Gender Recognition of Human from Face Images Using Multi-Class Support Vector Machine (SVM) Classifiers

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Abstract—In the realm of robotics and interactive systems, gender recognition is a crucial problem. Considering the several uses it has in security, web search, human-computer interactions, etc., gender recognition from facial photos has garnered a lot of attention. The need to use and enhance gender recognition techniques is felt more strongly today due to a significant development in the design of facial recognition systems. Relatively speaking to other approaches, the progress gained in this area thus far is not exceptional. Thus, a novel method has been adopted in this study to improve accuracy in comparison to earlier research. To create the best rate of accuracy and efficiency in the suggested method of this research, we choose a minimal set of characteristics. Testing on the FERET and UTK-Face datasets reveals that our suggested algorithm has a lower degree of inaccuracy. In this article, the input image of the person's face is pre-processed to extract the right features from the face once the person's face has been recognized. Gender separation is achieved using Multi-class Support Vector Machine (SVM) Classifiers after features from normalized images have been extracted using Histogram Oriented Gradient (HOG), Gabor Filters, and Speeded Up Robust Features (SURF), as well as their combination to select the most appropriate feature from them as input for gender classification. As a feature reduction feature, the Principal Component Analysis (PCA) algorithm is also employed. Using the proposed approach, 98.75% gender recognition precision has been accomplished on the FERET database and a runtime performance of 0.4 Sec. on the UTK-Face database, 97.43% gender recognition accuracy has been accomplished and a runtime performance of 0.5 Sec.

Keywords—gender recognition, Gabor, HOG, SURF, SVM

1 Introduction

The face is a very important biometric component of a human being. It is through the face that valuable information such as race, identity, age, gender, and facial expressions are retrieved [1, 2]. In the topic of demography, Gender is an important feature of human beings. A human-computer interaction system can behave in a humanly manner when it can recognize the gender of the user. In the discussion of machine vision, automatic gender recognition is a difficult problem with various applications. In human beings, gender recognition is often carried out through the human eyes. This recognition is not easily done in machines. In the machine vision science, a lot of exertive methods have been done to develop and create algorithms and tools to appraise and recognize gender. If the person's gender can be identified prior to identification verification in the facial image problem, processing time is reduced by a half and face recognition speed is increased by double. In human-computer interaction, credit card security, advertising and psychology, surveillance, human-society, and criminal identification, automatic facial recognition and analysis serve a variety of purposes [3, 4]. The need to design systems that can recognize gender has risen and it continues to rise along with the notable advancement in the design of facial recognition systems. In machine vision, the automatic recognition of gender from facial images is because of challenging elements such as photo quality and light intensity, face position, the presence of emotions on the face, and whether the face is covered with a hat, scarf, and glasses [5, 6]. It is an arduous task, whereas gender recognition is an easy decision for human beings. Gender recognition can be utilized as a pre-processing step in face recognition, and since the studied space is cut in half (assumed to be equal for men and women), face recognition calculations can be performed twice as quickly. Pre-processing is the first general stage in the process of determining gender from a face photograph. The second stage is the Features of Extraction. Then the third stage is Categorization. These actions are displayed in Figure 1,2. The format of this article is such that, first, in the second part, an overview of the prior works is given, and then, in the third and fourth parts, respectively, the suggested approach and the outcomes of the application of various evaluation scenarios are described. Finally, we give a summary of the findings from the suggested method along with recommendations for the future.

Fig. 1. Block Diagram of Gender Recognition from Face Images

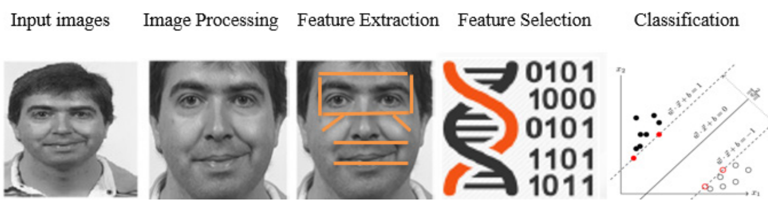

Fig. 2. Block Diagram of Gender Recognition from Face Images

2 Related works

One of the most crucial and difficult challenges of the object recognition branch, which has various applications in human-computer interaction, human-society, psychology, and security issues, is the automatic face recognition and analysis. A binary classification problem, gender detection determines if the target image belongs to a man or a woman. Although humans can make this choice easily, machine recognition confronts a number of difficulties. Gender recognition can be employed as a pre-processing step in face recognition, and it doubles the speed of computations linked to face recognition since it cuts the examined space in half (assumes an equal number of men and women) [7-9].

According to the data used to identify gender, there have been several studies conducted in the previous 20 years that can be grouped into two primary categories. Techniques based on geometric traits fall into the first group, where they employ size information (distance between key facial features including the eyes, nose, lips, and chin) to determine gender [10, 11]. The methods based on appearance features fall into the second category. In these techniques, image pixels are transformed or subjected to mathematical operations [12, 13]. In comparison to other approaches, the development made in this area so far is insignificant. Many methods have been used for this purpose. Pre-trained Inception network, a neural technique based on the Face net model, is suggested in [14]. The suggested approach may be broken down into three steps: first, faces in the provided photos are recognized and clipped; second, the face images are sent to the neural network; and third, gender is classified with modified weights. The UTK Face dataset and 1x1, 3x3, and 5x5 filters have been used to train and test this network's model. Also, this article has a review of all machine learning techniques.

