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Facial Image Classification Based on Age and Gender

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***Abstract*— Automatic face identification and verification from facial images attain good accuracy with large sets of training data while face attribute recognition from facial images still remain challengeable. We propose a methodology for automatic age and gender classification based on feature extraction from facial images, namely, primary and secondary features. Our methodology includes three main iterations: Preprocessing, Feature extraction and Classification. Our solution is able to classify images in different lighting conditions and different illumination conditions. Classification is done using Artificial Neural Networks according to the different shape and texture variations of wrinkles on face images.**

***Keywords*— Age classification, Gender classification, Feature extraction, Texture, Wrinkles**

I. Introduction

Personal monitoring, identification and verification using facial images are known to be an actively growing area of research in many computer vision applications. Some examples in this area are face recognition, face action classification, poses recognition, skin colour classification, age estimation, gender recognition and ethnicity recognition. Face recognition has achieved better results according to the research done for nearly three decades [1], [2] and [3]. However, similar accuracy of classification could not be gained from facial attribute recognition [4].

Human brain is the most powerful and accurate classifier in pattern recognition. It has the brilliant power as it is a dynamic organ involved with training and learning for a specific period of time. Researchers' main attempt is to convert this biological and behavioural characteristic of human brain into artificial neurons in order to attain the same or better results. One of the primary uses of this work is to classify human attributes like age, gender and ethnicity using facial images. Our attempt in this research is to come up with an accurate method for age and gender classification from facial images.

Gender classification is done according to the geometric difference of primary features in male and female [11]. This algorithm can classify the facial images in to four age groups 8-13, 14-25, 26-45 and 46-60. Age classification is based on the texture variation of wrinkle density in the forehead, eye lids and cheek area. Classification is done using two separate neural networks for age and gender.

Dataset used for the proposed methodology contains images from both genders and different age groups. Those images represent different facial features, expressions, different angles and different lighting conditions. Figure1 shows a subset of data used in the experiment.

Figure1. Different types of images used in the experiment

II. Related Work

A. Age Classification

Y. H. Kwon and Niels da Victoria [4] introduced the first involvement for age classification from facial images. Images were classified into one of the three age groups from babies, young adults and senior adults. Primary features of the face are used to distinguish a baby from a young adult and a senior adult. After that wrinkle geography mapping is used to distinguish seniors from young adults and babies.

Wen-Bing Horng et al [5] developed an algorithm to identify age from grayscale images by using an Artificial Neural Network (ANN) classifier. Proposed method is able to classify images into one of four categories from babies, young adults, middle-aged adults, and elderly adults.

K B Raja and L M Patnaik [6] proposed an age and gender classifier using ANN classifiers and posterior class probability. Their algorithm consists of three main stages, preprocessing, feature extraction and classification.

Feng Gao and Haizhou Ai [7] developed their own algorithm to face the challenge of age classification using consumer images in various conditions. Gabor feature is extracted for face representation and a fuzzy version Linear Discriminant Analysis (LDA) is used for classification.

B. Gender Classification

Rodrigo Verschae et al [8] described a framework for classifying face images into the corresponding gender using Adaboost and domain-partitioning based classifiers. The proposed framework has the capability of building classification systems with high accuracy in dynamical

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environments, while maintaining a high processing and training speed. The paper presents that they have practiced the proposed framework by using several features like Local Binary Patterns (LBP), wavelets and rectangular features.

M. Mayo and E. Zhang [9] presented a novel method of face gender classification by using completely misaligned data such as translated or rotated data into the training set and obtained a remarkable accuracy. Proposed methodology used two classifiers for the experiment. One is based on weak features such as Local Binary Pattern histograms and the other classifier is based on SIFT key points. Finally the proposed system has achieved a high accuracy of 92.5%.

Wei Gao and Haizhou Ai [13] introduced a novel method in classifying face images in multiethnic environment by using consumer images. They have used Active Shape Model to overcome the non uniformity in consumer images by texture normalization. They have presented a probabilistic boosting tree approach in gender classification as well as consideration on ethnic factor on classification. The paper proves that gender classification using ethnic factor has achieved a higher accuracy of classification in multiethnic environment.

