Using Iris Texture to Predict Ethnicity: A Pattern Recognition Approach

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***Abstract*—Predicting ethnicity using the texture of an iris has become an interesting topic for researchers in the recent past. Artificial intelligence, Neural Network, Computer Vision and many other Machine Learning paradigms have been taken into consideration while classifying ethnicity using the iris texture. In addition, there have been many studies where it classifies the age, gender and other biometrics of a person compared to the ethnicity of a person. The purpose of this paper is to highlight and acknowledge how several researchers have studied in this field by differentiating and understanding their methods, algorithms and its subsequent outcomes.**

***Index Terms*—component, formatting, style, styling, insert**

I. Introduction

The study of iris biometrics results in a coded text of the iris which is obtained from the texture of the iris. This coded text is further analyzed to identify a person or age of a person or even gender of that person. [2] However, a small amount of research has been done regarding soft biometrics of the iris such as ethnicity. [1] This paper completely revolves around the previous excellent research work of the topic: ethnicity classification and prediction based on the texture of the iris. Additionally, this paper addresses and explains all the iris image datasets, various algorithms and its correspondent experiment results that were carried out by the researchers over the last two decades. The paper is organized in this manner where section II comprises detailed review work of the topic ethnicity prediction done by several researchers across the world. Section III depicts a summary table that elaborates and compares the different datasets, techniques and their accuracy that were achieved by the researchers. Lastly, a conclusion and future work is also provided in section III to provide a closure in predicting and classifying ethnicity.

II. Detailed Literature Review

A. Infrared Illumination to detect ethnicity

Stephen et al. [2] have used near-infrared illumination in order to take images of the iris to make an improved detection of ethnicity. They took Asians and Caucasians as their experiment subjects. From their experiment they could claim that their performance was better compared to those previous researchers. Also, they came up with the fact that predicting ethnicity for a female subject is arduous than male subjects

1) Datasets: The experiment was done with a collection of 1200 feature vectors data, where Asians and Caucasians were taken as subjects. From each of the subjects, five images of both of the iris were taken. Images were captured using the sensor called LG 4000 and its near-infrared illumination ability

makes it possible to produce 480x640 images. For segmentation and creating a normalized picture, IrisBee software was used. In order to avoid biases in their experimental result they have used the person-disjoint train and test data. This was done by randomly dividing the iris dataset into 10 sections, where each section consisted of images for 6 individuals of each different ethnicity.

2) Algorithm: Computation of texture features are done independently in order to classify the contrast between iris-sclera (white portion of the eye) and pupil-iris. Similarly, texture features are also calculated using some of the basic texture filters that include: ‘spot detectors’, ‘line detectors’, ‘S5S5’, ‘R5R5’ and ‘E5E5’. Each of the texture filters are then computationally summarized using five statistical measures. The five statistical measures are: mean value of the filter response, standard deviation, 90th percentile, 10th percentile and the range between 90th and 10th percentile. Thereby, resulting in 450 features with a grand total of 882 features. Numerous classifiers that were available in the Weka package were deployed to classify ethnicity. Altering the parameters in some of the classifiers has resulted in performance gains. Although, with the default parameters in the Weka’s system, that SMO (Sequential Minimum Optimization) algorithm has achieved the highest accuracy of 90.58% in predicting ethnicity. Random Forest and Bagged FT were also very close in predicting ethnicity. Naive Bayes had the lowest accuracy of 68.42% in predicting ethnicity. Furthermore, they have run the experiment once more by 10 fold cross-validation but this time without the condition of person-disjoint. The whole idea of person-disjoint condition is done to avoid the duplication of images for both training and test dataset.