In [15], they presented a technique for K-means clustering machine learning utilizing multi-Feature that, after improving the clarity and contrast of the images, uses a deep neural network to detect and cut the facial region. Then, using the FEI and SCIEN data sets, gender training and classification is carried out. Finally, features are extracted using the SIFT descriptor. In [16], they employed discriminant error analysis and independent component analysis to enhance the gender classifier. They employed an eye detection system to apply this strategy to 500 images that were 96 x 64 in size. In [17], Baluja et al. used the Adabust method to identify gender in photos that were 12x12 in size. This network's design aims to create a quick method for gender detection in massive databases. The etiquette algorithm, which was created by fusing multiple weak clauses, is utilized to speed up the process. The desired features are first retrieved using a feature extractor before being provided to the optimization method. For thumbnails, this approach is quick; but, if the network is given photos in big dimensions, the retrieved features are too numerous, and the algorithm operates very slowly. A neural network technique utilizing the ICA algorithm is suggested in [18] to modify the weights. The Viola Jones method extracts facial features, which are subsequently selected using the NSGA-II rhythm algorithm. Finally, a hybrid neural network (ANN) with (ANN-ICA) performs gender categorization by recognizing facial features.

Xu et al. performed face recognition by extracting facial outlines automatically and matching criterion points. With the use of the extracted features and the collection of two-dimensional photographs used to capture the face pattern, the differences between two faces are assessed. Four lines in front of the face and three lines on the side of the face are chosen using the feature-oriented orphans' algorithm in this article. The accuracy of the diagnosis increases with the number of selected components, as well as the calculation load [19].

Mian et al. used a region-based matching method to carry out automatic facial recognition. The forehead, eyes, nose, and chin sections of each photograph of a face in the gallery are separated into three groups using this technique. In order to prevent the impacts that can arise on faces with mustaches or beards, the diagnosis is only based on the forehead, eyes, and nose regions. The data collected indicate that the forehead and eyes are the key facial identification features [20]. Jofi et al in [21] focused on improving gender recognition by concentrating on the regions around the eyes. In order to extract features, the author of [22] used PCA and an enhanced SIFT constant scale feature transformation. In order to extract the features with a significant difference from photographs of the faces of women and men, this method was used to calculate the image matrix and choose the design of the input images through the clustering method. In a classifier based on fuzzy SVM, the author has employed a method based on gradual learning of the LVQ vector. The Gabor descriptor method is utilized in [23] combined with fuzzy classification-linear discriminant analysis to identify facial photographs from various age groups.

3 The proposed method

The goal of this article is to discover the most effective and ideal technique for identifying a person's gender from facial images. The standard procedure for identifying a person's gender from photos is reading the images from the image database and then extracting the facial image in accordance with the type of dataset. The characteristics are extracted after any necessary picture preprocessing. Following feature extraction, the size of the features is decreased to ensure good classification accuracy. Finally, the right classifier is chosen, and the photos are categorized or gendered. In this study, an attempt is made to use the facing image of the face. Features based on HOG, Gabor, and SURF as well as their combination are used for this purpose. Due to the demand for high-quality photos, several features are used, which increases the number of input data for classifiers and complicates categorization. Consequently, it is vital to appropriately minimize the size of the features, and this reduction should be done in a way that improves the classification's accuracy. After the features have been extracted, the PCA approach will be used to minimize the problem's dimensions and increase the algorithm's classification accuracy. Finally, as an appropriate classifier, Multi-class Support Vector Machine (SVM) is used. Figure 3 displays the proposed method's workflow.

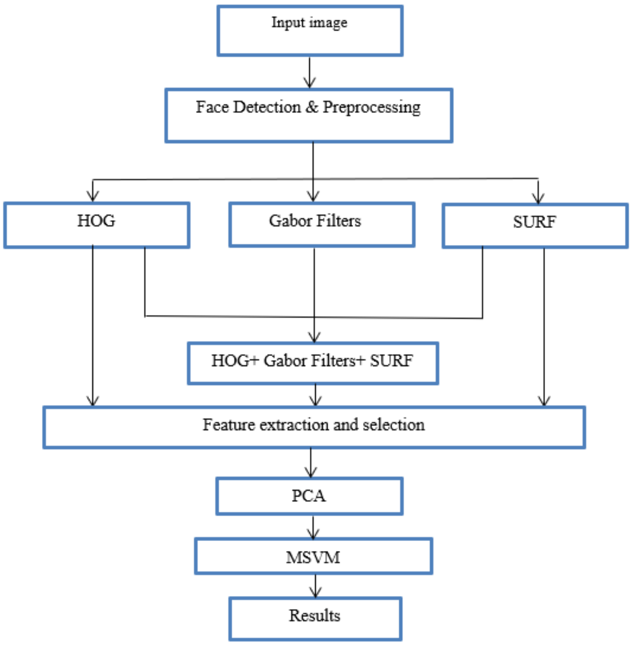

Fig. 3. The Proposed Method for Face-Based Gender Recognition

3.1 Pre-processing

Pre-processing is necessary for all of the photos in the image database, including normalization against brightness variations, scaling, and noise removal. The facial area is identified in this part utilizing image processing techniques. Each image in the dataset was subjected to the Viola-Jones technique, and the recognized faces were then scaled to a predetermined size of 128x128 pixels [24-27]. In Figures 4,5,6, the pre-processing procedures are displayed.

