



# Face recognition using artificial intelligence

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*Abstract - Face recognition technology has witnessed significant advancements in recent years, propelled by the rapid development of artificial intelligence (AI) techniques. This paper presents a comprehensive review of the latest methodologies, algorithms, and applications in the field of face recognition powered by AI. First, we delve into the foundational concepts of face recognition, discussing traditional techniques and their limitations. Subsequently, we explore how the integration of AI, particularly deep learning algorithms such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), has revolutionized face recognition systems by enabling more accurate, robust, and scalable solutions. We analyze various approaches to face recognition using AI, including face detection, feature extraction, and classification. Additionally, we examine the role of data augmentation, transfer learning, and ensemble methods in enhancing the performance of AI-based face recognition models. Moreover, this review discusses the challenges and ethical considerations associated with AI-driven face recognition systems, such as privacy concerns, bias mitigation, and the need for transparent decision-making processes. Furthermore, we highlight emerging trends and future directions in the field, including multimodal biometrics fusion, continual learning, and the integration of explainable AI techniques for enhanced interpretability and trustworthiness. Overall, this review provides valuable insights into the state-of-the-art in face recognition technology powered by artificial intelligence, offering guidance for researchers, practitioners, and policymakers interested in leveraging these advancements for various applications, ranging from security and surveillance to human-computer interaction and personalized services.*

## 1. Introduction

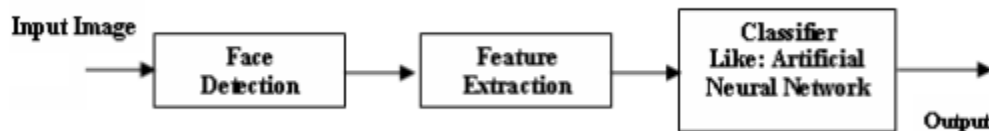
Humans have relied on physical attributes like facial features, voice, and gait for identification purposes for centuries. Biometrics, a technology that utilizes unique biological traits to recognize individuals, has emerged as a key tool in confirming identity based on inherent characteristics that cannot be misplaced, borrowed, or stolen. Various systems now require biometric authentication to grant access to resources, with methods such as fingerprint, face, iris, retina, hand, voice, and signature recognition being commonly used. Automated face recognition has garnered significant attention in recent years for its diverse applications in commercial and law enforcement sectors. While research in this field dates back to the 1960s, only recently have satisfactory results been achieved. Despite advancements, face recognition remains an active area of research due to the complexity of developing a universally successful model. Unlike humans who excel at facial recognition effortlessly, computers face challenges in this visual task. Face perception plays a vital role in human perception abilities, yet replicating this capability in computer systems remains an ongoing research focus. Early studies on face recognition trace back to the 1950s in psychology and the 1960s in engineering literature, with substantial progress made since the 1970s. Various experts have investigated

different aspects of face recognition by humans and machines, exploring issues like dedicated processes and holistic versus local feature analysis methods. Numerous techniques exist for face recognition, including correlation, Eigenface methods, and template matching. While template matching is effective under specific conditions, it can be laborious and lacks robustness. Elastic Bunch graph matching shows promise for less distortion-invariant object recognition with moderate database sizes. Principal Component Analysis (PCA) stands out as a widely used dimension reduction technique, offering advantages in generalization and computational efficiency. In our study, we propose a human face recognition system that employs PCA to extract key features from input images. These feature vectors are then utilized as input for a Generalized Regression Artificial Neural Network, functioning as a classifier for human faces.

