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Comparative Study of Human Gender Recognition by different face methods and their datasets

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Abstract: In the digital world, computer vision algorithms collect people's soft biometrics everywhere., Face recognition technology plays very important role in every state of identification process of the humans. Now the researchers are focused on Human Gender recognition with the support of Face Recognition algorithms. It provides an overview and comparative study of the state-of-the-art research techniques of methods of gender recognition by observing their features, classifying techniques and the standard face datasets used. Results of their approaches also presented with their strengths and weaknesses.

Keywords — Face Recognition, Face datasets, Gender recognition, pre-processing.

I. Introduction

Face has some special features to identify any human being. Now a days, Face recognition technology plays very important role in every state of identification process of the persons. In recent years, face recognition used as a biometric authentication. Over the past decades many researchers implemented several algorithms for face identification. To increase the work in this area face recognition was categorized based on the age, gender, expression etc. Among the face recognition categories, the gender identification by face plays a vital role. The gender identification problem states that identifying the genders of persons which are presented in images, photos or videos. Gender identification mainly useful in the field of statistics measures, security systems, video surveillance, and helpful in the field of human computer interaction systems to make them user friendly. This gender recognition offers an advanced research area in the field of theft identification, biometrics, and targeted advertising.

There are several techniques and algorithms are previously implemented for gender recognition by different researchers. For feature extraction, they used four techniques i) Principal component analysis (PCA)[1], ii) Linear Discriminant Analysis (LDA)[1],[9], iii) Local Binary Pattern (LBP)[1] and iv) Weber's Law Descriptor (WLD)[1]. With these techniques they retrieved the features related to each gender category to identify the human gender. For classification they used dot-diffused-based Adaboost classifier [3], [10] to reduce decision error of delicate classifier with the rest of delicate classifiers in the field of gender recognition. Duo Chen, Jun Cheng et al. [4] was proposed new algorithm, it uses k-means clustering [4],[7] to explore intra cluster sample for face gender recognition. In [8] Morteza Zahedi, Sahar Yousefi et al. used SIFT method for face detection and classification of gender in color images and in [2] semantic pyramid approach used in still images for gender recognition and also for action recognition.

Fig 1. Steps in Gender Recognition Process

Gender recognition is a complex task, first we have to identify the face, by face recognition algorithms then gender recognition system have to find some features to differentiate male gender and female gender. For face recognition Haritha et al. [6], [7] proposed algorithms on Doubly Truncated GMM with the use of DCT Coefficients, and hierarchical clustering techniques. The gender recognition is done by three steps see Fig 1. First step is pre-processing, second step is feature extraction and third step is classification. Taking Image as Input, Pre-processing involves the steps to remove variations in images, the

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technique of pre-processing are light normalization and face alignment. Feature extraction involves the identification of the suitable feature descriptors for recognition of male gender and female gender categories, the gender recognition system considers the various features (like lips, nose, eyes, chin…etc) for identifying the gender in [1] they explored two general (PCA, LDA) and two critical (LBP, WLD) descriptors. Classification involves SVM, K-nearest neighbor, Neural Network, Bayesian Classier etc. for classifying the gender, based on best feature descriptor. Based on these steps gender identification system will be developed.

For any human interaction applications Gender recognition is the basic step. I would like to compare various approaches applied by different researchers in recognition of gender with ponder of datasets used, features extracted, classification methods applied and their performances.

The paper is organized as different sections: dataset description and evaluation procedures in recent work are covered under section II. Feature descriptors and classification methods of gender recognition process are mentioned in section III. State-of-the art results are specified in section IV. And finally, Conclusion about gender recognition is covered under section V.

II. DATASETS DESCRIPTION

Gender image datasets are generally categorized in to two groups constrained and unconstrained. A constrained datasets having images with controlled poses and predefined scene conditions. FERET [1], [13], [15], Color FERET[3], AR[13],[16], PAL[13],[17], FEI database[18], and Lab2[19] are the examples of Constrained Datasets. Unconstrained datasets having images of real life, with different scene conditions and different poses. Gallagher[20], LFW[21],Genki-4K[22], KinFace[23] and Image of Groups[24] are the examples of Unconstrained face datasets used in Literature. The Unconstrained datasets are created by collecting images from Public Repository. Some of the above specified dataset details are observed below.