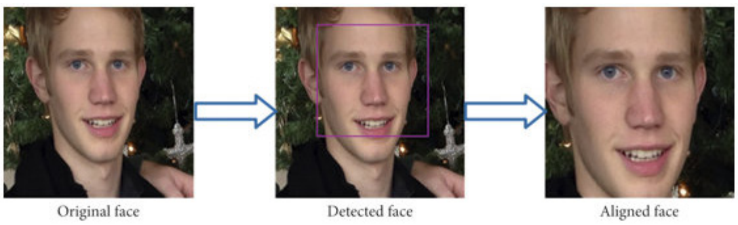

Fig. 4. Image Preprocessing Phase [27]

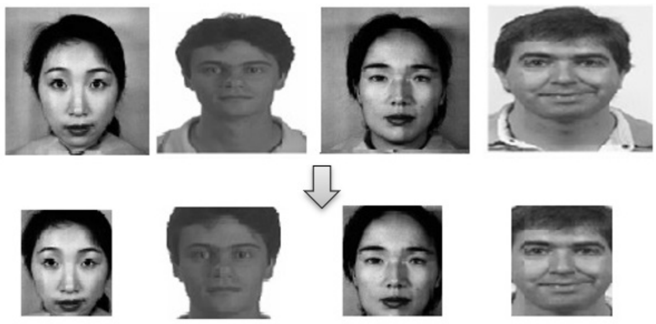

Fig. 5. Preprocessing on Sample from Images for FERET Database [28]

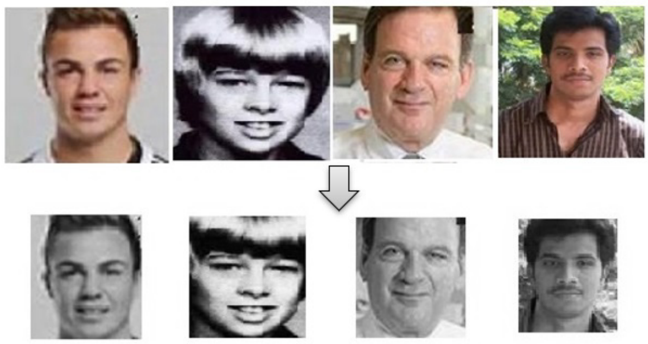

Fig. 6. Preprocessing on Sample from images for UTK-Face Database [29]

3.2 Feature extraction

Extraction of usable features from face photos is a crucial step in successful gender classification, much like in other applications of facial image analysis. Even the finest classifiers run the risk of falling short of achieving high recognition accuracy if inadequate features are used. Facets of the image are retrieved after the pre-processing stage. The retrieved features are often divided into two groups: global features, or features based on appearance, and local features, or features based on geometry [30-33]. Instead of extracting characteristics from individual face points, the appearance-based method extracts features from the entire face. These techniques rely on various adjustments and adjustments made to the image's pixels. Face characteristics like the nose and eyes are retrieved using the geometry-based technique. The relationships between the face points are typically used to extract the constant geometric properties, such as scale, rotation, distance, and angle. The characteristics provide a trained classifier access and represent the human face. The characteristics of the Histogram Oriented Gradient (HOG), Gabor Filters, and SURF are used in this article and combined as input for gender classification.

Histogram Oriented Gradient (HOG). Histogram Oriented Gradient is based on computing the gradient orientation histograms for each cell by dividing an image into smaller cells. Following that, the histograms are combined into a single feature vector that describes the overall structure of the image. HOG is especially helpful for locating items with a distinct shape, like people, animals, or cars. It is suitable for use in practical applications since it is resistant to variations in illumination and viewpoint [34] HOG-based facial image gender detection is a prevalent issue in computer vision and machine learning. Typically, to distinguish between male and female faces, a classifier, such as an SVM, is trained by first extracting HOG characteristics from face pictures. The photos are initially pre-processed to identify and align the faces in order to extract HOG features from the face images. Algorithms for face detection and facial landmark detection are commonly used for this. A single feature vector is then created by concatenating the HOG features computed for each face region [35, 36]. A classifier can be trained to distinguish between male and female faces using a dataset of labeled face images after the HOG characteristics have been extracted. By generating a new face image's HOG characteristics and utilizing the trained classifier to make a prediction, one can then use the trained classifier to predict the gender of the image. It's crucial to remember that the caliber of the training data and the classifier selected will determine how accurate a gender detection system based on HOG characteristics is. Furthermore, occlusions, illumination, and changes in facial expression may have an impact on it [37].

