International Journal of Scientific Research in Science, Engineering and Technology
Print ISSN: 2395-1990 | Online ISSN : 2394-4099 (www.ijsrset.com)
doi : https://doi.org/10.32628/IJSRSET218155

Identification of Human Facial Images using Visual Descriptors

Ayesha Aziz Prova*1, Md. Nazmul Hossain2
*1Computer Science and Engineering, Central Women's University, Dhaka, Bangladesh
2Computer Science and Engineering, Jagannath University, Dhaka, Bangladesh

Article Info
Volume 8 Issue 1
Page Number : 229-238

Publication Issue :
January-February-2021

Article History
Accepted : 20 Feb 2021
Published : 28 Feb 2021

ABSTRACT

Discovering people using his face image now a vital research area for the researchers. This process is named face recognition. Every organization and not an organization even a county's security system now ejected on a face image perception system. To evolve the face identifying complication the Local Binary Pattern Histogram (LBPH) is an unchanging way out method. But in the matter of illumination diversification, expression variation, and attitude deflection it gives less accurate than others. In our work, we have proposed a revised local binary pattern histogram (ReLBPH) for the way out of illumination diversification. We replace the gray form of LBP with a new threshold value, named instigator-threshold value instead of the threshold of the centric pixels of the sampled values of their neighbourhood sampling points. Using sub-blocks we extracted the features and then finally make the statistical histogram of these features. We use the FEI Standard database, DRFFI dataset and our constructed dataset for our experiment. We find maximum accuracy rate for the datasets.

Keywords: Face recognition, ReLBPH, instigator-threshold, Statistical histogram

I. INTRODUCTION

Human face authentication for experimentation activities from still and audiovisual pictures amplifies expressively over the previous 30 years. Customary resources of security like ID cards and passwords are not consistent or expedient adequate in the present day. For that reason, face authentication acquires a place as a foremost exploration attention zone of security. Face authentication is a key element for smart environments.

It is indispensable for inferring facial expressions, human feedback, intents, and activities [1], [2]. The look is an inbred character of somebody. An organism built on facial detection and recognition is complementarily applicable for persons who are not keen to collaborate with other possessions of biological data credentials system such as fingerprint, iris, or hand scan [3], [4]. Habitually, the lawbreakers get away with their bootee if there is no tracker system. It is feasible to isolate somebody compelling a crime using the assistance of face authentication. It is incrementally getting popularity among scholars around the biosphere in many zones such as security, medical, engineering, and so on [5], [6], [7]. Many years in a row, numerous scholars have manifested distinct types of face recognition algorithms. They are working together with Local Binary Pattern (LBP) method [8], [9], [10], Sparse Coding(SC) method [11], [12], [13], Deep Convolution Network method [14], [15], [16] different subfield founded interrelation strained faces [17], Histograms of Oriented Gradients(HOG) method [18], [19], [20], Gabor feature method [21], Laplacian methods to sustain native report [22], Linear Discriminant Analysis (LDA) method [23]. Aan naked emergence computer library that has ternary ingrained face recognition method, Fisherfaces [24], Eigenfaces [25], and Local Binary Pattern Histogram (LBPH) [26], Modified Local Binary Pattern Histogram (MLBPH) [14]. Face recognition diagnosis or verifies one or more persons in a prospect by associating input faces with face images put in storage in a database. The inclusive progression for face recognition can be framed by face uncovering, feature extraction, and concession. Feature vectors in the subordinate dimension of feature space typically embody images of human faces. Face recognition consists of spotting and verification. Face spotting takes a mysterious face as input. Then the system reports its identity after checking a known database. A pixel's gray level acquainted by an uncertain descriptor, LBP code [27]. Using a histogram Binary pattern codes are conserve. A bin in the histogram contests up to an exclusive binary code. Numerous variants of LBP anticipate expanding upon the basic LBP [14]. It embraces variants in neighborhood topology and thresholding and/or encoding. Some scholars have also anticipated substitute manners of exploiting the binary pattern codes; for example, "constant" arrangements clutch the binary decoration codes by way of the numeral of bit changeovers [28]. Linear and non-linear dimensional reduction schemes sought to utilize only worthwhile pattern codes [29], [30]. In this paper, we have proposed a revised LBPH (ReLBPH) to mend the vigor of the recognition procedure, founded on a newly proposed threshold, instigator-threshold. The gray value of the pixel swapped by the instigator-threshold of its neighborhood sampling value and then generating the face database, extracting the LBP feature, and ReLBP feature. We exert our method in illumination change where we contrivance that our algorithm exactly finds the accurate image. In addition, we have a device that other algorithms cannot recognize images during illumination changes. We experiment with our method of the public standard FEI image databases.

