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Gender Classification Techniques-From Machine Learning to Deep Learning

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ABSTRACT

Automated classification of gender has always been an active area of research in the field of Computer vision and Artificial Intelligence. Advancements in Machine Learning in last decade has produced bunch of state of the art techniques which has further eased the procedure when deployed in Gender classification algorithms used classically reduces the complexity to a great extent and has potential to provide much more efficiency in the prediction process. Currently available complex and cheap GPU chips, the outcome of rising GPU technology with evolving era of Deep Learning has provided further hopes to researchers in Machine Learning to build much more robust intelligent machines which can perform billions of calculation in a fraction of second. Also Cloud computing has been building news in past 5 years which lets us utilize their resources having faster processors, complex GPUs located at a remote server to be used by our own using Platform As A Service-PAAS[1]like Amazon Web Servers i.e. EC2.GPU programming languages like Nvidia's CUDA [2] have increased the speed of computation by sharing the calculation with CPU that gives a fast speed to Deep Leaning as well as Machine learning because they need million of calculation while training process. Thus there are great possibilities in these to be mentioned algorithms to reduce their complexity.

Keywords: *Gender classification, Pattern recognition, Machine learning, Deep learning*

1. INTRODUCTION

In this era of artificial intelligence Gender recognition for robots or automated machines has been equally important as it is for a human being. Our visual cortex in the brain is more sensitive and responsive to particular features of a scene as edges, lines and motion etc. Our brain stores this information of a scene in some patterns and recalls the same to retrieve information for classification of the objects. Gender classification has always been an attractive problem which started from SEXNET [3] in which gender recognition was tried for face images. But it is not preferred using face images because when cropped, resolution of the images goes very low that reduces the information also there are chances of the image to be occluded by glasses mask or face hair. So researchers also proposed methods using gait analysis [4] but it did not simply removed the flaws.

1.1. Objective of Study

1.1.1. Human Machine Interaction

A variety of useful human-computer interaction systems have been designed as- Robot receptionist at Henn na Hotel that extracts the demographic information of the person when he/she checks in, then interacts accordingly. I further thing think that there is much more possibilities in this human machine interaction. 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; without manually requiring any details about gender to address the human appropriately.

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1.1.2. Targeted & Adaptive Advertising

Conventional advertisement system has been used for decades to display the ads on flat panel displays cards in Supermarket or in cities. But a new approach of targeted advertising is considered which uses to display advertisement relevant to the person detected at the camera on attributes for example gender, age, race etc. For example, such system may choose to show ads of wallets when a male is detected, or party dresses if detected person is female. Thus we would make a person see what he/she wants or would be like to see. Further the purchase history of the targeted person can be fed to the system to better customize the advertisements thus will provide adaptive advertising.

1.1.3. Biometrics

Applicability of face recognition is widely known and getting utilized already at broad level. In classical techniques time for searching the face database can be minimized if the system gets to know about the gender of the person. Then it searches in the specified segment of male or female using gender information to enhance the accuracy of the result. It only needs to store the database accordingly.

1.1.4. Surveillance System

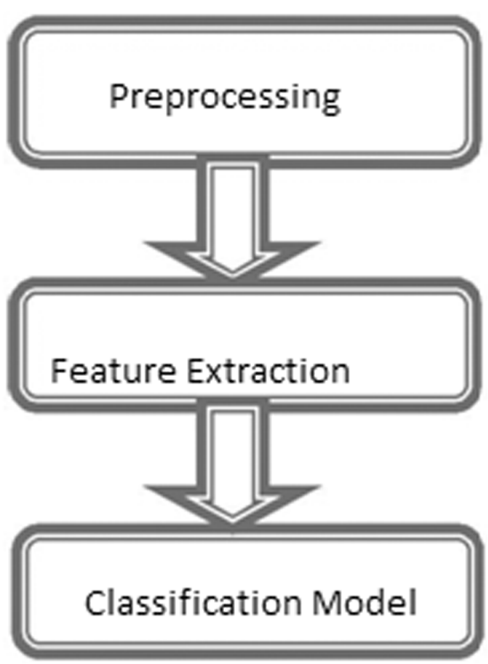
This is an important application area as security at building entrances such as hostels in which it can assist in restricting region to one gender only. Automated surveillance systems are also be very critical to pay more attention a higher threat level to a specific gender.

