Journal of Modern Applied Statistical Methods

Volume 23 | Issue 2 Article 5

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Received: 05-11-2023; Revised: 09-12-2023; Accepted: 31-12-2023; Published: 14-01-2024.

Recommended Citation

Muhammad Deo Pratama, Khoirin Nisa, La Zakaria, Mona Arif Muda (2024). Face Recognition Using Principal Component Analysis with Euclidean Distance and Artificial Neural Network Classification Methods. Journal of Modern Applied Statistical Methods, 23(2), https://doi.org/10.56801/Jmasm.V23.i2.5

Journal of Modern Applied Statistical Methods
2024, Vol. 23, No. 2,
Doi: 10.56801/Jmasm.V23.i2.5

ISSN 1538 – 9472

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Principal component analysis is a multivariate statistical method used for reducing data dimension which can be applied in various fields. One of them is in computer science application, i.e. dimension reduction of image data for face recognition. This research focuses on obtaining average faces matrix, eigenfaces, and data projection results based on principal component scores. The results were then used for further step in face recognition namely classification. Here two classification methods are used, namely Euclidean distance and artificial neural networks (ANN) with single and multi-layers. The data used are from AT&T Laboratories Cambridge collections in April 1992 - April 1994, each line of the data contains pixel from a single image that has 256 levels of black and white color between 0 and 1. Based on the analysis results, the accuracy rate of face recognition using the Euclidean distance method is 89%. At the same time, single-layer ANN produce the accuracy of 90.5% for two hidden layers, 89% for 3 and 4 hidden neurons, while multi-layer ANN produce the accuracy of 89.5% for hidden neurons (3.2), and 91% for hidden neurons (3,3) and (4,2). However, the smallest error was obtained by multi-layer ANN with hidden neurons (4,2) which resulted the error value of 7.5303. Thus we conclude that the multilayer ANN (4.2) outperformed the others and then is chosen as the best classification for the face recognition analysis of the data.

Keywords: Principal Component Analysis, Eigenfaces, Euclidean Distances, Artificial Neural Network.

1. Introduction

In statistics, multivariate analysis is very often used to solve a statistical problem, ranging from simple problems to very complex problems. In its own sense, multivariate analysis is statistical analysis used on data that has more than two variables simultaneously. In general, multivariate analysis deals with statistical methods that analyze more than two variables simultaneously on each object. Multivariate analysis is used because in reality, problems that occur in the field cannot be solved by involving only one or two variables, but involving many variables.

One of multivariate analysis techniques that are often used is principal component analysis. Principal component analysis is one of the most widely used techniques for dimension reduction. It is also known as the oldest and the most famous analysis of multivariate statistical techniques.

Nowadays principal component analysis methods can be applied in many fields, one of which is the face recognition process by combining several other statistical classification methods. Classification method is used to group or classify data that are systematically arranged such that each member in the data assigned into a particular group. Some of the classification methods that can be used are Euclidean distance and artificial neural network (ANN). Euclidean distance classifies data points by measuring the distance between 2 different points (Rizaldi et al., 2018), while ANN classifies data points using a learning algorithm to determine the specific configuration of the neural network (Gallo, 2014).

Human face is a main center of attention in human social life, it has an important role in conveying identity and emotion. Face recognition is a technology that recognizes a person by an image of his or her face. Nevertheless, face features have a very complex multidimensional structure and requires good computation for recognition; face is also one of the biometric characteristics used to recognize a person in addition to other characteristics such as speech, fingerprint, retina, and others (Abdullah et al., 2012). The problem of human face recognition is complex because it has a variety of parameters, including lighting, pose orientation, expression, head size, blurred images and face background (Kamencay et al., 2014). After more than 30 years of human research, the performance of face recognition systems has been improved (Li et al., 20111).

The process of face recognition carried out using computers is not as easy and fast as compared to the recognition process carried out by humans. Humans can recognize a person's face very quickly without having to think (Kustian, 2017). Using face recognition techniques, humans can remember hundreds if not thousands of faces in their lifetime, and are able to re-recognize them in different conditions and perspectives (Rini et al., 2012).

Applications of face recognition are no longer a rare and difficult system to find. Many applications exist around taps or housing, for instance, the attendance system, room security, and login system on the windows are being intensively applied by several computer vendors (Yazdani & Shojaeifard, 2023). The applications of face recognition has been very extensive, not only for offices but also for personal devices such as digital cameras, robots, smartphones, and laptops (Cho et al., 2014), and also the application in online shopping and online payments to verify account login and verify payment.