3) Experimental Results: Without the condition of person-disjoint there has been an improved accuracy of 96.17%. Stephen et al. [2] has found an enhanced accuracy c to the works of previous researchers. The success in p Asian and Caucasian ethnicity with the aid of subjec 10-fold cross validation on a collection of 1200 ima has exceeded 90

B. 2D Gabor Filter

Qui et al. [3] believes that the iris texture of an indi interconnected with their iris texture. Iris is the colou at the front of the eye that contains the pupil in th Qui and his team looked into huge amounts of iris i Asians and non-Asians. They discovered that these iris varied from one another in terms of the statistical an the iris texture. Thus, in short their reason to find a ne predicting ethnicity is that at a small scale, the featur texture are not dictated by genetics. Their proposed a requires 2D gabor filters to get the global texture inf and AdaBoost is used to learn the different categ principle from the group of the candidate feature set

1) Datasets: For their experiment they used databases from Chinese Academy of Sciences Institute of Automation (CASIA v2), University of Palackeho and Olomopuc (UPOL) and University of Beira Interior (UBIRIS). The CASIA database consisted of 2400 iris images of Asiand and UPOL and UBIRIS consisted of 1582 iris images of non-Asian. The images in the CASIA database were 8 bit depth grey images; thus, the images from UPOL and UBIRIS were also converted into that format to make the experiment more reliable.

2) Algorithm: The ethnic classification algorithm requires three steps: Image preprocessing Global Texture Analysis and Training.

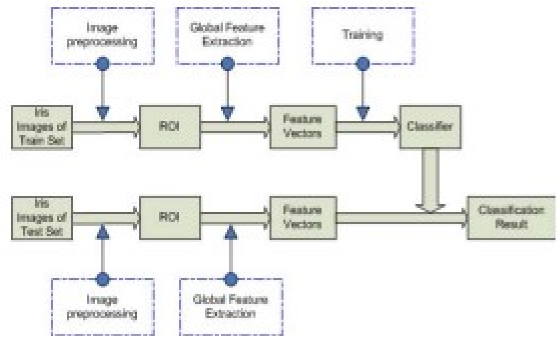

Fig. 1. Flowchart of the Algorithm.

Image Preprocessing: All iris recognition systems require this step. The step includes localization, normalisation and enhancement. The image consists of the eyelids and eyelashes, thus, to cut out those portions only the inner ¾ of the lower half of an iris region is used. This region is called the region of interest (ROI) and it is used for feature extraction. Qui and his team used a 60 x 256 pixel image for their ROI and it is then split into two equal regions, region A and region B.

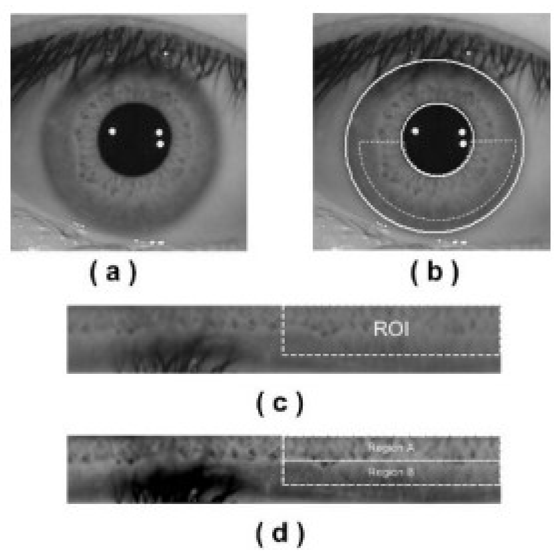

Fig. 2. Image Preprocessing

Global Feature Extraction: To extract the global feature from the ROI multichannel Gabor filtering. The input image (ROI), which consists of image points, is coiled together using a 2D Gabor filter to acquire a Gabor filtered image. The output of the Gabor filter in each image point can be combined into a single quantity called the Gabor energy. From this output, it was found that Asians have substantial texture in region A whereas for non-Asians the texture was rich in both the regions, region A and region B. Therefore, a high pass filtering system can be used to extract the differences between different races.

