Human Gender Classification Using different Feature Extraction and Classification Methods: A Review

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Abstract- Gender classification is used to authentic face images into pre-defined gender. Substantial enhancement has developed in this field because of its effectiveness in intelligent applications. But the classic approaches of gender classification represent their imperfect control of massive rates of disparities in those gender face images. Feature extraction and classification are performed with several parameters such as accuracy, precision, and so on. In the earlier year, automatic gender classification achieved vast popularity and became the most exciting research field domain. Several investigators have determined and developed the best superior research in this field. But this domain has massive potential due to its effectiveness in different sectors or regions such as controlling, observing, observation, marketable and human-computer interaction (HCI), etc. Gender classification provides higher security facilities by using human face detection. In this paper, wide-ranging gender classification, applications, and features are described, and several challenges and issues are also considered. Different feature extraction methods such as local and global methods, and classification methods, such as SVM, neural network (NN), Fisher's linear discriminant (FLD), real AdaBoost method, etc., are also defined for gender classification.

Keywords- Gender Classification, SVM, Real AdaBoost, Neural Network, FLD, Local and Global Feature Extraction.

I. INTRODUCTION

Gender classification (GC) is a twofold (binary) classification concern that is used to forecast (predict) an image of a male or female. It is a straightforward process for people, however challenging for human-computer interaction (HCI) technology to encounter the human's increasing request for protection and appropriate, consistent, and adapted services. It is also responsible for computer-vision methods such as gesture detection, face recognition, and feasibly highly essential gender classification plays a crucial part in daily human life [1]. The main motive of gender taxonomy is to identify the sexual category of people based on the features that distinguish between males and females, represented in figure 1. In the field of artificial intelligence (AI), the sexual role (gender) is measured to utmost significance. An application of some improvement of gender classification investigation is deriving different shape recognition approach [2]. The development of GC investigation determines several prospective applications. For example, an automated system using gender classification functions is widespread application as a central and realistic analysis field containing HCI [3], protection and observation market [4], demo-graphic study [5], economic progress [6], audio-visual games [7] and portable (mobile) application, etc. Also, multiple tools or technologies are developed to develop the recital (performance) of gender classification in the composition of efficiency and accuracy [8].

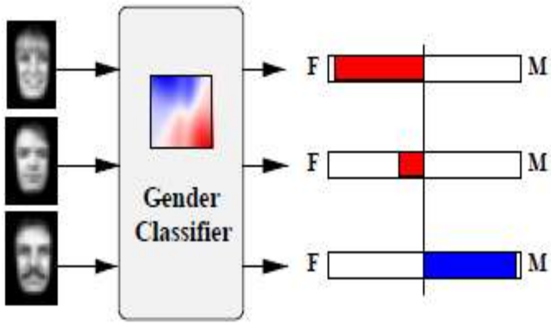

Figure 1. Basic Structure of Gender Classification [9]

Different kinds of features of gender recognition or classification are predicted in different phases. These features are counting collective, individuality, performance or improvement, and accumulating ability to perform gender recognition [10]. The collaborative features must be common between both distinct who can be utilized for unique gender. If these features cannot be extracted over particular, it is unsuitable for gender recognition. The features must be adequately distinctive among men or women in distinctiveness or individuality, such as biometrics, presence, collective network-based, bio-signal, etc. Another feature is that performance or improvement must be constant and not dynamic for a long time, irrespective of age and surroundings. The last feature is that accumulating ability must be calculated or predicted quantifiably, significantly impacting the applications. Several methods are based on characteristics using higher accumulating capacity such as computer-vision-based usefulness etc. It is perfect for concurrent or online applications. In disparity, the methods based on features using less collectability are particularly required in complex or offline applications [11]. In existing work, an innovative CNN-based model of four branch subnets using a modified AlexNet backbone (BSMAB) was constructed, required for feature extraction. The researchers deployed the ant colony system (ACS) method for a group of feature selection and softmax classifiers used to train the proposed model using the existing dataset of CIFAR-100. The features attained from standard ordinary datasets. The improved features group achieved using the ACS method was delivered to different classifiers such as support vector machine (SVM) and K-mean neural network (KNN) for pedestrian GC. The researchers also used a five-fold variety of cross-validation for the training and testing of the existing dataset. The existing method achieved the outcome of optimized feature groups using a hundred features developed over different parameters. In the feature extraction process, random features are considered for the entire implementation of GC. Different feature extraction methods, such as global and local features, are utilized for this purpose. Several kinds of classification methods were deployed for the accurate performance of the GC model. Several methods, such as SVM, discrete AdaBoost, FLD, real AdaBoost etc., offered appropriate results in existing research [12].

