Emotions recognition from human facial images based on fast learning network

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ABSTRACT

Systems of facial emotion recognition have witnessed a high significance in the research field. The face emotions are based on human facial expressions which play a crucial role in silent communication. Machine learning algorithms have widely used in systems of human facial emotion detection from images. However, many systems suffer from low accuracy rate. In this paper, we present a system of facial emotion recognition by using images. In this proposed system, the samples of facial emotions have taken from Yale Face database. In addition, the histograms of oriented gradients (HOG) is used to extract features from the images. The extracted features will feed the fast learning network (FLN) algorithm for the classification part to identify the images of facial emotions with respect to their subjects. Many evaluation measurements have used to evaluate the performance of the proposed system. Based on the results of the experiment, the proposed system achieves 95.04% for the highest accuracy, 72.73% precision. Also, the results of the proposed system in terms of recall, f-measure, and G-main are all equal to 72.73%, respectively.

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1. INTRODUCTION

The detection of human emotions is an active area and has witnessed a high significance recently. In general, the facial emotion of human can be classified into positive emotions and negative emotions. The positive emotions are including joy, love, and happiness. On the other hand, negative emotions are denoting to anger, lonely, disgust, fear, and rage [1]. Typically, in order to propose a technique for detecting facial emotion, there are three main phases that need to be performed. The first phase refers to the raw images database that is taken to be used in the detection of facial emotion. Subsequently, the second phase denotes to the feature extraction process in order to extract features from images. Finally, these extracted features will be fed into the classifier in order to identify the user emotion [2]. In sociality, humans are interacting with the help of facial emotions, where these emotions are considered as a universal language. Furthermore, these emotions transcend cultural diversities and ethnicity.

The expressions of the human face are responsible for conveying the information. These expressions represent the mental state of the people which are directly related to the physical efforts that they should be applying in order to perform tasks or just related to their intentions. Consequently, techniques of automatic emotion recognition with the cooperation of high-quality sensors can be a useful tool in different fields such as robotics, image processing, cyber security, and other various applications of virtual reality [3]. Machine learning (ML) and deep learning (DL) algorithms have been extensively applied due to such algorithms have proved their effectiveness and efficiency in the classification between subjects [4]. Moreover, the algorithms of ML and DL have improved the performance of many recent systems and in different fields such as images classification in the medical domain [5]-[7], language identification [8], [9], fog-cloud network [10], identification of spam emails [11], speech emotion recognition [12], vehicle detection [13] and voice pathology detection [14]-[16]. Additionally, the algorithms of DL and ML have been implemented as the main role in the methods of facial emotion recognition [17], [18]. The main purpose of using these algorithms is to train and build a system that is capable to classify subjects efficiently with high accuracy of the detection [19], [20]. The most challenges that faced by researchers in the domain of facial emotions detection is the shortage of the database for spontaneous expression of people. In other words, collecting and capturing spontaneous expressions of people on images is considered as the hugest challenge for researchers [21]. Lately, there are many systems and techniques have been presented in the state-of-the-art for the detection and recognition of facial emotion by using an image database.

Moghaddam *et al*. [22] is presented a new deep network for the recognition of facial emotion by using images. In this method, the deep network is used to extract spatial features by utilizing a VGG16 convolutional neural network (CNN). Subsequently, a neural network that named bidirectional long short-term memory (Bi-LSTM) is applied in order to learn features of spatio-angular. Furthermore, the extracted features have fed to the fusion scheme used for classifying the facial emotion recognition and obtain the results of the system. In this method, four facial emotions have been used which are natural, angry, surprised, and happy. The samples of images database have been taken from light field face database (LFFD). It includes 800 samples of facial emotion images. The achieved results have shown that the highest accuracy has reached to 94.00% that has been obtained from the happy subject. However, this method has been evaluated in terms of the accuracy only, where there are other important measurements such as sensitivity, specificity, and G-mean.

Another research paper has proposed in [23]. The authors have been presented an adversarial attack resistant based system for analysing and recognizing faces emotion through the landmarks. The proposed system has been outperformed the ResNet model in terms of the images classification in different cases after the data has faced an adversarial attack. Furthermore, the images samples have been taken from the Cohn-Kanade database. This image database contains 3,368 of facial emotions. There were seven facial emotions that have been included in the database which are anger, fear, sad, disgust, neutral, surprise, and happy. The proposed method has achieved 97.43% accuracy, while the ResNet has achieved 90% after the adversarial attack.

