Finding Faces for Gender Classification using Back Propagation Neural Networks and Principal Component Analysis based Recognition

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Rourkela

Certificate

This is to certify that the project entitled, '**Finding Faces for Gender Classification using Back Propagation Neural Networks and Principal Component Analysis based Recognition**' submitted by **Deepak Madan and Harsh Srivastava** is an authentic work carried out by them under my supervision and guidance for the partial fulfillment of the requirements for the award of **Bachelor of Technology Degree** in **Computer Science and Engineering** at **National Institute of Technology, Rourkela**.

To the best of my knowledge, the matter embodied in the project has not been submitted to any other University / Institute for the award of any Degree or Diploma.

Date - 09/05/2011
Rourkela

(Prof. Dr. B. Majhi)
Department of Computer Science and Engineering

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Date - 09/05/2011
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Deepak Madan
Harsh Srivastava

Abstract

Face Classification system is a computer program which will classify a face into different categories as per certain criterias. We will be training our systems to classify the images into two septum. The first would classify the images based on human or non–human characteristics. The second category of classification would be classifying the human faces as male or female face. We will implement this using Back Propagation Neural Network algorithm. This pre-classification will help in reducing the total time required to recognize an image and hence increasing the overall speed.

Face Recognition system is a computer applicaton that identifies a face of a person in a digital image by comparing the face in the image with the facial database of some trained images. This system can recognize images of a person with emotions and expressions different with those in the facial database. We will implement this using a mathematical tool called Principal Component Analysis and Mahalanobis Distance Algorithm. It can be used for security purposes at restricted places by granting access to only authorised persons. It can also be used for criminal identification.

We will develop a system which will focus on recognition of faces of individuals using the above mentioned algorithms to get better accuracy and speed. We will first use Back Propagation Neural Networks to classify whether the test image is a human face or not, and if it is a human face whether it is a male face or a female face and then we will recognize the image using Principal component analysis. This will help us in reducing the overhead calculations for non-human images and also in reducing the database size by maintaining different databases for male and female faces, as the speed of the system depends widely on the database size.

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1 Introduction

1.1 Problem Statement

Implement the Face Classification system using the Back Propagation Neural Networks algorithm based on human/ non-human as well as gender classification. Then, implement Face Recognition system using Principal Component Analysis and Mahalanobis Distance Algorithm.

1.2 Motivation and Challenges

The importance of using biometrics to detect impostors and establish personal authenticity is growing rapidly in the present global security concerns. Development of biometric system for personal identification which will fulfill the requirements for access control of high–security areas is felt to be the need of the day. Face Classification and Recognition is the process through which a person is identified by his facial image.With the help of this system, it is possible to use the facial image of a person to authenticate him into the secured system.An efficient Face classification algorithm can help us reduce the face recognition earch time required t o a great extent. Face recognition system can help in many ways [9]:

- Checking for criminal records .
- Enhancement of security by using surveillance cameras in collaboration with face recognition system.
- Detection of a criminal at public place.
- Can be used in different areas of science for comparing a entity with a set of entities.
- Pattern Recognition.

The digital images are noisy due to different lighting condition,facial expressions, poses, etc. But there are patterns which are present in every image, i.e the presence of eyes, nose and mouth and the relative distance between them. A face recognition system should be inexpenive enough to be used at multiple locations. It should have the ability to handle large databases and also have the ability to do recognition in varying environments. It should have the ability to learn and recognize new faces and should be weasy enough to be implemented. The most important characteristic of a facerecognition system is the ability of its to match the faces in the least time possible, that is, fast and accurate face recognition.

2 Face Classification using Neural Networks

Face is considered to be the most acceptable biometrics than others because image capturing and prediction is easier than other traits. The performance of any system depends on accuracy and speed. Despite high accuracy, low speed makes a system unacceptable. Accuracy depends on underlying algorithm but speed is inversely proportional to the size of the data base. For any real time application, the size of the database is usually very large. While dealing with such large databases, biometric systems suffer from an overhead of large number of computations. The common drawback of this is abundance of data. Thus, to overcome these problems, there have to be some methods to reduce the search space.

It has been shown that the number of false positives in a biometric identification system grows geometrically with the size of the database. If FAR and FRR indicate the false accept and reject rates, then FAR_s and FRR_s , the rates of false accepts and rejects in the identification mode with database size S are given by:

$$FAR_s = 1 - (1 - FAR)^s = S * FAR \; FRR_s = FRR$$
$$No.of False Accepts = S * (FAR_s) = S^2 * FAR$$

From the above mathematical equation, there is a need to increase the no. of false accepts and it can be achieved in two ways (i) By reducing FAR (ii) By reducing S. The FAR of a modality is limited by the recognition algorithm and cannot be reduced indefinitely. Thus, there is a need to decrease the value of S and this can be achieved with the help of some classification techniques. In any identification system, the database is divided into male and female categories then search space can be reduced by half the original database. Similarly in case of other traits, if database can be divided into two or more categories then search space can be reduced accordingly.[2]

Neural Networks, which is a simplified model of biological neuron system, is a highly parallel distributed processing system that is made up of massively inter-conneted neural computing elements which have the ability to learn and thus acquire knowledge and finally make it available for usage.

Different learning techniques exists to enable the Neural Network gain knowledge. Neural

Network architecture can be used for various classifications based on the learning techniques and other data features. Some classifications or classes of Neural Network refer to this learning mechanism as a training period and its ability to solve the problem using the acquired knowledge as inference.[3, 4]

The flow chart showing a face classification system using neural networks is shown below:

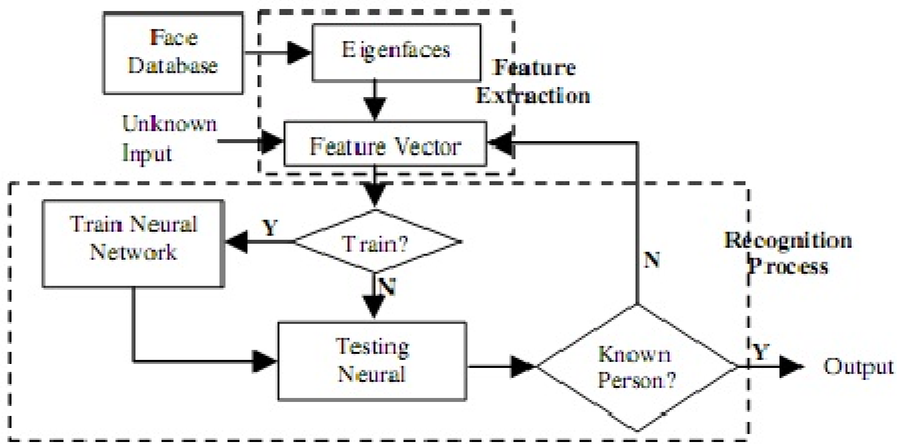

Figure 1: Face Classification System Using Neural Networks

The different types of Neural Netowrk architectures are as follows: [5]

- **Single Layer Feedforward Netowrk** :

  This kind of Neural network consists of two layers, called input layer and output layer. The input layer neurons receives all the input signals and output layer neurons receives all the output signals. The links carrying weight connect each input neuron to a output neuron but not its opposite.This kind of network is known as feedforward in type or having acyclic nature. Despite these two layer, the network is called single layer because only the output layer alone performs computation.The input layer only transmits signals to the output layer. Thats why it is called single layer feedforward network.

- **Multilayer Feedforward Network**:

  This network, as the name suggests consists up of multiple layers. Hence, architectures of this class besides having an input and an output layer it also has one or more intermediate layers known as hidden layers. The computational elements of the hidden layers are called as hidden neurons or units. The hidden layer helps in performing useful inter-mediate computations before sending the input to the output layer. Input layer neurons are linked to hidden layer's neurons and weight on these links is referred to as input hidden layer weight. Also, hidden layer neuron are linked to output layer neurons and its corresponding weight is referred to as hidden output layer weight.

