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A Novel Approach For The Gender Classification Through Trained Neural Networks

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ABSTRACT

The study presents an efficient gender classification technique which is based on novel feature selection method from Haar based wavelet packets and Eigen values of Gabor filters. This forms an effective feature vector to be used by the neural network classifier. The method presented in this paper enjoys the features like high speed and low space requirements.

KEYWORDS: Wavelet packets, Classification, Eigen Gabor Features, Feature selection, Neural networks classifier.

1. INTRODUCTION

Gender classification problem is an active and challenging research area which has attracted a great deal of attention recently. Gender classification techniques aims to determine the gender of a subject from face images. The face images analysis plays an important role in computer vision, e.g. it has been successfully used in many applications i.e. automated security/surveillance systems, demographic studies, safety monitoring systems, biometric and human-robotic interaction.

Most challenging task in gender classification is the representation of the face image in term of a vector. This vector provides input to a trained classifier and classifies the face images in gender classes. The overall process can be summarized in two main points (1) Effective feature extraction. (2) Pattern recognition through trained classifiers.

A number of different techniques based on facial images have been reported in the literature for solving this problem. These techniques include geometrical feature based methods [1], graph matching methods [2], local directional pattern (LDP) [3], support vector machine (SVM)[4-6] and neural network based methods [7]. These approaches are classified into feature based and feature and template based techniques.

The method presented in this paper is a feature based method of extracting texture information. Feature selection process presented in this paper works on two dimensions. First of all it analysis the input image on the base of best nodes of wavelet packets and secondly for one LL wavelet image it performs the detail Gabor analysis and selects a set of Eigen values to completely represent the Gabor features. When the feature selection process completes then neural networks classifier is trained on the acquired feature vector for classification purposes.

In practice, the dimension of a Gabor feature vector is so high that the computation and memory requirements are very large. For this reason, several sampling methods have been proposed to determine the "optimal" subset of Gabor features. This study proposes an effective Gabor feature selection method as well which completely represents the large set of values into a small one.

The overall process involves the following steps. For every image present in image database we determine the wavelet packets tree for that image. Then from set of all nodes of wavelet packets tree we determine the best nodes on the base of Shannon entropy. The reason to use the wavelet packets analysis is that it represents the local texture values quite efficiently. These selected nodes are then used for wavelet transformations to represent the local texture state in the feature vector. In second step we determine the mean of Eigen values obtained after the application of set of Gabor filters on one of LL component of the best nodes tree. Merging these features with wavelet features will give the required feature vector. In last step we trained the neural network classifier to classify the gender on the bases of obtained feature vectors.

Rest of this paper is structured as follow. In section 2 a brief description of the related work is provided. In section 3 wavelet packets are discussed in detail. Section 4 describes the proposed method. Section 5 describes our experimentation and results followed by discussion on the results obtained and section 6 concludes the paper.

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2. RELATED WORK

Gender classification is addressed in computer vision from a long period of time, but researchers are still searching for improved gender classification. Xu et al.[8]came with hybrid face coding method for facial feature extraction. They extracted geometry features and fused them with features extracted by AdaBoost algorithm to form a feature vector and used SVM classifier for classification. Lee and Wei [9] presented an effective technique using three features, facial texture features, hair geometry features and mustache features. The extracted features covering the global, local, geometry and texture properties. They designed a two phased AdaBoost classifier architecture to perform the gender classification. Tapia et al. [10] came with feature selection based on mutual information and feature fusion to improve gender classification. They compared the results of fusing three groups of features, three spatial scales, and four different mutual information measures to select features. The results improved by fusion of LBP features with different radii and spatial scales, and the selection of features using mutual information. They used minimum redundancy and maximal relevance (mRMR), normalized mutual information feature selection (NMIFS), conditional mutual information feature selection (CMIFS), and conditional mutual information maximization (CMIM) as the measure of mutual information.

Li et al. [11] came with a novel gender classification framework, that uses not only facial features, but also external information. They extracted features from five facial components that are forehead, eyes, nose, mouth and chin instead of the whole face and used SVM. Moghaddam and Yang[12] applied the SVMs to gender classification with low-resolution thumbnail faces. The SVMs produced much better results than the techniques such as Radial Basis Function (RBF) classifiers and large ensemble-RBF networks. Yang et al.[13]presented an experimental study on automatic face gender classification that focused on the different texture normalization methods to the performances of gender classification by SVM, Linear Discriminant Analysis (LDA) and Real Adaboost.