We perform the following steps to calculate the gradient histogram:

To extract the picture gradient in the x and y directions, the image is first filtered using Sobel kernels in the x and y directions:

$$G_x = I * D_x \tag{1}$$

$$G_y = I * D_y \tag{2}$$

I: is the original image, D x and D y are the Sobel kernels in the x, y direction, G x, G y are the image gradient in the y, x direction, and the sign*indicates the convolution operation. The gradient direction's size in each pixel is then determined as follows:

$$|G(i,j)| = \sqrt{(G_x(i,j))^2 + (G_y(i,j))^2} \tag{3}$$

$$\theta_G(i,j) = tan^{-1}\left(\frac{G_x(i,j)}{G_y(i,j)}\right) \tag{4}$$

That |G| The number of rows and columns in the image are represented by j and I respectively, and the gradient size θ G indicates the gradient's direction. For color images, the gradient is determined for each color channel independently, and the gradient vector for each pixel is chosen based on its biggest value. We initially restrict the gradient angle to the range of 0-180 degrees to calculate the gradient histogram as follows:

$$\theta'_G = \begin{cases} \theta_G \quad , & 0 \leq \quad \theta_G < 180 \\ \theta_G - 180 \quad , & 180 \leq \theta_G < 360 \end{cases} \tag{5}$$

The range from 0 to 180 degrees is then divided into n equal distances, each of which represents a histogram channel and indicates the number of gradient directions or histogram intervals.

Gabor filters. Gabor filters may encode the local frequency and orientation information of an image, making them ideal for feature extraction from images [38]. As a result, they can be used to identify edges, textures, and other components in an image. Gabor filters are frequently used in computer vision to extract characteristics from images for tasks including object detection, texture categorization, and face recognition. By convolving the image with the filter, the filters are applied to an image, producing a filtered image that emphasizes particular aspects of the original image. The attributes that are pertinent for the task at hand can subsequently be extracted from the filtered image by additional processing. The frequency and orientation of gabor filters are often adjustable, and these properties can be changed to match the important aspects of an image. They may thus be tailored to various image kinds and activities, making them a versatile tool for feature extraction. A computer vision task called "gender detection from face images using Gabor filters" entails first extracting features from the faces in the images using the Gabor filters, and then categorizing the faces according to their gender. The first step in applying Gabor filters to do gender recognition from face photographs is to pre-process the images to find and align the faces. Algorithms for face detection and facial landmark detection are commonly used for this. Gabor wavelet and Gabor filter are directly connected. A sine wave and a Gaussian wave are combined to create a Gabor wavelet. Since this filter operates in the frequency domain, it must first be created. Once it has been created, the images must also be converted to the frequency domain before the filter can be applied to the image [39].

Equation (6) is used to derive Gabor filter:

$$g(x, y, \lambda, \sigma, \gamma, \theta, \varphi) = g_R(x, y, \lambda, \sigma, \gamma, \theta, \varphi) + jg_1(x, y, \lambda, \sigma, \gamma, \theta, \varphi) \tag{6}$$

In formula 1, there are g_R analytical and g_1 imaginary parameters of the Gabor filter, which are calculated from formulas (7,8).

$$g_R(x, y, \lambda, \sigma, \gamma, \theta, \varphi) = \frac{\gamma}{2\pi\sigma^2} e^{\left(\frac{x_r^2 + y^2 y_r^2}{2\sigma^2}\right)} \cos\left(2\pi \frac{x_r}{\lambda} + \varphi\right) \tag{7}$$

$$g_1(x, y, \lambda, \sigma, \gamma, \theta, \varphi) = \frac{\gamma}{2\pi\sigma^2} e^{\left(\frac{x_r^2 + y^2 y_r^2}{2\sigma^2}\right)} \sin\left(2\pi \frac{x_r}{\lambda} + \varphi\right) \tag{8}$$

In formulas (7,8), parameters x_r and y_r are calculated using formulas (9,10).

$$x_r = xcos\theta + ysin\theta \tag{9}$$

$$y_r = xsin\theta + ycos\theta \tag{10}$$

The coordinates of a point in the image are represented by the parameters x and y. The Gabor filter's rotation angle is displayed by the parameter. The phase offset is the parameter φ. This parameter displays the Gabor filter's symmetry. The Gabor filter is either odd or even for φ values of 0 and 180, and it is either asymmetric or odd for φ values of 90 and -90. The value of the variance associated with the Gaussian function is specified by parameter σ. The spatial graph rate is parameter y. The supported range has a circular form I y f is equal to 1 and rotates to ellipses in the direction if it is less than 1. The sine wave frequency's wavelength is represented by the parameter λ.

Speeded Up Robust Features (SURF). A computer vision method called SURF is used to find and describe small details in images. A SIFT algorithm known as SURF is used to locate objects of interest in images that are independent of scale and orientation. The SURF algorithm is a quicker and more reliable variant of the SIFT method [40]. While using SURF, an image's stable key points are first found, and then their descriptors are computed. In order to match key points between images, descriptors—vectors that characterize the local image material surrounding the key point—are used. In many computer vision applications, including object detection, picture matching, and tracking, SURF is employed. In real-time processing-intensive applications like augmented reality and video surveillance, it is also helpful. A computer vision method called SURF is used to identify and describe features in photographs, especially in digital portraits of people. SURF is a valuable technique for gender recognition since the traits it picks up can be utilized to represent a picture and set it apart from other images [41]. The following steps are usually observed to use HOG, Gabor Filters and SURF technique for gender recognition:

1. Preprocessing: Input face images are preprocessed in order to enhance contrast, remove noise, and to align the faces to a standard pose.
2. Feature extraction: To extract the features from the preprocessed face images, HOG, Gabor Filters and SURF is used. These features are stored appropriately as a set of points with related descriptions.
3. 3-Dimensionality reduction: To decrease the risk of over fitting, the feature points and descriptions are usually reduced to speed up the classification process in dimensionality.
4. 4-Model training: The training of a machine learning model is carried out on the reduced feature representation through the use of labeled training data.
5. 5-Model evaluation: The evaluation of the trained model is carried out on a different validation set so that its accuracy can be measured.
6. Deployment: In a gender recognition system, the trained model is positioned where it can be used to arrange new face photographs into male or female categories.

3.3 Combining features and selection

The process of joining or merging different attributes of a data set into one feature representation refers to combining features. This is a common step in feature engineering, where the goal is to create powerful and meaningful depiction of data that can be used in machine learning algorithms. Various methods for combining features include:

1. Concatenation: This is basically connecting several features into a distinct vector, ensuing in a higher-dimensional feature representation.
2. Feature Crosses: Merging the values of two or more existing features in a non-linear manner in order to create new features.
3. Averaging: combining the average of multiple features into a one feature.

The chosen feature combining method will be dependent on the characteristics of the data and the specific problem being solved. It is crucial to thoroughly consider the effect of merging features on the performance of the machine learning algorithm, and to experiment using diverse methods to determine the best method [30]. We made use of all the above-mentioned combining methods in this article, and the Feature Crosses method emerged to be the best method. Creating new features by merging the values of two or more existing features in a non-linear way is defined as feature crosses. The purpose of feature crosses is to record interactions between features that the individual features do not record on their own.

3.4 Reducing the dimensions of the feature vector

PCA is a technique statistically used to decrease the dimensionality of data while maintaining a lot of information. It is a globally used method in data analysis and it is useful particularly for envisioning high-dimensional data, such as images in a lower-dimensional space [42]. The primary goal of PCA is to identify a new collection of orthogonal axes, known as principal components that will effectively capture the most significant information in the data. PCA is frequently used in pre-processing machine learning algorithms, as dimensionality reduction of data can foster the development and performance of the algorithm and diminish over fitting. It can be utilized for compressing data as well, because the first few key components naturally record most of the information in the data, and the rest of it can be gotten rid of. PCA is an unsupervised method, which means it is based on the statistical characteristics of the data rather than any labeled information about the data. PCA has some drawbacks despite its ease of use and widespread application, including its sensitivity to outliers and the fact that it can only identify linear correlations in the data. It is still a powerful and widespread tool for data analysis [43, 44]. The following are the steps in this method: The first step involves transforming the input image which is in the form of a two-dimensional matrix, into a one-dimensional vector and create the feature matrix before combining these vectors. The input image, which is a two-dimensional matrix, must first be transformed into a one-dimensional vector in the first phase before these vectors can be combined to create the feature matrix. The feature matrix is obtained as n*N, where n=p*q, if the total number of our photos is N and the size of each image is n=p*q.

$$X = (x_1, x_2, \dots \dots .. x_i, \dots \dots x_N) \tag{11}$$

The feature vector for each image with n dimensions in relation (11) X, the feature matrix xi, is n*N, where n=p*q

The average will then be calculated. In this stage, we first determine the average of each category of data, and then we deduct each category's data from its average until the data is converted to zero.

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{12}$$

In the third phase, the covariance matrix is calculated, and the eigenvalues and eigenvectors are then extracted from this matrix.

$$S_{T=} \sum_{i=1}^{N}(x_i - \mu)(x_i - \mu)^T \tag{13}$$

The idea of decreasing data dimensions is presented in the final step. Based on their special values, we order the special vectors acquired in the previous phase from large to small. The data elements are then arranged in order of importance, starting with the most important. In this case, we can eliminate the less significant data if we wish to lower the dimensions of the data. Of course, by doing this, we lose some of our information from the special space, which is the river of space created by these special vectors.

The following results can be achieved by implementing this methodology to the data:

1. Orthogonalization of input vector components.
2. Sorting and ranking the major components.
3. Eliminating components with little alterations

PCA is displayed for two-dimensional data in Figure 7.