1.1.5. Content based Indexing and retrieval

Indexing or annotating information such as number of people in the image or video, their demographic information as gender or age, will become easier with automated machines using computer vision and machine learning. In addition to this, for content-based searching such as looking for a photo of a person, identifying gender will reduce the amount of search and time required.

1.2. Gender classification flowchart

Gender classification consist of basically following steps-



1.2.1. Preprocessing

Every dataset needs some preprocessing to fit with your algorithm-such as cropping, face detection, normalization of pixel values etc.

1.2.2. Feature Extraction

Since images have complex representation in computer memory, so they need to be transformed into some simple representation upon which mathematical operations can be applied easily. So, features of the images can be extracted which can be Geometric features or appearance based features.

1.2.3. Classification Model

It is a mathematical model that separates the images into several categories based on the features of these images. Different kinds of classification algorithms are there-Logistic Regression, Support Vector Machine, K-Nearest Neighbor, Neural Networks etc.

1.3. Challenges

Different variations in the images as-pose, occlusion, scaling, and rotation affect the classification algorithms .While image capturing factors like- blurring, noise, resolution can make face image analysis a challenging task. Benabdelkader[5] observed that classifier efficiency and performance reduces due to variation in ages. Gua [6] claimed after performing gender classification on large datasets that gender classification accuracy is higher on adult faces compared to young ones.

1.4. Local Feature Extraction (Geometric based)

For gender classification throughout the body faces are considered to have maximum after of discriminative information. In geometric based feature extraction features are extracted by some facial points like nose, eyes, and eyebrows. These features are then piped to some discriminant analysis classifier. Li *et al.*,[7] utilized external information like cloths, hair features along with five facial features (nose, eyes, mouth, eyebrows, forehead) using FERET,BCMI and AR face dataset. Problem with this method was that their features extraction method was affected by background of images. Han et al.,[8] categorized features into 2 groups- local features and global features. They concluded that male eyebrow is thicker than female one and female nose is relatively smaller. Different landmarks were placed at face then facial features were extracted.

1.5. Appearance based Feature Extraction (Global Features)

In this method features are extracted from whole face rather from facial point. Golomb et al.[3], got 91.9% accuracy on 90 face image dataset-SEXNET. Nazir et al.[11] used discrete cosine transform to get features from face and train a K-Nearest Neighbor Classifier to train on these features. They have used SUMS dataset of face images. This algorithm faced the problem of occlusion. Liagliang et. al.[10] tried to estimate gender from body contrasting to majority of researchers which did the same using face images. They have found the edge maps and HOG features of the images. They have used Adaboost and Random forest classification techniques for gender detection. The issue which they have been facing was the background of the body images that actually has no useful information.

1.6. Image Features

Images have a complex representation when stored in computer memory. They are set of millions of pixels. So apply algebra on this one need to convert these into a feature vector of lesser dimension. Thus features are more dimensionally reduced informative and less redundant representation of images and lead to better human interpretations.

There are several features taken in concerned while classification-

1.6.1. SIFT-Scale Invariant Feature Transform

Published by David Lowe, SIFT is used to detect and describe local features. These features are not sensitive to uniform scaling, orientation and illumination changes. SIFT can recognize object even when semi occluded or cluttered. SIFT features show the similar properties of inferior temporal cortex which are responsible for object recognition in primary vision.

1.6.2. SURF- Speeded Up Robust Features

A local feature detector and descriptor that is much inspired by SIFT and several times faster as well. It is widely used for image recognition and classification. SIFT approximates Laplacian of Gaussian in form of box filter contrast to SIFT which does so in form of difference of Gaussian. It finds image interest points using Hessian Matrix. OpenCV, Matlab, R programming languages provide inbuilt library for SURF implementation.

