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A Comparative Analysis of Gender Classification Techniques

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Abstract: Over the period of time, automated classification of gender has gained enormous significance and has become an active area of research. Many researchers have put a lot of effort and have produced quality research in this area. Still, there is an immense potential in this field because of its utility in many areas like monitoring, surveillance, commercial profiling and human-computer interaction. Security applications have utmost importance in this area. Gender classification can be used as part of a face recognition process. This paper presents a comprehensive comparison of state-of-the-art research techniques. We have divided the classification process into three stages and have presented a categorical review of existing literatures. Their analysis has been presented along-with their strengths and weaknesses. We have also discussed standard data sets. This can help the novel researcher a comprehensive review. Future dimensions are presented considering the limitations found in the literature.

Key words: Gender Classification · Features extraction · Pattern Recognition · Comprehensive review · Processing.

INTRODUCTION

In modern age artificial Intelligence is a part of our daily life. Especially Image processing and machine learning are playing very important role in artificial intelligence. Different difficult jobs are performing by image processing and machine learning technique like Gender classification, face recognition, facial expression recognition and gesture recognition system. Face recognition is playing very important role in security, identification of a person, human interaction with computer, clinical system and in medical field. Gender recognition is very difficult job start from the last decade. Gender classification is a two class problem (Male or Female) in which the given face image is assign to any one of the class. It is an easy task for humans to classify gender but challenging task for machines. A large no of potential application areas are identified where gender recognition is very much involved including;

Human Computer Interaction: A variety of useful human-computer interaction systems can be designed if they are such that able to identify a human's attribute such as gender. The system can be made more human-like and respond correctly. A most simple scenario would be an intelligent robot that will interact with a human; it would require some details about gender to address the human appropriately (e.g. as Mr. or Miss).

Targeted Advertising: An electronic billboard system is used to display the ads on flat panel displays cards. The Targeted advertising is used to display advertisement relevant to the person looking at the billboard based on attributes for example gender. For example, the billboard may choose to show ads of wallets when a male is detected, or handbags in the case of female. In Japan, vending machines that use age and gender information of customer to recommend drinks have seen increased sales.

Biometrics: It is another useful application area of face recognition in which time for searching the face database can be minimize and separate face recognizers can be trained for separate gender to enhance the accuracy of the result.

Surveillance Systems: It is another important application area in which it can assist in restricting region to one gender only, for example in a train coach or hostel. Automated surveillance systems may also be very critical to pay more attention a higher threat level to a specific gender.

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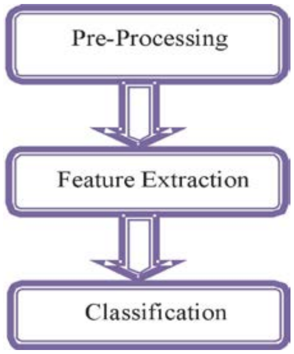

Fig. 1: Gender classification general steps

Content-Based Indexing and Searching: With the widespread use of consumer electronic devices such as cameras, a large number of digital media is being produced. Indexing or annotating information including the number of people in the image or video, their age and gender will become easier with automated systems using computer vision. In addition to this, for content-based searching such as looking for a photo of a person, identifying gender as a pre-processing step will reduce the amount of search required in the database.

Generally gender classification consists of the following steps. Figure 1 depicts these steps.

Pre-Processing: Every face database needs some pre-processing, like normalization of illumination and face detection etc.

Feature Extraction: After performing pre-processing we need to extract face features. Generally two types of features are extracted namely Geometric based features and appearance based features.

Classification: Classification is the last step of gender classification in which the face is successfully classified as that of a male or female. For this purpose different types of classifiers are used. e.g. K-nearest neighbour (KNN), neural network (NN) and support vector machine (SVM).

Challenges: The different variation in gender face may cause to affect the Image processing techniques. Variation in face images occurs due to illumination change, poses, occlusions, age and ethnicity. The classification techniques are also affected by different masks on face (i.e. glasses, jewelry and hats). Similarly during the image capturing process the factors like blurring, noise and low resolution also make the face image analysis a challenging task.

The age and ethnicity have also impact on accuracy rate. Benabdelkader [1] observed that the performance of classifier is degraded due to variability in ages. Gua *et al.* [2] claimed after performing different experiments on large face database that adult faces are having more classification accuracy rate as compared to young faces

Pre-Processing: Classifiers are sensitive to variation like illumination, poses and inaccuracies. To reduce this sensitivity some pre-processing steps are performed. Some basic Pre-processing steps are involved.

- Normalization of brightness using Histogram equalization function.
- Facial portion detection and removal of background regions.
- Face portion alignments
- Downsizing to reduce the data dimensions (i.e. Number of features)

Makinen *et al.* [3] compared the accuracy rate after performing the manual and automatic face alignments. They found that the accuracy rate is more improved in case of manual alignment as compared to automatic face alignment. In [4], it is suggested that the most appropriate time for face alignment is before downsizing. Shan [5], align the face images using commercial alignment software [6]. Nazir *et al.* [7] performed Histogram equalization operation before extracting the facial features in-order to normalize the illumination effects.

