

# GENDER CLASSIFICATION FROM THE IRIS CODE USED FOR RECOGNITION

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**Abstract-**In this paper, we present a new method for gender classification based on features of the iris texture selected by mutual information to improve gender classification of face images. The performance of the proposed approach has been investigated through extensive experiments performed on public database. We also showed improved results by fusion of texture features with best features selected independently from the left and right irises based on selection of features using rank feature selection method. The classification task has been achieved by using Support Vector Machine (SVM). We compared our method with existing gender classification methods based on texture feature with classifier being the same as SVM.

Key words: Recognition, LBP, SVM, rank features.

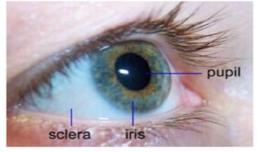
# **1. Introduction**

Iris recognition is an automated method of biometric identification that uses mathematical pattern-recognition techniques on video images of one or both of the irises of an individual's eyes, whose complex patterns are unique, stable, and can be seen from some distance. Retinal scanning is a different, ocular-based biometric technology that uses the unique patterns on a person's retina blood vessels and is often confused with iris recognition. Iris recognition uses video camera technology with subtle near infrared illumination to acquire images of the detail-rich, intricate structures of the iris which are visible externally. Digital templates encoded from these patterns by mathematical and statistical algorithms allow the identification of an individual or someone pretending to be that individual.[1] Databases of enrolled templates are searched by matcher engines at speeds measured in the millions of templates per second per (single-core) CPU, and with remarkably low false match rates.

Several hundred million persons in several countries around the world have been enrolled in iris recognition systems for convenience purposes such as passport-free automated border-crossings and some national ID programs. A key advantage of iris recognition, besides its speed of matching and its extreme resistance to false matches is the stability of the iris as an internal and protected, yet externally visible organ of the eye.



For a human being, it is always easy to recognize gender, but it is very difficult when it comes to computer vision. Generally, every subject is to be enrolled in a system, to be identified. This means that the subject0s biometric data is to be stored in the system. The system will try to match a user0s biometric data with the stored ones, whenever identification is to be made. The result is successful if a match is made. But this method cannot account for subjects which are not enrolled in the system. In such case, a system that could provide information about an anonymous subject, by examining the biometric data, would be more advantageous. This is where a gender recognition system can find its application. Both iris and fingerprint are unique to every individual. Iris is an internal organ of the eye, situated behind the cornea and the aqueous humour, but in front of the lens. The structure of human eye is as shown in figure 1. Human iris is formed in the third month of gestation and it is complete by the eighth month. It has an intricate pattern and it is very difficult to deceive an iris pattern.

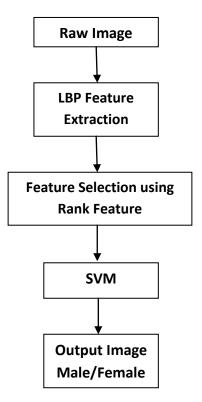


#### Iris of a Human eye

Nowadays, essentially all commercial systems to identify people from iris are based on the iriscode proposed by Daugman. Therefore, the iris-code is already being computed in iris recognition systems and could be used for other purposes such as gender prediction, either to help speed the matching process, and / or to know something about people who are not recognized. Commercial iris recognition systems typically do not also acquire face images or fingerprint images, and so gender-from-iris is the only option for gender info in an iris recognition system. Our approach is the first to classify gender from the same iris-code used to identify people. If the genderis computed before a search for a match to an enrolled iris code, then the average search time can potentially be cut in half. In instances where the person is not recognized, it may be useful to know the gender and other information about people trying to gain entry.



#### 1.1 Block Diagram



Flow Chart for Overall System

#### **1.2 System Modules**

#### **1.2.1. Feature Extraction & Selection Module**

Feature selection based on mutual information and feature fusion has been used in the proposed methodology. We also showed improved results by fusion of LBP features and the selection of features using rank feature selection method. Here features from LBP are selected based on rank priority. Then selected features are given as input to the classification stage.

