CHAPTER 5

FACE VERIFICATION WITH EXPRESSION AND
GENDER IDENTIFICATION SYSTEMS

5.1 INTRODUCTION

Face recognition algorithms try to solve the problem of both verification and identification. When verification is on demand, the face recognition system is given a face image and given a claimed identity. The system is expected to either reject or accept the claim. On the other hand, in the identification problem, the system is trained by some images of known individuals and given a test image. It decides which individual the test image belongs to. The problem of face recognition can be stated as follows: Given still images or video of a scene, identifying one or more persons in the scene by using a stored database of faces. The problem is mainly of classification. Training the face recognition system with images from the known individuals and classifying the newly coming test images into one of the classes is the main aspect of the face recognition systems. The topic seems to be easy for a human, where limited memory can be a main problem; whereas the problems in machine recognition are manifold.

In addition to face recognition systems as discussed in chapters 3 and 4, an integrated approach to human face recognition with expression and gender identification system was proposed in this chapter. The main objective of the proposed work is to identify the human faces with different lighting conditions and
also to identify with minimum false acceptance and rejection rate. The effectiveness of the system was studied by analyzing the performance of recognition time of the proposed method.

5.2 ALGORITHMIC DESIGN

Initially an approach to design the face detection and verification system was made and implemented using GLCM with KPCA and the performance was analyzed. As an extended version, a new integrated approach to human face detection and verification with expression identification system was implemented by extracting the features using LTP method and classifies the features using SVM technique. In addition, an approach to human face detection and verification with expression identification is proposed. This method applies GLCM operation to extract the features of face images to different classes for the purpose of image classification and verification by PCA technique and “expression identification” by extracting the features using LTP method and classifies it using SVM technique.

Another approach to human face detection and verification with gender identification is also proposed. The GLCM and KPCA technique is used for face recognition and Spatial Weber Local Descriptor (SWLD) and PNN is used for gender identification.

5.3 DIAGRAMMATIC FLOW FOR VARIOUS TECHNIQUES INVOLVED IN FACE VERIFICATION WITH EXPRESSION AND GENDER IDENTIFICATION SYSTEMS

The block diagram for face verification with expression and gender identification systems is shown in Figure 5.1.
Figure 5.1 Diagrammatic flow of various techniques involved in face verification with expression and gender identification systems

The proposed method uses the combination of GLCM and the KPCA which reduces the overall time for recognition system with minimum FAR & FRR. Both GLCM and KPCA are integrated to increase the accuracy of the recognition system. In addition a cropping function is included in our proposed method to crop the image to get the region of interest in a group.
GLCM features are extracted for all the images in the database and images are sorted in ascending order, so that images with similar energy features as the input image are sorted and the first ten images are stored for performing KPCA.

5.3.1 Cropping

The image of interest is cropped by performing cropping function. This function is used to crop only the image that we require for face recognition. It is performed in order to remove an unwanted subject or irrelevant detail from a photo, change its aspect ratio, or to improve the overall composition.

5.3.2 KPCA in Face Recognition

KPCA method is one of the methods which try to overcome ineffectiveness by extracting face image features in high-dimensional spaces. KPCA is a technique for nonlinear extraction, closely related to methods applied in SVM and so on. KPCA extracts feature sets more suitable for categorization than classical principal component analysis. KPCA is good at dimensional reduction, and it achieves better performance than PCA.

The Face recognition system using KPCA includes four steps as shown in Figure 5.2.

```
<table>
<thead>
<tr>
<th>Pre-processing</th>
</tr>
</thead>
<tbody>
<tr>
<td>↓</td>
</tr>
<tr>
<td>Discrete wavelet Transform</td>
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<tr>
<td>↓</td>
</tr>
<tr>
<td>Phase Congruency</td>
</tr>
<tr>
<td>↓</td>
</tr>
<tr>
<td>Calculation of Euclidean distance</td>
</tr>
</tbody>
</table>
```

**Figure 5.2 Steps in KPCA method**
5.3.2.1 Preprocessing

In the proposed method, the images are preprocessed to make them suitable for recognition purposes. They are divided into two mutually exclusive sets: the training set and the test set. The training set is used to initialize and prepare the system to recognize arbitrary images and to fine tune the algorithm parameters. The test set is the set of images which is used to evaluate the performance of the system after training is completed. The images are preprocessed to improve the recognition performance. This generally consists of the following steps as shown in Figure 5.3.