## 2. GENERAL FACE RECOGNITION SYSTEM

The general face recognition system has been designed to perform recognition on images. Figure (1) presents a block diagram of the general face recognition system that includes three major tasks [7,8,11]:

- **Face Detection** : The ultimate goal of the face detection is finding an object in an image as a face candidate that its shape resembles the shape of a face.
- **Feature Extraction** : Feature extraction abstracts high level information about individual patterns to facilitate recognition. Selection of feature extraction method is probably the single most important factor in achieving high recognition performance. To design a face recognition system with low to moderate complexity the feature vectors should contain the most pertinent information about the face to be recognized.
- **Classifier**: Comparison of the face to a database of known faces



## 3. Proposed Face Recognition System

The architecture of the proposed system is depicted in figure (2). The face recognition system developed comprises three major processing modules which are:

### 3.1. Face Detection

Face recognition relies on accurate face detection. Before recognizing a face, it is essential to locate a face and its features reliably. Many face detection systems focus on isolating a portion of the face, excluding unnecessary elements like background and hair. This is typically achieved by scanning a 'window' across the image. Manual face detection involves measuring facial proportions to identify key landmarks like the eyes. By referencing the average face proportions, a system can extract the facial region from an image. In an optimal facial image for recognition, the eyes are positioned at specific percentages from the image borders. Operators are guided to click below the subject's eyes, utilizing a single statistic to preserve natural facial variations.

### 3.2. Feature Extraction

Feature selection in pattern recognition involves deriving specific features from input data to decrease the data volume for classification and enhance discriminatory power. Feature extraction methods aim to reduce the feature dimensions utilized in classification. Principal Component Analysis (PCA) is a commonly employed technique in pattern recognition for this purpose, as it generalizes well and reduces feature space dimension by considering input data variance. PCA identifies the most suitable projections for representing input data structure, prioritizing those that capture the highest amount of information (i.e., maximum

variance) in the fewest feature space dimensions. By projecting data onto a subspace constructed by data eigenvectors, PCA ensures optimal data variance representation. In this context, eigenvectors' corresponding eigenvalues quantify the variance managed by each eigenvector. The proposed system utilizes Principal Component Analysis (PCA) to extract features from derived sub-images, enabling the extraction of facial image characteristics for classification purposes.

