A FEATURE-BASED MODEL FOR FEAR DETECTION INSPIRED BY BIOLOGY

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Abstract

Facial expressions determine the inner emotional states of people. Different emotional states such as anger, fear, happiness, etc. can be recognized on people's faces. One of the most important emotional states is the state of fear because it is used to diagnose many diseases such as panic syndrome, post-traumatic stress disorder, etc. The face is one of the biometrics that has been proposed to detect fear because it contains small features that increase the recognition rate. In this paper, a biological model inspired an early biological model is proposed to extract effective features for optimal fear detection. This model is inspired by the model of the brain and nervous system involved with the human brain, so it shows a similar function compare to brain. In this model, four computational layers were used. In the first layer, the input images will be pyramidal in six scales from large to small. Then the whole pyramid entered the next layer and Gabor filter was applied for each image and the results entered the next layer. In the third layer, a later reduction in feature extraction is performed. In the last layer, normalization will be done on the images. Finally, the outputs of the model are given to the svm classifier to perform the recognition operation. Experiments will be performed on JAFFE database images. In the experimental results, it can be seen that the proposed model shows better performance compared to other competing models such as BEL and Naive Bayes model with recognition accuracy, precision and recall of 99.33%, 99.71% and 99.5%, respectively

Keywords: Fear Recognition; Early Biological model; Support Vector Machine; Facial Expressions.

Introduction

Excitement is the general and short reaction of the body organism to an unexpected situation, which is accompanied by a pleasant emotional state. In terms of the root of the word, emotion means the factor that moves the organism. Emotion refers to positive and negative feelings that arise in a person in certain situations. The word emotion refers to feelings and does not mean behaviors. For example, we get upset when we are treated unfairly. Emotions such as anger, fear, sadness, hatred, surprise, jealousy, envy, shame, etc. are all examples of emotions, but defining all these states is very difficult. These states form important parts of emotional life because they manifest in important mental situations [1]. By using the characteristic of emotional states, psychological and physiological disorders can be diagnosed. In fact, the outward part of these disorders is called the manifestation of excitement. Emotions are response patterns that consist of three behavioral, autonomous, and hormonal elements. In the behavioral element, there are muscle movements that are called in appropriate situations. The autonomic element facilitates behaviors and stores energy for movement, in which case the sympathetic nervous system increases and the parasympathetic decreases. As a result, the person's heart rate increases and the size of the blood vessels changes, and the blood circulation is diverted from the side of the digestive organs to the muscles. In the hormonal element, autonomic responses are enhanced. The hormones epinephrine and norepinephrine increase the blood flow to the muscles, which causes the food stored in the muscles to be converted into glucose. In addition, the adrenal glands secrete steroid hormones that make glucose available to the muscles [2].

The emotional state of fear is one of the most common mental disorders in every human being. Some fears are illogical, which causes a person's situations and activities to be disturbed in life. Some fears are dependent on the situation, that is, the person himself is aware of his fear, but he cannot control the fear, therefore, when facing that situation or the factors he is afraid of, he experiences panic and anxiety [3]. The amygdala (almond) is responsible for the physiological reactions of fear and anger, which is located in the temporal part and detects and responds to threatening events. In the early 20th century, researchers identified the hypothalamus as a key structure in the nervous system, and the hypothalamus responds to emotional feelings in the brain [4]. Researchers have acknowledged that when a person feels fear and anger, signals are exchanged between the amygdala and the hypothalamus [5]. All kinds of emotional states are important in a person's daily life because they play an important role in the treatment of diseases.

human fear [7]. Studies that have been reviewed so far have shown that the simultaneous activation of the amygdala and other parts of the brain such as the hypothalamus causes the feeling of fear in humans. To prove that there is a connection between the amygdala and the hypothalamus during fear, scientists conducted experiments among nine people. They placed electrodes in the amygdala and hypothalamus in these 9 people and showed them scenes from horror movies and observed that when a person feels fear, signals are exchanged between the amygdala and the hypothalamus. it will be As a result, at the time of fear, information is exchanged in the brain, amygdala and hypothalamus parts [8].

