Gender Recognize and Reconstruction of Face using Eigen Values and Eigen Vector

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***Abstract*— Automatic gender classification has become relevant to an increasing amount of applications, particularly since the rise of social platforms and social media have gained more attraction. Nevertheless, performance of existing methods on real-world images is still significantly lacking, especially when compared to the tremendous leaps in performance recently reported for the related task of face recognition. In this paper we show that by learning representations through the use of feed forward neural networks, a significant increase in performance can be obtained on these tasks. To this end, we reconstruct the face image using the Eigen values and vectors. We evaluate our method gender estimation and show it to dramatically outperform current state-of-the-art methods.**

Keywords—Gender prediction, Eigen values, Eigen Vectors, Feed forward Neural Network (FNN), image processing.

I. INTRODUCTION

A major powerful medium of human communication is human face [1], there have been a lot of research works carried a lot of information about the person like emotional state, identity, gender, ethnicity. Simulation of face age and prediction of face is a recent research area with numerous applications in digital entertainment. The importance of our goal is that all the applications are to produce aging effects that are generally possible without changing the identity of a person. This is a different task from face recognition in biometrics because in this task two key assumptions are consider that extract those features which are constant over a long time period and evaluate the rate of inclination to which exterior look of face is changed in aging process. A logical model is needed to evaluate and analyze the sequel of aging on faces. Effectiveness and efficiency of automated face recognition system is greatly affected by the aging of faces. Light and photograph difference are other important factors to reduce the efficiency of face recognition system. Various face recognition models are divided into space and frequency domain on the basis of various algorithms .In space domain, geometric and Template Matching using Principle Components Analysis, Independent Component Analysis, and Linear Discriminate Analysis is generally used methods. DCT(Discrete Cosine Transforms) and Gabor Wavelet are generally used methods for frequency domain .As humans, man got complete command over human morphological genetics, face of a person totally depend upon natural features that are opulent and sturdy lines, unswerving nose, potent eyes, location of facial features, and left or right perfect symmetry that plays an important role . It is expected that human face is keep changing as time spent .In current time the size of human brain is three times

The size of inherent ancestors. Head get bigger with the growth of brain which leads to the expansion of skull causing facial feature to be more flat.

Past approaches to estimating or classifying these attributes from face images have relied on differences in facial feature dimensions [2] or "tailored" face descriptors (e.g., [3,4,5]). Most have employed classification schemes designed particularly for age or gender estimation tasks, including [6] and others. Few of these past methods were designed to handle the many challenges of unconstrained imaging conditions [3]. Moreover, the machine

Learning methods employed by these systems did not fully Figure 1. Faces from the Audience benchmark for age and gender classification [3]. These images represent some of the challenges of age and gender estimation from real-world, unconstrained images. Most notably, extreme blur (low-resolution), occlusions, out-of-plane pose variations, expressions and more. exploit the massive numbers of image examples and data available through the Internet in order to improve classification capabilities.

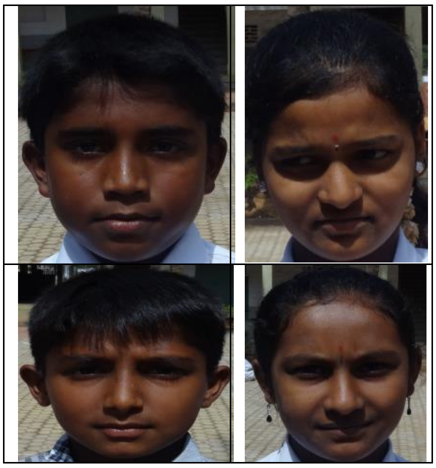

Figure 1: Sample Database of the human faces

In this paper we attempt to close the gap between automatic face recognition capabilities and gender estimation methods. To this end, we follow the successful example laid down by recent face recognition systems: Face recognition techniques described in the last few years have shown that tremendous progress can be made by the use of deep convolution neural networks (CNN) [7]. We demonstrate similar gains with simple network architecture, designed by considering the rather limited availability of accurate gender labels in existing face data sets.

1.2 Requirements for face prediction [1]

Following are the universal requirements for predicting the face .To get detailed information; we have to knowledge about these parameters:

1. **Essential:** For essential or invariant qualities face performs as an index like sex and race. Lots of researches show that Americans has intelligence by birth, while other culture looks it as socially reliant.