Pandey *et al*. [24] have been proposed a system for improving the performance of facial emotion recognition by using laplacian and gradient images. In this system, the images of laplacian and gradient have used as input data along with the original input into the CNN algorithm. These laplacian and gradient images have helped the network to learn with additional information. Besides, there were two well-known databases of facial images have used in this proposed system which are Face expression recognition (FERplus) and Karolinska directed emotional faces (KDEF). The total number of images in the Karolinska directed emotional faces (KDEF) database is 4,900 images, with an equal number of facial expressions for female and male. This database includes seven classes of expressions which are anger, fear, sadness, disgust, neutral, surprise, and happiness. Whilst, the total number of images in the FERplus database is 35,000 and it contains eight subjects, including contempt. In the proposed system, there were 28,000 samples of facial emotion images have used for the training phase, while the remaining images samples have divided equally for the validation and test phases. The experimental results have shown that this system has achieved 88.16% accuracy. However, the proposed system has evaluated in terms of accuracy only. Moreover, the obtained results are not encouraging yet in the classification process.

Fang [25] has presented a method in order to solve the image classification problem. In other words, to solve the problem of miss-classified cases in the recognition of facial emotion. In particular, the author has presented the backtracking algorithm for tracking down the activated pixels of the image between the last layers of feature maps. Subsequently, the facial features which are considered as miss-classifications will be visualized. In the recognition of facial emotion, the activations of the unique image pixels identify the classification results. The samples of facial emotion have been taken from radbound faces database (RaFD). In this database, there are 67 subjects for male and female and of different ages. Besides, for each subject, there were 120 samples of images. The facial emotions used in this method are neutral, surprise, happiness, disgust, contempt, anger, sadness, and fear. This method has achieved 90.97% classification accuracy for the recognition of facial human emotions.

2. METHOD

In this section, we will present the methodology of the proposed system for the recognition of facial emotion. The samples of the database are images of human faces in different emotions that include 11 subjects. These images samples will be analysed in the pre-processing process. Subsequently, the technique of histograms of oriented gradients (HOG) will be performed as a feature extraction method in order to extract the features of facial emotion images. It worth mention, the pre-processing and HOG processes are representing the entire features extraction step. Finally, the extracted features will be fed to the fast-learning network (FLN) algorithm to classify the images of human facial emotions. Furthermore, Figure 1 shows the general scheme of the proposed method.