In their research, researchers from Datmouth College in New Hampshire have succeeded in identifying a region of the brain that is associated with the feeling of fear caused by uncertainty about the future. In this study, 61 students underwent an MRI scan after filling out a questionnaire related to their ability to tolerate possible negative events in the future. MRI images were analyzed and compared with future uncertainty tolerance scores. The author of this study emphasized that the results of our research show that there is a relationship between a person's ability to deal with this uncertainty and the volume of gray matter in a specific region of the brain [9]. The biological model in humans is related to the brain and in computers it is related to machine vision. One of the recently presented models is the biologically inspired model of BIM (Biologically Inspired Features Model). This model was designed in such a way that it can function like the human brain. The BIM model includes four computational layers S1, C1, S2, and C2. where S and C are complex cells in the visual cortex, respectively. The units in the S1 layer are easily matched to the cells of the visual cortex. These units combine the primary inputs using an ensemble of Gabor filters, each of which is the product of a Gaussian ellipse and a complex plane. Gabor filter works like the human eye. Therefore, this type of dense input leads to a heavy computational cost in S units, because each image will be interlaced with Gabor filters of different parameters [10]. C units are complex because they are themselves a pool of inputs obtained through a maximization operation. BIM is the emotional state of fear has two states, conscious and unconscious, and many researches have tried to identify it optimally. In most researches, the recognition rate of fear is lower than other emotional states. Perhaps the reason is that some fears occur unconsciously, which causes the recognition rate to be low, such as when a person suddenly feels fear upon seeing a snake [6].

There are warning states in humans such as anger and fear. These feelings differ in different people (adults and children) according to environmental and social states. Functional magnetic resonance imaging (fMRI) studies have shown that the amygdala plays an important role in a forward process, which combines reactions S1, C1, S2 and C2. But due to the lack of a feedback step, it blindly selects features to indicate which features are important. Therefore, a large number of prototypes must be sampled to match features, and as a result, the computational cost of matching is very heavy [11]. Cereri and his colleagues tried to bridge the gap between computer and neuroscience perspectives with the standard model they presented for object recognition in the real world [12].

The biological model, due to problems such as heavy computational cost in S units, due to not having a feedback stage and uninformed selection of features, caused C units to become complicated. As a result, the researchers expanded the basic BIM model to include five layers. The image layer was added to improve the basic model and increase the features and maintain the amount of information space in the S2 feature [13].

The BEL model is an emotional model of the brain that corresponds to the human limbic system. In the BEL model, the network learns while training the parameters that are needed to reach the solution, to calculate this using the reward of a cost function that is in the form of reinforcement [14-16]. BEL model, in engineering systems, can increase the degree of freedom, control capacity, reliability and stability. Also, the performance of the BEL controller on various nonlinear systems has shown stable and high compatibility.

In 2017, researchers conducted a study in which different emotional states of people's images were tested. None of the participants had mental or nervous problems. For each identity, photographs of faces were selected in all major emotional states, including happiness, sadness, anger, fear, and disgust, plus a neutral state [17]. Each trial consisted of a face covered by a 6×8 grid of white tiles, with one tile revealed randomly and an additional tile revealed completely randomly every second. Participants were instructed to click the stop button below the image as soon as they were able to make a decision about the facial expression. After each decision, participants received feedback on whether they answered correctly. Examining the types of ambiguities in each case was analyzed. The values of all individual tiles were given as input to PCA

