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Gender recognition system based on human face picture

Keywords

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Abstract

The paper presents the analysis and discussion of gender recognition based on human face picture. The research combines different features selection techniques with the set of softcomputing classifiers. We are looking for not very complicated, fast and sensitive approach to create the theoretical basis for real safety systems where the correct "on-line" gender recognition is necessary. We start from the already known differences between the female and male face. This is the key point to tune the preprocessing mechanisms. We propose the quite classic classifiers, but we focus on sensible correlation between the feature extraction and the actual classification. The significant set of the results are discussed and the best solutions are pointed. All tests were realised based on the well known base of face pictures with added set of our own collection. The proposed solution can be an essential tool for the monitoring systems, safety guards and systems to point the dangerous situations based on video data.

1. Introduction

The problem of computer face recognition and its components are tested for years. While the previously established effective and fast face recognition algorithms on digital content, analysing the fragments and hence such gender recognition problem is still considered and perfected by scientists. Most of the examples of gender recognition based on facial image is quite futuristic, regarded as one of the tasks that should be solved by your robot mimicking human appearance and features. In recent years appear humanoid robots which are able to carry a conversation with the client and their sample destiny is to replace the man at the counter or desk. Identifying sex and age of the caller (client) is important (especially in Japan, where robots are created), because of the language the robot should use to contact with such person. In this case, however, gender recognition from the video can be supported or even replaced by detection and analysis of the speech. [4]

Recently, the use of less futuristic gender identify of the client can be used on a larger scale systems much less complicated than humanoid robots. A prime example of such application is the recognition of gender of people looking at advertising, for example, the display at the mall, in order to select an ad, for example, male or female cosmetics. The problem comes to detect human faces in an image recorded by the camera in the display localized and gender classification spectators and viewers, depending on the number of male and female, film random selection of one of two sets (or three, if you will be provided a set of neutral the case of equal gender distribution) and displayed it. The main features of this application is the lack of ability to recognize customers voices (which also simplifies the issue by eliminating the need to install microphones and implementation of speech recognition algorithms, and complicates it, eliminating the possibility of using well-known and effective algorithms based on the analysis of the human voice) and no need for a precise evaluation of gender, because people of both genders are looking on the screen, and sometimes making a mistake will not have any negative effects of poor advertising displayed in front of a small group of people. It occurs anyway when, for example, few men are standing in front of the display in a larger group of women.[4]

Also there are a lot of gender features on the face, such as [1, 3, 4]:

- size of the skull - male skull is bigger,
- slope of the forehead - male forehead is more sloped,
- shape of the eyebrows - female eyebrows are more round, and male eyebrows are bigger,
- depth of the eye socket - male eye sockets are much deeper,

- size of the jaw - male jaw is bigger,
- spacing between the eyes - female eyes are placed wider,
- size of the eyes - female eyes are bigger,
- size of the nose - male nose is bigger,
- size and colour of the mouth - female lips are more red and fuller,
- colour of the skin - male are more red and female are more green, but this can be considerate only without any make-up and in perfectly equal light conditions.

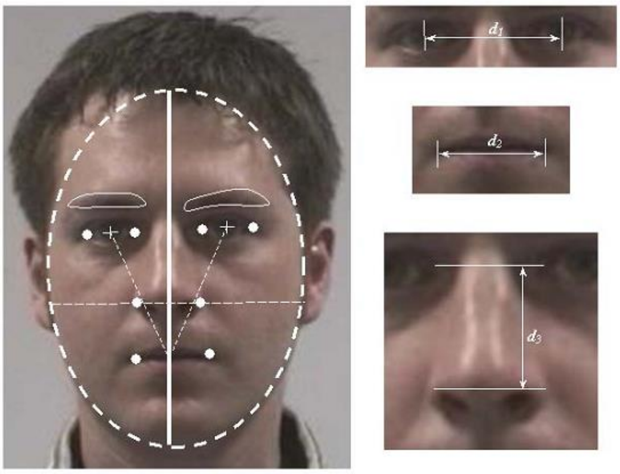

Figure 1. Gender features on the face [4]

The main aim of the paper is to create system which will recognize gender of the person in the photo. The second but not less important aim is to compare some existing softcomputing classification methods combined with features extraction algorithms in combinations not tested yet.

This way we are going to proof that simple features extraction algorithms combined with complex classification procedure can provide as good results as complex features extraction combined with the same algorithms of classification. The results can be used as a basis for the safety systems – to make better automatic human recognition.

