British Journal of Applied Science & Technology
10(4): 1-15, 2015, Article no.BJAST.19284
ISSN: 2231-0843

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Gender Classification and Age Detection Based on Human Facial Features Using Multi- Class SVM

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Authors' contributions

This work was carried out in collaboration between both authors. Author SG designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript and managed literature searches. Author SKB managed the analyses of the study and literature searches. Both authors read and approved the final manuscript.

Article Information

DOI: 10.9734/BJAST/2015/19284
Editor(s):
(1) A. Srinivasulu, Electronics and Communication Engineering Department, VITS, Proddatur, India.
Reviewers:
(1) Varun Shukla, Uttar Pradesh Technical University, India.
(2) Anonymous, China University of Mining and Technology, China.
Complete Peer review History: http://sciencedomain.org/review-history/10037

Original Research Article

Received 1st June 2015
Accepted 27th June 2015
Published 6th July 2015

ABSTRACT

Gender classification is a binary classification problem, which can be stated as inferring female or male from a collection of facial images. Although there exist different methods for gender classification, such as gait, iris, hand shape and hair, yet the prominent methods to achieve the goal is based on facial features.

In this paper, novel methodologies has been proposed to achieve the goal of (1) gender classification and (2) age detection in three step process. Firstly, input image set are pre- processed to perform noise removal, histogram equalization, size normalization and then face detection is performed. Secondly, Feature Extraction from facial image is performed. Finally to evaluate the performance of the proposed algorithm, experiments have been performed on various image set that contain equal proportion of male and female by using suitable binary SVM classifier which will classify the data set into two categories i.e male or female. To achieve the second goal, Multi- class SVM have been employed which will generate three classes i.e child, adult and old. The age of the input images are detected and classified into one of the three category.

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Keywords: Feature extraction; gender classification; SVM classifier; histogram equalization; multi-class SVM.

1. INTRODUCTION

In Human being the key characteristic feature is the face. The various emotions of a human can be determined and easily realized by the different facial expressions. The face is considered to be the most acceptable biometric trait than any other component as image capturing and prediction of images is easier to perform than other traits. Faces are normally classified as semi-rigid, semi-flexible, culturally significant, and part of our individual entity, and thus needs good computing techniques for face recognition and classification.

(1) Gender Detection and its classification into male /female and (2) Age Detection can be achieved by performing the following steps diligently. Fig. 1 depicts these steps:

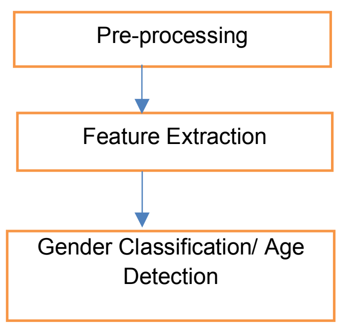

Fig. 1. Steps involved in gender classification

Gender recognition has found its strong applications in fields of authentication, search engine accuracy, demographic data collection, human computer interaction, access control and surveillance, involving frontal facial images. It can also be used as indexing technique to reduce the search space for automatic face recognition.

In this paper an attempt has been made to perform gender classification of human facial image based on the extracted feature from the input image set. The feature based on which gender recognition has been performed is the 'lip' which has been identified and extracted from a human facial image by following the Region of Interest (ROI) principle. Then the extracted feature is fed as input to the Support Vector Machine Classifier (SVM) which has the data set containing a combined set of lip images of both male and female. Besides this, the above mentioned technique has been implemented on a group image from which individual images of male/ female has been extracted. Then the similar procedure of Feature Extraction and Gender Classification is performed.

Finally an attempt has been made to perform age detection of a combined set of images and based on the age the images has been classified into either 'child' or 'adult' or 'old'. This classification is performed using Multi- Class SVM.

2. LITERATURE REVIEW

The significance of Gender Recognition and its Classification has been recognized and greatly identified in the field of research and development since the inception of research work on this field at the beginning of 1990s. Initially Golomb et al. [1] used multi -layer neural network to generate a solution to the problem of gender classification. The facial image was manually aligned for the experimental purpose. Around 900 unit images were squeezed into 40 images on which the classification was performed. An error rate of 8.1% was reported. En-Sheng Chu et al. [2] performed yet another experiment on the same problem by considering un-aligned face image, which uses only single face from which various poses were cropped and were combined into a set. The image set were converted into subspaces and correlation coefficient was used to generate the similarity between two subspaces. They used discriminate analysis of Canonical Correlation (DCC) for finding most accurate gender. FERET and MORPH face database were used for the experiment.

Shobeirinejad and Gao [3] proposed Interlaced Derivative Pattern (IDP) to extract facial features. IDP produces feature vector by extracting distinct facial features. The IDP image is a four-channel derivative image representing four directions that are 0°, 45°, 90°, and 135°. Thus this method contains more important information about gender face recognition.

