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MULTIPLE MODELS OF BINARY-SUPPORT-VECTOR-MACHINE FOR FACE VERIFICATION USING HISTOGRAM ORIENTATION GRADIENT FEATURES

[1]MUSTAFA GH. SAEED, [2]MAYSOON M. AZIZ, [3]FAHAD LAYTH MALALLAH, [4]BARAA T. SHAREF

[1]Computer science Department, College of Science, Cihan-Slemani University, Slimani, Iraq,
[2]Department of Mathematics, College of Computer Sciences and Mathematics, University of Mosul, Iraq.
[3]Computer and Information Technology, College of Electronic Engineering, Ninevah University, Mosul, Iraq,
[4]Information Technology Department, College of Information Technology, Ahlia University, Kingdom of Bahrain

E-mail: [1]mostafa.swe@gmail.com, [2]aziz_maysoon@yahoo.com, [3]fahad.layth.86@gmail.com, [4]bsharif@ahlia.edu.bh.

ABSTRACT

In the past decade, face recognition is considered as an important biometric type due to its wide applications in practice in terms of authentication. The verification process of a human face is not trivial task especially different face poses are captured to be matched. In this paper, an efficient algorithm for face recognition is proposed. In the beginning, the step is starting by capturing the image of the face, then applying some preprocessing operations, after that feature extraction is applied, which is exploiting Histogram Orientation Gradient (HOG) to build the most representative feature vector for each digital image of the face. Next, the feature vector is passed into binary Support Vector Machine classifier (SVM) to construct a binary-SVM model for one individual in order to either accept or reject this individual. In this research, multiple models of binary-SVM are utilized in this methodology, in which for each individual has its own SVM model, which is deemed as the contribution of this paper. Set of experiments have been conducted to estimate the accuracy and performance of the proposed algorithm by using ORL database, which has 400 images face captured from 40 users each user has 10 different images as variant possess lighting, etc. The result has given accuracy up to 99.23% as successful rate coming from both error types: False Accept Rate (FAR) is 0.25 % and False Reject Rate (FRR) is 0.52 %.

Keywords: *Face Recognition and verification, Biometrics, Histogram Oriented Gradient (HOG), Support Vector Machine (SVM).*

1. INTRODUCTION

Various applications are exploiting biometrics for achieving applications related to security [3]. Biometric system recognizes an individual based on a feature vector extracted from the physiological or behavioral characteristic of persons [4-6]. Face recognition and verification is deemed as physiological type, which is one of the most accepted verification methods for boosting security [7]. Currently, face recognition is considered as one of the famous biometric technique that researchers have focused on in both academic and industrial sectors, which might be used in airport, passport verification, mobile authentication, access building, verification in the police department for the criminal list, electrical identification, card security measure at ATMs, robotics, healthcare, surveillance monitoring and etc. Facial recognition is an effective computing research of different areas namely physiology, computer vision, image processing, pattern recognition and machine learning [8]. It is worth to mention that, biometric has two main modes of a system [9, 10]: First, the identification mode, which is matching the target biometric data with all the data available in the system, in other words, it can be translated into this question: “Who are you?”, or it performs a one-to-many (1: N) match, this mode consumes much time because it needs to do many comparison operations. The goal of user identification is to find out the closest matching identity. This type of biometric authentication is normally used in surveillance and forensic applications [9]. Second, the verification mode, which is based on this question: "Are you who you claim to be?", in this mode, the target biometric data is compared to the specific reference stored in the system to authenticate its identity. In other words, it performs a one-to-one (1:1) match. Usually, this mode needs less time than the identification mode [11-13]. The improvement of the recognition rate depends on several factors, some of them related to the physical conditions such as face position, image illumination and face emotional expressions. Besides that, preprocessing procedures and feature extractions can improve the recognition process by retransforming the image into a convenient dimension with a better representation called feature vector. In this research, Histogram Orientation Gradient (HOG) is the proposed feature extraction approach in the recognition process and using ORL database image set for testing.

The main aim of this paper is improving the recognition rate of the face verification by using multiple model of binary-SVM, which is deemed as the contribution knowledge of this paper. In other words, a trained binary-SVM model will be assigned to each individual separately, in order to make a decision for that specific individual as either accept or reject. As well as compare with the recently state-of-the-art papers that are using only ORL database, the reason of ORL exclusion is to come out with a fair result comparison.

