Gender Prediction using Individual Perceptual Image Aesthetics

Samiul Azam
University of Calgary
Dept. of Computer Sci.
Calgary, Alberta, Canada
samiul.azam@ucalgary.ca

Marina Gavrilova
University of Calgary
Dept. of Computer Sci.
Calgary, Alberta, Canada
mgavrilo@ucalgary.ca

ABSTRACT

Images have rarely been used for psychological behavior analysis or for person identification in the information technology domain of research. In this paper, we present one of the first methods that allows to accurately predict gender from a collection of person's favorite images. We select 56 image aesthetic features, and propose a mixture of expert models consisting of support vector machine, K-nearest neighbor and Decision tree. Final decision is taken based on the weighted combination of probability generated by individual classifiers. We introduce a genetic algorithm based method to improve the prediction accuracy of the model, which allows us to find the best combination of feature subset in 56D binary search space. Moreover, feature dimension is reduced significantly that decreases the testing time. Finally, three weights of the prediction model are adjusted using genetic algorithm in 3D real-number search space. Experimental results conducted on a true image database of 24000 images provided by 120 Flickr users. The experimental results demonstrate superiority of the proposed method over other approaches for gender prediction from perceptual image aesthetics preferences.

Keywords

Perceptual image features; Gender prediction; Image aesthetic features; Ensemble of classifiers; Probability; Genetic Algorithm

1 INTRODUCTION

Traditionally in computer graphics and image processing domains, images are used for classification [Iiv03, Lee03], visual data exploration [Mol14], landmark recognition [Pri13], pose estimation [Tew15] or image reconstruction [Ska13]. However, images have rarely been used for psychological behavior analysis or for person identification in the information technology domain. In this paper, we address this gap and study effects of human aesthetic perception, expressed through choice of favorite images, onto behavior and gender recognition of a person. Recently, it has been shown that a person's visual preferences can be measured using image aesthetic features and his or her favorite images [Lov14]. Moreover, there are differences between male and female neural correlation of aesthetic preferences [Cel09]. A study on website appearance concurred with the fact that males and females have differences in aesthetics perception [Mos06, Mos07]. This research motivates us to look deeper into the possibility of gender identification from a set of individual's favorite images.

Preliminary research on gender recognition was recently conducted in the Biometric Technologies Lab at the University of Calgary. It was relying on aesthetic preferences, tested on a database of 120 Flickr [Fli04] users, and has been accepted for publication to ICCI*CC 2016 [Aza16]. The main novelty of the current work is in proposing to use the genetic algorithm to improve the prediction accuracy. While both the preliminary and the current research use the same set of aesthetic features tested on the Flickr image database, the newly proposed method uses genetic algorithm (GA) for best feature subset selection, as well as choosing the best weighted combination of the three classifiers. This, in turn, and allows to achieve a higher accuracy of a gender recognition, compared both to similar research and the recently developed algorithm [Aza16].

This paper is organized as follows. Section 2 presents the literature review on social behavioral biometric and gender prediction research. The proposed methodology of gender prediction is described in Section 3. Section 4 presents the experiment conducted on Flickr users. Finally, discussions and future directions are outlined in Section 5.

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2 LITERATURE REVIEW

In the area of biometric, most of the research on person identification and gender estimation is conducted through processing of images or videos. A person's walking pattern (or gait) is a popular trait for identification and gender estimation where video data is collected using conventional surveillance camera or KINECT depth camera [Ahm15a, Ahm15b, Gur11]. Another large domain is the processing of face image for recognition and gender estimation [Sul15, Dan16, kuk04]. Besides that, social activities of a person can be used for identification and gender prediction which are known as social behavioral biometrics [Mad14]. In the recent years, with the rise of popularity of on-line social networks (OSN), such as Pinterest [Pin10] and Flickr [Fli04], more and more users sharing their views, choices and preferences in the form of images and videos. In the OSN Flickr [Fli04], people share their favorite images that contain a person's visual aesthetic preferences. A 2012 research proved that it is indeed possible to establish an identity of a person experiment from Flickr user's image preferences [Lov12]. They extracted contextual and perceptual image aesthetic features and generated a template for each Flickr user based on those features using LASSO regression. An improved version of this method was introduced two years later [Lov14]. By incorporating more distinctive image aesthetic features, they reported 96% accuracy at rank 20. Instead of LASSO regression, authors in [Seg14] applied counting grid model and support vector machine (SVM) to generate template, which resulted in 98% accuracy in Flickr user identification experiment conducted on the same database.