In this paper we present a case study of face recognition using principal component analysis Euclidean distance and ANN for analyzing face data from AT&T Laboratories Cambridge collections in April 1992 - April 1994. We aimed to compare the accuracy rate of Euclidean distance and ANN method in face recognition analysis of the data based in their principal components scores.

2. Research Methods

As mentioned previously, we used principal component analysis as dimension reduction technique and Euclidean distance and ANN methods for classification for face recognition analysis. We used R software version 4.3.1. for data processing. The procedure of the analysis is described in Figure 1.

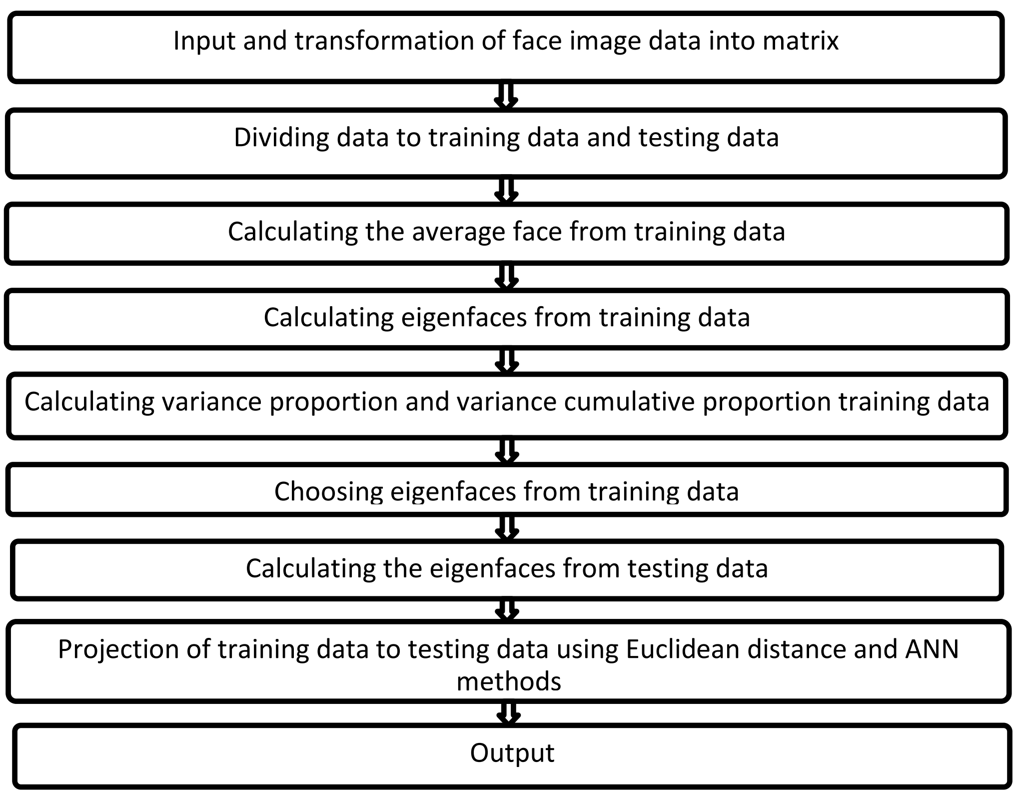

Figure 1. Analysis procedure for face recognition

The average faces value is simply calculated from training data by summing the values in each column and dividing them by the number of rows. Eigenfaces is a face recognition algorithm based on Principal Component Analysis (PCA). Eigenfaces reduce the input dimensions of an image by projecting it into sub-spaces found during the training process. Eigenfaces is one of the early recognition methods that has now been widely developed to produce performance and accuracy of the results of face detection (Ochango, 2023).

Let M be a matrix of order $n \times n$, a non-zero vector $a \in R^n$ is called eigenvector of M *associated* with the *eigenvalue* λ, where λ is a single scalar, if the following equation is satisfied (Anton et al., 2019):

$$Ma = \lambda a.$$

The eigenfaces calculated from the covariance matrix of training data. Let $x_1, x_2, \dots, x_n$ be sample of p dimensional random observations in training data. The sample covariance matrix S_n is defined as

$$S_n = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})(x_i - \bar{x})^T = \frac{1}{n-1}\sum_{i=1}^{n} x_i {x_i}^T - \frac{n}{n-1}\bar{x}\bar{x}^T$$

where $\bar{x} = n^{-1}\sum_i x_i$ is the sample mean ().