Feature Extraction: Extraction of different facial features is an important sub-task of gender classification. Gender classification approaches are categorized into two classes based on feature extraction. Global facial features and local facial features.

Geometric-Based Feature Extraction (Local Features): In geometric-based method, features are extracted from some facial points like face, nose and eyes. Some useful information is loss using geometric-based techniques. Burton *et al.* [8] reported 85% accuracy rate after locating 73 facial points. The facial points' extracted features are then passed to descriminant analysis classifier to classify gender. Fellous *et al.* [9] reported 90% accuracy rate after finding out 22 normalized distances using the face database containing 109 images. Li *et al.* [10] classified the gender by utilizing not only the five facial features (nose, eyes, mouth, forehead, brows) but also external information like clothes and hair features. They performed experiments on FERET, BCMI and AR face dataset.

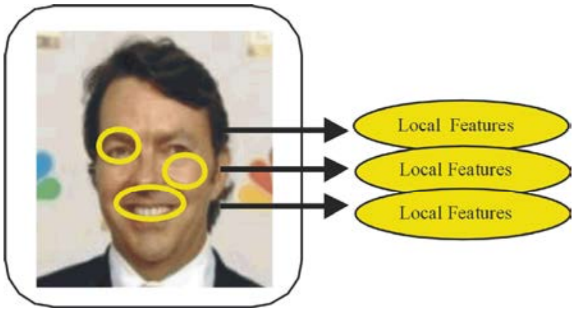

Fig. 2: Face Local Feature

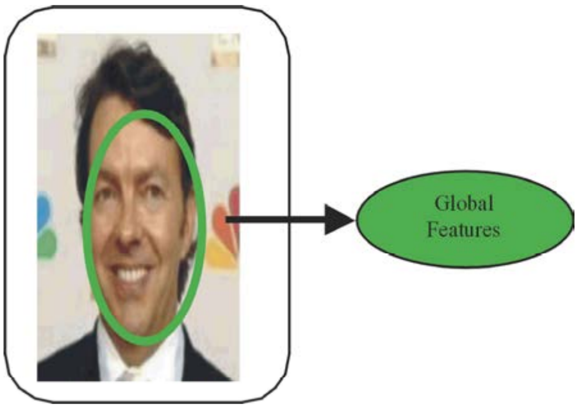

Fig. 3: Face Global Feature

Problem with their approach is that their feature extraction method is affected by complex background. Mozzafari *et al.* [11] extracts the geometric features after using aspect ratio for face eclipse fitting. Ardakany and Joula [12] claimed that the facial component based features extraction methods are time consuming and complex, there for to extract the geometric features they have obtained derivative map. This derivative map represents texture and geometric features as well. Shan [5] locate the facial points using Active shape Model (ASM) and then extracts the geometric features from these points using Local Binary Pattern (LBP). Han *et al.* [13] describe that features are categories into two groups, local features and global features. They notice the factors that cause the male face change from female face. The male eyebrow is thicker than female and female nose is smaller and having small bridge than male. Facial features are extracted by placing the landmark on different facial points. Xu and Lu [14] fused local and global features. Global features are extracted using Haar like features and for geometric features extraction they located 83 facial points. Fusion of both local and global features are performed using Min-Max method.

Appearance-based Feature Extraction (Global Features): In appearance-based method, features are extracted from the whole face part instead of extracting features from facial points. Colomb *et al.* [15] reported 91.9% accuracy after performing experiments on a face database containing 90 images. They used SEXNET network to classify gender. Nazir *et al.* [7] used discrete cosine transform (DCT) to extract face features. K-nearest neighbor classifier is trained and tested by these features. Experiments are performed on SUMS face database. Problem with their proposed method is that it is not robust to occlusion change. Mousavi *et al.* [16] reported 87.5% accuracy rate after applied fuzzy inference system to IMM face image database which contains 240 face images. The extracted geometric-based facial features by calculating distance between different face points. Problem with this method is the proper adjustment of threshold value. Rai and Khanna [17], proposed new technique to classify gender from face images. They combined wavelet and Randon transform to extract the important facial features. They have performed experiments on SUMS face database and reported 90% accuracy rate using 35 numbers of features. Their system consuming more time to locating face portion and also not supporting pose changes. Ravi and Wilson [18] presented a novel gender classification strategy. Face portion is located using skin color and then after extracting geometric-based facial features they applied support vector machine to classify gender. Drawback of this method is to choose the correct threshold value for face features extraction. Shobeirinejad and Gao [19] extracted discriminative facial features using Interlaced derivative pattern (IDP). Experiments are performed on FRGC face database and yield 91.2% classification accuracy rate. Xu *et al.* [13] fused appearance-based and geometric-based to classify gender. Appearance-based features are extracting using Haar wavelets and for geometric-based features extraction they have using active appearance model (AAM). Their method is robust to illumination, pose and expression change. To extract the geometric-based features they have to locate 83 face points for each face which make their system more time consuming.