![Diagram of pre-processing steps]

**Figure 5.3 Pre-processing steps**

5.3.2.1.1 Noise reduction

Noise reduction is performed to remove any unwanted information in the image which is treated as noise. Generally this process eliminates salt and pepper noise which typically present in an image.

5.3.2.1.2 Histogram equalization

This is typically done to enhance the visual appearance of the input image.
5.3.2.2 Discrete wavelet transform

The preprocessed image is then subjected to perform discrete wavelet transform which is a type of signal representation that can give the frequency content of the signal at a particular time or spatial location. It allows good localization both in time and frequency domain. The image is converted from time domain to frequency domain because processing an image having spatial information is more complex, and the image having spectral information contains more data to be processed.

5.3.2.3 Phase congruency

Phase congruency is a measure of significance in an images, a method of edge detection that is particularly robust against changes in illumination and contrast. It is a dimensionless quantity that is invariant to changes in image brightness or contrast and hence it provides an absolute measure of feature points. Edge detection is a technique in image processing and computer vision particularly in the areas of feature detection and feature extraction, which aim at identifying points in a digital image in which the image brightness changes sharply or, more formally, has discontinuities.

A key benefit of this technique is that it responds strongly to Mach bands, and avoids false positives typically found around roof edges. A roof edge is a discontinuity in the first order derivative of a gray-level profile.

In the proposed method, phase congruency is applied for the image obtained from discrete wavelet transform as shown in Figure 5.4. When the phase congruency features are extracted from the image, only the edge of the image is taken into consideration thereby the background is eliminated.
5.3.2.4 Euclidean distance

In the proposed method, the images, after taking phase congruency, are used to construct the covariance matrix. This covariance matrix is then processed to calculate the eigen values and eigen vectors of the matrix. From the eigen values, feature value is calculated to obtain the euclidean distance. The euclidean distance is probably the most widely used distance metric. It is a special case of a general class of norms and is given by equation (5.1).

$$\| X - Y \|_p = \sqrt[2]{| x - y |}$$  \hspace{1cm} (5.1)

If this euclidean distance is less than the threshold value the person is found to be authorized. On the contrary if the euclidean distance is greater than the threshold value the person will be treated as an unauthorized person.

5.3.3 Computation of Texture Feature using WLD

After face recognition, the next step is gender classification. In order to classify, the features have to be extracted first using the new texture descriptor called the WLD. This descriptor makes use of the Weber’s Law which states that the ratio of the incremental threshold to the background intensity of the given image is a constant. Although this new descriptor has been tested for gender classification, but,
as a novelty, it has been integrated with the GLCM and KPCA to analyze the improvement in the proposed technique. The WLD is basically a histogram, which integrates the differential excitation values according to the corresponding gradient orientations. The following steps are used to compute this descriptor.

**Step 1:** Computation of differential excitation

**Step 2:** Computation of gradient orientation

**Step 3:** Histogram computation

### 5.3.3.1 Differential excitation computation

It is computed as a ratio of the relative intensity difference of a current pixel and its neighbor to the current pixel intensity. This is used to extract the local salient features of the given input image.