- **Recurrent Networks**:
  This network differs from the feedforward architecture in the way that there will be atleast one feedback loop. Hence, in this network, for e.g., there could exist one layer for feedback connection. There can also be neurons with self feedback links, that is, the output of the neuron is fed back into itself as an input.

Some characterisitcs of neural networks are as follows:

- The Neural Network exhibits mapping capabilities, i.e., they could map input patterns to its associated output pattern.
- The Neural Network learns by means of examples. Hence, its architectures could be trained using known examples of the problem before they can be tested for its inference capabilites on an un-known instance of that problem. They could therefore identiy new objects which were previously untrained.
- The Neural Network possess capabilities to generalize. Hence, it can find new outcomes from the past trends.
- The Neural Network is a robust system and is fault tolerant. It can therefore recall the full patterns from the incomplete or partial, noisy patterns.
- The Neural Network can compute information in parallel at fast speed and in a very distributed manner.

2.1 Back-Propagation Neural Network Algorithm

A common back propagation neural network having multilayer feed forward with supervise learning is shown in the figure.

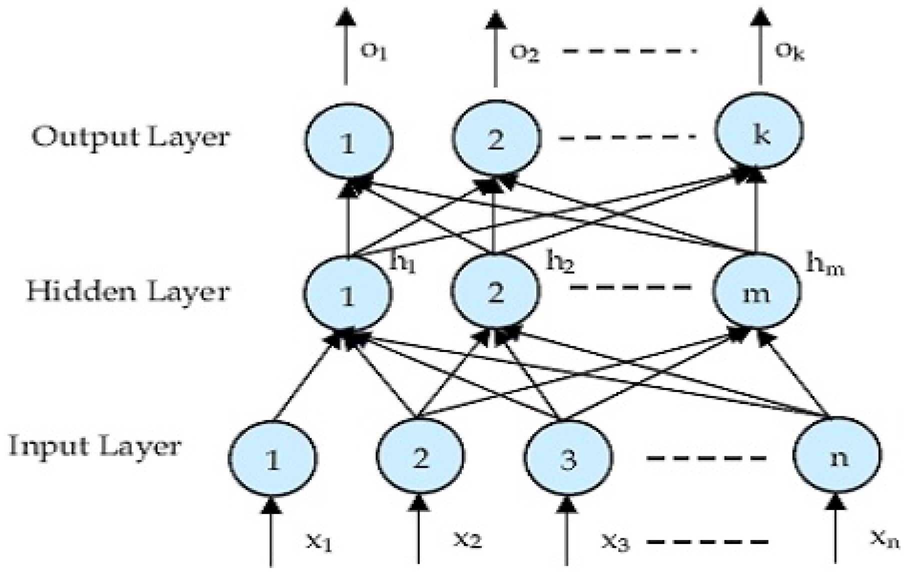

Figure 2: Basic Block of Back Propagation Neural Network

Here, learning process in back propagation requires pairs of input and target vectors. The output vector **O** is compared with target vector **t**. In case of difference of O and t vectors, the weights are adjusted to minimize the difference. Initially, random weights and threshoholds are assigned to the network. The weights have to be updated every iteration so as to minimize the mean square error between the target vector and the output vector. [5]
Input forthe hidden layer:

$$net_m = \sum_{z=1}^{n} x_z w_{mz}$$

The units of output vector of hidden layer, after passing through activation function is given by:

$$h_m = \frac{1}{1+exp(-net_m)}$$

Similarly, the output layer$'s$ input is given by

$$net_k = \sum_{z=1}^{m} h_z w_{kz}$$

The units of the output vector of the output layer is given by

$$o_k = \frac{1}{1+exp(-net_k)}$$

For updating the weights, erro needs to be calculated. This is done by:

$$E = \frac{1}{2}(\sum_{i=l}^{k}(o_i - t_i)^2)$$

o_i and t_i represents the target output and the real output at a neuron i in the output layer, respectively. If the error is less than tolerance, predefined limit, training process will stop, otherwise weights are to be updated. In case of weights betweeen hidden layer and output layer, the change of weights is given by:

$$\Delta w_{ij} = \alpha \delta_i h_j$$

where α is the training rate coefficient that is restricted between the range $[0.01, 1, 0]$, h_{ajj} is the output of neuron j in the hiddenneuron layer and δ_i can be obtained by:

$$\delta_i = (t_i - o_i)(o_i)(l - o_i)$$

Similarly, the change of the weights between output layer and the hidden layer is given by :

$$\Delta w_{ij} = \beta \delta_{Hi} x_j$$

where β is a training rate coefficient that is restricted to the range $[0.01, 1.0]$, x_j is the output of neuron j in the input layer, and δ_{Hi} can be obtained by:

$$\delta_{Hi} = x_i(l - x_i) \sum_{j=1}^{k} \delta_i w_{ij}$$

x_i is the outpu at neuron i in the input layer, and summation term represents the weighted sum of all δ_i values corresponding to neurons in output layerthat obtained in the equation. Post calculating the weights change in all layers, the weights are updated as:

$$w_{ij}(new) = w_{ij}(old) + \Delta w_{ij}$$

This process is repeated until the error reaches the minimum value.

3 Face Recognition using Principal Component Analysis

An image can be viewed as a vector. Number of components of the vector will be product of its width and height. So each pixel corresponds to one vector component. The image–vector transformation can be obtained via simple concatenation i.e. the rows of the image are placed beside one another. This image space is not an optimal space for face description. We need to build a face space, which better describes the face. The basis vector of this space is called the principal components. There is width x height pixels in image space. So, the dimension of the face–space is lesser than the dimension of the image–space. The goal of the Principal Component Analysis is to reduce the dimension of t his image space so that new basis better describes the typical model of the image space.

These eigenfaces are a set of eigen vectors used in computer vision problem for human face recognition. This approach of using eigenfaces for recognition was first developed by Sirovich and Kirby (1987) and further used by Matthew Turk and Alex Pentland in face recognition and classification. It is considered the first successful example of face recognition technology. These eigenvectors were derived from covariance matrix of the high-dimensional vector space of the possible faces of human beings.

The set of eigenfaces can be generated by the process called as the principal component analysis (PCA) on large set of different human face images. Eigenfaces can be considered as a set of ”standardized face ingredients”, derived from the statistical analysis of images of faces. Every human face can be considered as a combination of these standard faces. Since a person's face is not stored as a digital photograph, but just as a list of values (one value for each of the eigenface in the database used), space required to store each person's face is much lesser.

The eigenfaces that are being created will appear as dark areas arranged in some specific pattern. This pattern is how the different features of a particular face are singled out, evaluated and scored. There is a pattern to evaluate this symmetry, if there is any facial hair or where hairline is or evaluate the size of the mouth or nose. Other eigenfaces have some patterns that are slightly tougher to identify, and the eigenface may look very little like a face. This technique is used in creating eigenfaces and face recognition is hence done using them. This particular technique is also used for handwriting analysis, lip–reading, voice–recognition, sign–language and hand gestures interpretation and medical imaging analysis.[7, 9]

3.1 PCA Algorithm

Principal Component Analysis is a mathematical and statistical technique and is useful in face recognition & image compression. It is a very common technique used for finding patterns in high dimensioned data. It also highlights the differences and similarities amongst the dataset. It is also useful for the extraction of set of eigenfaces from the initial inputted images of human faces. And these eigenfaces can also be recombined in proper ratio to reconstruct the original face image.