Gender is one of the common demographic features used as a soft trait in the area of human authentication biometric [Gav13, Dan16]. Gender prediction from the context of social behavioral biometric has (if ever) rarely been explored in literature. Very recently, authors in [Qua14] used image based OSN Pinterest [Pin10] to predict gender from user's image posting behavior and image contextual features. They applied a bag of visual word model to identify the difference between male and female users. They conducted their experiment on 160 users (80 male and 80 female) from Pinterest, and depicted 72% accuracy in gender prediction. One of the shortcomings of the approach is that it used 33 board categories of Pinterest (posting behavior) as features for gender prediction, which makes the method very limited to a specific OSN. In this paper, we propose a gender prediction method where gender is predicted from a person's favorite list of images only. To make the method OSN independent, user's posting behavior is ignored as a feature. For experiment, we use the 200 Flickr users database (contains 40000 images) provided by one of the authors from the article [Lov12]. We have done a preliminary research on gender prediction using image aesthetics [Aza16] which shows 76.65% accuracy over the same database. In this paper, we present a different methodology which results in the improvement over the preliminary work. We use genetic algorithm for feature selection, as well as weight adjustment of the prediction model, which allows to reach approximately 83% accuracy of gender prediction. This is higher than all of the current state of the art methods (by 6% to 12%). Also, it's worth noting that unlike typical biometric identification based on much more concretely defined data (i.e. ear, palm, face, gait etc), gender identification is based on the soft biometric features which makes it a much harder problem.

3 METHODOLOGY

The detail description of the proposed gender prediction method is provided in the following subsections.

3.1 Collection of Aesthetic Features

The proposed gender prediction method uses a person's aesthetics as a cue to his or her gender prediction. Different types of aesthetic features were introduced by researchers for the purpose of automatic image ranking [Ayd15, Mar11, Rit06, Jia10], image classification [Xia13, Jan10] and person identification [Lov12, Lov14]. After a comprehensive review, we identify five categories of image aesthetic features that are mostly found in existing articles: 1) image content; 2) composition; 3) texture; 4) color and 5) image parameters. Detail description of all these features can be found in the previous works. For simplicity of implementation, we use a subset of the above features [Aza16] composed of image composition, texture, color and parameter features in our proposed model. The length of the features vector is 56. Brief description of the features are provided in Table 1 with assigned feature number.

Performance of a machine learning based model depends on the feature vector used in their training and testing. Convergence of decision boundary relies on the features. Some features are highly distinctive, and are sufficient to describe the model efficiently. On the other hand, some features are unnecessary which increase the training and testing time, as well as move the decision boundary away from the best position. So, the feature selection is a crucial step for our prediction model also. In the subsection 3.3, we describe the feature selection step used in the proposed prediction model. After the selection step, we identify a set of distinctive features for each classifier (in the mixture of expert model) that maximizes their classification accuracy, and speeds up the testing time by reducing dimension of the feature space. In the supervised learning phase, we train each classifier of our ensemble using the selected features. We group the images into two labels or classes: male