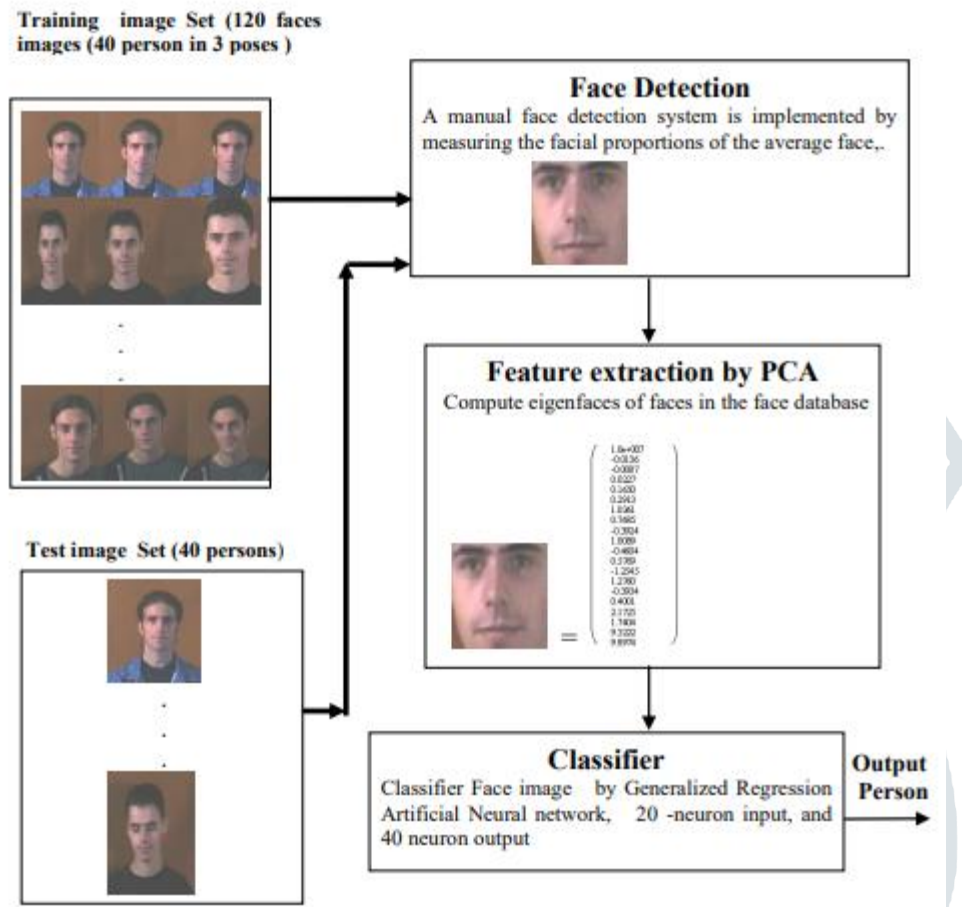


Figure 2 : Proposed Face Recognition System

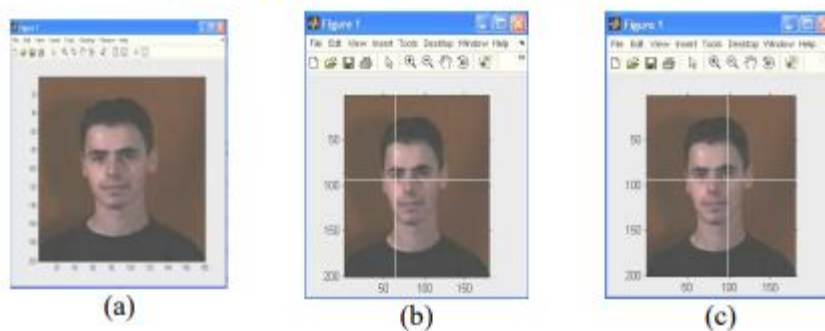


Figure 3: Manual Face Detection a- Original Image b- Click Under Eye on left , c- Click Under Eye on Right

### 3.2.1. Principle Component Analysis

PCA works to identify a group of perpendicular vectors that best represent the data's distribution. These vectors can be used to reconstruct any facial image through projections onto a new coordinate system. This process seeks to extract the key information from a facial image to create the basis vectors.

In Mathematics, a two-dimensional facial image can be transformed into a one-dimensional vector by combining each row (or column) into an elongated vector. Assuming we have  $M$  vectors of size  $N$  (equal to the image's rows multiplied by the columns), which represent a collection of sampled images, the pixel values  $p_j$  are depicted.

$$x_i = [p_1 \dots p_N]^T, \quad i = 1, \dots, M \quad \dots(1)$$

The images are mean centered by subtracting the mean image from each image vector. Let  $m$  represent the mean image.

$$m = \frac{1}{M} \sum_{i=1}^M x_i \quad \dots(2)$$

And let  $w_i$  be defined as a mean centered image

$$w_i = x_i - m \quad \dots(3)$$

Our goal is to find a set of  $e_i$ 's which have the largest possible projection onto each of the  $w_i$ 's. We wish to find a set of  $M$  orthonormal vectors  $e_i$  for which the quantity

$$\lambda_i = \frac{1}{M} \sum_{n=1}^M (e_i^T w_n)^2 \quad \dots(4)$$

is maximized with the orthonormality constraint

$$e_i^T e_k = \delta_{ik} \quad \dots(5)$$

It has been shown that the  $e_i$ 's and  $\lambda_i$ 's are given by the eigenvectors and eigenvalues of the covariance matrix

$$C = WW^T \quad \dots(6)$$

where  $W$  is a matrix composed of the column vectors  $w_i$  placed side by side. The size of  $C$  is  $N \times N$  which could be enormous. For example, images of size  $64 \times 64$  create the covariance matrix of size  $4096 \times 4096$ . It is not practical to solve for the eigenvectors of  $C$  directly. A common theorem in linear algebra states that the vectors  $e_i$  and scalars  $\lambda_i$  can be obtained by solving for the eigenvectors and eigenvalues of the  $M \times M$  matrix  $W^T W$ . Let  $d_i$  and  $\mu_i$  be the eigenvectors and eigenvalues of  $W^T W$ , respectively.