This paper has six sections organized as follows: Section Two is dedicated to literature review related to face verification using ORL database. In Section Three, the research methodology design is dully elaborated. Then, the experiment of this testing is described in Section Four. In Section Five, the result and discussion are presented. Finally, in Section Six, the conclusion is presented then, followed by the list of references.

2. LITERATURE REVIEW

Previous works related to the face recognition, which are using ORL database, are reviewed critically in this section specifically with Oracle Research Laboratory (ORL) database consists of 400 different subjects as 40 classes, for each class has 10 face images. In 2016, a technique of face recognition has presented in [14]. Here, Principal Components Analysis (PCA) is used as a feature extraction and for dimensional reduction, for the classifier Euclidean distance is used. The training and testing of this method are conducted on ORL database for assessing the performance, which is reported up to 97.5% as recognition rate.

Another work of face recognition has done in 2017, which is a hybrid component-based approach for facial recognition presented in [15], in this technique, the feature descriptor is composed of assembling two descriptors: Gabor Filters and Zernike Moments which have been used to extract textural and shape features, respectively. The accuracy of the experimental results achieved of this work, which is carried out on ORL database, is up to 93.9%. Another face recognition method proposed in 2017, which is also used ORL database. This method has noticeably higher accuracy than the previous techniques, which is up to 98.3%, the technique used here is deep learning as convolutional neural network (CNN), which stands or both feature extraction (convolution weights) and the classifier (neural network) [16]. Also, a comparison study between LDA and PCA for face recognition has been proposed in the literature. In which experimental results show that the LDA feature extraction technique has better performance than PCA technique. The highest recognition rate is recorded as 95.981% for the LDA technique, while the highest recognition rate that is recorded for PCA technique is 94.027% [17] . Another work in 2017 is using Hierarchical temporal memory (HTM) as a machine learning algorithm inspired by the information processing mechanisms of the human neocortex, which are consists of a spatial pooler (SP) and temporal memory (TM). The HTM SP is exploited here to demonstrate a face recognition system, using the standard ORL databases. The accuracy of The HTM SP achieved accuracies of 87.21%. However, it is low accuracy, the advantage of this work is the visual data processing using binary HTM SP features requires less storage and processing memory than required by the existing processing methods, with the area and power requirements for its implementation [18]. Another face recognition work proposed in 2017 for face recognition. Here, the algorithm called fuzzy linear regression discriminant projection (FLRDP), which is generating an efficient subspace for the LRC method and could effectively handle variations between facial images. This idea starts computing the gradual membership degrees of each sample to corresponding classes, and then incorporates such membership degree information into the construction of the fuzzy between-class and within-class reconstruction errors. The best achieved accuracy of this work is 96% as a result of experiments conducted on the ORL face database

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[19]. In 2016, many-kernel random discriminant analysis (MK-RDA) to discover discriminative patterns from the chaotic signals has been proposed for the face recognition, in the testing by using ORL database, the achieved accuracy is 95.7% as reported in [20].

Also in 2016, locality preserving projection (LPP) feature transfer is proposed for face recognition. In LPP operation, first, transfer sources are screened to obtain the selective sample source using the whitened cosine similarity metric. Then, we project the vectors of source faces and target faces into feature subspace by LPP, respectively, and calculate the feature transfer matrix to approximate the mapping relationship on source faces and target faces in subspace. For the classification of LPP features, the nearest neighbor classifier is used based on popular ORL databases, which achieved accuracy up to 92%. However, it is low accuracy, it is using single –sample training for the face [21].

Also, in 2017, a work of face recognition tried to solve a problem of pose and illumination variations of the faces by using Gradient-Orientation-Based PCA Subspace in the feature extraction stage. While a distance metric is used with the nearest neighbor classifier to measure the similarity between different faces in the classifier stage. This method is named SchurFaces by the author, which is tested in ORL database and achieved accuracy up to 85% [22].

To sum up, among the aforementioned works of face recognition listed in the literature review, there is no existing work for face recognition that has perfect recognition rate yet. It is worth to mention that the proposed system in this paper has a recognition rate that outperforms the state-of-the-art techniques.