Qui and their team designed a bank of Gabor filters to get the Gabor energy features. The frequency domain of the Gabor filters are of central symmetry thus only the half of the frequency plan is needed. By using four different values of orientation θ, 0, π / 4 , π / 2 , and 3π / 4, 240 pairs of Gabor channels were discovered. The pair of Gabor filters helped to get Gabor's energy image. From the Gabor energy values the average of region A and region B was calculated. Two statistical parameters of the Gabor energy picture, Gabor Energy (GE) and Gabor Energy Ratio (GER), are retrieved in order to define the global texture data associated with the ROI.

Training: A lot of the features have been extracted for each iris image, but not all the features are kept. The image goes through a rigorous process which disposes of most of the features. Then the AdaBoost algorithm is used to collect features automatically and train the classifier.

3) Experimental Results: The Gabor energy features helped to achieve a correct classification rate of 79.44% and the Gabor energy ratio features achieved a CCR of 84.95%. However, when features from both Gabor energy and Gabor energy ratio are used they achieved a higher CCR of 85.95%. Even though the classification rate is high there are some obvious errors: UBIRIS is a noisy image database and it has many images that are not focused. The ROI might be obstructed by eyelids and eyelashes. There are outliers in both classes.

C. Binarized Statistical Image Feature & Local Binary Patterns

Ross A. and Bobeldyk D. [4] focused mainly on iris biometric attributes. As it is difficult to detect the rich texture of dark colored iris in the visible wavelength, Ross A and Bobeldyk D. used images of iris that was imaged in the Near Infrared (NIR) spectrum as infrared has a longer wavelength. The long wavelength helped to penetrate deeper into the iris of dark-colored eyes. Moreover, the NIR picture capture procedure doesn't excite the pupil, thus the iris texture is protected from being unnecessarily altered by pupil dynamics.

1) Datasets: To carry out this experiment three datasets were used. The largest one is BioCOP2009 which was collected at West Virginia University and the other two were used for cross testing in order to display the generalizability of the proposed methods. Those datasets are Cosmetic Contact dataset and GFI dataset which were collected at Notre Dame University. All the datasets went through preprocessing and geometric alignment.

2) Algorithm: The main goal of this paper [4] is to demonstrate the usefulness of straightforward texture descriptors for feature prediction. The texture descriptors that performed well in extracting iris texture features from Outex and Curet texture dataset are local binary patterns (LBP) and binarized statistical image features (BSIF) along with local phase quantization (LPQ).

LBP: By comparing the values of each pixel in a picture with each of its corresponding neighbours, LBP [44] encodes local texture information. As a consequence, a binary code is created whose length is determined by how many adjacent pixels are taken into account.

The LBP code is created for each pixel in the image by first converting the binary sequence into a decimal value. LPQ: By leveraging an image's phase data, LPQ [46] encodes local texture data. The phase information from the 2-D Discrete Fourier Transform is utilized to construct an 8-bit binary code at each pixel point using a sliding rectangular window. A 256-dimensional vector of features is produced by creating a histogram of the produced data.

BSIF: As a texture descriptor, BSIF was initially developed by Kanala and Rahtu [45]. By organizing the picture using pre-made filters, BSIF casts the image into a domain. 13 natural photos were used to produce the pregenerated filters. The 13 natural photos are randomly picked to yield 50,000 patches of size k x k. Only the most significant n elements are kept after using principal component analysis. Then, independent element analysis is used to create n filters with a size of k x k. The pregenerated filters for k = $\{$ 3, 5, 7, 9, 11, 13, 15, 17 $\}$ and n = $\{$ 5 - 12$\}$.

The picture has been compressed with each of the n pregenerated filters, and the response is converted into a binary. A '1' is produced if the answer is larger than zero. A '0' is produced if the answer is less than or equal to zero. The replies are combined to create a binary string, which is then transformed into a decimal number (the BSIF code). The resultant decimal number would be '19', for instance, if the n binary replies were $\{$ 1, 0, 0, 1, 1 $\}$. The BSIF response will therefore vary from 0 to 2n - 1 for n filters.

