Human Face Detection in Color Images using Fusion of Ada Boost and LBP Feature

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ABSTRACT:
Face recognition has been one of the most widely used sub-disciplines of machine learning for so many years. Face detection has been employed as an effective method in a wide range of applications such as surveillance systems and Forensic pathology in the area of machine vision. However, the accuracy of face detection has dramatically declined over the past decade due to wide-ranging challenges such as face detection with changes in face angle, the density of the crowds in an image, quality of light, etc which require special attention of researchers in response to these challenges. In the present study, a new sustainable approach to light changes for face detection based on local features is employed. In this method, the local binary pattern is extracted from face images and Principal Component Analysis is utilized to reduce the feature vectors' dimension by the descriptor. Eventually, the features are classified using Ada Boost. Tests done on the images on the web show that face recognition accuracy is 100% in the low density crowd, 96% in the high-density crowd and proper light conditions, and 90% in the high-density crowd and poor light conditions.

KEYWORDS: Face Detection, Local Binary Pattern, Light Challenge.

1. INTRODUCTION

Currently, human face perception is an active research topic in the field of machine vision in which detecting or locating a human face considers to be a prerequisite [1]. Face detection is the first necessary stage in the face recognition systems. The purpose of face recognition is to segment the face in the image regardless of 3D mode, rotation, and light conditions in the surrounding environment [2]. Detecting skin is a common and effective method for detecting and recognizing different parts of the human body and has received much attention due to its extensive applications including face detection, body tracking, hand movement analysis, and retrieving or blocking inappropriate content [3]. General face recognition techniques can be divided into two feature-based and image-based categories which the first category relies on distinctive facial features such as skin color or geometrical form of the face whereas the latter detects the face pattern using samples and results obtained from statistical analysis and machine learning [4]. Face detection using skin color is a method based on features extracted from images. Methods of skin detection can be categorized into two general categories of pixel-based and segment-based. In the pixel-based method, features such as color are obtained from information extracted from one pixel and in the segment-based method, they are extracted from a pixel and its neighboring segment [5].

In recent years, skin detection techniques using skin color as key information have drawn lots of attention. Skin color can retain useful and effective information against face rotation, scaling and changes in facial expressions since skin appearance is influenced by various factors such as background light, camera features, and one's nationality, face recognition with the help of skin color information can be very effective and useful [6]. The reason behind the inefficiency of classic face detection techniques such as neural network lies in the low number of samples of different faces in comparison with the extractable facial features, and also the inability to learn and classify complex patterns of human facial expressions [7]. On the other hand, the most important feature resulting in the use of color-based skin detection is its high processing speed as other general face recognition techniques are often time-consuming [4]. The general framework used in skin detection is that RGB color space must be turned to another color space in the first place [3] since the first step in the recognition of skin pixels, which are process variables, is determining a suitable color space. RGB color space is chosen as the primary color space due to three types of light-sensitive cells in the human eye and also colors must be chosen in a way that the third color is not achieved from mixing the other two colors, that is why three colors of red, green and blue are selected [10]. After choosing the suitable color space, the light component must be separated from the image since the light created on the image due to the shooting image can affect the final result. In the end, skin modeling and classification is done using one of the three available methods. Skin segmentation and classification methods can be divided into three categories:

Parametric; which makes use of Gaussian distribution function so as to determine the probability of skin color pixels [11].

Nonparametric; which estimates the probability of skin color pixels using the histogram of the existing information without the help of any specific model and finally classification based on thresholding that uses clear and certain rules for color values and diversity in faces is higher than two other categories in such a way that they cannot be categorized in distinct groups [12]. Besides, variations such as head and facial hair being either short or long and their cutting style as well as the increase in age may change the face. Imaging conditions can also affect the face. These conditions include changes in light intensity or face and body position such as face rotation and the angle of camera while shooting faces which may cause fundamental problems in face identification. Therefore, it is necessary to adopt methods that are not only resistant to changes in environmental conditions especially light but can also classify different types of skins. Ban et al. applied an improved threshold algorithm with an emphasis on skin color information to fade or discolor non-skin parts. A stochastic model is used to discover the similarity between the color region and skin region in this method. Also, LBP is employed as a cascade classifier. On average, the accuracy of the above-mentioned method is 65% [1].

