A Comprehensive Survey of Facial Datasets for Human Age and Gender Identification

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Abstract

Human age and gender detection are interesting applications of computer vision and offers wide applications in video analytics and human-computer interaction. Publicly available datasets play the role of benchmarks for the performance evaluation of different algorithms applied to solve the same problem. Some separate surveys are available for age and gender detection which cover some datasets. Generally, gender information is provided with the age datasets and same datasets can be used for both age and gender detection. So we combine the analysis for both the problems in one survey. In recent years, large datasets have been created introducing state of the art techniques for age detection that are not discussed in presently available surveys. This survey tries to overcome lack of representations of those datasets in available literature as well as provide the strengths and weaknesses of all datasets from the perspective of both age and gender detection.

INTRODUCTION

Identification of demographic attributes of humans such as age and gender from the face has been given increased attention in recent years by computer vision experts [1], [2]. These attributes can help in many applications such as surveillance, human-computer interaction, targeted advertisement and content-based indexing and searching [3]. For example, in advertisements boards, products can be advertised smartly by targeting the age and gender of the viewer. Gender based face recognizers can help improving the accuracy of face recognition [4]. Some datasets are analysed in different surveys for gender detection [5] and age estimation [6] but there is no recent survey available for the face datasets for age and gender detection. Moreover, some datasets discussed in those references are not available now and large datasets CACD [7], IMDB-WIKI [8] have been crawled recently that are worth analysing along with the old datasets. Therefore, this survey tries to cover all important public datasets available for gender and age detection. The use of publicly available datasets has its advantages. It saves time of the researchers so that they can focus on their particular algorithms and implementations rather than collecting a new dataset. More importantly, different approaches can be compared for the same datasets for a quick review of improvements in accuracy. Gender detection is a binary classification [9] problem and age detection is addressed as a classification problem [10] when only age-group is estimated and a regression one[11] when apparent or actual age is predicted through the image. So, the annotations of the age vary from ground truth age to the age-groups the subjects ages belong to. Some of the datasets were collected by different research laboratories under controlled conditions [12], [13], while there are some datasets containing images taken in uncontrolled environments [14]. A cross-age dataset [7] is crawled from the internet that contains a number of images with different ages for the same persons. In most of the cases, individual datasets available for age detection can also be used for gender detection task due to presence of gender annotations with age information. Moreover, gender recognition is affected by age [15]. So, instead of analyzing the same datasets two times for gender and age detection separately, we provide the analysis collectively.

Providing information in the form of multiple age and gender groups have witnessed tremendous attention in the literature. There are two dimensions of this work; making more groups for age and gender make the task of recognition complex but provide useful results for research community. On the other hand, simpler groups are easy to identify by computer algorithms but produced results are not satisfactory by research community. The datasets define age-groups differently e.g. MORPH (2007) gives 5 groups and IMFDB (2013) gives 4 groups. We categorize the age groups as four age stages of human life (Figure 1) for later comparisons in the survey. The age-groups are child (0-15) years, young (16- 25) years, adult (26-59) and old (60+). South Asians constitute about 1/4th of the world population [16] and there is not enough representation of the South Asian people in these datasets. In fact, to our knowledge, there is only one dataset [17] available in this regard at the moment. Another dataset is collected [18] but its access is restricted. The rest of the paper is organized as follows. First of all the main characteristics of 10 public face datasets for gender and age detection are provided. After it, the datasets described in the previous section are analyzed from different angles. Finally, conclusion of this survey is presented.