$$W^T W d_i = \mu_i d_i \quad \dots(7)$$

By multiplying left to both sides by  $W$

$$W W^T (W d_i) = \mu_i (W d_i) \quad \dots(8)$$

which means that the first  $M - 1$  eigenvectors  $e_i$  and eigenvalues  $\lambda_i$  of  $W W^T$  are given by  $W d_i$  and  $\mu_i$ , respectively.  $W d_i$  needs to be normalized in order to be equal to  $e_i$ . Since we only sum up a finite number of image vectors,  $M$ , the rank of the covariance matrix cannot exceed  $M - 1$  (The  $-1$  come from the subtraction of the mean vector  $m$ ). The eigenvectors corresponding to nonzero eigenvalues of the covariance matrix produce an orthonormal basis for the subspace within which most image data can be represented with a small amount of error. The eigenvectors are sorted from high to low according to their corresponding eigenvalues. The eigenvector associated with the largest eigenvalue is one that reflects the greatest variance in the image. That is, the smallest eigenvalue is associated with the eigenvector that finds the least variance. They decrease in exponential fashion, meaning that the roughly 90% of the total variance is contained in the first 5% to 10% of the dimensions. A facial image can be projected onto  $M'$  ( $\ll M$ ) dimensions by computing

$$[v_1 \ v_2 \ \dots \ v_M]^T \quad \dots(9)$$

where  $v_i = e_i^T w_i$ .  $v_i$  is the  $i$ th coordinate of the facial image in the new space, which came to be the principal component. The vectors  $e_i$  are also images, so called, eigenimages, or eigenfaces

### 3.2.2. PCA Feature Extraction on Database for Proposed Face Recognition System

If the dimension of the input vector is too large, the network can be quite complex and therefore difficult to train and may take more time for classification; hence it is required to reduce the input vector dimension. In our research we used Principal Component Analysis (PCA) technique for dimension reduction in face recognition

**Face Database :** Face image databases (containing both training (120 faces image) and test (40 faces image) data) used from the Collection of Facial Images : Faces95 database is one that was created by Computer Vision Science Research Projects on Face Recognition [15] , see figure (4). This database was widely used by researchers to test face detection and recognition systems, see appendix (B).

**Faces95 database Description :** Number of individuals: 72, ( 40 individual are used in this research), image resolution: 180 by 200 pixels , contains images of male and female subjects



**Figure 4: Samples of Database used in Proposed Face Recognition System**

#### Input and Output Data of Feature Extraction (PCA) :

Image resolution for the database is 180 by 200 pixels, and for segmented images, it is 73 x 65 pixels. The column matrix of all images is transformed from (73 x 65) to a vector (4745, 1), which serves as the input matrix. The dimensions of the input matrix vary based on the number of poses 'n' of 'N' persons. For a database containing 'n' poses of 'N' persons, the size of the input matrix becomes (4745, n x N). Each set of n columns signifies the poses of each person. In our study, we use 3 poses from 40 persons for training, resulting in an input matrix of size (4745, 3 x 40) or (4745, 120). The output from the feature extraction PCA comprises 20 values that represent the Eigen vectors of the covariance matrix of the training database.

#### Output Data from Classifier :

The goal is to determine the individual associated with a specific test vector. If there are N individuals to be identified, the size of the target vector will be (N, 1). In a scenario where there are 120 images in the input matrix, the size of the target matrix will be (40, 120) - with 120 representing 3 variations of 40 individuals. Within the target matrix, all elements are zeros except for one element, which is assigned a value of 1 to signify the location of the respective individual.

#### PCA Feature Extraction :

In Figure 5, the principal components algorithm is shown working on input vectors to extract features. These input vectors exclusively contain the principal components. The input vectors are downsized from (4745, 120) to (20, 120) using Principal Component Analysis (PCA) implemented in the Matlab system.

### 3.3. Proposed Classifier of Face by Generalized Regression Artificial Neural Network (GRNN)

Neural networks have been used and compared to traditional classifiers in various classification scenarios. Findings indicate that the accuracy of neural network methods is on par with or slightly superior to other techniques. These types of classifiers are deemed more effective due to their simplicity, versatility, and strong learning capabilities. As such, the Generalized

Regression Artificial Neural Network is chosen as a classifier, proving to be a promising option for pattern applications and efforts are underway to enhance the learning speed in this classification approach.