Each of the NIR retinal pictures from our suggested technique is given a texture description before being tessellated into 2020 pixel sections. This patterning was carried out to make sure that the feature vector that was being produced had spatial data. Each tessellation's histogram was created, normalized, and concatenated into a single feature vector. The original NIR ocular picture was subjected to a geometric adjustment in order to offer uniform spatial data throughout every image.

3) Experimental Results:

i. BIOSCOPE2009: As a trade-off between prediction accuracy and computational processing time, the 8-bit BSIF was chosen in this study. The findings with 9-bit or 10-bit BSIF would be marginally better, but considering the size of the BioCOP2009 dataset, the additional memory and processing time needed to run each experiment were fairly significant. Using the retrieved BSIF features, an SVM classifier was honed on each of the 5 training sets. Each SVM model's classification of the experimental information was done. the accuracy of the predictions made using filters with sizes between 3 x 17 squares. Although the forecast accuracy changes significantly for each of the several filter sizes, there is no appreciable performance difference between them.

ii. IRIS-EXCLUDED OCULAR REGION VS. IRIS-ONLY REGION: When using BSIF to determine race, the iris-only region is more accurate than the iris-excluded ocular region, however when predicting gender, the converse is true.

iii. CROSS DATASET TESTING: A technique frequently performs well when both training and evaluation are carried out on the same dataset. We trained on the BioCOP2009 dataset and tested on the previously mentioned CCD1 and CCD2 datasets in order to show the generality of the suggested method. The pictures in CCD1 and CCD2 were classified using the 5 trained SVM models that were created using the BioCOP2009 dataset. It should be noted that although participants from the CCD1 and CCD2 datasets were categorized as ”White,” those from the BioCOP2009 dataset were given the ”Caucasian” designation. Images of individuals with contacts, without contacts, and with cosmetic contacts may be found in the CCD1 and CCD2 collections. Without contacts, CCD1 and CCD2 each carry 500 left and 500 right eye pictures and 200 left and 200 right eye images, respectively. In our studies, only the photos devoid of interactions were utilized.

D. Gender and Ethnicity Classification of Iris Images using Deep Class-Encoder [5]

1) DATASET: A set of 1200 images sourced from the iris image database at the University of Notre Dame is available for analysis. This dataset comprises iris images belonging to 60 Caucasian and 60 Asian subjects, with each subject having 5 right and 5 left iris images. The images were captured using an LG 4000 sensor and had a size of 480x640. After capturing the images, they were segmented using Notre Dame's IrisBEE software, and their size was reduced to 240x60 pixels for normalization purposes.

2) Algorithm: The study conducted experiments on two distinct datasets, namely ND-Iris-0405 and ND-Gender From Iris (ND-GFI). The former dataset comprised 64,980 images that belonged to 158 females and 198 males. For training purposes, 70% of the data from each gender group was used, amounting to a total of 42,899 images, while the remaining images constituted the test set. The latter dataset, ND-GFI, included 3,000 images belonging to 750 males and 750 females. A predefined protocol was followed, where 80% of the data from each gender group was utilized for training, and the rest 20% was used for testing. For evaluation purposes, a separate subject-disjoint set named UND V, which contained 1,944 images, was used to assess the model's performance. The study followed the same protocol for evaluating the proposed model, and both protocols guaranteed that the training and testing sets were mutually exclusive, with no image occurring in both partitions. Figure 3 displayed sample images from all three datasets, and Table 1 presented a summary of the experimental evaluation's protocols.

3) Experimental Results: *INSERT TABLE* The proposed model for gender and ethnicity classification on iris images has been compared to other deep learning models, including Stacked Autoencoder (SAE), Stacked Denoising Autoencoder (SDAE), Deep Belief Network (DBN), Discriminative Restricted Boltzmann Machine (DRBM), and AlexNet, which is a Convolutional Neural Network (CNN) based model. For consistency, the feature extraction models have the same architecture as the proposed Deep ClassEncoder. After feature extraction, a classifier (either RDF or NNet) is trained for classification. The test samples have a class imbalance, so the mean class wise accuracy is reported.

