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Design and analysis of face recognition system based on VGG-Face-16 with various classifiers

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ABSTRACT

This research presents a face recognition system based on different classifiers that deal with various face positions. The proposed system involves the extraction of features through the VGG-Face-16 deep neural network, which only extracts essential features of input images, leading to an improved recognition step and enhanced algorithm efficiency, while the recognition involves the radial basis function in support vector machine (SVM) classifier and evaluate the performance of the system. Also, the system is designed and implemented later by using other classifiers; they are K-neareste2 neighbour (KNN) classifiers, logistic regression (LR), gradient boosting (XGBoost), decision tree classifier (DT) and Naive Bayes classifier (NB). The proposed algorithm was tested with the four face databases: AT&T, PINs Face, linear friction welding (LFW) and real database. The database was divided into two groups: One contains a percentage of images that are used for training and the second contains a percentage of images (remainder) which was used for testing. The results show that the classification by RBF in SVM has the highest recognition rate in the case of using small, medium and large databases; it was 100% in AT&T and Real database, while its efficiency appears to be lower when using large-size databases whereas it is 96% in PINs database and 60.1% in LFW database.

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1. INTRODUCTION

Face recognition systems constitute an integral part of facial image processing applications. Even though there are other types of biometrics which are relied upon in many applications, such as fingerprint and iris scanners, they require cooperation from the subject, and the biometric information cannot be obtained without the awareness of the subject. In contrast, face recognition systems do not require subjects' cooperation, therefore, they are often the preferred choice for government and security organizations, since the biometric information can be gathered via cameras installed along the streets. Face recognition can be employed for civil applications such as passive person verification and authentication.

Face recognition compares the extracted information with stored information in the database of faces to find a suitable match. This information extracted from the geometry of human faces such as: the distance between eyes and the distance from forehead to chin. Moreover, eyes are nearly unique for each individual. These measures are called the facial landmarks which are used as keys for face recognition. The final stage of face recognition is the classifier which uses mathematical formula to compare to a database of known faces.

Following the isolation of faces from the input images, the facial features, such as nose, mouth, eyes, and chin, are subsequently detected, then extracted by using feature extraction methods. Finally, the face is identified by comparing the obtained feature vector against a pre-existing database which contains the data of all subjects [1]. Even though face recognition technology was conceived about 30 years ago, it still needs improvements due to the complexity of the facial features upto using neural networks to increase the accuracy level [2]–[4].

Face recognition has received much attention over the years due to its applications in different domains like mobile phone makers in products, colleges in the classroom, businesses at entrances and restricted areas, and religious groups at places of worship. Last decade has provided important improvement in the face recognition due to the advances in face analysis techniques and the rising of public security [5]. Face recognition system consists of several steps, the first of which is inserting the image and reading it, then Face area identification and detection by Haar cascade, followed by a pre-processing stage for the image, then the feature extraction process starts with VGG-Face-16 convolutional neural network (CNN). This process also includes dimensionality reduction to increase the efficacy of the process thus, a vector of length (2622) was obtained for each image, where feature vectors for all images are stored in the form of an excel file to be used later in the classification as training dataset. In the proposed system, the image first prepared for preprocessing and then trained the classifier to recognize the faces. The classification is done by matching the obtained score of the input image with a predefined database that contains the information of each subject. If the score matches an entry from the database, the face in the input image is given the identity of that entry. Otherwise, the classification produces negative results, which indicates that the face is not present in the database. As for the classification process, several classifiers were used, which are (SVM, KNN, LR, XGB, DT, NB) and they were compared in terms of performance accuracy and classification time.

- Haar cascade

Face detection has a wide range of applications in biometrics, security and monitoring, so the list is not limited to mobile apps. Where this process is performed using Haar cascade. Haar cascade is an object detection algorithm that detects faces in images and real-time videos. Viola and Jones [6] presented edge or line detection features, which are used in the algorithm. The advantages of the Haar cascade include its high detection accuracy rate and ease of implementation.

- VGG-Face-16 (convolutional neural networks (CNN))

Any CNN consists of two primary parts: the feature extractor and the classifier. For feature extraction VGG-Face-16 CNN was used and is presented in Figure 1. VGG-Face-16 CNN comprises several sequential connected layers, where each layer receives the output from the previous layer as input, then generates an output which is passed to the next layer as input [7], [8]. This layers are 3×3 convolution layers, 2×2 pooling layers, and 3 fully connected (FC) layers which are arranged in sequence [9]. The first set of layers is convolutional. Each convolution layer executes a filtering operation on the previous layer, it utilizes filters of the size (3×3), padding is same and strid, so the input mage size is (224×244×3), (224×224) is the size of image and 3 refers to RGB colors. Pooling is employed to reduce the dimensionality of the data through the use of downsampling on the activation maps [10]. It's filter size is 2×2 and strid is 2 therefor the size of image will become (112×112×128) which is used as input for the next layer [11]. So, the output of last pooling layer is (7×7×512) as shown in Figure 1. The resulting feature descriptors are subsequently extracted from the FC. The final three layers are referred to as Fully Connected (FC) and are similar to convolutional layers, except that the size of the filters matches the size of the input data, allowing every filter to "sense" data from the complete image. Depending on the loss functions utilized for optimization, the first two FC layers output 4,096 dimensions while the last FC layer output 2,622 dimensions. The rectified linear unit (ReLU) (also known as activation layer), which comes after the convolutional layer, is employed to increase the non-linearity of the feature maps obtained from the linear operations during processing through the convolutional layer [12]. ReLU is the most frequently used activation function in the VGG-Face-16 CNN. ReLU is used to remove the negative numbers from the feature maps. Here, a 2×2 filter with a stride of 2 is used. The max and average pooling functions constitute two of the most employed functions in pooling layer designs in the VGG-Face-16 CNN.