1.6.3. Principal Component Analysis

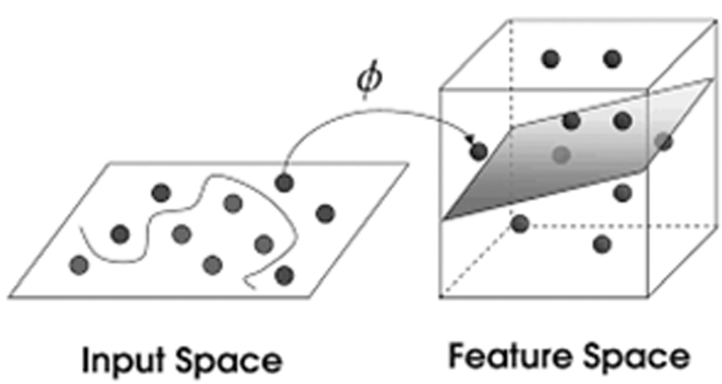
It is an orthogonal linear transformation that transforms data into new coordinate system in a way that greatest variance by some projection of data comes to fall on the first coordinate and second one on second coordinate and so on. It is very useful in dimensionality reduction that eases the visualization and processing of high dimensional dataset. It is sensitive to scaling of variables.

1.7. Classification Algorithms

These are mathematical models which when fed by features of a signal-audio, video, text or image classify them as per the rules defined. Most useful models used in concern are-

1.7.1. Support Vector Machine

Support Vector Machine is a supervised learning algorithm for feature or pattern classification. The basic idea behind SVM is to find the optimal linear hyperplane such that the expected classification error for test data is minimized .For linearly non-separable data, SVMs can (nonlinearly) map the input to a high dimensional feature space where instead of initially being nonlinear behaviour a linear hyperplane can be found easily. Although there is no guarantee that says -a linear separable line or plane will always exist in the high dimensional space, but in practice it is quite feasible to obtain one. It provides relatively less error than any other classification algorithm.



1.7.2. Boosting

It is a technique that is used to formulate a strong classifier by combining set of weak classifiers thus named boosting. There are several boosting algorithms but widely used one is Adaboost (Adaptive Boosting) invented by Robert Schapire in 1990.It is an ensemble learning algorithm which iteratively builds an additive classification model .In vision problem it is usually used with Decision trees as weak classifiers.

1.7.3. Decision Trees

It is a supervised model that is formed by series of questions and their respective answer. Finally at leaves no one has any questions. It consists of two or more branches and several leaves. Leaves provide the classified output value of target variable. It predicts the value of target variable based on simple learning rules inferred by data features. Along with classification they are also used for regression tasks.

1.7.4. K Nearest Neighbor

K nearest neighbor or KNN classification algorithm determines the decision boundary locally. For 1NN each training data sample is assigned to the class of its closest neighbor. For kNN each sample data is assigned to the majority class of its k closest neighbors where k is a parameter. The training data samples are vectors in a multidimensional feature space, each with a given target class label. While classification,*k* is a user-defined quantity, and a test point is classified by assigning the label which according to the distance calculated, is most frequent among the *k* training data samples nearest to that test value. A commonly used distance metric for continuous variables is Euclidean distance.

2. LITERATURE REVIEW

Liangliang Cao et al. [10] have build a model to classify gender from body images. They transformed images into raw pixels and edge maps as well because raw pixel gives poor efficiency because of variation of cloth color. They obtained edge maps using Canny operator given by John Canny at Purdue University. Small changes in illumination and position cause significant change in edge features so it does not give a robust representation. So they also found Histogram of gradients feature which represents edge with magnitude weighted histogram grouped according to edge direction. They used two classification techniques – Adaboost and Random Forest. Dataset used was MIT Pedestrian dataset that is available publicly. They manually labeled it since there is no body image dataset available. Their results are given in table below.