III. System Design

The main goal of the proposed algorithm is to identify corresponding age range and gender from human face images using a specific set of facial features. Facial feature extraction is the most important phase in this algorithm. Figure2 shows the main steps required to carry out in order to address the above problem. Proposed algorithm consists of three main steps; Pre-processing, Feature Extraction and Classification.

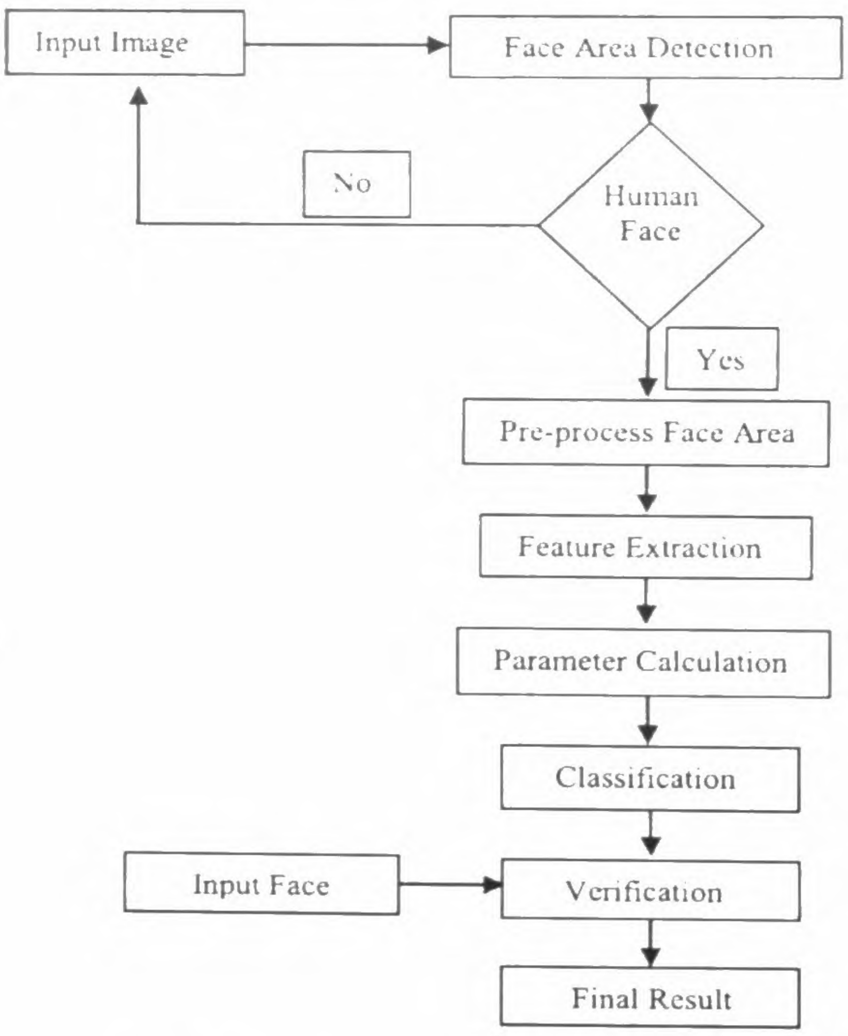


Figure2: Main steps of the proposed Age and Gender Classifier

A. Input Image

Input image is the image intended to test with the age and gender classifier. User can input any type of image format like .jpg, .png, .tiff, and .bmp. System will not accept face images with spectacles and images of little babies who are less than eight years of age.

B. Face Detection

First phase will proceed to check whether the given input image contains a face image or not. Algorithm will reject the input image if there isn't any face area in the input image. If facial images detected, classifier will identify the face areas from the images and create a separate image per every face in the input image as shown in Figure3. Classifier has been trained with a sufficient number of frontal, nearly frontal, rotated faces from 0 to 45 degrees and non face images. Detected face images are preprocessed to standardize the face images by converting them to a unique format.