System assumes that there are some existing algorithms to get the face from the picture without manually cropping of the photo. Because of the complexity of the problem there had to be put certain restrictions on people in the pictures, such as:

- caucasians - in every race gender features situated on the face looks slightly different,
- age from 20 to 50 - before 20 the features of the gender are not developed yet, and after 50 the features starts to blur,
- no visible diseases on the face - they can affect gender features,
- neutral facial expressions and no glasses,
- photo taken from front with ears visible,
- no plastic surgery - like the diseases it can affect gender features.

2. State of art

First system which managed with gender classification it is system made by Golomb, Lawrence and Sejnowski with usage of Multilayer Perceptron with manually aligned photos [5], they obtain 8.1% classification error rate on photos with young adults with no facial hairs, no jewellery and no make-up.

Cottrell and Metcalfe [4] used Principal Component Analysis to reduce dimensionality of 160 tested images (10 male and 10 female with different facial expressions). For this small number of people the system was perfect.

Brunelli and Poggio [2] used geometrical approach to extracting gender features from face and with HyberBF networks as classifier obtain 79% of correct classification with 20 male and 20 female in learning set.

Burton, Bruce and Dench [3] also used geometrical approach and reach better results (94% of accuracy), but for gender classification that used 2 photos for every person (frontal and profile) to measure 3D distances between geometric features of the face. Also people on the photos had swimming caps to cover the hair.

Shaknarovich, Viola and Moghaddam [9] used appearance approach with AdBoost and Support Vector Machine with Radial Basis Function kernel classifiers. The error rate was pretty high (21% with AdBoost classifier and 24.5% with SVM), but the photos was cropped automatically from video in real time. Faces were at different angle and with different light conditions.

Baluja and Rowley [1] also used AdBoost with appearance approach of extracting gender features from the face. They achieved over 93% of accuracy.

Rai and Khanna [7] used Radon and Wavelet transform to extract gender features from face with k-Nearest Neighbours classifier. They achieved 77% accuracy.

Nazir, Ishtiaq, Batool, Jaffar and Mirza [8] used AdaBoost to find the most important features of the face and Discrete Cosine Transform to extract them. They connected it with the k-Nearest Neighbours classifier with Euclidean distance. Achieved results was great - 99.3% in 50 to 50 ratio of training and testing set.

Jabid, Hasnual and Chae [7] used Local Directional Patterns for extracting gender features with Support Vectors Machine classifier and achieved 95.05% accuracy on photos taken from FERET database.

Jain, Huang and Fang [8] used Independent Component Analysis for dimension reduction of face features and Support Vector Machine for

classification. They achieved 96% accuracy. The best results on FERET database - 96.6% of correct classification - were achieved with Support Vector Machine classifier by Moghaddam and Yang. [6]
As we can see none of this systems achieved 100% accuracy, but some of them was really close (with k-Nearest Neighbours and Support Vector Machine Classifiers). All systems were using very complicated algorithms for gender features extraction but it is not clear which approach to that is the best one, because, most of them was tested only with one or two classifiers. The easiest way of extracting gender features - two colours conversion - had never been tested with the most successful classifiers this is why it was chosen to be starting point in the gender features extraction in the paper.

3. Possible solutions

3.1. Gender features extraction

Because working with unprepared photo can be very slow and yet not effective there have to be some gender feature extraction. We can observe two different types of features [4]:

- geometric-based features which are also called local features, they represents psychophysical face attributes such as size of the skull, space between the eyes, etc.,
- appearance-based features which are also called global features, they are extracted based on the values of pixels.

Appearance-based features can be divided into:

- various texture features, which can be extracted with:
  - Local Binary Pattern (LBP) [2],
  - Local Directional Pattern (LDP) [2],
  - Pixel-Pattern-Based Texture Feature (PPBTF) [2],
  - 2-colour conversion [5],
  - 8-colour conversion [5],
- histogram of gradients, which can be extracted with:
  - Scale-Invariant Feature Transform (SIFT) [2],
- coefficients of wavelet transformation of image, which can be extracted with:
  - Gabor wavelet [8],
  - Haar wavelet [9],
  - Radon transform [7].

After extraction of the features it is good to minimize number of them to quantity big enough to recognize the gender but small enough to accelerate learning. There are few methods to accomplish that:

- Principal Component Analysis (PCA) [4],
- Independent Component Analysis (ICA) [7],
- AdaBoost and Genetic Algorithm [4].