Singh et al. created a skin color-based face recognition algorithm by combining three color spaces of YCbCr, RGB, and HIS. This algorithm is capable of recognizing faces in color images with an accuracy of 95.18% [13]. Zhang et al. presented a method for face recognition with an accuracy of 97.9%. using the LBP feature and AdaBoost to select a set of local regions and their weights[14]. Biao et al. combined the Ada Boost algorithm with skin segmentation and face description based on LBP to develop an efficient method for face detection. This algorithm can detect faces correctly in more than 90% of the cases[15]. Yan Wu et al. presented a combination of the Ada Boost algorithm and skin color segmentation using a simple Gaussian model and a morphological operation on a binary image. This algorithm can correctly identify an individual's face in at most 92.2% cases[16]. In this study, MIT dataset consisting of 2429 face images and 4547 non-face images in the size of 19×19 pixels has been utilized. The skin color filter was employed through the YCbCr color space. The final classification is 1187 including a weak classifier. In order to assess the suggested method, they implemented the Viola-Jones algorithm and evaluated both methods on 30 test images from the standard datasets and the detection rate of 77.96 was reported in both methods[17]. Ma et al. employed the framework presented in [19] along with the Ada Boost algorithm in their study. Their innovation is introducing a new Haar-like feature called T-shape Haar-like feature. They trained their suggested method as well as Viola-Jones method on a common database in equal conditions and then they tested both methods on 139 images including 601 faces randomly collected from the internet. Their final classifier consists of 2452 weak classifiers of which 893 classifiers are reported to be based on the new T-shape Haar-like feature. They claimed that their average detection rate is only 19% less than that of the Viola-Jones method[18]. However, the number of samples mistakenly classified was 78 in their method and 229 in the method [19] implemented by them. Research carried out by Wu et al. Describing nesting cascade structure is among the successful work done for improving cascade architecture. The difference between this structure and classic cascade is that each layer functions as a weak classifier of the next layer. Therefore, a distinction among consecutive layers is maintained. RealBoost learning algorithm has been used in order to train classifiers using lookup tables of Haar-like features. Their system has 16 layers and 756 Haar-like features by training on a dataset consisted of 20000 faces in 24×24 pixels. The best result is reported to be 96.5% on the MIT+CMU test set with 213 incorrect detections. Zhang et al [14] introduced a new set of rectangular features called Multi-Block Local Binary Pattern. They made use of another GentleBoost learning algorithm to select the features and construct the "Viola-Joness" classifier and cascade structure. Since the value of the LBP operator is only a symbol for showing binary string, a multi-branch regression tree was designed as a weak classifier so as to solve this problem. This tree has 256 nodes, equal to the number of possible codes generated by the LBP operator[20]. Zhang et al. claimed that with the equal number of features and false detection rate of 0.001, their system achieved a 15% higher detection rate compared to that of Haar-like feature and 8% higher detection rate than that of basic LBP feature. 40000 face images and 20000 non-face images in the size of 20×20 pixels have been used to train this system. The final classifier includes 9 layers and 470 LBP-MB features. The best result is reported to be 93.7% on the MIT+CMU test set with 293 false detections.

Sirovich and Kirby developed a technique for efficient presentation of face images using principal component analysis. They calculated the best system coordinate for image compression that each coordinate axes are an image which is called “eigen-image” [21]. In order to develop an approach-based detection system, Pentland et al. pursued the suggested “eigen-image” approach. They stated that many face images can be restored using a small weighted set of features of eigen face. Perhaps, one method for learning and face detection is to obtain special features by experience and detecting faces by comparing the weight of the respected features with the relative weight of those of the identified faces. Therefore, each face is determined by a small set of features or weights of required faces for its description as well as restoration[22]. They made a huge transformation in the field of face recognition. In this method, they look for a way to make the data as independent as possible and make use of orthogonal vectors to do so. This method is called principal component analysis. In this method, the covariance of the data and then the matrix of the eigenvectors are calculated. Eigenvector matrix is the matrix of orthogonal vectors making up the feature subspace and data become independent after being transferred to this subspace. In order to move data to this subspace, the data matrix is multiplied in the matrix of eigenvectors or vectors of the new subspace. Eigenvectors used in this method are orthogonal and in the direction of the highest data dispersion and the image is expressed by using minimum mean square error in the new space. For the input image in this method, the image is first transmitted using the matrix of eigenvectors or subspace vectors and then is compared to the existing data in the reduced-dimension space and the most similar image to the identified image is selected. In the Fisher algorithm, the purpose is to obtain a better space for data expression considering data suitable for each class. Therefore, there must be as many classes as the number of people in the database.