In this paper section organization as follows: Section 2 represents different research papers regarding gender classification. It defines the methods, tools, and techniques used by different experts for gender classification. Section 3 describes several research issues and challenges of gender classification and section 4 represents various application areas of gender classification. Section 5 describes the different methods of feature extraction and classification methods. At the end, the section 6 represents the conclusion and further research direction for novel research.

II. LITERATURE SURVEY

Farhat Abbas et al. (2021) [12] described gender classification as only the critical task of pedestrian learning. It discovered real-world applications within content-related image retrieval people, indicators, human-computer interaction (HCI), healthcare, multimedia recovery models, demographic gathering, and learning observations. The authors proposed a model with the help of the deep learning (DL) method and constructed a novel 64-layer model called four BSMAB resultant from deep Alexnet was recommended. The recommended system was accomplished on the CIFAR100 datasets using the softmax-classifier (SC) and characteristics were extracted from beginning practice datasets using this pre-accomplished model. The achieved feature group was improved using the ACO optimization method. Several classifier tools were employed, such as the support-vector machine (SVM) and the k-mean neural network (KNN). These classifiers were required to implement gender classification with the optimized feature group or set. An extensive investigation was executed on the gender classification databases (datasets), and the proposed model manufactured outcomes as compared to the current work. The proposed model reached better performance with the highest accuracy of 85.4% and an area under of curve (AUC) of 92% from the MIT dataset. The most outstanding classification outcomes as an accuracy of 93% and an AUC of 96% in the PKU-Reid dataset. The proposed model's experimental results reached robust performance compared to existing models. **Olatunbosun Agbo Ajala et al. (2020) [13]** described age and gender forecasts on unfiltered faces. It was classified as free actual human being expressions into pre-defined age groups and gender. Major developments were considered in the investigation because of their effectiveness in intelligent applications. But, the classical approaches without filtering standards displayed their incompetence in managing significant rates of disparities in those available images. Further earlier convolutional neural networks (CNNs) based techniques were used for the taxonomy assignment unpaid to their unresolved performance in human face detection. The authors proposed a novel entire CNN method to reach a robust age set and sexual category ordering without filtered real faces. The binary level of the CNN model included FE and classification. The FE-extracted properties were dependable with age and gender during the classification and classified the human facial pictures to the exact age set and gender. Mainly, the authors addressed the significant differences in the uncleared real faces images using the complete image processing (IP) method that made and processed individual faces earlier fed into the CNN model. The proposed method was pre-trained using IMDb-WIKI by noisy labels and formerly modified on the MO-RPH-2 and the preparation group of the creative OIU Adience dataset. The experiment outcomes, while detected or classified accuracy on similar to the OIL – Adience standard. It represents the advanced performance of the recommended method in the composition of age-group and gender classification. The proposed method improved precise accuracy by 16.6%, one-off accuracy by 3.2% for age taxonomy, and enhanced specificity by 3.0% for gender classification. **Jaychand Upadhyay et al. (2022) [14]** described computer-vision usefulness and gait-based gender arrangement as challenging tasks such as individuals moving at different viewpoints based on the camera perspective. In different watching views, the individual branch measured can be impeded by the webcam and avoid the insight of the gait-based properties (features). The authors proposed a durable and inconsequential (lightweight) model for the gait-based masculinity taxonomy by eliminating these issues. It required gait pictures to display the gait of a specific. The discrete cosine transform was realistic based on the GEI to develop a gait-constructed feature vector. Additionally, the discrete cosine transform FV was functional to the X-GBoost classifier for implementing gender classification. The experimental outcomes of the proposed model were calculated based on the OU-MVLP dataset. For gender classification, it achieved a mean-correct organization ratio of 95.33%. These outcomes were acquired from different perspectives of the OU-MVLP, proving the strength of the developed model for gait-constructed classification. **Uraimov Jamoliddin et al. (2022) [15]** described artificial intelligence (AI) receiving a critical portion of human life with its incredible aids and technologies outperforming individuals in identifying things in pictures recognizing mostly organizing populations into precise age and gender collections. The gender classification field was considered highly popular among computer-vision investigators in recent years. The organization of CNN models obtained advanced presentation. But the highly critical CNN-based models were very difficult using different loads of training parameters. Thus they utilized considerable computation delay and assets. Because of this cause, the authors proposed a novel CNN-based classification method using expressively low training parameters metrics and training delay related to the current techniques. Although its less complicated, the proposed method achieved improved accuracy regarding age and gender classification using the UTKFace dataset. **Rajesh Mukherjee et al. (2022) [16]** described an easy biometrics model regarding age and gender and offered applicable data for individual credentials. The hand-related modalities were generally considered for straight biometric detection for several applications. But a slight study consideration was developed to tackle soft biometrics with hand pictures. The authors proposed gender classification with the help of forward (frontal) and dorsal hand pictures. For this proposed method, hand made novel dataset called U-HD-1 was utilized. It represented efficient disparities in unrestrained conditions. The authors composed the model hand images of fifty-seven people to integrate additional handler flexibility in posturing their hands. It consisted of further challenges to differentiate the sexual (gender) category of the individual. For this proposed method, the authors utilized five advanced deep neural (DN) systems as the pillars, and a modest deep model was required for the population gender perception. The proposed method reached an accuracy of 90.49 with the UHD-1 dataset and InceptionV3 model. **Chiranjeevi Pandi et al. (2022) [17]** described the gender classification and analysis of expressions or reactions that played a significant role in security. This classification was used to classify the individual's sexual category into man or woman, but reaction analysis was supported for identifying the individuals' reactions. Different machine learning (ML) methods were constructed for gender classification and the detection of responses of a person. The authors proposed a method to identify the reaction and gender classification parallelly over face pictures. The DL methods were operative over ML methods on massive data. The CNNs were one of the most critical DL models for organizing and identifying images. So the authors for this proposed method CNN's model required for the gender classification and analysis of reaction. The proposed method's experimental outcomes achieved better performance than classical ML methods.