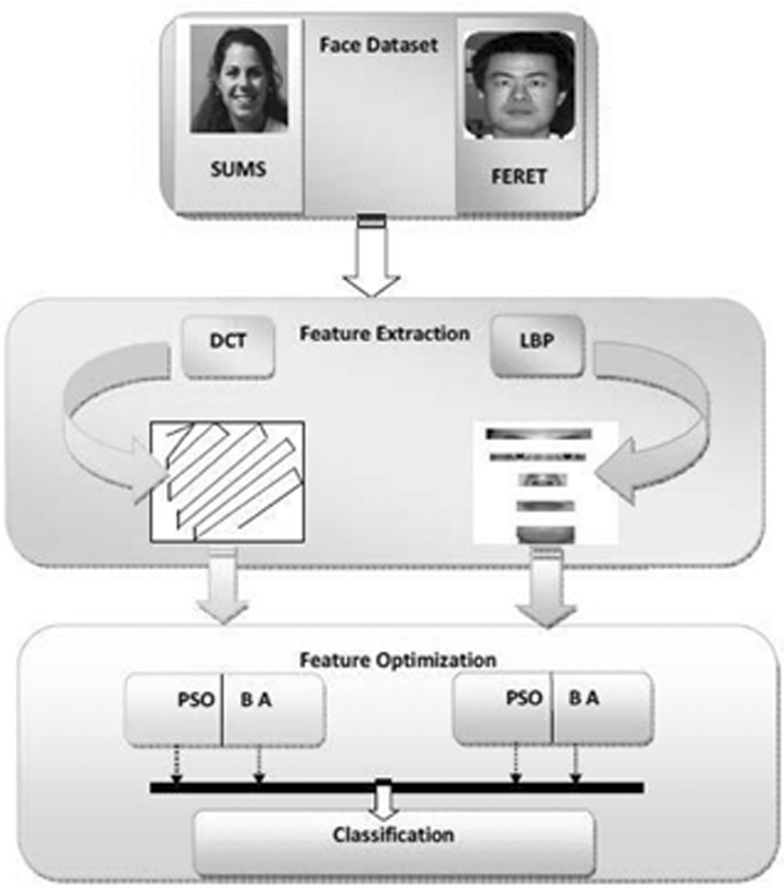
Table 1
Comparison table

Methods	*Frontal View*	*Back View*
Ada + Raw	71.7 ± 3.6%	61.5 ± 4.3%
RF + Raw	72.8 ± 3.7%	60.2 ± 4.4%
Ada + Edge Map	71.1 ± 3.6%	70.1 ± 3.7%
RF + Edge Map	73.1 ± 3.7%	63.9 ± 4.4%
Ada + HOG	70.9 ± 4.4%	63.0 ± 4.1%
RF + HOG	73.1 ± 3.5%	65.8 ± 4.2%
Ada + Part	71.9 ± 3.4%	71.2 ± 3.3%
RF + Part	73.2 ± 2.4%	65.4 ± 0.0%
PBGR	76.0 ± 1.2%	74.6 ± 3.4%

Nazir et al., [11] have proposed new method which classifies gender much more in relatively efficient way than other existing techniques. I preprocessing 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, then popular boosting technique AdaBoost algorithm is used to select key features in image, then Cascade of AdaBoost work as a classification model by which they discarded the background from an image. To bring the image lighting effects to its normal state histogram equalization is used. They already 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 utilized. They have stated that DCT is used for dimensionality reduction and it scans the image in zigzag manner, starting from the upper left corner. After using DCT, 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 picked up thus dimension has been reduced. Classification work is given to K-nearest neighbor (KNN) classifier which worked is based on Euclidean distance to find their closest neighbors. Experiment has been performed on Stanford university medical student (SUMS) face database. They have concluded that if the training and testing ratio for KNN classifier is 50 to 50 then accuracy of 99.3% is obtained. Their results are more accurate when compared with Support vector machine (SVM), Neural Networks (NN), and Linear discriminate analysis (LDA) techniques.