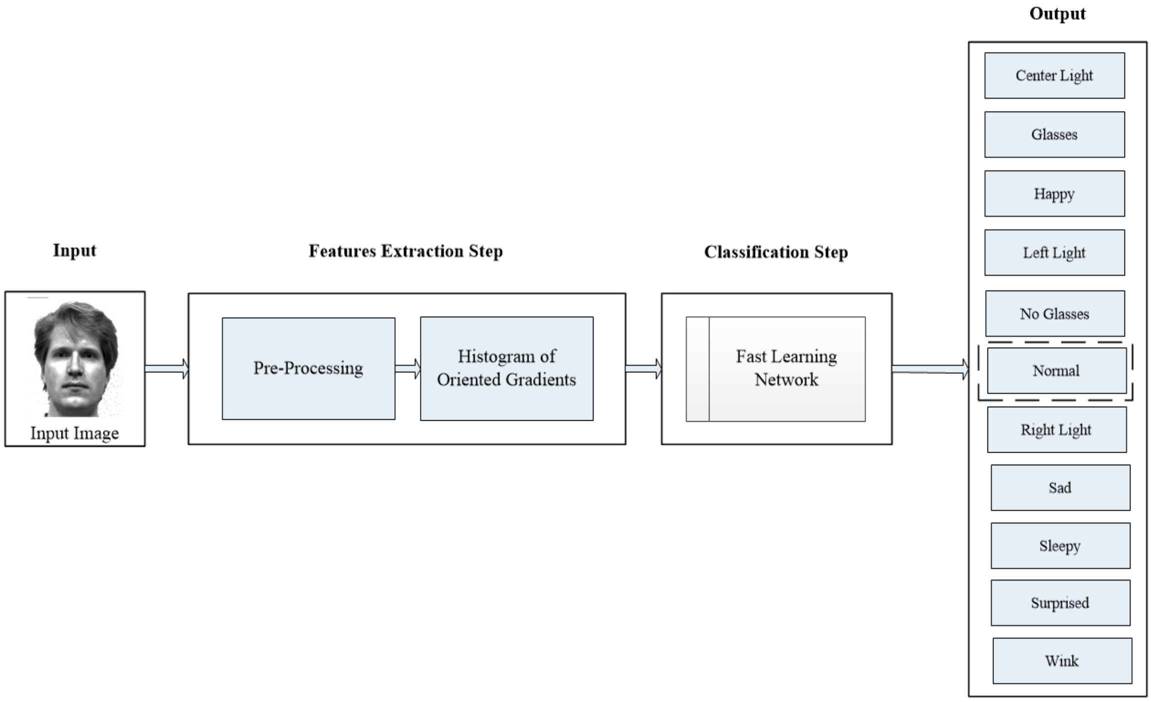

Figure 1. The general scheme of the proposed system

2.1. Yale faces images database

In our proposed system, the samples of facial emotions images have been taken from [26]. This database is called Yale faces and it is a well-known database, where it has been widely used in the recognition of facial emotions. The Yale face database consists of 11 subjects which are centre light, glasses, happy, left light, no glasses, normal, right light, sad, sleepy, surprised, and wink. Each subject contains 15 samples of human facial emotions images. Consequently, the total number of images is 165 samples in the Yale face database. The original images samples of Yale faces database have processed as an 8-bit 3D images with size of 231×195×3. In our experiment, we have been used all the samples of human facial emotions images in the Yale faces database. Furthermore, it worth mention that all images samples have converted and resized (see section 2.2 for the pre-processing step). In addition, we have divided the entire database into 80% (132 samples) for the training phase, and the remaining 20% have used for the testing phase (33 samples). In other words, the training set of each class has included 12 samples. While, the testing set of each class has included 3 samples. Table 1 illustrates the Yale faces database used in the proposed system.

2.2. Pre-processing

The pre-processing operation of the human facial emotions images in this study is consist of two main steps. The conversion and the image resize are considered the two main steps of the pre-processing operation. In the step of conversion, all the images of human facial emotions will be read and check their dimensionality. That means the 3D human facial emotions images will be converted into grayscale (2D). Whilst in the step of image resize, the dimensionality of all human facial emotions images will be resized into (150×150) dimensions. Thereafter, the output of the pre-processing operation will be as input into the HOG technique in order to extract the needed features from the facial emotions images.

Table 1. Details of the Yale faces database

Class name	Number of sample	Images samples of Yale faces database	Label
Centre Light	15		1
Glasses	15		2
Happy	15		3
Left Light	15		4
No Glasses	15		5
Normal	15		6
Right Light	15		7
Sad	15		8
Sleepy	15		9
Surprised	15		10
Wink	15		11

2.3. Feature extraction: HOG technique

The HOG technique relies on the accumulation of gradient directions through the image pixel for a certain region named "Cell". In the following construction for the histogram with one dimension which provides a series of features vector in order to be considered as input for the classification process. Suppose G refers to the function of the grayscale which has been utilized for analysing and describing images. Further, every image will be split into a set of cells with N×N pixels' size. Figure 2(I) presents the processes of image splitting into a set of cells. The calculation of the gradient orientation (i.e., θk, r) for each pixel is represented in (1). Figure 2(II and III) demonstrates the processes of the gradient orientation.

$$\theta_{k,r} = tan^{-1} \frac{G(k,r+1)-G(k,r-1)}{G(k+1,r)-G(k-1,r)} \quad (1)$$

Furthermore, the orientations θ_j^i $i = 1 \dots N^2$ for the same cell j are accumulated and quantized into an M-bins histogram as presented in Figure 2(IV and V). In the final step, all the obtained histograms will be ordered and concatenated into a HOG histogram as a final output of the process of features extraction as depicted in Figure 2(VI). Figure 2 has provided an example of 4 pixels' cell size and 8 orientation bins for the cell histograms.