One of the latest methods used in this area belongs to Chen et al. in which a convolution neural network is used for feature extraction as well as a support-vector machine classifier for classification. However, this method has high computational complexities and the need for faster methods is felt. Among the existing classification techniques, Ada Boost using the LBP feature can perform better than other similar investigations because it is capable of identifying faces with different facial expressions and complex backgrounds [23]. All the face recognition algorithms and techniques are developed with the purpose of commercialization or being practically used in important facilities. Thus, only algorithms can be successful and efficient which can understand real-world situations and come up with solutions addressing the challenges. Face recognition has been studied in research centers for many years but only a few numbers of these investigations ever reached a practical application because most of these studies did not address significant real-world challenges. One of the challenges which has not received lots of attention is testing these algorithms with images without uniform and stable light on the face. Responding to this challenge can make face recognition algorithms more advanced and efficient in different situations.

2. AN OVERVIEW OF A FACE RECOGNITION SYSTEM

An overview of a face recognition system is displayed in Fig. 1.

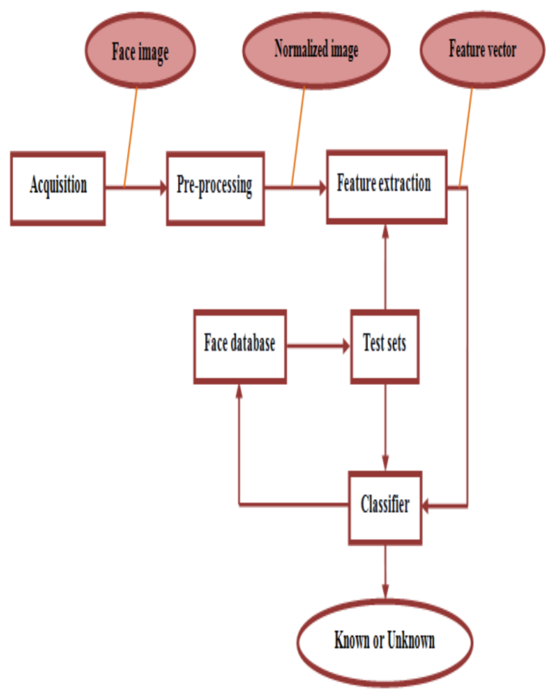

Fig. 1. A general face recognition system [11].

There are six main operation blocks in the Fig.. 1 described below:

- Acquisition

This is the starting point of the face recognition process. This is the stage by which the face image is presented to the system. Put differently, in this stage, the user is asked to provide a face image to the face recognition system.

- Pre-processing

In this stage, face images are normalized using various techniques of machine vision and enhanced, if necessary, to increase the efficiency of the detection system. Some or all of the following pre-processing stages may be implemented in a face recognition system:

1. Image size normalization: This is usually done in order to change the size of the image to a default size such as 128×128 pixels, as the same image size the face recognition system works with.
2. Illumination normalization: This is usually done in order to change the size of the image to a default light.

• Feature extraction

After performing pre-processing (if needed), the normalized image is sent to the feature extraction section for the key features to be fined. These features will be used for classification later on. In other words, this section is responsible for creating a feature vector that best represents a face image.

• Classifier

In this section, features extracted from face images are compared to those saved in the face database with the help of a pattern classifier. After the comparison is made, the face image is categorized as “known” or “unknown”.

• Test sets

Test sets are used during the learning phase of the face recognition process. The sections of feature extraction and classifier adjust their parameters using test sets to reach the optimal detection performance.

• Face database

After a face was categorized as “unknown”, face images along with their feature vectors can be added to the database for future comparisons. The classifier section directly makes use of the face database. The feature extraction and classifier are two sections that distinguish most of the different face recognition systems. It can almost be said that the difference in the performance of face recognition systems is due to the efficiency of these two sections. In the following, we will discuss different methods applied by face recognition systems in these two sections.

3. FACE DETECTION METHODS

Face detection methods can be divided into three categories knowledge-based methods, detail based methods and template-driven methods.

The fundamental problem in knowledge-based methods is implementing human knowledge. However, they have shown very good performance in identifying faces. One of the interesting strategies in these methods is the use of heuristic algorithms in such a way that lots of frames are omitted simply by applying some of the simpler rules on images with lower qualities and then the remaining frames are filtered out by applying stricter rules. In the end, any frame successfully passing all the rules is identified as a face.