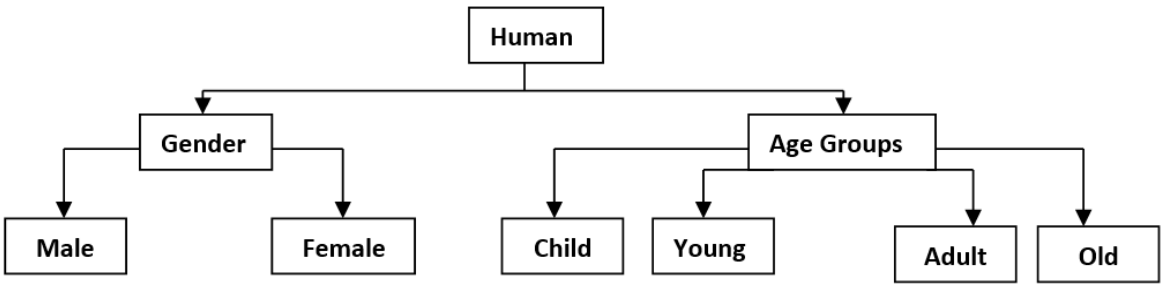

Figure 1: Gender and Age categories for research in age and gender detection

DATASET REVIEW

We present the datasets in an order as starting from those which can be used for age-group detection to actual or apparent age estimation based on the annotations available with the datasets. Some datasets simply provide the age range e.g., MORPH, VADANA, while other datasets attempt to provide ground truth ages with the images such as IMDB-WIKI and CACD. We first provide general overview of the datasets and then analyze them with respect to gender and age detection respectively. Gender and age-group defined in Figure 1 are shown along with the images throughout the section.

Adience Dataset [19]

The dataset has been collected from flicker using a simple mobile phone in this case, iPhone 5. It contains 26,580 images of different individuals in different environments. Mobile phone pictures are not directed and people often take pictures in a hurry. So is the case with this particular dataset. Some pictures are pretty good for analysis and are useful for development of algorithms while some pictures are blurred. Plenty of them are selfies and people have their own ways of taking own pictures. The variations in the quality of images and challenging backgrounds make the use of complete dataset impeding for a single algorithm. The associated metadata include gender title, age range file names and angles of the face in the image.

Sample images are shown in Figure 2. Gender annotation makes this dataset a good candidate for use in gender detection. Age range is available and thus this dataset is suitable or age-group estimation. The examples of publication that use this dataset are [20] for gender and [21] for age detection.

Figure 2: Images from Adience Dataset

Iranian Face Dataset [22]

The database contains about 3,600 images collected from 616 (487 men, 129 women) different human faces. It includes facial images of people between ages 2-85. Face images of persons with different ages is needed to generate a reliable age classification algorithm. The only illumination is daylight which restricts this dataset for day captured images resulting in poor results with images captured under dim lighting conditions. Age annotations are available. Only male dataset is available for research purposes, shown in Figure 3, so gender detection through this dataset is not possible. Age variety however is good for research in both age-group detection and apparent age estimation. This dataset has been used for age-group detection in [23] 7 groups and [24] 4 groups.

Figure 3: Sample instances from Iranian Face Dataset

10k US Adult Face Dataset [25]

The dataset was collected using an online random name generator based on the 1990 U.S. Census. Some 25,000 random first and last names were used for the experiment and images were downloaded from Google image search. In order to keep the distribution of images fair, some well-known celebrities were deleted from the dataset. The resulting 10k US Adult Faces Database has 10,168 individual faces, following gender, age, and race distributions of the adult. Landmark annotations are available for the dataset. Publishing friendly images are shown in Figure 4. The dataset has 57 percent male and 43 percent female distribution. This distribution is good for research in gender detection as almost equal contribution from both genders is present. This dataset contains frontal faces that are good for age detection but it does not cover full range of ages so it is not suitable for age stages detection alone.

Figure 4: Images from 10k US Adult Face Database

Indian Movie Face Dataset [26]

Indian Movie Face database contains 34,512 images of 100 Indian Movie actors. This dataset claims to be the only dataset representing South Asian community. But a large number of images cover such angles which are unnecessary because only 100 subjects are covered in the dataset. This dataset has large number of annotations available for age, face bounding boxes, gender and emotion of the actor for each image. Varying resolution of the images within subjects makes it undesirable for certain algorithms [27]. Two low quality and side pose images and two frontal face images of 4 different actors are shown in Figure 5. This dataset contains images of 67 male actors and 33 females with at least 200 images for each actor under varying camera settings. The bad quality and strong emotion images may not be good enough for gender and age detection. Age information available is in the form of age-group defined by the dataset and thus this dataset cannot be used for real age estimation.