- Classification

Face classification is done by using several types of classifiers. These are described as follows: support vector machine (SVM) [13], [14] is considered as one most powerful supervised learning algorithm. It uses a set of image inputs to classify it to a class label. The linear SVM finds the optimal hyperplane by maximizing the angle of perpendicularity relative to the support vectors. In such cases, a hyperplane (called kernel) needs to be transformed from one dimension to the N-th dimension. Examples of kernels include: linear, polynomial, and radial kernels (RBF) [15]–[17]. K-nearest neighbor (KNN) classifier is based on the Euclidean distance. It is simple in setup and powerful in performance, with less needed computation resources. The performance is primarily determined by the choice of K as well as the distance metric applied [1]. It is suffering from the following drawbacks: Low efficiency and dependency on the selection of good values for k. Logistic regression (LR) classifier is a parametric method used to build classification models of the binary type. LR is extensively used in data mining applications since it employs a weighted sum of some predictor variables to distinguish classes [18]–[20]. Gradient boosting (XGBoost) classifier is a type of decision trees that are gradient boosted [21], and are designed in a way that grants the highest performance and speed in the field of machine learning [1]. XGBoost, as the name suggests, uses a general method that boosts the gradient such that it yields accurate models for classification, regression and ranking operations [22]. The decision tree classifier (DT) classifier is a supervised learning classifier used for solving classification problems by creating a training model [23]. The training model can be used for prediction of testing class starting from the root of the tree [24], [25]. The Naive Bayes classifier (NB**)** is one of the Bayesian classifier techniques which also known as the state-of-the-art of the Bayesian classifiers. In many works it has been proven that Naïve Bayesian classifiers are one of the most computationally efficient and simple algorithms for ML and DM applications [26], [27].

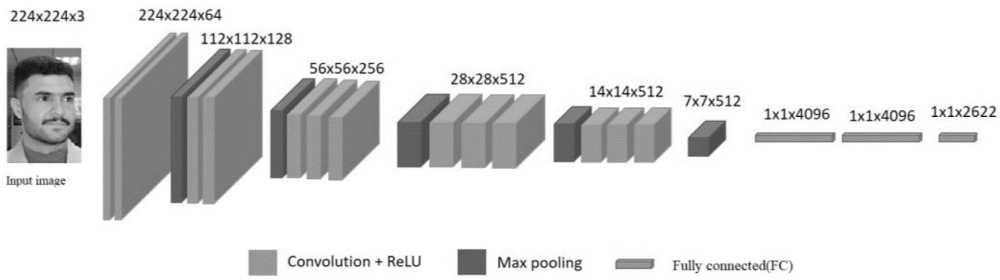

Figure 1. VGG Face-16 CNN architecture.

2. DESIGN OF THE PROPOSED SYSTEM

The main component of system is shown in Figure 2. The proposed system will be executed by the following steps:

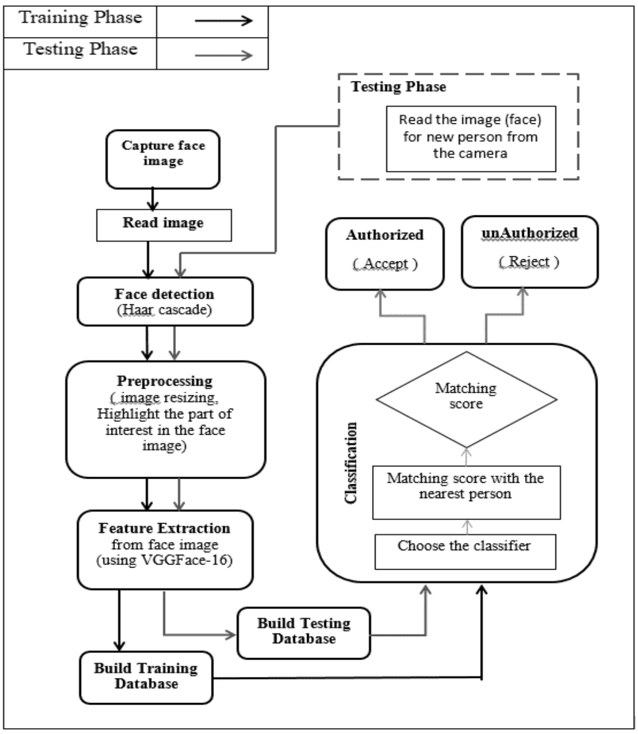

Figure 2. The steps for proposed face recognition system

i) Enrollment image

It is the first step in proposed face recognition system. The data is either ready likes AT&T or real data. For the ready, it is dealt with in two forms: training and testing phase. As for the collected real data, it went through stages, the first was the collection of images of the databases, the second was training on part of it, and the third stage was tested on these databases through the work of capture the image and compare it to see if it is authorized to enter or not.

ii) Feature extraction

The process of detecting the face is common for two phases (training and testing) so it is important to pick any face image in front of the camera. Haar Cascade was used. After detecting the face, a rectangle will be drawn around it and gives it a specific color and thickness. It will be drawn using the rectangle function found in cv2 library. The image Pre-Processing is applied in two phases training and testing, all facial images are resized to accommodate the next stage of feature extraction, which is done using deep learning with VGGFace-16 CNN, where the input image must be (224*224). Feature extraction process is also common in both phases training and testing. In this step VGGFace-16 pre-trained model and pre-trained weights are loaded. The image passes through a 16-layer neural network in order to obtain a feature vector of length 2622 for each input image.

iii) Classification

At this stage, the system is trained on features extracted from databases and stored in the form of an excel file. The data will be divided into two parts, the first for training and the second for testing, using the train_test_split function in the sklearn library. So, the size of the testing phase depends on the number of people and images captured for each person. Testing database size = (P*I*testing rate,2622), where P is the number of classes and I is the number of images for each person while Training database size = (P*I*training rate,2622) , where P is the number of classes and I is the number of images for each person. The original classifier of VGG-Face-16 is replaced with different types of classifiers (SVM, KNN, LR, XGB, DT and NB) in the proposed system. Each of them has been implemented with a specific library. Sklearn for SVM and DT, sklearn. neighbors for KNN, xgboost for XGB, sklearn. linear_model for LR and sklearn. naive_bayes for NB.

3. RESULTS AND DISCUSSION

The search was performed using Python 3.8 on Jupyter, 64-bit computer with Intel(R) Core(TM) i7-4810MQ CPU @ 2.80 GHz and 8 GB of RAM. The graphics card was of type Intel®HD Graphics 4600. In this work four datasets were used and tested:

a) AT&T Dataset: Each of the 40 subjects is represented by ten different images [28].
b) PIN face recognition dataset:105 subjects are represnted by ten different images [29].
c) Labeled faces in the wild (LFW) dataset: The dataset contains (1000) persons (3971) images of faces collected from the web. Each face has been labeled with the name of the person pictured. Each one has two or more distinct images in the data set [30].
d) Real dataset: To ensure the performance of the proposed system, a new database was constructed by acquisition pictures of real people from the surrounding community. They are (30) persons and each one of them has (10) images in different places and various backgrounds. The used camera was of type HUAWEI Y9s-Kirin 710F Octa-core Processor with 16-megapixel.

The face recognition process has been carried out through six different classifiers as mentioned previously. Each classifier was trained then tested separately by using: (60% of the database for training, 40% of the database for testing, 70% training, 30 % testing and 80% training, 20 % testing). For the various forms of data used in this study, the data has been divided into 85% known and 15% unknown. Iteration was also used to ensure that the results were reliable. knowing that the process of separating the data into a training portion and a test part was random, and the accuracy is recalculated each time before relying on the average.

3.1. Performance of the proposed system with AT&T database

The accuracy of the proposed system is obtained using two ratios of training and testing parts: 60% for training, 40% for testing and then the system is implemented when 70% for training, 30% for testing. Note that these portions are applied on the known data while the unknown has 15% of the database. The results of all the evaluation metrics are shown in Table 1. Here, the calculated accuracy of different types of classifiers was compared in the case of AT&T data and two training ratios. The results showed that the accuracy of SVM, KNN and LR classifiers has the highest level. On the other hand, the classification time for the implemented system with DT classifier has the least value but the accuracy is the worst. Also, the ratios of precision, recall and F1-score differed, where LR and KNN were the highest, followed by XGB, then NB and DT.

3.2. Performance of the proposed system with PINs celebrities' database

The accuracy of the system was obtained using three ratio of training and testing parts (60% training, 40% testing), (70% training, 30% testing), and (80% training, 20% testing) as shown in Table 2. Through the results, the accuracy ratios differed according to the different types of classifiers firstly and the training ratios secondly, as LR, SVM and KNN classifier have the best accuracy among the other classifiers and with an acceptable classification time estimated in milliseconds, but NB has the least accuracy and the least time consuming in the classification process, knowing that from extracting features is constant for all training ratios. As explained earlier, the reason for this decreasing in performance evaluation levels is that the images were captured in different conditions and with different styles, including the presence or absence of beards and mustaches, and different hairstyles.