Classification: In this step different classifiers are trained and tested by facial extracted features. To minimize the classification accuracy error rate different classifiers are also ensemble. Nazir *et al.* [7] trained and tested K-nearest neighbor classifier after facial features extraction. Rai and

Table 1: Different Face Databases

Face Database	Number of Face Images	Variation Controlled
FERET [22]	14126	Pose, Illumination and expression.
FRGC[23]	50000	Illumination and background.
LFW [24]	13233	Uncontrolled environments
AR[25]	More then 4000	Illumination, expressions and occlusions.
CAS-PEAL-R1 [26]	30900	Pose, Expressions, illumination and occlusions.

Khana [17] extracts the features using Randon and wavelet transform and then trained and tested KNN classifier to classify gender.

Ensemble Classifiers: Combining the outcomes of different classifiers is known as classifier ensemble [20]. As compare to ensemble classifiers, single classifier accuracy rate is less. There for to minimize the classification error rate, different classifiers are ensemble. In literature many researcher used this classifier ensemble process. Nazir *et al* [21] ensemble different classifiers (i.e. K-nearest neighbour, Mahalanobis distance, Linear Discriminant analysis and kmeans) using weight majority voting. After classifier ensemble task they have used Genetic algorithm to optimize the weights of different classifiers.

Face Datasets: We summarize different facial database in Table 1. Most of them are used for face detection and face recognition tasks. Researcher has performed different experiments with these databases. Some researcher discarded unsuitable images and used only subset of the images and some used a large combination of datasets by combining different databases. It is also a common practice that the facial portion is detected first and the background region is discarded.

Gait-Based Gender Classification: Gait-based gender classification includes recognizing the gender based on humans walking, climbing, running and jogging etc. The advantages of using Gait-based gender classification are;

- Non-noticeable and captured at distance
- No need of any cooperation or information about subject in public place
- The work on gender classification using gait as biometric is more latest as compare to other biometric like faces, voice and finger prints [27].

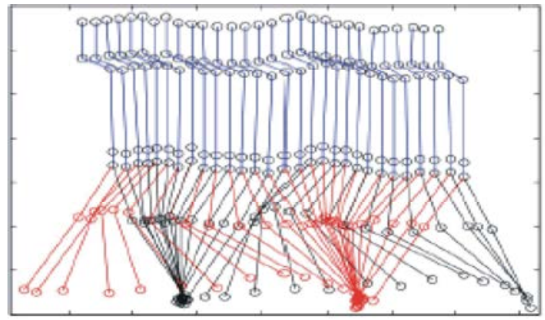

Fig. 4: Signature of Gait

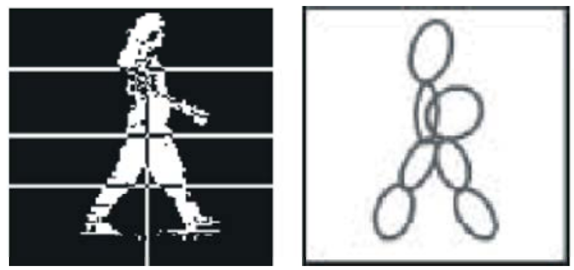

Fig. 5: Fitter Ellipses

The gait-based gender classification is useful in a situation when face portion is not clear or having some occlusion or noise etc. There are many factors which affects the gait-based gender classification. These factors are walking surface, load, fatigue etc. Hu *et al.* [28] noticed that the classification accuracy rate was decreases after a person carry bag or wearing overcoat.

Feature Extraction: Based on the type of features gait-based gender classification is divided into model-free and model-based. Model-based approaches are more computationally expensive as compare to Model-free approaches. Model-based approaches are based on accurate estimation of joints [29], so these are more expensive in term of time.

Model-Based: Yoo *et al.* [30] used 2-D sticks as a parameter for recognition which they have derived from body contour. These sticks are shown in Figure 4. The features selected from these sticks are kinematic parameters, temporal and spatial.

Model-Free: In this method first the sequence of representation of walking human are being obtained. Lee and Grimson [31] fitted ellipse into every region after separated the human representation into different parts as shown in Figure 5. Appearance features are obtained using the axis orientation and standard deviation of the ellipse regions.

Table 2: Different Gait Databases

Face Database	Number of Face Images	Variation Controlled
Human ID [32]	1870	Carry briefcases, walking surface and shoe.
BUAA-IRIP Gait [33]	4800	View
SOTON Large Gait [34]	More then 600	Front side view, outdoor and indoor scene.

Table 3: Different Gait Databases

Database	Number of Images	Views
Attributes of People [36]	8035	Uncontrolled
VIPER [37]	1264	Diagonal, back and front side.
MITCBCL[38]	924	Back and Front

Gait Databases: We summarize the databases in Table 2 used for gait-based gender classification.

Body-Based Gender Classification: Human body-based gender classification involved the recognition of the gender based on static human partial or whole body. Due to several aspects this is also a challenging task. With keeping the information like body shape and hair style some other information like accessories and clothes are also used to infer the gender. Some basic factors which make the body-based gender classification a challenging task are following.

- Different verity of clothes style chosen by same gender.
- Similarity between the male and female clothing styles.
- Similarity of hair style for both genders.
- Different illumination effects.