LU et al. [4] detected different facial regions to accomplish the task of gender classification. Support Vector Machine (SVM) [5] classifier was used on face images. They used CAS-PEAL database consisting of grey scale images of size

480 × 360. Grey scale image were transformed to a normalized whole face image and a normalized internal face image. Experiments were carried out on seven facial regions of varying resolution. They proposed a method based on significance of different facial regions. This methods based on fusion of multiple facial regions was able to compensate for facial expressions and lead to better overall performance. Han X. et al. [6] used 3D face GavabDB contains 427 three dimensional facial surface images. They used 61 frontal face images with geometric meshes (45 males, 16 females) are used. In this case non-linear support vector machines (SVMs) were used to perform gender classification. The SVM was applied to triangular meshes representing human faces. They extracted 3-d facial features from corresponding geometry meshes. The evaluated experimental error rate was around 17.44%.

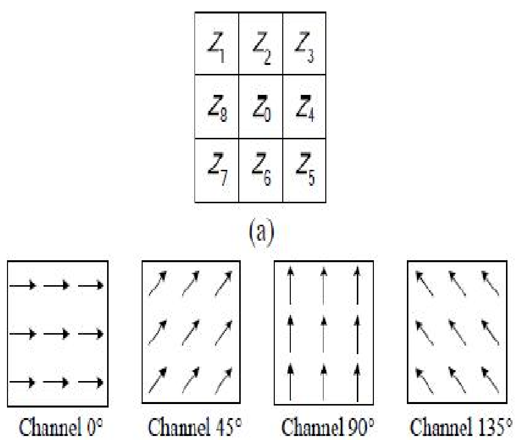

Fig 2. The interlaced Derivative Pattern image is a four channel derivative image representing four directions- 0°, 45°, 90°,135°

Wang Yiding et al. [7] used Feature extraction and classification using Scale Invariant feature Transform (SIFT) and FSVM. The proposed methodology produced accurate and stable result by reducing the Scale Invariant Feature Transform (SIFT) descriptor dimensions. The results were observed to be more accurate and robust on performing illumination change.

Similarly Ravi and Wilson [8] proposed a methodology which converted the RGB image into the YCbCr colour space in order to identify the skin regions in a facial image. However to detect the facial features, the RGB images was converted to grey scale images. Then face detection along with the identification of facial features were combined with gender classification in order to generate accurate results. Support Vector machine classifier was used to generate the solution to the classification problem.

Thus it can be concluded that Gender Detection and its Classification is a three step process where each step has its own significance and expediency.

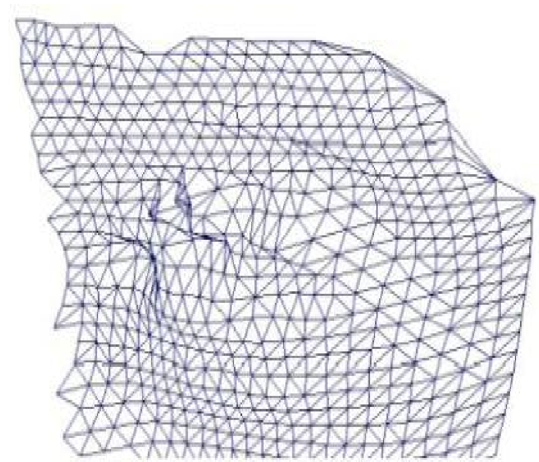

Fig. 3. Geometric mesh from which 3-d facial features were extracted

The pre-processing step involve operations like image normalization, histogram equalization, and noise removal. The adequacy of operation is explained below:

Image Normalization is a process of changing the intensity values of pixel range in an image.

Histogram Equalizations improves the contrast in an image, in order to stretch out the intensity range so that the area with lower contrast can achieve higher contrast. In this way the intensities can be better distributed on the histogram [9].

Noise Removal- In an image different type of noise can be incorporated that result in pixel values that do not reflect the true intensities of the image. There are several different ways that noise can be introduced into an image, depending on how the image is created. However noise removal can be achieved by implementing different techniques like Linear Filtering or Median Filtering [10].

The second phase involves Feature Detection and its appropriate extraction which can be achieved by adapting the following approaches:

Geometry-based Approach uses geometric information such as features relative positions and sizes of the face components as a features measure.

Template-based Approach in which previously designed standard face pattern template is used to match with the located face components. This uses appropriate energy function. The best match of a template in the facial image will yield the minimum energy. Genetic algorithms can be used for more efficient searching times and achieving more optimization in template matching.

Colour segmentation techniques makes use of skin colour to isolate the face. Any non-skin colour region within the face is viewed as a candidate for eyes and/or mouth localization. This method gives limited performance on facial image databases, due to the diversity of ethnical backgrounds.

Lastly in Appearance-based approaches the concept of "feature" varies from simple facial features such as eyes and mouth. Any extracted characteristic from the image is referred to as a feature. Traditional statistical techniques such as principal component analysis (PCA), independent component analysis, and Gabor wavelets are used to extract the facial feature vector. It projects the data images into Eigen-space that encodes the variation among known face images. This gives eigenvectors of the set of faces, which they do not necessarily correspond to isolated features such as eyes, ears, and nose. These approaches are commonly used for face recognition rather than person identification.