In contrast to knowledge-based methods, details-based methods search for different facial components to identify the face with. The underlying assumption in these methods is that humans can easily identify faces in different angles and light conditions. Different facial components like eyebrows, eyes, nose, and mouth can easily be extracted from by using an edge detector. Based on the extracted components, a statistical model from the relations among facial components is created to confirm the existence of a face. One of the problems in these methods is that the image obtained from different facial components may be distorted due to poor light conditions, noise or clothing. This problem also increases the chance of losing the edges of facial components or the algorithm being useless because of shadows. In template-driven methods, a standard of the human face is predetermined manually or using a mathematical function. By receiving the input image, the correlation between the edges of the face, eyes, etc. and the pattern is achieved. The final decision on image recognition will depend on the correlation value. Although this method is easy to implement, it’s not a good option to be used when there are face images with different conditions since it’s unable to deal with face images in various angles, scales, and shapes.

4. APPLIED ALGORITHMS

The local binary pattern was first proposed by Ojala in 1996 [26]. This method has been very successful in machine vision issues. The local binary pattern is considered for each pixel within 3×3 neighborhood. It can be expanded to a larger neighborhood calculated in a circular neighborhood. The computational complexities increase as the neighborhood radius raises. The local binary pattern is shown as $LBP_{(P, R)}$ in which P is the number of samples or the number of neighboring pixels of the central pixel in a circle with radius R. The value of each pixel is a decimal number. The value of the central pixel is selected as the threshold and the brightness of this pixel is shown as g_c the brightness intensity of neighboring pixels are indicated by g_p. The value of local binary pattern for each pixel g_c which is in the neighborhood of a circle $g_{p,(p=0,p=1,\dots p=p-1)}$ is calculated using relation 1 or relation 2. In order to calculate the value of local binary pattern as it is displayed in Fig. 2, for each central pixel, the brightness values of neighboring pixels are compared to the threshold which is the same as brightness of the central pixel using above-mentioned relations. Each of the neighboring pixels whose brightness is less than the central pixel brightness value is replaced by zero, and if the neighboring pixel brightness value is greater than the central pixel brightness value, it is replaced by one. This comparison results in a list of binary values. By multiplying binary values by their weights and adding them, the value of binary local pattern for each pixel is obtained. In order to show a spot, flat area, edge or corner, uniform local binary patterns are defined. A local binary pattern is called uniform if the binary pattern contains at most two 0-1 or 1-0 transitions. Feature extraction using local binary pattern may be easily implemented, but it faces high computational complexities when neighborhood radius increases. Local binary pattern operator creates P^2 different binary patterns. In a 3×3 neighborhood, the number of binary patterns created is 256 patterns. If the neighborhood radius increases, the number of binary patterns created will also increase. As the number of binary patterns raises, the weight calculation and subsequently the amount of time needed for calculation also increases. Moreover, the local binary pattern is disrupted when an image has noise [19].

$$\mathbf{LBP_{P,R}} = \sum_{\mathbf{p=0}}^{\mathbf{P-1}} \mathbf{S}(\mathbf{g_p} - \mathbf{g_c}) \times \mathbf{2^p} \tag{1}$$

$$\mathbf{S(x)} = \begin{cases} \mathbf{1} & \mathbf{if} \quad \mathbf{x} \geq \mathbf{0} \\ \mathbf{0} & \mathbf{if} \quad \mathbf{x} < 0 \end{cases} \tag{2}$$

In relation 1 and 2, g_p shows brightness of neighboring pixels g_c is the brightness intensity of the central pixel which is considered as the threshold and thresholding is carried out according to the brightness of this pixel. Also, p is the number of samples of neighboring pixels and R represents neighborhood radius.

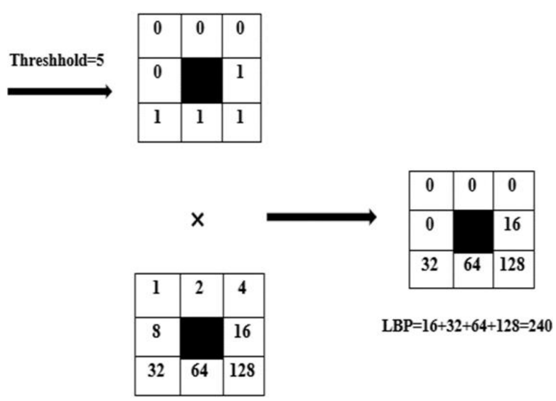

Fig. 2. How to calculuate a local binary pattern.