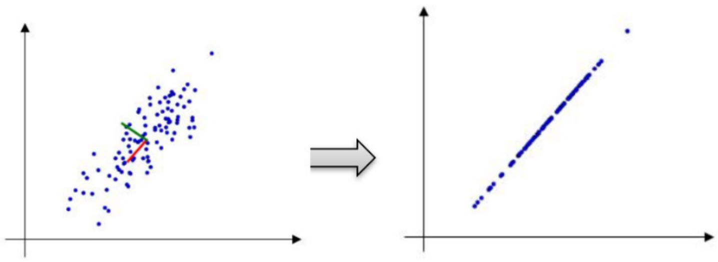

Fig. 7. Distribution of the data before and after processed to PCA

3.5 Classification

The classification is the final step in gender recognition. The level of classification accuracy is determined by the features extracted in the feature extraction step. The classification of faces is carried out by the classifier which categorizes the face images into two classes: female and male. As far as this step is concerned, a wide range of classifiers have been used overtime such as, K_NN [45], ANN [5], and SVM [46]. Gender recognition of humans has been achieved in this study by using Multi-class SVM Classifiers. This step involves training the SVM classifier so that it will be able to differentiate between multiple classes like female and male. Basically, a different binary classifier is trained for each pair of classes, and then the classifiers are combined to produce a multiclass classifier. This can be achieved using numerous methods such as error-correcting codes and one-vs-all. The latter is a simple technique which involves training a separate binary classifier for each class, with one class being positive and the others being negative. Consequently, the classifier which produces the highest output is then chosen as the prediction for the input. It is also a more complex approach that involves training a separate binary classifier for each pair of classes. The classifier is fed with input sample, and the outputs of the classifier are merged to determine the final prediction. On the other hand, the error-correcting output codes is a more advanced approach whereby, a set of binary classifiers are trained, and then the classifiers' outputs are used to make a final prediction. The main idea of this approach is to make use of the classifiers' outputs to correct any errors made by individual classifiers. For the recognition of human gender, a dataset of labeled face image can be used to train a multi-class SVM and to predict the gender of a new face image. A technique is selected based on the dataset's size as well as the desired accuracy of the classifier [47]. Figure 8 presents an image of a dataset belonging to two classes that are selected by the SVM method as the best hyper surface for their separation.

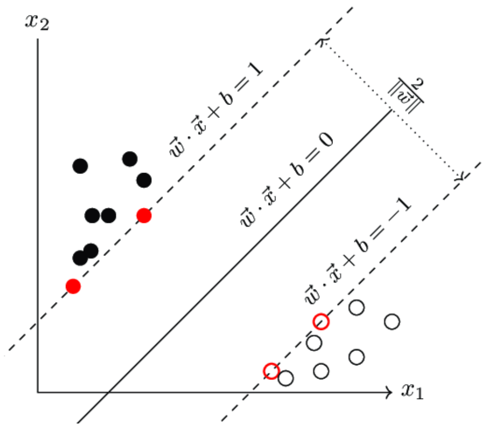

Fig. 8. SVM classification

Primarily, a linear decision boundary is presented as follows:

$$W.X + b = 0 \tag{14}$$

where the multiplication sign W denotes the normal vector, which is positioned perpendicularly to the super plane.

In order to maximize the distance between the parallel super planes separating the data, W,b are selected. Equations (15, 16) are used to described the hyper planes.

$$W.X + b = 1 \tag{15}$$

$$W.X + b = -1 \tag{16}$$

In a situation whereby the training data can be separated linearly, two hyper planes on the edge of the points re considered so that they do not have common points, and afterwards, their distance is maximizing. For the distance to maximized, the soft W must be minimized. Points are prevented from getting into the margin by making additions of the following conditions: for each i, one of the following conditions must be satisfied, relation (17,18).

$$W.X_i - b \geq 1 \qquad \text{for } X_i \tag{17}$$

$$W.X_i - b \leq -1 \qquad \text{for } X_i \tag{18}$$

The first condition is for the first class X_i while the second condition is for the second class X_i. The following expression represents the combination of the two conditions:

$$y_i(w.x_i + b) = 1 \tag{19}$$

$$y_i(w.x_i + b) > 1 \tag{20}$$

The following optimization problem must be solved as a way of calculating the optimal decision boundary

$$max_{w,b}\ min_{i=1,\dots,l} = \left[y_i \frac{w.x_i+b}{|w|}\right] \tag{21}$$

Base on Eq (21) and other mathematical calculations, the relationship above can be converted into the relationship below:

$$min_{w,b} \frac{1}{2}|w|^2, \quad y_i(w.x_i + b) - 1 > 0 \qquad i = 1, \dots., L \tag{22}$$

Solving the optimization problem (22) is a challenging operation. However, it can be simplified through the use of Lagrange's indefinite coefficients method; this optimization problem can be transformed into the following form where λ_i denotes Lagrange's coefficients.

$$max_{\lambda_{1,..}\lambda_L} = \left[-\frac{1}{2}\sum_{i=1}^{L}\sum_{j=1}^{L}\lambda_i y_i \left(x_i, x_j\right)\lambda_j y_j + \sum_{i=1}^{L}\lambda_i\right] \quad \lambda_i \geq 0 \quad i = 1, \dots, L \quad \sum_{i=1}^{L}\lambda_i\ y_j = 0 \tag{23}$$

Once the optimization problem has been solved, the equation below is used to calculate the Lagrange coefficients.

$$w = \sum_{i=1}^{L}\lambda_i\ y_j x_i \tag{24}$$

The support vectors are greater than zero, and λ_i will be zero at other points. Thus, giving that λ_i equals 6 and zero, corresponding to x_i which are not support vectors, only few training points which are support vectors are required for the derivation of the decision boundary, and they are all unnecessary. Consequently, just few training points will be required to classify hyper spectral images using support vector. Once w is derived using the following relationship, the calculation of b is done for a wide range of support vectors, and the all the b's derived are averaged in order to obtain the final b.

$$\lambda_i[y_i(w.x_i + b) - 1] = 0 \qquad i = 1, \dots., L \tag{25}$$

Eq (26) is used to obtain the final classifier.

$$f(X, W, b) = sgn(W.X + b) \tag{26}$$

In the case of multi-class, the aim is to obtain the hyper plane that separates the classes and to also maximize the margin between the classes.