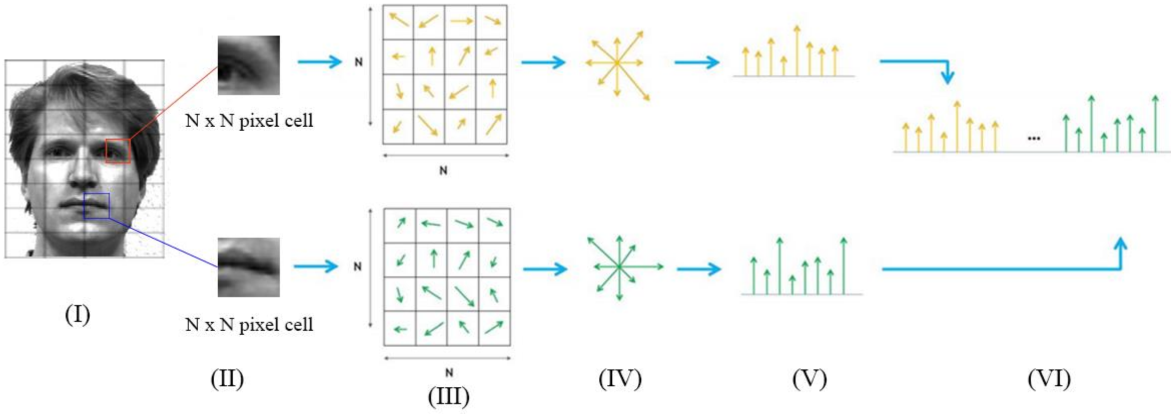

Figure 2. The HOG diagram

2.4. Classification: FLN algorithm

The fast learning network (FLN) is a novel double parallel forward artificial neural network proposed in [27]. The FLN algorithm is based on the methods of least squares. The diagram of the FLN is presented in Figure 3 and following that, a deep description of the FLN is provided.

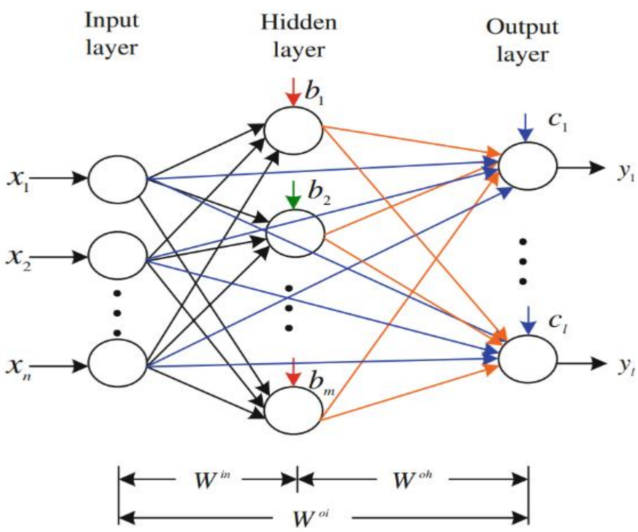

Figure 3. The FLN diagram

Suppose N is the arbitrary distinct samples $\{x_i, y_i\}$.

where:

- $x_i = [x_{i1}, x_{i2}, \dots, x_{in}]^T \in R^n$ is *ith* training sample with an *n* vector dimension; and
- $y_i = [y_{i1}, y_{i2}, \dots, y_{il}]^T \in R^l$ is the *ith* target vector with an *l* vector dimension.

The FLN algorithm has m neurons in the hidden layer. The $\mathbf{W}^{in}$ is a matrix of the input weights with $(m\times n)$ dimension which connects the neurons of the input and hidden layers. While $\mathbf{b}=[b_1, b_2, \ldots, b_m]^T$ is a matrix of the hidden neurons biases. $\mathbf{W}^{oh}$ is a matrix of weights with $(l\times m)$ dimension which connects the hidden and output layers. $\mathbf{W}^{oi}$ is a matrix of weights with $(l\times n)$ dimension which connects the neurons of the input and output layers. $\mathbf{c}=[c_1, c_2, \ldots c_l]^T$ is a matrix of the output biases neurons. The active functions of the output neurons and hidden neurons are $f(\cdot)$ and $g(\cdot)$, respectively. When the output biases neurons $\mathbf{c}=[c_1, c_2, \ldots c_l]^T$ are set equal to zeros, it will be ignored in the active function of the output neurons. Therefore, the mathematical model of the FLN algorithm is show as the following:

$$\begin{cases} y_{j1} = \sum_{r=1}^{n} W_{1r}^{oi} x_{jr} + \boldsymbol{c} + \sum_{k=1}^{m} W_{1k}^{oh} g\left(b_k + \sum_{t=1}^{n} W_{kt}^{in} x_{jt}\right) \\ y_{j2} = \sum_{r=1}^{n} W_{2r}^{oi} x_{jr} + \boldsymbol{c} + \sum_{k=1}^{m} W_{2k}^{oh} g\left(b_k + \sum_{t=1}^{n} W_{kt}^{in} x_{jt}\right) \\ \vdots \\ y_{jl} = \sum_{r=1}^{n} W_{lr}^{oi} x_{jr} + \boldsymbol{c} + \sum_{k=1}^{m} W_{lk}^{oh} g\left(b_k + \sum_{t=1}^{n} W_{kt}^{in} x_{jt}\right) \end{cases}, j = 1, 2, \cdots, N \tag{2}$$

as well as, it can be represented as shown in (3).

$$\mathbf{y}_j = f\left(\mathbf{W}^{oi}\mathbf{x}_j + \mathbf{c} + \sum_{k=1}^{m} \mathbf{W}_k^{oh} g\left(\mathbf{W}_k^{in}\mathbf{x}_j + b_k\right)\right), j = 1, 2, \cdots, N \tag{3}$$

where:

$\mathbf{W}^{oi} = \left[\mathrm{W}_1^{oi}, \mathrm{W}_2^{oi}, \ldots, \mathrm{W}_l^{oi}\right]$, it refers to the vector of weights that connecting the *jth* input neuron and the output neurons. $\mathbf{W}_k^{oh} = \left[W_{1k}^{oh}, W_{2k}^{oh}, \ldots, W_{lk}^{oh}\right]^T$, it refers to the vector of weights that connecting the *kth* hidden neuron and the output neurons. Also, $\mathbf{W}_k^{in} = \left[W_{k1}^{in}, W_{k2}^{in}, \ldots, W_{kn}^{in}\right]^T$, it refers to the vector of weights that connecting the *kth* hidden neuron and the input neurons. The output of the hidden layer neurons (**G**) are calculated as (4).

$$\boldsymbol{G}\left(\boldsymbol{W}_1^{in}, \cdots, \boldsymbol{W}_m^{in}, b_1, \cdots, b_m, \boldsymbol{x}_1, \cdots, \boldsymbol{x}_N\right) = \begin{bmatrix} g\left(\boldsymbol{W}_1^{in}\boldsymbol{x}_1 + b_1\right) & \cdots & g\left(\boldsymbol{W}_1^{in}\boldsymbol{x}_N + b_1\right) \\ \vdots & \ddots & \vdots \\ g\left(\boldsymbol{W}_m^{in}\boldsymbol{x}_1 + b_m\right) & \cdots & g\left(\boldsymbol{W}_m^{in}\boldsymbol{x}_N + b_m\right) \end{bmatrix}_{m\times N} \tag{4}$$

The matrix of the output weights $\widehat{\mathbf{W}} = [\mathrm{W}^{oi}\mathrm{W}^{oh}]$ can be determined via the inverse of the Moore–Penrose generalization as shown in (5).

$$\widehat{\mathbf{W}} = \mathbf{Y}\begin{bmatrix}\mathbf{X}\\ \mathbf{G}\end{bmatrix}^{+} = \mathbf{Y}\mathbf{H}^{+} \text{ where } \mathbf{H} = \begin{bmatrix}\mathbf{X}\\ \mathbf{G}\end{bmatrix} \tag{5}$$

The $\boldsymbol{W}^{oi}$ and $\boldsymbol{W}^{oh}$ are calculated as shown in (6).

$$\begin{aligned} \mathbf{W}^{oi} &= \widehat{\mathbf{W}}(1{:}\,l, 1{:}\,n) \\ \mathbf{W}^{oh} &= \widehat{\mathbf{W}}(1{:}\,l, n+1{:}\,(n+m)) \end{aligned} \tag{6}$$