Irtaza, et al. [14] presented an efficient gender classification technique using Gabor features. They selected Gabor features ranked on the basis of entropy and merged with mean Gabor features values. Their techniques is fast and space requirement is low. Lam, et al.[15] proposed a content based image retrieval system for computed tomography nodule images. Their system takes the input image and generates Haralik, Gabor, and Markov random field features. On the extracted features they perform Euclidian, Manhattan and Chebychev distances to find the relevant images from image database. This paper has made good contribution by effectively retrieving images from image database, so it is an effective guideline for gender classification problem as well. Scalzo et al.[16]came with a new Feature Fusion Hierarchical (FFH) method for gender classification using Genetic algorithm. There algorithm worked in two phases. In first phase, Gabor and Laplace features are extracted and used as input to feature fusion level. In second phase, classifiers fusion uses output of future fusion level to produce a result. Lee and Shih[17] proposed a facial expression recognition technique based on improved radial bases function network. Their technique is significant in a sense that they are using Gabor features for this purpose and they have introduced an efficient feature selection technique which is based on entropy criteria; the technique reduces the processing time and space requirement for the classification purposes.

3. TECHNICAL BACKGROUND

Wavelet packets and Gabor features are described here. So the experimentation can be understood very easily.

3.1 Wavelet Packets

To analyze the signals in a rich way the wavelet packet method is used which is a generalization of wavelet decomposition and can be described by the collection of functions$\{W_J(x) \mid J \in Z^+\}$ obtained from[18]:

$$2^{\frac{p-1}{2}} W_{2n}(2^{p-1}x-l)=\sum_m h_{m-2l} 2^{\frac{p}{2}} W_n(2^p x-m) \quad (1)$$

$$2^{\frac{p-1}{2}} W_{2n+1}(2^{p-1}x-l)=\sum_m g_{m-2l} 2^{\frac{p}{2}} W_n(2^p x-m) \quad (2)$$

Where ‘p’ is a scale index and ‘l’ is the translation index. $W_0 x = \Phi(x)$ is the scaling function. $W_1 x = \psi(x)$is the basic wavelet function [18]. $h_k$and g_k are the quadratic mirror filters. Wavelet packets are well localized in both time and frequency and thus provide an attractive alternative to pure frequency (Fourier) analysis. For a given orthogonal wavelet function, we obtain a library of bases called wavelet packet bases. Each of these bases offers a particular way of coding signals, reconstructing exact features and preserving global energy. The inverse relationship between wavelet packets of different scales can be shown through[18]:

$$2^{\frac{p}{2}} W_n(2^p x-k)=\sum_l h_{k-2l} 2^{\frac{p-1}{2}} W_{2n}(2^{p-1}x-l) + \sum_l g_{k-2l} 2^{\frac{p-1}{2}} W_{2n+1}(2^{p-1}x-l) \quad (3)$$

Equation (3) can be used to calculate the wavelet packets. Coefficients of coarser scale can be calculated using eq. 1 and eq. 2

$$S_{2n,l}^{p-1} = \sum_m hm - 2l\, S_{n,m}^{p} \quad (4)$$

$$S_{2n+1,l}^{p-1} = \sum_m gm - 2l\, S_{n,m}^{p} \quad (5)$$

The main difference between normal wavelet decomposition and wavelet packets decomposition is that despite of just splitting the approximation components wavelet packets decomposes the detail components as well. So by this richest analysis becomes possible.

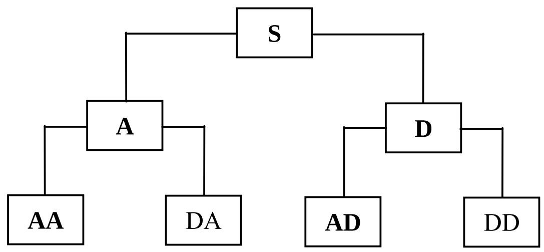

Figure 1. Wavelet packets decomposition at level 2

Wavelet packets procedure results in a large number of decompositions and its explicit enumerations are unmanageable. So it is necessary to find the optimal decomposition with respect to some reasonable criterion. One convenient criterion can be the selection of tree nodes on the base of best entropy values. In this paper we have used Shannon entropy measure to calculate the entropy. This can be calculated as:

$$\mathrm{E}(\mathrm{S_i}) = -\sum_{\mathrm{i}} \mathrm{s_i^2} \log(\mathrm{s_i^2}) \quad (6)$$

Using the Shannon entropy the optimal or the best tree can be calculated using the following scheme. A node N will be split into two nodes N1 and N2 if and only if the sum of the entropy of N1 and N2 is less than the entropy of N. This is a local criterion based only on the information available at the node N. It will lead in the form of a tree which is of much smaller size than the actual tree.