Finally, in the last phase the Support Vector Machine Classifier can be used for solving binary classification problem where the final result is to be classified into two classes.

A Support Vector Machine can therefore be defined as a learning algorithm for pattern classification and regression. The basic training principle behind SVMs is finding the optimal linear hyper plane such that the expected classification error for unseen test samples is minimized — i.e., good generalization performance [11]. However if the two classes are not linearly separable, the SVM makes an attempt to find the hyper plane that maximises the margin at the same time, minimising a quantity proportional to the number of misclassification errors. Thus to solve multi-class problems like Age Detection problem where the age is supposed to be categorized into three groups / classes i.e. 'child', 'adult' and 'old', a suitable multi- class classification technique is needed to be suitably designed and implemented. The approach to solve multi-class SVM problem has variables proportional to the number of classes. Thus for multi – class SVM problem, either several binary classifiers are to be constructed or a larger optimization problem is needed [12].

The strategies being adapted to solve a multi-class problem can be stated as (1) The "One against All" Strategy: This strategy aims at constructing one SVM per class, which is trained to distinguish the samples of one class from the samples of all remaining classes. Therefore, M binary SVM classifiers may be created where each classifier is trained to distinguish one class from the remaining M-1 classes. [13] This method is also known as winner-take-all classification. (2) One against One strategy involves "pairwise coupling", "all pairs" or "round robin". It involves the construction of one SVM for each pair of classes. Thus, for a problem with c classes, c(c-1)/2 SVMs are trained to distinguish the data points of one class from another class. Finally the classification of an unknown pattern is done according to the maximum voting, where each SVM votes for one class. [14]

3. PROPOSED METHODOLOGY FOR GENDER CLASSIFICATION USING LINEAR SVM

In this section we shall discuss about the technique being adapted to perform gender classification of a set of images into male and female.

3.1 Generalized Block Diagram of the Proposed Models

The block diagram of the proposed model is given below:

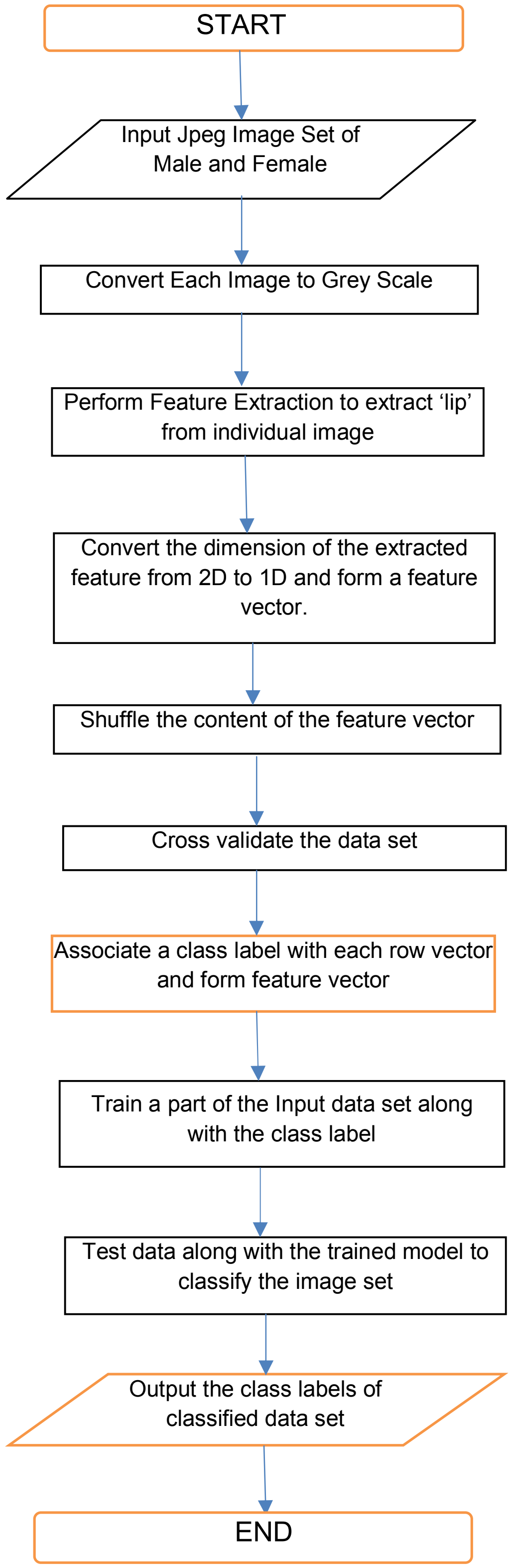

Fig. 4. Model developed for gender prediction

3.2 Algorithm

Step 1: Read Image Set of Male and Female
Step 2: Convert each input image to grey scale.
Step 3: Using ROI principle perform feature extraction from individual image.
  Step 3.1: for each image perform the following steps
    Step 3.1.1: Extract the 'lip' from individual image
    Step 3.1.2: Reshape the extracted image from 2 D to 1 D.
    Step 3.1.3: Associate with each image a class label. Assign +1 to female image and -1 to male image.
    Step 3.1.4: Form a Feature Vector consisting of the extracted images and the class label.
  end

Step 4: Shuffle the Feature Vector matrix.
Step 5: Cross- Validate the matrix and generate the train data set and the test data set.
Step 6: Perform training on the train data set of the SVM classifier.
Step 7: Perform testing on the test data set along with the train vector.
Step 8: Obtain the resultant classified data.