Assume that the N is the given training set, $\mathrm{N} = \{(\mathbf{x}_i, \mathbf{y}_i) \mid \mathbf{x}_i \in R^n, \mathbf{y}_i \in R^l\}$, the $g(\cdot)$ is the activation function, and the m is the number of hidden layer neurons. Subsequently, the learning procedure of the FLN algorithm will be summarized as following steps: i) generate the matrixes of the input weights and biases ($\mathbf{W}^{in}$ and $\mathbf{b}$) randomly, ii) calculate the matrix of the hidden layer output by utilising (4), iii) compute the combination matrix ($\widehat{\mathbf{W}}$) by utilising (5), and iv) identify the parameters model of the FLN algorithm by utilising (6).

3. RESULTS AND DISCUSSION

Facial emotion detection based on human face images is considered the main objective of this proposed system. In this system, we have used Yale faces database as input data. The features of these images samples have extracted using the HOG technique. Subsequently, the FLN algorithm has been performed to classify the facial emotions images according to their proper subjects. There were 11 subjects have included in this system which are Centre Light (Cen. Lig.), Glasses (Gla.), Happy (Hap.), Left Light (Lef. Lig.), No Glasses (No Gla.), Normal (Nor.), Right Light (Rig. Lig.), Sad, Sleepy (Sle.), Surprised (Sur.), and Wink (Win.). The emotion database has divided into 80% training and 20% testing. In addition, the experiments of this proposed system have implemented based on a different number of hidden neurons of the FLN algorithm. In other words, the experiments have started when the number of hidden neurons was 100 and ended when the number of hidden neurons was 600 with the increment step of 50. Therefore, the total number of implemented experiments is 11 times. Besides, there were various of the evaluation measures have used to evaluate the performance of the proposed system in the detection of human facial emotions such as accuracy, precision, recall (i.e., sensitivity), F-measure, and G-mean, as shown in (7)-(11) [28]. The experiments of this proposed system have carried out by using MATLAB.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{8}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{9}$$

$$\text{F} - \text{measure} = \frac{2 \times Precision \times Recall}{Recall + Precision} \tag{10}$$

$$\text{G} - \text{Mean} = \sqrt[2]{\text{Specificity} \times \text{Recall}} \tag{11}$$

Where: true positif (TP) and true negative (TN) are denote to the true positive and the true negative, respectively. FP refers to the false positive and FN refers to the false negative. Table 2 shows the achieved result of the proposed system in the detection of human facial emotions. Based on the results of the experiments, the proposed system has achieved the highest results when the number of hidden neurons of the foundational literacy and numeracy (FLN) algorithm was 500. The highest achieved results of the accuracy and precision were 95.04% and 72.73%, respectively. Furthermore, the highest obtained results of recall, f-measure, and G-mean were all equal to 72.73%. However, the proposed system using the FLN algorithm has achieved the lowest obtained results when the number of hidden neurons was 100. In this case, the obtained accuracy was equal to 91.74%. While the obtained results of precision, recall, f-measure, and G-mean were all equal to 54.55%. In addition, the achieved results of the proposed system for each class of facial emotion expression are shown in Table 3. The proposed system using the FLN algorithm has obtained the highest results for happy, left light, and the right light, where the results of accuracy, precision, recall, f-measure, and G-mean for all these classes were all equal to 100.00%. In this regard, the results of the proposed system have shown encouraging results for the recognition of facial human emotions. Furthermore, the confusion matrix of the proposed system is alliterated in Table 4.

In order to evaluate our proposed system with other methods, we have compared the performance of the proposed system with the methods in [29]-[33] in terms of the detection accuracy for distinguishing the human facial emotion from images. These methods have proposed various techniques of machine learning algorithms and deep learning for facial emotion recognition by using images as input data. Besides, all these methods have used the Yale faces database for the purpose of training and testing their systems. The results have shown that the performance of the proposed system using the FLN algorithm has outperformed all methods in terms of accuracy in the domain of emotion recognition. Table 5 shows the comparison between methods.