This methods also reduce the dimensionality and make computation easier.

3.2. Classification process

Like in the features extraction there are few ways to deal with classification problems, most common are:

- Support Vector Machine (SVM) [7],
- Neural Networks (NN), especially Multilayer Perceptron (MLP) [7],
- k-Nearest Neighbours Classifier (kNN) [5,7],
- Naive Bayes Classifier (NBC) [4],
- Genetic algorithms [4],
- Adaptive Boosting (AdBoost) [1,7,9],
- Radial Basis Functions (RBF) in HyperBF networks [2],
- Linear Discriminator Analysis (LDA) [7].

4. Proposed approach

First step - taking the picture - is done manually, faces are cropped by hand and save as the pictures 133x169px and 50x64px. Eyes on the cropped photos should be on the same level. This part should be done by another system which would automates human faces extraction from camera image.
Second step - transforming the picture - extracts the gender features from face. There are two different algorithms in the system which can do that:

- 2 colour conversion,
- 8 colour conversion.

All of the previous works used complicated algorithm for gender features extraction and still did not achieved 100% accuracy, because of that we decided to use the easiest way of extraction and find out if it can provide the same or better accuracy. Also the eight colours conversion was only mentioned as possible improvement of two colours conversion so in the paper we wanted to check correctness of that statement. Algorithms was chosen
also because of theirs low computational time and small memory consumption.
Third step - calculating the results - is actual classifier. There are three different
algorithms in the system which can do that:

- Multilayer Perceptron (MLP),
- k-Nearest Neighbours (kNN),
- Support Vector Machine (SVM).

MLP is well known neural network frequently used in gender classification [7]. Can be easy tuned to perform better results by changing number of hidden layer and neurons in them. Multilayer Perceptron Classifier was not tested before with chosen gender features extraction algorithms. Also eight colour conversion algorithms was only mentioned as possible improvement of two colour conversion in [8] and have never been tested with any mention classifier. kNN is memory based reasoning algorithm. This have slightly different approach to classification than the approach in neural networks. It also has the best results of all known classifiers which manage gender classification [8]. k-Nearest Neighbours Classifier was only tested until now with Euclidean distance [8], in this thesis also eight another distances was tested.

SVM is algorithm which mimics best the way in which human beings classify gender of other humans. Because of kernel trick this can also classify not-linear separable data [9]. It also has the best results [7] from all tested classifier on FERET database from which half of the learning and testing set was taken for tests provided for this paper.

Fourth step - displaying the results - is simple show of the persons gender. Male is coded as 0 and female as 1.

4.1. Testbed

Every classification algorithm was tested with every feature extraction algorithm attached. Classification algorithms was fine tuned during the tests to find parameters that will suit the best to presented problem. All tests were conducted on total number of 51 photos taken from FERET database [6] and 49 pictures taken by ourselves, there were 45 female and 55 male. For fine tuning the algorithms for every parameters set there were conducted three test:

- 75 photos in learning set (33 female and 42 male) and 25 photos in testing set,
- 50 photos in learning set (28 female and 22 male) and 25 photos in testing set,
- 25 photos in learning set (13 female and 12 male) and 25 photos in testing set.

After finding the best parameters classifiers was learned with learning set which grew from 25 to 75 photos with 5 picture threshold. Every person was represented by one photo. All tests were conducted with 25 pictures in testing set with 12 female and 13 male. Some of photos was not sharp and in some the light came from a different angle than in the most of other pictures. Provided results are given as the percent of correct classification in testing set. The best results for every test are highlighted.

5. Results

5.1. Multilayer perceptron classifier

Algorithm is implemented with backpropagation and logistic activation function. This activation function was chosen because its answer vary between 0 an 1 and expected results are in set {0,1}. Expected value of error after learning is set to 0.01, below that we can observe overfitting. There are 3 layers:

- input with 3200 neurons (size of input images in pixels),
- hidden with changing number of 100 and 200 neurons during tests - more neurons in hidden layer did not provide better results and computational time for learning started to be unacceptable.
- output with 1 neuron (gender are coded as 1 bit).

Learning rate vary from 0.05 to 0.5 with 0.05 threshold. Learning was conducted till mean square error reach 0.01 or number of iteration reach 20000.

