Journal of Modern Technology and Engineering
Vol.6, No.3, 2021, pp.191-204

RACE RECOGNITION FOR MALES USING LOCAL BINARY PATTERN AND PERFORMANCE EVALUATION OF THE SYSTEM

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Abstract. This paper investigates race recognition for males which is a challenging task for recognition systems. It can be very useful for criminality and biometric security systems to reduce search time and the detection process. Three major races have been researched which are Caucasian, Mongoloid and Negroid. In the study, we used the local binary pattern (LBP) approach for feature extraction which is a very effective feature descriptor and the Weighted Chi-Square Statistics method has been used for classification. For the classification process, race models have been created by using morphing. Furthermore, the improved system has been evaluated by statistical measures and a satisfactory recognition performance has been obtained.

Keywords: Race recognition, Local Binary Pattern, morphing, feature extraction, classification, performance evaluation.

AMS Subject Classification: 68T10, 68U10.

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Received: 2 October 2021; Revised: 27 November 2021; Accepted: 15 December 2021;
Published: 30 December 2021.

1 Introduction

Race is a classification system used to categorize humans into large and distinct populations or groups by heritable phenotypic characteristics, geographic ancestry, physical appearance, and ethnicity. In the early twentieth century, the term was often used, in its taxonomic sense, to denote genetically diverse human populations whose members possessed similar phenotypes (Wikipedia, 2017). This sense of "race" is still used within forensic anthropology (when analyzing skeletal remains), biomedical research, and race-based medicine (Bloche, 2004). In addition, law enforcement utilizes race in profiling suspects and reconstructing the faces of unidentified remains. Because in many societies, racial groupings correspond closely with patterns of social stratification, for social scientists studying social inequality, race can be a significant variable.

The classification of races has occurred during the discovery of the world by noticing the differences between the people. The 1775 treatise "The Natural Varieties of Mankind" by Johann Friedrich Blumenbach proposed five major divisions: the Caucasoid race, Mongoloid race, Ethiopian race (later termed the Negroid race), American Indian race, and Malayan race, but he did not propose any hierarchy among the races (Wikipedia, 2017).

Mike Mike is a South African photographer who travels the world taking photos of faces and integrating them into high-tech composites. The project is titled The Faces of Tomorrow. Figure 1 shows the average Turkish, Iranian, Azerbaijanian (people of Turkic origin) and Georgian adult male faces, which are an example of the Caucasian race.

For the classification of races, using genotype instead of phenotype means classifying races

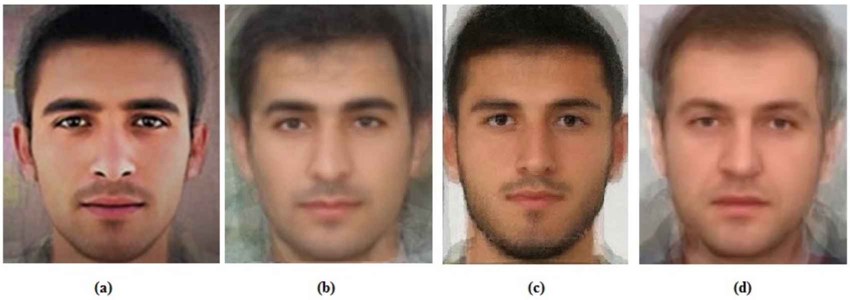

Figure 1: Average (a) Turkish, (b) Iranian, (c) Azerbaijanian and (d) Georgian adult male face (Gus, 2021)

according to appearance instead of the gene. Therefore, race can be recognized with computer methods by using facial features. Recognition of races is a complex cognitive process that is further complicated when the similarity between races, people, and faces is considered.

The race recognition system can be especially useful for airports, border gates, and other social domains to reduce the number of images of criminals whose races are known. In addition to these, it can be very convenient for biometric security systems. Furthermore, it can be used in anthropological studies where the development of races and their interaction with each other are being researched. In addition to these, for face recognition, race is a very important parameter. Therefore, race recognition can be useful for improving face recognition systems.

In the literature, there are only a few studies in this area. Cross et al. (1971) have searched for sex, race, age, and beauty factors in face recognition systems. The study was concerned with the ability of individuals, black and white, male and female, children, adolescents, and adults from racially segregated and racially integrated backgrounds, to recognize a wide range of facial types. Malpass & Kravitz (1969) concluded that experience with people of a given race was related to the ability to recognize the faces of that race.

In another study, it has been mentioned that the Cross-Race Effect (better recognition for same-race (SR) faces than for cross-race (CR) faces) is due to social-cognitive processes of categorization of out-group members, causing perceivers to attend to category-specificating information of CR faces at the expense of individuating information (Hugenberg et al., 2007). Another study (Muhammad et al., 2012) is about race recognition using two types of local descriptors: Local Binary Pattern (LBP) and Weber Local Descriptors (WLD). In our other studies (Nabiyev & Kurt, 2007; Kurt & Nabiyev, 2011), LBP is a very effective feature descriptor, which we have also used for facial expression and Down syndrome recognition.