3.1.1 Eigenface Generation

The first step is to prepare the training set of face images. The pictures belonging to the training set should be taken under similar lighting conditions, and must be normalized to have the eyes and mouth aligned across all the images. They must also be all resized to the same resolution. Every image is treated as a single vector, and simply by the concatenation of the rows of pixels in original image which results in a single row with r x c elements. It is also assumed that all the images of the training set are stored in a matrix T, where every row of the matrix is an image of a face.
The average image Av has to be calculated and then subtracted from each original image in T. Two different training set has been used from the facial database as mentioned in Section 4. Resolution of all the images is chosen as 291x243 pixels. The set of original facial images from 1st training set (yale database) has been shown in figure 3.[7, 6]

T is the image matrix of size (M x N).

M= (r.c) this is the dimension of each image.

N=number of images

Figure 3: Yale Pics Database

T_i represents ech row vector corresponding to each image.

Average Vector, $A_v = \sum_{i=1}^{N} T_i$

Subtracting the Mean Face, $X_i = T_i - A_v$

3.1.2 Covariance Matrix and EigenVectors

We then calculate the eigenvalues and eigenvectors for the covariance matrix S. Each eigenvector is having the same dimensionality as the original images, and thus can be seen as an image itself. These eigenvectors of the covariance matrix are thus known as eigenfaces. They are the directions in which the images differ from the mean image. Usually this will be a computationally expensive step, but the practicality of these eigenfaces roots from the possibility to compute the eigenvectors of S efficiently without computing S explicitly, as detailed below.

Covariance Matrix, S $= \frac{1}{N} \sum_{i=1}^{N} X_i X_i^T$

Eigenvectors u_i of S are:

$$XX^T u_i = \lambda_i u_i$$

But, the matrix XX^T is very large, hence, practically not feasible to calculate.

Let us consier matrix D $= X^T X$

$$\text{Eigenvectors of matrix D are } v_i$$
$$X^T X v_i = \lambda_i v_i$$
$$X(X^T X)v_i = X\lambda_i v_i$$
$$S(Xv_i = \lambda_i(Xv_i)) \text{ and } Su_i = \lambda_i u_i \text{ Thus, S and D have same eigenvalues}$$
$$\text{and their eigenvectors are related as}$$
$$u_i = Xv_i$$

The eigenvectors (eigenfaces) with largest associated eigenvalue are kept. The eigenfaces obtained are as shown in Figure 4.

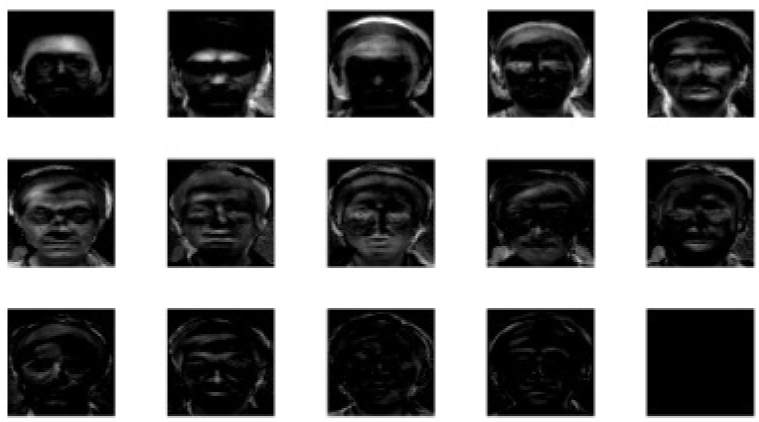

Figure 4: Eigenaces for Yale Pics

3.1.3 Weighted Vector

Weighted Vector of the facial image represents the component of every eigenface of that image. Weighted vector w of all the images is then calculated as

$$w = uTX$$

and vector space is formed using these weighted vectors of all facial images.
Each weighted vector of a face represents a point in the weighted vector space. Similarly, for every new image, its corresponding weighted vector is calculated and mapped into

this vector space. Face recognition is done by calculating the distance from its nearest vector using a distance measurement algorithm like Mahalanobis Distance, Eucledian Distance, etc

3.2 Reconstruction of Original Images

The original facial images can be reconstructed using the eigenfaces and the corresponding weighted vector of the images. Each Face Image (minus the average/mean face) can be represented as a linear combination of best k eigenvectors as:

$$T_i - A_v = \sum_{j=1}^{k} w_j^i u_j$$

where u represents eigenvectors and w weighted vectors.
An Example is shown in Figure 5 demonstrating the linear combination of eigenvectors to form the original image.

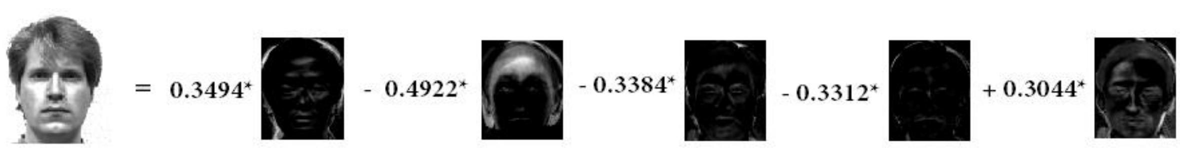

Figure 5: Linear Combination of Eigenvectors

The Reconstructed Images of the test faces taken from the yale database have been reconstructed using above procedure and shown in Figure 7.

3.3 Mahalanobis Distance Algorithm

We can use either of Euclidean distance algorithm or Mahalanobis Distance Algorithm to compute the distance between weighted vectors. However, Mahalanobis Algorithm gives better results.
In Euclidean Distance Algorithm distance between two points x and y is calculated as

Figure 6: Reconstruction of original faces

$$D(x,y) = \sqrt{(x-y)^t(x-y)}$$

Hence, variations along all axes are treated as equally significant.

In Statistical or Mahalanobis Algorithm distance between two points x and y is calculated as

$$D(x,y) = \sqrt{(x-y)^t(x-y)s^{-1}}$$

where S takes into account the variability of each direction component, i.e. component with high variability should receive less weightage from those having low variability. Next, when a new image is to be tested for its validitiy, its corresponding weighted vector is found and mapped into the vector space. The eigenface whose distance is least to the test–image and the distance valus is lesser than the accepted threshold value, then the unknown face can be recognised.

4 Facial Databases

Two different facial databases have been used from which set of test faces are taken for implementing the above face recognition algorithms.

Database 1 : Known persons

It consists of a set of 13 coloured images of 13 different known people (1 Image per Person) taken by us under almost same lighting and background conditions. Resolution of each image is taken as 320x240 pixels.

