Artificial Neural Network for Prediction of Ethnicity Based on Iris Texture

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***Abstract*—Iris is a reliable biometric that is unique, remarkably stable through the life of an individual, and easy to capture. Many applications include verifying the identity of a subject or identifying an unknown individual from a list of possibilities that involve searching a large database. Prediction of ethnicity separates the data into subcategories that will make this search much faster. We have proposed a new approach, namely artificial neural network to predict the ethnicity based on iris texture features. We have achieved the correct classification rate of 93.3% Caucasian/Asian on a person-disjoint set. This result outperforms the previous works using statistical methods on the same database.**

***Keywords*-artificial neural network; iris; ethnicity; biometric; security;**

I. Introduction

The iris is the ring-shaped structure in the eye that identifies the eye color and controls the amount of light that enters the eye. It has several features that makes it an ideal part of the human body for biometric identification. Similar to fingerprints, iris texture is very unique and the chance of false matches is extremely low. However, what distinguishes this well-protected organ from fingerprints is its invulnerability to factors such as old age or manual labor. The fine texture of the iris remains remarkably stable over decades. Another advantage of using iris as a biometric identifier is the ease of capture, the minimal intrusion, and the convenience of obtaining iris scans that can be performed from even a few meters away.

Biometric technology is increasingly used to meet the security needs in critical applications. Some of the major applications that use biometric traits include [1] Border Passage System at Heathrow Airport in London, PORTPASS at US-Canadian vehicle border crossing, Security and Immigration System at Ben Gurion Airport in Tel Aviv, BioPassword for network access control, FacePASS System for physical access control applications, and FaceIT for surveillance applications.

The focus of this work is to predict ethnicity of individuals based on their iris images, using artificial neural networks. This categorization can significantly speed the search of an iris database that could potentially contain millions of iris images. Furthermore, if the person does not belong to a database, this categorization provides additional information about the unknown subject that would facilitate pursuing alternative identity methods [2].

There have been several studies that looked into predicting demographic characteristics such as race and gender based on iris images, but none have used computational intelligence approach. Qiu *et al.* studied the correlation between race and iris texture and concluded that iris genetic information is illustrated in texture features [3]. Subsequently they used visual primitives to group CASIA-BioSecure iris data set into two race categories of Asian and non-Asian [4]. They obtained a correct classification rate of 88.31% for the test set, using Support Vector Machines (SVM). It must be noted that their training and test sets included the images of the same subjects, i.e. their training and test sets were non-person-disjoint. Specifically, the set included a total of 2400 images of 60 subjects (40 images per subject), half of which was randomly selected for testing and the other half for training. This overlap usually biases the model and increases the success rate.

Thomas *et al.* attempted to identify the gender based on iris images [2]. Their feature vector included geometric features (i.e. features that pertain to dimensions of the iris such as iris area, pupil area, distance between the center of the iris and the center of the pupil, etc.) and texture features (i.e. features that are obtained from applying image processing techniques such as Gabor filter). Utilizing decision trees, they achieved a 75% success rate of gender classification among various ethnicities. The result was improved to 80% when they solely considered the Caucasian population.

Lagree and Bowyer explored the possibility of ethnicity and gender prediction using iris texture features [5], [6]. They examined a variety of classification algorithms and obtained the best result using the Sequential Minimal Optimization (SMO) algorithm. They could successfully classify 90.58% of the subjects to Asian/Caucasian ethnicity and 62% to male/female. They also showed that predicting ethnicity is more challenging for an all-female dataset than an all-male dataset [6].

Neural networks have been used in iris segmentation, iris recognition, and reflection detection [7], [8], [9], [10]. They have also been used in clustering iris images based on differential of fractal dimension [11] and local entropy [12]. However, there have not been any studies to examine neural

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network ability to predict ethnicity based on iris texture features.

The remainder of this paper is organized as follows. Section II describes the data set followed by a background to artificial neural network architecture in Section III. Section IV discusses the feature set and network topology used in this work. Section V describes the results followed by the conclusion and summary of the paper.

II. Data Set

The data set includes 1200 images from the University of Notre Dame's iris image database [13]. It contains iris images of 60 Caucasian and 60 Asian subjects, with 5 right iris images and 5 left iris images per person. All images were captured using an LG 4000 sensor and were 480x640 in size. They were then segmented using Notre Dame's IrisBEE software [14] and were reduced to 240x60 pixel normalized images [5].

