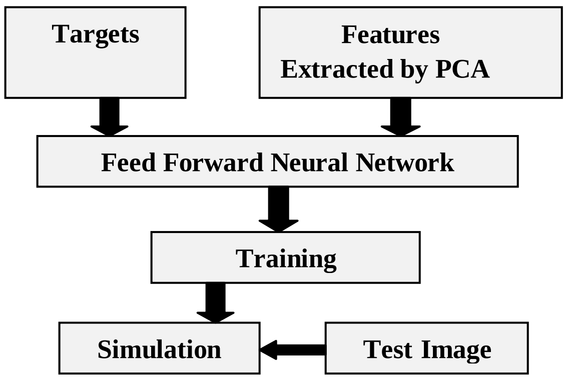


Fig. 3: *Flow Diagram for Neural Network Method.*

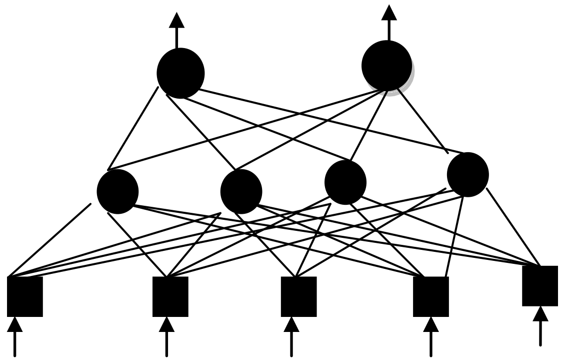


Fig. 4: An Example of Simple Feed Forward Network.

O Layer H Layer I Layer

The functionality of Neural Network in our project, which accept the features of training images and test image as an input a predefined target value has been set to perform feed forward neural network with gradient descent back propagation neural network algorithm in the presence of supervise learning [15, 16, 23, 25].

Feed-forward ANNs (Figure 4) as the name implies allow signals to travel in one way only; from input to output layer. There is no feedback loops or recurrent loops. They are highly used in pattern recognition and classification. The below diagram depicts the functionality of feed forward neural network [17, 18]. The general type of neural network consists of three groups of layers, or three groups of units. Figure 4 shows the representation of all layers of neural network [18, 20].

The Learning Process

There are basically two major categories of learning methods used for neural networks Supervise learning, unsupervised learning method. Supervised learning which work as an external teacher or guide, so that each output unit is told to perform what should be desired response to the respected input signals [20, 21, 22].

Transfer Function

The whole behavior of our Neural Network totally depends on both the weights and the input-output function that is specified in the all units. There are basically three categories of Transfer Functions:

- Linear (or ramp).
- Threshold.
- Sigmoid.

SIMULATION AND RESULTS

In this paper we have tested our proposed algorithm with YALE Face Database which contains 165 grayscale images (15*11). There are 15 individuals where each has 11 pictures with the size of 320*243. We have cropped those images in to 64*64 dimensions (height and width). Each individuals contains images having different facial expressions, and with or without glasses. The experiment is done using Matlab simulator.

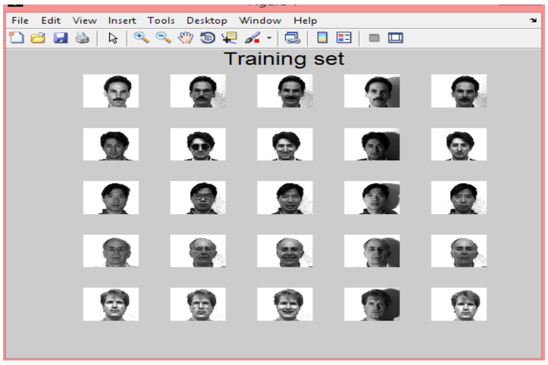


***Fig. 5:** Training Set of Face Images.*

Each face in the training set can be reconstructed by a linear combination of all the principal components. In Figure 5 training set for 5 image per person are prepared. Training set is formed by combining different face images.