As a first step the differential excitation \( \xi(p_c) \) for the current pixel \( p_c \) is computed as the relative difference between the current pixel \( p_c \) and its neighbor, which is given by the equation (5.2),

\[
\Delta p = \sum_{i=0}^{n-1} (p_i - p_c)
\]  

(5.2)

Next, the ratio of the relative intensity difference \( \Delta p \) to the current pixel intensity is calculated using equation (5.3),

\[
DF_{\text{rino}} = \sum_{i=0}^{n-1} \left[ \frac{\Delta p_i}{p_c} \right]
\]  

(5.3)
In order to eliminate the noise, the arctangent function filter is used. The arctangent filter function is given by the equation (5.4),

\[
\xi(x_c) = \arctan(\Delta E_{\text{min}}) = \arctan \left( \frac{\sum_{i=0}^{\Delta p_c} \Delta p_i}{p_c} \right)
\]  

(5.4)

The differential excitation \( \xi(p_c) \) values may be either positive or negative. The positive indicates the pixel is darker compared to its surroundings. And the negative indicate that the pixel is lighter compared to its surroundings.

5.3.3.2 Gradient orientation computation

After calculating the differential excitation component, the gradient orientation component is computed using the equation (5.5),

\[
\theta(p_c) = \arctan \left( \frac{p_{73}}{p_{51}} \right)
\]  

(5.5)

where \( p_{73} = p_7 - p_3 \) is the difference in the intensities of the two pixels which are on the left and right of the current pixel \( p_c \) and \( p_{51} = p_5 - p_1 \) is the difference in the intensities of the two pixels which are directly below and above the current pixel \( p_c \) and \( \theta \in (-\pi/2, \pi/2) \). The gradient orientations are further quantized into \( T \) dominant orientations which is given by the equation (5.6),

\[
\phi_i = \frac{2\pi}{T}, \text{where } t = \text{mod} \left( \left\lfloor \frac{\theta'}{2\pi/T} + \frac{1}{2} \right\rfloor, T \right)
\]  

(5.6)

where \( \theta' \in (0, 2\pi) \). Thus the gradient orientation is computed.
After extracting the two features, namely, the differential excitation and the gradient orientation, the WLD is computed as a histogram corresponding to the differential excitations and gradient orientations, which is in turn divided into subhistograms with S bins and processed. However, this descriptor lags in the spatial information, which is embedded by dividing the given image into a number of blocks and by computing and concatenating the WLD histogram for each block. Thus the SWLD is obtained. For the classification of gender using the PNN the euclidean distance classifier is used.

5.3.4 Probabilistic Neural Network

PNN has two layers. The radial basis neurons are in the first layer which computes its weighted inputs through euclidean distance. Compet neurons are present in the second layer for computing its weighted input with dot product. Weighted inputs and biases are combined to compute net input function.

\[ a' = \text{radbas}(\|W_i \cdot b + a - p\|_1) \]
\[ a^2 = \text{compet}(W_2 \cdot a) \]

**Figure 5.5 PNN architecture**

It is seen from the Figure 5.5, the first layer receives input test data to calculate the distance between the input and the training vector. The vector produced
will indicate closeness between two vectors. Net output vector is generated by the second layer. At the last stage the compete transfer function produces a 1 for male class and a 0 for female class. The algorithm for the proposed technique is given below

**Step 1:** Initialize Q and K, where Q is the number of input vector pairs which is equal to the number of neurons in layer 1 and K representing the number of classes of the input data is equal to the number of neurons in layer 2. In the proposed technique, K takes the value of 2 indicating the male and female classes.

**Step 2:** The first layer input weights are set to the transpose of the matrix formed from the Q training pairs $P^1$. Euclidean distance is calculated between the applied input vector and the trained vector. The radial basis function receives the elements which are multiplied by the bias.

**Step 3:** If the input vector is close to the training vector, it is represented by output vector $a^1$.

**Step 4:** The second layer weights represented by matrix $T$ has a value 1 only in the row associated with that particular class of input and 0's elsewhere. Then the second layer weights $T$ multiplied with $a^1$.