#### 1.2.2 LBP- Local binary patterns

Local binary patterns (LBP) are a type of visual descriptor used for classification in computer vision. It has since been found to be a powerful feature for texture classification; it has further been determined that when LBP is combined with the Histogram of oriented gradients (HOG) descriptor, it improves the detection performance considerably on some datasets.

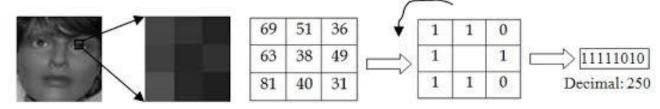
The LBP feature vector, in its simplest form, is created in the following manner:

• Divide the examined window into cells (e.g. 16x16 pixels for each cell).



- For each pixel in a cell, compare the pixel to each of its 8 neighbors (on its left-top, leftmiddle, left-bottom, right-top, etc.). Follow the pixels along a circle, i.e. clockwise or counter-clockwise.
- Where the center pixel's value is greater than the neighbour's value, write "0". Otherwise, write "1". This gives an 8-digit binary number (which is usually converted to decimal for convenience).
- Compute the histogram, over the cell, of the frequency of each "number" occurring (i.e., each combination of which pixels are smaller and which are greater than the center). This histogram can be seen as a 256-dimensional feature vector.
- Optionally normalize the histogram.
- Concatenate (normalized) histograms of all cells. This gives a feature vector for the entire window.

The feature vector can now be processed using the Support vector machineto classify images and used for face recognition or texture analysis.



**Example for LBP Feature Extraction** 

# **1.3. Feature Selection Module**

In machine learning and statistics, feature selection, also known as variable selection, attribute selection or variable subset selection, is the process of selecting a subset of relevant features (variables, predictors) for use in model construction. Feature selection techniques are used for four reasons:

- simplification of models to make them easier to interpret by researchers/users.
- shorter training times,
- to avoid the curse of dimensionality,
- enhanced generalization by reducing over fitting (formally, reduction of variance)

The central premise when using a feature selection technique is that the data contains many features that are either redundant or irrelevant, and can thus be removed without incurring much loss of information. Redundant or irrelevant features are two distinct notions, since one relevant feature may be redundant in the presence of another relevant feature with which it is strongly correlated.

Feature selection techniques should be distinguished from feature extraction. Feature extraction creates new features from functions of the original features, whereas feature selection returns a subset of the features. Feature selection techniques are often used in domains where



there are many features and comparatively few samples (or data points). Archetypal cases for the application of feature selection include the analysis of written texts and DNA microarray data, where there are many thousands of features, and a few tens to hundreds of samples.

# 1.4. Classifier Module

### **1.4.1 Support Vector Machine**

In machine learning, support vector machines SVMs, (also support vector networks) are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. Given a set of training examples, each marked for belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on. In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

With the above discrepancy measure, we will utilize the SVM classifier as our default classifier for its good performance. It follows that, given a training sample set and a test sample; we will compare the input test sample with all the training samples via the discrepancy measure and assign the class label of the closest training sample to it.

A Support Vector Machine (SVM) is a discriminative classifier formally defined by a separating hyper plane. In other words, given labeled training data (supervised learning), the algorithm outputs an optimal hyper plane which categorizes new examples. In which sense is the hyper plane obtained optimal? Let's consider the following simple problem:

For a linearly separable set of 2D-points which belong to one of two classes, find a separating straight line.

In the above picture you can see that there exist multiple lines that offer a solution to the problem. Is any of them better than the others? We can intuitively define a criterion to estimate the worth of the lines:

A line is bad if it passes too close to the points because it will be noise sensitive and it will not generalize correctly. Therefore, our goal should be to find the line passing as far as possible from all points. Then, the operation of the SVM algorithm is based on finding the hyper plane that gives the largest minimum distance to the training examples. Twice, this distance receives the important name of margin within SVM's theory. Therefore, the optimal separating hyper plane maximizes the margin of the training data.