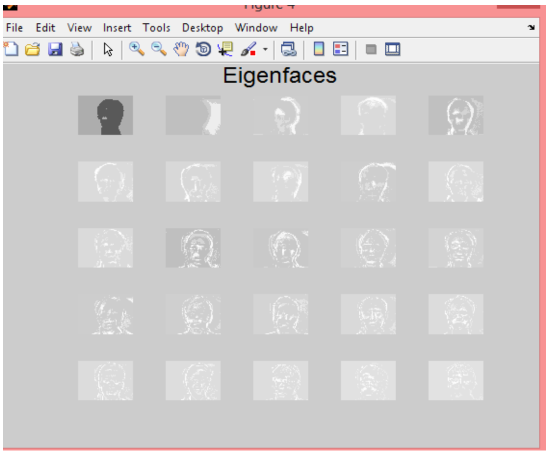


***Fig. 6:** Eigen Faces Calculated from Principal Component Analysis (PCA).*

Eigen faces is the name given to a set of eigenvectors when they are used for human face recognition. These are set of the features in the form of the vectors. The training set faces are run through a PCA, and the corresponding eigenvectors are found which can be displayed as eigen faces in Figure 6.

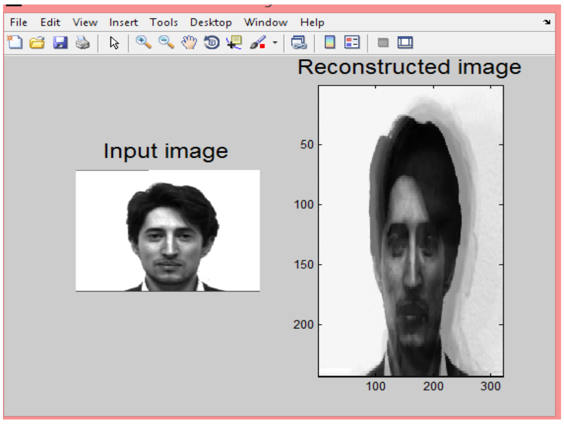


***Fig. 7:** Reconstructed Images from Principal Component Analysis.*

In Figure 7 face recognition that takes the face images from the test set the finally step is person identity as a result of recognition part. The reconstructed images come from the principal component analysis. The numbers of network are used equal to number of subjects in the database. The initial parameters of the Neural Network used in the experiment are given below:

- **Type:** Feed forward back propagation network.
- **Number of Layers:** 3 (input, hidden and output layer).

- **Number of Neurons in Input Layer:** Number of eigenfaces to describe the faces.
- **Number of Neurons in Hidden Layer:** 10.
- **Number of Epochs used in Training:** 1000.
- **Training Function:** Trainlm.
- **Performance Function**: mse.