**Step 5:** Finally, the second layer transfer function compete produces a value 1 corresponding to the target class male or 0's for female elsewhere. Thus, the proposed technique identifies the gender of the recognized face image.
5.3.5 LTP Feature Extraction

The LTP Feature extraction includes the following steps

1. Cropping
2. Histogram equalization
3. Feature vector and extraction

5.3.5.1 Cropping

This is a preliminary step used to remove unwanted portions of the image and to keep only the region of interest. This is required, as the unwanted non ROI parts affect the overall recognition rate of the system. The Figure 5.6 shows the sample of the database used in our approach after cropping. Once the cropping is done, the images undergo the process of histogram equalization.

![Figure 5.6](image)

*Figure 5.6 The sample images of the JAFFE database that have been excluded the non-face area*

5.3.5.2 Histogram equalization

Histogram equalization based on block division is performed on the temporary images where the images are divided into sub-blocks. Each sub-block of the temporary images may have different block sizes from one another. Secondly, the contrast factors of all equalized temporary images are calculated and a global contrast enhancement algorithm is applied by selecting the temporary image
possessing the largest contrast factor. The selected equalized temporary image is used to extract the global equalization function which is applied to the original image. It can be seen from the Figure 5.7, that a visually comfortable result image is produced by the proposed algorithm.

![Image before and after histogram equalization](image)

**Figure 5.7 Image before and after histogram equalization**

### 5.3.5.3 Feature vector and extraction

In general, feature extraction is used to reduce the amount of source required to describe any data with accuracy. Analysis with large number of variables will be the major problem because it needs high computation power and large memory which always over fits the training sample and poor generalization of new samples. Textural features of the images using Local Ternary Patterns (LTP) which is the combination of two LBP can be created in the following way.

The examined window is divided into cells.

- Compare each pixel with its 8 neighboring pixels in the clockwise or anti-clockwise direction.

- If the value of the center pixel is greater than its neighbor, "1" is written. On the contrary if it is lesser, then "0" is written. An 8 digit binary value which is obtained is then converted to decimal value.
The histogram is computed over the cell, where the frequency of each "number" occurs.

The histogram is then normalized.

The feature vector for the window is obtained by concatenating normalized histograms of all cells.

The LBP code which is a binary code is extended to a 3 level value and is called LTP in which gray levels in a zone are quantized to zero (i.e. If the values are same it is taken as "0") and gray levels having values above and below compared with the center pixel are quantized to “1”. Three level value codes are obtained by user specific threshold and hence it is more resistant to noise. The image after undergoing LTP operation is shown in Figure 5.8.

![Figure 5.8 The instance of LBP processing of facial expression image](image)

5.3.6 Classification

The support vector machine usually deals with pattern classification that means this algorithm is used mostly for classifying the different types of patterns. Now, there is different type of patterns i.e. Linear and non-linear. Linear patterns are those that are easily distinguishable or can be easily separated in low dimension whereas non-linear patterns are patterns that are not easily distinguishable or cannot be easily separated and hence these type of patterns need to be further manipulated so that they can be easily separated.
Basically, the main idea behind SVM is the construction of an optimal hyper plane, which can be used for classification, for linearly separable patterns. The optimal hyper plane is a hyper plane selected from the set of hyper planes for classifying patterns that maximizes the margin of the hyper plane i.e. the distance from the hyper plane to the nearest point of each pattern. The main objective of SVM is to maximize the margin so that it can correctly classify the given patterns i.e. larger the margin size more correctly it classifies the patterns. SVM is a type of the pattern classification method based on the statistical learning theory, and designed to minimize the construction risk. It not only distinguishes the class, but also finds the best separation line between the two classes. For higher dimensional data, SVM find a best classification hyper plane.

The equation (5.7) is the hyper plane representation:

Hyper plane, \(aX + bY = C\) \hspace{1cm} (5.7)

The Figure 5.9 shown below is the basic idea of the hyper plane describing how it looks like when two different patterns are separated using a hyper plane, in a three dimension. Basically, this plane comprises of three lines that separates two different in 3-D space, mainly marginal line and two other lines on either side of marginal lines where support vectors are located.