Feature Extraction: Cao *et al* [35] make a first attempt to classify gender based on the full body images. They first align the images and then portioned into different patches. Features are extracted using Histogram of Oriented Gradients.

Body-based Gender Classification Databases: We summarize the Body-based image database in Table 3.

In the above literature different state-of-the-art vision-based gender classification techniques has been studied. These approaches included face, gait and body-based gender classification.

In face-based gender classification, facial images are used for experiments. Poses, facial expressions and occlusions are the main challenges facing by this approach. Facial-based gender classification techniques are categories into local and global features. If local features are used then we might loss some of the important information and if global features used then these type of features are not robust to variation in facial expression and poses. Single classifier is unable to attain high accuracy so ensemble classifiers will increase the classification accuracy rate.

In Gait-based approach the gender are classify using human gait information like walking, climbing and running. Factors that affecting the accuracy rate are walking surface, load, drunkenness and fatigue etc. Gait-based gender classification techniques are divided into two category i.e. Model free and Model based.

In Body-bases approach the gender is classify using either human partially body or whole body images. Factors that affecting this technique are similarity of clothing style of both genders and same case for hair style. Different texture based techniques are used to extract the features.

Gait and body-based techniques are computationally more costly due to uncontrolled environments as compared to facial image-based gender classification. In this work we are focuses on face images.

All these techniques failed on real time data and also have limitation of dataset. These techniques could not yield Better results in classification phase when illumination is week or color intensity is low. These techniques showed less accuracy rate for recognition.

Gender classification using face images attain more importance so we critically evaluate different face-based gender classification techniques.

Literature Review: Nazir and Mirza [39] proposed a new technique to classify gender. They divided their classification process into two modules that is, gender classification and pose classification. First the image is resized to 100x100 pixels and then converted to gray scale. In the next step face detector is used to extract only the face portion. In the next step, features are extracted from face in the range of 4 to 20 using Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT). Principle Component Analysis (PCA) is used to select the important features and thus reduce the data dimensions. Different classifiers are tested in order to get the maximum classification accuracy rate. Two classifier, in which one is used to train for frontal face and one are used to train for side pose. Experiments are performed on three face datasets. 1) Indian face database 2) FERET faces database and 3) CVL. They have used 10-fold cross validation in all experiments. Best classification accuracy rate is obtained using feature set of size 7. It has been shown from the

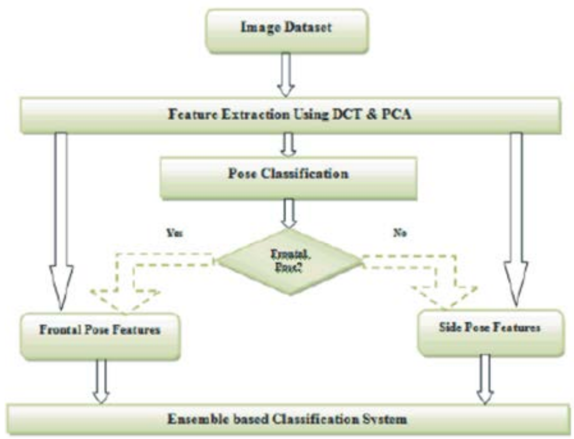

Fig. 6: [39] technique system architecture

experiments that classification accuracy rate is increases if different classifiers are combined. Figure 6, show the system architecture.

Nazir *et al.* [7] says that face is a prominent feature for gender classification. They proposed new method which classifies gender more efficiently than existing techniques. To make the processing fast they reduced the dimension by detecting the face from image using voila Jones technique.

Voila and Jones technique is based on three module that is first they represented image as integral image to make computation fast, second AdaBoost algorithm is used to select key features, third Cascade of AdaBoost work as a classifier through which they discarded the backgrounds from an image. To bring the image lighting effect to its normal form histogram equalization is performed. They resize the gender face image of size 32x32. Every face image contains some prominent features and to obtain these features Discrete Cosine Transformation technique (DCT) is implemented. They stated that DCT is used for dimension reduction and it scans the image in zigzag manner, starting from the upper left corner. After using DCT transformation the feature sorted in decreasing importance form and thus features having more importance lie on the top. Total of 16 coefficients are selected and then the first coefficient of each 16 is then picked thus dimension reduced. According to this paper classification work is given to K-nearest neighbor (KNN) classifier which worked is based on Euclidean distance to find closest neighbors. Experiment performed on Stanford university medical student (SUMS) face database. They concluded that if the training and testing ratio for KNN classifier is 50 to 50 then accuracy of 99.3% obtain. Their results are more

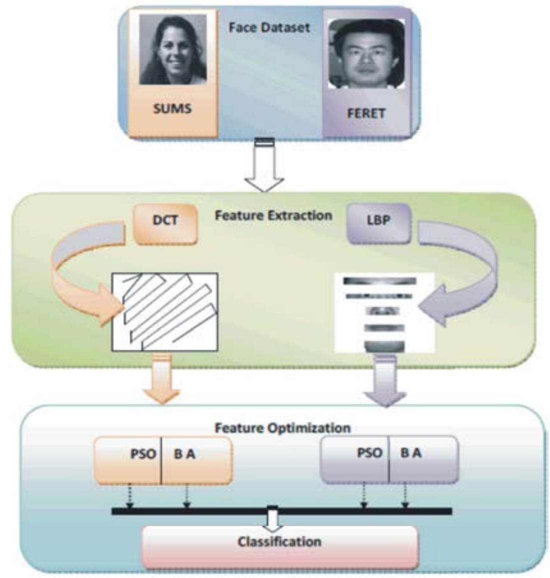

Fig. 7: [40] technique flow diagram

accurate comparing with Support vector machine (SVM), Neural Networks (NN) and Linear discriminate analysis (LDA) techniques.