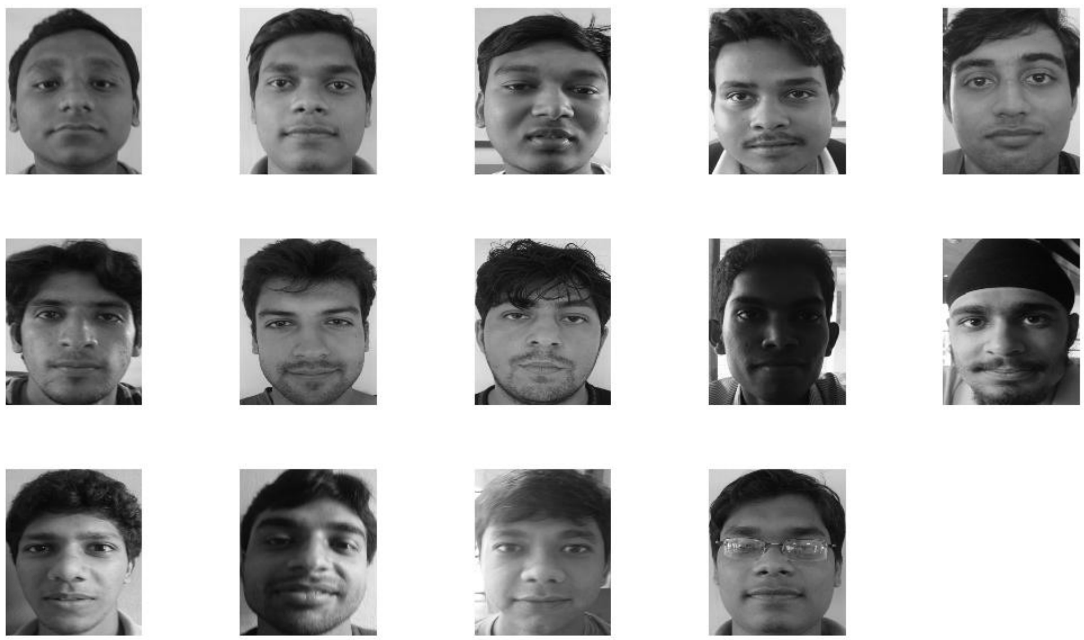

Figure 7: Known Faces Databse

Databse 2: The Yale Database

It consists of a set of standard 165 black n white images of 15 different people (11 Images per Person) taken from yale university standard database created by them for use in facial algorithm. All the images are properly aligned and taken in same and good lighting and background conditions. Resolution of each image is taken as 320x243 pixels. 11 Images of each person consists of different expressions and lighting effects as follows:

- Normal lights
- Centre Light, Left Light, Right Light
- Sad, Happy, Surprised
- Wink, Sleepy, Normal
- Glasses, Without Glasses

source: $http://face-rec.org/databases/$ [1]

The Yale Databse sample is as shown.

Figure 8: Yale Database

Database 3: The FERET Database, USA The database contains 1564 sets of images for a total of 14,126 images that includes 1199 individuals. All the images are of size 290x240. This database was cropped automatically and segregated into sets of 250 female and 250 male faces. [1]
source: $http : /face.nist.gov./colorferet/$
The FERET database is as shown in Figure–9.

Figure 9: FERET Database

Database 4: Animal faces database

This databse was created by obtaining different animal faces and different objects for the purpose of face classification. The animal faces were mostly obtained from the website of Washington state University [8] *http : //imagedb.vetmed.wsu.edu/*. The other animal faces and objects were obtained from *http : //images.google.com/*

A sample of the animal faces database is as shown in Figure–10.

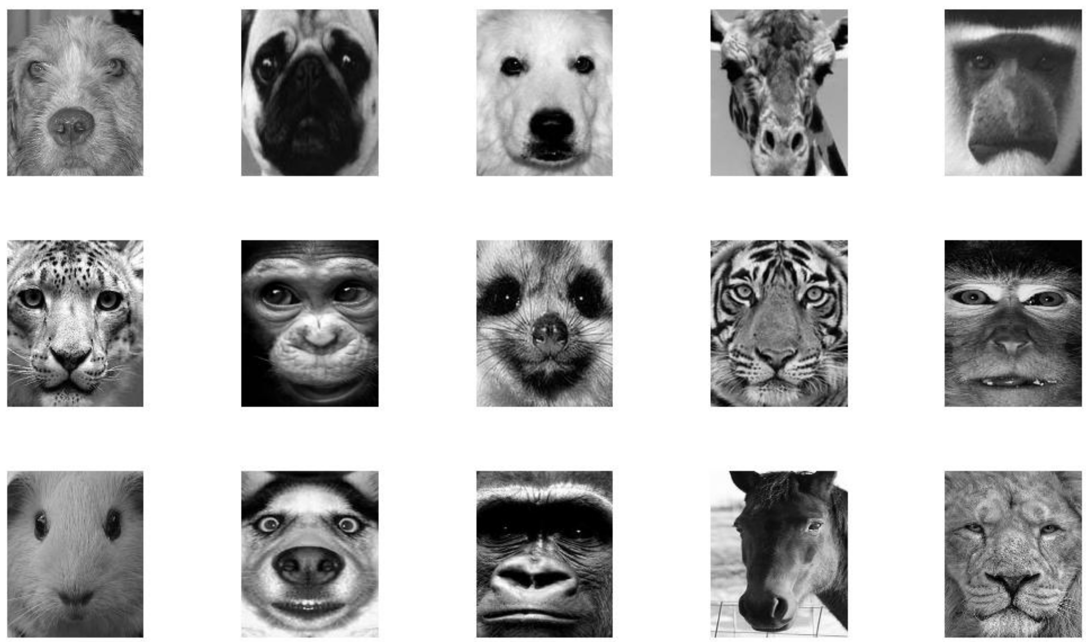

Figure 10: Animal Faces Database

5 Analysis and Results

5.1 Analysis of Face Classification using Neural Networks

5.1.1 Human-Non human face Classification

Given a set of animal and human faces, we train our system in a way that once a new image is inputted to the system, it can detect whether the new image is a human face or not. This was done with the help of Back Propagation algorithm using Neural Networks as described in section 2.1 .

The training was done using a set of images consisting of 51 non-human faces and 60 human faces (30 males and 30 females). The learning rate coefficient(α) was fixed at 0.5 and the momentum coefficient(η) was 0.76 . The model thus obtained was tuned repeatedly until the error value was lesser than the tolerance value of 0.01.

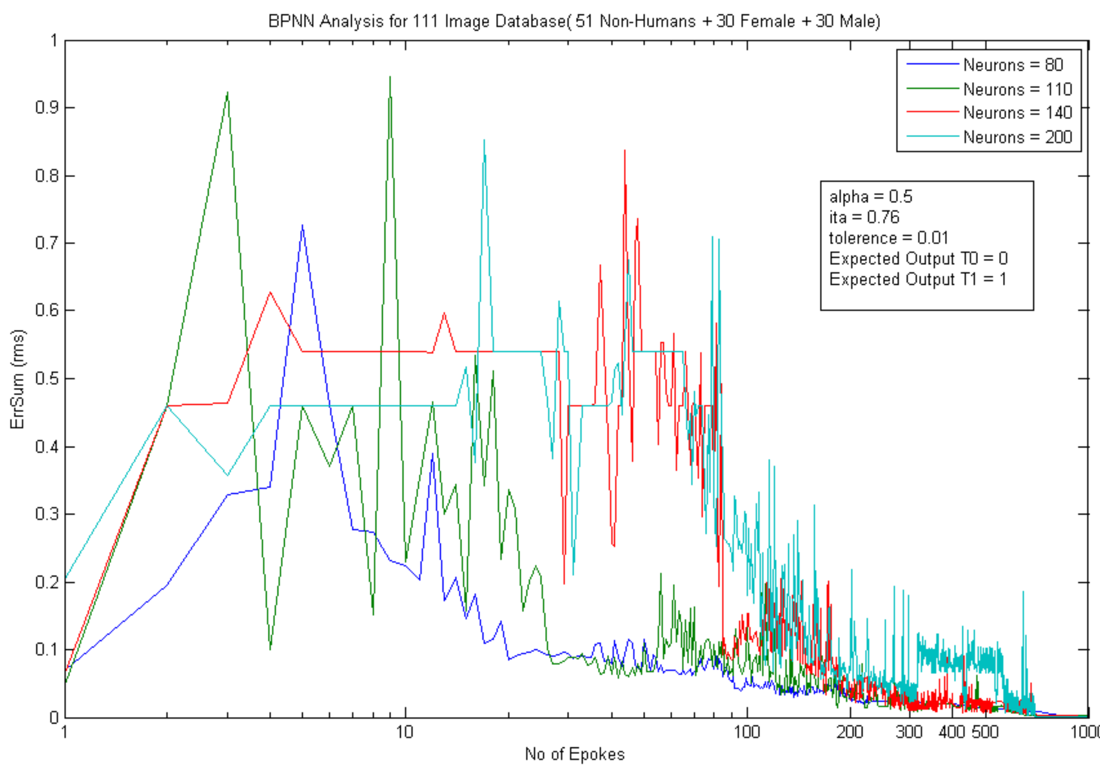

Figure 11: Tuning curve: BPNN

Also, the number of hidden layer neurons was chosen accordingly so as to get the best results on the test set of images. In this case, the test case consisted of 35 non-human images and 40 human faces (20 males and 20 females). The accuracy rate for different neurons is as shown.