FERET dataset: This dataset contains above 14000 grey scale images. These images consist of people faces with left, right and frontal view profiles. National Institute of Standards and Technology (NIST) is a technical agent to distribute FERET database.

Color FERET dataset: This dataset contains 591 male and 403 female face images. The images were captured by photographing of people faces with 13 different angles.

AR dataset: This face dataset contains over 4000 color images having frontal view faces of 126 people (70 male and 56 female) with variety of expressions. And these were created by U.A.B at the Computer Vision Center, under control conditions.

LFW dataset: LFW (Labeled Faces in the Wild) is a database of unconstrained face photos. More than 13000 face images are collected from web. The faces are labelled with the person names. There are four sets of LFW images, one set of original images and three sets with different types of "aligned" images.

Gallagher dataset: This dataset contains set of digital images captured in real life with real people at real events. Total 931 faces with 32 identities, 589 labeled images. visible eyes and frontal view of faces are considered for labelling.

Genki-4K dataset: This dataset contains 4000 face images with visible appearance of face, different illumination conditions, different geographical locations and different imaging conditions. The face images are labeled like smiling face or non-smiling face.

Images of Groups dataset: It is a largest dataset for group images. Total images count is 5080, and contain the labeled faces with age and gender are 28231.

UB KinFace dataset: This dataset contains total 600 images related to 400 persons and those can be organized into groups count of 200. And each group contains the images of old parent, young parent and a child. It is a real-world collection of famous people figures taken from the internet.

PAL dataset: This dataset contains total 575 images which covered the face out of it 225 faces related to male and 350 faces related to female categories. The images are captured between the ages of 19 and 93 years.

Table 1. [13] Used face datasets by different Gender Recognition Methods

Name of Face Dataset	Total no. of Face pictures	No. of Male pictures	No. of Female pictures
FERET[13]	14126	ND	ND
Color FERET	994	591	403
AR[13][36]	3016	1638	1378
LFW[39]	13233	10256	2977
Gallagher[13]	931	ND	ND
Genki-4K[13][40]	4000	ND	ND
Images Groups[13]	5080	10303	9532
UB KinFace[13]	600	440	160
PAL[13]	575	225	350

The above table 1 provides the consolidated list of total number of face pictures used by datasets, and corresponding Male and Female gender pictures. In the table ND represents individual values are Not Defined.

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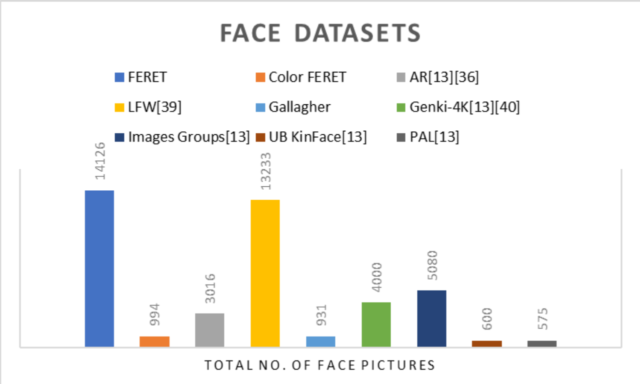

Figure 2. Count of Face Images based on Face Data sets

The values presented in Table1, are represented in graphical format in the above Figure 2. For the graph we considered values of Total number of Face Pictures only. By observing this graph, FERET and LFW datasets has a greater number of face pictures when compared with remaining datasets. And PAL[13] dataset has least number of face pictures.

Table 2. [37] Face databases

Name	Image Size	Total no. of unique people	No.of Males	No.of females	No.of pictures per person
AR [36]	576 x 768	126	70	56	26
Richard's MIT [37]	480 x 640	154	82	74	6
CVL [38]	640 x 480	114	108	6	7
Yale	640 x 480	10	ND	ND	576
LFW [39]	150 x 150	5749	ND	ND	2 – 3
Color FERET	128 x 192	2722	1713	1009	1
MUCT [37]	480 x 640	276	ND	ND	10-15

Table 2 represents Face databases along with image sizes. This table elevate total number of unique people in the database, number of Males and female images are taken, number of pictures per person taken out of total number of unique people presented in the images. In this table some other face databases are specified including Yale, MUCT, CVL and Richard's MIT. Most of the above databases uses 480x640 image size.