They stated that Support Vector machine (SVM) achieves 91.10% accuracy, Neural Networks (NN) classify gender with 82.30% accuracy, LDA accuracy rate is 85.80% and Bayes technique produced 77.62% accurate results.. Voila Jones techniques not support pose variation so if some variation in gender image then face will not detect.

Sajid *et al.* [40] stated that local facial features are robust to facial variation but slow, similarly global feature extraction process are fast but not robust to facial variations. In proposed technique local and global features are combined. First they have applied histogram equalization in order to normalize the illumination effects. Dimensions are reduced by extracting only the face portion from an image. Global face features are extracted using Discrete Cosine Transform (DCT) in zigzag manners and feature vector of size 100, 150 and 200 is obtained. Local face features like nose, mouth and eyes etc are crop from the face image after locating them and then Local Binary Pattern (LBP) is used to extract features from these key face portions. In the next step, Binary Particle Swarm Optimization (BPSO) and Bee Algorithm is used to select the more accurate face features and reduce the data dimension. Feature set of size 100, 150, 200 and 250 are passed to BPSO. BPSO eliminate the irrelevant features and features which are more contributing to recognize the gender is obtained. They gave classification accuracy rate

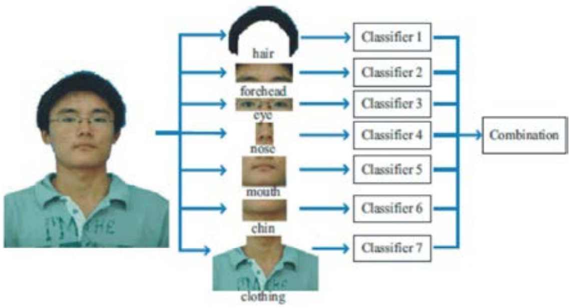

Figure 8. [10] technique flow diagram

of 97.5%. Two face databases, FERET and SUMS is used for experiments. Comparisons are performed with some existing techniques and found the proposed technique more accurate and robust. Figure 7, indicate the system flow;

Li *et al.* [10] proposed a novel technique to classify gender. They have used hair and clothing features along with face features in-order to increase the accuracy. They stated that key facial points like nose, mouth and eyebrows etc play more important role to recognize gender as compare to whole face portion. In the stage of feature extraction, face portion is divided into different portion like nose, eyes and mouth etc shown in figure 8.

Seven classifiers are trained for these seven key features. Classifiers are also combined to increase the accuracy rate using different classifiers combination techniques. Three face datasets (i.e. FERET, AR and BCMI) are used for experiments. Local Binary Pattern (LBP) strategy is used for extracting face features. Due to large variations in texture, color and style the feature extraction process from the cloths is complex. Two techniques are used to extract the clothing features. Color histogram is used to maintain the color information and local binary pattern is used to retain the texture information. Similarly due to a large variation hair feature extraction process is also complex. In this paper, Lapedriza [41] technique is used to extract the hair features. They stated that proposed technique is highly accurate and robust to noise and occlusions.

Shan [5] stated that gender classification is a very challenging task if the condition is not controlled. Normally a large number of applications exist which are using frontal face images but they are fail if some facial variations occur. Proposed technique is capable to classify gender using real world face images. Experiments are performed on new real life face database namely Labeled Faces in the Wild (LFW). All the faces are detected using face detector and then the image size is

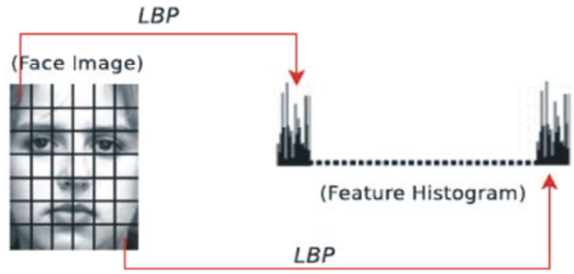

Fig. 9: [5] Technique feature extraction process

reduced to size 256x256. Local Binary Pattern (LBP) is used to extract the facial features. They used 7443 face images for experiment in which 4500 is male and 2943 is female face images. Five cross validation is used in all experiments. Adaboost algorithm was implied to select the more important facial features which more clearly represent the gender. Support Vector Machine (SVM) is trained and tested by using these boosted LBP features and classification accuracy rate of 94.81% is obtained. They have stated that the real world face images database is a public database and thus evaluation and future benchmark is possible using this database. Figure 7, depict the facial feature extraction.