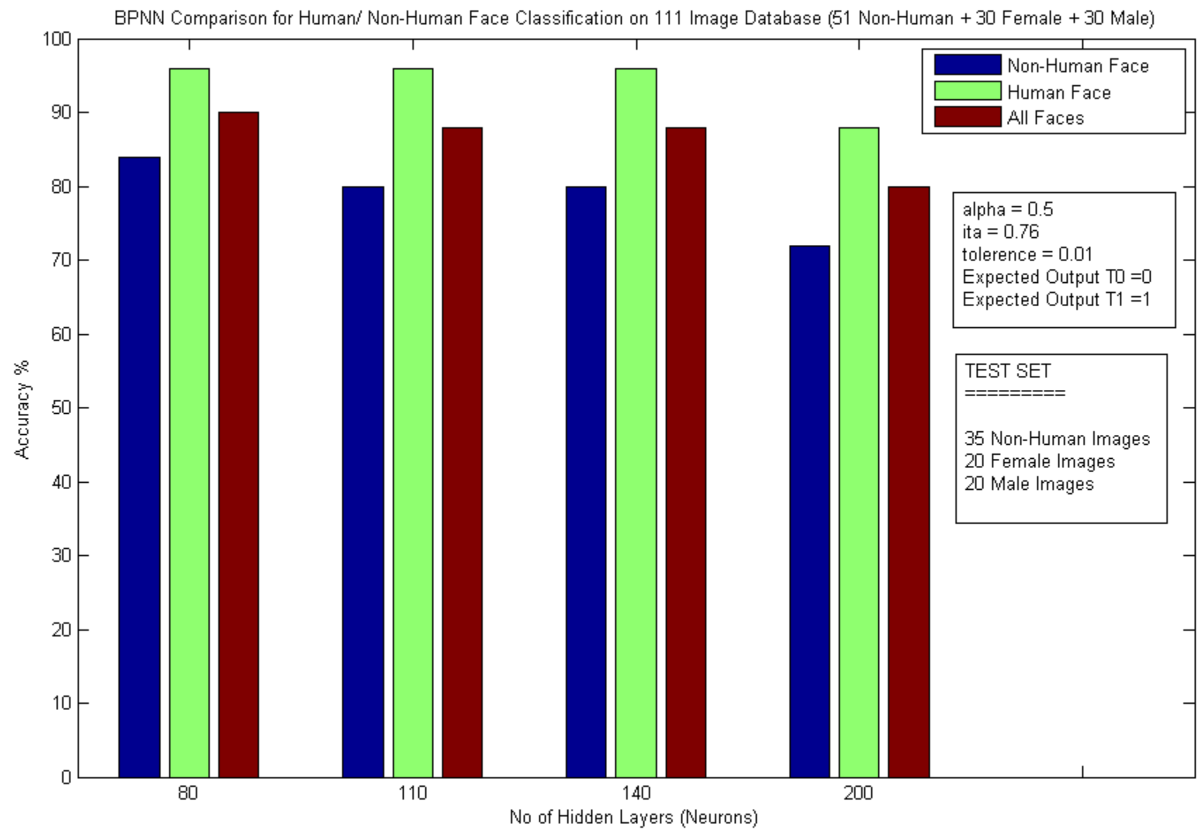

Figure 12: Accuracy Rate : BPNN

For most of the cases, human faces could be recognised 90%+ of the times. The non-human images which comprised of both animal faces and random non-face images were identified more than 80%+ of the times always. From the graph, it was concluded that the ideal number of neurons for the given problem and the train set was 80.

Another training was done using the Yale Database.The training set consisted of 15 images from the Yale Database and 15 random animal faces. The learning rate coefficient(α) was fixed at 0.5 and the momentum coefficient(η) was 0.76 . The model thus obtained was tuned repeatedly until the error value was lesser than the tolerance value of 0.01.The model tuning curve obtained was as shown in Figure 13.

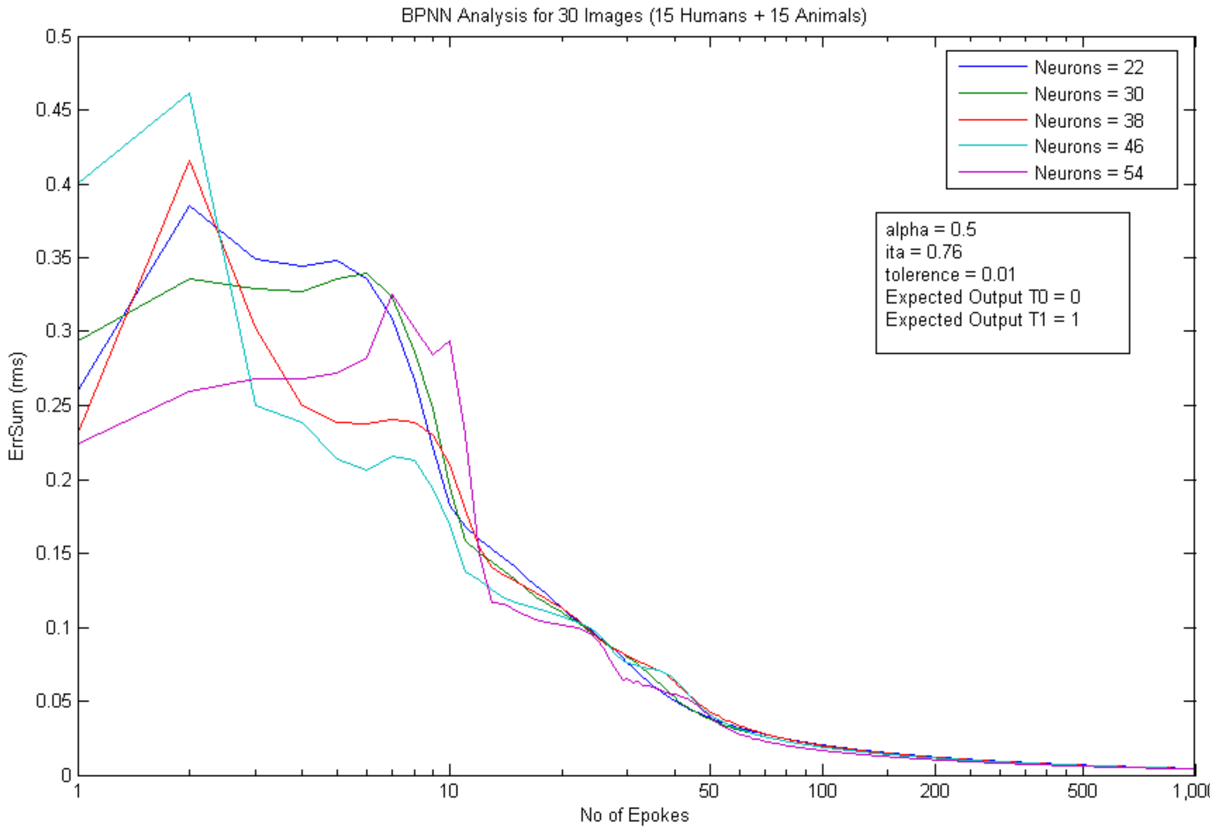

Figure 13: Training Curve BPNN: Yale Database

The test set of images consisted 30 images out of which 15 human faces were the same person but with different facial expressions and 15 different animal faces. The succes rate obtained was 100% for all the neuron cases.