3. METHODOLOGY

The proposed face verification system consists of three main separate processes [23]: pre-processing (re-sizing and RGB to Gray-Scale), feature extraction and classification. Face image samples are fed into the system as depicted in Figure 1, then a preprocessing operation is done to re-size each face image to [112 x 92] as image (ORL database is already in gray-scale format). Then, next stage is feature extraction operation by using Histogram Oriented Gradient (HOG) algorithm [24], which are deemed as the most powerful feature shape descriptor of an image as well as gradients are invariant to illumination and pose variations. Then, the feature vector is trained by using binary class of SVM (class for accept as “1”, class for reject as”-1” for the specific user) to

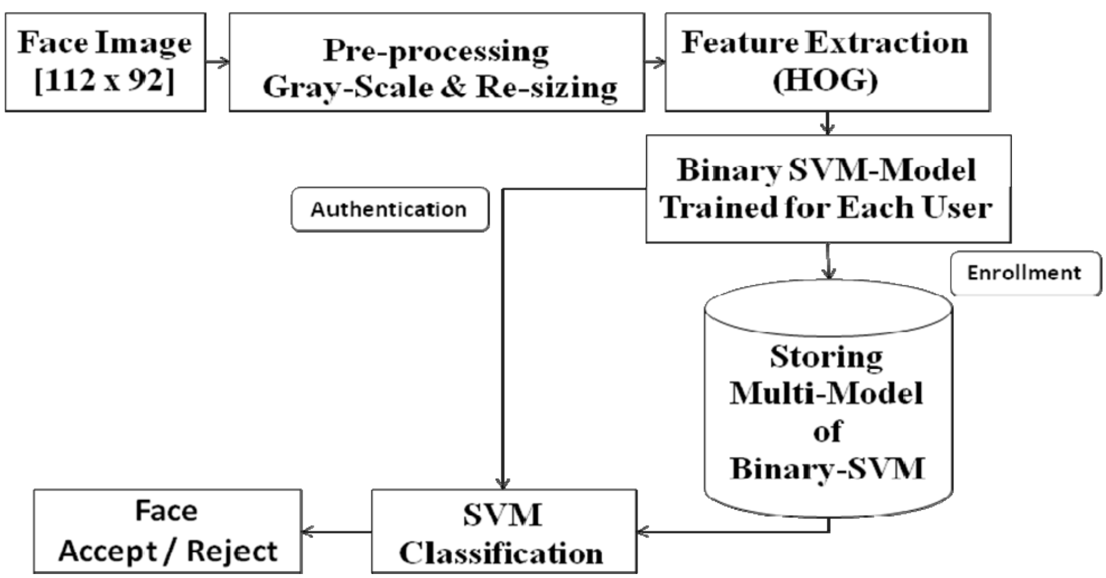

Figure 1: Diagram depicting the overall proposed biometric face recognition system.

be stored in the database as a reference model to be matched in the prospective authentication with anyone who wants to verify her / his face image. In other words, for each individual, the binary-SVM model will be created and stored in the database as a reference model. For instance, if the database has 40- individual, which means 40-binary-SVM-model will be stored in the database. In the authentication process, the queried identity face image will be read by the system, and same processes that have taken place during the enrollment operation should also be applied to the queried face image sample.
In the classification process, SVM is used to compare the enrolled specific binary-SVM-model against the queried features. Finally, decision maker, which is based on threshold decides whether the face is accepted or rejected.

3.1. Pre-processing

In the proposed face recognition, set of image processing tools will be applied to the face image so as to be adequate to the stage of feature extraction, one of which is converting from RGB image to gray-scale image. After that, re-size operation is done in rows and columns to be [112 x 92]. The aforementioned process operations are easily can be implemented by exploiting existing algorithm of digital image processing.

Some randomly selected users of ORL Database have been depicted in Figure 2. It is clear that this database has different poses and illuminations of training samples of each user and these differences give more challenges to the proposed recognition algorithm.

3.2. Feature Extraction (HOG)

Extracting features is an operation of selecting the most powerful information that can represent the samples to be passed to the classifier. In other words, it is the salient information to be extracted from the training examples.

