Deep Dive into Iris Texture-Based Ethnicity Classification: Approaches, Datasets and Performance

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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*—iris texture, iris texture analysis, iris image classification, iris datasets, etnicity detection.**

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. [1] However, a small amount of research has been done regarding soft biometrics of the iris such as ethnicity. [2] 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 IV to provide a closure in predicting and classifying ethnicity.

II. Literature Review

A. Infrared Illumination to detect ethnicity

Stephen et al. [1] 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. [1] has found an enhanced accuracy compared to the works of previous researchers. The success in predicting Asian and Caucasian ethnicity with the aid of subject-disjoint 10-fold cross validation on a collection of 1200 images data has exceeded 90%.

B. 2D Gabor Filter

Qui et al. [3] believes that the iris texture of an individual is interconnected with their iris texture. Qui and his team looked into huge amounts of iris images of Asians and non-Asians. They discovered that these iris patterns varied from one another in terms of the statistical analysis of the iris texture. The motivation behind discovering a novel method to find ethnicity is that only the major components present in the iris texture are defined by genetics. Qui et al [3] proposed an algorithm which requires 2D Gabor filters and AdaBoost to classify the features present in the iris texture.

1) Datasets: Qui et al. [3] chose databases from three different science Institutes. First is the CASIA v2 obtained from Chinese Academy of Sciences Institute of Automation, second is UPOL collected from University of Palackeho and Olomouc and lastly UBIRIS which was taken from University of Beira Interior. These databases had images of iris of Asians and non-Asians. There were 2400 images of Asians present in CASIA v2 and 1582 images of non-Asians present in UBIRIS and UPOL.The images in the CASIA database were 8 bit depth grey images; thus, the pictures from UPOL and UBIRIS were also transformed into that format to make the experiment more reliable

2) Algorithm: The process by which the paper classified the images consists of 3 steps: Image preprocessing, Global Texture Analysis and Training.

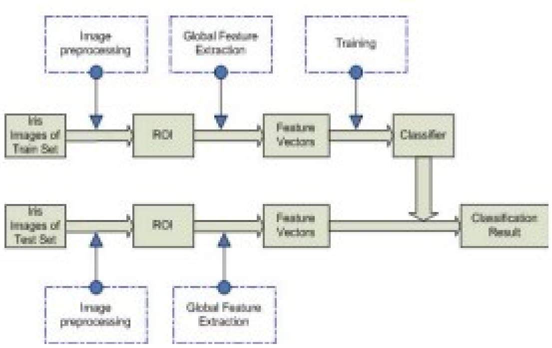

Fig. 1. Flowchart of the Algorithm.

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 and get the region that Qui is interested in, the region of Interest (ROI), the image is processed in such a way that makes sure the inner 3/4th of the iris is used. The region of interest was equally divided into two parts to get two regions, one was labelled with A and the other with B. The images were of 60 x 256 pixels.

Global Feature Extraction: Gabor filtering was used to extract the global features that were present in the region of interest. To get a filtered Gabor image, an image of the regions are fed into a 2D Gabor filter. The images consist of points and they are coiled using the filter. The filtered image consists of points which were merged together to obtain Gabor Energy (GE) which has a single value. From this output, it was found that Asians have substantial texture in region A whereas for nonAsians both the regions had rich texture. Therefore, a high pass filtering system can be used to extract the differences between different races. By designing an accumulation of Gabor filters, Qui was able to obtain Gabor energy features. They used only half of the frequency domain that was produced by the Gabor filters as the domains are of central symmetry. 240 pairs of Gabor channels were found by using four different values. The pairs of Gabor filters produced Gabor energy for each image. The total energy was calculated and divided by the number of images to get the Gabor mean Gabor energy. To define the global texture associated with the region of interest, Qui and his team extracted two statistical variables, Gabor Energy Ratio (GER) and GE from the Gabor energy picture.

Training: Even though many features are extracted from each iris image, only some of the features are kept. The features that are selected use an algorithm known as AdaBoost and then the algorithm trains the classifier.

3) Experimental Results: 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, we get a CCR of 85.95% when features from both GE and GER are used. Even though the classification rate is high there are some obvious errors: UBIRIS consists of distorted images in its database. The ROI might be obstructed by eyelids and eyelashes. There are outliers in both classes.

C. Texture Descriptors to extract iris texture features

Ross A. and Bobeldyk D. [4] focused mainly on iris biometric attributes. As it is difficult to extract abundant features present in deep coloured iris in the visible wavelength, Ross A and Bobeldyk D. used images of iris that was produced in the Near Infrared (NIR) spectrum as infrared has a longer wavelength. The long wavelength helped to reach even greater depth of the iris of dark-coloured 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 collected from

West Virginia University. Two more databases, Cosmetic Contact database and CFI database, were obtained from Notre Dame University for surveying. Preprocessing and geometric alignment was applied to all of the databases.