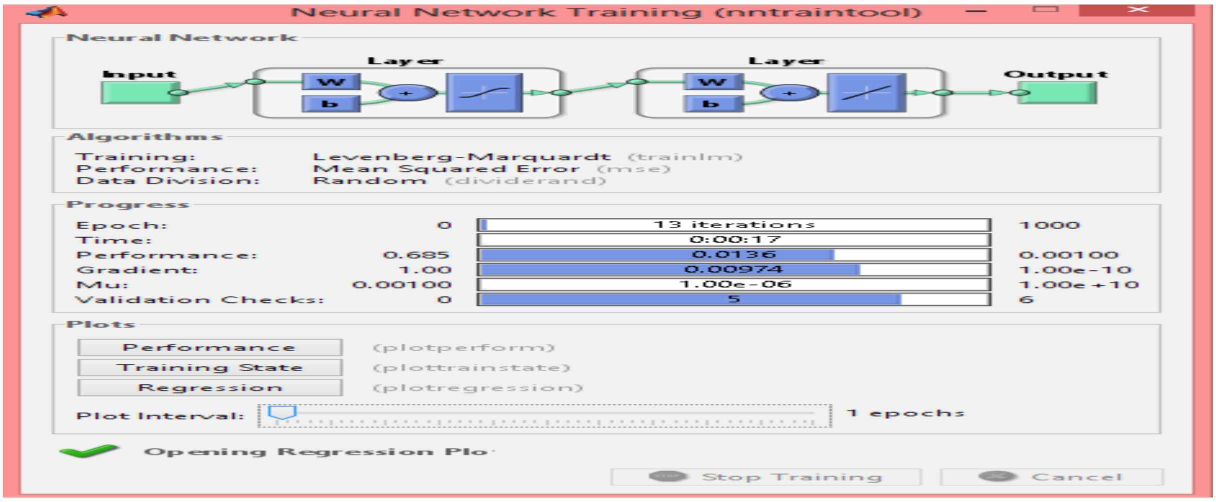


***Fig. 8:** Display Training Process.*

In Figure 8 the default performance function for feed forward neural network is mse-the average squared error between the network output and target.

Performance Measures:

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} * 100$$

$$Specify = \frac{True\ Negative}{False\ Positive + True\ Negative} * 100$$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} * 100$$

Recall measures the actual members of the class which are accurately recognized as such the total no of samples assigned to that class. Precision measures the fraction of samples that truly turns out to be positive in the group the classifier has categorized as a positive class. Represent the capacity of a classification model not to include samples of other classes in the considered class. Specificity also referred as True Negative Rate (TNR) describes the mode ability to correctly recognize samples belongs to that class.

Table 1: *Performance Analysis of Proposed System of Five Persons using Confusion Matrix.*

Class	Recall	Specificity	Precision	Accuracy
1	100%	90.0%	71.4%	92.0%
2	80.0%	90.0%	66.7%	88.0%
3	60.0%	90.0%	75.0%	88.0%
4	40.0%	90.0%	66.7%	84.0%
5	80.0%	90.0%	80.0%	92.0%

For person1 TP=5, FP= 2, FN=0 and TN=18 then calculate the recall (100%) using the formula described above. Recall is 100% for person1. Similarly calculate for all classes. For person1 TN=18, FP=2 using the formula specificity is 71.4% is calculated. Accuracy of five person classes which shows the overall accuracy of test data set is 88.8%.

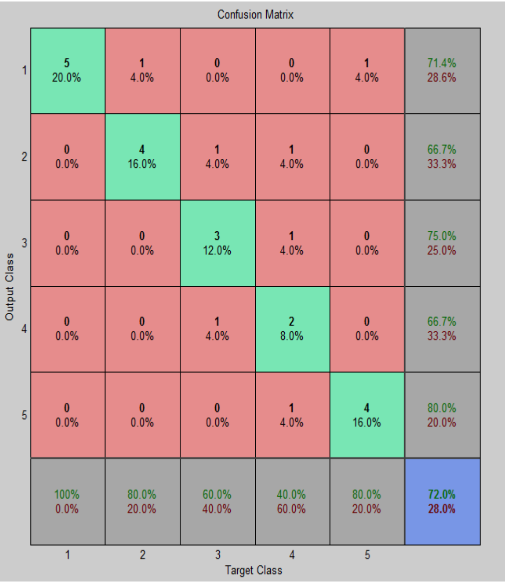


Fig. 9: *Confusion Matrix for Five Persons (1, 2, 3, 4 and 5).*

The diagonal cells show the number of cases that were correctly classified, and the off-diagonal cells show the misclassified cases. The blue cell in the bottom right shows the total percent of correctly classified cases (in green) and the total percent of misclassified cases (in red). Figure 9 Shows the confusion matrix of actual (represent the total no of persons) and predicted values of five people. The values in the diagonal would always be the true positives (TP).

Table 2: *Performance Analysis of Proposed System of Ten Persons using Confusion Matrix.*

Class	Recall	Specificity	Precision	Accuracy
1	80.0%	91.1%	50.0%	90.0%
2	60.0%	97.7%	75.0%	94.0%
3	100%	100%	100%	100%
4	100%	100%	100%	100%
5	60.0%	100%	100%	96.0%
6	100%	97.7%	83.3%	98.0%
7	100%	100%	83.3%	98.0%
8	80.0%	97.7%	80.0%	96.0%
9	60.0%	100%	100%	96.0%
10	80.0%	97.7%	80.0%	96.0%

For person1 TP=4, FP= 4, FN=1 and TN=41 then calculate the recall (80.0%) using the formula described above. For person1 TN=41, FP=4 using the formula specificity is 91.1% is calculated. Overall accuracy of test data set is 96.4% using the confusion matrix.