Figure 5: Indian Movie Face dataset sample faces

MUCT [28]

This dataset was prepared from subjects around the University of Cape Town. The dataset was created with 5 cameras and different illumination levels to achieve complexity and variety in the images. Images are captured indoor with uniform background. With these available 3,755 images 76 manual landmarks are available. That includes the coordinates of facial features. These fiducial points help in face recognition mainly but have their usage in age and gender detection as well. Two images of different gender and age-group as well as different illuminations are shown in Figure 6. The dataset has approximately equal number of male and female subjects and gender information is available within the names of images and thus can be used for gender detection easily. Age range is above 18, so, it can be used for age-group detection as well in combination with some under 18 datasets. MUCT database has been used for verification of a system for age detection using the facial landmarks in [26].

Figure 6: MUCT dataset sample images

FEI Face Database [29]

This dataset contains 14 images per person covering 10 different angles along with a frontal face and happy and sad expressions and one dark illumination. All faces are mainly represented by students and staff at FEI, between 19 and 40 years old with distinct appearance, hairstyle, and adorns. The number of male and female subjects are exactly the same and equal to 100. It gives 46 manually landmarked fiducial points as the metadata to the dataset. It is a good dataset for gender detection since gender distribution is even. Bright and dark illumination and the light expressions provide a good measure to test the effect of these features in gender and age detection. Sample images are shown in Figure 7

Figure 7: Two young females and one young male with bright and dark illumination from FEI Database

MORPH Dataset [30]

MORPH non-commercial dataset contains 55,000 unique images of more than 13,000 subjects. Age distribution is from 16 to 77 years with a median age of 33. There are 4 images per subject on average. The average time between capturing of photos is 164 days that vary from minimum time delay of 1 day to maximum being 1,681 days (4.60 years). The dataset is rich in ethnicity variety with African, European, Asian and Hispanic communities representation but Asian ethnicity gets ignored with only 144 images as compared to European 7,691 and African about 37,000 images. This dataset has the unique feature of cross-age category and can be used for cross-age face recognition systems. This dataset is not freely available. Moreover, there is also a commercial version [31] with more than race, date of birth of the individual and image date. The sample images from the white paper of MORPH are shown in Figure 8. Gender distribution is pretty uneven in this dataset with only 8,489 images for females that makes it a poor choice for using solely for gender detection.

Age categories and variety on the other hand makes this dataset a stronger candidate for research in age detection. Some publications using this data set for age detection are [28], [32]-[34].

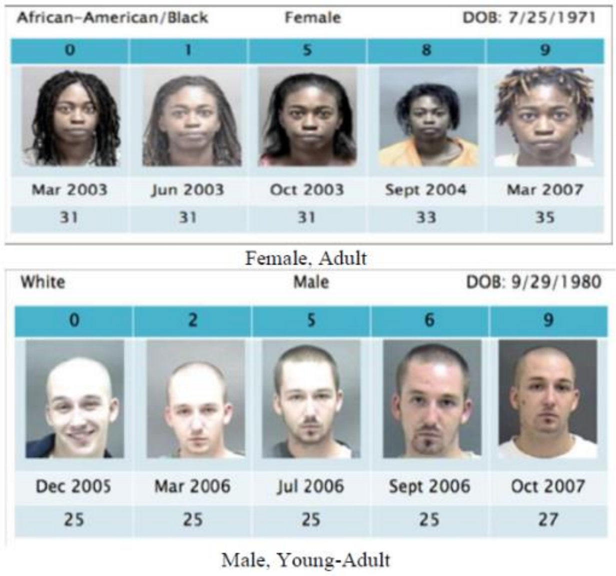

Figure 8: Age progressing on one female (upper half) and one male (lower half) from MORPH dataset

IMDB-WIKI Dataset [8]

This dataset has been crawled from IMDB and Wikipedia and contains images from around 100,000 celebrities around the globe. Aging information has been the key point of collecting this dataset and thus images without time stamps were removed after crawling and almost each image has biological age annotation for it. Moreover, all of the images do not strictly contain a single person, i.e., in some images more than single human is present. To remedy this problem a threshold-based face truncation was applied to remove the second face from the image resulting only in one face per image.