Feature	Brief description
f_1	Average intensity of V channel in HSV image
f_2	Average intensity of S channel in HSV image
f_3	Standard deviation of V channel in HSV image
f_4	Standard deviation of S channel in HSV image
f_5	Entropy of RGB image
f_6	Aspect ratio of the image
f_7	Rule of thirds in H channel
f_8	Rule of thirds in S channel
f_9	Rule of thirds in V channel
f_{10}	Hue Circular Variance
f_{11}	Canny edge pixel count
f_{12}	Emotion based: Pleasure
f_{13}	Emotion based: Arousal
f_{14}	Emotion based: Dominance
f_{15}	Colorfulness
f_{16}	Tamura directionality
f_{17}	Tamura contrast
f_{18}	Wavelet Textures in H channel: level 3
f_{19}	Wavelet Textures in H channel: level 2
f_{20}	Wavelet Textures in H channel: level 1
f_{21}	Sum of f_{18}, f_{19}, f_{20}
f_{22}	Wavelet Textures in S channel: level 3
f_{23}	Wavelet Textures in S channel: level 2
f_{24}	Wavelet Textures in S channel: level 1
f_{25}	Sum of f_{22}, f_{23}, f_{24}
f_{26}	Wavelet Textures in V channel: level 3
f_{27}	Wavelet Textures in V channel: level 2
f_{28}	Wavelet Textures in V channel: level 1
f_{29}	Sum of f_{26}, f_{27}, f_{28}
f_{30}	low depth of field: H channel
f_{31}	low depth of field: S channel
f_{32}	low depth of field: V channel
f_{33}	GLCM texture features in H channel: Contrast
f_{34}	GLCM texture features in H channel: Correlation
f_{35}	GLCM texture features in H channel: Energy
f_{36}	GLCM texture features in H channel: Homogeneity
f_{37}	GLCM texture features in S channel: Contrast
f_{38}	GLCM texture features in S channel: Correlation
f_{39}	GLCM texture features in S channel: Energy
f_{40}	GLCM texture features in S channel: Homogeneity
f_{41}	GLCM texture features in V channel: Contrast
f_{42}	GLCM texture features in V channel: Correlation
f_{43}	GLCM texture features in V channel: Energy
f_{44}	GLCM texture features in V channel: Homogeneity
f_{45}	Color pixels in HSV image: Black
f_{46}	Color pixels in HSV image: White
f_{47}	Color pixels in HSV image: Gray
f_{48}	Color pixels in HSV image: Red
f_{49}	Color pixels in HSV image: Orange
f_{50}	Color pixels in HSV image: Yellow
f_{51}	Color pixels in HSV image: Green
f_{52}	Color pixels in HSV image: Cyan
f_{53}	Color pixels in HSV image: Blue
f_{54}	Color pixels in HSV image: Purple
f_{55}	Color pixels in HSV image: Magenta
f_{56}	Color pixels in HSV image: Pink

Table 1: All the image aesthetic features [Aza16] considered in our prediction model.

and female. During training each classifier, we ignore the user information (only consider it as a two class classification problem). Later, these trained classifiers are used in the proposed model to predict gender from a person's bag of favorite images. Figure 1 shows the steps of feature selection and training phase. In the figure, S_F and S_M means set of images selected by female and male persons respectively.

3.2 Prediction Model

In this paper, we use the same prediction model that we proposed in [Aza16] for gender prediction using perceptual image aesthetic features. The model is a mixture of experts [Mik11, Dym05] where decision (probability of being female) of three well known binary classifiers: support vector machine (SVM), decision tree (D-Tree) and k-nearest-neighbor (KNN) are combined to make the final prediction [The08]. Here, each individual classifier is trained based on different feature spaces (having different dimensions) which make them distinct from each other. So combining their results minimizes the final prediction error. Figure 2 shows the block diagram of the prediction model. In the model, the probability of a person being female (P_f^{mix}) is calculated based on the weighted ($w^{'}$, $w^{''}$ and $w^{'''}$) combination of individual probabilities ($P_f^{'}$, $P_f^{''}$ and $P_f^{'''}$) generated by each classifier. The equation for P_f^{mix} is as follows

$$P_f^{mix} = w^{'} P_f^{'} + w^{''} P_f^{''} + w^{'''} P_f^{'''}. \quad (1)$$

The positive weight values multiplied with each classifier's prediction define the influence of individual classifier. Assigning higher weight to a classifier means it is contributed more than others. Moreover, negative weight value is possible in the case where one classifier needs to minimize the error of higher weighted classifier. In the subsection 3.4, we describe the process of adjusting values of $w^{'}$, $w^{''}$ and $w^{'''}$ using genetic algorithm. Finally, the decision of gender is taken using P_f^{mix} and P_m^{mix}. If $P_f^{mix} > P_m^{mix}$ then the person is female. If $P_m^{mix} > P_f^{mix}$ then the person is male. The model takes random decision in the case of equal probability. In our experiment, we consider this case as "undecided", and include it in the classification error.

3.3 Searching Best Feature Subset

Initially, we select all the aforementioned 56 features to train each classifier. We use the fine-tuned classifiers to ensure maximum accuracy as individual, as well as in the mixture of expert model. The way of fine-tuning is described in details at the experiment section. Table 2 shows the classification accuracy, number of selected features and overall testing time. Among them decision tree shows highest performance having 72.50% classification accuracy.