Ada Boost is one of the most renowned group classifier algorithms and also among the top ten data mining algorithms. Ada Boost stands for Adaptive Boosting which is a boosting algorithm. Ada Boost origins from PAC learning. Those who proposed PAC proved that a combination of simple learners, which have better results than random selection, can lead to a good final classification. This is the whole idea behind boosting. After several relatively successful algorithms with some limitations, Ada Boost was introduced by Freund and Schapire in 1999 as the practical algorithm of boosting theory [27].

In the beginning, boosting algorithms were well-received due to their efficiency in working with low noise data but the initial algorithms for noisy data obtained very poor results because of over fitting problems. therefore, boosting applications were limited. Ada Boost can be considered as a gradient method by limiting the error function to marginal value. Ada Boost conducts classification using straight lines forming a curve in such a way that it only focuses on a small number of difficult samples that is similar to support vector from one perspective. There is a close connection between boosting and optimization theory. The definition of regression, multiclass problem, and unsupervised machine learning by boosting algorithms as well as convergence proof for boosting algorithms using the results of optimization theory approve this connection.

5. THE SUGGESTED METHOD

The developed algorithm is a complete system containing methods based on LBP and if needed, PCA coordinates actions and reactions of facial components and performs analysis on facial parts. In most humans, the facial expression change system consists of two central and lateral parts.

5.1. Training Section

It can be seen in Fig. 3, the first step is to receive the input image which can be either online (filming the scene and then converting it to image frames) or offline (using images saved in the database). The purpose of pre-processing is to prepare the image for entering the algorithm and it includes all the steps that must be performed on images. These steps will be different depending on the image. Like: normalization, compression, format conversion, grayscale transformation, binarization, etc. After feature extraction conducted using binary local patterns, the Ada Boost classifier is performed on features and the image containing faces is identified and added to the database. Fig. 3, shows the block diagram of training section.

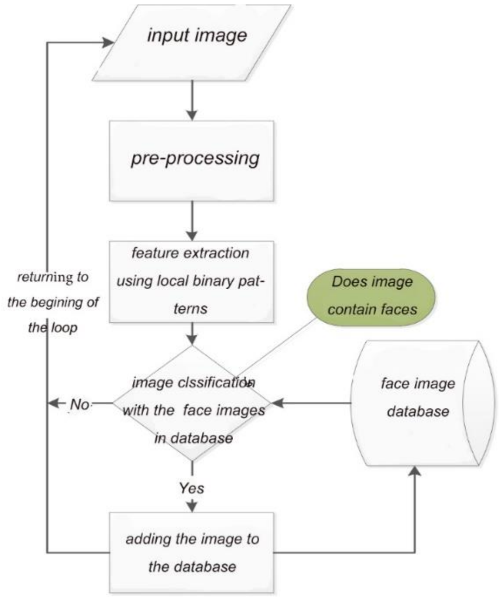

Fig. 3. The block diagram of training section.

5.2. Testing Section (Face Detection)

In the implementation of the main algorithm, like the training algorithm, it is necessary to carry out the preprocessing of the initial image. Then the image must be transferred to the face space which means each image with the dimensions of n×m is turned to a vector with nm components. This is done to reduce the size so that data dispersion can be observed better. The input image can be identified by vector representation of the human face which is achieved by putting together matrix columns of the image. These vectors are vectors of local binary patterns.

In Fig. 4, which shows the block diagram of suggested method, i represents the number of feeding layers which are considered 2 layers in the suggested method. In each layer, the number of critical points is increased to improve the identification accuracy and 16 facial critical points are achieved at the end of the third layer including:

- The corners of the lips, the corners of the nose, the corners of the eyes.
- The corners of the lips, the corners of the nose, the corners of the eyes, under the chin, tip of the nose and above the forehead.
- The corners of the lips, the corners of the nose, the corners of the eyes, under the chin, tip of the nose and above the forehead, below ears, above eyebrows, on the cheeks, above the lip.
- Fact, at each stage, in addition to the critical points used in the previous layer, new critical points will be added.

Implementing two above layers in the algorithm, the output is given to the Ada Boost algorithm for a more precise classification of the image features as well as an increase in identification accuracy.