Table 1: Multilayer Perceptron - 100 hidden neurons

	Size of learning set					
	Conversion					
	2 colours			8 colours		
Learning rate	75	50	25	75	50	25
0,05	72%	72%	72%	80%	84%	64%
0,1	*72%*	*80%*	*68%*	84%	88%	68%
0,15	72%	76%	68%	*84%*	*88%*	*72%*
0,2	72%	76%	68%	80%	88%	72%
0,25	76%	76%	68%	80%	88%	72%
0,3	72%	76%	68%	72%	88%	72%
0,35	72%	76%	68%	76%	88%	72%
0,4	72%	76%	68%	76%	88%	72%
0,45	72%	76%	68%	76%	84%	72%
0,5	72%	76%	68%	76%	88%	72%

Table 2: Multilayer Perceptron - 200 hidden neurons

	Size of learning set					
	Conversion					
	2 colours			8 colours		
Learning rate	75	50	25	75	50	25
0,05	72%	64%	48%	64%	60%	48%
0,1	*84%*	*76%*	*68%*	84%	68%	64%
0,15	84%	72%	64%	88%	88%	64%
0,2	72%	72%	64%	88%	88%	64%
0,25	72%	72%	64%	84%	88%	72%
0,3	72%	76%	68%	*88%*	*88%*	*72%*
0,35	72%	72%	64%	80%	88%	72%
0,4	72%	76%	68%	80%	88%	72%
0,45	72%	72%	68%	84%	88%	72%
0,5	72%	76%	68%	84%	88%	72%

5.2. Support vector machine classifier

Learning was conducted with Sequential Minimal Optimization method of finding separating hyperplane. Classifier was tested with 5 different kernel functions provided by MATLAB build-in function *svmtrain*:

- Linear,
- Quadratic,
- Polynomial,
- Gaussian Radial Basis Function (RBF),
- Multilayer Perceptron (MLP).

Table 3: SVM with different kernel functions

	Size of learning set					
	Conversion					
	2 colours			8 colours		
Kernel function	75	50	25	75	50	25
Linear	72 %	72 %	64 %	72 %	80 %	76 %
Quadratic	*88 %*	*60 %*	*48 %*	*80 %*	*68 %*	*72 %*
Polynomial	56 %	44 %	44 %	56 %	44 %	56 %
RBF	56 %	44 %	44 %	56 %	44 %	44 %
MLP	56 %	48 %	60 %	64 %	52 %	60 %
Linear	72 %	72 %	64 %	72 %	80 %	76 %

What was surprising Radial Basis Function kernel did not provides good results (as it was in Shaknarovich, Viola and Moghaddam work [9]), in fact gave the worst accuracy of classification from all tested kernels.

5.3. k-Nearest neighbours classiffer

To tune this classifier number of neighbours varied from 1 to 15 (testing set contain only 25 photos, more neighbours would not provide any improvement), and test was conducted for nine different distances which can be found in build-in function of MATLAB - *knnsearch*:

- City block:

Table 4: kNN with city block distance

	Size of learning set					
	Conversion					
	2 colours			8 colours		
Number of neighbours	75	50	25	75	50	25
1	88%	80%	72%	80%	68%	68%
2	88%	80%	72%	*80%*	*72%*	*68%*
3	88%	80%	72%	80%	68%	68%
4	88%	80%	72%	80%	72%	68%
5	88%	80%	72%	80%	68%	68%
6	88%	80%	72%	80%	72%	68%
7	88%	80%	72%	80%	68%	68%
8	88%	80%	72%	80%	72%	68%
9	88%	80%	72%	80%	68%	68%
10	88%	80%	72%	80%	72%	68%
11	88%	80%	72%	80%	68%	68%
12	88%	80%	72%	80%	72%	68%
13	88%	80%	72%	80%	68%	68%
14	*92%*	*80%*	*72%*	80%	72%	68%
15	88%	80%	72%	80%	68%	68%

kNN with city block distance achieved best results from all tested distances for two colour conversion but almost the worst for eight colours conversion. Accuracy of classification is comparable with best results achieved in previous works in gender recognition subject.

- Chebyshev:

Chebyshev distance (Table 5) turns out as the worst distance that can be used in the gender classification with chosen algorithms of features extraction.