Many traditional multivariate statistics are functions of the eigenvalue (λ_k) of sample covariance matrix S_n. In the most basic form such statistics can be written as (Yao et al., 2015):

$$T_n = \frac{1}{p}\sum_{k=1}^{p}\varphi(\lambda_k),$$

or it can be expressed in matrix form:

$$S_{i,j} = [S_{11}\ S_{12}\ S_{21}\ S_{22}\ \cdots\ S_{1j}\ \cdots\ S_{1j}\ \vdots\ \vdots\ S_{i1}\ S_{i2}\ \ddots\ \vdots\ \cdots\ S_{ij}].$$

Once the covariance matrix obtained, the vector eigen is then can calculated from the covariance matrix. The vector must be normalized to define the axis line of the principal component, and the corresponding eigen value determines the variance of the principal component.

Another way to perform PCA is by using singular value decomposition (SVD). SVD is the process of factoring a matrix into more than one matrix, i.e. multiplication between diagonal matrices that contain singular values (Σ) with a matrix that contains corresponding singular vectors (U and V) (Sadek, 2012).

Suppose a matrix $M \in R^{n \times k}$, we assume $n \geq k$. SVD of matrix M is a factorization that can be expressed as $M = U\Sigma V^T$. SVD can be calculated using a very stable numerical algorithm. Given A a matrix with rank r, positive eigenvalue of $(A^T A)^{\frac{1}{2}}$ is called the singular value of A. In other words, if σ is the singular value of A so σ is the positive eigenvalue of $(A^T A)^{\frac{1}{2}}$, or σ^2 is the eigenvalues of $A^T A$ (Sadek, 2012).

3. Results and Discussion

3.1 Data Input and Transformation

The data contains 400 gray scale images of human faces with 256 black and white color grades from 0 to 1. The 400 faces were presenting 40 persons with 10 different expressions. The data were transformed into a matrix with dimensions 400×4096. The matrix rows represent all photos and the matrix columns identify the number of pixels, i.e. $2^7 \times 2^5$. The data were then divided into training and testing data, each one containing 50% of the 400 data points.

3.2 Eigenfaces

Using the covariance matrix of the training data we obtained eigen values and eigenvectors of the covariance matrix. The proportion of the variance and the cumulative proportion on the variance are presented in Figure 2. In the figure, the x-axis describes the eigen value and the y-axis describes the percentage of the variance.

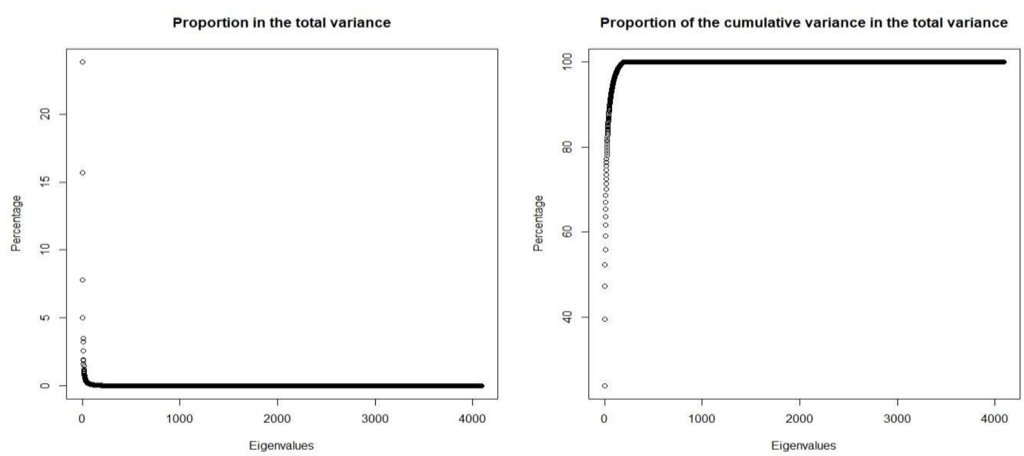

Figure 2. Variance proportions and cumulative variance proportions

Selected eigenfaces that are used for further analysis must describe the variance at least 95% of the training data. We display an example of the comparison of original image and image created from eigenfaces values in Figure 3.