2) Algorithm: The paper [4] aims to demonstrate how texture descriptors can be used to predict features. It was found that Local Binary Pattern (LBP) and Binarized Statistical Image Features (BSIF) along with Local Phase Quantization (LPQ) was best suited to extract iris texture features from Outex and Curet texture dataset.

LBP: This algorithm encrypts localised texture data by comparing the pixel values present in a picture with its neighbouring pixels. 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 [4] encodes local texture data. The phase data generated by the 2-D Discrete Fourier Transform is utilised 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: BSIF texture descriptor was initially developed by Kanala and Rahtu [4]. By organising the picture using premade 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. K holds odd values starting from three to seventeen included and n ranges from five to twelve. The output produced by compressing the pregenerated filters is converted to binary. The binary output is 1 if the produced result is positive and the output is 0 if a negative value is found. After getting all the binary outputs it is concatenated by considering each value as a string and later the whole string is transformed into a decimal number known as 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 histogram was transformed into a single feature vector after normalising. The original NIR ocular picture was subjected to a geometric adjustment in order to offer uniform spatial data throughout every image. 3)

3) Experimental Results: The BioScope2009 comprises a huge dataset and applying a 9-bit or 10-bit BSIF increases the accuracy to some degree rather than applying 8-bit BSIF. However, the 8-bit BSIF was selected as the 9-bit and 10-bit BSIF require more memory and processing time. The features extracted by BSIF produced 5 training sets and each of the training sets went through an SVM classifier. The paper [4] tested different sizes of filters, starting from filter size of 3x3 to filter size of 17x17, to check which filter size provided the best prediction. It was found that on average the race prediction accuracy was 87%.

The paper [4] compared the race prediction accuracy when images with iris-excluded ocular regions were used versus when images with iris-only regions were used. They found that the latter provided a better prediction.

Ross A. and Bobeldyk D. [4] also made sure that their suggested algorithm is universal by applying the trained SVM model to two other cross testing datasets, CCD1 and CCD2. They applied their algorithm on images with no contacts and found that the prediction accuracy acquired from the testing dataset gave a similar output. The average accuracy was 85%.

D. Gender and Ethnicity sorting of Iris Images applying Deep Class Encoder [5]

1) Dataset: This study operated the Deep caste- Encoder for sorting the gender and nation of iris illustrations. To begin with, in this case categorized by 2 datasets, ND- Iris- 0405 and Multi ethnicity Iris Dataset, were included, with the one-time sorting of 64,980 illustrations from 356 participants, initially Caucasian and Asian. The dataset was served into practice and testing factions, with 26,272 and 34,707 images, altogether. The reverie also operated the first dataset from Iris dataset, and then it is sorting 3,000 illustrations from 750 males and 750 ladies. A predefined protocol was followed for training and testing, with 80 percent of the data applied for exercise and hanging around 20 for testing. A separate subject-disjoint set named UND was used for evaluation. The study followed an analogous protocol for assessing the proposed model, icing. Some images from all three were carried in that the below briefed the experimental procedure.

2) Algorithm and Works: Methods for autonomous feature learning have been effective recently. The hidden representation WeX can be mapped to its appropriate class label C using an association matrix M, that can also be employed in a guided method. By reducing the proportional Frobenius norm of the discrepancy between the structure of the multiplication MWeX and the label for the category C, this can be described analytically.

min M kC - MWeXk 2 F

The classification label of the data sample is represented by a binary vector C in the formula. There are n rows and l sections in the vector, where l is the total number of separate categories. The vector's i-th member is 1 if the sample corresponds to class i, and a value of 0. The feature vector (WeX) is mapped to its matching class label via the matrix M. The class label for samples belonging to the same class should match when M and We are fixed. This term is included in and extends Equation 2's coefficient function in the intended Class-Encoder.

min M,Wd,We kX - WdWeXk 2 F + λ kC - WeEk 2 F

An example of a least squares formulation is the fourth equation. But the process of computing is expensive due to the big dimensions of the engaged matrix structures and the nonconvex aspect of the issue. The researchers have employed the Majorization-Minimization (MM) technique and the Alternative The motion Approach of The effects of multipliers (ADMM) to handle this problem. By dissecting difficult optimization problems to simpler parts, the MM approach reduces complex equations. In contrast to a conventional Stacked Autoencoder, ADAM's lack of the need to compute products at every moment greatly reduces the training period.