E. Artificial Neural Network for Prediction of Ethnicity Based on Iris Texture [6]

1) DATASET: The dataset comprises 1200 iris images sourced from the iris image database of the University of Notre Dame. It comprises 60 Caucasian and 60 Asian subjects, with each person having 5 images of their right iris and 5 images of their left iris. The images were captured using an LG 4000 sensor and initially had a size of 480x640 pixels. They underwent processing using Notre Dame's IrisBEE software and were subsequently normalized to 240x60 pixels.

2) Algorithm and work process: Before training the neural networks, the data underwent several preprocessing steps. Firstly, the input vector was normalized by mapping it to the interval [-1, 1] to prevent network saturation. Secondly, missing values in the input feature vector due to eyelid or eyelash occlusion were replaced with the corresponding feature's average value from the remaining images of the same subject. The dataset was then divided into three subsets, with the first subset containing 60% of the data being designated as the training set to adjust the network's weight values and optimize its performance. The second subset, which consisted of 20% of the data, was used as the validation set. During the training process, the validation error was monitored, and training was stopped if the validation error increased for five consecutive iterations. Although the validation and training error usually decreased during the initial phase of training, the validation error would often begin to rise when the network began to overfit the data. Finally, the network weights and biases were saved when the validation set error was at its minimum.

3) RESULTS: The study evaluated the performance of two neural networks trained on iris images from the University of Notre Dame's database. The networks were trained using either disjoint or non-disjoint sets of images. The non-disjoint network achieved a smaller Minimum Mean Square Error (MSE) value and performed better in the Confusion Matrix and Receiver Operating Characteristic (ROC) curve analyses. The Confusion Matrix showed the number of correctly and incorrectly classified cases for both networks. The ROC curve analysis demonstrated the tradeoff between true positives and false positives at different decision thresholds. Network 2 was found to be more accurate in classification, indicating that using different images of the same iris in both the test and training sets improved the model's performance. The study also compared the performance of neural networks versus

SMO for the same database and feature vectors in the table below *INSERT TABLE* *INSERT PICTURE 4) CONCLUSION: To conclude, the study aims to classify gender and ethnicity from iris images using a supervised autoencoder model called Deep Class-Encoder. This model uses class labels during feature learning to acquire discriminative features. The model was evaluated on two datasets for gender and ethnicity classification, and the results indicate that the proposed model is effective in learning class-specific discriminative features. Besides, we presented a texture-based classification approach for predicting ethnicity using artificial neural networks. Our approach achieved accuracy rates of 93.3% and 97.5% for person-disjoint and non-person-disjoint test sets, respectively. These results surpassed the previous state-of-the-art methods applied to the same database. The success of our neural network classifiers demonstrated their potential for use in a new application domain.

F. LEARNING APPEARANCE PRIMITIVES OF IRIS IMAGES FOR ETHNIC CLASSIFICATION

1) Dataset: The experiment used the CASIA-BioSecure iris database containing 2400 images from 60 subjects, with each having 120 eyes. Half of the pictures were taken in China from Asians and the other half in France from non-Asians. The images were split into a training set of 1200 images and a testing set of 1200 images. The training set had 600 images randomly selected from Asian and non-Asian categories, and the remaining images were used in the testing set.

2) Algorithm and work process:The first step is filtering. They can be used to classify textures based on their response to a set of filters that cover the frequency space. In this process, an input image is convolved with a 2D Gabor filter to produce a filtered image. This is done using even Gabor filters in this experiment. They used a total of 40 filters to transform each pixel into a 40-dimensional vector. The second step is to cluster these vectors into a small set of prototypes, which are called Iris-Textons. Then they used the K-means clustering algorithm to find these prototypes. Then they used Iris-Texton histograms to represent the visual appearance of iris images. The Iris-Texton histogram is a mapping of 40-dimensional vectors to 64 different Iris-Textons. They used this histogram to characterize the visual appearance of iris images. Before using this histogram with SVM, They needed to scale each bin value to the range of 0 to 1. They used Radial Basis Function as their kernel function with a specific value for σ and the upper limit. To avoid overfitting, they used cross-validation.