Due to the ability of the multi-class SVM to handle large datasets and the ease with which it is implemented, it was used in the proposed technique. It demonstrated superior performance as presented in the results section.

The primary function for a multi-class SVM can represented as given below:

$$L(w,b) = \frac{1}{2}\left||w|\right|^2 + C\,\Sigma_{\{i=1\}}^{n}\Sigma_{\{j=1\}}^{C}[y_i = j]max\left(0, 1 - y_j\left(w.x_i + b_j\right)\right) \tag{27}$$

where w denotes weight vector, b is bias vector, x_i ith feature vector, $y_i$class label for the ith feature vector, $y_j$class label for class j, C a regularization parameter that trades off the margin size and the misclassification error, n number of samples for training. The use of a quadratic programming algorithm can be employed in solving the problem. Using this solution, biases and weights for each class can be derived and employed in making predictions for new data points. In the one-vs-all approach, the multi-class problem is minimized to multiple binary classification problems, and a separate hyper plane is derived for each class. Here, the objective function is represented as follows:

$$L(w,b) = \frac{1}{2}\left||w|\right|^2 + C\,\Sigma_{\{i=1\}}^{n}max\left(0, 1 - y_i(w.x_i + b)\right) \tag{28}$$

where w is the weight vector, b denotes bias value, x_i ith feature vector, y_i class label for the ith feature vector, C is a regularization parameter through which a tradeoff between the misclassification error, margin size, and n number of training samples is achieved.

4 Experimental results and analysis

Generally, the steps involved in writing this paper are highlighted as follows:

1. Data Preparation
2. Modification of raw data to be fed to the network
3. Creation of an appropriate network
4. Training of the network.

Generally, the process involves taking the sample as raw data in the first step. Subsequently, the use of the pre-processing function is employed in eliminating the initial parts of the raw data. An example of the pre-processing function applied is normalizing the data against changes in brightness, scale, and elimination of noise. The training and evaluation of the method presented in this study are carried out using FERET and UTK-Face databases. More than 14,000 images of 1,000 individuals obtained over a period of many years are contained in the database used in this study. The images were captured under regulated conditions, and are characterized by numerous poses, facial expressions, and lighting conditions. FERET is one of the benchmark datasets that is extensively used in the field of facial recognition, and its application has been made in a wide range of researches to assess and compare the performance of different facial recognition algorithms. Researchers in the field of facial recognition are presented with a challenging test set in the dataset. The results derived from experiments using FERET database are extensively cited [23]. On the other hand, the UTK-Face is a large dataset containing more than 20,000 face images captured from people of different genders, ages, and ethnicities. The images contained in the database were captured and collated by the University of Tennessee, Knoxville. It is a robust dataset that contains a variety of facial images for machine learning and computer vision research. Extensive use of the UTK-Face dataset is employed research and development in different applications, including estimation of age, recognition of age, and analysis of facial features. The dataset contains annotations for the facial attributes, like ethnicity, gender, and age, making it possible to train and assess machine learning models for the aforementioned tasks [24]. Subsequent to the reading of images from the dataset and application of image preprocessing, features extraction is performed, and then they are combined together so that the most suitable feature is selected. After the selection, features reduction is carried out with the aim of achieving high classification accuracy. Lastly, the selection of the most suitable classifier is made and used to classify the images of determine gender. In this study, this achieved using the face image of individuals. To accomplish this purpose, features based on Gabor, HOG, and SURF are combined and used. The use of multiple features because of the need to obtain high-quality images, results in an increase in the volume of input data for classifiers, thereby making the process of classification challenging. Thus, it becomes of important for the reduction of features' dimensions to be done in the most appropriate manner so that the classification accuracy can be improved. For this reason, upon completion of the process of features extraction for the reduction of the problems' dimensions, the PCA algorithm is used to enhance the accuracy of classification. Finally, Multi-class SVM is used as a suitable classifier.

The data obtained from the FERET and UTK-Face databases is used to test the implemented model. These tests also involved the evaluation of the performance of the proposed model from different perspectives, and the results have been presented. Based on the experimental tests, the proposed model has demonstrated high level of accuracy in terms of recognizing the gender of people using images of their faces, and can be employed as an efficient tool in real applications. The performance evaluation of the proposed method was done based on some parameters including root mean square error. This parameter shows the mean square difference between the values predicted by the proposed method and the real age of people. The mean square of error represents the square of the prediction error of the classification algorithm, and it is derived through the following equation:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(p_i - s_i)^2} \quad (29)$$

In the relationship presented above, N is the number of test samples, p_i denotes the value predicted for the age of the individual in the test sample i, and s_i represents the value of the real age in this sample.

This aimed at deriving the lowest mean squared error in prediction.

Normal error percentage: this parameter is used calculate the error percentage of the prediction model, and this can be derived by computing the ratio between the error's average absolute value and the series of changes of the target values. This is calculated using the formulae below:

$$Normalized_{error} = 100 \times \frac{MAE}{max(s) - min\,(s)} \tag{30}$$

In the relationship above, s represents the actual values of the target in the test samples, and min and max represent the calculation functions of the maximum and minimum, respectively.