Table 2. The achieved results of the proposed system

Hidden Neurons Number	TP	TN	FP	FN	Accuracy	Precision	Recall	F-measure	G-mean
100	18	315	15	15	91.74	54.55	54.55	54.55	54.55
150	23	320	10	10	94.49	69.70	69.70	69.70	69.70
200	22	319	11	11	93.94	66.67	66.67	66.67	66.67
250	23	320	10	10	94.49	69.70	69.70	69.70	69.70
300	21	318	12	12	93.39	63.64	63.64	63.64	63.64
350	20	317	13	13	92.84	60.61	60.61	60.61	60.61
400	22	319	11	11	93.94	66.67	66.67	66.67	66.67
450	21	318	12	12	93.39	63.64	63.64	63.64	63.64
500	24	321	9	9	95.04	72.73	72.73	72.73	72.73
550	22	319	11	11	93.94	66.67	66.67	66.67	66.67
600	21	318	12	12	93.39	63.64	63.64	63.64	63.64

Table 3. The achieved results of the proposed system for each class

Emotion Expression	TP	TN	FP	FN	Accuracy	Precision	Recall	F-measure	G-mean
Centre light	2	30	0	1	96.97	100.00	66.67	80.00	81.65
Glasses	3	26	4	0	87.88	42.86	100.00	60.00	65.47
Happy	3	30	0	0	100.00	100.00	100.00	100.00	100.00
Left light	3	30	0	0	100.00	100.00	100.00	100.00	100.00
No glasses	0	30	0	3	90.91	0	0	0	0
normal	1	30	0	2	93.94	100.00	33.33	50.00	57.74
Right light	3	30	0	0	100.00	100.00	100.00	100.00	100.00
sad	2	29	1	1	93.94	66.67	66.67	66.67	66.67
Sleepy	2	30	0	1	96.97	100.00	66.67	80.00	81.65
Surprised	2	30	0	1	96.97	100.00	66.67	80.00	81.65
Wink	3	26	4	0	87.88	42.86	100.00	60.00	65.47

Table 4. The confusion matrix of the proposed system

Actual	Predicted										
	Cen. Lig.	Gla.	Hap.	Lef. Lig.	No Gla.	Nor.	Rig. Lig.	Sad	Sle.	Sur.	Win.
Centre light	2	1	0	0	0	0	0	0	0	0	0
Glasses	0	3	0	0	0	0	0	0	0	0	0
Happy	0	0	3	0	0	0	0	0	0	0	0
Left light	0	0	0	3	0	0	0	0	0	0	0
No glasses	0	0	0	0	0	0	0	1	0	0	2
normal	0	1	0	0	0	1	0	0	0	0	1
Right light	0	0	0	0	0	0	3	0	0	0	0
sad	0	0	0	0	0	0	0	2	0	0	1
Sleepy	0	1	0	0	0	0	0	0	2	0	0
Surprised	0	1	0	0	0	0	0	0	0	2	0
Wink	0	0	0	0	0	0	0	0	0	0	3

Table 5. The comparison between methods

Methods	Accuracy
Our Method using FLN algorithm	95.04%
Li *et al*. [29]	90.3%
Cao *et al*. [30]	74.55%
Aly [31]	91.7%
Dandpat and Meher [32]	92.8%
Zhou *et al*. [33]	93.33%

4. CONCLUSION

Machine learning algorithms have played a vital role in systems of facial emotion recognition from images. These algorithms are considered as the main part in such systems. However, there is a need to investigate other algorithms of machine learning in the recognition of facial emotions. This paper has presented a system of facial emotions recognition from images. The samples of facial images have taken from Yale face database. In this proposed system, there were 11 expressions have used for human facial emotions which are centre light, glasses, happy, left light, no glasses, normal, right light, sad, sleepy, surprised, and wink. Furthermore, the HOG technique has used as feature extraction to extract the needed features from facial images. While the FLN algorithm has used as a classifier to identify the images of the facial emotions with respect to their subjects. Based on the experiments, the results of the proposed system have shown that the highest accuracy is reached to 95.04%. Besides, the highest result of precision, recall, e-measure, and G-mean were all equal to 72.73%, respectively. The performance of the proposed system has shown promising results in the recognition of facial emotions from images. In future work, we can use the FLN algorithm in a different database of facial emotions.

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