3) Results: Correct Classification Rate(%)

TABLE I
CORRECT CLASSIFICATION RATE (%)

Method	Training Set	Testing Set	Overall
Global Texture Analysis	84.83	85.67	85.25
The proposed method	93.73	88.31	91.02

A statistical test was used to evaluate the accuracy of the algorithm, specifically by examining the Correct Classification Rate (CCR) of the algorithm. Table 1 shows the ethnic classification result. The proposed method had a higher CCR of 91.02% than the previous method.

G. Ethnicity Distinctiveness Through Iris Texture Features Using Gabor Filters

1) Dataset: Because there is no existing database of iris images for African individuals, the images used in this study were obtained by the researchers themselves in an uncontrolled environment with consent from 15 Black males and 15 White females. Each participant provided four images of their left and right eyes using the Vista EY2 dual iris and face camera, which uses near-infrared light and produces 8-bitmap images with dimensions of 640 × 480 pixels. Before any processing was done, the images were converted to grayscale.

2) Algorithm and work process: Bresenham's circle algorithm, which is based on the midpoint circle algorithm, is used to determine the centers of the pupil and iris and to locate their boundaries. To segment the iris, the Chan-Vese algorithm is used. This algorithm finds a curve that separates the object of interest from the rest of the image by minimizing energy-based segmentation, which includes regularizing terms that reduce the fitting term. The evolving curve C is defined as the boundary of an open subset ω of Ω, where Ω represents the spatial domain of an image. Regularizing terms are added to the energy function, which includes the length of the curve C and the area of the region inside C. The parameters, such as diameter, radii, and centers of the pupil and iris, are computed by Bresenham's algorithm and used as additional regularizing terms to influence the segmentation of the iris. The iris image is improved using two methods: sharpening and contrast limited adaptive histogram equalization (CLAHE) to make it clearer and more visually appealing. Then, the enhanced image is resized to a standard size. Texture features are extracted using a group of Gabor filters with different wavelengths and orientations. The Gabor filters are particularly useful for texture representation and discrimination. The filter bank includes three wavelengths and five orientations and produces a 1x15 Gabor array. This array is used to compute the magnitude and phase components of the Gabor filter bank for the input image. Finally, the mean amplitude (MA) and local energy (LE) are calculated from these components to use as texture features.

3) Results:

TABLE II
CORRECT CLASSIFICATION RATE (%) FOR VARIOUS AUTHORS AND TECHNIQUES

Authors	Database	Ethnicity	Technique	CCR
Qui et al.	CAS, UP, UB	Asian, non-Asian	Gabor filters	89.95%
Qui et al.	CAS, UP, UB	Asian, non-Asian	Iris Textons	89.95%
Lag, Bow	Notre Dame	Asian, Caucasian	9 Filters	90.58%
Proposed method	Independent	Black, Caucasian	Gabor filters	93.33%

Figures are given below. Figure 2: Iris segmentation using the Chan-Vese algorithm which performs faster, produces accurate and reliable results, and is computationally inexpensive compared to the traditional integro differential equation used for iris segmentation by Daugman. Enhancing the segmented iris highlights the smaller texture details of the iris edges needed for extraction. Figure 3: Filter outputs of the designed Gabor envelope of size 1×15. Figure 4: Iris image convolved with each filter output at each specified wavelength and orientation. Figure 5: Total magnitude and phase response of the designed filter bank for each iris image. This complex response is used to compute the Local Energy (LE) and Mean Amplitude (MA) to be used as iris texture features. The computed LE and MA of size 1×15 each are further horizontally concatenated to finally produce a feature vector of size 1×30 per individual. After computing and scaling the mean and standard deviation for all subjects per each of the 30 features belonging to one ethnic group, a reduced feature dimension for both ethnicities is achieved. With a total of 15 Blacks and Whites respectively, it is observed that Blacks always fall on the negative of the z-plane while Caucasians fall on the positive. The distinction between both ethnicities is most clearly witnessed at the lower wavelengths of only the mean amplitude features, with an error rate (ER) of 6%.