![Hyper Plane](image)

**Figure 5.9** A hyper plane
For non-linear separable patterns, the given pattern by mapping it into
new space usually a higher dimension space so that in higher dimension space, the
pattern becomes linearly separable. The given pattern can be mapped into higher
dimension space using kernel function, \( \Phi(x) \).

i.e. \( x \rightarrow \Phi(x) \)

Selecting different kernel function is an important aspect in the
SVM-based classification, commonly used kernel functions include LINEAR,
POLY, RBF, and SIGMOID. For e.g.: the equation for Poly Kernel function is given
by equation (5.8).

\[
K(x, y) = \langle x, y \rangle^p
\]  (5.8)

Different kernel functions create different mapping for creating non-
linear separation surfaces. Another important parameter in SVM is the parameter C.
It is also called a complexity parameter and is the sum of the distances of all points
which are on the wrong side of the hyper plane. Basically, the complexity parameter
is the amount of error that can be ignored during the classification process. But the
value of classification process cannot be either too large or too small. If the value of
complexity parameter is too large then the performance of classification is low and
vice versa.

The main principle of support vector machine is that given a set of
independent and identically distributed training sample \( \{(x_i, y_i)\}_{i=1}^N \), where \( x \in \mathbb{R}^d \)
and \( y \in \{-1, 1\} \), denote the input and output of the classification. The goal is to find a
hyper plane \( w^T x + b = 0 \), which separate the two different samples accurately.
5.4 RESULTS AND DISCUSSION

Different set of databases have been used to analyze the proposed algorithm for different parameters like

1. Evaluation of FRR and FAR
2. Evaluation of accuracy

The performance of FAR and FRR is analyzed by setting different threshold values for the recognition algorithm. In general, the outcome of a biometric verification process consists of either a “match” (genuine-user) or a “non-match” (imposter) output. In practice, when an enrolled user or a genuine-user receives a “non-match” output, a False Reject (FR) occurs. Conversely, when a non-enrolled user or an imposter receives a “match” output, a False Accept (FA) occurs. The rate of false rejection of a genuine-user is called the FRR and the rate of falsely accepting an imposter is called the FAR. The errors rates FRR and FAR are interrelated and together they define the accuracy of a verification system as given in equation (5.9).

\[
Accuracy = \frac{(1 - FRR) + s(1 - FAR)}{1 + s}
\]  

(5.9)

where \( s \) is a scalar skew parameter indicating the relative importance between the two categories of genuine-users and imposters. The FAR and FRR can be adjusted by altering a threshold on the confidence scores. They are interrelated in the sense that when one is lowered, the other will be raised, and vice versa. The rate at which FAR equals FRR is called the Equal Error Rate (EER). In biometrics community, the EER is frequently adopted as the performance measure because it provides
information regarding the operating condition (at one unique threshold, as well as information about FAR, FRR) as compared to accuracy. For efficient recognition rate there should always exist a minimal FAR and FRR.

5.4.1 Output GUI for the Approach using GLCM and KPCA

The first step is to browse and select the required input image as shown in Figure 5.10.

![Figure 5.10 GUI of proposed method](image)

In the next step the image of interest is selected by using the crop function as shown in Figure 5.11.

![Figure 5.11 GUI after cropping ROI](image)

In Figure 5.12, GLCM features are extracted and the first ten images are sorted and stored in another database.
Figure 5.12 GUI after performing GLCM

The next step is performing wavelet transform and phase congruency for the LL band of the wavelet transform as shown in Figure 5.13.

Figure 5.13 GUI after taking phase congruency of image

Finally the Euclidian distance is calculated i.e. KPCA is performed for the ten images in the new database and the image is recognized as shown in Figure 5.14.