In recent years, many researchers have switched from focusing on race recognition of popular race groups such as African Americans, Caucasians, and Asians to that of sub-ethnic groups such as Koreans, Japanese, Vietnamese, and Chinese (Roh & Lee, Yıl; Bastanfard et al., 2007; Gao et al., 2007; Vo et al., 2018). General systems for race recognition, on the other hand, are generally based on deep learning without creating a model (Coe & Atay, 2021; Xu et al., 2018; Larmuseau et al., 2021; Khan et al., 2021; Xiong et al., 2018; Ahmed et al., 2020). One is the earliest paper published in the area of race recognition (Nabiyev & Bölükbaş, 2009). In our previous study, we improved a very successful race recognition system for males by using Local Binary Pattern (LBP). Race recognition is a difficult problem to solve completely. To contribute towards solving that problem, this article investigates using a race model approach. In this paper, we have developed and evaluated our system using performance measures and added race models to the database. Race models were obtained by morphing instead of averaging. The morphing-based model approach has been used for the age recognition problem (Yılmaz & Nabiyev, 2019).

In this paper, we have improved a novel system for race recognition where we have used LBP for feature extraction and Weighted Chi-Square Statistics for classification. Furthermore,

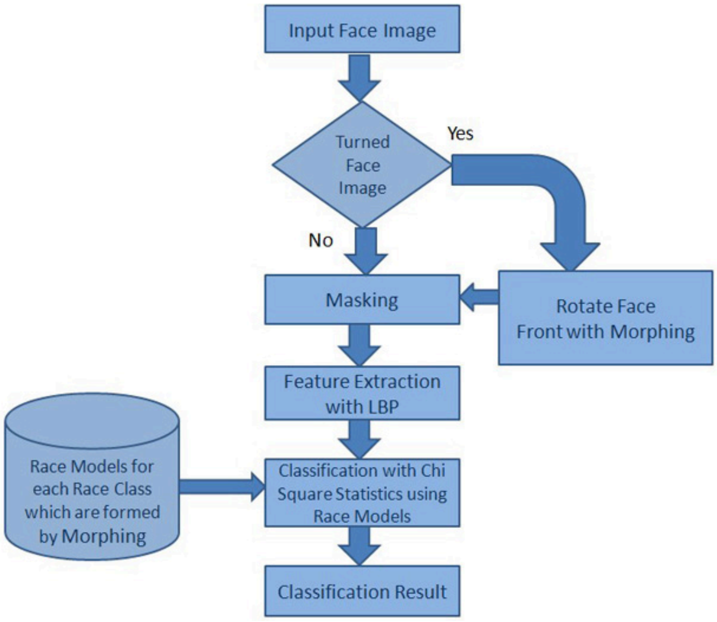

Figure 2: Improved system schema

models of races have been formed by the morphing method, which is more effective than average. The flow schema for the improved system can be seen Figure 2.

As seen in Figure 2, firstly, if the face image was turned then to obtain the front face image, we would have rotated the image by morphing. In the second step, the masking process has been applied to remove undesired parts of the face, such as hair. After these preprocessing steps, face features have been extracted using LBP, and in the last step, the obtained features have been classified with Chi-Square Statistics using race models that were formed for each race class. In this way, the recognition process has been completed.

In addition to these, the improved system has been evaluated by using the measures of Positive Predictive Value (PPV) and Receiver Operating Characteristic (ROC). As a result, according to these performance measures, a novel race recognition algorithm has been improved.

2 Database

In the study, three major race classes, which are Caucasian, Mongoloid, and Negroid, have been observed. For the study, 515 face images (183 Caucasian, 142 Mongoloid, and 190 Negroid) have been used, which were provided by FERET, Yale face databases, and the internet.

Figure 3 shows face image examples from the database. First, 183 Caucasian, 142 Mongoloid, and 190 Negroid races were selected from these databases, and then only facial regions were taken to create a model from these images with artificial neural networks. In the next step, the facial images taken were subjected to morphing, and Caucasian, Mongoloid, and Negroid race models were created. As a result of the morphing of approximately 125 images, no significant change was observed in the model structure. For this reason, the number of samples selected from the databases is limited.

3 Preprocessing

The preprocessing steps for the system are rotating face images to obtain front-facing images using morphing and then masking processes to remove undesired parts of the face.

