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REVIEW ARTICLE

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A SURVEY OF FACIAL GENDER CLASSIFICATION

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Abstract: Gender is the most critical demographic attribute of human beings. Gender classification from facial images is widely used in computer vision for surveillance, a straightforward task for humans, and a challenging task for machines. This paper provides a study of facial gender classification in the field of computer vision. We highlight the challenges faced during the image capturing process due to factors such as illumination, angle, occlusion, and expressions. We also review various feature extraction approaches used by previous researchers to perform the facial gender classification task. This paper also compares the performances of previous methods on various face datasets to perform gender classification. We observed from the previous studies that good performance had been achieved for a dataset of facial images taken in a controlled environment. However, much more work needs to be done to increase the accuracy and robustness of facial gender classification, especially in uncontrolled environments.

Keywords: Face recognition, Gender classification, Feature extraction, CNN.

1. INTRODUCTION

The face of the human being reveals valuable information about their identity, gender, age, expression, and emotions. According to the studies, a human can quickly distinguish between a female and male simply by looking at their face [1]. Gender classification from facial images is one of the basic capabilities of human beings; extending this capability to the machine is a crucial task in computer vision that has received much attention recently. Gender classification is utilized in a wide range of real-life applications, including surveillance systems, human-computer interaction (HCI) systems, and advertising.

The system should not require the co-operation, physical contact, or attention of the human subject in many applications. Human parts like the iris, fingerprints, and hand would require human co-operation. A human face has the benefit of being an effectively recognizable trait of an individual. Humans utilize facial images as the most popular biometric attribute to identify each other [2]. As a result, several researchers have turned to facial analysis to determine gender based on information obtained via face recognition. External aspects of the face, such as the neck area and hair, may also be used to classify a gender of a person; they provide additional information about the person.

Recognizing the gender of a person; can be divided into several steps such as face detection, preprocessing, feature extraction, and classification. The face region is detected by cropping the acquired face image, and then preprocessing steps are performed, such as normalizing the image. Viola and Jones [3] proposed a face detection method that is used by many researchers for further research. In the feature extraction step, relevant features of the face are selected, and in the last step, the binary classifier is used to classify the gender of a person. Support Vector Machine (SVM), Neural Networks, and Adaboost are popular classifiers that are primarily used for gender classification.

In This paper, we discussed the background of gender classification in section 1. The rest of the paper is organized as follows: Section 2 discusses the application where the gender classification is utilized. In Section3, we highlighted the challenges for gender classification. Section 4 describes the previous studies of feature extraction methods. Section 5 evaluates the performance of various datasets used for gender classification. Finally, the conclusion is discussed in Section 6.

2. APPLICATION

We identify several application areas where gender classification can be used. They are listed as follows:

- **Biometrics:** Biometrics is a uniquely human characteristic that may be used to recognize an individual automatically. Face, fingerprints, voice, iris, and gait are examples of biometrics that may measure both physiological and behavioral features. Soft biometrics are features like gender, age, weight, and height that can provide important information about a person. Using face recognition in a biometrics system can reduce the time spent scanning the face database, and different face recognizers can be trained for each gender to improve accuracy [4].
- **Human-computer interaction system (HCI):** HCI systems provide the interaction between the human and computer. In HCI systems, robots or computers need to identify and verify gender to improve the performance of the system. After determining gender, the system can provide customized services for users.
- **Demographic collection:** When a customer enters a store or looks at a billboard, the demographic research system collects demographic information such as gender,

race, ethnicity, and age. A computer vision system can be utilized to automate the task of recording the demographic information of customers. The information gathered is then utilized to determine the effectiveness of marketing efforts.

- **Targeted advertising:** To present the advertisements on the screen electronic billboard system is used. Targeted advertising is possible if the system successfully recognizes traits like gender and age. In a supermarket, knowing the number of male and female customers helps the store managers to make effective decisions.
- **Surveillance systems:** These systems are widely installed in both public and private places for security monitoring. It can help restrict places to one gender only for safety reasons, such as in a hostel or train coach, and can be monitored and implemented using surveillance systems.
- **Mobile Application and video Games:** Gender classification can provide helpful information to improve the user experience in mobile applications (apps) and video games. In the mobile application, some researchers use this method to assist the use of the mobile internet by customizing apps according to gender. In video games, males and females have different preferences, which would enable the use of gender information to provide their preferred game characters or contents.