The fourth equation is able to be modified as indicated below in order to be applied to a Deep Class-Encoder structure with k layers.

min M,Wd,We X - (W1 dW2 d...Wk d(Wk e ...W2 eW1 eX)) 2 F + X k i=1 λ C - Mi (Wi eXi) 2 F

By including extra training pictures via classify-preserving modifications, overestimation is frequently addressed. This strategy is frequently used in conjunction with strategies for data enhancement to increase the model's resistance to pixels vibration, observations, and magnification. Every snapshot in the source collection is altered during enrichment.

3) Experimental Results: Our proposed Iris gender and ethnicity classifier has been cross-checked with the following deep learning models, including Stacked Autoencoder (SAE), AlexNet is based on models built with the Stacked Denoising Autoencoder (SDAE), Deep Belief Network (DBN), Discriminative Restricted Boltzmann Machine (DRBM), and Convolutional Neural Network (CNN). For consistency, the feature extraction models have similar structure as the proposed Deep ClassEncoder. After feature extraction, Depending on the situation, a trained classifier (RDF or NNet) is used. The test samples have a class imbalance, so the mean class-wise accuracy is reported.

E. Artificial Neural Network to identify Ethnicity By Iris Texture [6]

1) Dataset: The dataset comprises 1200 iris images sourced from the iris clone database of the University of Notre Dame. It comprises 60 Caucasian and 60 Asian contents, with each person having 5 illustrations of their exact iris and 5 illustrations of their left iris. The images were carried out using an LG 4000 detector and primarily owned a size of 480x640 pixels. Lastly, they observed the advancement of the Notre Dame IrisBEE software prior to its standardization to 240x60 pixel resolution.

2) Algorithm and work process: Before seasoning the neural nets, the data suffered several preprocessing paths. Initially, In order to improve the network contrast, the principal vector was formalized by mapping it to the interruption(- 1, 1). Secondly, skipping values in the input affection vector due to eyelid or eyelash occlusion were displaced with the corresponding point's median valuation from the staying illustrations of the duplicate motive. The dataset was additionally resolved into three subsets, with the foremost subset holding 60 of the data living appointed as the routine set to accommodate the network's load worths and optimize its interpretation. The successive subset, which agreed on 20 percent of the data, substitute utilized as the confirmation set. During the training process, the evidence error was watched, and training was broken up if the confirmation error increased for five sequent duplications. Although at first the confirmation the confirmation error would frequently start to rise when the net began to overfit the data. Finally,, the network weights and impulses were saved when the voucher set error was at its minimum.

3) RESULTS: The study evaluated the performance of Two neural networks trained using iris illustrations. 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 number of examples for both networks that were successfully and wrongly classified was displayed in the Confusion Matrix. 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 all of these two the training methods, multiple representations of the same iris enhanced the model's performance. To this current database and the applied vectors, the study also contrasted the performance of neural networks and SMO, as shown in the table I.

TABLE I
HIGH SPOT DETECTOR FILTER

-1/16	-1/16	-1/16	-1/16	-1/16
-1/16	+1/9	+1/9	+1/9	-1/16
-1/16	+1/9	+1/9	+1/9	-1/16
-1/16	+1/9	+1/9	+1/9	-1/16
-1/16	-1/16	-1/16	-1/16	-1/16

To conclude, the study aims to classify Deep Class-Encoder (CSE) is a supervised Autoencoder model that is used to classify iris images based on their gender and ethnicity. In order to train discriminate features, this approach uses class labels in feature learning. Moreover, this investigation successfully learns it owns discriminate oaths. Besides, this model was tested on two datasets for the classification of gender and ethnicity. Besides, we presented a texture-based classification approach for predicting ethnicity using artificial neural networks. Our approach achieved accuracy rates of 93.3 percent and 97.5 percent for person-disjoint and non-person-disjoint test sets, respectively. All of 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. Using appearance primitives of iris images for ethnicity prediction. [7]

1) Dataset: The CASIA-BioSecure iris database was used in this experiment. For this database, 2400 images were taken from 60 subjects. Out of 2400 images, half of them were from China which represented Asians. And the other half was taken from France as a representation of non-Asians. Again, among the 2400 images, 1200 were training sets and the other 1200