Recently, those images were selected to be part of this dataset which have secondary individuals face detection below a threshold. It contains 523,051 images and with age information, this dataset provides much variety to use as compared to all other datasets discussed above. But even this dataset does not contain sufficient images for South Asian community which has no considerable representation in publicly available datasets. This dataset has been trained for deep learning and Caffe [35], popular deep learning framework, models are also available along with the metadata of this dataset.

Gender information makes the task easier for researchers as manually tagging a large number of images is not an easy task. The size of the dataset annotations for gender and ground truth age make this dataset a strong candidate to use for research in apparent age and gender detection. Two male and two female subjects are shown in Figure 9. A publication using this dataset for age detection using deep learning is [36].

Figure 9: Two males and two females from IMDB-WIKI dataset

IMM Frontal Face Dataset [13]

The IMM Frontal Face Database comprises 240 still images of 40 different human faces, all without glasses. The images are in high resolution therefore provide good opportunity to explore the complexities or feasibilities offered by high resolution. Real age annotations are available for all the images. The gender distribution is 7 females and 33 males. But the dataset available for download consists of 12 male subjects 5 only with age variation of 24-51 years so it cannot be used for gender detection as well as age-group detection. Sample images are shown in Figure 10. This is the smallest dataset among all the datasets analyzed in this survey. A recent use of this dataset for age detection using deep convolution networks is found in [19].

Figure 10: Images from IMMFDB Database

CACD Dataset [7]

The images are collected from search engines using celebrity name and year (2004-2013) as keywords. Images are of almost 2000 celebrities. Subjects age range is from 14-62 years. The metadata of dataset include the image age of the celebrity and 75,520 dimensional LBP features that were extracted using 16 facial landmarks that are also available for all the images. Downloadable dataset contains faces cropped and detected using Open CV face detector. Main objective of this dataset is cross age face recognition based on CARC coding that were introduced in the reference paper. Age gap for images of same subject range 0-10 years and 82 images are present on average for one subject. A sample collage is shown in Figure 11 that shows the age of the actor below the image.

The images were taken at the events and thus the lightening conditions are different than daily life environments. Gender information is not available as such because the primary objective of this dataset was not gender detection. Anyhow, names of the celebrities can be used to determine the gender of the person in the image and can be used for gender detection. Actual age information is available but we have noticed that annotations to some images are wrong and need manual inspection. This dataset is good for both age-group and apparent age detection. This dataset has been used for age detection using deep learning in [38].

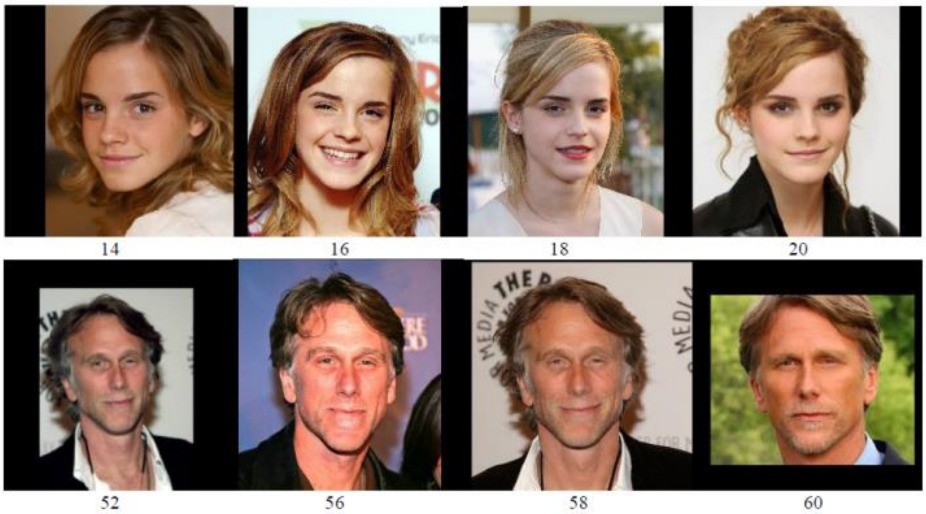

Figure 11: Age progressing of one female child celebrity to young female and one male adult celebrity to old male from CACD dataset

EGA Database [39]

EGA is a one of its kind of datasets which can be updated and expanded and is derived from 6 datasets to provide more variety in ethnicity, age and gender marked images. There is no physical repository of EGA dataset but Matlab script is provided to users for building their own datasets. Gender information is available in this repository and age annotations are also provided, so this dataset may be used for gender detection and age-group or actual age estimation. Furthermore, this dataset provides a good platform to store available datasets for age and gender detection in one place and even add private datasets to the collection.