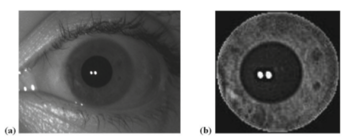

Fig. 2. Input image with segmented iris

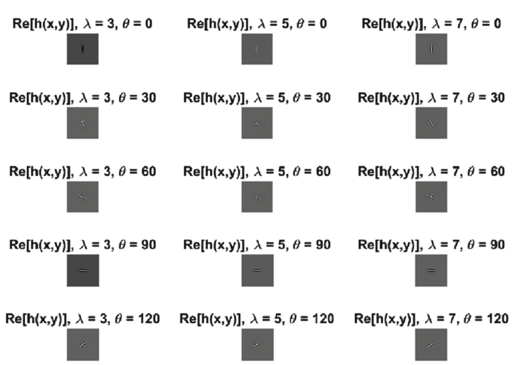

Fig. 3. Gabor envelope at different wavelenghts and orientations

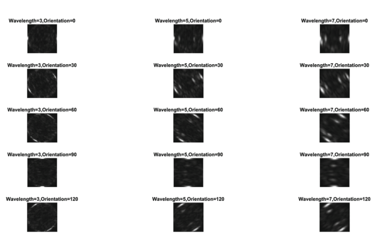

Fig. 4. Iris image convolved with Gabor array

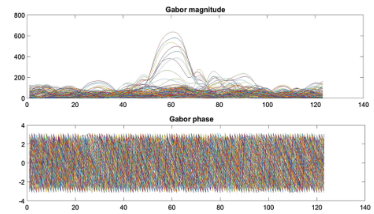

Fig. 5. Gabor magnitude and phase for one iris image

III. COMPARISION TABLE OF THE PAPERS

TABLE III
COMPARISON TABLE

Authors	**Year**	**Database**	**Ethnicity**	**Technique**	**CCR**
Anahita Zarei, Duxing Mou	2012	Notre Dame	Caucasian, Asian	Artificial neural network	93.3%
Xianchao Qio, Zhenan Sun, T. Tan	2007	CASIA-Biosecure iris database	Asian (China), Non-Asian (French)	Ethnic classification method based on learning appearance primitives of iris images	93.33%
G.Mabuza-Hocquet, F.Nelwamondo, T.Marwala	2017	Personal dataset from African continent	Black males and Caucasian females	Gabor filters	93.33%
Stephen et al.	2011	1200 feature vectors data	Asians and Caucasians	Infrared Illumination	96.17%
Qui et al.	2006	CASIA, UPOL, UBIRIS	Asians and Caucasians	Ethnic classification algorithm	85.95%
Ross A. and Bobeldyk D.	2018	BioCOP2009, Cosmetic Contact dataset, GFI dataset	White, Caucasian	LBP, LPQ, BSIF	Not mentioned
Maneet Singh, Shruti Nagpal, Mayank Vasta, Richa Singh, A. Noore, A. Majumdar	2017	Notre Dame	Caucasian, Asian	Deep Class-Encoder	93.3% (person disjoint), 97.5% (non-person disjoint)

IV. CONCLUSION, AND FUTURE WORK

This paper is about different works done by different researchers in the field of ‘Ethnicity prediction by iris recognition system'. It shows a comparison between different methods using different datasets. All of them had a high accuracy rate. As we can see that there are not enough datasets available for all ethnicities, so In future work, it would be beneficial to include a more diverse range of ethnic groups to increase the model's accuracy and robustness. We can also experiment with different data augmentation techniques, and learning rates to optimize the model.

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