Figure 5.14 GUI after performing KPCA and identifying
The Eigenface approach for face recognition process is fast and simple and works well in a constrained environment. It is one of the best practical solutions for the problem of face recognition with minimum FAR and FRR. Many applications which require face recognition do not require perfect identification but just a low error rate. So instead of searching large database of faces, it is better to give small set of likely matches. By using the Eigenface approach, this small set of likely matches for given images can be easily obtained. For a given set of images, due to high dimensionality of images, the space spanned is very large. But, in reality, all these images are closely related and actually span a lower dimensional space. By using the Eigenface approach, we try to reduce this dimensionality. The Eigenfaces are the eigenvectors of covariance matrix representing the image space. The lower the dimensionality of this image space, the easier it would be for face recognition. Any new image can be expressed as linear combination of these Eigenfaces.

5.4.2 Output GUI for the Approach using GLCM and KPCA with WLD and PNN

A GUI (Graphical User Interface) has been created, using five buttons namely browse, crop, GLCM + KPCA, Gender Identification and Clear which is shown in Figure 5.15. Browse is used to browse the input query image and crop is used to crop the face for recognition as required by the user. GLCM + KPCA button is used to recognize the face and gender identification button is used to identify the gender using SWLD and PNN and displays the recognition rate as well. Clear button is used to clear all the images displayed using the GUI.
Figure 5.15 GUI performing KPCA technique with GLCM feature extraction for face recognition and SWLD and PNN for gender identification

5.4.3 Output GUI for the Approach using GLCM and KPCA with LTP and SVM

The output GUI for this proposed work is shown in Figure 5.16.

Figure 5.16 GUI Performing PCA technique with GLCM feature extraction for face verification with LTP technique for expression identification

The method based on Gray Level Co-occurrence matrix and KPCA experimentally proves that it achieves a minimum FAR and FRR and a higher recognition rate and a lesser computational time for the images with different facial expressions and also with different tilt angles when compared with the other existing methods.
5.4.4 Output GUI for the Approach using GLCM and PCA with LTP and SVM

A Graphical User Interface (GUI) was created with four push buttons; one to select the query image, the second is for cropping and the third is for recognition and the last one to clear the images. Figure 5.17 shows the Query image being loaded into the GUI, where the GLCM features are extracted and the first ten images are stored in another database. Finally the Euclidian distance is calculated i.e., SSM of the Eigen face using PCA is performed for the ten images in the new database and the image is recognized. And for expression identification the features are extracted using LTP and classifies using SVM technique.

![An Integration Approach to Human Face Recognition and Expression Identification](image)

Figure 5.17 GUI Performing PCA technique with GLCM feature extraction for face verification with LTP technique for expression identification

5.5 SUMMARY

Thus the methods presented above perform recognition of facial images with different lighting conditions and also evaluated with minimum false acceptance and rejection rate. The performance analysis are also carried out to study the effectiveness of the system with minimum recognition time.
The following conclusions have been drawn from the present study:

Thus the proposed algorithm experimentally proves that the time taken for the face classification and verification is very much less when compared with the existing method. The Eigenface approach for face recognition process is fast and simple and works well under a constrained environment. It is one of the best practical solutions for the problem of face recognition with minimum FAR and FRR. Many applications which require face recognition do not require perfect identification but just low error rate. So instead of searching large database of faces, it is better to give small set of likely matches. By using the Eigenface approach, this small set of likely matches for given images can be easily obtained.

For a given set of images, due to high dimensionality of images, the space spanned is very large. But in reality, all these images are closely related and actually span a lower dimensional space. By using the Eigenface approach, the dimensionality is reduced. The Eigenfaces are the eigenvectors of covariance matrix representing the image space. The lower the dimensionality of this image space, the easier it would be for face recognition. Any new image can be expressed as linear combination of these Eigenfaces. This makes it easier to match any two images and thus face recognition.

Thus the proposed method using the combination of GLCM and the KPCA highly reduces the overall time of the recognition system with minimum FAR and FRR as shown in Figure 5.18. This is significant from the analysis carried out for both the JAFEE and GTAV databases for various facial expressions under different illumination conditions with different face angles and for various threshold values. Hence, the accuracy of the recognition system is increased because of the integrated approach.
Figure 5.18 Analysis of FAR and FRR for 30 threshold value

The proposed technique involves an integrated approach of GLCM and KPCA for face recognition and WLD and PNN for gender identification which performs better than the existing systems. The performance of proposed integrated system was evaluated for different and large databases and the standard parameters like FAR and FRR are highly improved on large databases.