Figure 3. Comparison between original image and eigenface image

3.3 Projection

In this stage, the training data is compared with the data matrix formed by the previously selected eigenfaces. The same procedure was also done on testing data and resulted the eigenfaces matrix for the testing data. Testing data eigenfaces were used in the projection between testing data and testing data eigenfaces using the euclidean distance method and artificial neural network method to calculate the proportion of accuracy in recognising facial image data using testing data and testing data eigenfaces.

Projection using the Euclidean distance method is done by calculating the distance between testing data and eigenfaces data using the Euclidean distance formula. For example, the projection results of the Euclidean distance for the first image can be seen in Figure 4 below. The number of training eigenfaces data selected in the eigenfaces selection process is only 85 eigenfaces out of 200 training eigenfaces.

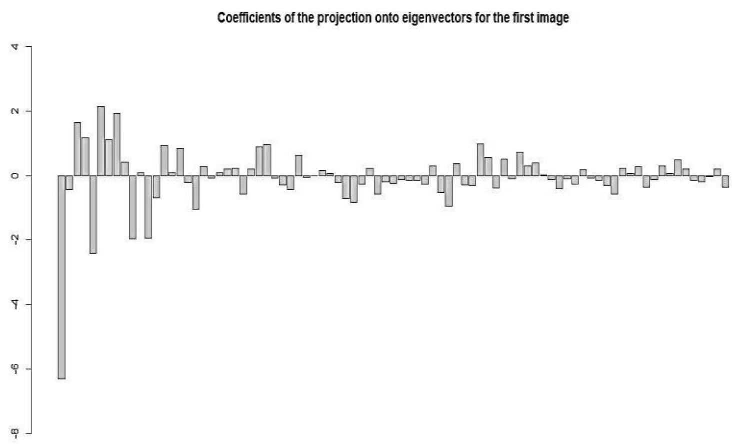

Figure 4. Projection coefficient using Eucledian method for the first image of training data

For face recognition improvement the projection results then were used in the artificial neural network analysis to establish the output values of the feed-forward propagation and back propagation processes. The statistics summaries used in this method are the eigenvalues data matrix, the proportion of variants, the cumulative proportion of variants, the projection results, and the distance of projected data training and data testing from Euclidean distance methods. The number of hidden neurons to be used in this study are using 2, 3, 4 neurons for single layers and (3.2), (3.3), (4.2) for multi layers. The graph of each ANN model can be seen in the following figures 5-10.