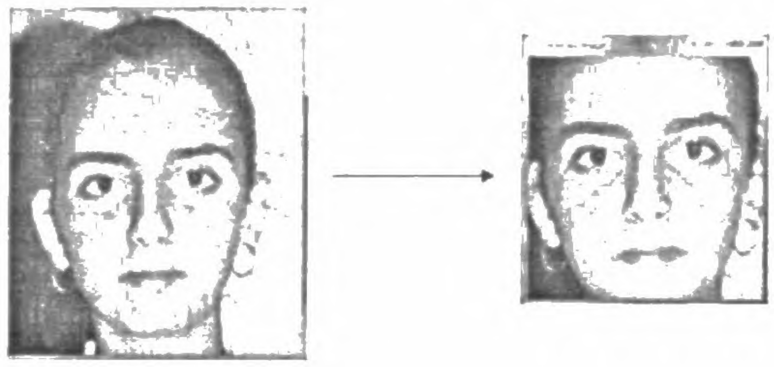


Figure3: Detected face area from the Input face image

C. Preprocessing

Images used in the experiment are in different conditions such as presence of noisy data, different lighting conditions and different intensity levels. Thus, detected face images need to undergo a preprocessing step before forwarding to the classification stage.

1. Resize Detected Face Image

Collected images from the initial face detection are in different sizes. Therefore to standardize the data set first step in preprocessing is to modify each image into a standard width and height (Ex. 255*255 in this research).

2. Colour Conversion

Images used in this research need to be in standard colour format. Therefore to overcome the complexity, all the images are converted into grayscale and finally do a histogram equalization to have a uniform distribution of intensity values in the image. First the red, green and blue values of every pixel in the image are obtained. The following formula is used to convert the RGB image into a grayscale image:

$$G(x,y) = 0.21\,R + 0.71\,G + 0.07\,B \qquad 1$$

3. Noise Reduction

Dirt on camera lenses, imperfections in camera flash lighting may result to create noise in natural images taken from digital cameras. Colour converted images are sent to the noise reduction filter. Gaussian smoothing is used to remove the noise in the images. Gaussian smoothing of f(x, y) can be given as,

$$G\sigma \equiv \frac{1}{2\pi\sigma^2} \exp\{-\frac{x^2+y^2}{2\sigma^2}\} \quad — \quad 2$$

This function can be used to calculate the weight for each pixel in the image. Assume the centre point of weight matrix is (0,0). Then the nearest coordinate values can be represented as,

(-1,1)	(0,1)	(1,1)
(-1,0)	(0,0)	(1,0)
(-1,-1)	(0,-1)	(1,-1)

Then the weight matrix i calculated by setting a value to σ. The output weight matrix for a sample data set by using σ =1.0 is:

0.0453	0.0556	0.0453
0.0556	0.0707	0.0556
0.0453	0.0556	0.0453

The sum of the weighted matrix is calculated using the formula (3):

$$sum(w) = \sum_{i=1}^{9} w(i) \quad — \quad 3$$

Then the weighted average of the nine points is calculated by.

$$avg(w) = \frac{w(i)}{sum(w)} \quad — \quad 4$$

The Gaussian blur for each point in the matrix is calculated by multiplying the colour value of each point by the weighted value. Each colour value is between 0-255.

$$G(i) = int(i) * avg(w) \quad — \quad 5$$

These values of the matrix help to calculate the Gaussian blur value for the center point.

$$blur(middle) = \sum_{i=1}^{9} G(i) \quad — \quad 6$$

By repeating the above steps for all the points in the image, the Gaussian blur for the face images can be calculated.

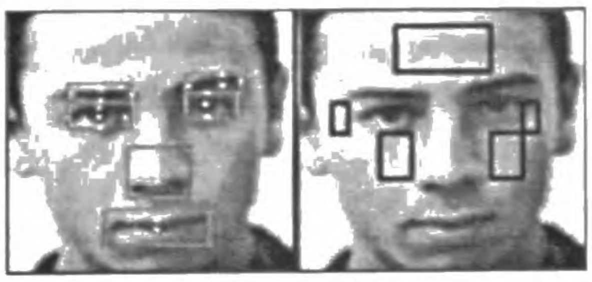
D. *Feature Extraction*

Human face contains 66 feature points of landmarks according to the research done in [10] by using images from FG-NET database. Relevant features important for the classification should be extracted from the face images. According to human gender variation there is a considerable difference in geometric size, shape and distance variations in the facial content. Some of these variations are described in Table 1.