UMDFaces Dataset [40]

UMDFaces is large dataset, build for training of state-of-the-art deep neural networks. This benchmark due to its size is more varied and provides accessible link mainly for face-recognition applications. Dataset has annotations about the estimated pose (yaw, pitch, and roll), twenty-one key points, and gender information. It has both video and image data. This dataset has been used to train caffe model for human fiducial key point detection and can be used to identify gender by training deep convolutional networks. Diversity in dataset is induced by downloading images of subjects from different search engines and redundancy is avoided by removing duplicate images.

APPA-REAL database 2017 [41]

This database provides annotations for both real age and apparent age of facial images. Apparent age votes were collected by using a WebAPI, that contains an average 38 votes per image. Dataset covers more than 7000 subjects that enhance the variation in dataset. Figure 12 shows some samples from this database with provided annotations of real and apparent ages. Database covers ages from 0-95 years.

Figure 12: Sample Images from APPA-REAL database

Face Image Dataset-Gaface Dataset [42]

Wang *et al.*, [42] collected their own dataset for gender and age classification. Dataset collected from google images and has subjects from Malaysian celebrities and politicians. This dataset provides only two age groups that is below 40 and above 40 images.

COMPARISON OF DATASETS

***Availability*:**

Often the availability of datasets tells about the importance of that dataset in the relevant field. So it is always a good measure to rank the datasets based upon their usage referenced by the research papers. Such effort is made to rank the datasets collected for age and gender detection based on their number of citations by Google scholar [43] in Table 1. It is worth mentioning here that datasets gain increased citations based on several factors such as ease of availability, coverage of scenarios, scalability to different problem sets, date of publication (age of dataset) etc.

Table 1: Datasets along with their number of citations from google scholar

Dataset Name	No. of citations
MORPH	424
IMMFDB	177
FEI Face	164
Adience	42
CACD2000	37
Iranian Face	30
IMDB-WIKI	25
10k US	21
VADANA	20
IMFDB	15
VADANA	10
UMDFaces Dataset	26
APPA-REAL Database	7
GAFace Dataset	5

Gender and Age-groups representation:

We present a comparison of datasets discussed in the previous section for the availability of gender and age variations according to the age-groups, defined in Figure 1 & Table 2. As shown in Table 2, almost all the datasets have labelled images for gender identification i.e., male and female. Difference exist in variety of age groups where adult age group is present in almost every dataset. Collecting data related to children looks quite complex which is evident from the number of datasets dealing with children datasets. On a similar note, datasets dealing with persons of ages above 60 are quite scarce.

Table 2: Gender and age-group availability among public datasets

Sr. No.	Datasets	Male	Female	Child (0-15)	Young (16-25)	Adult (26-59)	Senior (60+)
1.	Adiance Dataset	✓	✓	✓	✓	✓	✓
2.	IMFDB	✓	✓		✓	✓	
3.	CACD	✓	✓	✓	✓	✓	✓
4.	IMMAFDB	✓			✓	✓	
5.	IMDB-WIKI	✓	✓	✓	✓	✓	✓
6.	FEI face database	✓	✓		✓	✓	
7.	MUCT database	✓	✓		✓	✓	✓
8.	10k US Adult	✓	✓			✓	
9.	MORPH	✓	✓	✓	✓	✓	✓
10.	Iranian	✓	✓	✓	✓	✓	✓
11.	UMDFaces Dataset	✓	✓	✓	✓	✓	✓
12.	APPA-REAL Database	✓	✓	✓	✓	✓	✓
13.	GAFace Dataset	✓	✓				

Pros and Cons:

Every dataset is biased towards its primary usage as to which algorithms will be tested on the dataset and which community it is intended for. This inequity becomes its strength in some cases and can be regarded as the deficiency in other scenarios. Image resolution is important for image processing operations and thus age and gender detection via faces. So we give the details about the resolution as well as the publishing year of the dataset. All these statistics and analysis is given in Table 3 and 4 respectively.