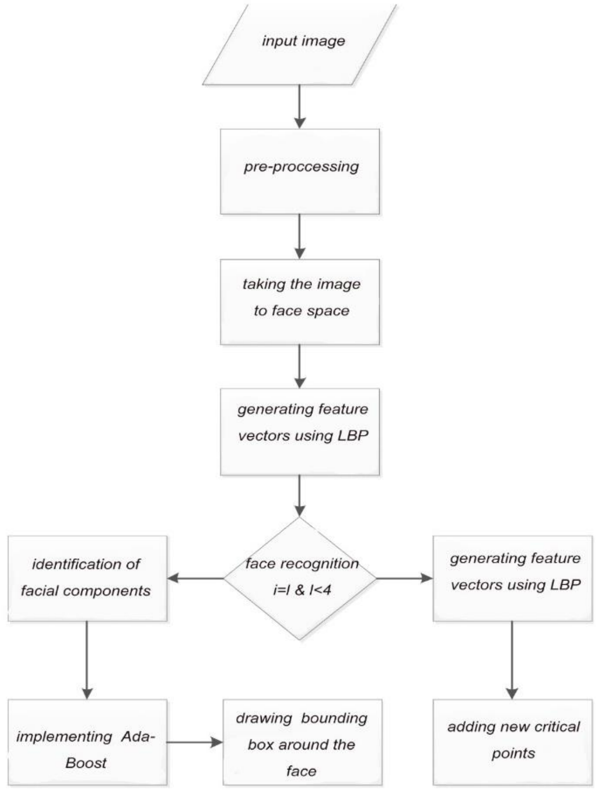

Fig. 4. The block diagram of suggested method.

In the pre-processing section, the image is enhanced in case there were any defects in the image such as noise and the image goes through the suggested method perfectly fine and unblemished. Although, image enhancement techniques can be used such as light intensity adjustment on the subjects' faces in this phase to improve the detection rate.

- The stage of feature extraction. The features of the normalized images are extracted using the descriptors mentioned earlier and feature vectors suitable for each image are generated.
- Settings and parameters applied to the descriptor of binary local patterns are as follows:
  1. In the beginning, the number of pixels used in the histogram calculation is increased to improve feature extraction and increase the accuracy of feature vectors. In order to do so, the calculation radius is 2 and the number of pixels used in the histogram calculation is 12 pixels.
  2. After calculating the histogram of the pixels of the image according to the mentioned features and based on the local binary patterns, normalization is done on the histogram which

somewhat counts as an improvement in the feature vector.

3. In the final step, the histogram of all pixels is aggregated and the feature vector is created.

After examining the dimensions of feature vectors generated by descriptors, it can be predicted that the classification of feature vectors with these dimensions is time-consuming and also has a very high computational complexity. For instance, feature vectors generated by the descriptor of local binary patterns for each image have very high dimensions (1×9819). Therefore, principal component analysis is used to address this challenge. After being analyzed by a feature selector, the feature vector has become smaller maintaining its qualities and is ready to enter the classifier for identification. At the stage of critical points identification, several facial critical points are identified. It should be noted that this step, itself, is consisted of three stages:

1: The corners of the lips, the corners of the nose, the corners of the eyes.

2: The corners of the lips, the corners of the nose, the corners of the eyes, under the chin, tip of the nose and above forehead.

3: The corners of the lips, the corners of the nose, the corners of the eyes, under the chin, tip of the nose and above the forehead, below ears, above eyebrows, on the cheeks, above the lip.

The above points are applied to the image using local binary.

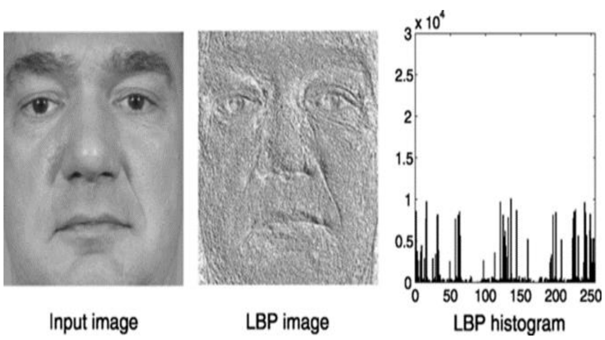

Fig. 5. The output image of the local binary pattern.

As it can be seen in Fig. 5, an approximately uniform image is obtained after applying this descriptor on the image in which only some lines can be seen in areas like around the lips, around the nose and eyebrows, and also around the face and eyes and somewhat are the image edges and all the points are the same as critical points. As the final step in this study, the optimized feature vectors are classified using the classifiers discussed earlier and a box is drawn around the face and finally, the detection accuracy of each of the classification in Ada Boost and Ada Boost classifier is calculated. Fig. 5 is an example of the faces identified using the suggested method.