### Generalized Regression Artificial Neural Network Architecture (GRNN)

Nadaraya and Watson introduced the Generalized Regression Neural Network (GRNN). This model is utilized for various purposes such as prediction, control, plant process modeling, general mapping problems, and classification. The GRNN concept is rooted in nonparametric estimation commonly found in statistics. The GRNN consists of a radial basis layer and a special linear layer. Its architecture, as shown in figure (6), resembles that of a radial basis network with a unique second layer. The radial basis layer in the first layer calculates each neuron's weighted input based on the distance between the input vector and its weight vector. The net input of each neuron is the result of multiplying its weighted input with its bias. When a neuron's weight vector matches the input vector, the weighted input and net input are both 0, resulting in an output of 1. The second hidden layer contains units dedicated to estimating the weighted average, a specialized process. Each output in this layer is assigned a special unit responsible for forming the weighted sum for that specific output. The weighted average is obtained by dividing the weighted sum by the sum of the weighting factors, calculated by a single special unit in the second layer. The output layer carries out the division using special division units. Consequently, the second hidden layer always contains one additional unit compared to the output layer. The GRNN duplicates the training cases within the network to estimate responses at new points. The output is determined using a weighted average of the training cases' outputs, where the weighting is influenced by the distance from the point being estimated.

Enter Segmented image from Face Detection step with size of (73 x 65) , for 120 (3 poses x 40 persons) images in the training database the length of one dimension vectors is 4745 and it will be ( 4745 x 120 ) Two Dimensional matrix. or enter Segmented image with size (73 x 65) for test image .



Example of Segmented image

Calculate mean for image by using matlab function **mean** to computing the average face image

Calculate deviation of each image from mean image by computing the difference image for each image in the training set

Calculate eigenvalues and eigenvector : This is programmed by using matlab function . Syntax :  $[V,D] = \text{eig}(A)$  produces matrices of eigenvalues (D) and eigenvectors (V) of matrix A see appendix (A)

Sorting and eliminating eigenvalues : All eigenvalues of matrix X are sorted and those who are less than a specified threshold (less than 1), are eliminated.

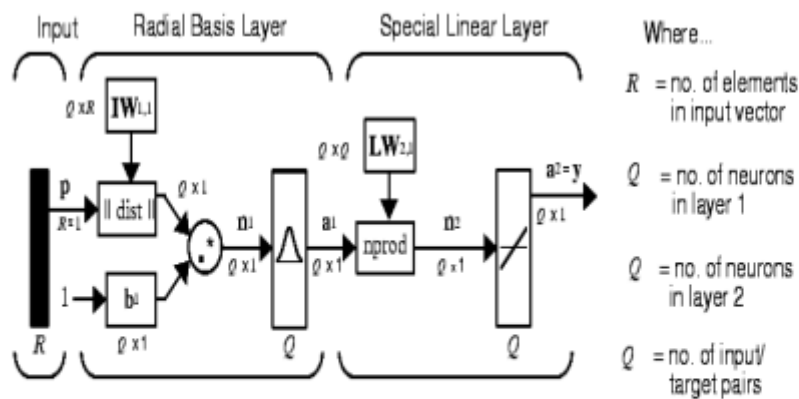
Calculate eigenvectors of covariance matrix : Eigenvectors of covariance matrix (or so-called "Eigenfaces") can be recovered from X's eigenvectors.

All centered images are projected into facespace by multiplying in Eigenface basis's. Projected vector of each face will be its corresponding feature vector.

Save Resulte in three Variables 1) Eigenface: Eigen vectors of the covariance matrix of the training database, 2) Mean : Mean of the training database, 3) Centered image : Matrix of centered image vectors



Example of output



**Figure 6 : Generalized Regression Artificial Neural Network Architecture**

### • Design Proposed Generalized Regression Artificial Neural Network

We developed a face recognition system utilizing a GRNN. The goal is to train the neural network to identify 40 different faces, with the output used to distinguish one face from a pool of 40. To construct a classifier using GRNN, we matched the number of input nodes in the input layer of the neural network with the number of elements in the feature vector. The output layer's node count corresponds to the total image classes. The neural network is comprised of a Radial basis layer with 20 input neurons (representative of PCA) and a Special linear layer with 40 output neurons, generating outputs  $y_1$  to  $y_{40}$ . Refer to Figure (6) for the structural diagram of the neural network. To train the network, we will utilize 120 face images (40 individuals in 3 poses). To evaluate the network's learning and recognition capabilities, 40 face images will be used. In the network training process for face recognition, we applied 20 PCA values to the network's input.