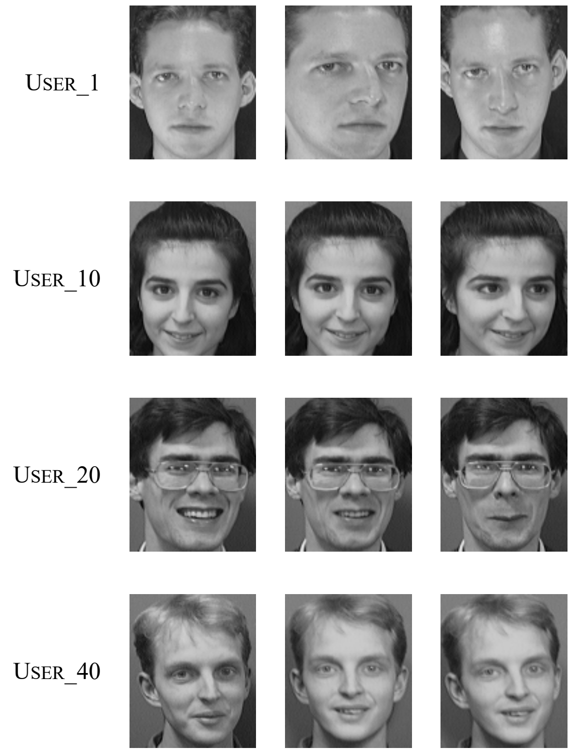

Figure 2: ORL Faces Random View Samples.

It is worth to mention that, the accuracy of the recognition largely depends on the algorithm of how to build a unique feature vector among other users. In other words, whether the feature vector *FV* is unique to those of other individuals or not. In this paper, the proposed feature extraction consists of Histogram Orientation Gradient (HOG), which is one of the most pioneer feature shape representation introduced by Dalal and Triggs at the CVPR conference in 2005 [24]. HOG is basically used for person detector, which stands for Histograms of Oriented Gradients. The basic implementation of the HOG descriptor is as follows: Divide the image into small connected regions (cells), and for each region compute a histogram of gradient directions or edge orientations for the pixels within the cell. These gradients (*G*) are computed from the image (*I*) by applying convolution operation between the derivative mask for both of the horizontal and vertical directions and the image (*I*), as below in (1) and (2):

$$\text{Horizontal Gradient: } G_x = I \otimes [-1\ 0\ 1] \qquad (1)$$

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Vertical Gradient: $G_y = I \otimes [-1\ 0\ 1]^T$ (2)

For example the *Gx* and *Gy* are extracted from the sub-image of below matrix after convolving with masks.

61	64	146	74	69	72
117	111	211	140	111	92
107	133	214	254	148	158
176	254	168	254	254	190
193	254	255	231	187	201
193	234	255	195	126	204

G_x

3	85	10	-77	-2	3
-6	94	29	-100	-48	-19
26	107	121	-66	-96	10
78	-8	0	86	-64	-64
61	62	-23	-68	-30	14
41	62	-39	-129	9	78

G_y

56	47	65	66	42	20
46	69	68	180	79	86
59	143	-43	114	143	98
86	121	41	-23	39	43
17	-20	87	-59	-128	14
0	-20	0	-36	-61	3

After that, the formula for magnitude (*m*) and direction (θ) are as follows in (3) and (4):

Magnitude: $$m = \sqrt{G_x^2 + G_y^2} \quad (3)$$

Direction: $$\theta = \tan^{-1}\left(\frac{G_y}{G_x}\right) \quad (4)$$

And the magnitude (*m*) of the above *Gx* and *Gy* are calculated according to equation (3), and the result is shown in the below matrix:

56	97	66	101	42	20
46	117	74	206	92	88
64	179	128	132	172	99
116	121	41	89	75	77
63	65	90	90	131	20
41	65	39	134	62	78

And the direction (θ) of the above *Gx* and *Gy* are calculated according to equation (4), and the result is shown in the below matrix:

87	29	81	139	93	81
97	36	67	119	121	102
66	53	20	120	124	84
48	94	90	15	149	146
16	18	105	139	103	45
1	18	180	164	82	2

Then, using the gradient orientation obtained, discretize each cell into angular bins. Each cell's pixel contributes weighted gradient to its corresponding angular bin. The adjacent cells are grouped into blocks in the spatial region, which forms the basis for grouping and normalization of histograms. Normalized group of histograms represents the block histogram and the set of these blocks histograms represents the HOG descriptor. The reason behind normalization operation is to overcome the illumination changes of the image. Normalization can be defined as an operation of taking the maximum range of a signal and stretches it to take up the maximum possible range as the formula in (1):

$$p_n = (p_{non\_n} - \min) \times \left(\frac{\max - \min}{255}\right) \quad (5)$$

Where p_{non_n}: pixel as non-normalized, p_n: Pixel as normalized.