Table 1. The experimental results using (SVM, KNN, LR, XGB, DT and NB) classifier for AT&T database

60 % Training, 40 % Testing							
Type of database	Classifiers	FE Time (sec.)	CT (ms)	Acc. (%)	precision (%)	Recall (%)	f1-score (%)
AT&T	SVM	101.75 s	3 ms	100	100	100	100
40 person	KNN		53.9 ms	100	100	100	100
	LR		4 ms	100	100	100	100
	XGB		43 ms	96	95	96	95
	DT		5.31 ms	71.8	77.8	74.9	73
	NB		571 ms	90	94	94	93
70 % Training, 30 % Testing							
	SVM	101.75 s	3 ms	100	100	100	100
	KNN		44.9 ms	100	100	100	100
	LR		3.99 ms	100	100	100	100
	XGB		34 ms	94	94	96	94
	DT		3.96 ms	69	75	71	70
	NB		384 ms	90	93	95	93

Table 2. The experimental results for using (SVM, KNN, LR, XGB, DT and NB) classifiers with PINs database

60% Training, 40% Testing							
Type of database	Classifiers	FE Time (sec.)	CT (ms)	Acc. (%)	precision (%)	Recall (%)	f1-score (%)
PINs celebrities (105)	SVM	571.33 s	7 ms	86	87	91	87
	KNN		127 ms	88	89	89	87
	LR		14 ms	97	97	98	97
	XGB		85.9 ms	78	80	82	78
	DT		17 ms	45	51	52	48
	NB		3.1 s	67	77	76	71
70% Training, 30% Testing							
	SVM	571.33 s	8 ms	90	91	94	91
	KNN		344 ms	88	90	90	88
	LR		155 ms	97	99	98	98
	XGB		235 ms	83.5	87	87	84
	DT		34 ms	52	60	59	55
	NB		235 ms	84	85	88	84
80% Training, 20% Testing							
	SVM	571.33 s	8.99 ms	94	97	96	96
	KNN		86.9 ms	90	91	90	89
	LR		105 ms	96	98	97	97
	XGB		65.9 ms	83	83	83	81
	DT		6.96 ms	54	60	58	55
	NB		1.71 ms	92	89	90	88

3.3. Performance of the proposed system with Real database

The accuracy of the proposed system was calculated in two cases: 60% of the database is used for training the system and 40% is applied for testing the performance of the system. The other case is implemented with 70% for training and 30% for testing as shown in Table 3. When using real data in both cases (training ratios), it gave excellent results in the three types SVM, KNN and LR, as well as the classification time was small but, DT gave the least accuracy and the least classification time.

3.4. Performance of the proposed system with LFW database

For this large database the system is implemented as depended for SVM, i.e. the database is divided into folds according to the number of pictures for each person. Then the system is evaluated for two cases: (70% training, 30% testing) and (80% training, 20% testing). The results were averaged in the case of SVM which was the best, followed by LR, KNN, and the lowest percentage was DT, which gave the least accuracy and the least time for classification as shown in Table 4. Note that the accuracy was calculated by the method of aggregates and averaging them. The ratios of precision a, recall and F1-score ranged from (11-100) at testing rate 20% and from (16 to 90) at testing rate of 30%.

3.5. Performance of the proposed system with LFW database

For this large database the system is implemented as depended for SVM, i.e. the database is divided into folds according to the number of pictures for each person. Then the system is evaluated for two cases: (70% training, 30% testing) and (80% training, 20% testing). The results were averaged in the case of SVM which was the best, followed by LR, KNN, and the lowest percentage was DT, which gave the least accuracy and the least time for classification as shown in Table 4. Note that the accuracy was calculated by the method of aggregates and averaging them. The ratios of precision a, recall and F1-score ranged from (11-100) at testing rate 20% and from (16 to 90) at testing rate of 30%.

Table 3. The experimental results using (SVM, KNN, LR, XGB, DT and NB) classifiers for Real database

60 % Training, 40 % Testing							
Type of database	Classifiers	FE Time (sec.)	CT (ms)	Acc. (%)	precision (%)	Recall (%)	f1-score (%)
Real database (30 person)	SVM	233.51 s	2 ms	100	100	100	100
	KNN		129 ms	100	100	100	100
	LR		31 ms	100	100	100	100
	XGB		101 ms	91	91	91	90
	DT		10.9 ms	52	58	58	53
	NB		863 ms	91	92	94	92
70% Training, 30% Testing							
	SVM	233.51 s	3 ms	100	100	100	100
	KNN		24 ms	100	100	100	100
	LR		7 ms	100	100	100	100
	XGB		3.1 ms	88	87	88	86
	DT		3 ms	61	69.1	65.3	63
	NB		90.9 ms	90	93	95	93

Table 4. The experimental results using (SVM, KNN, LR, XGB, DT and NB) classifiers for LFW database