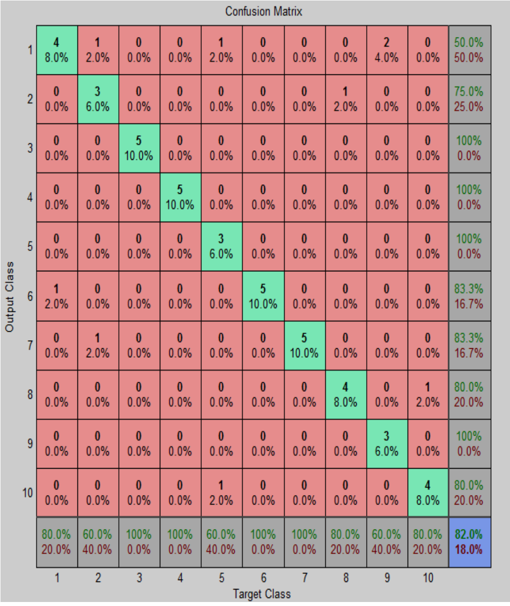


Fig. 10: *Confusion Matrix for Ten Persons (1 to 10).*

Figure 10 shows the confusion matrix of actual and predicted values of ten people each person has five images using the confusion matrix recall and precision are calculate.

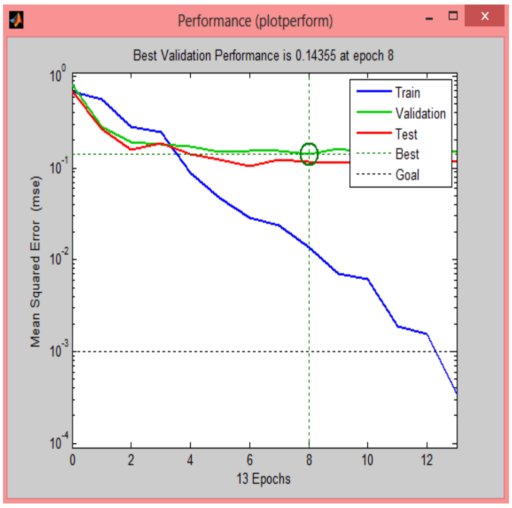


Fig. 11: *Mean Squared Error Validation.*

The validation and test curves are very similar. In Figure 11 the x-axis show the maximum no of epochs is reached=13 epochs. The red and green line show test and validation the best validation performance is 0.14355 at epoch 8.

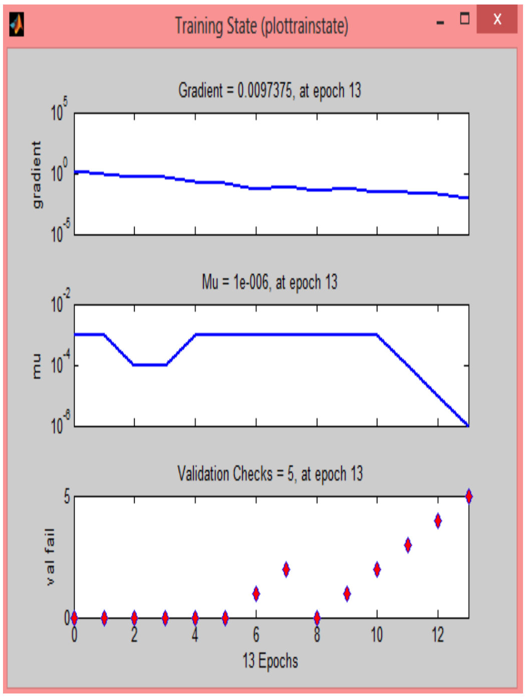


Fig. 12: *Training Plot for the System.*

Figure 12 x-axis shows the maximum No. of epochs is reached 13 epochs. Y-axis show the performance gradient falls below min_grad: gradient=0.0097375, at epoch 13. And the mu exceeds mu_max: mu=1e-006, at epoch 13 valfail validation performance has increased more than max_fail since the last time it decreased validation checks=5, at epoch 13.