3.2 Gabor Features

Gabor filtering is effectively used for pattern classification and texture information extraction. The main application areas in the field of computer vision include face recognition, gender identification, Iris recognition, directional image enhancement and content based retrieval of images from large image repositories. An important fact about Gabor filteringis that they can be used to model the receptive fields of simple cells in the mammalian primary visual cortex as complex 2-D Gabor filters [19].

Gabor filter is a sinusoid function modulated by a Gaussian and extracts feature information from an image in the form of a response images by applying varying parameters[15]. Such filters after convolution generate the set of response images which are based on different frequencies and orientations; and from these response images we generate the representative feature vectors based on salient points.

In our implementation the filters we used are defined by the following equation[15].

$$G(x,y) = e^{\left(\frac{x_\theta^2 - \gamma^2 y_\theta^2}{\alpha^2} + \frac{2\pi x \theta^{i}}{\lambda}\right)} \quad (7)$$

Where

$$x_\theta = x\cos\theta + y\sin\theta \quad (8)$$

$$y_\theta = -x\sin\theta + y\sin\theta \quad (9)$$

And σ is the standard deviation of the Gaussian function, λ is the wavelength of the harmonic function, θ is the orientation, and γ is the spatial aspect ratio which is left constant at 0.5. The spatial frequency bandwidth is the ratio σ/λ and is held constant and equal to 0.56. Thus there are two parameters which changes when forming a Gabor filter θ and λ.

The input image is divided into 9x9 non-overlapping regions. The Gabor filter is then convolved with different parameters; and it will generate the response images. As per the work done by Lam et.al [15] we are using only the odd component of the Gabor filter which does not produce imaginary output:

$$\mathrm{G_o}(\mathrm{x,y}) = \exp\left(\frac{\mathrm{x_\theta^2} - \gamma^2 \mathrm{y_\theta^2}}{\alpha^2}\right)\sin\left(\frac{2\pi \mathrm{x}\theta}{\lambda}\right) \quad (10)$$

We convolve the image with 12 Gabor filters tuned to four orientations (θ) and three frequencies (1/λ). Orientation varied from 0 to 3π/4 (stepping by π/4) and frequency varied from 0.3 to 0.5 (stepping by 0.1).

4. PROPOSED METHOD

In this section we will present our methodology for the gender classification. The overall process consists of following steps. For every image in the image database, we will calculate the corresponding wavelet packets tree; after calculation of the wavelet packets tree, we will select the most optimum nodes of the tree at every level as the corresponding best tree nodes on the base of entropy. This best tree will be used for the further processing. Which is, to generate the wavelet signatures, and from this set of best nodes we select one node corresponding to the LL wavelet packet. This node is used to select the eigen based Gabor features generation and selection; which are merged with wavelet signature values to finalize the corresponding feature vector. This feature vector will be used by the neural network classifier for the classification purposes. Subsections will define the procedure in detail.