Facial Feature	Male	Female
Hairline	Usually has higher peeks on the sides and tend to be 'M' shaped	Rounded shape
Eyebrows	Usually thick and just under the orbital rims	Generally sit higher and more arched
Eyes	Appear small	Appear large
Distance between eye and eyebrow	Lower	Higher
Nose	Relatively bigger and smaller	Small and short
Lips	Distance between the nose and the upper lip is large	Distance between the nose and the upper lip is small
Chin	Wider chin	Rounded chine
Checks	Hollow check	More rounded
Face shape	Square appearance	Heart shape

Table 1: Facial Characteristic Variation between Male and Female

Algorithm uses the primary features such as eyes, nose, mouth and eyebrow area according to Figure3 (a) and secondly we detect secondary features which are extracted from the three areas located on the forehead, cheeks and eyelid area according to Figure3 (b). As mentioned in [10], there are 66 feature points on the face area. However, we use only a subset of feature points as we are concerned about the accuracy and complexity.



(a)Primary features (b) Secondary features
Figure4: Features of interest

A classifier is used to identify the eye area from the images as in Figure5. The classifier has been trained with eye images and non eye images. Horizontal and vertical projections are used to locate feature points. Valley points and peak points of the horizontal and vertical projection can be used to locate the feature points as shown in Figure6.

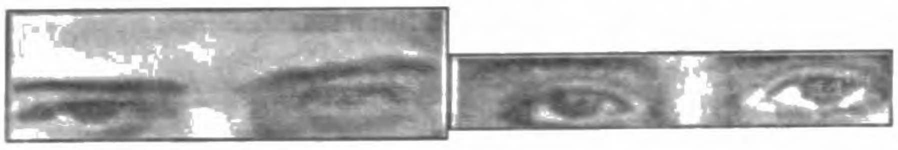


Figure5: Extracting the eye area

Figure6: Projections used to locate eyes

A classifier is used to identify the nose areas from the images. The classifier has trained with nose images and non nose images. It is intelligent enough to locate nose areas and represent as a square region and take the big enough area to locate the nose tip. Feature point locating is done by the horizontal and vertical projection to the cropped big enough area. Crossing point of valleys of the horizontal and vertical projection can be used to locate the nose tip as shown in the Figure7.

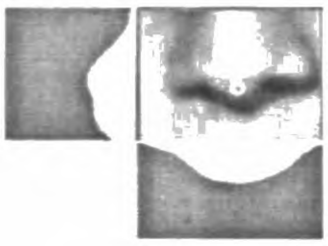


Figure7: Nose tip location

Another classifier has been used to identify the area of the mouth in the images. The classifier has been trained with images with and without mouth areas. It is intelligent enough to locate mouth areas and represent them as a square region and also to locate the end points of the mouth as well. Feature point locating is again done by the horizontal and vertical projections.

For the age classification, our algorithm used wrinkle feature variation from young age to old age. The wrinkle areas are located manually and the Sobel edge magnitude is calculated for each area. Figure 8 represents the corresponding Sobel edge magnitude image of an input image.

Figure8: Sobel edge image of the face area

E. Parameter Calculation

A specific set of parameters are required to proceed with age and gender classification. Figure9 shows the parameters we have calculated after feature point extraction.

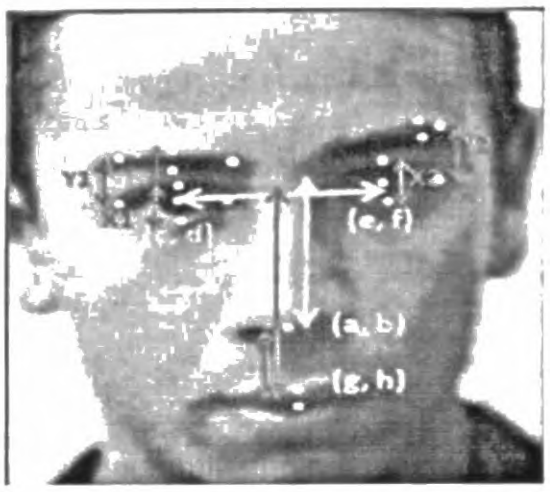


Figure9: Parameters calculated for gender classification

Description of the parameters is given below;