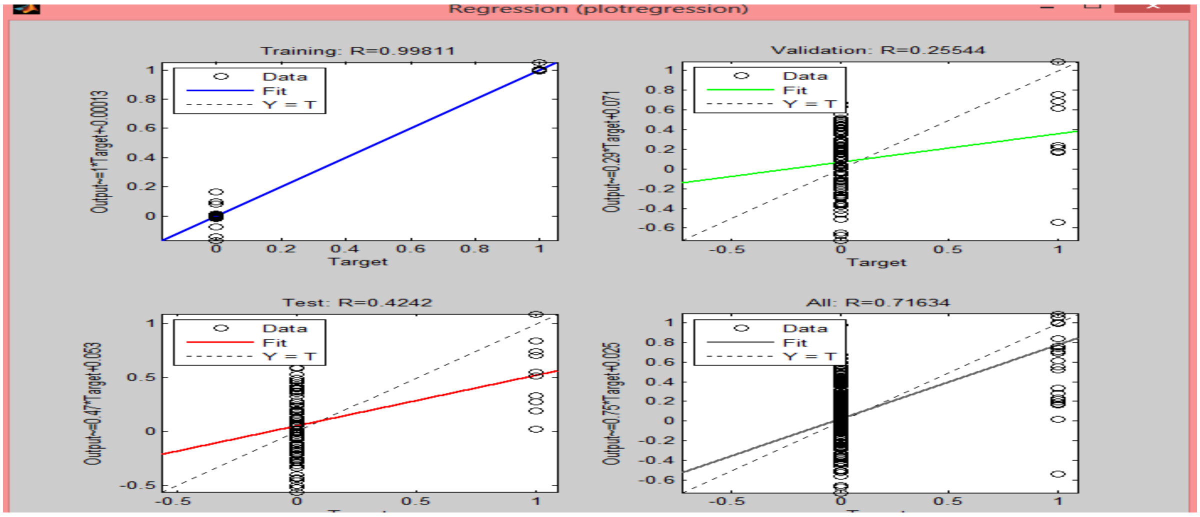


Fig. 13: *Plots the Linear Regression of Targets Relative to Outputs.*

In Figure 13 the R value indicates relationship between the outputs and targets. If R = 1, this indicates that there is an exact linear relationship between outputs and targets. In this R =0.99811 would be equal to 1 for training so that there is an exact linear relationship between output and target.

Table 3: *Recognition Rate.s*

Dataset	PCA with Euclidean Distance	PCA with Neural Network
I (25)	85.0%	88.8%
II (50)	94.5%	96.4%

The recognition ratio by using PCA with Euclidean Distance is 94.5% that is improved by using the PCA with NN, the recognition ratio is 96.4%. It is clear from the Table 3 that the neural network gives better results than the PCA with euclidean distance method in terms of recognition rate.

CONCLUSION

The paper presents a face recognition approach using Euclidean Distance and Neural Network classifier techniques. In the Table 3 see the recognition rate by using Principal Component Analysis with Euclidean Distance is 94.5% and the maximum recognition rate obtained by using PCA with Neural Network is 96.4%. A hybrid technique of feature extraction of face recognition using PCA and training is performed with neural network for robust and reliable face recognition system.

REFERENCES

1. D.S.Chaudhari, Saurabh PB. Principal component analysis for face

recognition *International Journal of Engineering and Advanced Technology*. 2012; 1(5): 2249–8958p.