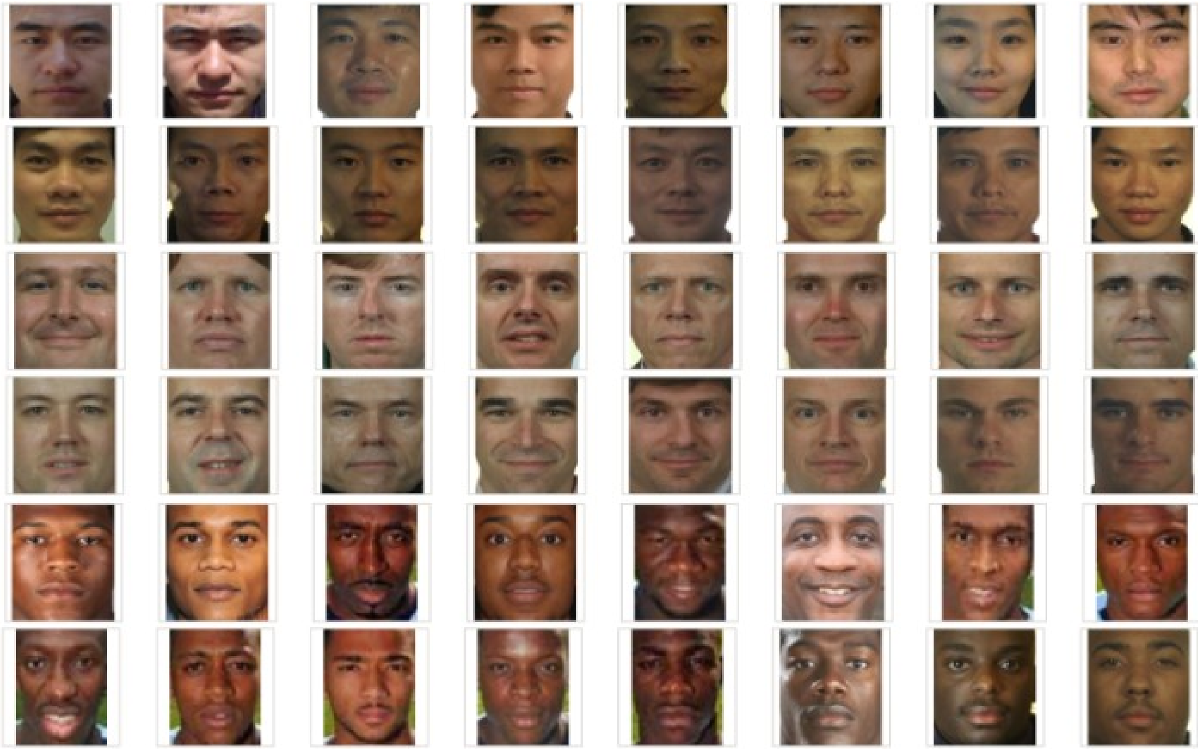

Figure 3: Face image examples from database

3.1 Face Image Rotation

Morphing is an image processing technique used for the metamorphosis of one image to another. The idea is to get a sequence of intermediate images which, when put together with the original images, would represent the change from one image to the other.

Morphing can be applied to two different images or the same images which are different geometrically. The field morphing algorithm uses lines to relate features in the source image to features in the destination image. The morphing process includes three steps. First, define corresponding lines in source image I_0 and destination image I_1, and then each intermediate frame I of the metamorphosis is defined by creating a new set of line segments by interpolating the lines from their positions in I_0 to the positions in I_1, and last, both images I_0 and I_1 are distorted toward the position of the lines in I.

For obtaining the front face image from a turned face image, we applied field morphing to the same images, which are different geometrically, as seen Figure 4.

The resulting image has been obtained by morphing the same face images into different geometrical types with 50% ratios.

3.2 Masking

There is unnecessary information in the four corners of the face images. The sources of the information in the bottom and top corners are background and hair, respectively. Therefore, a special mask has been applied to the input image for these parts not to be taken into consideration. This special mask is a binary matrix that includes 0 and 1 values for undesired and desired parts, respectively. Figure 5 shows the general structure of a face mask.

4 Local Binary Pattern (LBP)

To describe image texture, the local binary pattern (LBP) operator, which works by comparing the gray value of the central pixel with its surrounding 8 pixels (for a given size of 3x3 pixels), was proposed by Ojala et al. (1996).

LBP is a non-parametric kernel that can outline the structure of local space. The most important property of LBP in real world applications is its tolerance against illumination changes because of being oblivious to monotonic gray level changes, which is a common problem for recognition systems. Furthermore, LBP can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis. Another important property is its computational simplicity, which makes it possible to analyze images in challenging real-time settings. LBP can be used in various applications such as face recognition, facial expression analysis, moving object tracking, image retrieval, remote sensing, environmental modeling, outdoor scene analysis, etc. (Zhao et al., 2011; Shan et al., 2009; Yuan et al., 2011; Pietikäinen, 2005).

The LBP operator can be seen as an ordered set of binary comparisons between the gray values of the central pixels and their surrounding pixels, where the number of pixels in the chosen neighborhood can be changed. From the comparison, a binary value is obtained for the central pixel, and its equivalent in the decimal system is assigned to the central pixel to characterize the local texture. This process can be shown in the Figure 6.