Table 5: kNN with Chebyshev distance

	Size of learning set					
	Conversion					
	2 colours			8 colours		
Number of neighbours	75	50	25	75	50	25
1	*60%*	*56%*	*56%*	*60%*	*56%*	*56%*
2	56%	56%	56%	56%	56%	56%
3	56%	56%	56%	56%	56%	56%
4	56%	56%	56%	56%	56%	56%
5	48%	48%	48%	48%	48%	48%
6	60%	56%	56%	60%	56%	56%
7	48%	48%	48%	48%	48%	48%
8	48%	48%	48%	48%	48%	48%
9	48%	48%	48%	48%	48%	48%
10	48%	48%	48%	48%	48%	48%
11	48%	48%	48%	48%	48%	48%
12	48%	48%	48%	48%	48%	48%
13	48%	48%	48%	48%	48%	48%
14	48%	48%	48%	48%	48%	48%
15	48%	48%	48%	48%	48%	48%

Table 6: kNN with linear correlation distance

	Size of learning set					
	Conversion					
	2 colours			8 colours		
Number of neighbours	75	50	25	75	50	25
1	88%	80%	72%	84%	80%	72%
2	84%	80%	68%	*96%*	*88%*	*64%*
3	88%	76%	72%	80%	72%	68%
4	88%	84%	80%	84%	84%	84%
5	88%	76%	68%	92%	68%	72%
6	88%	72%	72%	84%	76%	88%
7	84%	76%	72%	84%	72%	76%
8	88%	76%	72%	88%	80%	84%
9	88%	72%	64%	80%	76%	80%
10	92%	76%	72%	84%	80%	80%
11	*92%*	*80%*	*64%*	84%	80%	76%
12	88%	84%	72%	92%	84%	76%
13	92%	72%	76%	88%	80%	84%
14	84%	76%	64%	92%	88%	84%
15	92%	76%	72%	88%	80%	80%

Linear correlation distance has as good as city block and Euclidean distance results for big databases, but do not classify correctly when the size of database is decreasing.

- Cosine:

Like in linear correlation distance cosine distance achieve good results only for big databases.

Table 7: kNN with cosine distance

	Size of learning set					
	Conversion					
	2 colours			8 colours		
Number of neighbours	75	50	25	75	50	25
1	88%	80%	72%	84%	76%	72%
2	88%	88%	76%	92%	88%	64%
3	88%	84%	76%	84%	76%	72%
4	88%	84%	84%	84%	84%	84%
5	88%	76%	72%	92%	76%	76%
6	88%	72%	72%	84%	80%	88%
7	88%	76%	72%	84%	72%	84%
8	88%	76%	68%	88%	88%	84%
9	88%	72%	68%	92%	80%	80%
10	92%	76%	72%	88%	84%	84%
11	*92%*	*80%*	*64%*	88%	76%	80%
12	88%	80%	72%	*92%*	*88%*	*80%*
13	92%	72%	72%	92%	80%	88%
14	84%	76%	64%	92%	84%	72%
15	92%	76%	72%	88%	84%	72%

Table 8: kNN with Euclidean distance

	Size of learning set					
	Conversion					
	2 colours			8 colours		
Number of neighbours	75	50	25	75	50	25
1	88%	80%	72%	76%	72%	68%
2	84%	80%	72%	80%	76%	60%
3	88%	76%	72%	88%	80%	68%
4	88%	84%	84%	84%	84%	84%
5	88%	76%	72%	92%	88%	76%
6	88%	72%	76%	*96%*	*92%*	*84%*
7	84%	76%	72%	92%	80%	88%
8	88%	76%	76%	88%	92%	84%
9	88%	72%	64%	92%	84%	84%
10	92%	76%	80%	88%	80%	84%
11	*92%*	*80%*	*68%*	88%	76%	84%
12	92%	84%	84%	88%	88%	84%
13	92%	72%	80%	88%	80%	84%
14	88%	76%	80%	92%	84%	84%
15	92%	76%	76%	92%	80%	72%

- Euclidean:

Euclidean distance was found to be the best distance for eight colour conversion and second best for two colour conversion.

- Hamming:

Hamming distance provides the same results like cosine distance.

- Jaccard similarity coefficient:

Jaccard similarity coefficient distance has the best results for small databases but worse than Euclidean an Minkowski distance for big databases in eight colours conversion.