III. RECENT ISSUES AND CHALLENGES

Several alternations in gender classification face some reasons to affect the methods of gender classification. This alternation obtains because of its posture change, brightness, age, culture, etc. For gender classification, Human face image variations such as blur, noise, poor resolution, etc, also impact the gender recognition process. Different impacting issues and challenges are considered as:

- In preparation, the GC is challenging binary issues in which the existing data is allotted to men or women. The GC is a moderately simple process for people but still a complex technological task.
- People can often create an efficient and quick decision based on gender using a graphical representation such as based on the most fundamental feature of gender, which is a relatively distinctive characteristic of shapes [18].
- Persons can freely define gender for the best shapes. Extra data from different features such as body posture, hairstyle, dress, eyebrows, and shape drive aids the indication of growth over the graphical image [19].
- Researchers have debated the acoustic alternations between man and women's speeches [20]. Also, the variations among masculinity and femininity in bodily properties and emotional and neural indications deliver active signs or signal gender classification.
- Earlier psychometric and neural pieces of training specified the dissimilarity of gender represents the change in fluctuating face reactions shown in figure 2, and human head movement during stimulation [21][22].

Figure 2. Different Face Expression [1]

- Furthermore, in existing investigations considering physical dimensions consisting electro encephalon graph (EEG) and deoxyribose nucleic acid (DNA) and day-to-day social data such as electronic mail, blog, writing, etc., men and women are also exposed to several features or attributes for the tool to catalog.

IV. APPLICATIONS

The growth and evaluation of the gender classification approach have led to different essential practices in an extensive application zone. Because the gender analysis methods can expressively enhance the automated observational and non-observational abilities. Gender recognition can enhance the smart functions of observation or prediction models. It also analyses the persons' requests for stock supervision and permits the robotics to identify the sexual category. Several applications of the GC are represented in figure 3.