Instead of using all features, we need to find a subset of features that maximizes the prediction. One of the naive approach can be the brute force algorithm: checking all 2^N combinations of features where N is the number of features. In our case, N = 56 and each checking means

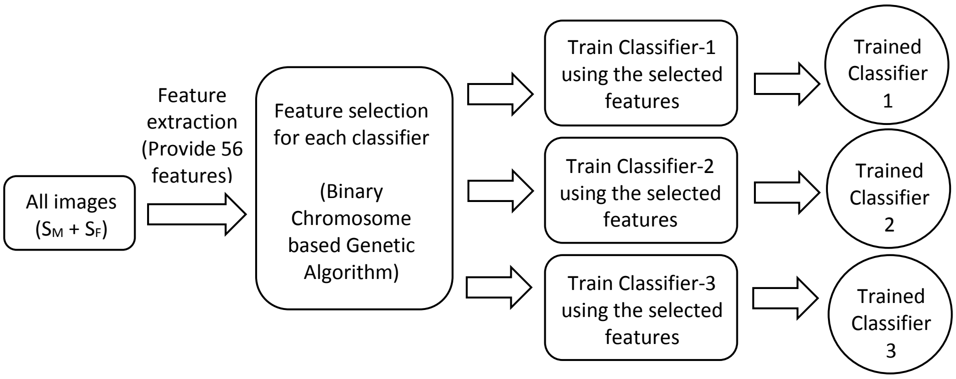

Figure 1: High level view of the feature selection and training phase.

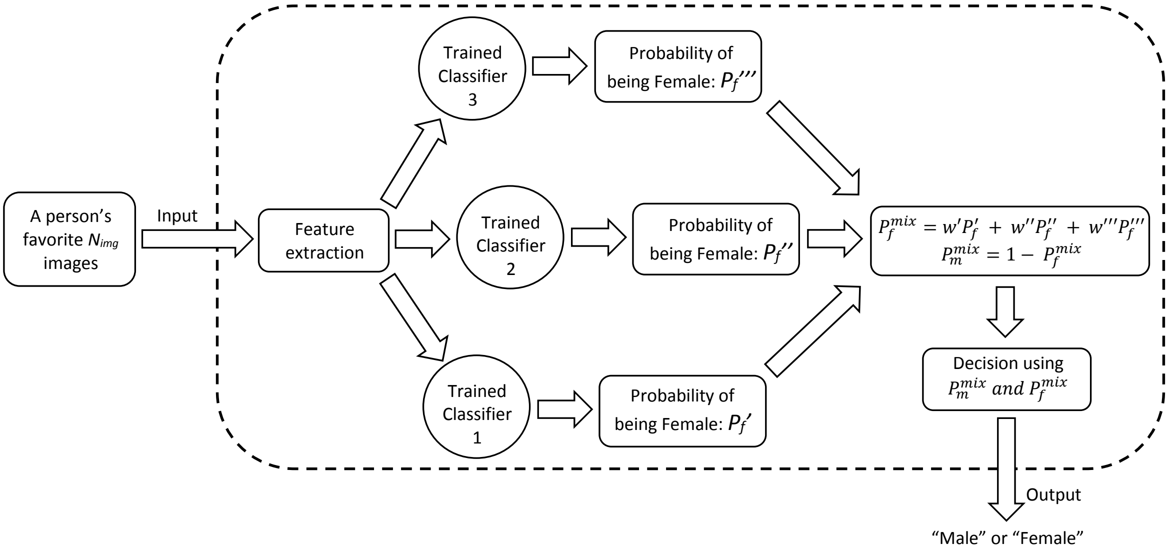

Figure 2: Block diagram of the gender prediction model.

Classifiers	Number of selected Features (out of 56)	Gender prediction accuracy (%)	Overall testing time (in seconds)
D-tree	All 56	72.50	1.43
SVM	All 56	70.83	14.48
KNN	All 56	66.67	33.28

Table 2: Performance of individual classifier when all 56 features are selected.

2 fold cross validation using 24000 $\times$ N feature matrix. So it is not feasible, even impossible to run the brute force algorithm. One of the best way of feature selection is binary chromosome based genetic algorithm (GA) [Ray00]. Genetic algorithm is a stochastic search process for an optimal solution to a given problem. It can find the optimal or near optimal solution within a reasonable GA generations [Eng05]. For feature selection, we use binary chromosome of length 56 (56 dimensional binary search space) as an individual in the population where one bit represents one gene. Binary 1 means the corresponding feature is selected, binary 0 means the corresponding feature is not selected. We run the GA algorithm for each classifier for 50 generations considering gender prediction error as fitness function. The parameter settings of the GA algorithm is provided in Section 4. Figure 3 shows the graph of GA generations (x-axis) vs prediction error (y-axis) for each classifiers. A black dot is the best individual (having minimum error), and a red dot is the average of fitness value of all individuals in a specific generation. From these graphs, we see that as the generation passes it minimizes the fitness values among all the individual in the population. We take the chromosome of the best individual and select the features according to the chromosome bit pattern. Table 3 shows all the features selected by GA for each classifiers. Here, the feature number is according to Table 1.