Table 9: kNN with Hamming distance

	Size of learning set					
	Conversion					
	2 colours			8 colours		
Number of neighbours	75	50	25	75	50	25
1	88%	80%	72%	88%	80%	76%
2	84%	80%	68%	*92%*	*88%*	*84%*
3	88%	76%	72%	92%	88%	72%
4	88%	84%	80%	88%	88%	84%
5	88%	76%	68%	88%	72%	56%
6	88%	72%	72%	88%	76%	76%
7	84%	76%	72%	92%	68%	72%
8	88%	76%	72%	92%	72%	72%
9	88%	72%	64%	84%	64%	68%
10	92%	76%	72%	88%	68%	84%
11	*92%*	*80%*	*64%*	88%	64%	80%
12	88%	84%	72%	84%	68%	84%
13	92%	72%	76%	80%	60%	72%
14	84%	76%	64%	80%	64%	72%
15	92%	76%	72%	88%	60%	68%

Table 10: kNN with Jaccard similarity coefficient distance

	Size of learning set					
	Conversion					
	2 colours			8 colours		
Number of neighbours	75	50	25	75	50	25
1	88%	80%	72%	88%	84%	80%
2	88%	88%	76%	*92%*	*88%*	*88%*
3	88%	84%	76%	92%	84%	76%
4	88%	84%	84%	88%	84%	80%
5	88%	76%	72%	84%	72%	56%
6	88%	72%	72%	88%	76%	84%
7	88%	76%	72%	88%	72%	76%
8	88%	76%	68%	88%	72%	72%
9	88%	72%	68%	80%	68%	68%
10	92%	76%	72%	84%	68%	84%
11	*92%*	*80%*	*64%*	84%	68%	80%
12	88%	80%	72%	88%	72%	84%
13	92%	72%	72%	88%	64%	72%
14	84%	76%	64%	84%	68%	76%
15	92%	76%	72%	84%	64%	64%

- Minkowski:

Minkowski distance was found to be the same good as the Euclidean distance, butis more computationally demanding so was not chose as the best.

- Spearman's rank correlation:

Spearman's rank correlation distance has almost the worst results for both features extraction algorithms.

6. Results analysis

For Multilayer Perceptron best results was conducted for network with 200 hidden neurons - learning rate

Table 11: kNN with Minkowski distance

	Size of learning set					
	Conversion					
	2 colours			8 colours		
Number of neighbours	75	50	25	75	50	25
1	88%	80%	72%	76%	72%	68%
2	84%	80%	72%	80%	76%	60%
3	88%	76%	72%	88%	80%	68%
4	88%	84%	84%	84%	84%	84%
5	88%	76%	72%	92%	88%	76%
6	88%	72%	76%	*96%*	*92%*	*84%*
7	84%	76%	72%	92%	80%	88%
8	88%	76%	76%	88%	92%	84%
9	88%	72%	64%	92%	84%	84%
10	92%	76%	80%	88%	80%	84%
11	*92%*	*80%*	*68%*	88%	76%	84%
12	92%	84%	84%	88%	88%	84%
13	92%	72%	80%	88%	80%	84%
14	88%	76%	80%	92%	84%	84%
15	92%	76%	76%	92%	80%	72%

Table 12: kNN with Spearman's rank correlation distance

	Size of learning set					
	Conversion					
	2 colours			8 colours		
Number of neighbours	75	50	25	75	50	25
1	88%	80%	72%	80%	76%	72%
2	84%	80%	68%	*92%*	*84%*	*76%*
3	88%	76%	72%	84%	76%	72%
4	88%	84%	80%	84%	84%	84%
5	88%	76%	68%	84%	68%	68%
6	88%	72%	72%	88%	72%	80%
7	84%	76%	72%	84%	64%	72%
8	88%	76%	72%	88%	80%	88%
9	88%	72%	64%	88%	76%	76%
10	92%	76%	72%	88%	80%	80%
11	*92%*	*80%*	*64%*	88%	80%	76%
12	88%	84%	72%	92%	80%	84%
13	92%	72%	76%	88%	76%	84%
14	84%	76%	64%	92%	84%	72%
15	92%	76%	72%	88%	80%	76%

0.1 for two colour conversion as feature extraction and 0.3 for eight colour conversion as feature extraction. Eight colour conversion algorithm turned out as more suitable for this neural network than two colour conversion. Number of correct classified photos is almost stable between 75 and 50 pictures in learning set, and fall noticeable when the learning set decrease to only 30 photos.

For Support vector Machine the best results was conducted with quadratic kernel function. Here also eight colour conversion was more suitable algorithm of gender features extraction.