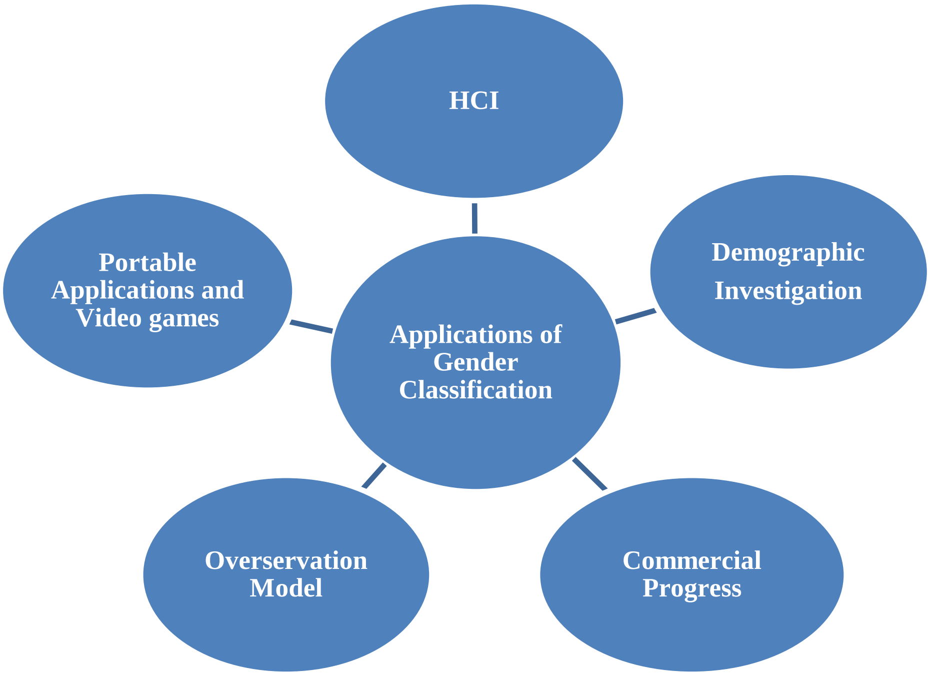

Figure 3. Gender Classification Applications [1]

- **HCI (Human Computer Interface)**

In HCI, robotics or automated machines require to recognize and authenticate people's sexual (gender) classification to enhance the recital of the prototypical or method based on adapted data [14]. By positively defining gender, the model can offer suitable and modified facilities for individuals by familiarizing them with their gender [5].

- **Observation Model**

They categorize gender in observation models for unrestricted locations such as banks and schools. It supports smart security services and observation models to track moving items and sense irregular behaviors. It helps the security research of convicts who intentionally try to hide their specific data. Furthermore, this classification (gender) considered surveillance to help evaluate the risk level for individual gender data that can be robotically achieved in progress [10].

- **Commercial Progress**

The GC is beneficial for administrative and operational marketing and for beginning smart shopping background, in which manufacturers concentrate on particular persons using online websites, e-commerce, e-advertising, etc [23]. For example, in the case of a superstore or departmental store, significant men and women consumers aid the supply administrators in developing proficient trades and dealing resolutions.

- **Demographic Investigation**

The GC is also offers demographic investigation, effectively collecting demographic data [7]. The automated identification of people's sexual categories develops demographic measurements such as race description, disability position, and gender population analysis [24]. The capability to computerize and classify gender data is a different approach to the demographic investigation leading to the website or community spaces [25].

- **Portable Applications and Audio-visual Games**

The GC offers valuable data to enhance human practice in portable mobile apps and audio-video games. In portable mobile applications, specific experts use gender classification techniques to deliver the approach of mobile data (internet) by adapting apps permitting gender. in the field of audio-video games, men and women often have more preferences. It provides help to enable access to gender data to offer their desired game types or content, such as to improve the practicality of audio-video games and letter properties like gait. It can be predicted with the help of the GC methods. Formerly put on several gait shapes to simulate fonts in the audio-video games giving to masculinity enhance the sense of reality [26].

V. SEVERAL METHODS USED IN HUMAN GENDER CLASSIFICATION

Several kinds of classification methods are used for gender recognition. The classification method accepts a face or shape as an input image for implementation. Then, some classification method or technique on this given input face or shape image to achieve accurate results, as represented in figure 6. Several classification methods, such as neural networks (NNs), support vector machines (SVM), real AdaBoost, and Fisher's linear discriminant (FLD), discrete Adaboost, are used for a specific purpose and to develop efficient outcomes. Feature extraction is defined as the process in which some valuable features are predicted or extracted from whole parts of the image dataset. Different feature extraction methods, such as local and global, are used for extraction motives. In local, specific features are extracted from the whole image dataset, and complete image features are extracted in the global feature extraction method. Different classification and feature extraction methods are elaborated as;

5.1 Feature Extraction Method

The main motive of this process is to extract the human facial features of men or women for gender classification, such as different human body posture features of men and women. it is a play vital role in human image gender classification. Features extraction methods extract the complete or random features from the male and female image datasets. It is a very important factor or method for human gender classification. With the help of feature extraction, the gender classification field delivers high security, as it is very helpful for authentication, biometrics purpose, etc.