5.1.2 Gender Classification

Given a set of human faces, our aim was to distinguish them among male and female categories. For this classification, again back propagation algorithm was used. The training set consisted of 100 human faces out of which 50 were male and 50 were female faces. The learning rate coefficient(α) was fixed at 0.5 and the momentum coefficient(η) was 0.76 . The model thus obtained was tuned repeatedly until the error value was lesser than the tolerance value of 0.01.

The test set consisted of 50 images out of which 25 were male and 25 were female faces. The results obtained are shown in the Figure 14.

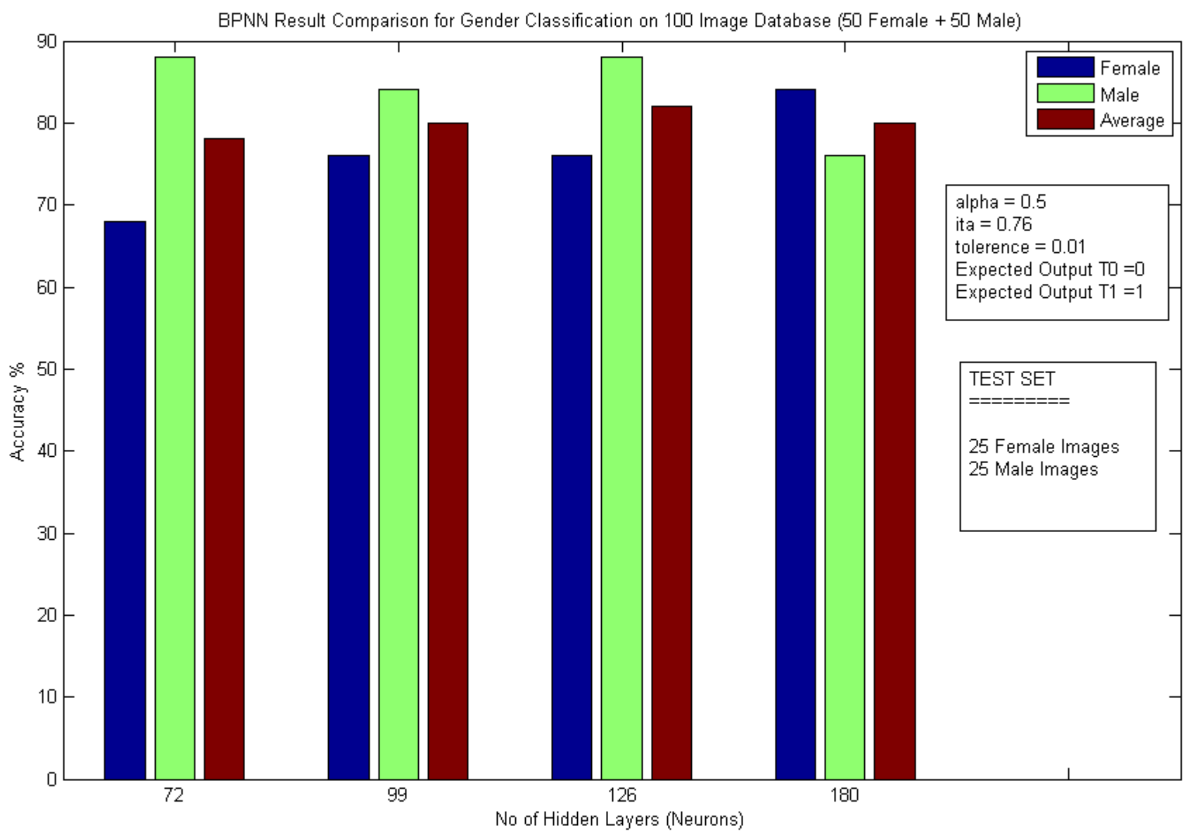

Figure 14: Gender Classification Results

Female faces were recognised around 75% of the times accurately while the male faces were recognised around 90% of the times.

5.2 Analysis of Face Recognition using Principal Component Analysis

5.2.1 Analysis on Yale database:

Step 1: Cropping of Images

Initially, all the images were of the size 320x243 where in the images were captured in front of a white screen. Two different ways were adopted to crop the images and extract the face out of the images.

Using theConventional Triangularization Approach, we had to click the Left eye, Right eye and then the lips. The system would then automatically crop the image using these three coordiantes and the face extracted would contain the face minus the ears and a part of forehead. All the images cropped using this method are of uniform size of 293x241.

Using the manual cropping method, all the images are cropped manually using the *im-crop* crop command of MATLAB. The resultant images contain the entire face. And, hence, more number of features are extracted using the manual cropping method.

Figure 15: Manual Cropping

Step 2: Image Pre-processing

All the cropped images were then normalized, and images are store in a matrix form where each row represents an image vector. Next, an average vector is calculated for all the images and is subtracted from all the image vectors. Next, the covariance matrix is generated and corresponding eigefaces are generated. The top eigenfaces are chosen for

Figure 16: Conventional Triangularization Approach

the further analysis. In our caase, we chose the top 90% of the eigenfaces. Weighted vector w of all images is calculated representing the appropriate proportion of each eigenface.Using these eigenfaces and the mean face, the images are reconstructed to check the accuracy of the eigenfaces. If the images are reconstructed properly, we can now proceed to the recognition part.

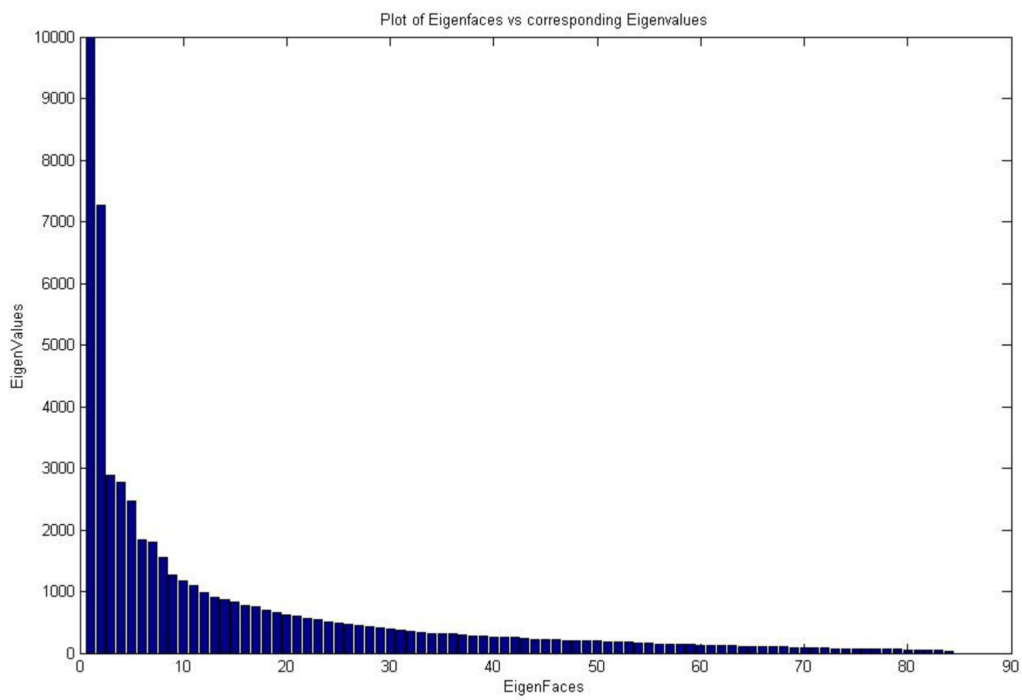

Figure 17: Plot of Eigenfaces vs corresponding Eigenvalues

Step 3: Recognition of faces:

Next, when a new image is to be tested for its validitiy, its corresponding weighted vector is found and mapped into the vector space. The eigenface whose distance is least to the test–image and the distance valus is lesser than the accepted threshold value, then the unknown face can be recognised.