- Height of Eye = (X1 + X2) / 2
- Distance between Eye and Eye brow = (Y1 + Y2) /2
- Height of Nose (N) = b – (d + f) / 2
- Distance between Lip and Nose = h - b
- Width of Eyebrow = Q
- Distance between Eyes (E) = e – c
- Eye to Upper Lip Distance (L) = h – (f + d) / 2
- Ratio1 = Eye Distance /Nose Distance = E / N
- Ratio2 = Eye Distance / Eye to Upper Lip Distance = E / L

F. Classification

Classification is done in two main steps. First the gender classifier will identify the corresponding gender of the query image. After that, the image is transferred to the age classifier to identify the corresponding age group. Gender classification is basically done using shape variations of the features on face and the age classification is based on the texture variations in the wrinkle areas.

G. Evaluation

Evaluation of the proposed methodology can be summarized using the classification accuracies of each set of data. Accuracy of correctly classified image depending on the age, gender and even the combination of age and gender can be calculated by,

$$Ratio = \frac{No\ of\ Correctly\ Classified\ Images}{Total\ no\ of\ Images\ in\ Subset} * 100 \quad — 7$$

Number of correctly classified images is calculated by comparing the results of the algorithm and the stored age and gender values of the corresponding images in the image database.

H. Image Databases

System uses face images from the famous facial databases namely FERET database [12], FGNET database [14] and images collected by the authors as well. Researches must request from authorized people to download the FERET and FGNET databases. All the instructions to download FERET database can be found in [15].

IV. IMPLEMENTATION

A. Face Area Identification

Identifying the face area from the input image is an important task since an input image may contain unnecessary data other than the face area. To do this task, a classifier is trained using a number of images which include face images (positive set of face images) as well as non face images (negative set of face images). During the training process, distinct features of the objects are extracted. Later these extracted features are used to classify the objects in the unseen images. Outputs from the preprocessing step are shown in Figure10.

Haar wavelets are single wavelength square waves which contain one high interval and one low interval. In two dimensions, a square wave is represented by two adjacent rectangles where the pair contains one light colour and a dark colour. Determination process of the presence of a Haar feature is done by subtracting the average dark region pixel value from the average light-region pixel value. A threshold value is provided during the learning process and it checks whether the difference is greater than the threshold value or not. If it is greater than the threshold value, then it indicates that the feature is present.

(a) (b) (c) (d)

Figure10: (a) Input image (b) Detected face area (c) Grayscale image of the face area (d) Smoothed and histogram equalized image

B. Locating Features

Primary feature extraction is the most important phase in our research. Primary features in the human face are eyes, nose, mouth and eyebrow. There exists a specific region where each facial feature falls in an image and therefore, the search space for a facial feature could be minimized. According to this observation, we can divide the face area into several pieces and start to locate each feature point using a trained classifier for each feature.

1. Locating Primary Features

Once the corresponding primary feature region is found, each feature is located using trained classifiers for each feature. Face regions are first sent to the corresponding classifier to detect the respective feature areas. Then we separately find the nearest big enough region including the located feature area. Feature point location is detected by applying the integral projection on each feature area. Since eyes have strong intensity variation, the major peak is formed at the position of the eyes in horizontal projection and most probably the lowest valleys in vertical projection represent the eyelid areas. Similarly, the nose can be located by the intensity value difference in the nose trill and the mouth is also located by the same mechanism and "References".

2. Locating Secondary Features

Wrinkles on the face become clearer when people get older. Therefore, wrinkles are the best features to identify the age of an adult person. The general wrinkle areas are; Forehead, Eye Corners and Cheek.

After locating the wrinkle areas we use Sobel edge magnitude to identify the measurement of wrinkles in corresponding face images. Wrinkles definitely can be identified from the normal skin because wrinkles have higher Sobel edge magnitudes.

C. Calculate Parameter

The calculated parameter vector for the gender classification consists of the Eye height (H E), Distance between eye and eye brow (Dist E & EB), Height of the nose (H N), Width of the eye brow (W EB) and Distance between upper lip and nose top (Dist N & L).

Similarly, the calculated parameter vector for the age classification contains two ratios, ratio between eyes to nose distance and eyes to mouth distance (R ENM) and ratio between distance from eyes to mouth and distance between the two eyes (R EM).