III. Artificial Neural Network

Artificial neural network is a form of computational intelligence that can be trained to perform various operations such as function approximation, classification, and data clustering. The configuration of artificial neural network is similar to the biological nervous system. It is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and utilizing it in future when necessary. Just like the human brain, it collects information through a learning process, and then distributes the information through the network using the internal connections. [15]

We created two (person-disjoint and non-person-disjoint) multi-layer perceptron (MLP) feedforward neural networks to classify the subjects based on their ethnicity. MLP is one of the most common neural network architectures. It consists of an input layer, a hidden layer, and an output layer. Each layer has a certain number of neurons. The number of neurons in the input and output layer depends on number of inputs and outputs of the network. However, the number of neurons in the hidden layer is the designer's choice and is usually selected throughout experiments. The layers are connected in parallel with mathematical weights between them. During the process of supervised training, the network is exposed to the training data set that consists of the input values (features that describe the iris images) and the target values (ethnicity). The weights of the network are iteratively updated to minimize the difference between the target and the neural network output values. [15]

One of the main advantages of neural network over classical statistical methods used in other iris classification works is that it does not require any a priori knowledge about probability distribution of the data; instead it learns the statistical distribution of each class during training. Neural network creates decision boundaries that are multidimensional and based on the properties of the training data. [15]

-1/8	-1/8	-1/8
-1/8	+1	-1/8
-1/8	-1/8	-1/8

Table I
Small 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

Table II
Large Spot Detector Filter

IV. Feature Set and Network Topology

The features used as input to the networks consist of 882 measurements that were calculated by applying several filters to the segmented and normalized images produced by IrisBEE [14]. We used the same input features as Lagree and Bowyer in [5] to be able to compare the results in a consistent manner.

Each image was divided into eight horizontal and ten vertical bands in order to determine statistics measures for smaller subregions. Two spot detector filters (tables I and II), four vertical and horizontal line detector filters (tables III - VI), and two Law filters (table VII - VIII) were applied to each band.

Several statistics measures (table IX) were calculated for the filter response of each band. The statistics measures 1 to 5 were calculated for the horizontal and all 6 measures were calculated for the vertical bands. This scheme resulted in an 882 feature-set. [10 (vertical regions) $\times$ 9 (filters) $\times$ 5 (statistics measures) + 8 (horizontal regions) $\times$ 9 (filters) $\times$ 6 (statistics measures) = 450 + 432 =882].

-1/20	-1/20	+1/5	-1/20	-1/20
-1/20	-1/20	+1/5	-1/20	-1/20
-1/20	-1/20	+1/5	-1/20	-1/20
-1/20	-1/20	+1/5	-1/20	-1/20
-1/20	-1/20	+1/5	-1/20	-1/20

Table III
Vertical Line Detector Filter

-1/10	+1/15	+1/15	+1/15	-1/10
-1/10	+1/15	+1/15	+1/15	-1/10
-1/10	+1/15	+1/15	+1/15	-1/10
-1/10	+1/15	+1/15	+1/15	-1/10
-1/10	+1/15	+1/15	+1/15	-1/10

Table IV
Wide Vertical Line Detector Filter

-1/20	-1/20	-1/20	-1/20	-1/20
-1/20	-1/20	-1/20	-1/20	-1/20
+1/5	+1/5	+1/5	+1/5	+1/5
-1/20	-1/20	-1/20	-1/20	-1/20
-1/20	-1/20	-1/20	-1/20	-1/20

Table V
HORIZONTAL LINE DETECTOR FILTER

-1/10	-1/10	-1/10	-1/10	-1/10
+1/15	+1/15	+1/15	+1/15	+1/15
+1/15	+1/15	+1/15	+1/15	+1/15
+1/15	+1/15	+1/15	+1/15	+1/15
-1/10	-1/10	-1/10	-1/10	-1/10

Table VI
WIDE HORIZONTAL LINE DETECTOR FILTER

Several steps were taken to preprocess the data prior to training the networks. First, in order to avoid network saturation, we normalized the input vector by mapping it to the interval [-1,1]. The input feature vector contained some unknown entries corresponding to pixels that were occluded by eyelid or eyelash. We replaced these unknown values by the average value of that feature for corresponding pixels from the remaining images of that subject.