The organization of this document is as follows. Section II presents an overview of the system model and defines the problem. It also describes the details of the proposed ReLBPH method. Section III evaluates the approach by proper analysis and shows the experimental results. Section IV summarizes the paper.

II. METHODS AND MATERIALS

The facial recognition system consists of four main components: Data wining scruple, feature deduction scruple, testing and training classified database scruple. The wining scruple will be used as a test sample for analysis. In the feature deduction scruple, there are several featured features that can present human identity information extraction and analysis. In the testing and training classified database scruple, classifiers are used to classify tests to determine the marking report of the parts. The main objective of face recognition is to extract and demonstrate the inherent features. In this paper, the proposed extraction method, namely ReLBPH is used for face recognition. This proposed method Fig. 1 is briefly discussed in the following subsections.

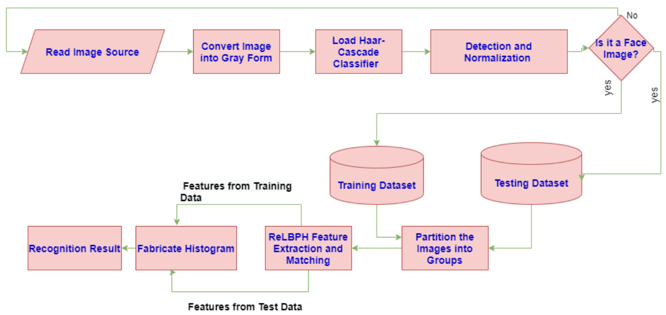

Figure 1 : Proposed image recognition system

A. Image Dataset of Faces

We have executed our research using the public FEI Face Dataset [31], DRFFI (Discriminate Real and Fake Face Images) dataset [32], and the Constructed dataset. FEI Face Dataset carts a collection of facial Fig. 2 that are captured between June 2006 and March 200 at FIIs Artificial Intelligence Laboratory in Sao Paulo, Sao Bernardo Campo, and Brazil. The FEI dataset divides into various subgroups, where handpicked one among many subgroups for the testing. The subgroup embraces 14 images with regard to a piece of 200 persons, an aggregate of 2800, along with light, facial terminologies, and gesture deviations. Entire images are colourful and captured contrary to a white homogenous contextual in a standing anterior point with a sketch whirl of up to about 180 degrees. The scale might fluctuate about 10%. The real shape of all Figures is 16.93cm by 12.7cm. All the Figures of FEI are of its students and staff, ages between 19 and 40 with an exclusive outlook, haircut, and adorns. The amount of male and female Figures is exactly the same and it is 100. Fig. 2 shows some examples of face images from the FEI face database. Fig. 3 shows some examples of face image variations from the FEI face database.

Figure 2 : Face dataset sample of FEI dataset

Figure 3: Image variations of individuals of FEI dataset

Figure 4: Face dataset sample of DRFFI dataset

DRFFI dataset holds masterly-created elevated-standard photographic facial images where the images are combined of various faces, differentiated by various organs of a face or entire face. It contains 2041 different facial images of a total where 1081images are real images and other 960 images are fake images. Fig. 4 shows some examples of face images from the DRFFI face database.