Next, we apply the selected features (using GA) to train and test each classifier individually. Table 4 shows that the classifier's performance increases in terms of feature reduction, testing time, as well as prediction accuracy after selecting features by GA. In Figure 4, a horizontal bar chart depicts the improvement for each classifier. The prediction accuracy of KNN, SVM and

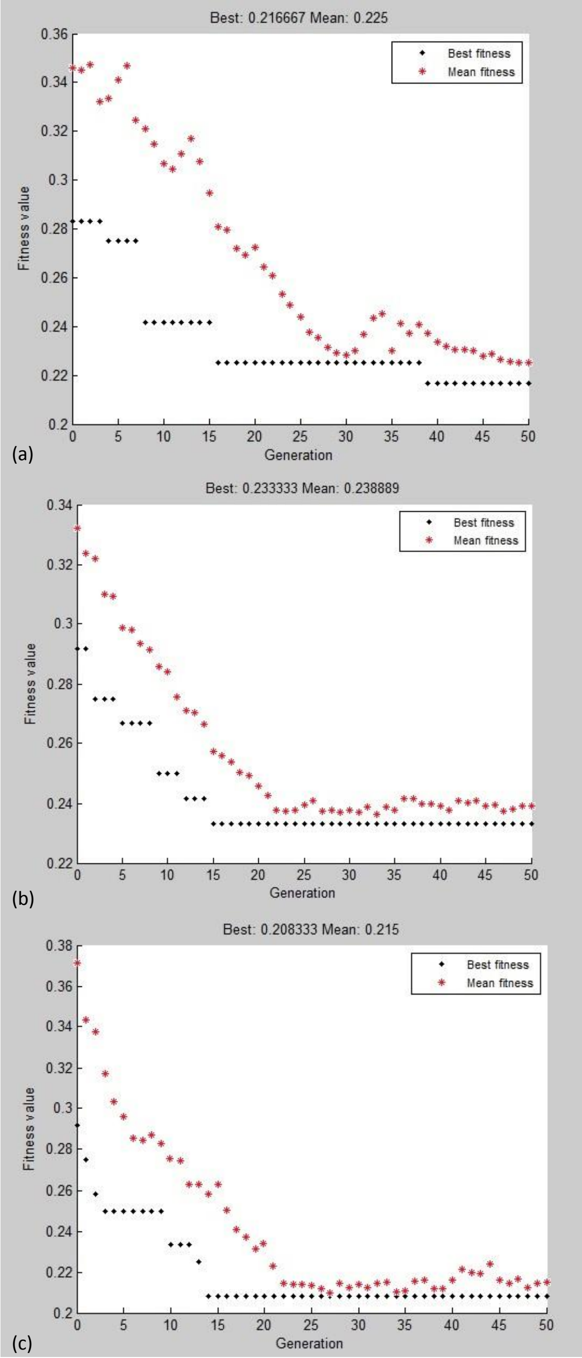

Figure 3: Graph shows the best fitness values (black dots) and the mean of population fitness values (red dots) over 50 generations. We see that best fitness value minimizes as the generation passes. Here the fitness value is the prediction error scaled to the range 0-1. Three graphs for the (a) Decision tree, (b) Support vector machine, and (c) K-nearest neighbor. At the top of each graph, the best fitness value and the mean fitness value of 50th generation are also provided.

D-tree are improved by 12.5%, 5.84% and 5.83%, respectively. Also the dimension of the feature spaces and the overall testing times are minimized noticeably (see Table 2 and 4).