We divided the data set into three subsets. The first subset (60% of the data) was the training set that is used for tuning the weight values of the network to optimize network performance. The second subset (20% of the data) was the validation set. The error on the validation set was monitored during the training process, and the training was stopped when the validation increases over 5 consecutive iterations. The validation and training error typically decrease during the initial phase of training. However, when the network begins to overfit the data, the error on the validation set usually begins to rise. The network weights and biases were saved at the minimum of the validation set error (figures 1 and 2). The third subset (the remaining 20%) was the test set that was solely used for evaluation of the network and comparing the generalization error of different models.

+1	0	-2	0	+1
0	0	0	0	0
-2	0	+4	0	-2
0	0	0	0	0
+1	0	-1	0	+1

Table VII
LAW FILTER S5S5

-1	-4	+6	-4	+1
-4	+16	-24	+16	-4
+6	-24	+36	-24	+6
-4	+16	-24	+16	-4
+1	-4	+6	-4	+1

Table VIII
LAW FILTER R5R5

1	average value of filter response over the region
2	standard deviation of filter response
3	90^{th} percentile value of filter response
4	10^{th} percentile value of filter response
5	range between 9^{th} and 10^{th} percentile value
6	local horizontal window difference

Table IX
STATISTICS MEASURES

To examine the effect of including iris images of the same person in both training and test sets on the model performance, we created two sets of networks: person-disjoint (network 1) and non-person-disjoint (network 2). For the person-disjoint network, there was no overlap between the subjects used in the test set and training/validation sets. In other words, if an image of a subject was used in the test set, then no other images of the same subject were used in the training or validation. For the non-person-disjoint network, distinct images of the same subjects that were used in training/validation were also used in testing. Therefore, even though there was no overlap between the images, there were common subjects in the test and training/validation sets.

We examined several topologies and achieved the best outcome when employed 10 neurons in the hidden layer. Applying more than 10 neurons mostly aggravated the generalization error, indicating the appearance of over-fitting. Both network configurations included 882 neurons in the input layer, 10 neurons in the hidden layer, and 1 neuron in the output.

V. RESULTS

Minimum Mean Square Error (MSE) values of 0.043 and 0.011 were achieved at the 37^{th} and 110^{th} epoch for person-disjoint and non-person-disjoint networks, respectively (figures 1 and 2). The smaller error for network 2 indicates that including different images of the same iris in both test and training sets optimistically affects the results.

Figures 3 and 4 summarize the performance of the networks for training, validation, test, and overall data in a Confusion Matrix. The rows in the Confusion Matrix represent the predicted target class from the network and columns represent the actual target class. The diagonal cells show the number of cases that were correctly classified while the off-diagonal cells show the misclassified cases.

Since the best way to measure the performance of a neural network is by evaluating the outcomes of the network for the test set, we analyze the numbers in the “Test Confusion Matrix” in figures 3 and 4. As indicated in this matrix, network 1 classified 113 out of 120 cases of Caucasian (Class 1) and 111 out of 120 cases of Asian (Class 2) correctly. It misclassified 7 Caucasians and 9 Asians. Network