### **1.4.2.** Set up the training data

The training data of this exercise is formed by a set of labeled 2D-points that belong to one of two different classes; one of the classes consists of one point and the other of three points.



### 1.4.3. Set up SVM's parameters

In this tutorial we have introduced the theory of SVMs in the simplest case, when the training examples are spread into two classes that are linearly separable. However, SVMs can be used in a wide variety of problems (e.g. problems with non-linearly separable data, a SVM using a kernel function to raise the dimensionality of the examples, etc). As a consequence of this, we have to define some parameters before training the SVM. These parameters are stored in an object of the class CvSVMParams.

### 1.4.4. Train the SVM

We call the method CvSVM::train to build the SVM model.

### 1.4.5. Regions classified by the SVM

The method CvSVM::predict is used to classify an input sample using a trained SVM. In this example we have used this method in order to color the space depending on the prediction done by the SVM. In other words, an image is traversed interpreting its pixels as points of the Cartesian plane. Each of the points is colored depending on the class predicted by the SVM; in green if it is the class with label 1 and in blue if it is the class with label -1.

#### **1.4.6. Support vectors**

We use here a couple of methods to obtain information about the support vectors. The method CvSVM::get\_support\_vector\_count outputs the total number of support vectors used in the problem and with the method CvSVM::get\_support\_vector we obtain each of the support vectors using an index. We have used these methods here to find the training examples that are support vectors and highlight them.

## 2. Literature Survey

This paper is concerned with predicting the gender of a person based on analysis of features of the iris texture. Previous researchers have explored various approaches for predicting the gender of a person based on iris texture. We explore using different implementations of Local Binary Patterns from the iris image using the masked information. Uniform LBP with concatenated histograms significantly improves accuracy of gender prediction relative to using the whole iris image[1]The gender will be classified by selecting a feature using mutual information of an image through Spatial Scales, Histogram, LBP, Intensity and Shape.The result of fusion LBP features with different radii and spatial scales, and the selection of features using mutual information will also improve.We use four databases: FERET and UND, under controlled conditions, the LFW database under unconstrained scenarios, and AR for occlusions for testing the results.[2]This paper investigates for the first time an approach to gender prediction from iris images using different types of features (including a small number of very simple geometric features, texture features and a combination of geometric and texture features) and a more versatile and intelligent classifier structure.[3]



Iris images have also been used for identification but there exists a very few references reporting the identification of human attributes such as gender with the help of iris images. In this paper gender has been identified using iris images. Statistical features and texture features using wavelets have been extracted from iris images. A classification model based on Support Vector Machine (SVM) has been developed to classify gender.[4]

Gender is a significant demographic attribute that can classify individuals. There are various biometric traits that have been used to classify gender. This paper, fusion of two biometric traits viz., iris and fingerprint, is done to classify gender. Mean and standard deviation are the features extracted from an iris image, whereas Ridge Thickness to Valley Thickness Ratio (RTVTR) is extracted from a fingerprint image. The features extracted from both iris and fingerprint images are used to train a neural network. As a result, a suitable feature vector is formed which is used for classifying gender.[5]

Different methods have been used for gender classification like gait, iris and hand shape. However, majority of techniques for gender classification are based on facial information. A comparative study of gender classification using different techniques is presented. The major emphasis of this work is on the critical evaluation of different techniques used for gender classification. The comparative evaluation has highlighted major strengths and limitations of existing gender classification techniques. Taking an overview of these major problems, our research is focused on summarizing the literature by highlighting its strengths and limitations.[6] This paper employs machine learning techniques to develop models that predict gender based on the iris texture features. While there is a large body of research that explores biometrics as a means of verifying identity, there has been very little work done to determine if biometric measures can be used to determine specific human attributes. If it is possible to discover such attributes, they would be useful in situations where a biometric system fails to identify an individual that has not been enrolled, yet still needs to be identified. The iris was selected as the biometric to analyze for two major reasons: (1) quality methods have already been developed to segment and encode an iris image, (2) current iris encoding methods are conducive to selecting and extracting attributes from an iris texture and creating a meaningful feature vector.[7]