Sajid *et al.* [42] proposed an efficient gender recognition technique. First Voila and Jones [43] algorithm is used to extract only the face portion. To normalize the irregular illumination effects Histogram equalization technique is applied. Interlaced Derivative Pattern (IDP) is used to found the four direction (0, 45, 90 and 135) image. As the features are extracted from all the four direction so these features are very strong and discriminative to represents the gender face. Data high dimensions are also one of the major problems in this research. Principle Component Analysis (PCA) is used to select the features with high variance. Features sets of size 7, 10 ,15 and 20 is generated. Single classifier is un-able to produce the high accuracy so three state-of-the-art classifiers are ensemble. Weighted Majority Voting technique is found more suitable to ensemble different classifiers. Stanford University Medical Student (SUMS) face database is used for experiments which contains 400 face images. Classification accuracy rate of 97% is obtained. Proposed system architecture is shown in Figure 10.

Ravi and Wilson [18] proposed technique which classify gender under non uniform background and color scheme. First the face region is identified using skin color strategy in which the input face image is converted from RGB color space to YCbCR. In the proposed technique

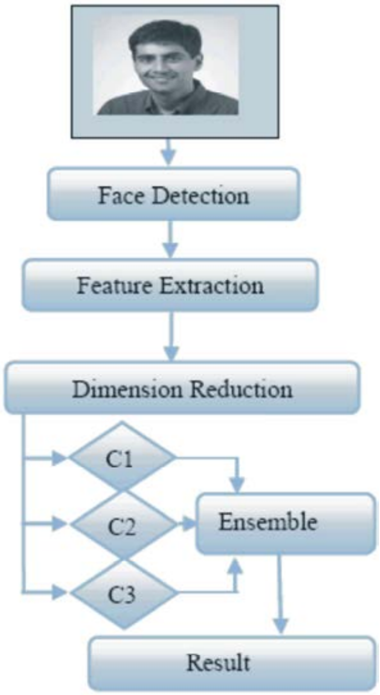

Fig. 10: [42] technique steps flow

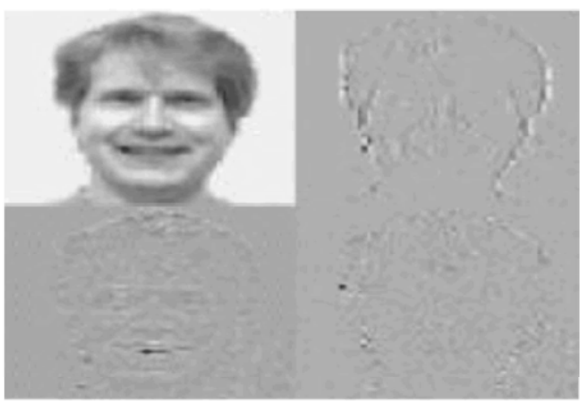

Fig. 11: [44] Face image decomposition

each pixel is classify into skin and non-skin pixel. In the features extraction step, different facial point's areas are estimated like locating the eyes, Nose and Lip determination. In the classification step, Linear Support Vector Machine (SVM) is used to trained and tested on the extracted features. After setting the estimated threshold value to 0.07 the SVM classify weather given input image as male or female. One of the problems facing by this technique is the selection of correct threshold value. If appropriate threshold value is not selected then it might results in the system failure.

Sajid *et al.* [44] stated that the practical applications of gender classification are suffering from the problems like high data dimensions and different facial variations.

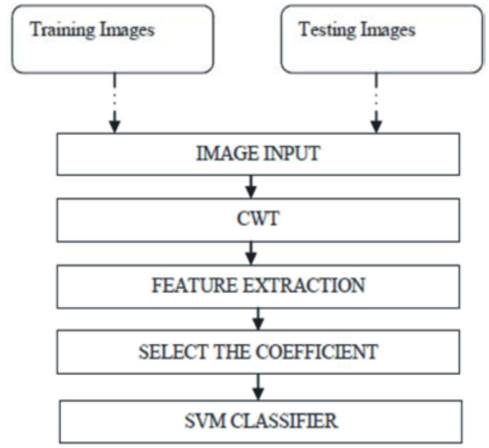

Fig. 12: Proposed [45] technique flow diagram

They discarded the background region and detect only the facial portion. The input image is converted into four new images namely LL, HH, HL and LH using 2-D Wavelet Transform (DWT). The new four images represent the details and approximate coefficients of the image respectively. Figure 11, shows these facts.

It is stated that approximate coefficient contains more discriminative and important information that why these coefficients are passed to next step and four other new images are produced. Some of the irrelevant features are eliminate after applying Principle Component Analysis (PCA) which is a power data dimension tool. SUMS database is used for experiments and training to testing ratio of 50 to 60 is maintained. Proposed technique is found more accurate to recognize gender by utilizing less number of feature sets.