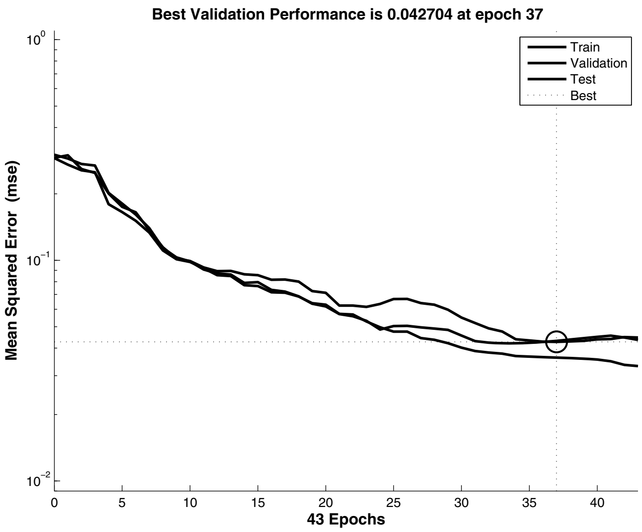

Figure 1. MSE curves for person-disjoint neural network

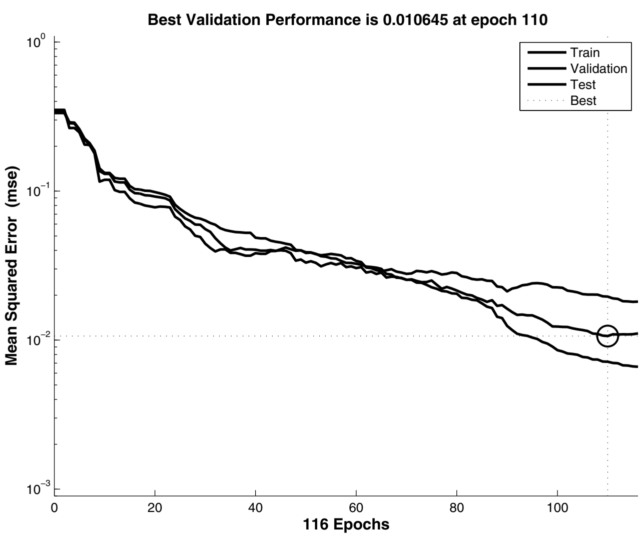

Figure 2. MSE curves for non-person-disjoint neural network

2 classified 110 out of 113 cases of Caucasian and 124 out of 127 cases of Asian correctly. It only misclassified 3 Caucasians and Asians.

The bottom row of this matrix in figure 3 indicates that given that the class was actually Caucasian, network 1 correctly classified 94.2% of cases; where the class was actually Asian, the network correctly classified 92.5% of entries. The right column in the same matrix shows that provided that the network classified an entry as Caucasian, it correctly classified 92.6% of entries; given that the network classified an entry as Asian, it was correct for 94.1% of entries. For network 2 these numbers were increased to 97.3%, 97.6%, 97.3%, and 97.6% respectively.

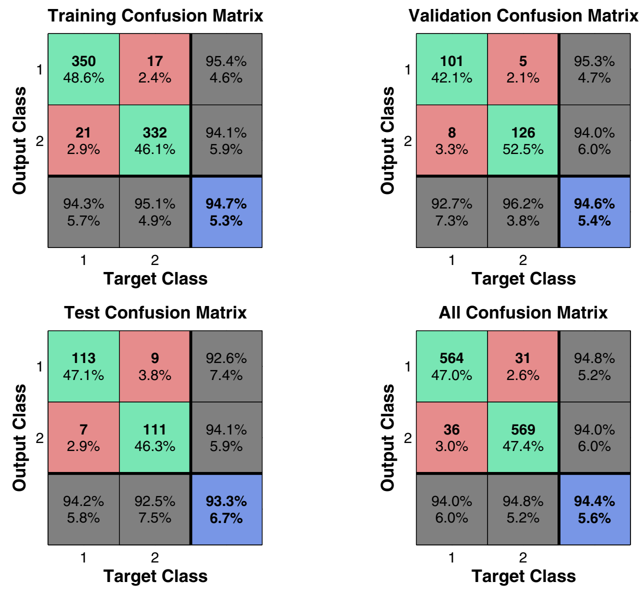

Figure 3. Confusion Matrix for Person-Disjoint Network

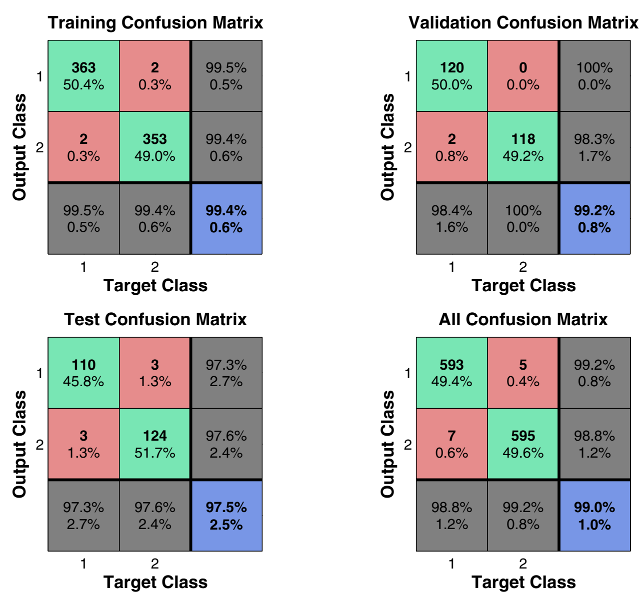

Figure 4. Confusion Matrix for Non-Person-Disjoint Network

The two numbers in the bottom right cell of the Confusion Matrix show the total percentage of correctly classified and misclassified cases. We achieved an overall accuracy rate of 93.3% and 97.5% for the person-disjoint and non-person-dijoint test sets. These result indicate the superior neural network performance over reported values of 90.58% in [5] for person-disjoint, and 88.3% in [4] and 96.17% in [5]