Different LBP operators can be defined according to their neighbors. In general $\mathrm{LBP}_{\mathrm{P,R}}$, where R is defined by a set of three different circular symmetric neighborhoods, P is the number of neighbors, and R indicates the radius of the sample. The original LBP operator can be defined as:

$$LBP_{P,R} = \sum_{p=0}^{P-1} s\left(g_p - g_c\right) 2^p, s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \tag{1}$$

In the study, the $\mathrm{LBP}_{8,2}$ operator was used for the 5x5 neighborhood.

However, it is possible to decrease the number of patterns in an LBP histogram by only using uniform patterns without losing much information. An LBP pattern is a uniform pattern if it contains at most two bitwise transitions from 0 to 1 or 1 to 0 in its binary representation when the binary string is considered circular (Orkhonselenge & Lucieer, 2004). For example, 11000011, 00111110, and 10000011 are uniform patterns. For LBP with 8 neighbor pixels, we get a feature vector of $2^8 = 256$ bins. However, using only uniform patterns, a feature vector of

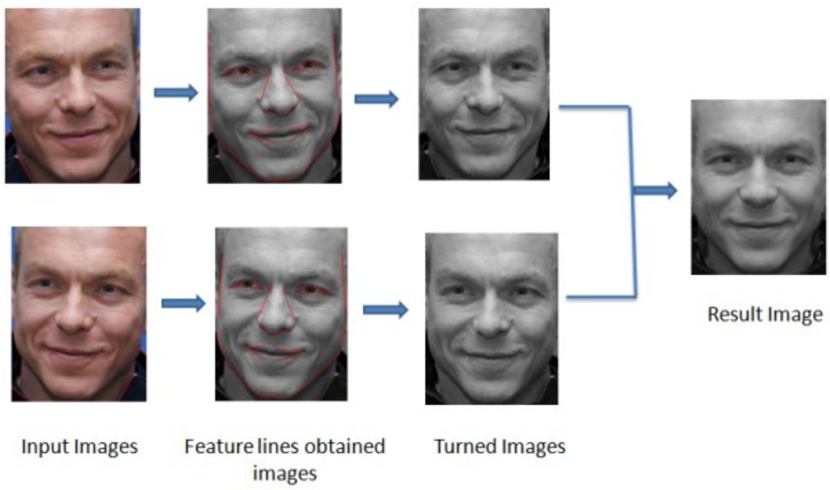

Figure 4: Rotation steps of face image

Figure 5: General structure of face mask

59 bins has been obtained. They mainly represent primitive micro-features such as lines, edges, and corners. The LBP histogram of the labeled image can be defined as follows:

$$H_i = \sum_{x,y} I(f(x,y) = i), \quad i = 0, 1, \ldots, n-1 \tag{2}$$

Where n is the number of different labels produced by the LBP operator, f(x, y) is the labeled image, and I(A) is a decision function that returns 1 if the event A occurs and 0 otherwise.

To form the LBP histogram, the image has to be divided into sub-regions. In this paper, each face image has been divided into 150 sub-regions, so we have obtained $150x59 = 8850$ features for each image.

4.1 Feature Extraction

Firstly, the face image has been divided into 150 sub-regions as we have mentioned before. Secondly, for each sub-region, the LBP histogram has been computed, and finally, by adding these histograms consecutively, the feature vector of the image has been obtained. Figure 7 shows how to get the LBP code from a face image.

Scaling the image into different sizes, local and global feature information can be observed in more detail. By combining the features of the multi-resolution image in different sizes, the feature vector is formed more precisely, completely, and correctly.

In the study, the face image has been analyzed in three different sizes, which are 130x100, 90x60, and 65x50. The LBP histograms of the image for these three different dimensions have been combined to form the feature vector of the image, as seen in Figure 8. In this way, the facial features have been effectively extracted using LBP.

5 Creating Race Class Models With Morphing

We aimed to extract the models of the race classes for the classification process. For this work, we have used the morphing method instead of averaging. In the study, 200 x 230 sized face images were used for morphing.