The block diagram of the model accepts a set of male and female face image in .jpeg format. Each RGB image was then converted to greyscale. Lip feature extraction is performed for each image and is used for classification of each image into either of the two classes (Male and Female) using a SVM classifier.

3.3 Implementation

A set of 100 Jpeg images are selected as the input image set for the experiment of which 50 are of male images and 50 are of female images. Each image is of size 128*115.

The input image set are pre-processed , as mentioned below and subjected to the svmtrain() routine for the generation of the train vector and then test images are applied to the svmclassify() routine where the test data set are tested and the class labels are determined.

3.3.1 Feature extraction

Feature Detection and its Extraction is considered to be an indispensable process which is needed to be followed and implemented to accomplish the task of gender detection and its classification.

The facial feature which has been identified for extraction is the ‘lip’. The process of extraction of the selected feature involves the following steps.

- The Region of Interest (ROI) principle is followed. A specific window size is selected and is applied to the input facial image.
- The desired location is identified using the window dimension from where the required feature can be extracted.
- The feature is then detected and extracted from the selected location using the imcrop () function.
- Each extracted image is then resized into a single vector of dimension 1581.
- A matrix containing the features of training images in its column wise is formed along with the class labels which is associated with each image. A class label of +1 is assigned to the female image and a class label -1 is assigned to the male image.

3.3.2 Shuffling

The feature vector thus obtained is shuffled. The resultant shuffled matrix is subjected for further processing.

3.3.3 Cross-validation

The objective of cross- validation is to identify a good value of (C,Y) so as to predict the unknown data set(test data) [7].

By following one of the cross- validation technique as mentioned below, the data set can be classified into train set and test set. The train data set along with class label can be used to train the SVM by invoking the appropriate routine with regard to the training data supplied to it. Then, the test data along with the trained model will be tested which will predict the class labels of the test data.

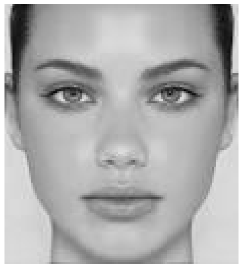

Fig. 5. Original grayscale female Image

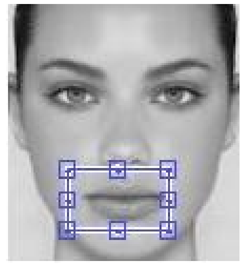

Fig. 5.1. Detected region of interest

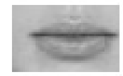

Fig. 5.2. Extracted feature

Fig. 6. Original grayscale male image

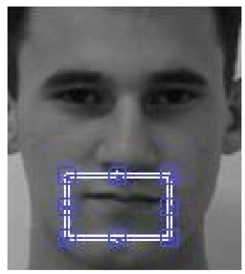

Fig. 6.1. Detected region of interest

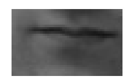

Fig. 6.2. Extracted feature

Besides this, cross- validation also helps to prevent over fitting problem. [15]

1. The **holdout method** is the simplest form of cross validation. It is also known as two fold cross validation. The data set is divided into two sets i.e. the training set and the testing set. It is also known as two-fold cross validation. The function approximation fits a function using the training set. The advantage of this method is that its computational time is low. However, the challenge is on its evaluation which can have a high variance. The evaluation result highly depends on the data points chosen for the training set and n the test set, and thus the accuracy of the final result may significantly vary depending on the division made on the data points.
2. **K-fold cross validation** technique aims at achieving a higher degree of accuracy over the holdout technique. In this method the data set is divided into *k* subsets, and the holdout method is repeated 'k' times. Each time, one of the *k* subsets is used as the test set and the other 'k-1' subsets are put together to form a training set.

   The advantage of this method is that the evaluation result does not directly depend on the division of the data points. The variance of the resulting estimate is reduced as 'k' is increased.

   The disadvantage of this method is that the computation time is high as the training algorithm has to be rerun for (k-1) subsets.

3. **Leave-one-out cross validation** is K-fold cross validation taken to its logical extreme, with K equal to N, the number of data points in the set. That means that N separate times, the function approximation is trained on all the data except for one point and a prediction is made for that point.

   The advantage of this method is that the evaluation given by leave-one-out cross validation error is good.

   However, it is computationally expensive [16].

In the proposed model, the shuffled matrix is cross- validated and appropriate division of the data points is performed into train set and the test set.

Among the three different technique as discussed above, (1) the hold- out method and (2) the K- fold cross validation method has been implemented on the resultant shuffled matrix. Different train set and test set is obtained.