3. CHALLENGES

In a computer vision system, the face image of a person reveals valuable information about their identity, such as gender, age, and race, etc., and also shows many variations related to face, which may impair the ability to identify gender. These variations can be attributed to either the image capture method or the human. Human elements include things like gender, age, ethnicity, and facial expressions like closed eyes, smiling, natural, and so on., face occlusions, such as those caused by accessories, for example, hats, eyeglasses, and facial hairstyles. However, because they might differ between genders, they may serve as sound discriminative cues. The head posture, illumination or lightning, and image quality are all factors that affect the image capturing process. The yaw (left-right rotation), roll (in-plane rotation), and pitch (up-down rotation) angles represent the three degrees of freedom available to the human head [5].

In some cases, the other factor can be reduced to some extent by providing adequate illumination and a high-quality camera. To perform gender classification, Wang et al. [6] used a dataset that consists of a large number of non-adults faces. Ozbudak et al. [7] observed that the gender of Asian people was simpler to distinguish than the gender of African people.

4. Feature extraction methods

Feature extraction is a type of dimensionality reduction in which a large number of pixels in an image are efficiently represented so that the most critical parts of the image are effectively captured. For facial gender classification, feature extraction methods can be classified into geometric and appearance-based methods [8][9], and CNN-based methods are also used for gender classification.

Appearance-based methods rely on the operation done on pixels of an image, such as transformation, and the operation is performed at the local and global levels. At the local level, an image of the face is divided into sub-regions, e.g., forehead, eye, nose, and mouth [10]. At the global level, features are calculated from the entire face image to form a single feature vector. The appearance-based methods for gender recognition used both texture and shape information from face images. Active Appearance Models (AAM) is an appearance-based method initially proposed for image coding [11]. In global methods, the whole face of the person is observed for gender classification. The face image of the person shows many variations, including illumination, occlusion, different view, and expressions[8]. Andreu et al. [12] observed that the local method performs much better than the global method. A combination of local and global features has also been discovered in [8].

Recently, CNNs based methods have been mainly used for the gender recognition task. We have various CNN models; the difference between these models is the choice of the network architecture. CNNs can be roughly split into shallow networks and deep networks. The shallow networks have up to 5-6 convolutional layers, whereas the deep networks have more number convolutional layers. In the studies, we have observed that [13][14][15], which train gender CNN, from scratch used shallow network architectures, while the works employed deeper network architectures like AlexNet [16] or VGG16 [17] fine-tune already pre-trained CNNs [18].

The various feature extraction methods are discussed in detail in the following subsections. All the methods are categorized as appearance-based methods except fiducial distances.

Fiducial distances

Facial landmarks or fiducial points are prime locations on the face that spot facial features like eyes, hair, nose, mouth corners, chin, and ears. The distances that distinguish between these places are known as fiducial distances. Brunelli and Poggio [19] developed a template matching method and geometrical features for gender recognition, and they used a HyperBF classifier to recognize features of the face. Fellous [20] selected 24 vertical and horizontal fiducial distances of a human face, and discriminant analysis was used to create five normalized dimensions from these fiducial distances to categorize gender.

Rectangle features

Rectangle features are proposed by Viola and Jones [21] for face detection. Rectangle features are also known as Haar-like features, and Figure 1 displays examples of two rectangle and three rectangle features. The value of these rectangle features is the subtracted amount of pixels in the white rectangles from the sum of pixels in the black rectangles. An AdaBoost algorithm is used to select the features, and an integral image representation can be utilized for quick computation of these rectangle features.

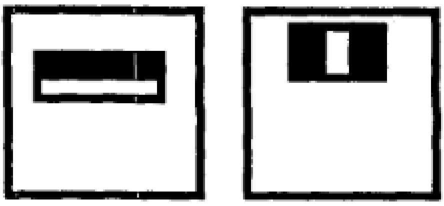

Figure 1 Rectangle features

Shakhnarovich et al. [22] used an SVM classifier and rectangles features for ethnicity and gender classification in real-time. For ethnicity and gender classification, they collected human face images from the World Wide Web. Xu et al. [23] used rectangle features for gender classification and also extracted the local and global features of an image. Adaboost algorithm is used to extract the global features and combine them with the local features, which are extracted by the active appearance model (AAM). Rectangle feature vector (RFV) is used by Shen et al. [24] to identify human gender and to obtain more discriminative features of face they used SVM classifier.