They have 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 do not support pose variation so if some variation in gender image then face will not detect.



Technique Flow Diagram

Graf et al. [12] have address the issue of combining pre-processing methods and dimensionality reduction using technique called Principal Component Analysis. (PCA) and Locally Linear Embedding (LLE) along with Support Vector Machine (SVM) . An altered and processed version of the MPI head database has been used.PCA removes the redundancy in face images. Particularly, Eigen face features has been calculated that is PCA decomposition with eigen vectors of non zero values. Classification has been performed with Support Vector Machines having normalized kernel.

They confronted with 3 parameters optimization problem-

1. Tradeoff parameter c of SVM
2. Kernel Function
3. Number of nearest neighbors of LLE

They found that c for minimum classification error is not equal to c for least number of support vectors but first one has been considered as more relevant to problem. By doing the same for LLE with polynomial kernel of order 2, classification error does not show a global minima and number of support vectors is constant. So they have chosen the same optimum c value of PCA here too. They concluded that PCA face space is superior to that introduced by LLE. For classification task but PCA face space is linearly separable with respect to gender.

Sun et al., [13] have used Local Binary Pattern that is a powerful operator for texture description, proposed by Ojala originally, which has been defined as a grayscale invariant texture measure, derived from a general definition of texture in a local neighborhood. They used FERET dataset with 2000 training images having 1200 male and 800 female persons. They have cropped the face area from original image based on the two eyes location. The cropped images are scaled to 144 pixels high by 120 pixels wide and then processed by illumination compensations and histogram equalization technique. Using LBP features a face image is equally divided into small sub windows from which LBP features have been obtained and concatenated into a single entity, spatially enhanced feature histogram. They divide 144×120 pixels facial image into 24×20 pixels.

They have applied the Self Organizing Maps (SOM) method to separate the training set into10 classes, 5 for male images and 5 for female images. After SOM training, the final weight vector for each node is the centroid of the class, i.e., the template vector, which corresponds to the template of each class. Classifying the male and female images from training set, they have found out that the area of eyebrow, bridge of a nose, and chin contribute the most effective features to discriminate men and women. As a result, a weights set corresponding to the divided face images is designed to improve the performance of the gender classification.

In second experiment performed by them scaling and shifting sub windows are used to obtain the features and boosting algorithm Adaboost is applied to select the useful features and computed the weights, which can overcome several drawbacks of first experiment effectively. In this experiment there are 12221 LBP features in total extracted by scanning the each face image with scalable windows. The LBP histograms in a given class are averaged to generate a histogram template for this class.

Ning Sun et. al.,[13] have designed two experiments for gender classification based on Local Binary Pattern operator. The two experiments are all made on the image set collected from FERET. Experiment A is performed to test the effectiveness of LBP feature for gender classification Here a face image is equally divided into small sub windows from which LBP features are obtained and concentrated into a single, spatially enhanced feature histogram. Experiment B is an experiment of classifying gender based on boosting LBP. There are obviously two aspects that can be improved in experiment A (1) The equal division of five image limits the variety of the size and position of the extracted features (2) The weight set of chi square distance is pre-defined, which may be rough and subjective.

Xiao-Chen Lian et. al., [7] have made experiment on gender classification system which makes decisions by integrating face and hair information. To represent the face information, only local facial features are used, that is, the eyes, nose and mouth regions of a face are extracted and discard the rest parts. Hair is hard to represent due to its large variation. In the literature of pattern recognition, there are generally two categories of information integration approaches. One is feature combination and the other is classifier combination.

One major contribution of this paper is integrating hair and face features through fuzzy-integration-based classifier combination approach. Moreover, instead of using the whole face, features of facial components are extracted by MMC. The experimental results show that MMC outperforms PCA and FDA, and the gender classification benefits from incorporation of hair. A future extension of this work is to utilize clothing information.