The accuracy level varied with the two technique. The accuracy percentage of the training- testing combination by using the former cross validation technique varied from 76 percent to 84 percent while in case of the latter technique, the accuracy percentage was considerably high. It varied from 80 percent to 90 percent. At one instance the classification of the test data set resulted100 percent accuracy. This is achieved by applying the K-Fold cross validation technique where 'k=5' .It divides the shuffled matrix into five subsets sets, among which the four sets are used for the training purpose and the remaining one set are tested and classified to obtain the output labels.

<u>3.3.4 Train / Test</u>

The cross – validated data points are separated into train set and set. The train set are trained by invoking the 'svmtrain ()' routine. Based on the output labels, the accuracy of the SVM is determined.

The accuracy for the training- testing combination has been discussed in the Experimental Result section.

4. PROPOSED METHODOLOGY FOR GENDER CLASSIFICATION ON GROUP IMAGE

In this section we shall emphasise on the implementation of the human gender detection and its classification from a group image which contains a set of male and female images.

The technique that has been adapted in this model is similar to the one as discussed in the previous section. Except, that the individual image of male / female is first extracted from a group image which contain multiple facial images of male and female. Once the facial images are retrieved, the pre-processing of these images, the feature extraction and finally the classification of the gender is achieved by following the steps as discussed in the previous section.

4.1 Implementation

A group image consisting of 30 facial images are read as input .The input image contain 15 male images and 15 female images. Each individual image is of dimension 300*250.

After the individual images are extracted, each original facial image is resized to dimension 128*115.

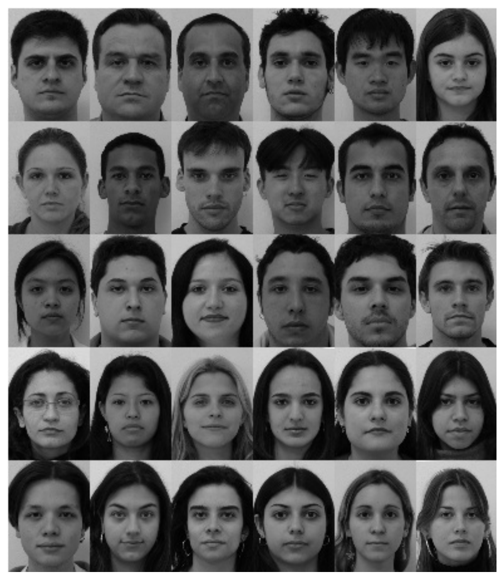

Fig. 7. Original group Image

Fig. 8. Extracted grey scale

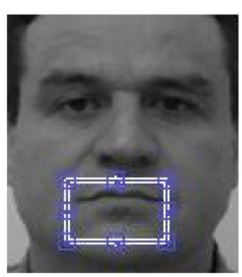

Fig. 8.1. Detected region of interest

Fig. 8.2. Extracted feature

male image from group image

Fig. 9. Extracted grey scale female image from group image

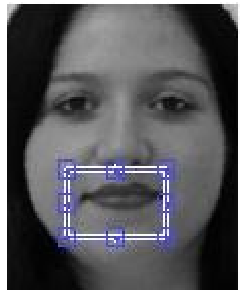

Fig. 9.1. Detected region of interest

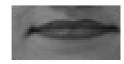

Fig. 9.2. Extracted feature

5. PROPOSED METHODOLOGY FOR AGE DETECTION USING MULTICLASS- SVM

This section illustrates the technique which has been adapted to perform age detection and classification of the same from an image set into three classes i.e 'child', 'adult', 'old'. The classifier used for the implementation and the evaluation of the proposed algorithm is the Multi- Class SVM. Unlike binary classifiers, this type of SVM can effectively classify the input data set into multiple classes.

The design and implementation of the proposed methodology is discussed in the following sub-section.

5.1 Algorithm

Step 1: Read Input Image Set.
Step 2: Convert individual input image to grey scale.
Step 3: Perform Histogram Equalization of the grey scale image.
Step 4: Use ROI principle perform feature extraction from the individual image.
    Step 4.1: for each image perform the following steps
        Step 4.1.1: Extract the 'lip' from individual image
        Step 4.1.2: Reshape the extracted image from 2 D to 1 D.
Step 4.1.3: Associate with each image a class label. Assign +1 to child image, +2 to adult images and +3 to old image.
        Step 4.1.4: Form a Feature Vector consisting of the extracted images and the class label.
        end
Step 5: Shuffle the Feature Vector matrix.
Step 6: Cross- Validate the matrix and generate the train data set and the test data set.
Step 7: Perform training on the train data set using SVM classifier.
Step 8: Perform testing on the test data set along with the train vector.
Step 9: Obtain the resultant classified data.

5.2 Implementation

A set of 119 Jpeg images have been considered for the input image set of which 'child image' and 'adult image' are of equal ratio of 40 images each. The remaining 39 images are the images of old people. Each image has been resized to the dimension of 128*115.

On these image set, histogram equalization is performed which improves the contrast of the input image set.