Figure 5: Face dataset sample of constructed dataset

Constructed face dataset our self-facial-images. It is constructed using the principle of detection of faces. We made various facial vents and poses to identify the faces. We put our images in the same file to make the constructed face dataset. Fig. 5 shows some examples of face image variations from the Constructed face dataset.

B. Detection of Face Image

We have used OpenCV for image detection. It serves Haar cascade classifier for face detection. This classifier applies the AdaBoost method to detect different facial parts. To recognize objects Haar-like classifiers are good enough. They have concerned with their name to their instinctive resemblance with Haar wavelets. They also were applied in the first actual period facial image locator [33], [34], [35]. With reference to past events, performing with mere image severities formed the job of feature prediction mathematically extravagant. A proclamation by Papa Georgiou et al [36] viewed performing with a moving feature kit depends on Haar-like wavelets as a substitute for the customary image severity [37], [38]. It takes the images and changes them to gray form for checking either the image is the human face or not [39] [40].

C. Face Recognition Using Proposed ReLBPH Method

The LBPH algorithm uses a developed rounded LBP operator. For the texture spectrum modelling, local binary patterns (LBP) can be used as the precise instant. In image recognition, we can use this algorithm as a visual descriptor for texture classification. LBP is used to label the contrast information of a pixel to its neighbourhood pixels. LBP is used to label the contrast information of a pixel to its neighbourhood pixels. The OLBP eigenvalue can be described in Fig. 6.

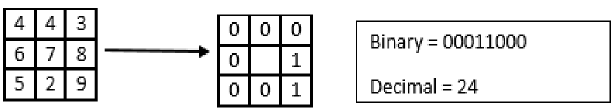

Figure 6 : Original local binary pattern (OLBP) operator

The LBP feature vector is can be made by using the following steps:

1) Step-1: Divide the inspected frame into cells (original LBP is defined in the window of 3*3).

2) Step-2: Contrast the pixel separately of every one of its neighbors in a cell. Track the pixels along a circle, i.e. clockwise or counterclockwise. The pixel point is noted as 1 if the surroundings pixel value is higher than or same as the center pixel value, else noted as 0. In this way, the centric pixel points (LBP values) of the frame obtained, which used to reflect the texture features of the region.

3) Step-3: The frequency of each "number" illustrates the histogram above the cell. Each grouping determines which pixels are smaller and which are larger than the center. This can gained as a 256-dimensional property vector. Optionally normalizes the histogram. The final concatenation (normalized) of the histogram of entire cells gives the feature vector for the whole frame.

The eigenvalue of ReLBP describe in Fig. 7.

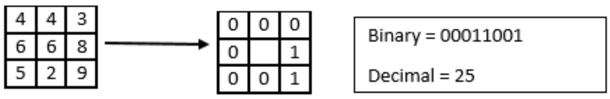

Figure 7: Revised local binary pattern (ReLBP) operator.

The phases of the proposed ReLBPH algorithm are as following:

4) Step-1: Divide the inspected frame into cells (original LBP is defined in the window of 3*3).

5) Step-2: Replace the central pixels value by the newly proposed threshold value, named instigator-threshold.

The formula for the threshold value is as follows:

$$\Gamma = \frac{(\text{minValue} + \text{maxValue}) + \text{medianvalue}}{\beta} \quad (1)$$

Where, Γ = instigator-threshold, and β is an accuracy gain factor and it ranges from 1.07 to 1.27. Contrast the pixel separately of every one of its neighbors in a cell. Track the pixels along a circle, i.e. clockwise or counterclockwise. The pixel point is noted as 1 if the surroundings pixel value is higher than or same as the center pixel value, else noted as 0. In this way, the centric pixel points (LBP values) of the frame obtained, which used to reflect the texture features of the region.

6) Step-3: The frequency of each “number” illustrates the histogram above the cell. Each grouping determines which pixels are smaller and which are larger than the center. This can *gain* as a 256-dimensional property vector. Optionally normalizes the histogram. The final concatenation (normalized) of the histogram of entire cells gives the feature vector for the whole frame.