Scale Invariant Feature Transform (SIFT)

SIFT is a feature detection algorithm in computer vision that is used to detect and describe various key points of an image. Lowe [25] used SIFT for extracting unique features from the images, and these features are used to match diverse views of an image. The features are invariant to image rotation and scale and also provide partially invariant to change in illumination. Wang et al. [26] used SIFT descriptors for gender recognition. Wang et al. [27] combined the SIFT descriptors with Gabor features, and Adaboost is used to select the features for gender recognition. In another work, the Markovian temporal model is used to recognize face gender from unconstrained video sequences in natural scenes [28]. Figure 2 shows key features of the face using SIFT descriptors.

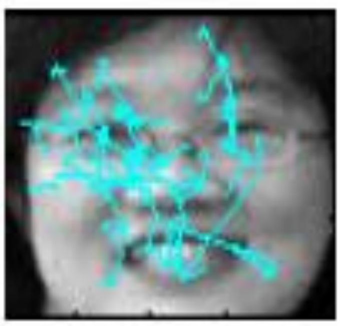

Figure 2 Visualization of key features of the face using SIFT descriptors

Local binary patterns

Local Binary Patterns (LBP) is a popular feature extraction method, which is used by Ojala et al. [29] for texture classification. LBP features can detect microstructures such as corners, edges, and spots. LBP is a very simple and efficient algorithm for local texture information extraction, and it is also stable under illumination changes and rotation.

Ahonen et al. [30] first introduced LBP for face recognition using biologically inspired features. To extract features from the face, Lian and Lu [31] used LBP, and for gender classification, they used an SVM classifier. Alexandre [32] performs gender classification based on shape, texture, and intensity features. Tapia and Perez [33] perform gender classification based on feature selection using mutual information and also use feature fusion to improve the accuracy of gender classification. Shan [34] used boosed LBP features with an SVM classifier for gender classification on real-life faces. Shih [35] used a precise patch histogram facial feature extraction method to improve the robustness and accuracy of gender classification. Ardakany et al. [36] used LBP with three additional patterns to extract more data from a particular facial region. Javid et al. [37] used local directional pattern (LDP) with SVM classifier to perform facial gender classification.

Gabor wavelets

A Gabor wavelet is defined by frequency, scale, and orientation which are used to detect an edge in the face. 2D Gabor wavelets are used by Lee [38] for image representation. Xia et al. [39] used a local Gabor binary mapping pattern (LGBMP) for gender recognition. Dago-Casas et al. [40] used Gabor with the LBP method for feature extraction and SVM with LDA classifier for gender classification. Meyers and Wolf [30] used biologically inspired features (BIF) for face processing.

Pixel intensity values

The classifier, such as support vector machine (SVM) or neural network (NN), used pixel intensity values for classification problems such as image classification and gender classification. In the preprocessing step, the image of the face is cropped and after performing normalization, resize the image in smaller dimensions for faster calculations. A pixel intensity value is used to extract the features from the images. Principal Component Analysis (PCA) is used to reduce the dimension of an image. Gutta et al. [41] used SVM with radial basis functions(RBF) and inductive decision trees of 64 x 72-pixel face images for gender classification. To determine the gender from facial images Moghaddam and Yang [42] used a 21 x 12-pixel value of image and SVM classifier. Sun et al. [43] used Genetic Algorithm (GA) to perform gender classification. For dimension reduction, two-dimensional PCA (2DPCA) has also been used [44]. For facial gender classification, Jain et al. [45] proposed Independent Component Analysis (ICA). Buchala et al. [46] discovered that different components of PCA encode different features of the facial image, such as gender, age and, ethnicity. 2D neural network architectures such as Convolutional Neural Networks [47] and Pyramidal Neural Networks have also been applied for gender recognition. In these neural networks, feature extraction is integrated with classification. Baluja and Rowley [48] used the AdaBoost method to identify the sex of a person, and the face images were normalized into 20 x 20 pixels. To obtain features, Lu and Shi [49] used 2DPCA on several facial regions. SVM was used on each face region and the classification result was based on a consensus decision.