Then a similar procedure as discussed in previous methodologies have been employed to perform Feature Extraction and Age Detection from the input data points.

In the process of Age Detection and classification, the' *"One against All" Strategy* of Multi- class SVM has been utilized. Based on the principle of this strategy, three different SVM classifier is created for the three classes of data point's i.e child, adult and old.

Finally the output class labels of the tested data points are obtained which determines the accuracy of the SVM classifier.

Fig. 10. Image with original contrast

Fig. 10.1. Resultant Image with enhanced contrast

(a) Processing of Child Image

Fig. 11. Original grayscale image

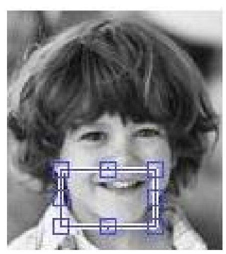

Fig. 11.1. Detected region of interest

Fig. 11.2. Extracted feature

(b) Processing of Adult Image

Fig. 12. Original grayscale image

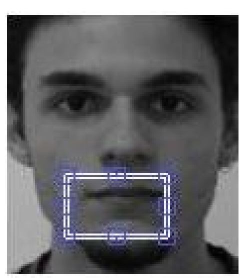

Fig. 12.1. Detected region of interest

Fig. 12.2. Extracted feature

(c) Processing of Old Image

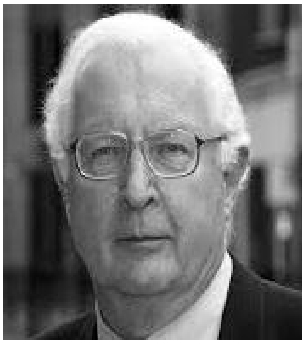

Fig. 13. Original grayscale image

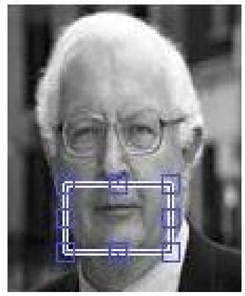

Fig. 13.1. Detected region of interest

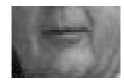

Fig. 13.2. Extracted feature

6. EXPERIMENTAL RESULTS

This section demonstrates the result obtained after the implementation of the proposed models as discussed in the previous sections. The input images are read from different websites. The input images with which the experiment is carried out in each model varies in number.

An attempt has been made to calculate the (a) ACCURACY (b) SENSITIVITY and (c) SPECIFICITY of each input image set of the proposed methodology. These calculations are done in the following way:

Accuracy= (TP+TN)/ (TP+TN+FP+FN).

Sensitivity= (TP)/ (TP+FN).

Specificity = (TN)/ (TN+FP).

The results obtained from the experiment are discussed below:

6.1 Results of Gender Classification using Distinct Input Images

Total Input Images: 100
Total male images: 50
Total female images: 50

Image Type: Frontal Facial Images (JPEG Images).
Extracted feature: LIP.
Kernel Type: Linear

Table 1.1. Confusion matrix depicting the result of gender classification

Serial no	Cross validation technique	Training set	Testing set	Output class label
1.	Hold-out	50	50	+1,+1,+1,+1,-1,-1,+1,+1,-1,-1,+1,+1,-1,-1,+1,-1,+1,+1,-1,-1,-1,+1,-1,-1,+1,-1,-1,-1,-1,-1,+1,+1,+1,-1,-1,-1,+1,-1,-1,-1,-1,+1,+1,+1,+1,-1,-1,-1,-1,-1
2.	Hold-out	50	50	-1,+1,+1,+1,-1,+1,+1,-1,-1,+1,+1,+1,+1,+1,-1,+1,+1,-1,+1,+1,-1,+1,-1,-1,+1,+1,-1,-1,+1,-1,+1,+1,+1,+1,+1,-1,-1,+1,-1,-1,+1,-1,+1,-1,+1,+1,+1,-1,+1,+1
3.	K-fold(5)	80	20	+1,+1,-1,-1,+1,+1,+1,-1,+1,-1,-1,+1,-1,+1,+1,-1,-1,+1,-1,+1
4.	K-fold(5)	80	20	+1,+1,+1,+1,-1,+1,+1,+1,+1,-1,-1,+1,+1,+1,-1,+1,-1,-1,-1,-1
5.	K-fold(10)	90	10	-1,-1,-1,-1,+1,-1,+1,-1,+1,-1
6.	K-fold(10)	90	10	-1,+1,+1,+1,-1,+1,+1,+1,-1,-1

Table 1.2. Confusion matrix depicting the result of gender classification

Serial no	True positive(TP)	False negative (FN)	True negative (TN)	False positive (FP)	Accuracy %	Sensitivity %	Specificity %
1.	17	4	21	8	76	80.95	72.41
2.	23	8	17	2	80	74.19	89.47
3.	9	2	8	1	85	81.81	88.89
4.	10	2	8	0	90	83.33	100
5.	3	0	5	2	80	100	71.42
6.	5	1	4	0	90	83.33	100