- **Geometric-based (Local) Feature Extraction Method**

The geometric-based feature extraction method eliminates features from different face attributes such as nose, eyes, etc. Several accurate data are lost with local feature methods [33]. The human face feature eliminated some features approved for a discriminant prediction classifier to dimensions with gender dataset [34]. Several experts have required face feature extraction with external data such as dresses, hair features, etc. In existing research, different experts utilized feature extraction facial recognition technology (FERET) datasets, augmented reality (AR) face datasets, and B-cell mediated immunity (BCMI). But this method is not suitable for complicated backgrounds [35]. Figure 4, represents local feature elimination.

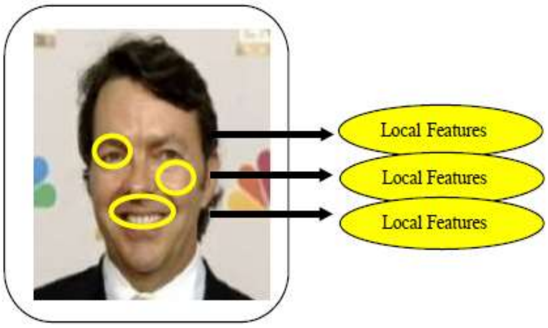

Figure 4. Example of Local Feature Extraction [36]

- **Global Feature Extraction Method**

This method has extracted the complete features from all parts of the human face. In existing research, many experts performed this method, such as the SEXNet model contracted for gender classification and the discrete cosine transform method used for the global method [37]. The k-means method is also required for feature extraction. A novel approach is used to classify gender over human images and it extracts thirty-five features [38]. Another human face investigation found that skin colour and features are extracted using geometric-based human facial features [39] and figure 5, represents global feature extraction.

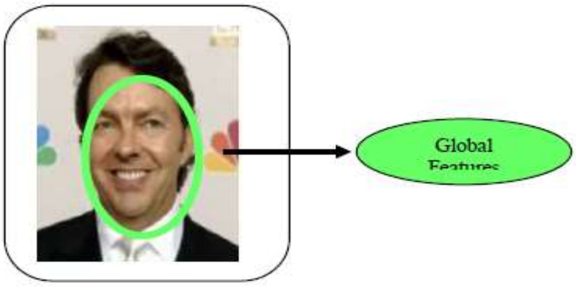

Figure 5. Example of the global feature method [36]

- **Local Binay Pattern (LBP) Method**

This method is feature classification and is measured from pixel amounts in an image pixel neighborhood [30]. The straightforward notion is that term is in different composed values that are made according to the nearest location to the centroid pixel. Finally, these are combined into a single binary weight. Initially, this method is restricted to a 3*3 pixel neighborhood. But it in advance extended into several neighborhoods and fewer other changes were completed [31]. The revolution invariant constant shapes are a delay of the actual LBP. They are resolving the applied problem that more irregular shapes happen too infrequently to make consistent statistics for particular prediction problems.

- **Discrete AdaBoost Method**

This method selects particular features for classification, and low-quality classifiers are required using the chosen features composed of a robust classifier [32]. Features and low-quality classifiers are extensive and organize the existing information instances, such as human face images, to specify the men or women. Triple weak classifiers such as mean, threshold, and look-up table (LUT) are together for human face classification as input data and binary classes as men or women. The threshold classifier collects all weak weights. When human images are classified using a low-quality classifier, the weight evaluated for the human face image by the classifier is associated with the inception. The classification is absolute, either for men or women, based on whether the evaluated weight is low to the weight of the threshold. The optimum threshold weight is chosen at preparation time. So, the lowest potential number of instances of human faces is non-categorized using the feature.

5.2 Classification Models

Human gender classification is a wide-ranging field of classification and delivers several advantages through an accurate model or methods of human gender classification. In human gender classification, different classification methods exist that provide appropriate results. This is required to train and test the gender classification model or method. Various methods are considered as; SVM, FLD, real Adabbost, and discrete AdaBoost.

- **Neural Network (NN)**

Earlier, the face or shape picture is input to the NN with some pre-processing stages. Initially, the human facial picture is mounted. The dimension is 48-48 pixels if required for a particular dimension. The total input weights in the model are equivalent to the number of pixels in cropped face pictures. Formally, the cropped face picture is histogram matched, and its concentration weights are mounted to the array, and these weights are managed in a vector. This manageable vector is provided to the model, which generates the outcome. The negative weight is well-defined as a woman classification, and the true weight represents the men's classification in figure 6.