Xuelong Li et. al., [14] have done an experiment on human giant recognition. Gender recognition has received a fair amount of attention in the psychophysical and computer vision literature, especially in the case of gender recognition based on face. There are relatively few giant-based studies. A human face image is treated as a vector and independent component analysis (ICA) is then applied to reduce the dimension of the data space. A support vector machine (SVM) is used to further improve the classification performance. The SVM is also used for gender recognition based on face images.

Caifeng Shan et. al. [15] have investigated gender classification from human gaits and faces using machine learning method. Experiments on the CASIA Gait Database are carried out, currently one of the largest gait databases in the gait-research community. The databases consists of 124 subjects aged between 20 and 30 years, of which 93 were male and 31 female and 123 were Asian and 1 was European. Each subject first walked naturally along a straight line six times, then put on his/her coat and walked twice, and finally walked twice carrying a bag (knapsack, satchel, or handbag). Each subject walked a total of ten times in the scene (6 normal + 2 with a coat + 2 with a bag).

Before fusing gait and face modalities, first gender recognition with faces is performed, and reports the results in Table 2. By comparing Table 1 and Table 2, one can see that recognition results based on faces alone were consistently inferior to that based on gaits, which indicates that it is hard to learn human gender from low-resolution faces captured in unconstrained environments. For face-based gender recognition, SVMs have a clear margin of superiority over the linear subspace method PCA+LDA; the polynomial kernel also achieved the same performance with the linear kernel, but RBF kernel was found to perform best. This indicates that the face data can be better gender classified by the nonlinear decision surfaces. The numbers of support vectors of the linear/polynomial kernels were 23-24 percent of the total number of training samples, while the RBF kernel employed 25-39 percent.

In this paper, an important but understudied problem in visual surveillance is investigated, gender classification from human gaits. A method to effectively fuse gait and face at the feature level is proposed for improved gender discrimination. Experiments demonstrate that multimodal gender recognition system achieves the superior recognition performance of 97.2% in large datasets.

Bo Chunjuan et. al. [16] have studied gender classification which has been investigated from both psychological and computational perspectives used for face recognition, identification, etc. In these experiments, 661 images of 248 subjects are collected from the FERET database which are cropped and resized into 32×32 pixels. 200 images (100 male and 100 female) are selected for training and use the remaining 461 images for testing. For the raw pixels and Gabor (sum) features, the Gaussian kernel is chosen to train the SVM classifier. In this study novel texture feature, relaxed pixel-pattern-based texture feature (RPPBTF) is proposed for gender classification. Compared to the original PPBTF method, the proposed RPPBTF algorithm adopts a soft operation for extracting texture features which alleviates information loss without introducing much computational load.

Yunus Saatci et. al. [17] investigate many different approaches for facial expression in static images which have been evaluated in the recent past years. Pantic and Rothkrantz survey the large variety of such techniques and find that all of them consist of three majors steps: face detection, a mechanism for extracting facial expression information, and a mechanism to classify the information extracted according to some pre-defined set of categories. Though gender classification has attracted the interest of many cognitive psychologists, the number of attempts made at automating the process has been fewer in comparison. The first attempt was made by Gollomb et. al. who trained multi-layer neural network, SEXNET, to classify gender in 90 image samples of men and women. Brunelli and Poggio [1] followed a feature-based approach where two competing Radial Basis Functions (RBFs) (one for male and one for female) were trained on the geometric relationships between facial features.

Moghaddam and Yang [9] have proposed a non-linear SVM for gender classification using the FERET database where the feature vectors for the SVMs were given by the grayscale values of "thumbnail" face images. They quote an error rate of 3.4%, which seems to be the best result in the open literature. In order to train an AAM will be useful for expression classification system, it was necessary to have an annotated dataset of full-frontal face images in which subjects displays each of the four expressions genuinely.