After many experiments we apply the following parameters :

Learning rate parameter is 0.00001, Performance function is 'MSE', The performance goal (or tolerance limit) is 0.1.

The network is trained for 1850 epochs.

It is trained with standard data sets 20 -neuron input (represent PCA of segmented image), and 40 neuron output. These parameters make the algorithm converge and it is trained and tested the network with a set of train and test data. After the training, then next comes the simulation part, where the network identifies a person when a pattern is to be presented to it. Before presenting the input pattern it must be converted to a form acceptable by the neural net. The input pattern may be one of the trained patterns or unknown pattern. The unknown image feature PCA is selected. By presenting this as an input pattern, the neural network computes the output using the set values of weights. The output vector has only one element having value 1 and remaining elements are zeros, which indicates to which class.

## 4. Experimental Results

To check advantages of our proposed algorithm experimental, studies are carried out on the Collection of Facial Images: Faces95 databases (containing both training and test data). 120 face images from 40 individuals in 3 poses, Faces95 database have been used to evaluate the performance of the proposed method. None of the 40 samples are identical to each other. They vary in position, rotation, scale and expression. In this database each person has changed his face expression in each of 40 samples. A PCA feature domains and the Generalized Regression Artificial Neural Network has been developed. In this example, for the PCA feature vector has been created based on the 20 largest PCA number for each image. A total of 120 images have been used to train and another 40 for test. Recognition rate of training data set is 99.6% and 94.32 % was obtained for test data set using this proposed technique, see table(1).

**Table (1) Face Recognition Accuracy Rate**

Number of faces image (person)		Number of poses		Accuracy Rate %	
Training data set	Testing data set	Training data set	Testing data set	Training data set	Testing data set
120 face images (3 poses * 40)	40	3	At any poses	99.6%	94.32

## 5. Comparisons with other algorithms

To check the utility of our proposed algorithm and Experimental results, we compare between proposed algorithm (using PCA and GRNN) with other algorithms used to recognized faces, table (2) Shows that the proposed method is better than other existing methods.

**Table (2) Comparisons of Face Recognition Accuracy Rate with other algorithms**

Algorithms	Number of faces image (person)		Number of poses		Accuracy Rate %	
	Training data set	Testing data set	Training data set	Testing data set	Training data set	Testing data set
Proposed Algorithm PCA with GRNN	120 face images (3 poses * 40)	40	3	At any poses	99.6%	94.32
PCA [3]	450	30	-	At any poses	100%	93%
SOM+CN <sup>m</sup> (Self-Organizing Map combined with a CN Database)	ORL + FERET Database	-	-	-	96%	-
BP ANN with Wavelets transform coefficient [9]	30	7	3	7	99%	96%

## 6. Conclusion

This paper introduces a new approach for identifying human faces in 2D digital images. It utilizes the Generalized Regression Artificial Neural Network and PCA feature domains. The proposed algorithm achieved a 99.6% training recognition rate and a 94.32% testing rate with the Faces95 database, highlighting the effectiveness of the technique. Experimental results demonstrate the utility of PCA and GRNN in face recognition systems. PCA is particularly effective in extracting image information and serves as the distinguishing feature of facial images. It excels in capturing facial features at various angles. GRNN is employed for classification, with input being the PCA extracted from the faces. Principal Component Analysis is used to reduce input dimensions and enhance performance. The study shows that the proposed method outperforms existing approaches and can be seamlessly integrated into any face recognition system. Future research will involve applying genetic algorithms to identify optimal features for face recognition by analyzing key interest points on faces and utilizing a different type of ANN for classification.



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