The error's average absolute value: this parameter is used to determine the difference between the average predicted values for the people's age and the actual state.

The equation below is used to derive the average absolute value of the error:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y_i}| \tag{31}$$

The aim of using this parameter is obtain the minimum average absolute value of the error for prediction. In the approach proposed in this work, equation 18 below was used to calculate the average absolute error:

Where n denotes the number of data points, y_i is the actual value of the *i*-th data point.

$\hat{y_i}$ is the predicted value of the *i*-th data point.

$\sum_{i=1}^{n} |y_i - \hat{y_i}|$ represents the sum of the absolute differences between the actual and predicted values over all data points. Tables 1 and 2 present the results of simulation performed using the FERET database. It can be seen from the tables that the proposed technique was evaluated based on seven features, out of which three are individual (Gabor Filters, HOG and SURF), and the remaining four are combined (HOG+ Gabor, HOG+ SURF, Gabor+ SURF and HOG+ Gabor+ SURF). The results obtained from the simulation are significantly influenced by the selection of the most suitable feature. Also, the accuracy of the system increases when the most appropriate feature is chosen. Rather than using individual features, combined features were used, and this resulted in better system performance. However, the use of the combined features caused an increase in the running time of the algorithm as seen in Tables 1 and 2. This can be attributed to the increased size of features resulting from combining them, and the use of PCA algorithm is employed in addressing the issue of increased running time. The PCA algorithm achieves this by deleting features that do not affect the results of simulation, thereby increasing the speed of the algorithm as well as the accuracy of the results. It can be clearly seen from Table 2 that PCA has an effect on the proposed technique, as the results presented in Table 1 show a higher running time and lower accuracy as compared to the results on Table 2. The results presented in Table 1 were obtained before the application of the PCA algorithm, while that on Table 2 were obtained after the use of PCA algorithm was employed. From the Table 2 it can also be seen that when HOG+ Gabor+ SURF features are combined, higher accuracy and lesser running time are achieved as compared to using individual features. Tables 3 and 4 present the results of simulation for UTK-Face database. It can be seen from Tables 1 and 2 that the simulation results and performance of the system are significantly influenced by the combination of features and selection of the most appropriate features. The combination of features also improves the accuracy of the system as compared to when individual features are used. More so, combining the HOG+ Gabor+ SURF features reduces the running time of the system.

Table 1. Percentage accuracy and a runtime with FERET database for all features without PCA algorithm

Features	HOG	Gabor	SURF	HOG+ Gabor	HOG+ SURF	Gabor+ SURF	HOG+ Gabor+ SURF
Accu %.	90.77	91.63	90.36	94.28	94.45	95.67	96.98
Time Sec	0.6	0.6	0.7	0.8	0.8	0.8	0.8

Table 2. Percentage Accuracy and a runtime with FERET Database for All Features with PCA Algorithm

Features	HOG	Gabor	SURF	HOG+ Gabor	HOG+ SURF	Gabor+ SURF	HOG+ Gabor+ SURF
Accu %.	93.82	95.43	95.39	96.41	96.1	97.67	98.75
Time Sec	0.2	0.2	0.2	0.3	0.3	0.3	0.4

Table 3. Percentage accuracy and a runtime with UTK-Face database for all features without PCA algorithm

Features	HOG	Gabor	SURF	HOG+ Gabor	HOG+ SURF	Gabor+ SURF	HOG+ Gabor+ SURF
Accu %.	91.42	91.66	91.31	93.25	95.43	95.39	96.46
Time Sec	0.5	0.6	0.6	0.7	0.8	0.8	0.9

Table 4. Percentage Accuracy and A Runtime with UTK-Face Database for All Features with PCA Algorithm

Features	HOG	Gabor	SURF	HOG+ Gabor	HOG+ SURF	Gabor+ SURF	HOG+ Gabor+ SURF
Accu %.	94.17	94.88	95.76	97.27	96.91	97.22	97.43
Time Sec	0.3	0.3	0.2	0.5	0.4	0.5	0.5

5 Conclusion

This research was aimed at finding an efficient and optimal technique for the recognition gender using facial images. This was achieved by determining the most critical features of people's faces that should be considered, and how the features should be applied and utilized to achieve the best performance. Features based on Gabor, HOG, and SURF, and a combination of the features are used in selecting the appropriate feature from them as input for gender classification. The use of multiple features due to the need for high-quality images results in increased volume of input data for classifiers, thereby making the process of classifying the features very challenging. Thus, it is important that the features' dimensions be reduced in a manner that results in improved classification accuracy. For this reason, the use of the PCA is employed after the features have been extracted for reduction of dimensions of the problem and for the improvement of classification accuracy. Lastly, efficient and suitable classifiers by Multi-class SVM were used in this work, with an accuracy of 98.75% achieved by the proposed technique in terms of recognition of gender on the facial images obtained from the FERET database and a runtime execution of 0.4 Sec., with gender recognition accuracy of 97.43% achieved for the facial images obtained from the UTK-Face database and a runtime execution 0.5 Sec.

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