Classifiers	Selected features by GA for each classifier.
D-tree	1, 2, 3, 6, 7, 10, 11, 13, 16, 17, 18, 20, 24, 26, 27, 30, 31, 35, 36, 37, 38, 39, 41, 42, 44, 46, 47, 49, 51, 52, 53, 55, 56
SVM	3, 5, 6, 7, 11, 12, 14, 15, 16, 17, 19, 20, 23, 24, 29, 31, 33, 34, 41, 43, 44, 46, 47, 51, 52, 53, 54, 55
KNN	3, 4, 5, 6, 7, 10, 14, 18, 19, 20, 21, 22, 24, 28, 29, 30, 32, 34, 37, 39, 43, 44, 46, 47, 48, 49, 50, 52, 54, 55, 56

Table 3: Selected features by GA for each classifier.

Classifiers	Number of selected Features (out of 56)	Gender prediction accuracy (%)	Overall testing time (in seconds)
D-tree	34	78.33	1.13
SVM	28	76.67	13.10
KNN	31	79.17	20.48

Table 4: Showing the performance of individual classifier when features are selected by GA.

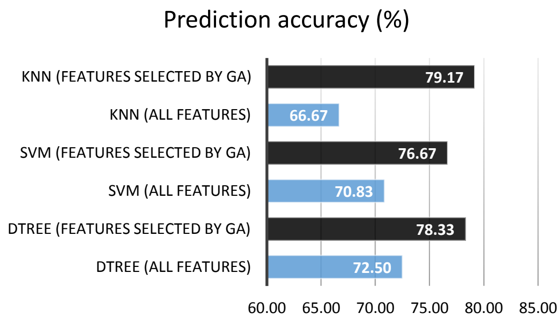

Figure 4: Bar chart showing the significant improvement of prediction accuracy after using GA based feature selection

3.4 Weight Adjustment Using GA

The key contribution of this paper is in the use of genetic algorithm (GA) for feature selection and weight assignment. In the mixture of expert models, we combine three classifiers by using simple weighted sum of the individual prediction. Before taking the final decision, the weighted probability is rescaled to 0 to 1. Assigning appropriate weights gives the benefit of using ensemble. Each weight controls the influence of individual prediction, as well as overall ensemble performance. Finding appropriate weights is a crucial step. In the experiment section, we show that assigning weights based on the partial participation and separate performance doesn't help to improve the model performance. Even it reaches only the maximum among classifiers. Moreover, empirically assigning weight values is not a trivial task because of large search space and highly non-linear function (ensemble accuracy). Due to three weights w', w'' and w''', our search space become 3D floating number. To find the best values of weights that minimizes prediction error, we use genetic algorithm where a chromosome consists of three genes (floating point number) [Fli04]. Parameter settings of GA are provided in the experiment section. After 50 generations, GA gives 82.50% prediction accuracy at weight vector ($w^{'}$, $w^{''}$, $w^{'''}$) = (-1, 2.33, 0.88) where $w^{'}$, $w^{''}$ and $w^{'''}$ are the weights associated with D-tree, KNN and SVM respectively. Figure 5 shows the GA graph for weight adjustment. The axis setup of the graph is same as graphs in Figure 3.

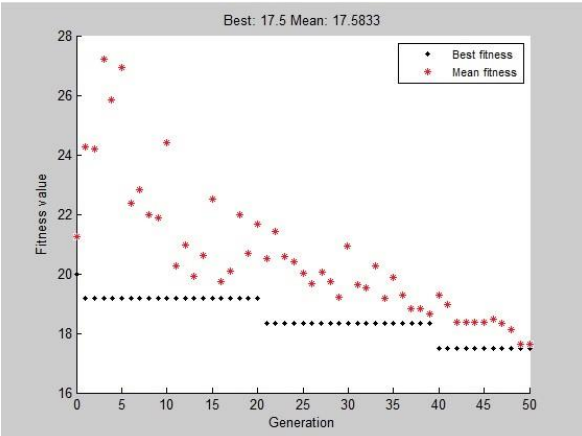

Figure 5: GA Graph showing Generation vs Fitness value (prediction error) for the purpose of weights adjustment.

4 EXPERIMENT

In our experiment, we consider a real database of 40000 color images collected from 200 Flickr users along with their profile reference. Each user provided 200 images from his or her favorite picture collection in OSN Flickr. Out of 200, we collect the gender information of 120 users: 60 male and 60 female. We conduct experiment on these 120 user's gender information and their 24000 favorite images. This is the same database used in [Aza16] for gender prediction experiment. According to [Lov14], duplicate images across users are less than 0.05%. The images are in different file format and resolution. Before using them into our experiment, we convert all images into JPEG file format. Then we extract all 56 features from these 24000 images, and make a data matrix of size 24000 $\times$ 57. The 57th column contains the gender information of the Flickr users considering real-number 0 as male and 1 as female. Starts from row 1, consecutive 200 feature vectors are from a single user's 200 images. For implementation, we use MATLAB 2012 with image processing, machine learning and global optimization toolbox [Mat94], and a workstation having AMD A8-7410 APU 2.2 GHz processor with 8 GB RAM. Experimental setups, results and analysis are described in the following subsections.