External cues

External features of the face region such as hair, lips, clothes, and neck region are also cues used by humans to identify the gender of the person. Clothing and hairstyles differ between males and females. Li et al. [9] used features from hair and upper body clothing to perform gender classification using an SVM classifier. Castrillon-Santana et al. [50] used the head and shoulder of the person to extract the feature, and they used SVM, Naïve Bayes, and Neural Network classifier for gender classification. Similarly, Min Li et al. [51] used the head and shoulder parts of the body to classify the gender of the person. To recognize the gender from images, Gallagher and Chen [52] used social context information based on the position of a face of a person in a group of individuals. Similarly, to classify the gender of the person, Khorsandi and Abdel-Mottaleb [53] used images of the ear, and to perform feature extraction, they used Gabor filters.

To recognize the gender, Lee et al. 2010 [54] first decomposed a face into several vertical and horizontal stripes. The likelihood that a strip patch belongs to a given gender is determined using a regression function for each strip. The likelihoods from all strips are combined to generate a new feature, which is used to make the final decision by a gender classifier.

Other methods

There are some other feature extraction methods used to perform gender classification. Lu et al. [55] used the pixel-pattern-based texture feature (PPBTF) extraction method for automatic gender recognition. Li et al. [58] used spatial information considering both global and local information, and for feature extraction, they used Discrete Cosine Transform (DCT) method to perform gender recognition. Rai and Khanna [59] proposed a new method called Radon and Wavelet Transforms to extract features from an image, and these features are used to classify the face images. To perform gender recognition, Hussain et al. [56] used Nonsubsampled Contourlet Transform and Weber Local Descriptor based feature extraction method. Lee et al. [57] used Local Binary Patterns (LBP) and Histogram of Oriented Gradient (HOG) to extract features from the images and also used an SVM classifier to classify the face images. Chen et al. [60] used moment descriptors called the Eigen-moment method for gender classification; these moments are used to describe a geometrical feature of an image. A genetic algorithm-based adjusted order Pseudo- Zernike Moment (PZM) is proposed by Khoshkerdar et al. [61], which is used to extract features from a face image.

5. DATASETS AND EVALUATION

There are several publicly available datasets used for the gender classification task. Table 1 summarizes some of the publicly available datasets that have been used to evaluate gender classification, and to the best of our knowledge, the number of images and the number of unique individuals in each dataset is also displayed. The controlled variations during data collection are also mentioned. The majority of these datasets were collected for evaluating face recognition and for other detection systems. As a result, there may be a lack of gender labels, so that researchers must manually label the ground truth via visual inspection, either alone or with the assistance of annotators. Some researchers also use a subset of the dataset for evaluating the performance of gender classification.

FERET [62] is an old and popular dataset that is mainly used for face and gender recognition problems. All the images in the dataset were collected in indoor lab conditions; therefore, the dataset is comparatively simple. The dataset contains 14,126 images of 1199 individuals. The faces have a variation in illumination, expression, and pose. The images in the dataset are without background clutter, noise-free and consistent lighting. There is no gender annotation given with the dataset, although Makinen and Rai [63] proposed a subset of images with 212 males and 199 females.

Images of Groups (IOG) [52] dataset consists of 5.1 k images of a group of people and consists of 28.2 k total faces. The dataset is annotated with age and gender, with seven age categories. The images of people are collected in uncontrolled environments from websites and present several differences in an image, including facial expressions and face occlusions. Images in a dataset may include the entire person, half-body shots, and close-ups of the face.

CAS-PEAL [72] database contains images of Chinese faces that consist of 99,594 face images of 1040 unique individuals, each with a different expression, lighting, pose, and accessories. A subset named by the CAS_PEAL-R1 database is also available that consists of 30,900 face images. The gender information is also contained in the image file. In the CAS-PEAL dataset person's face images were taken in a controlled condition, and also different backgrounds and various accessories such as hats and glasses are used to capture the image of a person.

Labeled Faces in the Wild (LFW) [71] dataset was also collected in the wild conditions. It contains a total of 13,233 face images of 5749 individuals. The dataset is not labeled and requires the manual labeling of images. There are a varying number of face images for an individual present in the dataset. Face images in the dataset are captured in uncontrolled environments and show extreme variations in lighting, pose race, background, and occlusions. All the face images were collected from the internet, and the quality of these images is very low, and most of the face images are in compressed form. The dataset is highly imbalanced as the number of male subjects is 10,256, whereas female subjects are 2977.