III.RESULTS AND DISCUSSION

We have used Python, an inferred high-level programming language, for our experiment. We used our proposed Revised Local Binary Pattern Histogram to recognize face images and compare its accuracy with LBPH, and MLBPH. First of all, we have trained the dataset and compost the texture features. Then we have classified and recognized the face reports. We have shown the accuracy comparison of all classifiers for FEI, DRFFI and Constructed dataset. We also have presented the graphical representation of our result.

A. Experimental Results of Proposed ReLBPH Classifier

We have showed the accuracy results of LBPH, MLBPH [14] and ReLBPH methods in table I of FEI dataset. From the table we can say that the proposed ReLBPH achieves better result and higher classification accuracy (99.25%) than LBPH (85.714%) and MLBPH (85.714%).

TABLE I

ACCURACY COMPARISON OF FEI DATASET

Algorithm	Correctly Classified	Incorrectly Classified	Accuracy (%)
LBPH	1029	191	85.71
MLBPH	1029	171	85.71
ReLBPH	1191	09	99.25

Fig. 8, 9, 10 shows the recognition result LBPH, MLBPH and ReLBPH. From Fig. 11 shows the graphical presentation of accuracy.

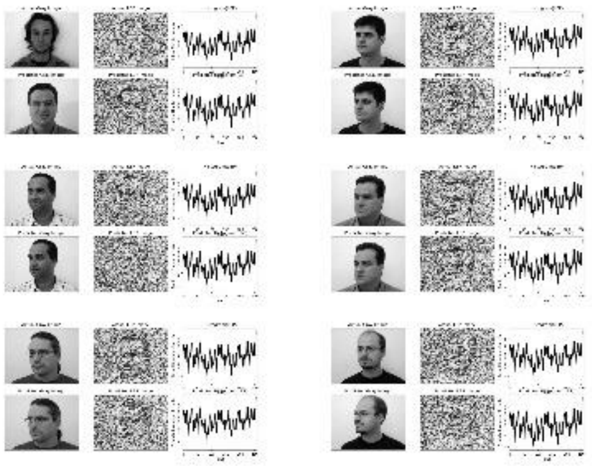

Figure 8: Image recognition result of OLPBH

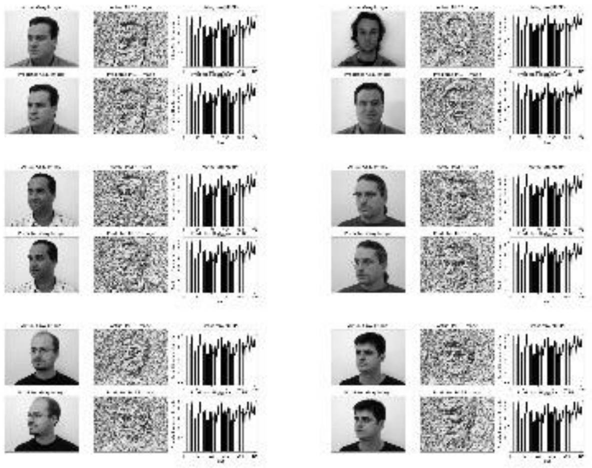

Figure 9 : Image recognition result of MLPBH