According to Dalal [24] the recommended values for the HOG parameters are: *1-D* centered derivative mask is *[-1, 0, +1]*, detection window size is *64x128*, cell size is 8x8 and block size is *16x16* (*2x2* cells), HOG is fully described and explained well in [10, 25]. Generally, the steps of HOG feature descriptor can be summarized in Figure 3, at the end of these steps concatenate operation is done to the histograms to be as 1-D for feature vector representing.

In this work, HOG has been applied to the face image using *2x2* block size and *14* cell size with *9* bin histogram per cell resulting in the *1260*-dimensional feature vector. The HOG features provide us with the edge information of the face images. The features for all training images are computed and stored in the database. As the size of the input image is [*112 x 92*], the length of current feature vector comes from the result of the multiplication of 5 cell per column multiplied to 7 cell per row multiplied to *4* blocks with *9* bin of histogram, the length is:

$$\overline{FV\_HOG} = 1,2,3\ldots1260.$$

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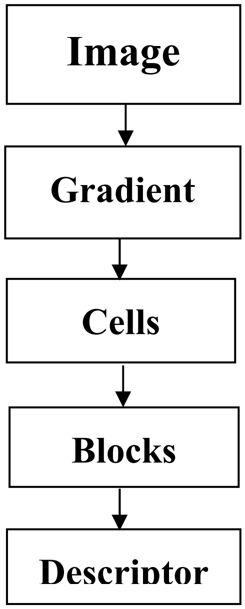

Figure 3: HOG basic steps for extracting feature descriptors.

To visualize the effect of the HOG to the digital face image, Figure 4 illustrates that effect for faces of two users taken randomly user 1 and user 15 respectively from ORL database. Each user has been applied to the HOG with different Cell Size as *8, 10, 14*, and *32* respectively, as well as, fixed block size as [*2x2*] and *9* bin of the histogram. As it is shown in Figure 4, by increasing number of cell size, the numbers of plotted HOG are decreasing as it is reversing proportion, as well as the resulted HOG features number also decreased. Finally, the feature vector length that will be passed to the SVM classifier as has 1260 weights.

3.3. Classifier (SVM)

SVM is a discriminative classifier formally defined by a separating hyperplane. SVM was developed from Statistical Learning Theory (Vapnik & Chervonenkis) [26]. It is defined as a representation of the training examples in space, mapped so that the examples of the separate categories divided by a clear gap, which is as wide as possible, this operation is named training. In terms of testing or