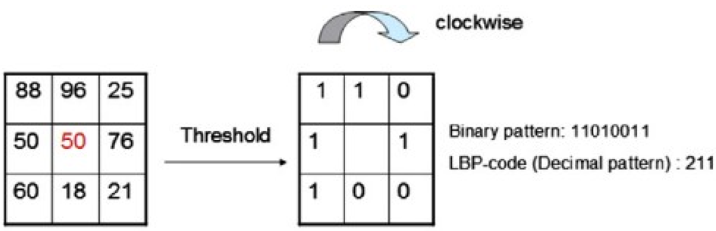

Figure 6: The original LBP operator

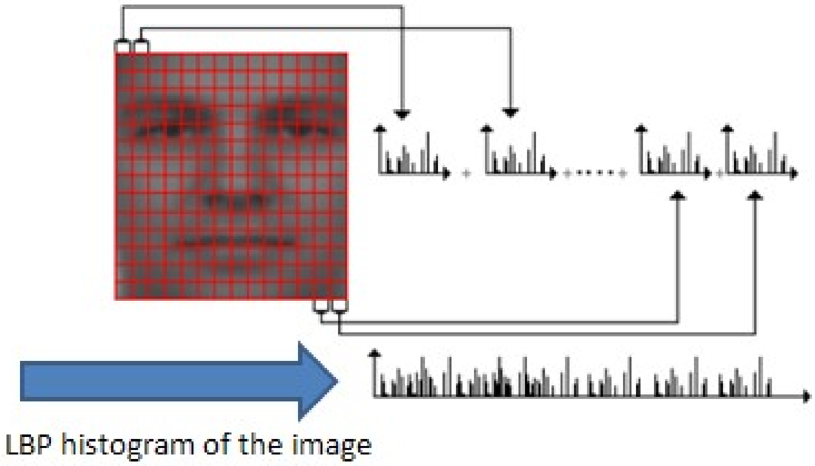

Figure 7: Obtaining LBP histogram of face image

In the study, the morphing phase consists of a mixture of areas morphing using facial landmark points. A limited number of fixed 23 facial landmark points were determined on the face and field morphing was performed according to these points. Generally, in studies, facial landmark points are determined in regions such as the eyes, nose, eyebrows, etc. In this study, the boundaries of the area, including the eye, nose, and eyebrow regions, were determined as landmark points. The location of these points was applied as a template for all input images after normalization. By using these facial landmark points, quadrilateral and triangular areas have been formed (Figure 9).

A coefficient has been identified for each image that is used in morphing, and this coefficient has defined its contribution to the resulting image. The sum of coefficients of the input images for morphing must be 1. In the morphing process, the coordinates of the feature points of each image have been multiplied with these coefficients and summed. Thus, coordinates of the interesting feature for the resulting image have been obtained.

In the resulting image, each pixel has been computed with affine and bilinear interpolation methods for triangular and quadrilateral areas, respectively (Günay & Nabiyev, 2009). An example (Caucasian) of the morphing process can be seen in Figure 10.

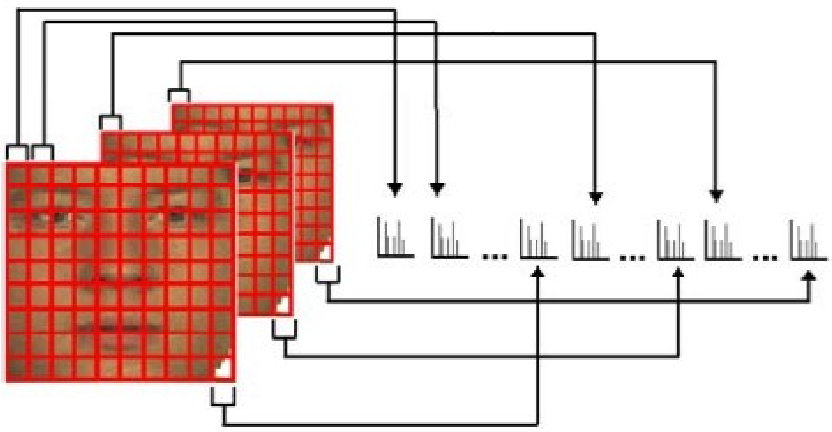

Figure 8: LBP histogram of multi-resolution face image

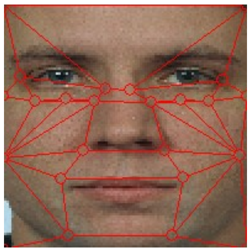

Figure 9: Extracted regions for face image

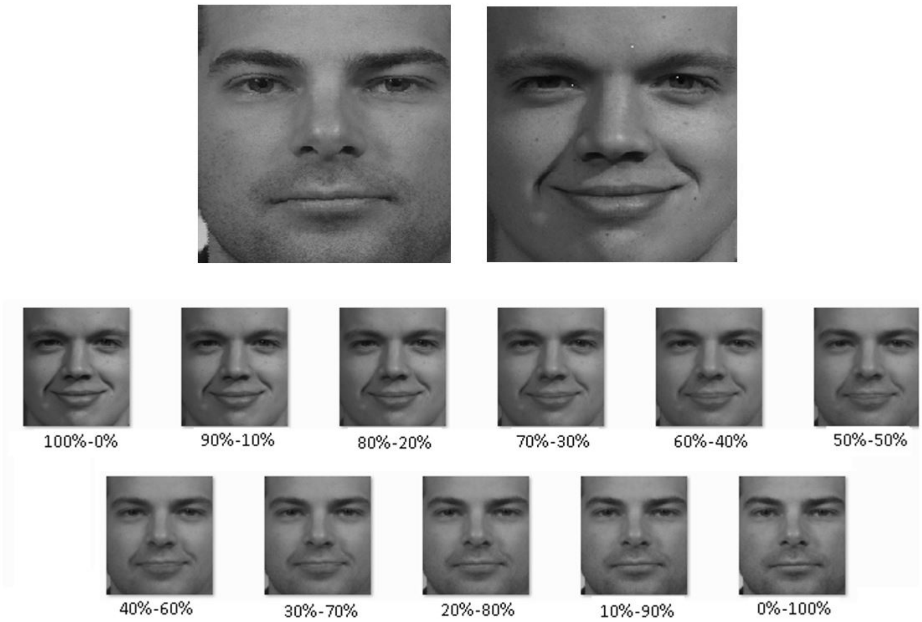

Figure 10: (top) input images, (bottom) result images with different morphing coefficients