Adience [73] dataset consist of 26580 images of 2284 individuals with frontal and non-frontal facial images of people belonging to different age groups, races, and countries. The dataset was collected in the un-constrained conditions and was used for age and gender classification. Along with the dataset, their label information is given. The face images in the dataset were captured with smartphones. Due to this capturing, uploaded images were without filtering, reflecting real-world facial images. Therefore, images in a dataset have extreme variations in lighting quality, background, occlusion, and expression. Patel et al. [74] proposed a subset of images with 840 males and 917 females. Figure 3 shows the sample images from the Adience dataset.

Table 1 List of publicly available datasets

Dataset	**Year**	**No. of images in the dataset**	**No. of unique individuals in the dataset**	**Gender labels**	**Variations**
AR [64]	1998	<4000	126	Yes	L, O, X
XM2VTS [65]	1999	5900	295	No	L, P
FERET [62]	2000	14126	1199	No	L, P,X
BioID [66]	2001	1521	23	No	L, face size, background
CMU-PIE [67]	2003	<40000	68	Yes	L, P, X
UND Biometric-B [68]	2003	33287	487	No	L,X
FRGC [69]	2005	50000	688	No	L, X, background
MORPH [70]	2006	55134	13000	Yes	Age
LFW [71]	2008	13233	5749	No	Uncontrolled
CAS-PEAL-R1 [72]	2008	30900	1040	Yes	L,O,P,X
Images of Groups [52]	2009	5080	28231	Yes	Uncontrolled
Adience [73]	2014	26,580	2,284	Yes	Uncontrolled

L lighting or illumination, *O* occlusion, *P* pose or view, *X* expression

Figure 3 Sample images from Adience dataset

Table 2 Classification results for FERET dataset

References	**Year**	**Feature Extraction**	**Classifier**	**Training data**	**Testing data**	**Average Accuracy %**
Moghaddam and Yang [42]	2002	Pixel values	SVM, RBF Networks	1755t	5-CV	96.62
Jain et al.[75]	2005	ICA	SVM	200t	300 t	95.67
Tivive and Bouzedown [76]	2006	Pixel values	CNN	1762t	5-CV	97.2
Baluja and Rowley [48]	2007	Pixel comparisons	Adaboost	2509 t (914f 1495m)	5-CV	94.3
Leng and Wang [77]	2008	Gabor wavelet	(FSVM) Fuzzy SVM	300 t (140f 160m)	5-CV	98.09
Lu and Shi [10]	2009	2-DPCA	SVM	800t	5-CV	94.83
Demirkus et al.[78]	2010	SIFT	Bayesian	3560t	Video frames	90
Lee et al.[54]	2010	Regression function	SVM	1773t (615f 1158m)	5-CV	98.8

Alexandre [32]	2010	Shape, Texture ,and Decision fusion	SVM	304t	107t	99.07
Zheng and Lu [79]	2011	LGBP, LDA	SVMAC	564t (282f 282 m)	428t (121f 307m)	99.1
Ahmed and Kabir [80]	2012	DTP	SVM	1800t, 900 f 900 m	10-CV	93.11
Berbar [81]	2014	GLCM, DCT	SVM	644t (104 f 540m)	5-CV	93.11
Andreu et al.[12]	2014	grey levels, PCA and LBP	1-NN, PCA + LDA and SVM	2015t (841f 1173m)	5-CV	94.06
Rai and Khanna [82]	2015	2DPCA on real Gabor space	SVM	1199t (459f 740 m)	2-CV	98.18
Patel et al.[74]	2016	coLBP	SVM	987t (400 f 587 m)	5-CV	93.92
Bhattacharyya et al.[83]	2019	coLBP	SVM	987t (400 f 587m)	5-CV	95.75
Afifi and Abdelrahman [84]	2019	CNN	AdaBoost	3500t	5-CV	99.49
Khan et al. [85]	2019	GC-MSFS-CRFs	Random Decision Forest (RDF)	100t	10.CV	100

Table 3 Classification results for the datasets in which most images are taken in controlled conditions.