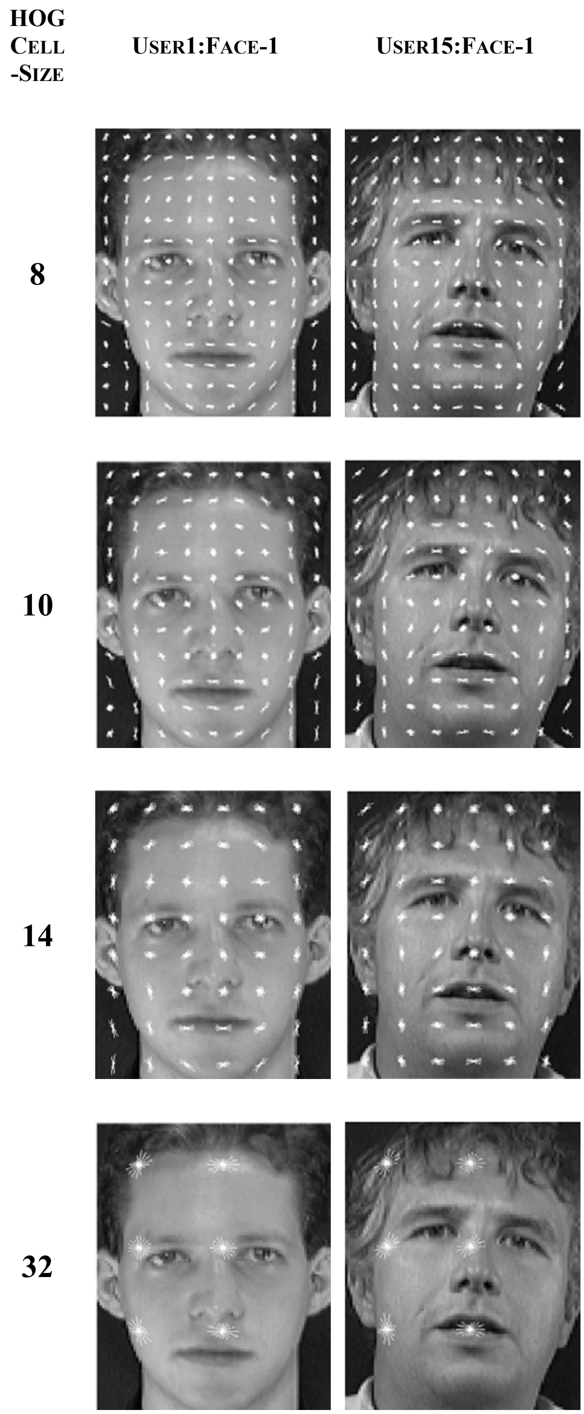

Figure 4: Shows HOG Implementation On Image Faces With 4-Set Cell Size.

predicting, new examples are mapped into that same space and predicted to a category based on which side of the gap they fall as shown in Figure 5. In addition to performing linear classification,

SVMs can efficiently perform a non-linear classification using different Kernel types.
Linear kernel SVM has been used for the classification, as experimentally, it is noticed to give a better result than other kernels such as polynomial, RBF, quadratic, etc.
Assume there is a training dataset of n points of the form, $\vec{x_i}$ is input features and $\vec{y_i}$ is the class for the input features [10], then:

$$(\vec{x_i}, y_i)...(\vec{x_n}, y_n)$$

Where the y_i has binary classes either $+1$ or -1 of the SVM model, each indicating the class to which point $(\vec{x_i})$ belongs. Each $(\vec{x_i})$ is a p-dimensional feature vector. For training SVM, it is an operation to find out the maximum-margin hyperplane that divides the group of points $(\vec{x_i})$ for which $y_i = +1$ from the other group of points for which $y_i = -1$, so that the distance between the hyperplane and the closest point $(\vec{x_i})$ from either group is maximized. Any hyperplane is formed as the set of points $(\vec{x_i})$ satisfying this formula in (6):

$$(\vec{w}.\vec{x} - b = 0) \tag{6}$$

Where $(\vec{w}.\vec{x} - b = -1)$ is considered as a separate of one class, while $(\vec{w}.\vec{x} - b = +1)$ represent the other class. Where $(\vec{w})$ is the normal vector to the hyperplane. The parameter $\frac{b}{\|w\|}$, which is in Figure 5 computes the offset of the hyperplane from the origin along the normal vector $(\vec{w})$.
It is worth to mention that, the training kernel for SVM used in this paper is (ISDA), which stands for Iterative Single Data Algorithm that is useful for huge dataset. As this techniques have proven to offer significant advantages over the traditional approach when dealing with large data as well as efficient when there are many training examples.

Multiclass SVM aims to assign labels to individuals by using support vector machines, where the labels are drawn from a finite set of several elements. The dominant approach for doing so is to reduce the single multiclass problem into multiple binary classification problems Common methods for such reduction include in [27].

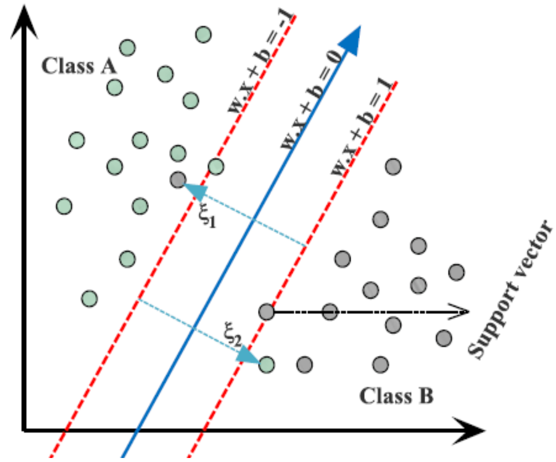

Figure 5: Depicting Single Binary-SVM Model Separating Between Two Classes.