Fig. 6. An example of the suggested method output.

6. EVALUATION OF THE RESULTS

In this research, two classification accuracy and consistency criteria for evaluating the suggested method are being used. Identification accuracy is a criterion based on calculating a number of precise identifications to all Identifications and subjects, and identification precision in a criterion based on the number of precise identifications to all the exiting identifications in the picture. To compute identification accuracy, first, the output parameters of the classification should be measured. These parameters are specified in Table 1.

Table 1. Parameters for calculating identification accuracy and precision.

	Specified by the suggested method		
True subjects	Identified		Not Identified
	Face	TP	FP
	No face	FN	-

TP: True Positive, the number of detections that are faces.

FN: False Negative, the number of detections that are not faces.

FP: False Positive, the number of faces that are not detected.

S: The number of all the faces in the picture.

The detection accuracy and detection precision are shown in equations 3,4.

$$Ac = \frac{TP}{S} \quad (3)$$

$$Pre = \frac{TP}{TP + TN + FN} \quad (4)$$

6.1. Examining the Suggested Method Without Employing the Ada Boost Technique (one classifier)

In this phase, the results for one classifier in this research (support-vector machines classifier) is pointed out (in chapter 2), and they will be compared in two different aspects of with and without light challenge. Figs. 7 to 10 are examples of these pictures.

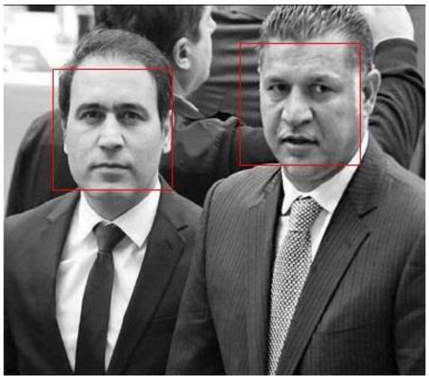

Fig. 7. Detection with one classifier and in normal light conditions with few subjects.

Fig. 8. Detection with one classifier and in normal light conditions with a lot of subjects.

Fig. 9. Detection with one classifier and in abnormal light conditions and a few subjects.

Fig. 10. Detection with one classifier and in abnormal light conditions and a lot of subjects.

As it is shown in the figures above, first of all, the low number of classifiers in the pictures with the high number of faces is impactful, but this impact is multiplied with abnormal optic environment. Considering Fig. 7, this picture has a low number of subjects, but the light conditions are appropriate, and both faces are identified. But in Fig. 8, despite having appropriate light conditions the number of subjects in the picture is too high, which in this picture, one classifier could not identify faces good enough and had a lot of errors. In Fig. 9, the low number of subjects in an inappropriate light condition is examined, which also in this case, the faces are identified. But in Fig. 10, also the number of subjects is too high and the light conditions are inappropriate, which in this case, identification is done with a lot of errors. Table 2 shows the results for 4 groups of this stage.

Table 2. Comparing the results of one classifier method (support-vector machines) and with the light challenge.

	Detection accuracy	Detection precision
Appropriate light conditions and a few subjects	100%	100%
In appropriate light conditions and a few subjects	96%	98%
Appropriate light conditions and a lot of subjects	80%	74%
In appropriate light conditions and a lot of subjects	58%	50%

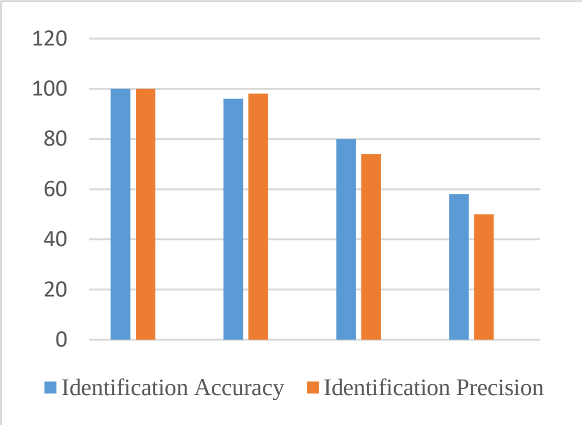

Fig. 11. The charted results of one classifier method.