In [45] it is stated that recognizing gender from face image is very easy task for humans but challenging for machines. A novel approach to identify gender from face image is proposed in this paper. The input image is read first and then Continuous Wavelet Transform (CWT) is applied to extract the 100 first important facial features. CWT is an efficient technique and it avoids the redundant information. ORL face database is used to test the technique. All the images were gray scale. Five-fold cross validation is performed in all experiments. Support Vector Machine (SVM) is was trained on 400 images and 200 images were used for testing. Proposed technique was found less expensive after comparison performed with techniques like Discrete Wavelet Transform (DWT) and Randon Transform. Similarly the classification accuracy rate is also high (98%). Proposed technique system architecture is shown in figure 12.

Moallem *et al* [46] says that gender classification is an important task in pattern recognition. The approach which is presented in this paper is based on texture and shape information. This information is used to design a fuzzy system. It has been stated that the flexibility of the system increases with usage of Fuzzy inference system. Zernik moment technique is also exercised to the system input due to which the system output is improved. Classification accuracy rate of 85% is obtained using FERET face database which contains 1199 face images with different facial variations. Results are also compared with other existing techniques and found proposed technique more acceptable.

In [47] face detection and gender classification modules are combined. Color space technique is used to extract the face portion from an image. The color RGB image is converted into YCbCr and then the skin region is detected after setting the threshold value. They have suggested the 2D Gabor Wavelet is more appropriate in the case of gender recognition. The converted Gabor coefficients are of 8 orientations and 4 scales. FFT technique was used in frequency domain to boost the process as the Gabor filter operation is slow and complex. The Gabor-based extracted facial features are used to train the Support Vector Machine (SVM) classifier. SVM classifier shows more superior performance in the area of classification. In this paper, different kernels functions are also tested in-order to overcome the non-linear separable problems. Experiments are performed on random internet images and classification accuracy rate of 88% is achieved. Figure 13 shows the architecture diagram.

In [48] Tin stated that one of the challenging tasks in computer vision is gender recognition using face images. The existing techniques of gender recognition is still having the problem to get failed if some facial variations like occlusions, expression change and illumination change occur. In this paper, the proposed technique is divided into two modules namely features extraction and classification. Important facial feature points are detected and un-necessary points are discarded in this technique. Principle Component Analysis (PCA) is used to extract the important features. In the classification step, Nearest Neighbor classifier is used to predict whether the input image is of male or female. Proposed technique is applied to over 140 face images. Classification accuracy rate of 96% is obtained and results show that proposed technique is less complex. The algorithm steps are shown by figure 14.

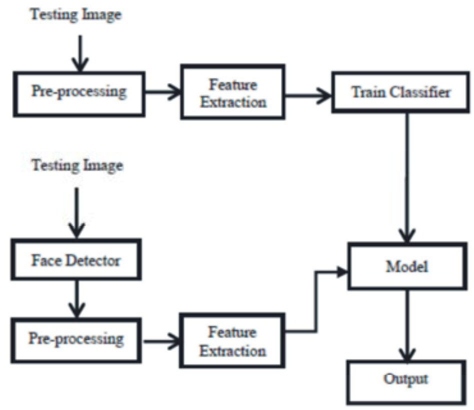

Fig. 13: Proposed [47] technique flow diagram

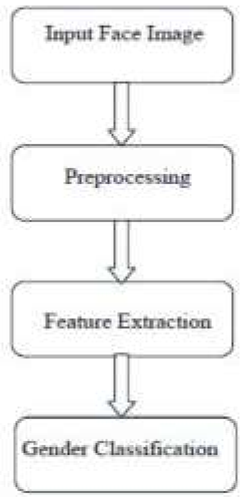

Fig. 14: [48] technique steps

Fig. 15: Haar Features

In [49] Khan *et al.* combined face detection and gender classification module. In the face detection module, Haar features as shown in figure 15, are used to represent face and Adaboost technique is used to boost the weak classifiers.

The main theme behind this approach is to form a highly correct prediction rule using the weak learning of the features. The whole image is analyzed in block form and Bayesian classifier applied to predict weather given face image is of male or female. In this paper the images are collected from the web which contains different variations like occlusions and expressions change.