The pupil localization is inaccurate due to noisy artifacts, resulted by corneal reflection present in an iris image. Hence, the performance of iris-based recognition system is degraded. This paper describes a unique approach to detect noisy pixels that are present in the pupil. This technique is based on thresholding. The detected reflection noisy pixels are replaced with the neighborhood non-reflection pixels. Finally, local binary pattern (LBP) is used for extracting texture features and they are matched using radial basis function and probabilistic neural network classifiers. To evaluate the performance of the proposed technique, the approach has been applied on PHOENIX, MMU, IITD and CASIA 4.0 databases.[8]

Iris region extraction is the most controversial issue in the iris recognition system, since the poor results for this stage will spoil or break the effectiveness of the iris recognition system. In this paper a sophisticated system method to localize iris region is proposed by employing different image processing techniques: morphological operators (i.e., erosion and dilation), seed filling, rotation, 8 neighborhood operators. The proposed system is based on the formal attributes of an image of the iris, taking into consideration the noise area had been found in different parts of the eye image such as specular reflections, focus and small visible iris part. And the experiment was



conducted using 1877 iris images of standard color data UBIRIS, and the result shows that the proposed method had a high rate of accuracy[9].

The calculation of binary iris codes from feature values (e.g. the result of Gabor transform) is a key step in iris recognition systems. Traditional binarization method based on the sign of feature values has achieved very promising performance. However, currently, little research focuses on a deeper insight into this binarization method to produce iris codes. In this paper, we illustrate the iris code calculation from the perspective of optimization. We demonstrate that the traditional iris code is the solution of an optimization problem which minimizes the distance between the feature values and iris codes. Furthermore, we show that more effective iris codes can be obtained by adding terms to the objective function of this optimization problem. We investigate two additional objective terms. The first objective term exploits the spatial relationships of the bits in different positions of an iris code. The second objective term mitigates the influence of less reliable bits in iris codes. The two objective terms can be applied to the optimization problem individually, or in a combined scheme. We conduct experiments on four benchmark datasets with varying image quality. The experimental results demonstrate that the iris code produced by solving the optimization problem with the two additional objective terms achieves a generally improved performance in comparison to the traditional iris code calculated by binarizing feature values based on their signs.[10]

Iris Recognition, an evolving biometric identification technique which provides individual authentication based on unique feature or characteristic possessed by the individual. This paper provides general framework and related work in the iris recognition. Iris recognition improves the efficiency of biometric identification. This paper provides a critical review on different wavelet based feature extraction techniques proposed up till now along with efficiency comparison of each technique.[11]

Iris is one of the popular biometrics that is widely used for identity authentication. Different features have been used to perform iris recognition in the past. Most of them are based on hand-crafted features designed by biometrics experts. Due to tremendous success of deep learning in computer vision problems, there has been a lot of interest in applying features learned by convolutional neural networks on general image recognition to other tasks such as segmentation, face recognition, and object detection. In this paper, we have investigated the application of deep features extracted from VGG-Net for iris recognition.[12]

Iris recognition systems are increasingly deployed for large-scale applications such as national ID programs which continue to acquire millions of iris images to establish identity among billions. However with the availability of variety of iris sensors that are deployed for the iris imaging under different illumination/environment, significant performance degradation is expected while matching such iris images acquired under two different domains (either sensor-specific or wavelength-specific). This paper develops a domain adaptation framework to address this problem and introduces a new algorithm using Markov random fields (MRF) model to significantly improve cross-domain iris recognition. The proposed domain adaptation framework based on the naive Bayes nearest neighbor classification uses a real-valued feature representation which is capable of learning domain knowledge. Our approach to estimate corresponding visible iris patterns from the synthesis of iris patches in the near infrared iris images achieves outperforming results for the crossspectral iris recognition. In this paper, a new class of bi-



spectral iris recognition system that can simultaneously acquire visible and near infra-red images with pixel-to-pixel correspondences is proposed and evaluated. We present reproducible experimental results from three publicly available databases; PolyU crossspectral iris image database, IIITD CLI and UND database, and achieve outperforming results for the cross-sensor and crossspectral iris matching.[13]