III. GENDER RECOGNITION PROCESS

Gender recognition process is comprised of three steps that we observed in the fig1. Under this section, we describe the methods of gender recognition by observing the techniques of current state-of-the-art.

1. Pre-Processing

Pre-processing is the first stage of gender recognition process in this process the face of the person has to be detected. Generally, classifiers are very sensitive to some variations like illuminations. To reduce the sensitivity, we have to follow some steps like brightness normalization using histograms, detection of facial region, alignment of face portion, removal of background area, and dimensionality reduction. For this purpose, we can use a Viola and Jones et al. [10] framework. The algorithm is able to process real time images with high detection rates. We discard the background image regions by combining different classifiers in a cascade manner.

2. Feature Extraction

The obtained images after preprocessing step are collected to extract features. From the facial images we can extract several features. Generally, they divide in to Geometric based features and Appearance based features [29]. Geometric related features are extracted from specific portions of the face images like nose, mouth, eyes etc. these features also called as local features. From the whole face portion appearance related features are extracted, these features are also called as global features. Different feature extraction methods are used for recognition of gender. The approaches are work on PCA, LDA, LBP, WLD, SIFT, HOG, and also combined with Gabor features, Color Histograms to improve its performances.

- **PCA [1],[14]**
  Principal Component Analysis [1],[14] is a method that converts image greyscales into uncorrelated attributes called Principal Components. It is mainly used for reducing the dimensionality.

- **LDA [1],[9]**
  Linear Discriminant Analysis [1],[9] is a method that used to make a well separated classes, by elevating the face images into a low dimensional space.

- **LBP descriptor [1]**
  Local Binary Pattern [1] is widely used texture descriptor. Used to create labels by comparison of local nearby pixels, and these are aggregated from histograms.
- **WLD descriptor [1]**
  Weber's Law Descriptor [1] is consider based on Weber's law. And it is proposed for image texture classification. By using neighborhoods of different sizes, we can define multi scale WLD descriptor.
- **SIFT descriptor [8]**

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Scale Invariant Feature Transform [8] descriptor is invariant to scale, rotation, and translation. It is robust to local geometric distortion and partially invariant to illumination changes.

- **HOG Method**

  In Histogram Oriented Gradient (HOG) method the images are divided into a cell-based block structure. Each block is mirrored by histogram of oriented gradients with subject to normalization of contrast.

Each of the above descriptors have redundant features in large number. To select the suitable features, some use two-stage feature selection approaches. The best one is to reduce the redundant features by apply fisher method on selected features.

3. Classification

In classification step different classifiers are tested by extracted facial features. Haritha et al., [6], [7] used k-means clustering. Most of the methods used for gender classification are Support Vector Machine (SVM), nearest neighbor (NN) classifier [1]. In literature survey many researchers used these classifiers to decrease the error rate of classification accuracy. To build strong classifiers from weaker classifiers, the best method to use is Adaboost [3], [10] approach.

IV. Results

This section presents the results of state-of-the art approaches. We provide the descriptions for each approach.

- **Muhammad Hussain et al.[1]**

  In this paper they observed gender recognition by category specific face features. These people use FERET dataset. Four feature descriptors are investigated for this purpose. They are PCA, LDA, LBP, and WLD. PCA and LDA give less performance than LDA and WLD. For classification they use NN classifier and tested the classification rate by different metrics. LBP gives the accuracy of Male as 99.16%, for female 98.50% and combined 98.49%, WLD performs better for male gender i.e. 99.32% and for female gender 98.25%.

- **Jing-Ming et al.[3]**

  In this paper they proposed dot-diffusion-based Adaboost classifier method for face gender recognition. Color FERET dataset used for testing with the goal of improving the performance of classification with low resolution and non-aligned thumbnail images. Accuracy of this system is 86.85%.

- **Duo Chen et al.[4]**

  In this paper they proposed a method clustering-based discriminative locality alignment by improved manifold learning method. FERET dataset is used in this method. K-means clustering is effective of utilizing the variance information. Accuracy it gives 87.44%. The CLDA method is working more faster than SVM method in recognition.