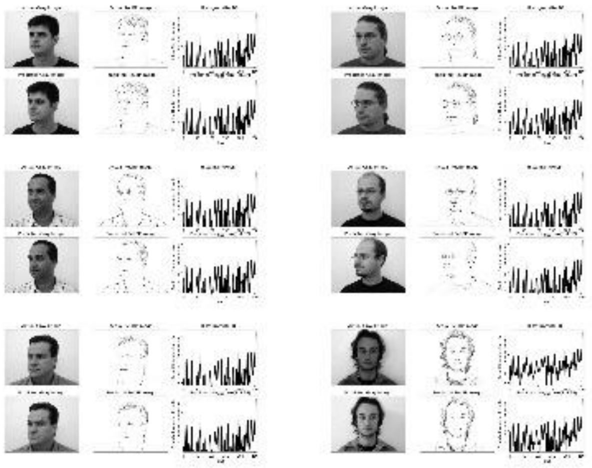

Figure 10 : Image recognition result of ReLPBH

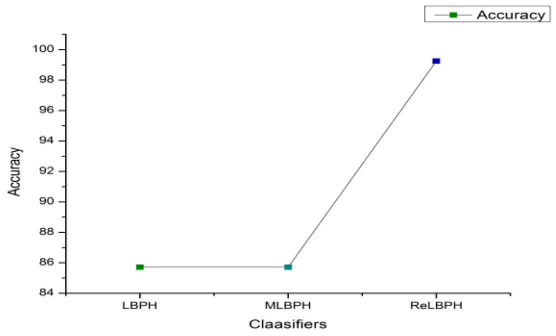

Figure 11 : Graphical representation accuracy comparison of FEI dataset

We have showed the accuracy results of LBPH, MLBPH and ReLBPH methods in table II of DRFFI dataset. From the table we can say that the proposed ReLBPH achieves better result and higher classification accuracy (83.33%) than LBPH (75.00%) and MLBPH (72.22%). From Fig. 12 shows the graphical presentation of accuracy.

TABLE II
ACCURACY COMPARISON OF DRFFI DATASET

Algorithm	**Correctly Classified**	**Incorrectly Classified**	**Accuracy**
LBPH	900	300	75.00
MLBPH	867	333	72.22
ReLBPH	1000	200	83.33

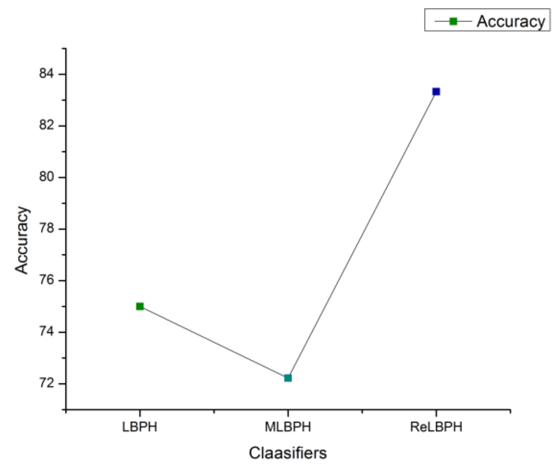

Figure 12 : Graphical representation Accuracy Comparison of DRFFI dataset

B. Experimental Results of Illumination Change

The LBPH algorithm during dull illumination gives a poor accuracy rate. Therefore, to remove this matter we collect the dull illumination Figures as the testing set. In addition, other Figures applied for making the training dataset. To sew up the illumination change problem, a revised LBPH (ReLBPH) method depends on the neighbourhood gray instigator-threshold value is applied. Applying the threshold of the instigator-threshold value, we increase the recognition rate during illumination change.