In this paper we proposed an improved novel approach to identify the person using iris recognition technique. This approach is based on Artificial Neural Network and Support Vector Machine (SVM) as an iris pattern classifier. Prior to classifier, region of interest i.e. iris region is segmented using Canny edge detector and Hough transform. Provided that the effect of eyelid and eyelashes get reduced. Daugman'srubber sheet model used to get normalized iris to improve computational efficiency and proper dimensionality. Further, discriminating feature sequence is obtained by feature extraction from segmented iris image using 1D Log Gabor wavelet. Encoding is done using phase quantization to get feature vectors. These binary sequence feature vectors are used to train SVM and ANN as iris pattern classifier. The experimental tests are performed over standard CASIAIrisV4 database.[14]This paper employs machine learning techniques to develop models that predict gender based on the iris texture features. While there is a large body of research that explores biometrics as a means of verifying identity, there has been very little work done to determine if biometric measures can be used to determine specific human attributes. If it is possible to discover such attributes, they would be useful in situations where a biometric system fails to identify an individual that has not been enrolled, yet still needs to be identified. The iris was selected as the biometric to analyze for two major reasons: (1) quality methods have already been developed to segment and encode an iris image, (2) current iris encoding methods are conducive to selecting and extracting attributes from an iris texture and creating a meaningful feature vector.[15]

# **3. Existing Method**

The existing system used the mutual information technique for feature extraction stage. Here, found that using selected features representing a subset of the iris region and used measures of mutual information to guide the selection of bits from the iris code to use as features in gender prediction. Finally gender classification based on SVM classifier.

### Disadvantages

- Mutual Information is computationally very expensive
- as well as being sensitive to the interpolation procedure.
- The minimum found can be a local one, and not be the correct/optimal one.

# 4. Proposed Method

The proposed system of this paper uses the LBP. The LBP transformation is used to extract features from iris images because of its low computational cost and effective texture



description ability. Features are selected based on the rank feature selection for best result.SVM Classifier is used for classify the images whether it is male or female.

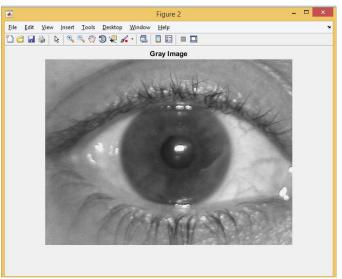


Fig. Proposed System input Image

## Advantages

- Better accuracy can be obtained by fusing these features before classification.
- Features had large variability and random selection.
- Using the best gender SVM classifier.

## 5. Results and Discussion

We have tested LBP feature method and SVM classifier on the dataset. It will be difficult to select an optimal subset of features to classify the gender based on iris code without an automatic feature selection method. Hence, an efficient and accurate feature selection method is required to classify the gender. Here rank based feature selection method is proposed. The classification stage used a novel SVM classifier to classify the images as male or female. The overall accuracy using rank feature selection method of the proposed system is 93.7%.



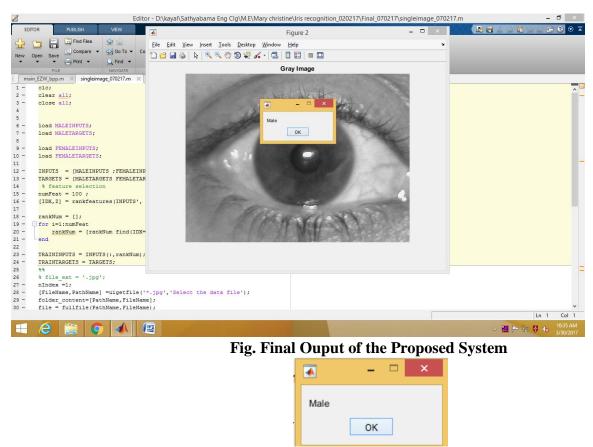


Fig. Dialog Box for recognition Output

# 6. Conclusion

An efficient approach for gender classification based on LBP features with rank based feature selection and SVM classifier is presented. First the features are extracted using LBP features and then the extracted features are selected based on rank based feature selection method. The effectiveness of the proposed system is analyzed on public database images. The obtained maximum classification rate using LBP features for male is 100% and female is 87.5%.