6.2. Examining the Suggested Method Using the Ada Boost Technique

In this phase, the results of Ada Boost classifier will be compared in two different aspects of with and without the light challenge. Figs. 12 to 15 are examples of these pictures.

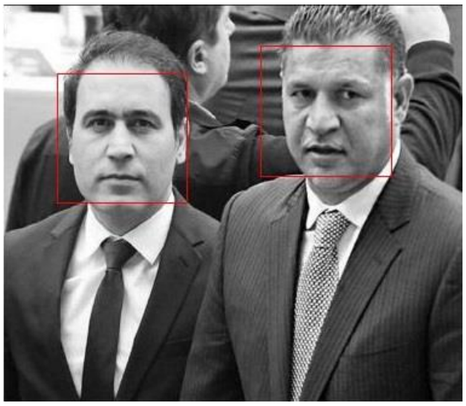

Fig. 12. Detection with Ada Boost classifier and in normal light conditions with a few subjects.

Fig. 13. Detection with Ada Boost classifier and in normal light conditions with a lot of subjects.

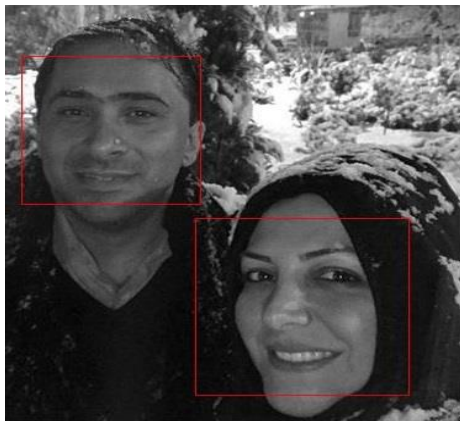

Fig. 14. Detection with Ada Boost classifier and in abnormal light conditions with a few subjects.

Fig. 15. Detection with Ada Boost classifier and in abnormal light conditions with a lot of subjects.

As it is shown in Figs. 12 to 15, it is clear that, first of all, the number of classifiers (in Ada Boost algorithm) is very impactful, and second, this impact in inappropriate light condition is much more understandable. If we pay attention to Fig. 12, in this picture, the number of subjects is low, but the light condition is appropriate and both faces are identified. But in Fig. 13, despite having appropriate light conditions, the number of subjects in the picture is too high, which in this case, Ada Boost classifier has done identifying well enough, and these are a few errors. In Fig. 14, the low number of subjects with inappropriate light condition are examined, which also in this case, the identification is done. But the impact of this method in Fig. 15 is sensible. Where despite having a lot of subjects in the picture, the error rate is too low. Table 3 shows results for 4 groups of the examinations of this stage.

Table 3. Comparing the results of Ada Boost classifier method and with the light challenge.

	Detection accuracy	Detection precision
Appropriate light conditions and a few subjects	100%	100%
In appropriate light conditions and a few subjects	100%	100%
Appropriate light conditions and a lot of subjects	96%	90%
In appropriate light conditions and a lot of subjects	90%	86%

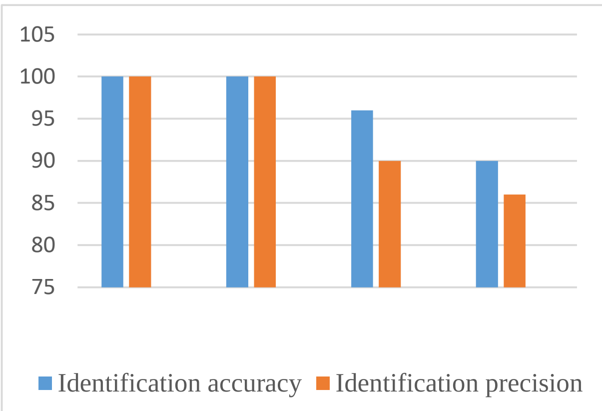

Fig. 16. The charted results of Ada Boost method.

7. CONCLUSION

With respect to the conducted analysis, it can be concluded that the combination of classifier (AdaBoost) method show better results, in terms of limiting identification methods rather than using only one type of classifier. And with the sum of these classifiers, the challenge of change in the environmental light has been addressed very well, and it can be concluded that this method can be also impactful when having similar challenges such as having a hat, etc. Tests done on the images on the web show that face recognition accuracy is 100% in the low-density crowd, 96% in the high-density crowd and proper light condition, and 90% in the high-density crowd and poor light conditions.

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