70% training, 30% testing												
Accuracy												
Types of database	Classifiers	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Fold 6	Fold 7	Fold 8	Fold 9	Fold 10	AVG.
LFW (1000 Person)	SVM	15	17	20	31	40	60	51	81	90	94	49.9
	KNN	45	47	41	63	64	70	56	76	90	92	64.4
	LR	69	71	72	93	94	87	88	92	100	94	86
	XGB	25	28	30	52	45	47	60	66	60	64	47.7
	DT	12	14	12	28	30	32	40	40	60	61	32.9
	NB	9	10	13	17	36	51	56	71	80	86	42.9
80% training, 20% testing												
	SVM	22	23	31	53	55	64	65	92	100	96	60.1
	KNN	53	55	52	67	74	78	59	88	90	96	71.2
	LR	70	75	79	92	87	81	82	97	100	92	85.5
	XGB	24	25	37	53	58	58	76	71	50	88	54
	DT	12	14	10	39	23	34	53	37	72.5	71	36.5
	NB	13	15	19	31	45	56	65	86	100	92	52.2

3 PERFORMANCE EVALUATION CRITERIA

The confusion matrix for real data base is shown in Figure 3 for RBF-SVM, KNN and LR classifiers and the ROC curve is shown in Figure 4. They are showing good performance of the system when SVM classification model is used. The vertical axis of the Figure 3 represents the names of all the real classes, while the horizontal axis represents the names of the predicted classes, for example in the cell with address (P1, P1) if it is correctly predicted, it will contain the total number of images (20% testing rate) of the person P1, so if it is the prediction is true for all people. The values of the predictions will be arranged as a diagonal line, while the rest of the cells will contain zero, meaning that no one has been wrongly predicted. It is important to note that when the system is implemented using KNN and LR they had similar confusion matrix due to their level of 100% accuracy. The same idea is happened with ROC curve so it is similar to ROC curve of the system with SVM classifier. At Figure 4 the efficiency of the system when it is applied to the real data at 30% training and testing rate, and since the accuracy was equal for all classes and its value was 100%, all of them were painted one above the other, and each class was painted in a different color from the other.

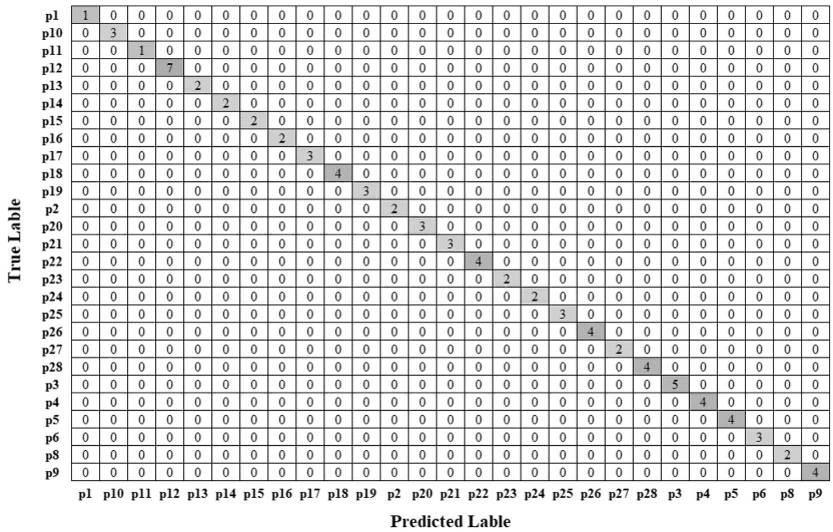

Figure 3. The confusion matrix for the system with SVM, KNN and LR classifiers at testing rate of 30%