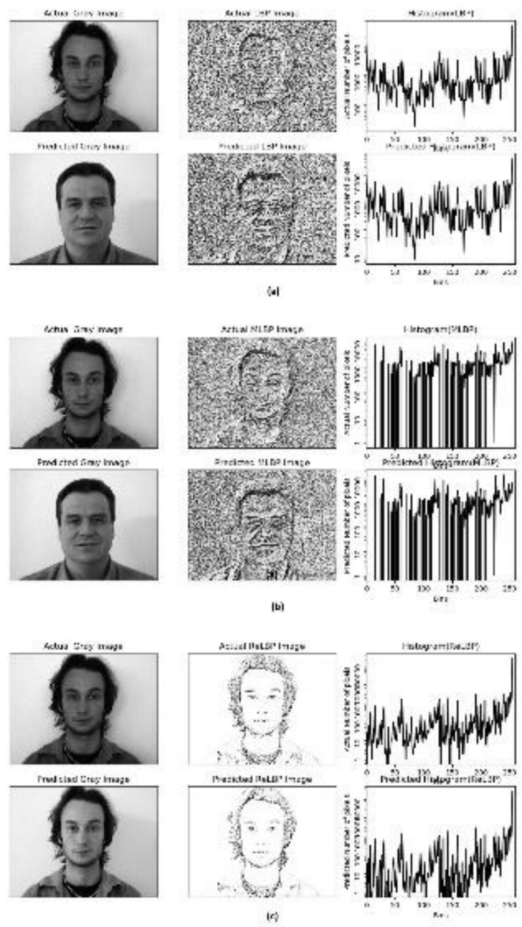

Figure 13: Image recognition result of illumination change, (a) Image recognition result of OLPBH, (b) Image recognition result of MLPBH, (c) Image recognition result of ReLPBH

From Fig. 13 we can see easily that our proposed method recognize the exact image where other cannot recognize. We have showed the accuracy results of LBPH, MLBPH and ReLBPH methods in table III.

TABLE III

ACCURACY COMPARISON OF FEI DATASET

Algorithm	Correctly Classified	Incorrectly Classified	Accuracy
LBPH	196	404	33.33
MLBPH	172	428	29.17
ReLBPH	343	257	58.33

From the table we can say that the proposed ReLBPH achieves better result and higher classification accuracy (58.33%) than LBPH (33.33%) and MLBPH (29.17%). Fig. 14 shows the graphical presentation of accuracy.

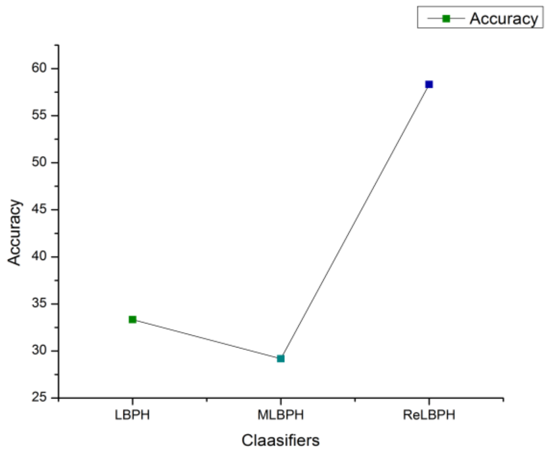

Figure 14: Graphical representation accuracy comparison of FEI dataset during illumination change

We have showed the accuracy results of LBPH, MLBPH and ReLBPH methods in table IV of DRFFI dataset. From the table we can say that the proposed ReLBPH achieves better result and higher classification accuracy (46.88%) than LBPH (38.74%) and LBPH (41.72%). Fig. 15 shows the graphical presentation of accuracy.

TABLE IV

ACCURACY COMPARISON OF DRFFI DATASET

Algorithm	Correctly Classified	Incorrectly Classified	Accuracy
LBPH	250	350	38.74
MLBPH	300	300	41.72
ReLBPH	350	250	46.88

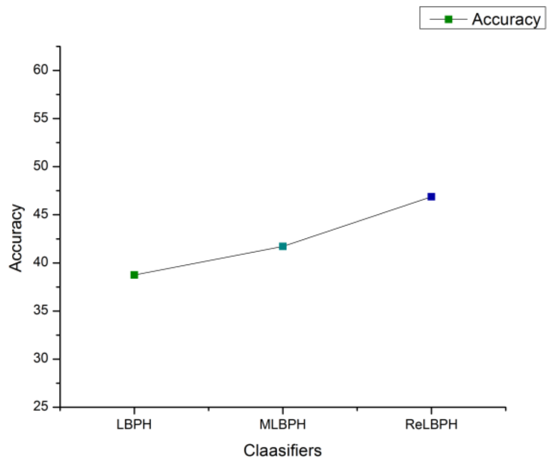

Figure 15: Graphical representation accuracy comparison of DRFFI dataset during illumination change

We have showed the accuracy results of LBPH, MLBPH and ReLBPH methods in table V of our Constructed dataset.