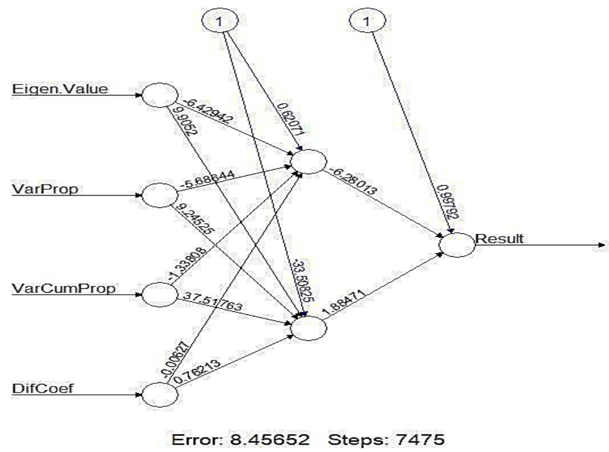

Figure 5. Single layer artificial neural network with 2 hidden neuron

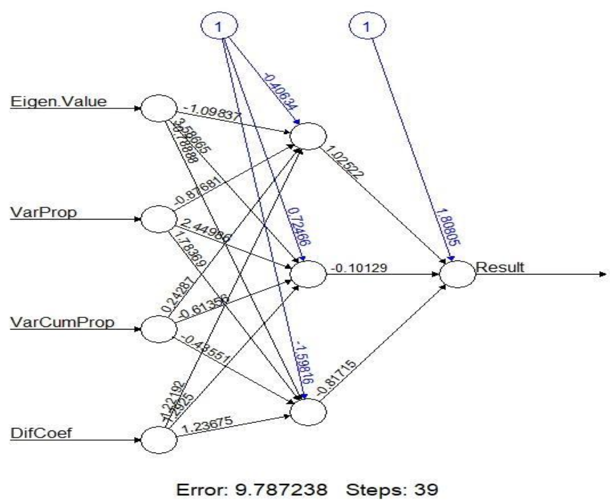

Figure 6. Single layer artificial neural network with 3 hidden neurons

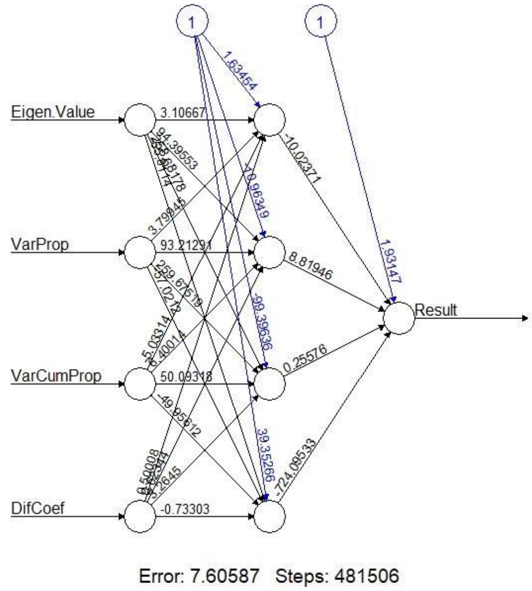

Figure 7. Single layer artificial neural network with 4 hidden neurons

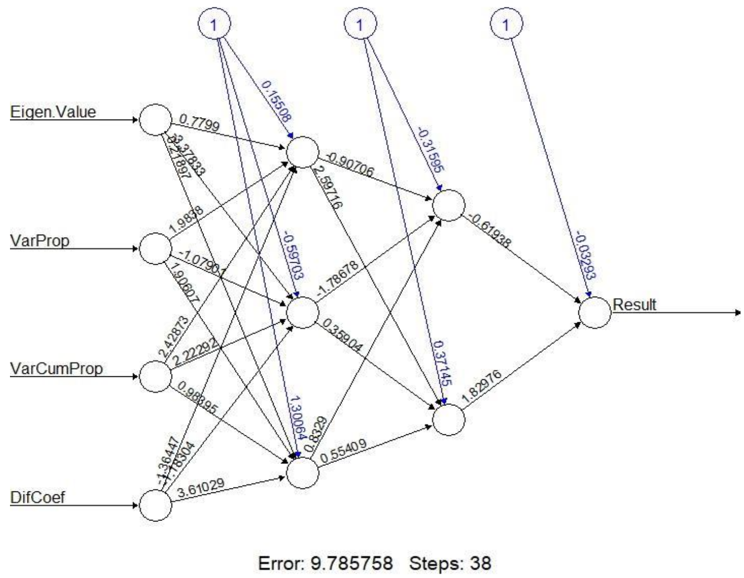

Figure 8. Multi-layer artificial neural network with (3,2) hidden neurons

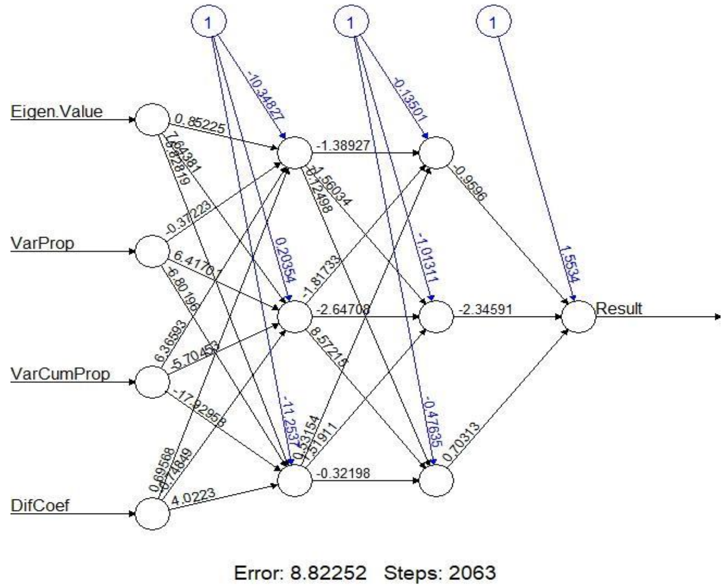

Figure 9. Multi-layer artificial neural network with (3,3) neurons

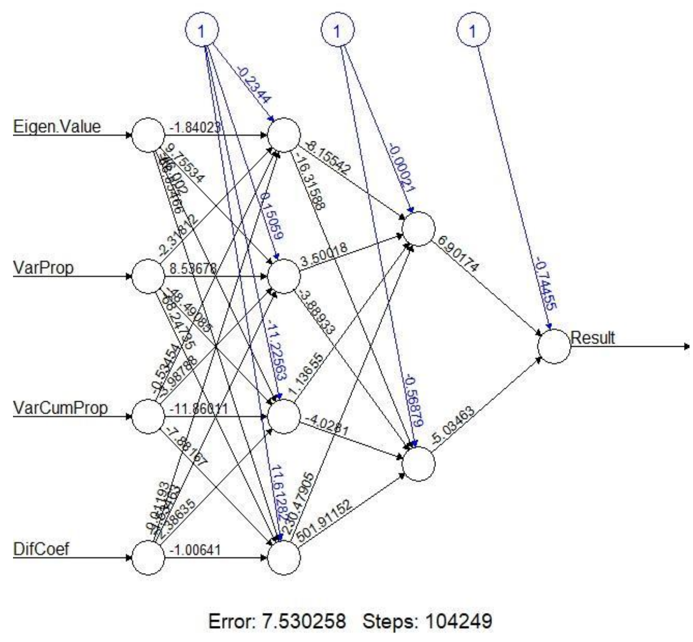

Figure 10. Multi-layer artificial neural network with (4,2) neurons

The comparison of the number of iterations and the error values for each model on training data are presented in Table 1. The table shows that the highest number of iterations occurs in the single-4 model while the smallest error value occurs in the multi (3-4) model. The error basically signifies how well your network is performing on training data.

Table 1. Comparison of the number of iterations and error values for each model

Model	#Layer - #Neurons	Number of Iterations	Error
ANN(2)	Single - 2	7475	8.4565
ANN(3)	Single - 3	39	9.7872
ANN(4)	Single - 4	481506	7.6059
ANN(3,2)	Multi – (3,2)	38	9.7858
ANN(3,3)	Multi – (3,3)	2063	8.8225
ANN(4,2)	Multi – (4,2)	104249	7.5303

3.4 The Accuracy

In this section we will examine the Euclidean and ANN methods to determine the best method by comparing the accuracy values obtained. The accuracy value in face recognition provides a quantitative measure of how well a system is able to correctly identify individuals in a given dataset. It is typically expressed as a percentage and is calculated by dividing the number of correctly identified faces (true positives and true negatives) by the total number of faces in the dataset. The formula for accuracy (ACC) is:

$$ACC(100\%)\left(\frac{TP+TN}{TP+FN+FP+TN}\right)\ x\ 100,$$

where:

- TP = true positive, a test result that correctly indicates the presence of a condition or characteristic