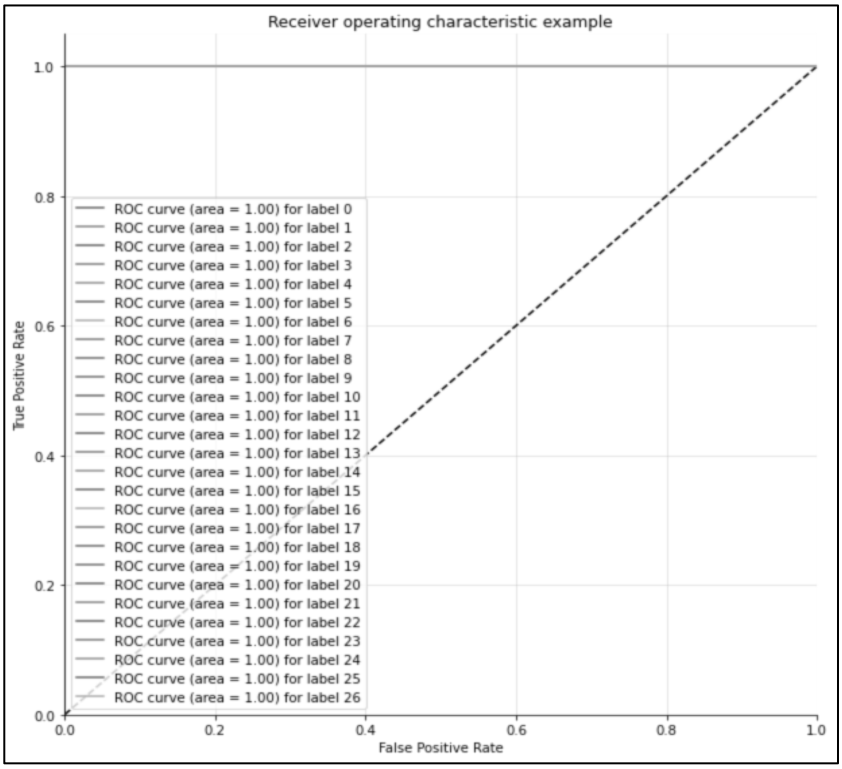

Figure 4. ROC for the system with SVM, KNN and LR classifiers at testing rate of 30%

The confusion matrix for the system is shown in Figure 5 when the proposed system with XGB classifier is applied on Real database. ROC curve is shown in Figure 6 for this system. The figures are showing good performance of the XGB classification model.

The confusion matrix for Real database is shown in Figure 7 for the proposed system with DT classifier and the ROC curve is shown in Figure 8. In Figure 7 the confusion matrix shows that some classes (persons) have a false prediction, by showing some numbers outside the matrix diameter, where the strength of the prediction lies when all the numbers are all fall on matrix diameter. In Figure 8 the accuracy rates are less than 100% and for this reason some of ROC curves are less than one at a training rate of 30%.

True Lable \ Predicted Lable	p1	p10	p11	p12	p13	p14	p15	p16	p17	p18	p19	p2	p20	p21	p22	p23	p24	p25	p26	p27	p28	p3	p4	p5	p6	p8	p9
p1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
p10	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
p11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
p12	0	0	0	5	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
p13	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
p14	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
p15	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
p16	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
p17	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
p18	0	0	1	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
p19	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
p2	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
p20	0	0	0	0	0	1	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
p21	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0
p22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0
p23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0
p24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0
p25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0
p26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	1
p27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0
p28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0
p3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0
p4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0
p5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	2	0	0	0
p6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0
p8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0
p9	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3

Figure 5. The confusion matrix for the proposed system with XGB classifier at testing rate of 30%

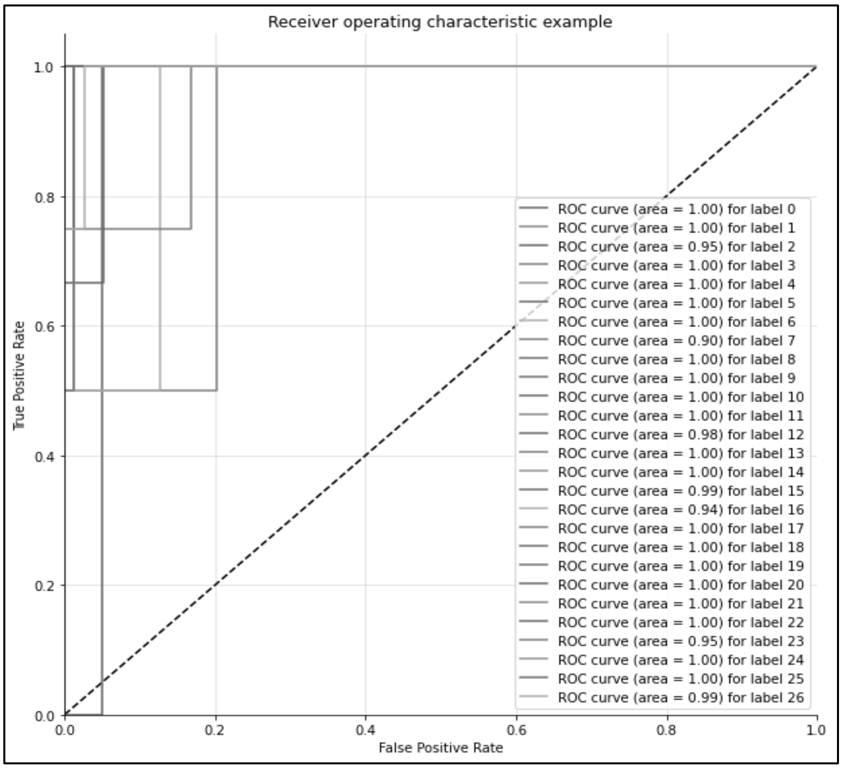

Figure 6. ROC for the proposed system with XGB classifier at testing rate of 30%

Now for the proposed system with DT classifier the confusion matrix is shown in Figure 9 and the ROC curve is shown in Figure 10. The system shows good performance of the DT classification model at all classification thresholds when it applied on real data base. In the confusion matrix Figure 9 there is one false prediction for person P12 and it may have misidentified it as p19 due to the presence of the number 7 when the

P12 line meets the column p19 where the number 7 represents the number of images for P12. In Figure 10 also, the accuracy ratios differed, for this reason some of labels has ROC curves with less than one level which indicated the lower system efficiency. Since the red line represents the correct prediction rate for the class with address label of 3, and so on for the rest of the lines, where each color represents the correct prediction rate for the class it represents or the rest of the classes, their proportions were 100%, so they fit on top of each other horizontally at the number one in the vertical axis.