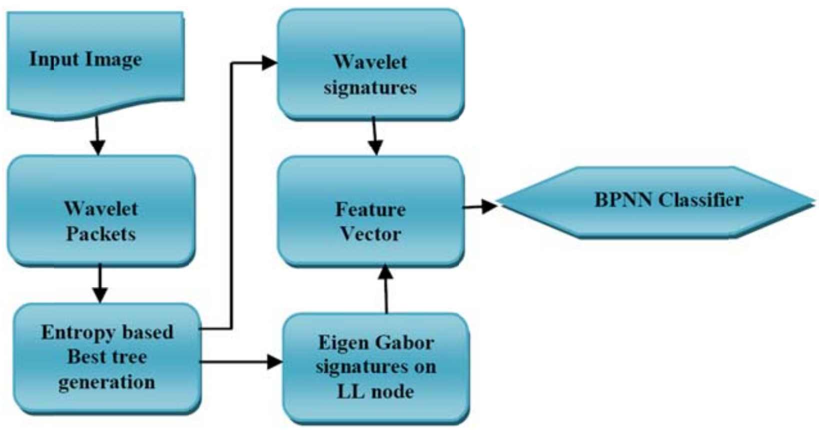

Figure 2. Architecture of Gender Classification

4.1 Haar Wavelet Packets Signatures

For the generation of Haar signatures we have computed the complete Shannon entropy based wavelet packets of the corresponding input images up to the 3rd level. This will result in the form of 64 nodes of wavelet packets tree. But we are concerned with only those nodes which have the best entropy values, as those nodes form the most representative set of signatures used for the identification purposes. So for this purpose we have generated the best entropy valued tree as corresponding best tree.

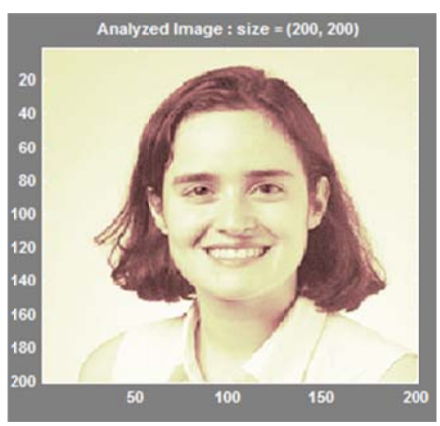

Figure 3. Input image

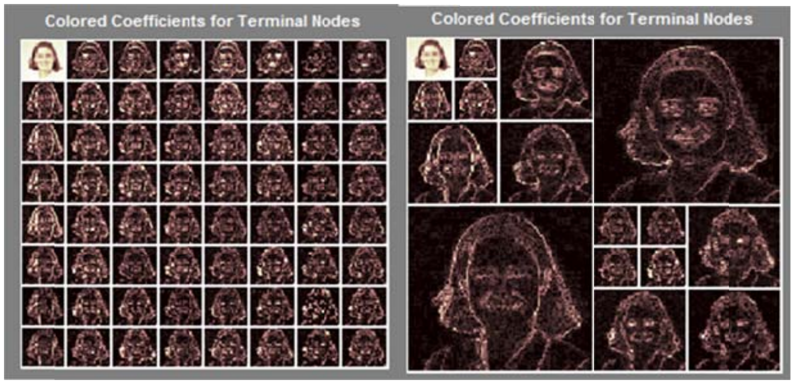

Figure 4. (a) Complete wavelet packets tree. (b) Corresponding best nodes on the base of entropy. These best nodes are used for signatures generation