TABLE V

ACCURACY COMPARISON OF CONSTRUCTED DATASET

Algorithm	Correctly Classified	Incorrectly Classified	Accuracy
LBPH	260	339	40.57
MLBPH	287	313	42.85
ReLBPH	340	260	43.33

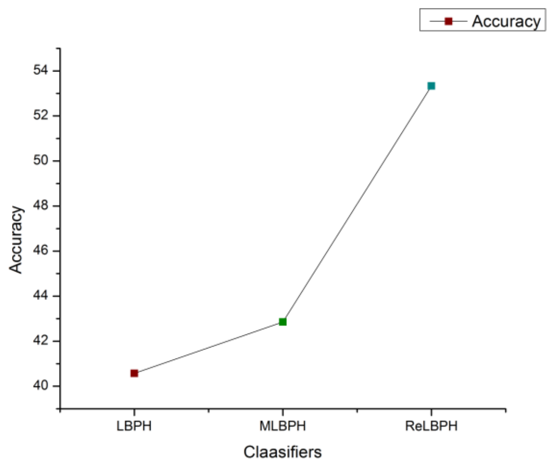

Figure 15 : Graphical representation accuracy comparison of constructed dataset during illumination change

We scan the images in low light and take 600 images. From the table we can say that the proposed ReLBPH achieves better result and higher classification accuracy (53.33%) than LBPH (40.57%) and MLBPH (42.85%). The recognition result of our constructed database shown in Figureure 16. Figureure 17 shows the graphical presentation of accuracy. And in all cases we find that our proposed algorithm works better with higher accuracy rate.

IV.CONCLUSION

The recognition rate of the local binary pattern histogram (LBPH) algorithm depends on illumination, expression change, and attitude deflection. To solve the illumination change problem, a revised LBPH (ReLBPH) algorithm based on neighborhood gray instigator-threshold recommend here. Using the instigator-threshold of the neighborhood sampling values as a replacement for intermediate values. Experiments carried out on a FEI, DRFFI and generated face datasets. In addition, the accuracy (99.25%) demonstrated that the ReLBPH algorithm is superior to the LBPH (85.714%) and MLBPH (85.714%) algorithms in recognition percentage of in the case of FEI dataset. For the DRFFI dataset, the accuracy of LBPH, MLBPH and ReLBPH is (83.33%) than LBPH (75.00%) and MLBPH (72.22%). Using the instigator-threshold of the neighborhood sampling values as a replacement for intermediate values, thereby decreasing the effects of extraction disorders on the distinguishing value of illumination. ReLBPH with β = 1.67 is affected by best results and sensitiveness to illumination changes than MLBP and LBPH. For that reason, Proposed ReLBH algorithms finds the exact person where the other algorithms cannot in FEI dataset. Moreover, ReLBH (58.33%) gains the highest accuracy rate instead of LBPH (33.33%) and MLBPH (29.16%) in FEI dataset. For the DRFFI dataset, the accuracy of LBPH, MLBPH and ReLBPH during illumination change is (46.88%) than LBPH (38.74%) and MLBPH (41.72%). Finally for our Constructed dataset the accuracy (53.33%) than LBPH (40.57%) and MLBPH (42.85%).

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Cite this article as :

Ayesha Aziz Prova, Md. Nazmul Hossain, "Identification of Human Facial Images using Visual Descriptors", International Journal of Scientific Research in Science, Engineering and Technology (IJSRSET), Online ISSN : 2394-4099, Print ISSN : 2395-1990, Volume 8 Issue 1, pp. 229-238, January-February 2021. Available at doi : https://doi.org/10.32628/IJSRSET218155
Journal URL : https://ijsrset.com/IJSRSET218155