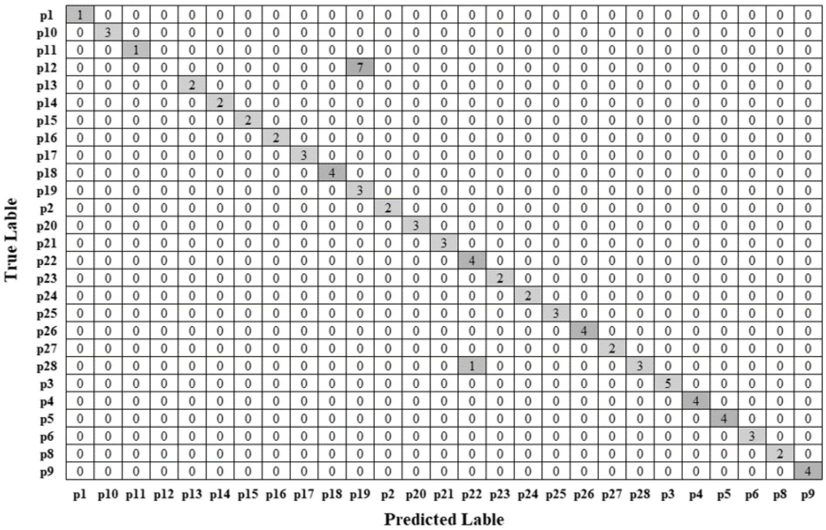

Figure 7. The confusion matrix for the proposed system with DT classifier at testing rate of 30%