Table 5.1 Mean recognition time for existing and proposed method (GLCM and KPCA with WLD and PNN)

<table>
<thead>
<tr>
<th>Database images</th>
<th>Existing method</th>
<th>Proposed method</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>GLCM+KPCA for face recognition and WLD and PNN for gender identification</td>
</tr>
<tr>
<td>JAFFE (100 images)</td>
<td>154.35</td>
<td>4.38</td>
</tr>
<tr>
<td>GATV (40 images)</td>
<td>8.35</td>
<td>3.85</td>
</tr>
<tr>
<td>FERET (40 images)</td>
<td>8.79</td>
<td>3.62</td>
</tr>
</tbody>
</table>
From Table 5.1, it can be seen that, on an average the mean recognition time taken by the proposed technique is 4.38 sec only for 100 images of the JAFFE database of various face expressions. Also, the time taken for 40 images using the existing technique is 8.35 sec while in the proposed technique it is only 3.85 sec for GTAV database of various tilt angles. The time taken for 40 images using the existing technique is 8.79 sec while in the proposed technique it is only 3.62 sec for FERET database.

Table 5.2 FAR, FRR and mean recognition rate for the proposed method (GLCM and KPCA with WLD and PNN)

<table>
<thead>
<tr>
<th>No. of input images</th>
<th>FAR and FRR in % for threshold value =31</th>
<th>Mean Recognition rate for the proposed method</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>1</td>
<td>99.73%</td>
</tr>
<tr>
<td>20</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>30</td>
<td>7</td>
<td></td>
</tr>
<tr>
<td>40</td>
<td>11</td>
<td></td>
</tr>
</tbody>
</table>

From the Table 5.2, it is understood that the accuracy of the system increases with the threshold value of 31 which inferences minimum FAR and FRR. This increase in system accuracy denotes the optimum value of recognition rate using FERET database. Finally, the system proved to be very efficient and accurate with the highest recognition rate of 99.73%, as compared to the various techniques employed in the literature. In the present investigation, gender identification is tested only for the FERET database and as a future work it could be tested for the various other databases.

The proposed method based on GLCM and SSM of the eigen face using KPCA with WLD and PNN experimentally proves that it achieves a minimum FAR
and FRR for an optimum threshold value of 31 as shown in Table 5.3. The method also achieves a higher recognition rate and a lesser computational time for the images with different facial expressions and also with different tilt angles when compared with the other existing methods. For different expressions and poses, the proposed method works well for the JAFFE database with high recognition rate.

**Table 5.3 FAR and FRR for the proposed method for threshold value of 31**

<table>
<thead>
<tr>
<th>Number of input images</th>
<th>Analysis of FAR and FRR for threshold value = 31</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FAR</td>
</tr>
<tr>
<td>10</td>
<td>1</td>
</tr>
<tr>
<td>20</td>
<td>4</td>
</tr>
<tr>
<td>30</td>
<td>7</td>
</tr>
<tr>
<td>40</td>
<td>11</td>
</tr>
</tbody>
</table>

The proposed method based on GLCM and SSM of the eigen face using PCA and expression identification using SVM experimentally proves that it can perform recognition effectively. From the Table 5.4, it is seen that, for an optimum threshold value of 0.4 it achieves a minimum FAR and FRR.

**Table 5.4 FAR and FRR for the proposed method for threshold value of 0.4**

<table>
<thead>
<tr>
<th>Number of input images from JAFFE and GTAV Database</th>
<th>Analysis of FAR and FRR for threshold value = 0.4</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>0</td>
</tr>
<tr>
<td>20</td>
<td>2</td>
</tr>
<tr>
<td>30</td>
<td>2</td>
</tr>
<tr>
<td>40</td>
<td>5</td>
</tr>
</tbody>
</table>