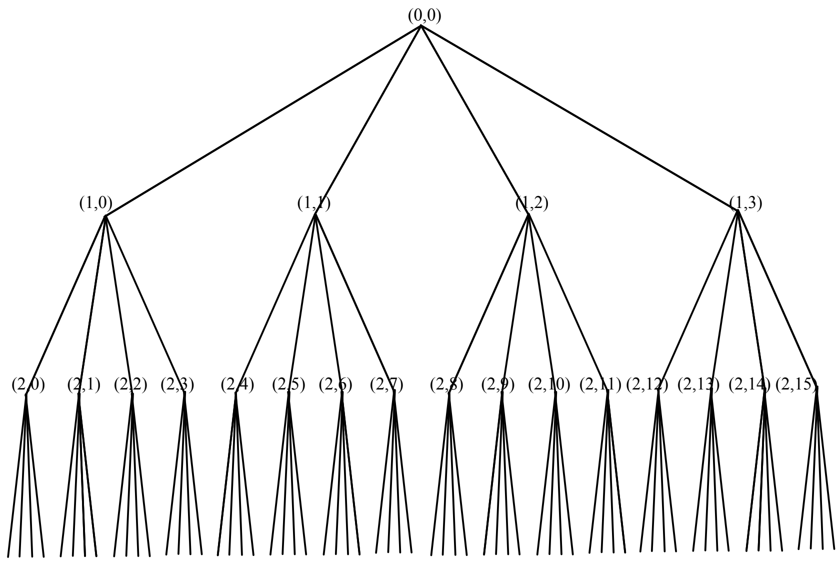

Figure 5. Full wavelet packets tree structure

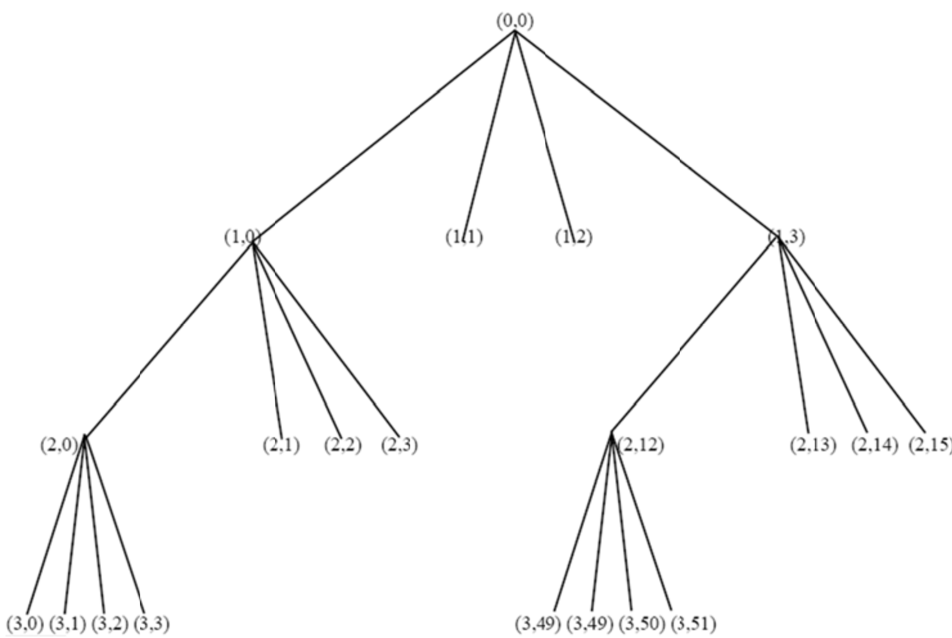

Figure 6. Corresponding best tree extracted from the wavelet packets tree.

Figure 3 is an example input image which will be passed to the system for the feature vector generation; Figure 4(a) is showing the corresponding full wavelet packets tree in image format for input image of Figure 3. Full wavelet packets tree structure can be found in figure 5. Figure 4(b) is showing the best tree generated from the full wavelet packets tree in image format. Best tree nodes information can be found in figure 6.

Nodes of the best tree are used for the Haar based signatures generation using the following formula[19]:

$$f_r = \sqrt{\frac{\sum c_{ij}^2}{i * j}} \tag{11}$$

Where f_r is the computed Wavelet signature (texture feature representation) of the sub image, C_{ij} is the representation of the intensity value of all elements of sub image and $i \times j$ is the size of the sub image [19].

4.2 Gabor Features

After convolution of the Gabor filters with varying parameters we will have a set of twelve response images. The pixels of those images will represent the Gabor response values which should be incorporated in the feature vector; but if we will follow this scheme this will result in hundreds of thousands of features, which demands heavy memory and processing requirements. So to avoid this problem in our implementation we have chosen the following scheme:

- Obtain the twelve Gabor based response images after applying parameters.
- Obtain the Eigen values vector corresponding to every Gabor response image. This will result in the form of twelve Eigen values vectors.
- Take the mean of every Eigen values vector.
- Merge the values in one vector.

So after the application of these steps we will have twelve values corresponding to the every Gabor response image. The benefit of this scheme is that we have reduced the thousands of Gabor based features in the form of just twelve values; and this reduced set is the most representative set of the Gabor based features.

4.3 Feature Vector Generation

Our feature vector consists of the values from wavelet signatures vector and Eigen Gabor features response vector. Merging of the vectors in one vector will be the corresponding feature vector on which our neural networks classifier will run. In our implementation the feature vector corresponding to the input images consists of twenty two signature features. Ten features are representing the Haar wavelet signatures and twelve features are representing the Eigen based Gabor feature signatures. The benefit of this scheme is that due to the small set of features neural networks classifier takes less amount of time on processing of the vectors for training and testing purposes.