It has been also an important that the faces in the training set had different appearances as determined by gender, race and the existence of facial hair and/or glasses, since this would improve the generalization performance of the final recognition system. With these considerations in mind, dataset of 1,135 samples drawn from the Purdue AR dataset [8], the IMM dataset by the Denmark Technical University [13] and the search procedure are used. It is also worth noting that the final AAM had 60 control parameters and hence 60 dimensional feature vectors.

After obtaining AAM feature vectors from the full-frontal face image dataset, gender classification involved constructing a training set by using 60% of the feature vectors (randomly chosen) to train a family of SVMs (just as in Section 4.2). The SVM which gave the highest accuracy whilst being tested on the remainder (40%) of the dataset was chosen to be the most superior gender classifier. The optimal classifier was found to have a staggering accuracy of 97.6% and a false positive rate of 0.735%. The area under the ROC curve, as shown in Figure 5, was close to its ideal value: 0.986. In the ROC curve, the positive class was arbitrarily chosen to correspond to the male class.

The architecture and performance of an expression and gender recognition system is described that uses AAMs for feature extraction and SVMs for classification. By iteratively optimizing accuracy over a test set, an optimal cascade consisting of binary SVM classifiers for a set of 4 basic expressions is constructed. The cascade performs significantly better at recognition and disambiguation than other classification combination schemes such as maximum margin. Performance can be improved further by combining gender and expression classification. Best results were obtained using a tree structure consisting of two expression classification cascades that were selectively trained on male and female images respectively as determined by an initial gender classifier.

Gil Levi and Tal Hassner [18] have presented an unprecedented approach called Convolutional Neural Networks that derives intelligence from massive data available on internet. This method is really a novel approach emerged with rise of Deep learning in past 5 years pioneered by research led by Google, Microsoft, Baidu, Nvidia etc. It outperforms all previous methods discussed by a huge margin. They have used LeNet, a pertained Convolutional neural network model to extract features and classify gender. Method is implemented on Caffe, open source framework[19]. Training was done on Amazon web service GPU with 1536 CUDA cores and 4 GB of data. It provides more than 99% accuracy. Mistakes are done frequently on images of babies with obvious reason that gender attributes are not visible.

Table 2
Techniques Critical Evaluation

Lite Ref.	*Technique Used*	*Focus Area*	*Proc*	*Cons*
[11]	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.
[13]	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
[20]	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
[21]	Feature extraction for face detection and gender recognition using support vector Machine information	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.
[22]	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
[10]	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
[7]	Hybrid gender recognition approach using facial and hair information	Feature extraction using maximum margin criterion	Less redundant Facial features robust due to hair information used	Need of aligned faces and hair information is not much discriminative
[13]	Boosting local binary Pattern (LBP)	Adaboost ensemble classifier	Strong classifier by using weak ones	Slower due to being built of multiple classifiers
[17]	Gender recognition using Active appearance Model	Active appearance Model with SVM	Proposed technique leads towards better results because of cascaded binary SVMs used recognition multi- view face images	In shape model it needs all aligned images of faces that is tedious task in preprocessing

3. CONCLUSION

Thus it has been tried to address all the advanced and novel techniques that have been used in the area of demographic information estimation**.** The approaches used to classify gender are broadly gait-based, body-based and face-based. Most of the researchers focus to classify gender using face images. But advancements in machine learning and computer vision have made it possible to do the same using full body images and even with images having partial information. Some of the significant problems which are still facing by the researchers are facial variations like occlusions, expression changes, pose variations illumination and intensity effects, computational time and high dimensionality. Working on pixels to classify gender is more computationally expensive so researchers prefer to extract face features rather than direct work on pixels. Feature-based methods are categories into two i.e. global feature and local features. It is concluded that in the classification step, support vector machine is performing well as compared to other classifier algorithms. Similarly, on the other hand classification accuracy rate is also enhanced by combining different classifiers called ensemble classifiers. To overcome the facial variation problems occurred, most of the researchers have first performed some pre-processing steps on the face and body data sets like face alignment and face detection etc. Highlighting the weakness of up-to-date techniques is the main emphasis of this literary work, which will help the researchers to continue their works in this concern.

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