4. EXPERIMENT

In order to the evaluate the proposed face recognition system, set of experiments have been conducted on a standard ORL database, which contains 10 different images of 40 distinct individuals in PGM file format with a pixel resolution of [*112×92*]. These *8*-bit gray images were captured at different times, facial expressions (smiling / non-smiling, open/closed eyes), varying lighting slightly and facial details (without glasses / with glasses). This database was populated at the Olivetti Research Laboratory in Cambridge, UK.

In this paper, SVM has been used as a binary classification as the positive and negative user, here user 40 in ORL database has been selected as a negative user for all the rest 39-user of the mentioned database. In other words, the positive user is assigned to as +1 class while the user 40 is assigned to a -1 class for training and testing. Accordingly, there are 39 users in the database, it means there will be 39 binary-SVM model training operation in the experiment, in each training there will be testing classification to predict *+1* class for the positive user (the same trained user) or *-1* class for the user 40.
Certainly, the threshold used here for making the decision is *0*, as it is the unbiased separation between *-1* and *+1* predicted scores.
The experiment has been conducted on the ORL database, which has been implemented according to the following steps:

1- Using ORL database (consisting of the following characteristics: Face Pose Variation, expression, illumination changes, and/or aging illumination Variations), the SVM training matrix is built. The training matrix consists of face images from 39 individuals, for each individual, 5 genuine samples are obtained. Each face image sample is represented by *1260* features. Accordingly, the training matrix size is $[10 \times 1260]$ (*1260* features for each sample with 5 samples for the true trained individual and the other 5 samples of the user 40, which has been considered as a negative user for entire database). Training is run by SVM for the faces of each individual separately.

2- The evaluation of the result produced by SVM is done by extracting the False Accept Rate (FAR) and the False Reject Rate (FRR) for each individual separately. The testing matrix is built similar to the way the training matrix that was built.

3- In the training target (destination) of SVM, a sign $+1$ is assigned to the first 5 face image samples of the trained matrix, conversely, -1 is assigned to the second 5face image samples of the training matrix to train the SVM that the first 5 are genuine face samples and the second 5 are forged face samples.
4- The threshold that has been selected is (zero).

5- FRR is computed by evaluating the resulting scores of the first 5 samples. If any sign of the first 5 samples is less than the threshold, False Rejection (FR) counter will be increased by one $(FR = FR + 1)$, since they are supposed to be as accepted (signs are larger than the threshold) but they are wrongly rejected by the verifying system.
On the other hand, if the results of the second 5 face image samples have a sign more than the threshold, they are considered as False Accept (FA) and the counter will be incremented by one $(FA = FA + 1)$. The FAR and FRR are computed as in (7) and (7) respectively:

$$FAR = \frac{FA}{10} \times 100\ \% \tag{7}$$

$$FRR = \frac{FR}{10} \times 100\ \% \tag{8}$$

6- The accuracy of each user is computed by using (9):

$$Accuracy\ \% = 100 - \frac{FAR + FRR}{2} \tag{9}$$

7- Then, to include the effect of all individuals in the ORL database, an average (*AVR*) of the 39 individuals' accuracy is computed by using (10):

$$AVR_{Accuracy}\ \% = \frac{1}{39}\sum_{u=1}^{39} user_{accuracy}[u] \tag{10}$$

Finally, It is worth to mention that the implantation of both HOG and SVM has been done by using matlab 2018a workstation with Microsoft windows 7 as operating system. The computer hardware has 2.1 core2due CPU with 2GB RAM.

5. RESULT AND DISCUSSION

Concerning the result of the experiment, the performance as successful accuracy has been reported up to 99.23% after applying the experiment using ORL database that contains 400 face images using 40 individuals, it is worth to mention that, ORL database is characterized by illumination, pose and expression changes between images of the same individual. The result of this paper has been reported in Table 1.

Table 1. Result Of The Proposed Face Recognition System:

Method / Database	FRR %	FAR%	Total Accuracy%
HOG-SVM/ ORL	0.53	0.25	99.23

As a result of the experiments of this paper, all users have resulted in 100% as accuracy,

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Table 2. The Performance Of Proposed Method Compared With The State-Of-The-Art Face Recognition Systems.