TABLE II
COMPARISON TABLE

Authors	Year	Database	Ethnicity	Technique	CCR
Anahita Zarei et al. [6]	2012	Notre Dame	Caucasian, Asian	Artificial neural network	93.3%
Xianchao Qio et al. [7]	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 el al. [2]	2017	Personal dataset from African continent	Black males and Caucasian females	Gabor filters	93.33%
Stephen et al. [1]	2011	1200 feature vectors data	Asians and Caucasians	Infrared Illumination	96.17%
Qui et al. [3]	2006	CASIA, UPOL, UBIRIS	Asians and Caucasians	Ethnic classification algorithm	85.95%
Ross A. et al. [4]	2018	BioCOP2009, Cosmetic Contact dataset, GFI dataset	White, Caucasian	LBP, LPQ, BSIF	87%
Maneet Singhel al. [8]	2017	Notre Dame	Caucasian, Asian	Deep Class-Encoder	93.3% (person disjoint), 97.5% (non-person disjoint)

were testing sets. For the training set, 600 images were used for Asian representation, and 600 images were used for non-Asian representation. And lastly, the rest of the images were used in the testing set.

2) Algorithm and work process: The experiment takes place in a few steps and the first step is filtering. A specific filter is used in the process. The filter covers the frequency space and the texture of the iris gets classified based on the set of filters. To produce a filtered image, it has to be convolved with a 2D Gabor filter which is an even Gabor filter. A total of 40 filters were used to transform each pixel into a 40-dimensional vector. After filtering the image, the vectors have to be clustered into sets of prototypes and these prototypes are called Iris-Textons. After that K-means clustering algorithm is used to find these prototypes. Histogram is a map that represents 64 different iris-Textons of 40-dimensional vectors. Then they scaled the bin value from the range of 0 to 1 for all the irises. After that, they used histograms with SVM. 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: The process was done using the training set and Testing set data. For the Global Texture Analysis method, the CCR of the training set is 84.83 and the CCR of the testing set is 85.67. The overall CCR of this process is 85.25Again, for the proposed method, the CCR of the training set is 93.73 and the CCR of the testing set is 88.31. The overall CCR of this process is 91.02%. So, we can say that the proposed method has a higher CCR than the previous method.

G. Using Gabor filters to predict ethnicity through the iris texture feature. [8]

1) Dataset: Due to the absence of any datasets for African individuals, the researchers took samples from subjects with their permission. They had fifteen black men and fifteen Caucasian women as their subjects for the experiment. Four images of left and right eyes were provided by each subject. They used the Vista EY2 dual iris and face camera which has a near-infrared ray that creates 8-bitmap versions of the images. The images turn into grayscale images before any processing starts.

2) Algorithm and work process: The researchers used an algorithm named 'Bresenham's circle algorithm'. Using this algorithm researchers can determine where the center of pupil and iris are which helps them to fix their boundaries.

Afterward, the researchers used the Chan-vase algorithm. This algorithm finds the curves of the iris and it helps to segment the iris. This process is done by minimizing energy-based segmentation; it also regularizes the terms that reduce the fitting term. The curve C is represented as the borderline of a subset ω of Ω. Here Ω, it represents the spatial domain of each image. The regularizing terms which include the length of the curve C and the area of the region inside C are added to the energy function. There are several parameters such as radii, diameter, center of the iris and pupil, etc. They are calculated using Bresenham's algorithm. They are also used as additional regularizing terms to influence the segmentation of the iris.

There are two methods to improve the iris image. They are sharpening and contrasting limited adaptive histogram equalization (CLAHE). They make the image clearer and visually appealing. Using a collection of Gabor filters with various wavelengths and orientations, texture characteristics are retrieved. The Gabor filters are exceptionally useful with texture representation and discrimination. The filter bank has three wavelengths and five orientations. They are used for producing a 1x15 Gabor array. The Phase component and Magnitude of the Gabor filter bank are generated using the array. The input images are also generated using this array. Eventually, the Mean Amplitude (MA) and the Local energy (LE) are calculated from these components which are used as texture features.

3) Results: Here, several studies done by different authors are described. Each of the studies was done by using different datasets and following different methods. As a result, each method gave a different CCR. Two of the studies were done by Qui et al. using the same database, that is CAS, UP, and UB. And both had the same subject ethnicity, that is Asian and non-Asian. The difference between the studies was the technique. In one study, they used Gabor filters and in the other one, they used Iris Textons. Both of the studies had a CCR of 89.95Another study that is compared here was done by Lag, Bow using the database from Notre Dame. His subjects were Asian and Caucasian. And the technique used there was '9 Filters'. The CCR achieved by this study is 90.58Lastly, for the proposed method, Gabor filters were used using the independent database. Black and Caucasian subjects were used for this study. The CCR obtained by this study is 93.33%. Which is the highest CCR out of all the other methods.

III. Comparision Table of the Papers

Based on the papers reviewed the correct classification rate of each algorithm is presented in a table to portray the differences in CCR of the different algorithms used. A thorough comparison of the papers is shown in table II.

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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