6.2 Results of Gender Classification using Group Image

Total Input Images: Group Image of 30 Images
Total male images: 15
Total female images: 15

Image Type: Frontal Facial Images (JPEG Images).
Extracted feature: LIP.
Kernel Type: Linear

Table 2.1. Confusion matrix depicting result of gender classification from group image

Serial no	Cross validation technique	Training set	Testing set	Output class label
1.	Hold- out	15	15	-1,+1,+1,+1,-1,-1,+1,+1,-1,+1,-1,-1,+1,-1,+1
2.	Hold- out	15	15	+1,-1,-1,-1,-1,-1,-1,+1,-1,+1,-1,-1,+1,+1,-1

Table 2.2. Confusion matrix depicting result of gender classification from group image

Serial no	True positive(TP)	False negative (FN)	True negative (TN)	False positive (FP)	Accuracy %	Sensitivity %	Specificity %
1.	6	2	6	1	80	75	85.71
2.	5	0	8	2	86.67	100	80

6.3 Results of Age Detection using Multi-class SVM

Total Input Images: 119
Total child images: 40
Total adult images: 40
Total old people images: 39

Image Type: Frontal Facial Images (JPEG Images).
Extracted feature: LIP.
Kernel Type: Linear

Table 3.1. Confusion matrix depicting age detection for child images

Serial no	Cross validation technique	Training set	Testing set	Output class label
1.	Hold-out	60	59	+1,+1,-1,+1,-1,+1,-1,-1,+1,-1,-1,+1,-1,-1,+1,-1,+1,-1,-1,-1,+1,-1,-1,+1,-1,-1,-1,+1,-1,+1,-1,-1,-1,-1,-1,-1,+1,-1,-1,-1,+1,+1,+1,+1,-1,-1,+1,-1,-1,+1,-1,-1,-1,+1,-1,-1,+1,-1,+1,+1,+1,-1,-1,-1,-1,-1,+1,-1,-1,-1,-1,-1

Serial no	Cross validation technique	Training set	Testing set	Output class label
2.	Hold-out	60	59	-1,-1,-1,+1,+1,+1,-1,-1,-1,-1,-1,-1,-1,-1,-1,+1,+1,-1,-1,-1,-1,-1,-1,-1,-1,-1,+1,-1,+1,+1,+1,-1,+1,-1,+1,-1,+1,-1,-1,-1,+1,-1,-1,+1,-1,-1,-1,-1,+1,-1,+1,-1,-1,-1,+1,-1,+1,-1,+1
3.	K-fold(5)	95	24	-1,-1,-1,-1,-1,+1,-1,-1,-1,-1,-1,+1,-1,-1,-1,-1,-1,-1,-1,-1,+1,-1,-1,-1
4.	K-fold(5)	96	23	-1,-1,-1,-1,-1,-1,+1,-1,-1,+1,-1,-1,+1,-1,-1,-1,+1,-1,-1,+1,+1,+1,-1
5.	K-fold(10)	107	12	-1,-1,-1,-1,-1,+1,-1,+1,-1,+1,+1,-1
6.	K-fold(10)	107	12	+1,-1,-1,-1,-1,-1,+1,-1,+1,-1,-1,-1

Table 3.2. Confusion matrix depicting age detection for child images

Serial no	True positive(TP)	False negative (FN)	True negative (TN)	False positive (FP)	Accuracy %	Sensitivity %	Specificity %
1.	11	11	28	9	66.10	50	75.67
2.	14	6	33	6	79.67	70	84.61
3.	2	1	16	4	78.33	66.67	80.0
4.	6	2	14	2	83.33	75	87.5
5.	4	0	8	0	100	100	100
6.	2	1	7	2	75	66.67	77.78

Table 4.1. Confusion matrix depicting age detection for adult images

Serial no	Cross validation technique	Training set	Testing set	Output class label
1.	Hold-out	60	59	-1,+1,+1,-1,+1,-1,-1,-1,+1,+1,+1,-1,+1,+1,-1,+1,-1,-1,-1,-1,-1,-1,-1,-1,+1,+1,-1,-1,-1,-1,-1,-1,+1,+1,+1,-1,+1,-1,-1,+1,-1,-1,-1,-1,-1,-1,-1,-1,-1,+1,+1,-1,-1,-1,-1,-1,-1,-1,-1
2.	Hold-out	60	59	-1,-1,-1,-1,-1,-1,-1,+1,+1,-1,-1,+1,-1,-1,+1,-1,-1,+1,+1,-1,-1,-1,-1,+1,-1,-1,-1,+1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,+1,-1,-1,-1,-1,-1,-1,+1,-1,-1,-1,-1,-1
3.	K-fold(5)	95	24	-1,+1,-1,-1,+1,-1,-1,+1,-1,-1,+1,-1,-1,+1,-1,+1,+1,-1,-1,-1,-1,-1,-1,+1
4.	K-fold(5)	95	24	-1,+1,-1,+1,+1,-1,+1,-1,-1,-1,-1,+1,-1,-1,-1,-1,-1,-1,+1,+1,-1,-1,-1,+1
5.	K-fold(10)	107	12	-1,-1,-1,+1,+1,-1,-1,-1,+1,-1,-1,-1
6.	K-fold(10)	107	12	-1,+1,-1,-1,-1,-1,+1,-1,-1,-1,-1,-1