No.	Face Recognition Methodology	Successful Recognition rate %	Reference / Year
1	PCA + Euclidean distance	97.5	2016 / [14]
2	Gabor Filters and Zernike Moments	93.9	2017 / [15]
3	convolutional neural network (CNN),	98.3	2017 / [16]
4	PCA LDA	94.02 95.98	2018 / [17]
5	Hierarchical temporal memory The HTM SP	87.21	2017 / [18]
6	fuzzy linear regression discriminant projection (FLRDP),	96	2017 / [19]
7	many-kernel random discriminant analysis (MK-RDA)	95.7	2016 / [20]
8	locality preserving projection (LPP) feature transfer	92	2016 / [21]
9	Gradient-Orientation-Based PCA Subspace	85	2017 / [22]
10	System Using PCA and DCT in HMM	95.2	2015 / [1]
11	Multi Region Prominent LBP Representation	97	2016 / [2]
12	**Proposed:** **System utilized** **HOG with multiple models of**	**99.23**	

except the following user-ID, 5, 10 and 17 that have accuracy 90%, which means that each user containing 10 testing samples, only one of them is wrongly classified or predicted by the proposed face recognition system.

As overall, only 3 samples have been wrongly predicted by the proposed system over 390 samples (as 39 users each users has 10 samples for testing, 5 of them are genuine and the other five are forges face samples).

To assess the power of the proposed face recognition system, a comparison with the existing techniques that have used especially ORL database is presented in Table 2, the proposed method outperforms the state-of-the-art work in terms of the successful accuracy.

As it is clear from Table 2, the results obtained of the proposed method outperform the state-of-the-art techniques as compared with the latest updated work of face recognition in 2016, 2017, 2018. In terms of the training and testing operations, a number of training samples of the SVM model plays the major rule of computing the overall accuracy. Obviously, with larger number of training samples, higher accuracy of the database achieves. Therefore, it is very important to make balancing between the numbers of training and testing samples to avoid biasing of the accuracy report. Accordingly, in this research paper, half of the samples used for training and the remaining have used for testing. The biometric has two basic systems as aforementioned in the introduction, in this paper, it is required to remind that the reported accuracy is based on verification experiment testing, in other words, to verify each individual separately, whether he/she is the true individual or not. From Table 2, the closest accuracy to the proposed work is the technique which used convolutional neural network (CNN), where the accuracy is 98.3%, which is kind of deep learning algorithm that is newly proposed by scientist of machine learning. Another high recognition rate, which reported in Table 2 as near accuracy to the proposed system, is technique exploited PCA for feature extraction operation with Euclidean distance for classifier operation.

The limitation of this work is that the proposed recognition system can only be applied to a signal of 2 dimensions (2D) such as image (row x column). The reason is that, HOG feature extraction, which is exploited in this system, can be applied only for 2 dimensions signals. Accordingly, if any signal having single dimension might be not suitable to be used with proposed recognition system or must be converted into 2D before HOG stage of the proposed algorithm.

6. CONCLUSION

Face verification system is proposed in this paper as it is considered as an active research recently. The proposed idea in terms of feature extraction is by using HOG characterized by using block size [*2x2*], and cell size [*14 x 14*] with a digital image size [*112 x 92*] in order to construct a feature vector, which has a length up to *1260* features. However, the aforementioned HOG parameters have been selected as a result of conducting many experiments to outcome with the best parameters yields best verification accuracy as reported. Afterward, multiple models of binary-SVM have been used for the training and classification. Specifically, as for each user must hold with its own binary-SVM model, the 39-binary-SVM model is created and stored in the reference database. The experiment has been conducted to evaluate the proposed method resulted in an accuracy up to 99.23%. The experiment is conducted on ORL database, which has 40 users each user has 10 samples of the face images containing different lighting and posed characteristics. For the future work, joining more than one shape descriptor as feature extraction and selection such as PCA or DWT together with HOG might consolidate the represented feature vector. As expected, a better recognition rate might be attained. Besides that, the proposed algorithm might be applicable for face recognition of surveillance monitoring only with a static digital face image.

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