and then the recognition process was performed. In this method, the accuracy of recognizing the emotional state of fear was 60% in men and 50% in women [17].
Sima et al presented a method based on convolutional neural network to show the effects of facial changes in people. They used a generative adversarial network to generate the main frame for identity recognition and expression of individual differences, and they also used CNN to extract emotion features [18].
Cambpell et al. tried to detect the fear state and face using GLM. They studied the act of detection on men and women and concluded that there is no difference in the detection of fear in the face in different genders [19].
Rinck et al investigated how face masks impair facial emotion recognition. They used facial expressions from the Radboud database and concluded in experiments that the mask interferes with the detection of disgust, fear, surprise, sadness and happiness [20].
Mellouk and et al. conducted a study on the recent works in the field of automatic recognition of emotions using faces through deep learning and by reviewing the recent works of researchers, they compared their works with each other[21].
Recently, emotion detection methods based on CNN, CNN-LSTM and 3D-CNN have been carried out, which have achieved an accuracy of more than 99%, but in fear detection.the accuracy is still not very high[22-24].
Humans and animals perform better than machines from a system point of view, and being able to simulate a system point of view that can recognize objects well has been one of the dreams of neuroscientists and computer engineers. There are different learning models for emotional state recognition, but in most models, the accuracy of fear recognition is lower than other models. In this article a biological model is used to increase the accuracy of fear identification. The biological model used in the proposed method is the EBIF model "Early Biologically Inspired Features". This model is an improvement of the basic biological BIM model. The reason for choosing this model is that because the nervous system involved with the human brain works very well, it is expected that any model inspired by the human brain model will also work well. Here, for the first time, a biological model has been used to extract the feature and recognize the emotional state of the face and then with the SVM, the emotion recognition is done. In this model, due to the use of the Gabor filter, which has good and multiple resolution properties in the space and frequency domain and is considered a powerful tool for texture analysis, it is expected to achieve good results of the recognition rate.
This article is organized in such a way that after the introduction, the proposed method is presented in the second part. In the third part, the results will be analyzed and in the fourth part, the conclusion will be expressed.

Proposed Model for Fear Recognition

One of the most important biometrics for recognition is the face, because this biometric contains small features that increase the recognition rate. There are different models to recognize the emotional state, but in most models, the accuracy of fear recognition is lower than other models, so this article deals with this issue, used the EBIF (Early Biologically Inspired Features) model for the recognition. In this article, the following model is used to improve fear recognition. The flowchart of the proposed method is shown in Figure (1).

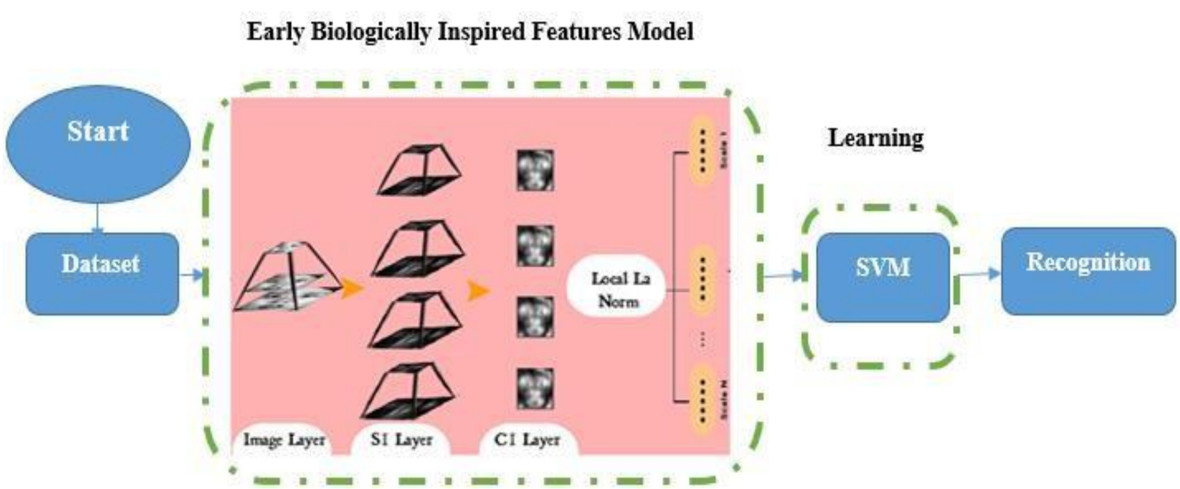

Fig. 1. Flowchart of the proposed method

In the proposed model, first the face images are called from the dataset, then they are scaled as a pyramid, and the images are entered into the S1 layer as a pyramid. Then the Gabor filter is applied to the pyramid images. The result entered in layer C1 is then reduced by Maxpooling in this layer so that two matrices of the same size are finally obtained because each layer is different from the higher layer in the pyramid. If both layers are selected in a row, the same matrices will be obtained and finally the average of the layers will be calculated. In the normalization stage, the brightness variance is obtained according to formula (5).