References	**Year**	**Feature extraction**	**Classifier**	**Training Data**	**Testing Data**	**Average accuracy %**
Buchala et al. [86]	2005	PCA	SVM	Combination of FERET, AR, BioID 400 t	5-CV	92.25
Leng and Wang [77]	2008	Gabor wavelet	FSVM(Fuzzy SVM)	CAS-PEAL 800t	5-CV	89
Xu et al.[23]	2008	Haar-like features	SVM with RBF kernel	Combination of FERET, AR, Web (1000t)	5-CV	92.38
Zhen Li [58]	2009	DCT	Sapatial Gaussian Mixture Models (SGMM)	YGA 6096 t	1524 t	92.5
Lu and Shi [49]	2009	2DPCA	SVM	CAS-PEAL 300m 300f	1800 t	95.33
Wang et al. [27]	2010	Gabor filter, SIFT feature	AdaBoost	Combination of FERET,PEAL, Yale,I2R (4659 t)	10-CV	97
Alexandre [32]	2010	Shape, Texture, and Decision fusion	Linear SVM	UND dataset 260 t (130 f 130 m)	227 t (56f 171m)	91.19
Zheng and Lu [79]	2011	Gabor + LBP + MLGBP	SVMAC	CAS-PEAL dataset 2706f 2706 m (Total 9 set)	1164 f 2175 m	≥99.8per set
Zhang and Wang [87]	2011	SIFT	SVM+HIK(Histogram Intersection Kernel)	UND Biometric 942 t	10-CV	97.65
Li et al. [9]	2012	LBP	SVM +RBF	BCMI 1642 t	548 t	95.3
Wu et al. [88]	2012	MLGBP	SVM	CAS-PEAL 4284t	2989t	91-97 per set

Tapia and Perez [33]	2013	Intensity, edge directions, LBP	SVM-RBF	UND set B 301m 186f	5-CV	94.1
Antipov et al. [89]	2017	CNN	CNN	MORPH-II	5-CV	99.4
Dhomne et al. [90]	2018	D-CNN	D-CNN	Celebrity dataset 160t	40 t	0.95
Lin et al.[91]	2020	Feature fusion	CNN	MORPH 8492 f 46569 m	3-CV	99.11
Lin et al. [92]	2020	CNN	CNN	MORPH 8492 f 46569 m	5-CV	98.72

Table 4 Classification accuracy of the datasets in which most images are taken in uncontrolled condition

References	**Year**	**Feature extraction method**	**Classifier**	**Training data**	**Testing data**	**Average accuracy %**
Shakhnarovich et al. [22]	2002	Haar-like	Adaboost	Web images	5-CV	79
Aghajanian et al. [93]	2009	Pixel values	Bayesian classifier	Web images 32000 t	Web images 1000t	89
Dago-Casas et al. [40]	2011	Gabor filter, LBP	SVM	Images of Group 14760 t	5-CV	86.61
Bekios-Calfa et al. [94]	2014	LDA	KNN	Images of Group 11932 f 11016 m	5-CV	77.89
Eidinger et al.[73]	2014	LBP+FPLBP	Linear-SVM	Images of group	5-CV	88.6

Table 5 Classification results for the LFW dataset

References	**Year**	**Feature Extraction**	**Classifier**	**Training data**	**Test data**	**Average Accuracy %**
Dago-Casas et al [40]	2011	Gabor	SVM-linear	2959 f 10129 m	5-CV	94.01
Shan [34]	2012	Boosted LBP	SVM	2943 f 4500 m	5-CV	94.81
Tapia and Perez [33]	2013	LBP	SVM	2943 f 4500 m	5-CV	98.01
Rai and Khanna [82]	2015	2DPCA on real Gabor space	SVM	13,010 t	2-CV	88.34
Mansanet et al. [95]	2016	Learned	LDNN	2977 f 10256 m	5-CV	96.25
Patel et al.[74]	2016	coLBP	SVM	1477 f 4259 m	5-CV	89.70
Antipov et al.[89]	2017	Learned	CNN	13233 t	5-CV	99.3
Bhattacharyya et al.[83]	2019	coLBP	SVM	5749 t	5-CV	92.29
Khan et al. [85]	2019	GC-MSFS-CRFs	Random Decision Forest (RDF)	100 t	10-CV	93.9
Afifi and Abdelhamed [84]	2019	CNN	Adaboost	2950 t	5-CV	95.98