2. **Biologic Antiquity**: A person's face shows its biological Antiquity, by virtue of which it can make judgment of some qualities like person's age, health, and energy level, are found to be most important dimensions for predicting future performance.

3. **Moral Antiquity:** Frequent occurrence of intention and emotion might leave spot onto the face of a person which produce qualities like learned kindness, generosity and honesty.

4. **Social History:** From the human face, anyone can easily read a person's social history which produce qualities like grooming level, wealth, confidence and dominance.

II. RELATED WORK

Gender classification. A detailed survey of gender classification methods can be found in [8] and more recently in [9]. Here we quickly survey relevant methods. One of the early methods for gender classification [10] used a neural network trained on a small set of near-frontal face images. In [11] the combined 3D structure of the head (obtained using a laser scanner) and image intensities were used for classifying gender. SVM classifiers were used by [12], applied directly to image intensities. Rather than using SVM, [13] used AdaBoost for the same purpose, here again, applied to image intensities. Finally, viewpoint-invariant age and gender classification was presented by [14]. More recently, [15] used the Weber's Local texture Descriptor [16] for gender recognition, demonstrating near perfect performance on the FERET benchmark [17].

In [18], intensity, shape and texture features were used with mutual information, again obtaining near-perfect results on the FERET benchmark. Most of the methods discussed above used the FERET benchmark [17] both to develop the proposed systems and to evaluate performances. FERET images were taken under highly controlled condition and are therefore much less challenging than in-the-wild face images. Moreover, the results obtained on this benchmark suggest that it is saturated and not challenging for modern methods. It is therefore difficult to estimate the actual relative benefit of these techniques. As a consequence, [19] experimented on the popular Labeled Faces in the Wild (LFW) [20] benchmark, primarily used for face recognition. Their method is a combination of LBP features with an AdaBoost classifier. As with age estimation, here too, we focus on the Audience set which contains images more challenging than those provided by LFW, reporting performance using a more robust system, designed to better exploit information from massive example training sets.

III. METHODOLOGY

The images used in this work were acquired from the pupils of Siddaganga group of institutes. The subjects involved were mostly students and faculty numbering around 600. In each acquisition session, the subject sat approximately one meter away with the side of the face in front of the camera in outdoor environment without flash. The images were obtained simultaneously. Care was taken to provide same illumination conditions for all the captures. All the images were enrolled in the gallery of database. A cross section of sample database is presented in Figure1

The images so obtained were resized in such a way that only faces portion covers the entire frame having pixel matrix. The color images were made a separate chancel to store all them into a separate database. The conceptual presentation of the process involved is shown in Figure 2.

a. Feature Extraction

Firstly the images are used based on the region of interest, ie the faces then the cropped images are used for next processes, and then the images are reduced to the standard size, the feature used for our work are the Eigen values and the Eigen vector of the images of the red, green and blue chancel, stored separately in the database. In our work we considered the red chancel Eigen values and Eigen vector are used in our work.

b. Application of FNN

As a sequel to the first step, the data base was assorted into two groups. The sample segment of the database is shown in table 1. In the training mode of FNN 70% of the database of features values were selected from each of the groups 15%

for testing and 15% for validating the dataset. For this purpose a topology of the FNN has highlighted in the Table 3 was used.
The methodology used is conceptually shown in a block diagram depicted in Figure 3.

Table 1: Salient details of FNN implemented

No of input layer neurons	250
No of neurons in hidden layer	510
The basis function	sigmoid
Training function	trainlm
No of output neuron	2