- **Hadeel Fahad et al.[29]**

  In this paper they are done facial gender recognition by eyes images. They are using 2D-wavelet Transform, Discrete Cosine Transform, and Gray Level Co-occurrence matrix as their feature extraction methods. They are used SVM classification technique, and they are used AR dataset, and Faces94 databases. They are getting the accuracies 98.49% for GLCM, 99.49% for 2D-wavelet Transform, and 99.62% with DCT.

- **Danisman et al.[35]**

  In this paper they show us how the preprocessing step improves the performance of gender recognition under unconstrained datasets. The datasets used in these approaches are LFW, Genki-4k, and Groups dataset. They are using SVM classifier with RBF kernel. Accuracies obtained are for LFW it is 91.87%, for Genki-4K it is 91.07%, and for Groups dataset it is 88.16%.

Table 3. Comparative study of Gender Recognition State-of-the art Approaches

State-of-the art Approaches	Used Classifier Name	Used Data Set Name	Accuracy
Muhammad Hussain et al.[1]	NN Classifiers	FERET	98.49%
Jing-Ming et al.[3]	Adaboost Classifier	FERET	86.85%
Hadeel Fahad et al.[29]	SVM classifier	Faces94	99.69%
Duo Chen et al.[4]	CLDA	FERET	87.44%
Danisman et al.[35]	SVM classifier with RBF Kernel	LFW	91.87%
		Genki-4K	91.07%
		Groups Datasets	88.16%

Here we observed the accuracies of gender recognition by different state-of-the art approaches in the Table 3. Out of the Five approaches most were used FERET Dataset for Gender Classification. Regarding the accuracies Hadeel Fahad et al. [29] approach on Faces94 Dataset with DCT technique used got the highest accuracy**.** Among the usage

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of FERET dataset, Muhammad Hussain et al. [1] approach got the highest accuracy with LBP face descriptor. Danisman et al. [35] approach used three types of datasets for gender recognition, LFW dataset with SVM classifier produces better accuracy than the remaining datasets. This result was displayed in graphical format in the Figure 3.

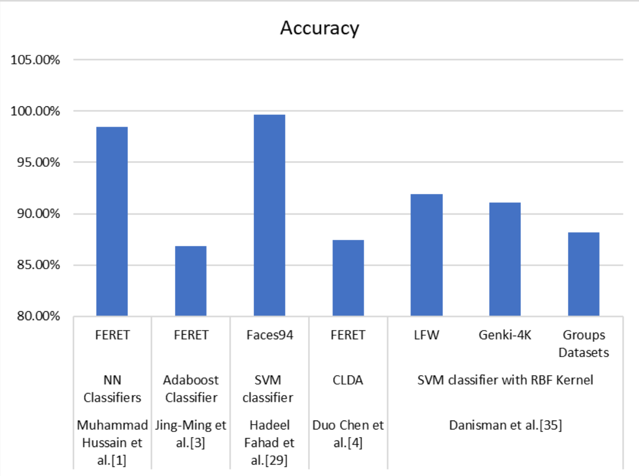

Figure 3. Comparative study of State-of-the art approaches based on their Accuracies.

Figure 3 represents the comparative study of gender recognition based on face images by different state-of-the art approaches according to their accuracies. Among all techniques Hadeel Fahad et al. [29] approach got the highest accuracy on Faces94 database with Discrete Cosine Transform Technique.

V. CONCLUSION

This paper discussed the state-of-the-art approaches followed in the field of gender recognition by taking face images. We are identified the types of face datasets used by different researchers, and identified the types of feature extraction methods used by the researchers, and the type of classification technique used by the researchers. By studying the previous literatures of various researchers, different gender recognition techniques are implemented based on gait position, and body shape etc. In this paper we focused on gender recognition by face images only. In this regard some researchers are facing problems regarding the illumination effects, facial expressions, and low-resolution images. Still there is a gap on the recognition rate of the gender and system time complexity, which is not up to mark. There is a scope to increase the recognition rate of the gender and reduce the system time complexity using various new techniques. The gender recognition system considers only few descriptors for classification of the gender. There is a need for searching better descriptors to recognize the gender, and to reduce the system time complexity. We are proposed to implement a methodology to reduce the above specified problems.

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