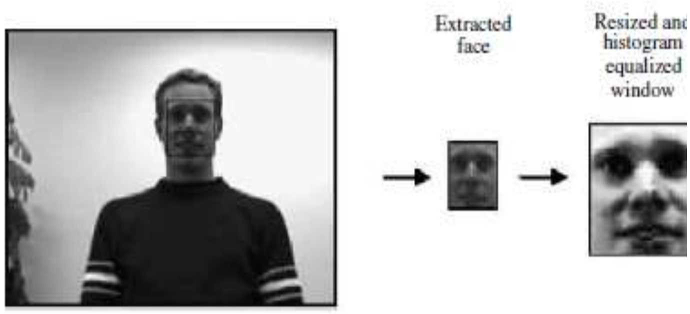

Figure 6. Example of NN classifier [27]

The NN chooses the number of unseen nodes in accumulating the image input nodes and a single output node. There are links among the nodes and links have specific values, and figure 7, represents the NN with multiple layers.

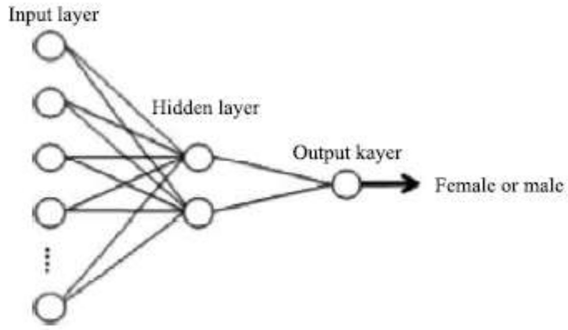

Figure 7. The NN with multiple Layers [27]

- **SVM (Support Vector Machine)**

This method has indicated illustrations such as human face images of several classes, such as men or women. It can be split into a high-size space with swapped features. This classification method attempts to discover an optimum hyperplane for a direct divisible (linear) issue. Assumed S preparation tasters. In equation (i), pi ∈ r^n and qi $= \pm 1$. The hyperplane is described as

SVM = $(\{pi, qi\})$………………..….(i)

w *p + c =0……..………………….(ii)

in equation (ii), w, c = normal vector, and the optimum splitting function is represented as the equation (iii), for linear non-splitting information

$f(p) = SGN\{(w * p) + c\}$ ……………….(iii)

The kernel function maps the image input sample. At the same time, a direct hyperplane may be discovered, and it is represented as;

$f(p) = SGN(\sum_{i=1}^{S} qi, \alpha_i K(p, pi) + c)$…………………(iv)

In equation (iv), $K(p, pi) = kernel\ function$ [28].

- **Fisher's Linear Discriminant (FLD)**

This classification method aims to find the optimum direct (linear) projection. Set the sample group as;

$(p) = SGN\{(w * p) - c\}$…………………..(v)

In equation (v), w = max vector, it is a ratio amongst men and women. c = threshold.

- **Real AdaBoost Method**

This classification method is based on mathematical learning, increasing the classification boundary iteratively [29]. A single poor (weak), T*H*p is predicted from a massive hypothesis placed in all iterations T. The classifiers are composed to build a powerful classifier. The robust classifier is described as;

H$(p) = SGN(\sum_{i=1}^{T} Hi, \alpha_i K(p) -$………………(vi)

in equation (vi), c = empirical threshold, H = Haar feature. The composing uses haar as a feature by integrating pictures. This method is an efficient and fast computational method. It is based on a look-up table (LUT); weak classifiers develop haar as feature additional expressive [28].

VI. CONCLUSION AND FUTURE SCOPE

This paper considers various classification methods using a human face or shape image dataset and feature extraction methods such as local and global FEs. The classification methods such as NN, SVM, FLD, real AdaBoost, and discrete AdaBoost methods are defined and describe several applications and challenges of human gender classification. These methods are provided efficient results for gender classification. This review paper describes the latest feature extraction and various classification methods for gender classification. The development of GC investigation determines several prospective applications. For example, an automated system using gender classification functions is a widespread application as a central and realistic analysis field containing HCI, protection and observation market, etc. In this paper, gender classifications such as gait, human body-based, and human face detection are defined. Existing several feature extraction methods and classification methods are considered for further novel methods or techniques to develop for gender classification. The SVM offered an efficient outcome as compared to other classification methods. The SVM reduces the error rate accurately as compared to other methods. This review paper is beneficial for experts to investigate further research using these classification and feature extraction methods for human gender classification.

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