Table 4: Techniques critical evaluation

Lite Ref.	Technique Used	Focus Area	Proc	Cons
[39]	Hybrid feature extraction using DCT and PCA	Multi-view face classification	Elimination of the redundant features.	CVL database have few female images. This dataset can be used for pose classification but not suitable for gender classification.
[7]	Discrete Cosine Transform (DCT) based facial global feature extraction	To get more efficiency in-term of time complexity	Robust to illumination effects, highly accurate	This technique only classifies gender with frontal view and fails if some occlusion occurs.
[40]	Facial feature extraction using LBP and DCT	Optimize features selection	Data Dimensions reduction by selecting more optimal features	PSO and BA algorithm take more time to process the data
[10]	Face Local features extraction using ASM and LBP	Increases the classification accuracy rate	Highly accurate and robust to variations	Complex background can affect the feature extraction process using hairs. Features extracted from clothing may contribute less for gender classification.
[5]	Local Binary Pattern based real world face images classification.	Gender recognition from real world face images.	Novel technique for real life image classification in un-constrained environments.	Computationally expensive due to local face feature extraction
[42]	Interlaced Derivative Pattern (IDP) based feature extraction	Enhanced classification accuracy rate with utilization of minimum number of features.	Less computational expensive	They used only frontal face images.
[18]	Feature extraction for face detection and gender recognition using support vector machine	Local facial point extraction	More accurate and overcome different facial variations	Choosing the correct threshold value for classification is the problematic part of this research
[44]	Discrete Wavelet Transform (DWT) based face features extraction	Combining the outcomes of different classifiers to enhance the accuracy rate	This technique is more accurate than existing technique	SUMS database contains less number of face images and mostly frontal faces are used in this database.
[45]	Continuous Wavelet Transform (CWT) based feature extraction	To boost the features extraction process	CWT technique is fast and computationally efficient	ORL face database contains very small number of face images and not having occlusions
[46]	Fuzzy inference system for Gender recognition using texture and shape information.	To produce robust facial expression and occlusion technique.	Robust to illumination and expression change.	It is very difficult to find the optimal threshold value for each weak classifier, less classification accuracy rate
[47]	Gender classification from color face images using Gabor filter and SVM	To produce fast and accurate technique	More accurate, error rate reduced	It is difficult to bench mark their database because their database is not publically available
[48]	Appearance -based features extraction using Principle Component Analysis (PCA)	To handle real time face animations	Their results are more stable in the presence of noise and facial variations	Database contains very small number of images and not available publically
[49]	Hybrid gender recognition approach	To stable the performance under pose and illumination change	Robust to illumination and pose change	More time consuming to detect face and classify gender
[50]	ICA based facial feature extraction	To target low quality images	Robust to facial variations	Classification rate is low
[51]	Gender recognition using symmetry of face images	Multi-view gender recognition technique	Proposed technique is Computationally efficient and recognition multi-view face images	Complex background affect the proposed feature extraction technique

Classification accuracy rate of 95% is achieved for male faces and accuracy rate of 91% for female faces. They stated that their blocking technique is similar to DCT block approach. After performing huge number of experiments the found proposed technique more accurate and efficient as compared to other techniques.

In this paper [50] kumara *et al.* says that in previous work different researchers attempt to extract the local features from face which is computationally intensive but in contrast to those techniques proposed technique is computationally efficient. Proposed techniques are shown in Figure 16.

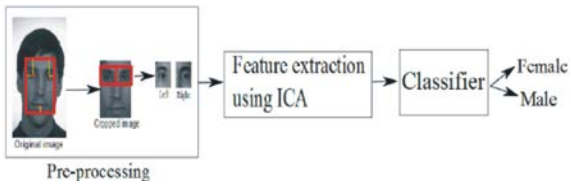

Fig. 16: [50] technique steps

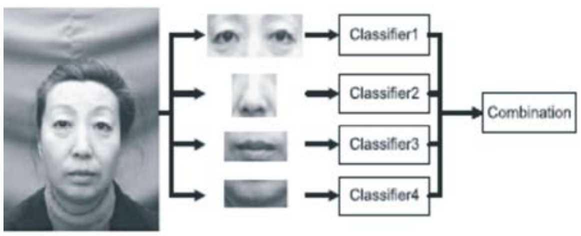

Fig. 17: Image classification into groups

In this paper global features are extracted from face using Independent Component Analysis (ICA). Very poor quality face images are used for the experiments. Large number of classifiers is tested using face features but the performance of neural network is better than the rest of classifiers. Classification accuracy rate proposed technique is measured with other state-of-the-art technique and found their technique more suitable for low quality images.

A hierarchical method is proposed for multi-view gender recognition in this paper [51]. The image is first classified into different groups by the classifiers as shown in figure 17.

The solution they have found for different face views is facial symmetry. Moreover, the boundaries effect problem is solved by using soft assignment when data division is performed. In proposed technique, expert name is given to the classifier (i.e. Support Vector Machine or neural network) which is trained for each group. The face alignment, occlusions and illumination causes different facial variation. To overcome this problem, different facial portions are extracted instead of whole face which causes robustness to facial variations. Proposed technique experimental results are quite good and comparative more efficient to existing techniques.

Critical Analysis: Table 4, enlightened the strengths and weakness of different gender recognition existing techniques.

CONCLUSION

The survey presented in this paper is to deal with up-to-date different gender recognition techniques. The approaches used to classify gender are gait-based, body-based and face-based. Most the researcher focuses on classify gender using face images. In this paper, critical analysis of different face-based gender classification techniques is performed. Some of the significant problems which are still facing by the researchers are facial variations like occlusions, expression changes, illumination effects, computational time and high data dimensions. Working on pixels to classify gender is more computationally expensive so a researcher prefers to extract face features rather than direct work on pixels. Feature-based methods are categories into two i.e. global feature and local features. We conclude that in the classification step, support vector machine is performing well as compared to other classifiers. Similarly, classification accuracy rate is also enhanced by combining different classifiers. To overcome the facial variation problem most of the researcher first performed some pre-processing steps on the face data sets like face alignment and face detection, etc. Highlighting the weakness of up-to-date techniques is the main emphasis of this work, which will help the researchers to continue their work in this regard.

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