## References

- [1] Juan E. Tapia, Claudio A. Perez & Kevin W. Bowyer. Gender Classification from Iris Images Using Fusion of Uniform Local Binary Patterns, 10.1007/978-3-319-16181-5 57.
- [2] Pavithra A, Saravanan P, Venkataraman N L,' Gender Classification Based on Selecting Features LBP, Intensity, and Shape', International Journal of Engineering Research & Technology (IJERT) ISSN: 2278-0181, Vol. 3 Issue 3, March – 2014.
- [3] Michael Fairhurst1, Meryem Erbilek2, Marjory Da Costa-Abreu. EXPLORING GENDER PREDICTION FROM IRIS BIOMETRICS. ©2015 Gesellschaft für Informatik e.V., Bonn, Germany.



- [4] Atul Bansal & Ravinder Agarwal, R.K. Sharma. SVM Based Gender Classification Using Iris Images, 978-0-7695-4850-0/12 \$26.00 © 2012 IEEE
- [5] Ms.Bindhu K. Rajan, Ms.Nimpha Anto &Ms.Sneha Jose. Fusion of Iris & Fingerprint Biometrics for Gender Classification Using Neural Network.
- [6] Khan, S. A., Nazir, M., Akram, S., & Riaz, N. (2011, December). Gender classification using image processing techniques: A survey. In Multitopic Conference (INMIC), 2011 IEEE 14th International (pp. 25-30).
- [7] Thomas, V., Chawla, N. V., Bowyer, K. W., & Flynn, P. J. (2007, September). Learning to predict gender from iris images. BTAS. First IEEE International Conference on In Biometrics: Theory, Applications, and Systems, (pp. 1-5).
- [8] Gawande, U., Hajari, K., & Golhar, Y. (2016, October). Novel technique for removing corneal reflection in noisy environment—Enhancing iris recognition performance. In Signal and Information Processing (IConSIP), International Conference on (pp. 1-5). IEEE.
- [9] Hashim, A. T., & Noori, D. A. (2016, September). An Approach of Noisy Color Iris Segmentation Based on Hybrid Image Processing Techniques. In Cyberworlds (CW), 2016 International Conference on (pp. 183-188). IEEE.
- [10] Hu, Y., Sirlantzis, K., & Howells, G. (2017). Optimal Generation of Iris Codes for Iris Recognition. IEEE Transactions on Information Forensics and Security, 12(1), 157-171.
- [11] Balap, P., Khoje, S., & Pardeshi, P. (2017, January). A critical review on wavelet based feature extraction for Iris Recognition. In Intelligent Systems and Control (ISCO), 2017 11th International Conference on (pp. 235-240). IEEE.
- [12] Minaee, S., Abdolrashidiy, A., & Wang, Y. (2016, December). An experimental study of deep convolutional features for iris recognition. In Signal Processing in Medicine and Biology Symposium (SPMB), 2016 IEEE (pp. 1-6). IEEE.
- [13] Nalla, P. R., & Kumar, A. (2017). Toward More Accurate Iris Recognition Using Cross-Spectral Matching. IEEE Transactions on Image Processing, 26(1), 208-221.
- [14] Salve, S. S., & Narote, S. P. (2016, March). Iris recognition using SVM and ANN. In Wireless Communications, Signal Processing and Networking (WiSPNET), International Conference on (pp. 474-478). IEEE.
- [15] Thomas, V., Chawla, N. V., Bowyer, K. W., & Flynn, P. J. (2007, September). Learning to predict gender from iris images. In Biometrics: Theory, Applications, and Systems, 2007. BTAS 2007. First IEEE International Conference on (pp. 1-5). IEEE.