	Person-Disjoint	Non-Person-Disjoint
SMO	90.58%	96.17%
Neural Net	93.3%	97.5%

Table X
CORRECT CLASSIFICATION RATES FOR TEST SETS

for non-person-dijoint sets using other methods. Table X compares the performance of neural network versus SMO in [5] for the same database and feature vectors.

Figures 5 and 6 depict the Receiver Operating Characteristic (ROC) curve for the two networks. The ROC curve is a fundamental tool to check the quality of classifiers. The vertical axis represents the True Positive Ratio (i.e. the number of cases in Class 1 that were classified by the network as Class 1 divided by the total number of actual cases in Class 1). The horizontal axis represents the False Positive Ratio (i.e. the number of cases in Class 2 that were classified by the network as Class 1 divided by the total number of actual cases in Class 2). For example in Test Confusion Matrix in figure 3, the True Positive Ratio is $\frac{113}{120} = 94.2\%$ and the False Positive Ratio is $\frac{9}{120} = 7.5\%$. Each point on the ROC curve represents a True Positive Ratio/False Positive Ratio pair corresponding to a particular decision threshold.

The upper left corner of an ROC diagram represents a perfect classification system (no false positives, only hits). The closer any verification is to this upper left corner, the higher the accuracy rate. Figures 5 and 6 show that ROC of network 2 depicts a more desired behavior than ROC of network 1, indicating again that including different images of the same iris in both test and training sets will bias the model.

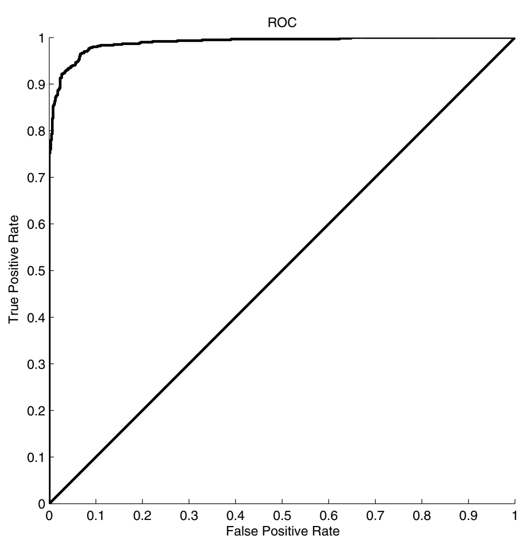

Figure 5. ROC for person-disjoint classifier

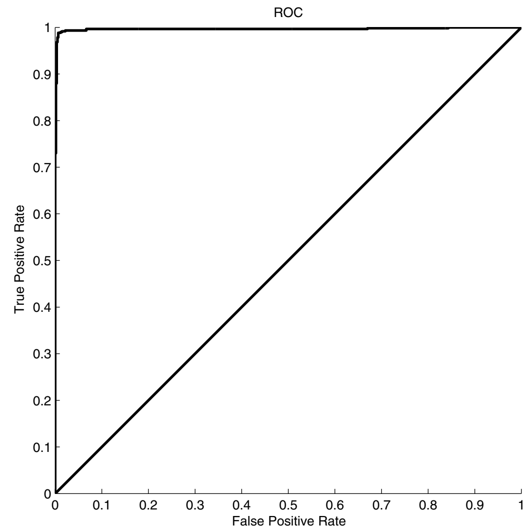

Figure 6. ROC for non-person-disjoint classifier

VI. CONCLUSION

We have introduced a texture-based classification of ethnicity using artificial neural networks. The accuracy rate for ethnicity prediction for person-disjoint and non-person-disjoint test sets were 93.3% and 97.5% respectively. These results outperformed the previous work using other methods on the same database. We have shown the potential of neural network classifiers for a new application domain.

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