Table 6 Classification results for the Adience dataset

References	Year	Feature Extraction	Classifier	Training data	Test data	Average accuracy %
Eidinger et al. [73]	2014	LBP, FPLBP	SVM	8192 m 9411 f	5-CV	76.1
Levi et al. [15]	2015	Learned	CNN	8192 m 9411 f	5-CV	86.8
Wolfshaar [96]	2015	Learned	CNN	17492 t	5-CV	87.2
Ozbulak [18]	2016	Learned	CNN	17393 t	5-CV	92.0
Patel et al. [74]	2016	coLBP	SVM	840 m 917 f	5-CV	83.89
Rodríguez et al. [97]	2017	Learned	CNN	8192 m 9411 f	5-CV	93.0
Duan et al. [98]	2018	CNN	ELM (Extreme Learning Machine)	8192 m 9411 f	5-CV	88.2
Bhattacharyya et al. [83]	2019	coLBP	SVM	840 m 917 f	5-CV	87.71
Khan et al. [85]	2019	GC-MSFS-CRFs	Random Decision Forest (RDF)	100 t	10-CV	91.4
Afifi and Abdelhamed [84]	2019	CNN	Adaboost	4850 t	5-CV	90.59

5.1 Evaluation and results

In **Error! Reference source not found.**, **Error! Reference source not found.**, **Error! Reference source not found.**, **Error! Reference source not found.**, and **Error! Reference source not found.**, we describe the previous results on a various dataset which is used for face gender classification task. From these results, we have observed that the FERET is a commonly used dataset to perform face gender classification. In **Error! Reference source not found.**, we show results for the FERET dataset, and different training FERET dataset is used by the researchers. Table 3 and Table 4 demonstrate the results of different face datasets where the majority of the images were taken under controlled and uncontrolled conditions, respectively. In **Error! Reference source not found.**, we demonstrate results for the LFW dataset, and in Table 6, we demonstrate results for the Adience dataset.

For each study, the feature extraction method and classifier employed are displayed. The training data and testing data describe the datasets from which the images for training and testing the classifier were extracted. Male and female faces are also analyzed; for example, 100m and 100f correspond to 100 male and female faces, respectively. The total faces used are provided in cases where the analysis could not be defined (e.g., 200 t), and average overall classification accuracy attained is also provided. 5-CV refers to the five-fold cross-validation. The ratio of successfully categorized test samples to the total number of test samples is known as the classification accuracy. Typically, the average classification accuracy gained from cross-validation results is presented. Mostly 5-CV is used to evaluate the average classification accuracy. Some researchers will test their approach on a separate dataset for generalization ability, while others will make sure that the training and testing datasets have the same number of male and female faces.

It is difficult to make a comparison between the methods because different parameters and datasets are used for evaluation. Some of the researchers use only frontal face images, and others may include the non-frontal face images, for example, variation in pose and expressions. The variations present in the datasets are also different. The majority of current research has focused on uncontrolled datasets, e.g., LFW, Adience, and Images of Groups.

Based on the results, we have observed that FERET is the most widely used dataset. The researchers used a different subset of images from the dataset. Images in the FERET dataset are captured under controlled conditions and only deal with frontal face images. Several researchers achieved almost 100% accuracy on the FERET dataset. Zheng and Lu [79] achieved 99.8% accuracy on the CAS-PEAL dataset. Other datasets, such as FRGC and MORPH, have also yielded promising results. LFW dataset contains frontal and non-frontal face images; all the images were captured in the unconstrained environment. Antipov et al. [89] obtained 99.3% accuracy on the LFW dataset. The most challenging uncontrolled dataset, Images of Group, contains frontal and near frontal face images, Eidinger et al. [73] was obtained 88.6% accuracy on images of the group dataset. The images in the Adience dataset were also captured in the unconstrained environment, Rodríguez et al. [97] obtained 93% accuracy.

6. CONCLUSION

In this paper, we have described a comprehensive study of the facial gender classification method in the field of computer vision. Based on the studies of previous research, we have observed that a number of works have already been done using facial information such as gender classification. We have also highlighted the application areas, challenges, and confusing factors such as illumination, angle, occlusion, and expression. A list of datasets is used for gender classification is also described. Based on the results of previous studies in gender classification, good performance has been achieved for frontal face images captured in controlled environments. For real-life situations (containing both frontal and non-frontal faces), there is still room for improvement, especially in uncontrolled environments. Indeed, more development is needed to improve the robustness and accuracy of facial gender classifiers in computer vision.

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