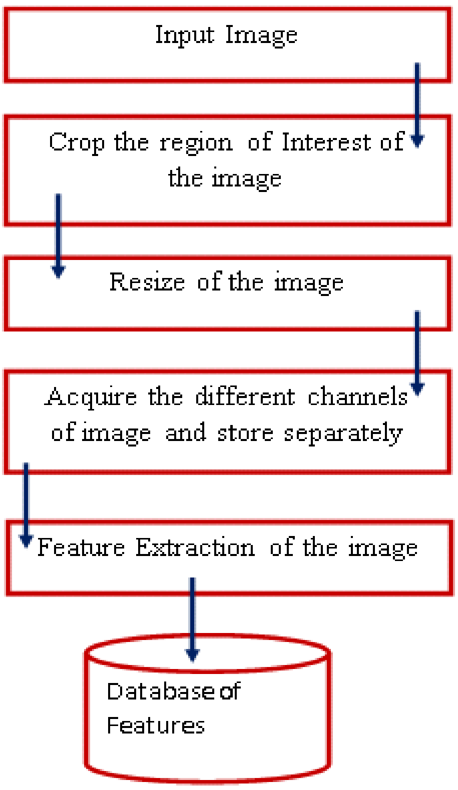

Figure 2. The Steps involved in Human face extraction

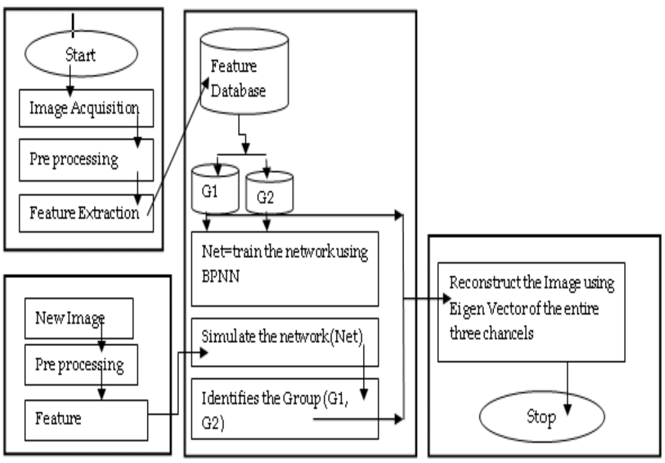

Figure 3: The flow of the work.

The methodology used is conceptually shown in a block diagram depicted in Figure 3. First we capture the image the face as region of interest, we reduce to the standard size, later we find out the Eigen values and Eigen vector of the each image and store in the database separately, and we use the concept of the feed forward neural network to train the dataset to also we use to predicate the person is either male or female for testing we use the sample image, we extract the feature of the sample image and simulate the features with the trained network, the network predicated based on the output will be displayed either the identified person is male or female.

IV. RESULTS AND DISCUSSION

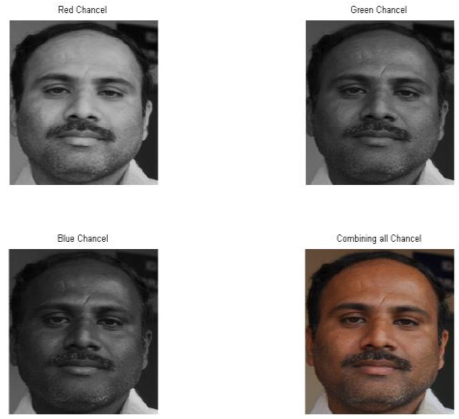

Figure 4: Snap shot of reconstruction of image

The image of the person identified or recognized has male person and the person face image have been reconstructed using the Eigen value and Eigen vector of the red, green and blues the chancel separately, also by combing the entire chancel also has been depicted in figure 4.

a. Evaluation of the system:

The evaluation of the system helps us to make the system more realistic, efficient and in a efficient way, for this purpose twenty face images are considered which were not used during the development of the system. To evaluate the system percentage of correct detected images, specificity, sensitivity and accuracy were estimated. The sensitivity is defined as percentage of correctly identified instances and specificity is defined as percentage of incorrect identified instances. Accuracy is the overall success rate of the classifier [21]. These metrics are computed by using the following equations. The computed values are shown in Table 2.

$$\text{Sensitivity} = \frac{TP}{TP+FN} \text{ ---- (1)}$$

$$\text{Specificity} = \frac{TP}{TP+FP} \text{ --- (2)}$$

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN} \text{ --- (3)}$$

Where TP=True Positive, TN=True Negative, FN=False Negative, and FP= False Positive.

Table 2: Evaluation of the system

Sl.no	No. of test Images	TP	TN	FP	FN
1.	20	16	3	0	01
Percentage					
Sensitivity		Specificity		Accuracy	
94.11		100		95	

V. CONCLUSION

This paper presented the development of gender identification system which founded on based on the feed forward neural network, Eigen as a feature the system was developed using 600 images. The evaluation of the system yielded satisfying results confirming applicability of the gender recognition system and reconstructing the image using the Eigen values and vectors in processes.

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