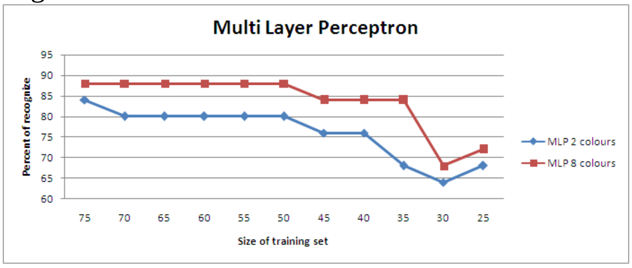

Figure 2. Multilayer Perceptron best results

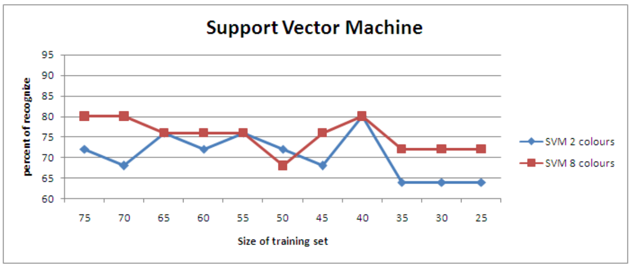

Figure 3. Support Vector Machine best results

This classifier is really dependent of what pictures are in learning set. Sometimes removing some noisy photos from this set leaded to bigger number of correctly classified pictures.

For k-Nearest Neighbours the best results was conducted with city block distance and 14 neighbours for two colours conversion and Euclidean distance and 6 neighbours for eight colours conversion. Like in the rest of classifiers eight colours conversion is more suitable algorithm of gender features extraction.

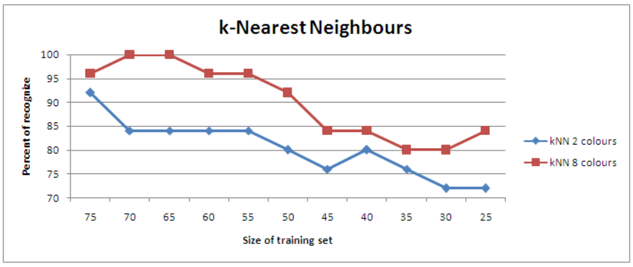

Figure 4. k-Nearest Neighbours best results

kNN need large database to classify correctly, but it reaches even 100% accuracy. It has the best results of all tested classifiers. The results was better than Nazir, Ishtiaq, Batool, Jaffar and Mirza [8] work, where Discrete Cosine Transformation was used to extract gender features from face.

7. Conclusions

Eight colours conversion is better algorithm of gender features extraction than two colours conversion for all tested classifiers as it was mentioned in [8] where only two colours conversion was implemented. It preserve more information and make all important parts of face visible even when the photo does not have the best quality. But still easy algorithms of gender features extraction can work really good with all classifiers and in some cases even better (k-Nearest Neighbours with Discrete Cosine Transformation algorithm as gender features extraction achieved at most 99.3% of correct classification of testing set in [8], with eight colours conversion in this thesis even 100%).

Like in [8] k-Nearest Neighbours is the best classifier in the case of described system but need big database and a lot of neighbours to classify correctly. When database of photos is big and contains a wide variety of faces memory based reasoned can be even 100% effective and works better than any mentioned in recent works and tested here neural networks classifier.

Support Vector Machine is faster than Multilayer Perceptron but is really dependent on small changes in learning data set. Multilayer Perceptron is not so depended on the size of learning set, in fact this is the most stable classifier. But both classifiers need more complicated algorithms of gender features extraction than simple conversions to two or eight colours like in works of Moghaddam and Young [1] or Jain, Huang and Fang [8]. Low accuracy of Multilayer Perceptron Classifier can be caused by small size of learning set combined with big number of neurons in two first layers of this classifier.

The new way of preprocessing of the image - eight colours conversion - was presented and tested with three chosen classifiers: Multilayer Perceptron, Support Vector Machine, k-Nearest Neighbours.

Algorithm tested before with some others classifiers - two colours conversion - was combined with another classifier - Multilayer Perceptron Classifier - which was never tested with this way of preprocessing before.

The easy algorithms of gender features extraction can work really great when we want to classify gender of people that are the most common in some particular region, like in this case only Caucasians. It works with most successful classifier with 100% accuracy, this is why there had been no need of developing other way of picture preprocessing.

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