Table 4.2. Confusion matrix depicting age detection for adult images

Serial no	True positive(TP)	False negative (FN)	True negative (TN)	False positive (FP)	Accuracy %	Sensitivity %	Specificity %
1.	13	6	29	11	71.18	68.42	72.5
2.	7	4	37	11	74.58	63.63	77.08
3.	2	1	16	4	78.33	66.67	80
4.	5	3	13	3	78.33	62	81.25
5.	3	0	8	1	91.67	100	88.89
6.	2	2	6	2	87.5	50	75

Table 5.1. Confusion matrix depicting age detection for old people images

Serial no	Cross validation technique	Training set	Testing set	Output class label
1.	Hold-out	60	59	-1,-1,-1,+1,-1,+1,+1,-1,-1,-1,-1,-1,-1,-1,-1,+1,-1,+1,-1,+1,-1,+1,+1,-1,-1,-1,+1,-1,+1,-1,-1,-1,-1,-1,-1,-1,-1,+1,+1,-1,-1,-1,-1,-1,-1,-1,-1,+1,-1,-1,+1,+1,-1,-1,+1,+1,-1,+1
2.	Hold-out	60	59	-1,+1,+1,-1,-1,-1,+1,-1,-1,+1,+1,-1,-1,+1,-1,-1,-1,-1,-1,-1,-1,+1,-1,-1,-1,+1,-1,-1,-1,-1,-1,+1,-1,+1,+1,-1,+1,+1,+1,+1,-1,+1,+1,-1,-1,+1,-1,+1,-1,+1,-1,+1,-1,-1,-1,-1,-1,+1,-1
3.	K-fold(5)	95	24	-1,-1,+1,-1,-1,-1,+1,-1,+1,+1,+1,-1,+1,-1,+1,-1,-1,+1,+1,+1,-1,-1,+1,-1
4.	K-fold(5)	95	24	-1,-1,-1,-1,-1,+1,-1,-1,-1,+1,-1,-1,+1,-1,+1,+1,+1,-1,-1,-1,-1,-1,-1,-1
5.	K-fold(10)	107	12	-1,+1,+1,-1,-1,-1,+1,-1,-1,-1,+1,+1
6.	K-fold(10)	107	12	-1,+1,-1,+1,+1,-1,-1,-1,-1,+1,-1,+1

Table 5.2. Confusion matrix depicting age detection for old people images

Serial no	True positive(TP)	False negative (FN)	True negative (TN)	False positive (FP)	Accuracy %	Sensitivity %	Specificity %
1.	12	8	36	3	81.35	60	92.30
2.	17	5	33	4	86.44	77.27	89.18
3.	9	3	11	0	83.33	75	100
4.	6	0	16	2	91.67	100	88.89
5.	4	1	7	0	91.67	80	100
6.	4	1	7	0	91.67	80	100

7. CONCLUSION

It has been observed and realized that the nature, behaviour and social interaction of people is greatly dominated by his/ her gender. Therefore an efficient gender recognition and classification system would play a pivotal role in enhancing the interaction between human and the machine.

Moreover, there are several other applications where gender recognition plays a crucial role which includes biometric authentication, high-technology surveillance and security systems, image retrieval, and passive demographical data collections.

Identification of the gender and its classification based on the distinguishable characteristics between male and female facial image can be achieved easily by the human eye. However, machines cannot visualize this difference, hence the same task becomes difficult for the computer to accomplish. Machines need meaningful data to perform gender classification. These data are usually the facial features based on which a computer classifies a facial image into either male or female.

Gender Classification is a binary Classification problem. There exist several algorithms which have been already implemented to generate a solution to the stated problem. This study addresses the issue of gender classification and age detection of the identified gender using Support Vector Machine Classifier. Although the stated methodologies have been implemented on facial image data set and results are obtained with a level of accuracy, yet there are areas which are yet to be cultivated and where further enhancement can be achieved. Thus the future scope of development of the proposed models have been discussed in the following section.

8. FUTURE SCOPE

In the future, the specified methodologies can be further improved by incorporating the below mentioned specifications in the implementation of the proposed mechanisms.

- The Gender Classification and Age Detection algorithms can be implemented with an increased number of facial image data set. This will increase the accuracy level of the output.
- The Proposed Models have been trained and tested on data sets using Linear Kernel. However the similar evaluation can be performed using other kernels of SVM Classifier like 'rbf kernel', 'quadratic kernel', etc.
- Gender Classification is performed based on the extracted feature' lip'. The same algorithm is can be implemented on other feature(s) like eyes, nose or combination of more than one feature in human facial image.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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Peer-review history:
The peer review history for this paper can be accessed here:
http://sciencedomain.org/review-history/10037