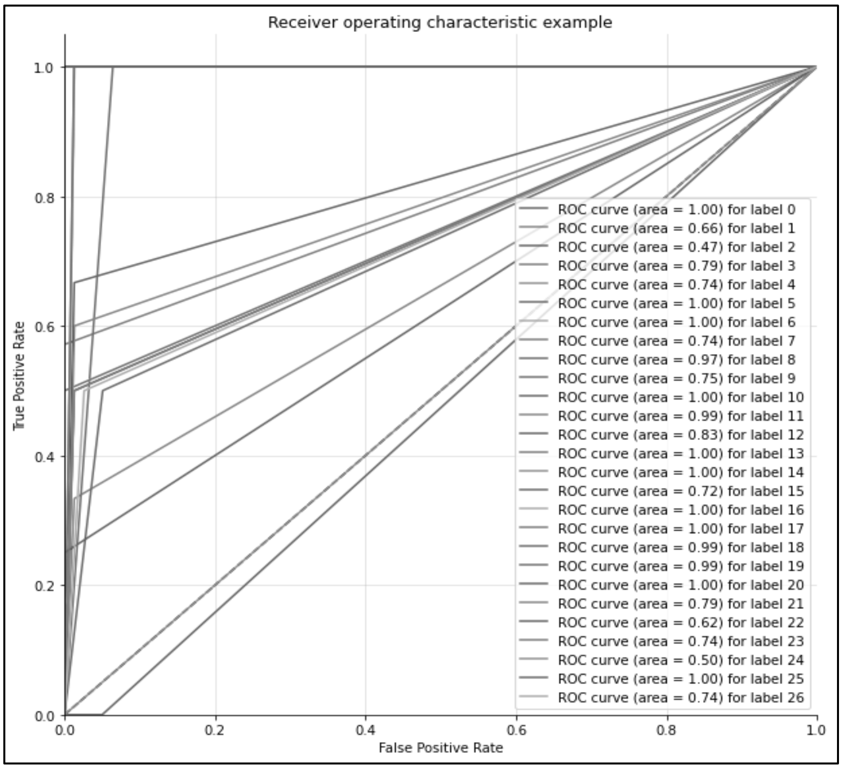

Figure 8. ROC for the proposed system with DT classifier at testing rate of 30%

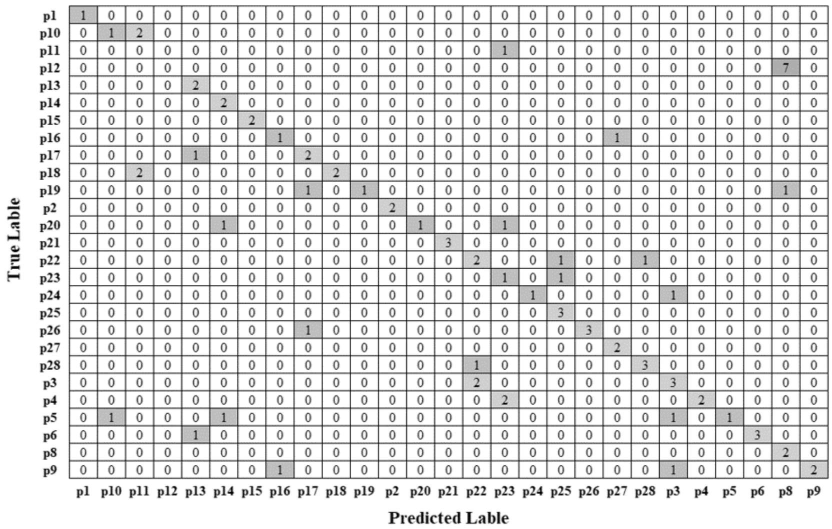

Figure 9. The confusion matrix for the proposed system with NB classifier at testing rate of 30%

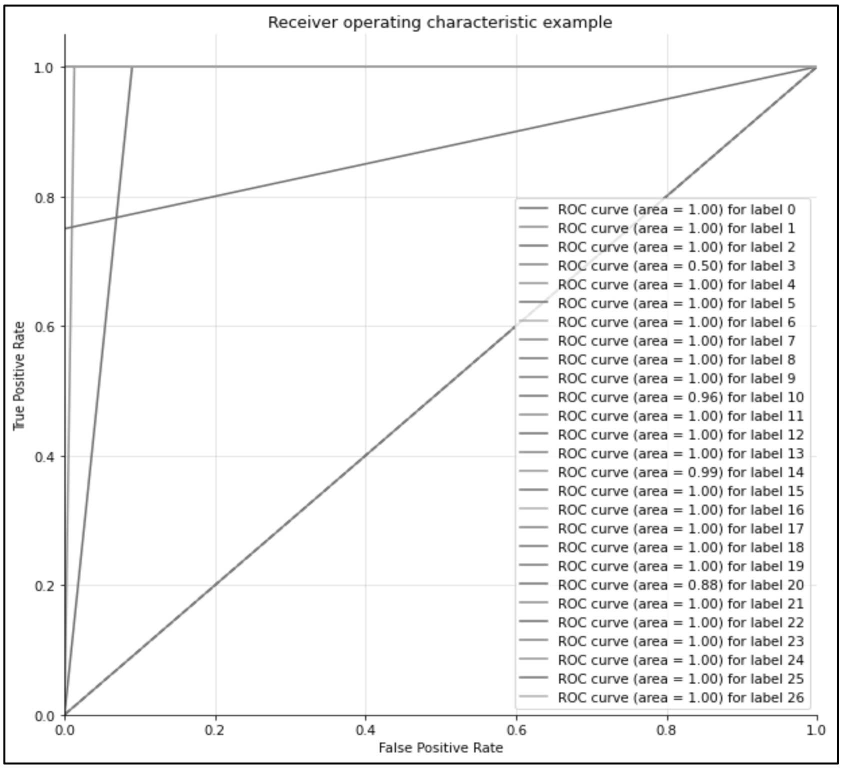

Figure 10. ROC for the proposed system with NB classifier at testing rate of 30%

4 CONCLUSION

The proposed VGG-Face-16 based face recognition model based on radial basis function in SVM, KNN or LR classifier have achieved the objectives of the study as judged by its face recognition results for medium and small database. The system has good performance and can recognize faces from different angles moreover, achieve the high accuracy of the model using the real and AT&T database of faces. Implementing a face recognition system that handles many of the obstacles that face recognition systems, such as shifting picture positions, face rotation angles, facial expressions, closing and opening eyes, smiling and sadness, and changing lighting intensity. On the other hand, obtaining high accuracy for the proposed system in identifying people in the event of changing some features when applying make-up, changing the haircut, wearing and removing medical freshness and in the case of men, the presence or absence of a beard, as our proposed system has proven to overcome these problems through our experiment. This point was very clear when the system is applied on PINs database because the accuracy was 97% when LR classifier is used. Later when LFW database is applied the maximum value for accuracy was 86 with LR classifier. The reason for this level of performance is that this database contains 1680 persons, some of them have only two images and this exhausts the feature vector and reduces the accuracy of the system. All of the classifiers' execution times were satisfactory, allowing the suggested system to be used in real-time applications. According to the results of all types of classifiers used, SVM, KNN, LR give the best results with VGGFace-16 in the AT&T, Real and PINs databases where the accuracy of the system ranges from (94-100) within a record time estimated in milliseconds. On the other side, it gives accuracy of 60% when LFW database is used because SVM does not deal efficiently with large data, its efficiency is inversely proportional to the number of people and directly to the number of images per person because it will be more difficult to split the planes in classification. Finally, the accuracy increases as the percentage of training increases, which is natural because the feature vector will be filled with more features of each person as the number of photos grows. It can be concluded that LR has the best performance and high accuracy especially with large databases.

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