- TN = true negative, a test result that correctly indicates the absence of a condition or characteristic
- FP = false positive, a test result which wrongly indicates that a particular condition or attribute is present
- FN = false negative, a test result which wrongly indicates that a particular condition or attribute is absent

The accuracy of the Euclidean and ANN methods are presented in Table 2 below.

Table 2. Comparison of the accuracy value using euclidean and ANN methods

Methods	**Negative**		**Positive**		**Accuracy**
	TN	**FP**	**FN**	**TP**	
Euclidean					0.89
ANN(2)	3	0	19	178	0.905
ANN(3)	0	22	0	178	0.89
ANN(4)	4	0	18	178	0.89
ANN(3,2)	0	22	0	178	0.895
ANN(3,3)	2	1	20	177	0.91
ANN(4,2)	4	0	18	178	0.91

Based on the results in Table 2 for the Euclidean method and six different ANN models, it is found that the best accuracy value is obtained by ANN (3,3,) and ANN (4,2) with a value of 0.91. This implies that, out of all the faces presented to the system for recognition, it correctly identifies 91% of them. The remaining 9% consist of both false positives (non-faces incorrectly identified as faces) and false negatives (faces incorrectly rejected) as seen in Table 2. Although both models produce the same accuracy value, by considering the error value in Table 1 we can conclude that ANN(4.2) is better than ANN(3,3) because it produces a smaller error.

4. Conclusions

In this paper we present the application of PCA, ANN, and Euclidean Distance methods for face recognition using Cambridge AT&T Laboratories data. Based on the results obtained, using the Euclidean method and several ANN models in the face classification; we conclude that the multilayer ANN (4.2) outperform the others with an accuracy of 0.91 and an error of 7.5303. For future work we will extend this study on the performance of other methods for image classification as Fisherfaces of linear discriminant analysis, local binary patterns, histogram of oriented gradients.

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