The system was trained using 15 images captured under normal lighting conditions. The images were cropped both manually and automatically.Set of Test Images consists of all the normal expression images and the other expression images are used during the recognition part. To test the correctness of the algorithm implemented, all the faces were checked for all the possible present facial expressions.

The following is the result obtained for recognition done using the manual cropping. Except for the images in which lighting conditions varied, 90%+ recognition rate was achieved for all the facial expression.

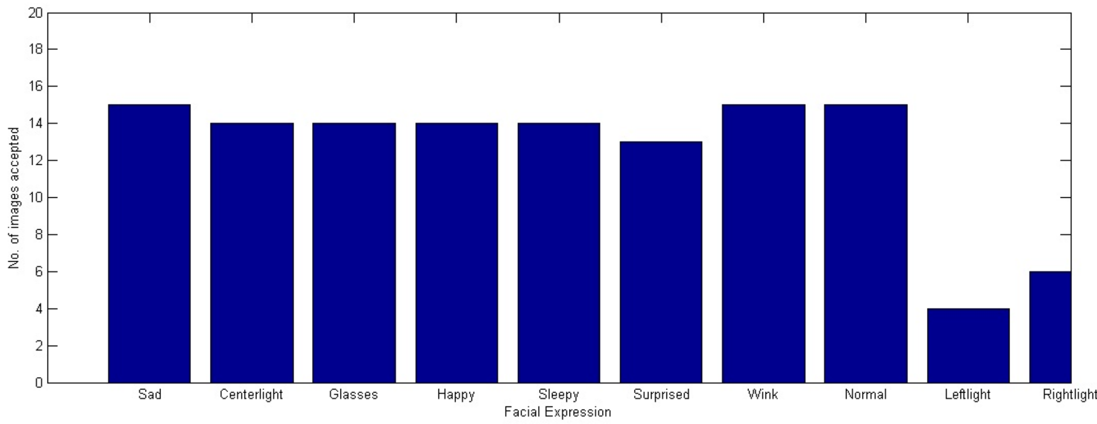

Figure 18: Recognition of faces done using Manual Cropping

The result obtained for the recognition done for the images cropped using the Conventional Triangularization Approach is shown graphically in Figure–19.

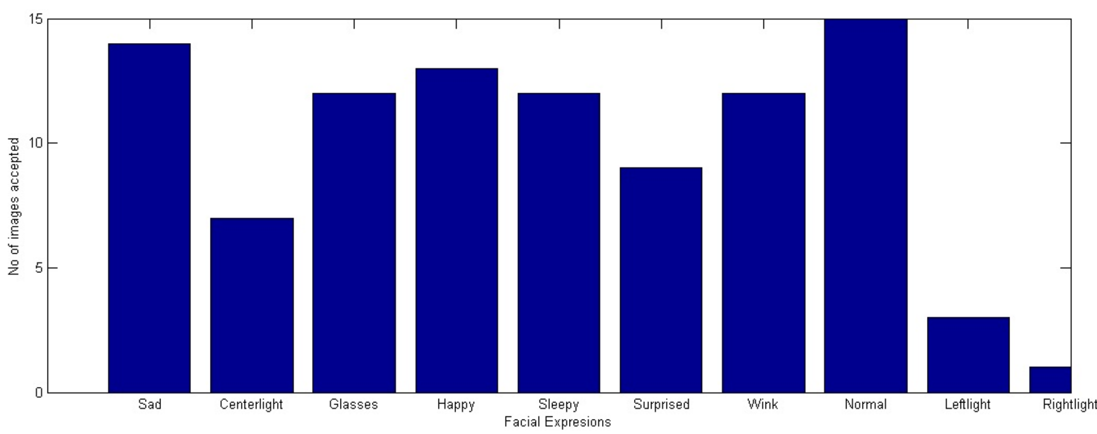

Figure 19: Recognition of images cropped using Conventional Triangularization Approach

During the recognition for images cropped automatically, the recognition rate declined to a great extent in case of varied lighting conditions. The results also dropped when the images features were changed to a greater extent, say in the case of surprised and winking expression.

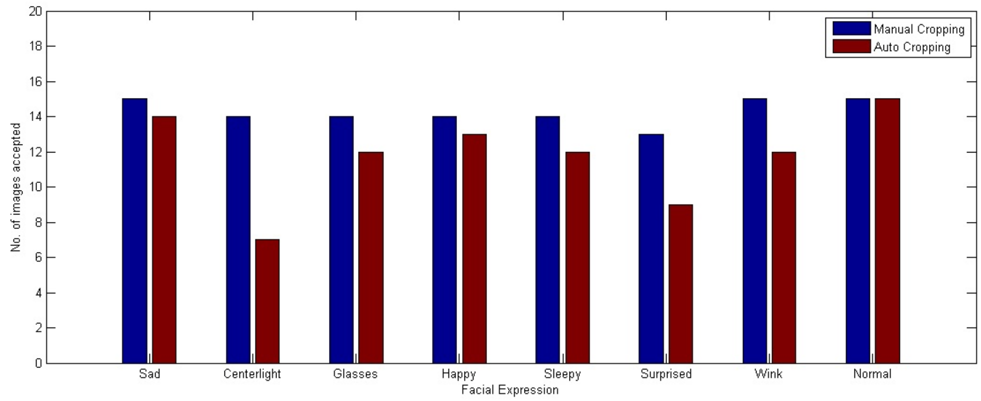

Figure 20: Comparision of Recognition rates of different Cropping techniques

Overall, the images which were cropped manually contained more features then the ones cropped otherwise.A comparision on the two sets of images is as follows. The recognition rates of the image cropped manually were better and a considerable difference in the results were noted.

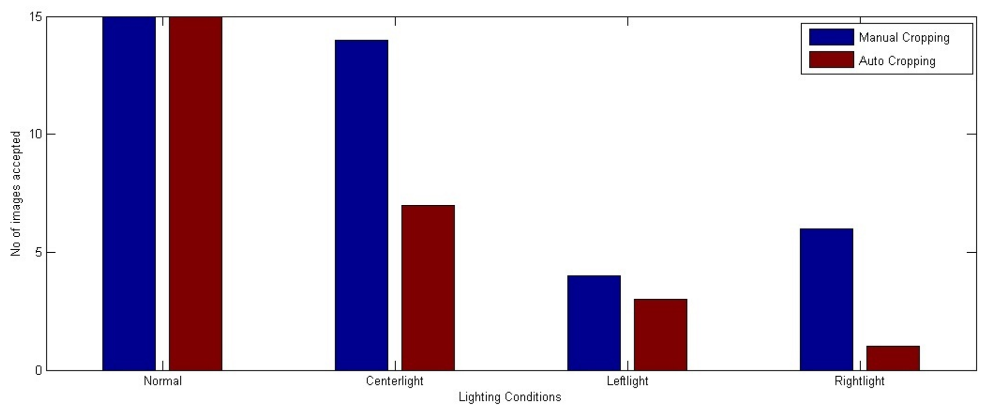

Figure 21: Effect of lighting conditions on recognition

Another point worth noticing here is the effect of different lighting conditions. Images in which lighting varied uniformly had a higher percentage of recognition rate than compared to the ones in a which light was projected from right or left sides. Hence, the besic assumption of the algorithm implemented that the images taken should be under uniform lighting conditions. Another important neccesity was the clarity of the images captured. Image-wise analysis for all the eight expressions is as follows.