Two wrinkle parameters from each wrinkle area are also calculated:

- Wrinkle Density (Wdensity) = No of all wrinkle pixels/ No of all pixels in the area
- Wrinkle Depth (Wdepth) = Total Sobel Magnitude of wrinkle pixels/Total no of pixels in the area.

D. Classification

Classification is done using the calculated parameters from the neural networks. The neural networks are trained using data taken from nearly 1500 images including the two gender groups and different age groups which are images from frontal and nearly frontal faces. Figure11 shows the structure of the neural network used for age classification.

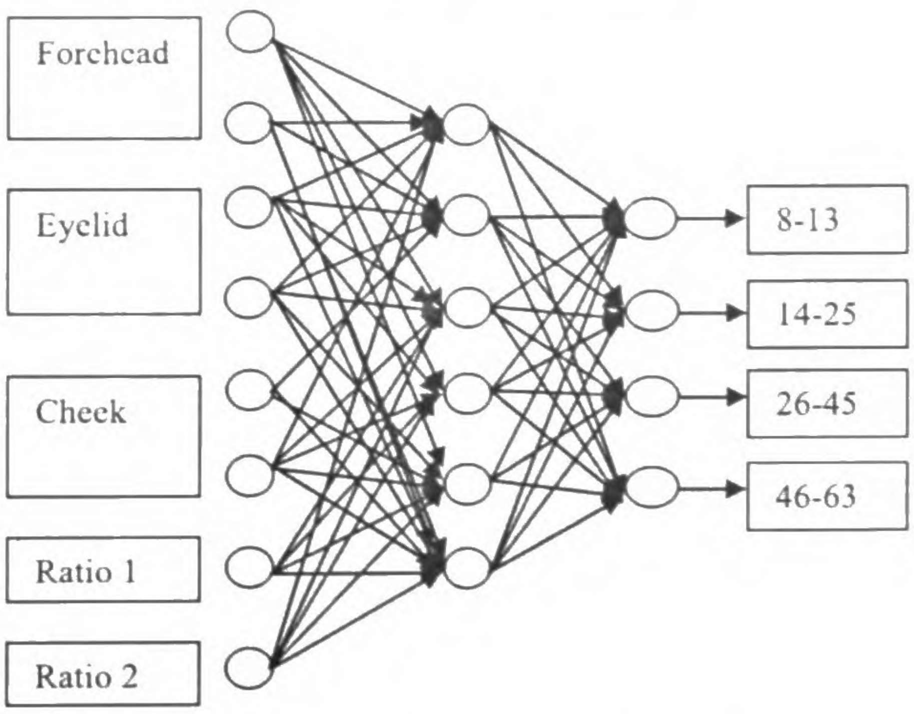


Figure11: Neural network structure used for Age Classification

Calculated parameters are sent to the corresponding neural network to classify the images according to age and gender. Neural network used for gender classification contains five input nodes and two output nodes 0 and 1 corresponding to the two gender groups, male (0 – 0.5) and female (0.5 – 1.0). Output value from the neural network is used to classify the image into one of the gender groups.

The neural network used to classify the given input image in to a corresponding age group has eight input nodes and the output layer contains four nodes namely 0, 1, 2 and 3 to represent the age groups 8-13, 14-25, 26-45 and 46-63 respectively. The neuron with the highest response is considered as the output of the age classification neural network.

E. Evaluation

Experiment has used a training data set consisting of nearly 1500 images. Training phase is done by testing the output by changing the number of hidden layer nodes, number of hidden layers and the minimum error value to identify the best classification for the data set provided. A test data set of 200 images is used to measure the performance of the proposed age and gender classification algorithm. Test data set consists of images from both genders and images correspond to the four age groups considered. Table 2, Table 3 and Table 4 show the results of the proposed methodology.