4.1 Experimental Setup

In every stages of the proposed method, we evaluate each classifier and the prediction model based on average accuracy of 2 fold cross validation [Cro16]. Moreover, the fitness function in the GA is average misclassification error of 2 fold cross validation. We partition the whole image database into two folds, where fold 1 contains 12000 images from 30 male and 30 female persons, and fold 2 contains rest of the 12000 images from remaining 30 male and 30 female persons. There is no overlapping between these two folds. In any training and testing phase, we first train the model with fold 1, and test with fold 2. Then again train with fold 2 and test with fold 1. Finally, the average accuracy of fold 1 and fold 2 is considered as overall accuracy of a single classifier or the prediction model.

Before using three classifiers: SVM, KNN and D-tree in the mixture of expert models, we fine-tune them to ensure maximum performance as individual. For fine-tuning we apply iterative approach. In KNN classifier, one of the sensitive parameter is number-of-neighbor. We evaluate KNN for a range of number-of-neighbor values, and choose the number-of-neighbor where KNN shows maximum accuracy. Figure 6 shows the line graph of KNN for the number-of-neighbor range 1 to 50. Similarly, we iteratively fine-tune SVM (RBF kernel) and D-tree for their sensitive parameters sigma and minimum-leaf, respectively.

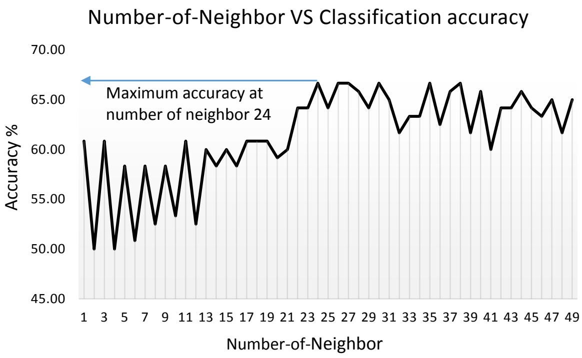

Figure 6: Line graph showing the iterative fine-tuning of KNN for the parameter number-of-neighbor.

In the proposed prediction method, we use genetic algorithm (GA) for feature selection and weight adjustment. In GA, several parameters are associated with it [Gen16]. Fine-tuning some of them may produce more optimal result, as well as speed up the GA execution. For simplicity, we keep most of the parameters to its default value as per MATLAB function documentation. Moreover, iterative approach is not a good way to tune GA because of stochastic nature. For same reason, we run GA multiple times for feature selection and weight adjustment, and keep the best result. Table 5 shows all the parameter values of three classifiers and the genetic algorithm used in the experiment. Other parameters are set to their default value as per MATLAB function documentation.

Classifiers / GA	Parameter settings
KNN	Number of neighbors: 24.
D-tree	Minimum-leaf: 34.
SVM	Non-linear kernel: Radial Basis Function (RBF); Sigma value of RBF: 2.9; Maximum iteration: 30000.
GA	Population type: bit-string (during feature selection) and double-vector (during weight adjustment), Population size: 20, Fitness limit: 0.05; Generations: 50.

Table 5: Parameter settings for each binary classifier and GA.