5.1 Race Models

For extracting the model of each race, face images of persons who have dominant features of their own race have been morphed.

The face models for each race can be seen in Figure 11. In the study, it has been observed that after the 125 input race images, the morphing result image, which is called the race model, has changed under a 1% ratio. Therefore, we can say that the obtained race models are optimum models for races.

6 Classification

The Chi square statistic can be used as the dissimilarity measure for histograms, and some facial features can show differences between races. Therefore, a weight can be set for each face region based on the importance of the information it contains. The weighted statistic can be defined as:

$$X_w^2(S, M) = \sum_{i,j} w_j \frac{(S_{i,j} - M_{i,j})^2}{S_{i,j} + M_{i,j}} \tag{3}$$

where S and M are two LBP histograms, wj is the weight for region j.

Chi-square statistics were used to compare the race models in this paper. Each sub-region was compared to the others, and the differences between the races in each sub-region were

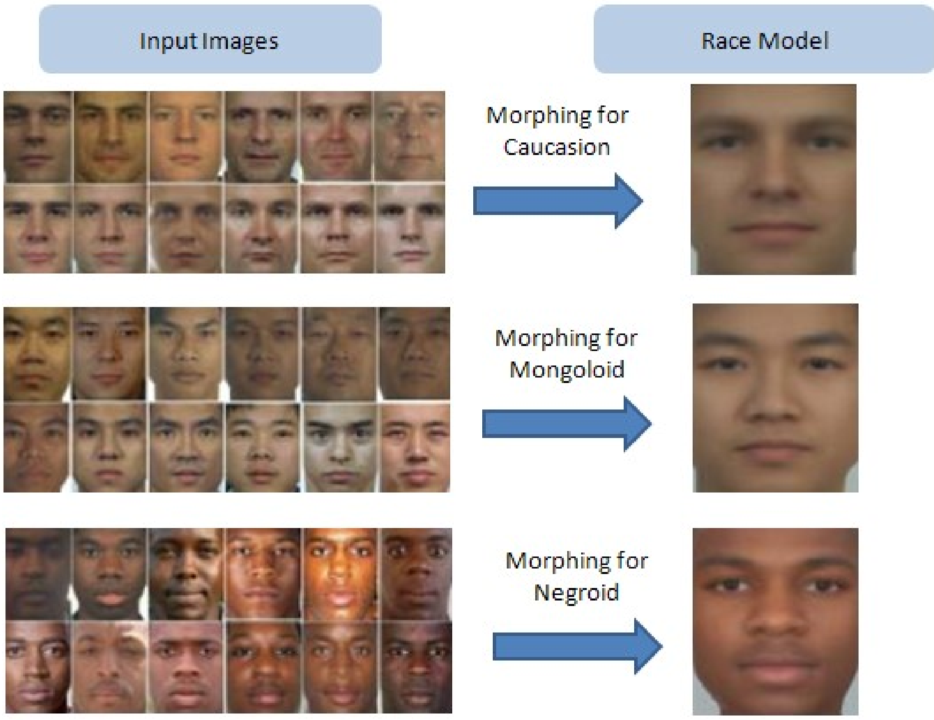

Figure 11: Obtained race models with morphing

determined in this way. The overall classification weights were calculated by taking the average of all the results from the two race groups.

As the difference increases, the black color is used, while as it decreases, the white color is used. According to Figure 12, we can say that the difference between Caucasian and Mongoloid races is seen in the eye regions, while the difference between Mongoloid and Negroid races is seen in the nose and mouth regions.

7 Performance Measures

The success of the recognition test can be defined with performance measures to evaluate the system more accurately. As we mentioned before, the database has 515 face images, which consist of 183 Caucasian, 142 Mongoloid, and 190 Negroid race face samples. The program interface is given in Figure 13.