Type of Data Set	Sample Size	Correctly Classified Size	Rate	Classification Rate
Test Set	Male - 80	68	85%	85.83%
	Female – 120	104	86.66%	
Training Set	Male - 95	84	88.42%	89.92%
	Female - 105	96	91.42%	
Training+ Test Set	Male - 90	79	87.77%	87.06%
	Female - 110	95	86.36%	

Table 2: Performance Evaluation of Gender Classification

Data Set	Sample Size According to Age Group	Classification Accuracy Size	Rate	Overall Classification Rate
Test Data Set	8-13 - 30	24	80%	74.39%
	14-25 - 81	58	71.60%	
	26-45 - 60	40	66.66%	
	46-60 - 29	23	79.31%	
Training Data Set	8-13 - 45	32	71.11%	79.09%
	14-25 - 50	41	82%	
	26-45 - 55	37	67.27%	
	46-60 - 50	48	96%	

Table 3: Performance Evaluation of Age Classification

Data Set	Sample Size	Correctly Classified no of Images	Accuracy of the whole Classifier
Test data set	200	141	70.5%

Table 4: Performance Evaluation of Age and Gender Classification Together

V. Conclusion and Future Work

This paper introduced an approach to classify facial images into their corresponding gender and age. The main emphasis of this research is to apply the training and learning process of the human brain in pattern recognition and classification from the normal computer. Automatic classification of facial images into age and gender has been used in several applications in the commercial world such as video surveillance systems and enhance image searching in search engines. The proposed methodology used parameters taken from the geometric facial feature variations influenced by the two gender types and the facial skin texture variation in the ageing process. These parameters are then used to classify the images into corresponding gender and age by using a neural network. Facial images for our research are taken from the two databases namely FERET and FGNET which include the gender and age details along with each image.

We use facial images in the range of 8 – 63 as it is very difficult to recognize the gender of little babies by the geometric facial feature variations and also there are not enough facial images of people older than 64 to use in our experiment. For the effectiveness of identifying the age of a given facial image we have used four age groups namely 8 – 13, 14 – 25, 26 – 45 and 45 – 63 where each range has remarkable variations. We have used nearly 550 images for the training process including both male and female images within our interested age groups. Face detection and the facial parts such as eyes, nose and mouth area are located using the OpenCV Haar cascade classifiers. After that feature points required for the experiment are extracted using horizontal and vertical projections. There are many difficulties of correctly locating the feature points automatically in some cases when the face area contains birthmarks like patches and also due to different lighting conditions.

Parameters in the training data set is input to the neural network to train the system and it is used to classify a given query image into the corresponding gender and age group according to the learning done from the parameters used in the training process. There are two neural networks used for the classification of age and gender. Each of the neural networks performs accurately with one hidden layer comprising with suitable number of neurons.

According to the results taken from the proposed age and gender classification methodology, gender classification from facial images has significantly higher accuracy in classification training data as well as testing data. For the testing data the gender classifier results with a correct classification of 85.83% while the training data set gives 89.92% accuracy when using data from 40 images from each data set. This implies that the classification accuracy for the testing data set is very closer to the classification rate for the training dataset. This can be further interpreted that our proposed method for gender classification is a considerably accurate mechanism and it can be used as a successful mechanism in gender classification. According to the results taken from age classifier we can see that the accuracy for the training data set is 79.09% and 74.39% of accuracy for the testing data where we have used data from 40 images. Overall accuracy for the age and gender classifier is 70.5% which is a considerable high accuracy when compared to the overall classification accuracy by human brain which gives a 75% of accuracy. This shows that gender classification by human brain is 100% but when we come to age classification it is 75%, which shows the difficulty for the classification. Therefore we can conclude that the proposed age and gender classification methodology can be accepted as a successful mechanism.

Proposed methodology can be improved further to gain higher accuracy in classification. More parameters can be added to represent the geometric variation of gender to our classifier in order to increase the performance. Reducing the gap between age ranges would result with a better classification of images in to several age groups.

Identification of wrinkles is not 100% accurate as it depends on several external conditions such as facial make-up and smoothing done for the images. Therefore in future it is required to find out another set of parameters which do not cause these problems. In the literature there are lots of solutions suggested using Gabor features with Fuzzy Linear Discriminate Analysis methods and they have concluded with a high accuracy in classification. It will be better to analyse the performance behaviour by using this Fuzzy LDA method combined with the parameters used in the method of age classification.

Proposed algorithm can be enhanced to perform accurately under any condition of images in the future. Reducing the gap between the present age ranges would also be a reasonable suggestion to end up with a better classification.

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