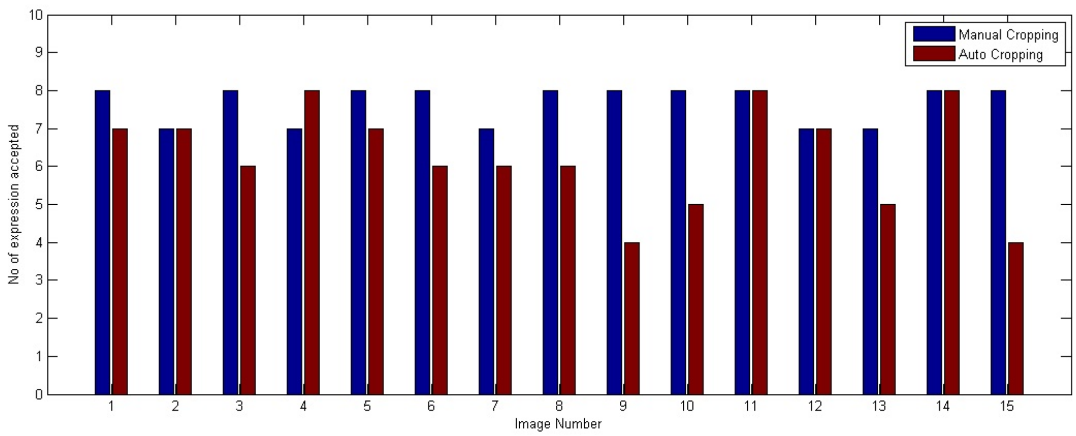

Figure 22: Image-wise analysis

5.2.2 Analysis on Feret Database:

We had a set of 114 distinct faces available to us. Though it was concluded in the previous section that manual cropping leads to better results, we opted for automatic cropping of the images. Automatic cropping is the real practical approach which is implented in reality. The system was trained using 85 distinct images. The image pre-processing was same as the case of analysis of the yale databse. The system was tested using 40 known/trained images with different facial expression and 10 unknown faces. During the image recognition phase, the main analysis point was deciding the threshold values. For this, we tested the accuracy rate of the program for different threshold values starting from 0.50 to 1.20 with an increment of 0.01. The accuracy of program was determined using two different parameters:

- FAR: Flase Acceptance Ratio: This rate determines the number of unknown faces that were falsely accepted during the recognition.
- FRR: False Rejection Ratio: This rate determines the number of known faces that were falsely rejected during the recognition.The results obtained were as follows.

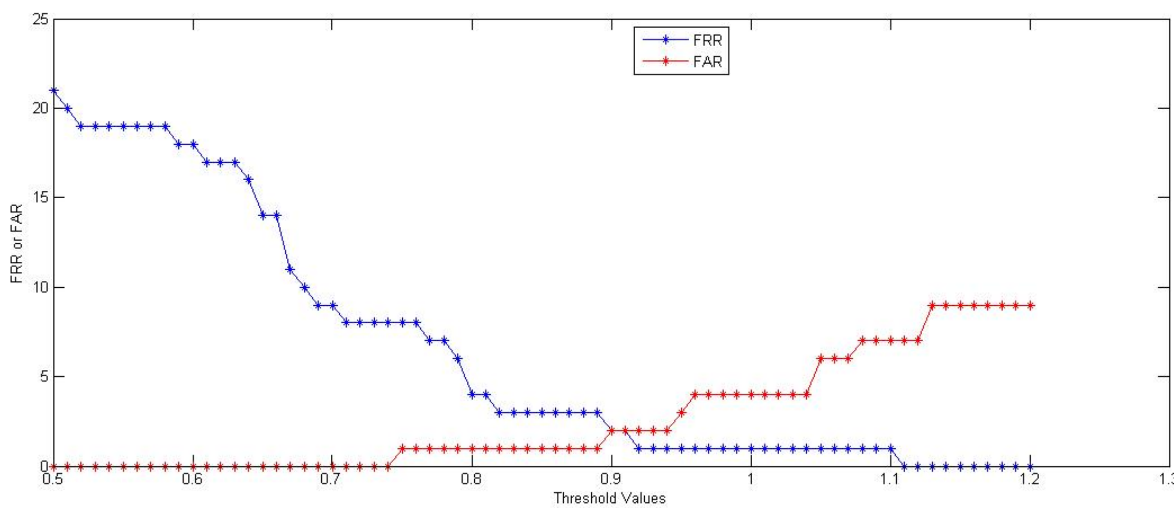

Figure 23: Feret Analysis: FAR, FRR

A high FAR value poses a serious securtiy threat to the environment. A high FRR value is undesirable as it poses a lot of hassles for the authorised personnels to use the environment. Hence, for optimum resultsm we should have a low value of both FRR and FAR.

Success rate is defined as the maximum sum of known face acceptance and the unknown face rejection rate, or in other words the minimum sum of known face rejection and the unknown face acceptance. The succes rate graph obtained is as shown in the Figure–24.

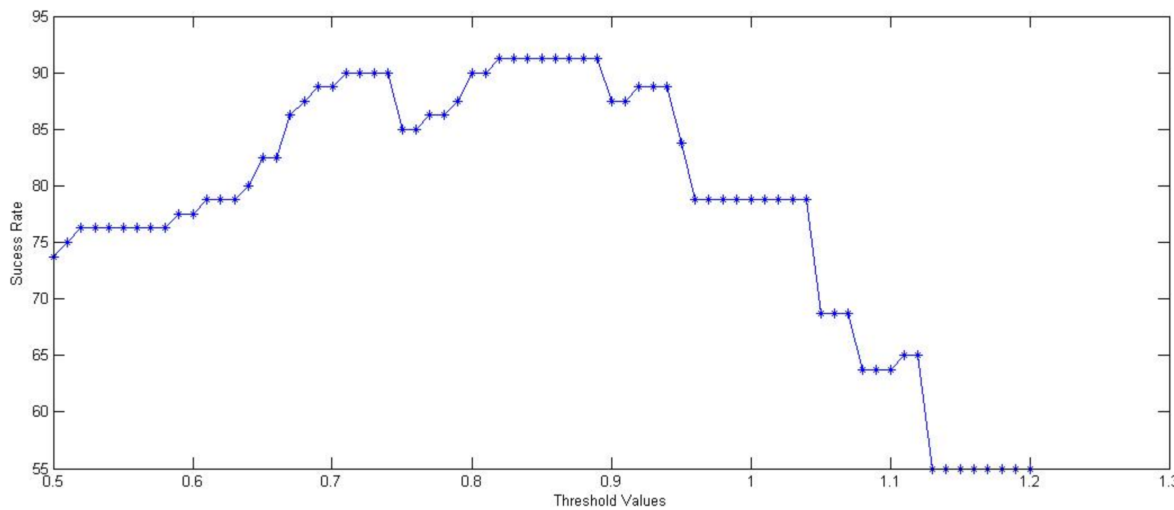

Figure 24: Feret Analysis: Success Rates

From the graphs obtained, the maximum success rate is obtained for threshold values 0.82 to 0.89 (sucess rate of 91.5%). At this threshold value, 1 out of 10 unknown images were falsely accepted and 3 out of 40 known faces were falsely rejected.

6 Conclusion

Training of the system is the most important step for any classification and recognition system. A good and efficient classification algorithm can save a considerable amount of search space for recognition purposes. The necessary parameters should be carefully chosen and neural network model be tuned properly for best results for the classification phase.

The number of features extracted from the training faces directly affect the recognition rate. It is also very sensitive to lighting conditions and the clarity of the images. Threshold distance values for acceptable recognition of images should be carefully chosen so as to find a proper balance between the FAR and the FRR.

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