4.4 Classification

For classification purposes we have used back propagation neural network classifier. Our classifier consists of one input layer having twenty two neurons; one hidden layer having five neurons and one output layer having one neuron. We have used 40% of the images present in image database for the training purposes and remaining 60% of the images for the testing purposes. After testing of the network we have calculated the numbers of correct detections for female images, false positive detections for female images, true positive detections for male images, and false alarms for male images; and on the base of this we have calculated the average accuracy, median accuracy, average sensitivity and average specificity of the classification.

5. EXPERIMENTS AND RESULTS

The proposed method is applied on the image database having male and female images and gender classification was performed. The detail of the procedure is present in the following subsections.

5.1 Data

We used Stanford University Medical Student (SUMS) database as our image database. The database contains two hundred male images and two hundred female images. The size of each image is 200x200. Eighty male and eighty female images are used for the training of neural networks classifier, and remaining images from both sets are used for the testing purposes. Figure 7 shows some example images from the image database.

Figure7. A sample of SUMS face database

5.2 Procedure

For every image present in the image database we have generated the corresponding feature vectors according to the procedure mentioned in section 4. In the next step of implementation we have assigned class labels to these feature vectors.'1' is used to represent female images; and '0' is used to represent male images. When this process is complete our neural networks classifier was trained on 40% of the data both from male and female images. Table 1 shows the parameter settings for our classifier.

Table 1. Parameter settings for the classifier

Method	Conditions
Classification method	Neural network classification trained with back propagation algorithm.
Number of runs	Classifier was trained and tested for the ten iterations.
Epochs per run	50 epochs were used in every iteration.
Training set female images	Contained 40% of the female images.
Training set male images	Contained 40% of the male images.
Testing set female images	Contained 60% of male images.
Testing set male images	Contained 60% of male images.

In every iteration; we have calculated the numbers of correct detections for female images. We also have calculated the detections of the female images which were considered as male images by the classifier; we have labeled them as false positive detections for female images. True positive detections for male images were determined as well, means male images which were classified correctly. Finally the false alarms for male images were calculated which means the male images which were considered as the female images; and on the base of this we have calculated the average accuracy, median accuracy, average sensitivity and average specificity of the classification.

Average accuracy is used to determine the efficiency of our proposed method. Average Accuracy can be calculated as:

$$\text{Average Accuracy} = \frac{\text{Accuracy at each iteration}}{\text{total number of iterations}} \qquad (12)$$

Sensitivity was calculated to determine the efficiency of classifier in terms of male gender identification. Sensitivity can be calculated as:

$$\text{Sensitivity} = \frac{\text{True Positives}}{\text{true positive+false alarms}} \qquad (13)$$

Specificity was calculated as a measure to determine the efficiency of classifier in terms of female gender classification.

$$\text{Specificity} = \frac{\text{Female Detections}}{\text{female detections+false positive}} \qquad (14)$$

According to our criteria of efficiency measurement average accuracy, average sensitivity and average specificity should be close to 100%.

5.3 Results

The average accuracy of the algorithm after 10 iteration is 100%; which means that sensitivity and specificity will be 100% as well as there are no misclassifications. So if we summarize the experimentation results it is proved that it is the best technique presented so far for the gender classification purposes. Table 2 formally presents the results of the classification.

Table 2. Classification results

Iteration	Accuracy (%)	Female Detection (%)	True Positive (%)	False Positive	False Alarm	Sensitivity(%)	Specificity(%)
1	97.75	98.5	97.0	3	6	0.94	0.97
2	97.75	98.0	97.5	4	5	0.95	0.96
3	97.50	98.5	96.5	3	7	0.93	0.97
4	97.50	98.0	97.0	4	6	0.94	0.96
5	97.00	97.5	96.5	5	7	0.93	0.95
6	98.00	98.5	97.5	3	5	0.95	0.97
7	97.75	97.0	98.5	6	3	0.97	0.94
8	97.25	97.5	97.0	5	6	0.94	0.95
9	97.00	98.0	96.0	4	8	0.92	0.96
10	97.75	98.5	97.0	3	6	0.94	0.97
Average	**97.525**	**98.0**	**97.05**	**4**	**5.9**	**0.941**	**0.96**

6. CONCLUSION

In this paper, problem of gender classification has been addressed. The observations have shown that Gabor features are when ranked and combined with random mean feature values they improve classification accuracy. The proposed method is robust to varying illumination effects and un-even size images. The method is very efficient because high classification accuracies can be obtained with the proposed technique.

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