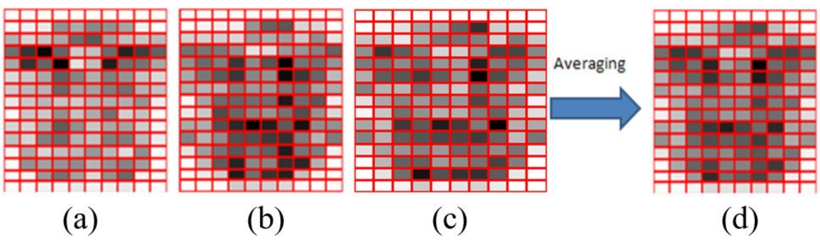

Figure 12: (a) Caucasian – Mongoloid comparison, (b) Mongoloid – Negroid comparison, (c) Caucasian – Negroid comparison, (d) Obtained general weights

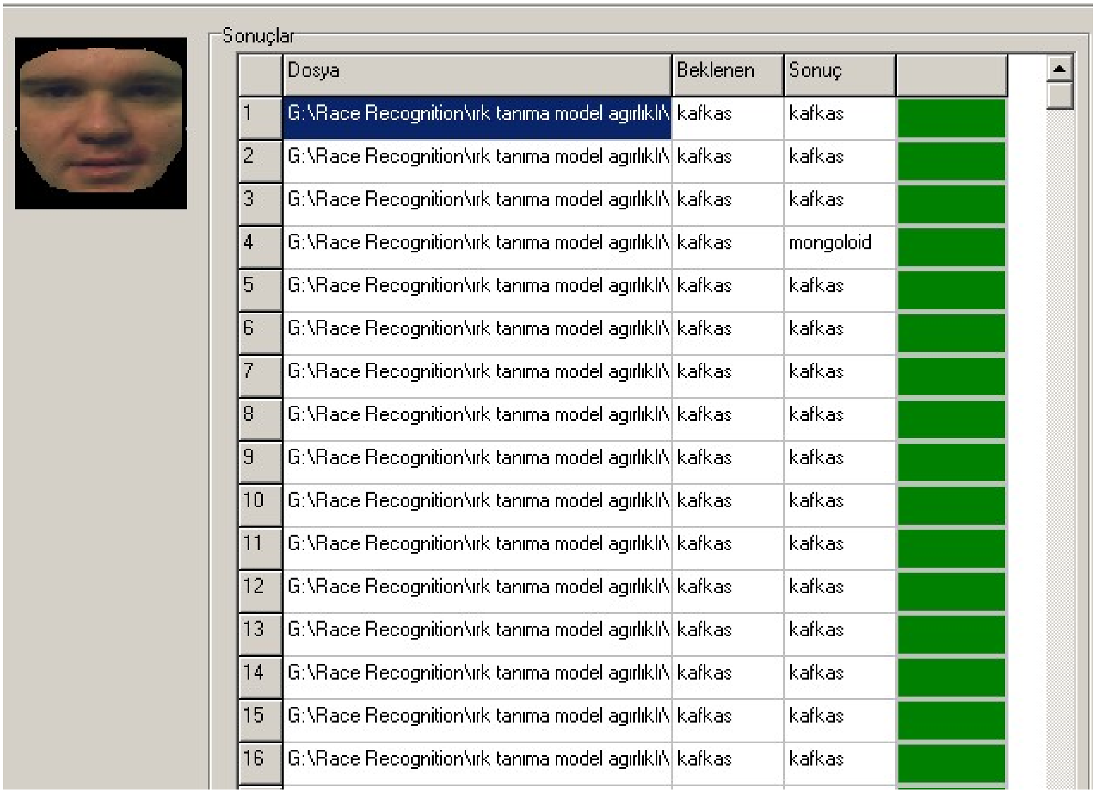

Figure 13: Program test interface

7.1 Sensitivity and Specificity

Sensitivity and specificity are statistical measures of the performance of a binary classification test, also known in statistics as a classification function. Sensitivity (also called recall rate in some fields) measures the proportion of actual positives which are correctly identified as such (e.g., the percentage of sick people who are correctly identified as having the condition).

Specificity measures the proportion of negatives that are correctly identified (e.g., the percentage of healthy people who are correctly identified as not having the condition). A perfect predictor would be described as having 100% sensitivity (i.e., predicting all people from the sick group as sick) and 100% specificity (i.e., not predicting anyone from the healthy group as sick). However, theoretically, any predictor will possess a minimum error bound known as the Bayes error rate (Wikipedia, 2021a).

Sensitivity relates to the test's ability to identify positive results and can be defined as:

$$Sensitivity = \frac{TruePositives}{TruePositives + FalseNegatives} \tag{4}$$

Specificity relates to the ability of the test to identify negative results can be defined as:

$$Specificity = \frac{TrueNegatives}{TrueNegatives + FalsePositives} \tag{5}$$

The test results for all races are given in Table 1.

In Table 1, TP (True Positive), FP (False Positive), TN (True Negative), and FN (False Negative) values are seen for each race. As a result, for all races, one example has been missed, and the sensitivity and specificity values are very high.