2. G. Dashore, B. V. Cyril Raj. An efficient method for face recognition using principal component analysis. *International Journal of Advanced Technology & Engineering Research (IJATER)*. 2012; 2(2): 2250–3536p.
3. H. Rady. Face recognition using principle component analysis with different distance classifiers. IJCSNS *International Journal of Computer Science and Network Security*. 2011; 11(10).
4. R. He, W. S Zheng, B.G Hu, X.W Kong. Two-stage non negative sparse representation for large-scale face recognition. *IEEE Transactions on Neural Networks and Learning Systems*. 2013; 24(1).
5. J. Gan, D. Zhou, C. Li. A method for improved PCA in face recognition. *International Journal of Information Technology*. 2005; 11.
6. P.N. Belhumeour, J.P. Hespanha, D.J. Kriegman. Eigenfaces vs. Fisherfaces: Recognition using class specific linear projection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 1997; 19(7): 711–720p.
7. Kumar Singh, A., Tiwari, S., P Shukla, V. Wavelet based multi class image classification using neural network. *International Journal of Computer Applications*. 2012; 37(4): 21–25p.
8. Roberto B, Tomaso P; Face Recognition: features versus templates. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 1993; 15(10).
9. Kyungnam K. Face recognition using principal component analysis. *International Journal of Engineering and Advanced Technology*. 2000.
10. K. Karande, S. Talbar. Face recognition under variation of pose and illumination using independent component analysis. *ICGST–GVIP*. 2008; 8(4): 1687–3980p.
11. S.Saurabh, P.Bahurupi, D.S.Chaudhari. Principal component analysis for face recognition. *International Journal of Engineering and Advanced Technology (IJEAT)*. 2012; 1(5): 2249–8958p.
12. Turk M, Pentland A. Eigenfaces for recognition. *Journal of Cognitive Neuroscience*. 1991; 3: 71–86p.
13. Liton CP, Abdulla AS. Face recognition using principal component analysis method. *International Journal*

of Advanced Research in Computer Engineering & Technology (IJARCET). 2012; 1(9).

14. T. Mandal, Q. Jonathan Wu. Face recognition using curvelet based PCA. *IEEE*. 2008.
15. Feraud R., O.J. Bernier, J.-E. Villet, M. Collobert. A fast and accuract face detector based on neural networks. *IEEE Trans. Pattern Analysis and Machine Intelligence*. 2001; 22(1): 42–53p.
16. Vivek B. Principal component analysis based face recognition system using fuzzy c-means clustering classifier. *International Journal of Digital Application & Contemporary Research*. 2013; 1(6).
17. J. Yang, Member, L. Zhang, Y. Xu, J. Yang. Sparse representation classifier steered discriminative projection with application to face recognition. *IEEE Transactions on Neural Networks and Learning Systems*. 2013; 24(7).
18. S. Zafeiriou, G. Tzimiropoulos, M. Petrou, T. Stathaki. Regularized kernel discriminant analysis with a robust kernel for face recognition and verification. *IEEE Trans. Neural Network. Learn. Syst*. 2012; 23(3): 526–534p.
19. Rowley H., S. Baluja, T. Kanade. Neural network-based face detection. I*EEE Trans. Pattern Analysis and Machine Intelligence*. 1998; 20(1): 23–38p.
20. S. Lawrence, C. L. Giles, A. C. Tsoi A. D. Back. Face Recognition: A convolutional neural networks approach. *IEEE Trans. on Neural Networks, Special Issue on Neural Networks and Pattern Recognition*. 1997; 8(1): 98–113p.
21. J. Haddadnia, K. Faez. Neural network human face recognition based on moment invariants. *IEEE International Conference on Image*. 2011; 6: 26–30p.
22. Choudhary, D., Tiwari, S., Singh, A.K. A survey: Feature extraction methods for iris recognition. *International Journal of Electronics Communication and Computer Technology*. 2012; 2(6): 275–279p.
23. Singh, A.K., Shukla, V.P., Tiwari, S. Biradar, S.R. Wavelet based histogram of oriented gradients feature descriptors for classification of partially occluded objects. *International Journal of Intelligent Systems and Applications (IJISA)*. 2015; 7(3): 54p.

24. Singh, A.K., Shukla, V.P., Biradar, S.R. and Tiwari, S. Enhanced performance of multi class classification of anonymous noisy images. *Energy*. 2014; 2: 6p.
25. Choudhary, D., Singh, A.K., Tiwari, S., Shukla, V.P. Performance analysis of texture image classification using wavelet feature. *International Journal of Image, Graphics and Signal Processing*. 2013; 5(1): 58p.