4.2 Experimental Results

At first, we assign different combination of weights in the equation (1) considering either zero or one as weight value. For weight combination (0, 0, 1), (0, 1, 0), and (1, 0, 0), the prediction model actually shows individual performance of SVM, KNN and D-tree. As separate classifier, KNN performs maximum (79.17%) among them. Table 6 shows the prediction accuracy, male and female counting, as well as count of undecided cases for different weight combinations. In the table, we see that pair combinations (1, 1, 0), (0, 1, 1) and (1, 0, 1) show degraded performance of 77.50% which is less than the maximum performed classifier within the pair. After observing each case, we found that in few cases when a well formed classifier gives correct prediction with marginal probability (0.51 to 0.55), the other one gives incorrect prediction with low probability (0.45 to 0.49). So weighted probability drops below 0.5. Due to similar reason, the prediction model shows more degraded performance for the weight vector (1, 1, 1). Another weight assignment can be based on ranking of individual performance. According to classification accuracy, we rank D-tree, KNN and SVM as 2, 3, and 1. After assigning these rankings as weights in the prediction model, we get 79.17% accuracy which is equal to the best individual performance by KNN. Even after increasing the weight value of top two classifiers, it doesn't show any improvement in accuracy (see the Table 6 for weight vector (3, 4, 1)). Overall, weight assignment based on performance and participation doesn't show good results. To find the best combination of weights for this non-linear function, we apply genetic algorithm. After 50 generations, it gives the weight vector (-1, 2.33, 0.88) which brings 82.50% of prediction accuracy (99 users out of 120) with zero undecided situation. Here, the noticeable weight value is negative 1 for D-tree, which actually minimizes the female prediction error done by KNN.

For comparing the proposed method, we select our previous image aesthetic based gender prediction method [Aza16] as the best result reported so far in the literature on the subject. We applied greedy feature selection and ranking based weight adjustment which reported 76.65% of accuracy over the same database. The overall testing time (all 120 users) of the method [Aza16] is 12 seconds, whereas the proposed method takes 21.6 seconds. The number of features (after GA selection process) used in the proposed method is higher than the method in [Aza16]. Experimentally we find that the testing time of KNN increases with the number of features. The required memory for both of these methods is approximately 13.62 MB, because they using the same prediction model. The memory effect of increased number of features in the proposed method is insignificant. Another image based gender prediction method is [Qua14], which considered favorite images and posting behavior of OSN Pinterest [Pin10] users, and reported accuracy is 72% [Qua14]. The required time and memory for the system is not reported by the authors. Figure 7 shows the performance of [Aza16] with ranking based weight assignment, and the proposed method with same weight assignment, as well as after weight adjustment using GA. The proposed method shows further close to 83% gender prediction accuracy and thus proves the superiority of the currently proposed method over the existing approaches.

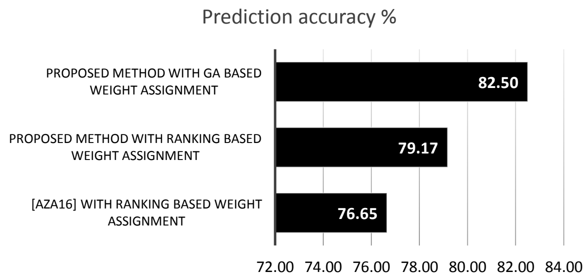

Figure 7: Bar chart showing the accuracy of the proposed gender prediction method and the method in article [Aza16].

5 CONCLUSIONS AND FUTURE WORKS

In this paper, we propose a new method to predict gender from a person's favorite images. We consider 56 image aesthetic features from existing literatures, and a mixture of expert models consisting of SVM, KNN and D-tree. Final decision is taken based on the weighted combination of probability generated by individual classifiers. To improve the prediction accuracy of the model, we find the best combination of feature subset using genetic algorithm in 56D binary search space. Moreover, feature dimension is reduced significantly that decreases the testing time. Finally, three weights of the prediction model are adjusted using genetic algorithm in 3D real-number search space.

Weights (W_{dtree},W_{knn},W_{svm})	No. of Undecided situation (out of 120)	No. of correct male prediction (out of 60)	No. of correct female prediction (out of 60)	Accuracy (%)
(0,0,1)	0	41	51	76.67
(1,0,0)	2	48	46	78.33
(0,1,0)	2	53	42	79.17
(1,1,0)	0	50	43	77.50
(1,0,1)	1	44	49	77.50
(0,1,1)	0	47	46	77.50
(1,1,1)	3	46	46	76.67
(2,3,1)	0	49	46	79.17
(3,4,1)	0	49	46	79.17
(-1, 2.33, 0.88)	**0**	**53**	**46**	**82.50**

Table 6: Prediction performance for different weighted combination of three binary classifiers.

Experiment is conducted on a real image database of 24000 images provided by 120 Flickr users. The proposed method shows 82.50% accuracy in gender prediction. As our future work, we will incorporate contextual image aesthetic features to improve the prediction accuracy. Investigation will be needed to see the performance of other machine learning algorithms to make sophisticated and well performed prediction model. Moreover, fine-tuning of GA parameters can be applied to hope for better weight adjustment.

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