Table 1: Evaluation of classification results for races

		Caucasion		Mongoloid		Negroid	
		Desired Outcome		*Desired Outcome*		*Desired Outcome*	
		Positive	Negative	Positive	Negative	Positive	Negative
Test Outcome	Positive	TP 125	FP 1	TP 121	FP 1	TP 189	FP 1
	Negative	FN 1	TN 311	FN 1	TN 315	FN 1	TN 247
Sensitivity (%)		0.992		0.991		0.994	
Specificity (%)		0.996		0.996		0.995	

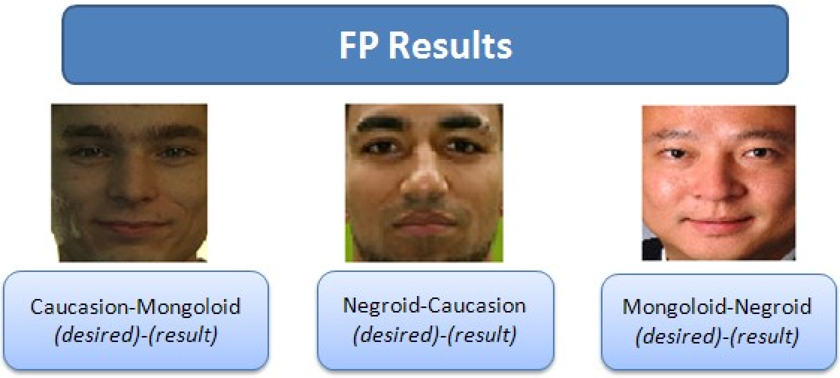

Figure 14: FP test samples

There are three FP results total, and these face samples can be seen in Figure 14. According to the results, we can say that the desired and program outputs of the wrongly recognized samples are similar.

Furthermore, we have tested albino face samples, which are Caucasian and Negroid, and they have been recognized as true. This shows that LBP is a textural feature extraction method and works independently of color. Albino Caucasian and Negroid face samples are given in Figure 15.

Figure 15: Albino Caucasian and Negroid face samples

In addition to sensitivity and specificity, the performance of a binary classification test can be measured with positive (PPV) and negative predictive values (NPV) (Wikipedia, 2021b).

7.2 Positive and Negative Predictive Values (PPV-NPV)

The positive predictive value (PPV) or precision rate is the proportion of subjects with positive test results who are correctly diagnosed (Wikipedia, 2021b). It is a critical measure of the performance of a diagnostic method as it reflects the probability that a positive test reflects the underlying condition being tested for. Its value does, however, depend on the prevalence of the outcome of interest, which may be unknown for a particular target population.

Positive Predictive Value is defined as:

$$PPV = \frac{TruePositives}{TruePositives + FalsePositives} \tag{6}$$

The negative predictive value (NPV) is a summary statistic used to describe the performance of a diagnostic testing procedure. It is defined as the proportion of subjects with a negative test result who are correctly diagnosed. A high NPV means that when the test yields a negative result, it is most likely correct in its assessment (Wikipedia, 2021b).

Negative Predictive Value is defined as:

$$NPV = \frac{TrueNegatives}{TrueNegatives + FalseNegatives} \tag{7}$$

The PPV measures the statistic over the classification algorithm's performance on a test set and is also referred to as precision. The complement of PPV in this context appears in the form of the negative predictive value (NPV), which measures the proportion of correctly assigned negative examples (Japkowicz & Shah, 2011).

The PPV and NPV values for the improved race recognition system for each class can be seen in Table 2 below.

Table 2: PPV and NPV values of the improved system

Caucasion		**Mongoloid**		**Negroid**	
PPV	NPV	PPV	NPV	PPV	NPV
0.992	0.996	0.991	0.996	0.994	0.995

8 Conclusion

In this paper, we propose a race recognition method using morph-based age models. We can say that for the proposed system, the results are very satisfactory. As seen in Table 1, the sensitivity of races in % is 0.992 in the Caucasian race, 0.991 in the Mongoloid race and 0.994 in the Negroid race. At the same time, the specificity values are 0.996 in the Caucasian race, 0.996 in the Mongoloid race, and 0.995 in the Negroid race. Looking at Table 2, the PPV and NPV values of the developed system are as follows. The Caucasian race has a PPV of 0.992, an NPV of 0.991, the mongoloid race has a PPV of 0.991 and an NPV of 0.996, and the negroid race has a PPV of 0.994 and an NPV of 0.995. It is seen that the sensitivity and specificity values in Table 1 are the same as the PPV and NPV values in Table 2. This situation is completely coincidental and is due to the fact that the numbers of FP and FN are equal in each class type.

By using morphing instead of averaging, effective race models have been formed. As a result, the classification performance became very successful. Furthermore, by employing weighted Chi-square statistics for classification, we have increased the reliability of the difference points between races. In future work, the database can be widened and the recognition system can be developed for females as well as for recognition of sub-ethnic groups. Furthermore, the system can be used for similar recognition problems.

9 Acknowledgement

The authors would like to thank the Editor and anonymous reviewers for their valuable comments and suggestions to improve the quality of the manuscript.

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