Table 3: Comparison of datasets with respect to the size of the datasets

Sr. No.	Name of dataset	Number of images	Resolution of images	year
1.	10k US Adult faces	10,168	72 pixels in jpg 256 pixels height	1990 Published 2013
2.	Audience Database	26,580	816*8169 Depth 24 bit	2014
3.	CACD2000	163,446	250*250 Depth 24 bit	2014
4.	FaceScrub	106863	Varying resolution jpg Depth 24 bit	Latest change 2016
5.	IMDB-WIKI Dataset	523,051	Varying resolution jpg Depth 24 bit	Crawled 2015
6.	IMFDB	34,512	Varying resolution jpg Depth 24 bit	2013
7.	IMM frontal face DB	120	Varying resolution jpg Depth 24 bit	2001, published in 2004
8.	Iranian Face Database	3,600	2560*1920 jpg Depth 24 bit colors RGB	2007
9.	VADANA	2,298	480*640 JPEG 24 bit depth	2011
10.	UMDfaces Dataset	36,7888	JPEG Depth 24-bit varying resolution	2017 v2
11.	APPA-REAL database	7,591	JPEG Depth 24 bit varying resolution	2017
12.	GAFace Dataset	310		2017

Table 4: Comparison of datasets with respect to relative strengths and weaknesses

Sr. No.	Name of dataset	Strengths	Weakness
1.	10k US Adult faces	Only US based images are available and taking images from internet provides diversity	Only adults are covered in this dataset
2.	Adience Database	Data consists of almost all age groups. Data is aligned and contains information about the angles too.	Not all images are of same quality, some are highly blurred that a human cannot extract exact features and data is unfiltered. For instance, it includes more than one face in few images with the second face out of focus
3.	CACD2000	Large dataset consists of both male and female subjects. Includes posing and expressions too. Large cross-age dataset.	Only celebrities are covered.
4.	FaceScrub	Large number of images with 256 subjects from both males and females each	The downloaded images are about 3/4th of the total number and images could be taken down from the sites referred in the dataset.
5.	MDB-WIKI Dataset	Large number of images and subjects	Since dataset has been collected from internet resolution of images vary extensively.
6.	IMFDB	A large number of annotations are available from each image. Data is of South Asia ethnicity suitable for people of South Asia.	A large number of images cover such angles, which are unnecessary because only 100 subjects are covered in the dataset. Varying resolution of images within subjects.
7.	IMM frontal face DB	High resolution images available and 10 images per subject available with the slight variation of facial expression.	Number of unique subjects are not sufficient for training of large systems.
8.	Iranian Face Databse	Only available dataset of middle East	Only male dataset is available to research.
9.	VADANA	Ethnicity is India based, not much datasets are available from same ethnicity	However, 2298 is a good number, but subjects observed are only 43.
10.	UMDfaces Dataset	Dataset has 8,277 subjects with maximum variations in pose	Varying resolution of images with in subjects, age annotations are not provided
11.	APPA-REAL database	Covers all age groups and 7000+subjects are involved	It contains gender diversity but do not provide annotations for gender.
12.	GAFace Dataset	Malaysian face dataset.	Dataset is small, not available publicly and provide annotations, two age groups only.

CONCLUSION

There are not many datasets available for human age and gender identification through faces. We have reported 14 public datasets in this survey. Some of the datasets require license agreements while others are distributed openly. These datasets have regional diversity as well along with the age and gender variety covering Asians, Americans, Europeans and Africans. Gender and age detection through images are open problems as we move towards faster and more robust algorithms and techniques for computer vision in particular and machine learning in general. Finally, this survey tries to cover the lack of the comparison of the most recent and important available public datasets for face based human age and gender detection and to guide the researchers in the selection of the most suitable dataset for benchmarking their algorithms.

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