After extracting effective features by that model, classification will be done using SVM. Using this algorithm increases the efficiency and accuracy of the system. The evaluator in dividing the data is based on the k-fold method, where k=10 is considered. Below, the pseudo code and each step of the proposed model will be explained.

```
Inputs: Determine the training and test images
//EBIF model
while(stopping condition is not met) do
{Image Layer
S1 Layer
C1 Layer
Local L2 Norm}
end while
training SVM
Outputs: Determine the precision, accuracy and recall
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EBIF Model

The improved EBIF model is the BIM model, which is used here to extract features to increase the recognition rate of the emotional state of fear. This model includes four layers: Image Layer, S1 Layer, C1 Layer, Local L2- norm Layer, the tasks of each of which are described below.

Image Layer: In the image layer, first the images are converted to gray scale and then they are obtained as a pyramid in N scale (in this research, N=6) from large to small. Each scale of the upper image is a factor of √2 smaller than the current image. The pyramids are scaled from K to K+1 so that (k=1,2,...,N-1). In fact, the images become a pyramid in six scales after graying. Database images enter the S1 layer when they are created as K to K+1 scales.

S1 Layer: Gabor filter bank is used in layer S_1. Gabor filters are used to extract features from facial regions. The most important reason for using Gabor filters is their resistance to rotation and scaling. In addition, it also counteracts photometric disorders such as brightness, image noise, etc. [25-29]. If the Gabor filters are properly and accurately adjusted, they have a very good performance in detecting the features of the texture and the edge of the texture. Another important feature of Gabor filters is their high common separation degree. This means that their response is completely local and adjustable both in the field of place and in the field of frequency. Gabor filter with M orientation filters all parts of pyramid images. The convolution kernel of the Gabor filter is the product of a complex exponential and Gaussian function. The formula used in the Gabor filter in the proposed model is given below.

$$G(x,y) = \exp\left(-\frac{X^2+\gamma^2 Y^2}{2\sigma^2}\right) COS\left(\frac{2\pi}{\lambda}X\right) \qquad (1)$$

Where X=x cosϴ+y sinϴ and Y=-xsinϴ+ycosϴ. So that ϴ controls the orientations of the filter. The filter bank contains M orientations, where M=9. The orientations are equally distributed in the range $[0,\pi)$. The size of each filter is 5x5 and x and y are variable between 2 and -2. The parameters of aspect ratio, effective width and wavelength are set to 1, 3 and 5 respectively. Equation (2) shows the response of the Gabor filter to an image.

$$R = G \times I \qquad (2)$$

Gabor filter responses can localize the object and distinguish its structure with different orientations [29].

C1 Layer: From The C1 layer functions according to the complex cells of the visual cortex. In this part, the Gabor pyramid is divided equally according to a specific direction and the sub-pyramids are set. At the bottom, the size of the pyramids is 4x4 and at the top, the size is 3x3, which is in accordance with the basic BIM model. In this layer, dimension reduction is done by Max Pooling. In fact, a pyramid combination is used, and the mean and standard deviation are used instead of the highest response to display each sub-pyramid. The advantage of using the C1 layer is that each element in this layer is obtained by combining the response of the local Gabor filter which is based on edge detection and quantitative position and tolerable scale on the neighboring position and different orientations.

A)Dimension reduction by Pooling

The function of Pooling is to reduce the dimensions in depth. In this way, the spatial size (width and height) of the image is reduced in order to reduce the number of parameters and calculations inside the network. The Pooling layer operates independently on each depth slice of the input mass and spatially resizes it using the Max operation. The most common way to use this layer is to use this layer with 2 x 2 filters with step 2 (S=2), which reduces each depth cut in the input by removing two elements from the width and two elements from the height and causes Removing 75% of the values in it becomes a deep cut. Each Max operation here obtains the maximum between 4 numbers (a 2x2 region in the depth slice). In general, the Pooling layer receives a mass of size W1×H1×D1 as input. where W indicates width, H indicates height and D indicates its depth. Pooling requires two meta parameters: - The size of spatial extent (size (x and y filters) perceptual area) F - step size or S Then it produces an output mass with the size of 2 × H2 × D2, which:

$$W2 = \frac{W1 - F + 2P}{S} + 1 \tag{3}$$

$$H2 = \frac{H1 - F + 2P}{S} + 1 \tag{4}$$

The above relations show that both width and height are calculated equally symmetrically. Max Pooling also performs Noise Suppressant. Max Pooling works very well due to faster convergence and better generalization and selection of optimal features [30].

Local Normal Layer L2: In the L2 local normal layer, the variance of brightness, which is a very important feature for face recognition, is calculated. To have a powerful EBIF model against light changes, it must be normalized first. The feature dimensions of vector f are calculated from each location of layer C1 with L2-norm as follows.

$$\tilde{f} = \frac{f}{\sqrt{||f||^2 + \xi}} \tag{5}$$

Here ξ is a constant. The vector features are normalized in different positions of the C1 layer of the subsets feature form for the response of scale k objects. All N-1s are subsets of multi-scale features that contain edge information and local normalized multi-orientation that are quantitatively position and scale-tolerant of the final EBIF feature response.

Illustrations or pictures: All halftone illustrations or pictures can be black and white and/or colored. Supply the best quality illustrations or pictures possible.

Support Vector Machine (SVM) Category

Support vector machine (SVM) is a classification algorithm that is considered one of the best classification techniques. The primary basis of the SVM classifier is the linear classification of data, in which, in the linear division of the data, an attempt is made to select a line that has a higher confidence margin. Various kernel functions can be used in svm, including exponential, polynomial and sigmoid kernels. The choice of non-linear kernels allows us to construct linear separators in the feature space if they are non-linear in the original space. They are also very good at solving computational problems that have many dimensions. In addition, it enables the use of infinite dimensions and is efficient in terms of time and memory [31]. In this article, the polynomial kernel that obtained the best result in svm is used, and its equation is given below.

$$k(x_i, x_j) = (1 + x_i^T x_j)^d \tag{6}$$

where x is the training data and d is the degree of the function for the polynomial kernel.

Discussion and Results

The proposed model is simulated in the MATLAB 2021 software environment. The simulation part is divided into two parts, the first part is the simulation of the proposed model and training, and the second part is the test and comparison of the proposed model with Naive Bayes and BEL categories.

Dataset

In this article, JAFFE (Japanese) authentic dataset is used which contains 213, 256×256 pixel images of Japanese women's facial expressions. This dataset contains images of ten Japanese women who showed different emotions, including six emotional states: angry, disgust, happy, sad, fear, surprise, and a normal state. In this experiment, first, 200 images are selected from the JAFFE dataset, and then the features of the face are extracted from the images by the proposed model and the classification process is performed and it has been tried to distinguish fear from different states with high accuracy. Figure (2) shows an example of some used dataset images.

Fig. 2. An example of some dataset images

1-1- Obtained Results

The results of accuracy, precision and recall with SVM method are obtained using the following formula:

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (7)$$

$$\text{Accuracy} = \frac{True\ Positive + True\ Negative}{All\ test\ sample} \quad (8)$$

Recall (9)

Where Fn is unrecalled related images, Tp recalled related images, Tn unrecalled unrelated images and Fp recalled unrelated images.

To train and validate the proposed model k-fold and k=10 have been used. In this type of partitioning, the data is divided into k-1 training sets and 1 testing set. In this type of validation, the data is divided into K subsets. From these K subsets, each time one is used for validation and another K-1 is used for training. This procedure is repeated K times and all data are used exactly once for training and once for validation. The figure below shows the ROC chart, based on the proposed model, Naive Bayes and BEL.
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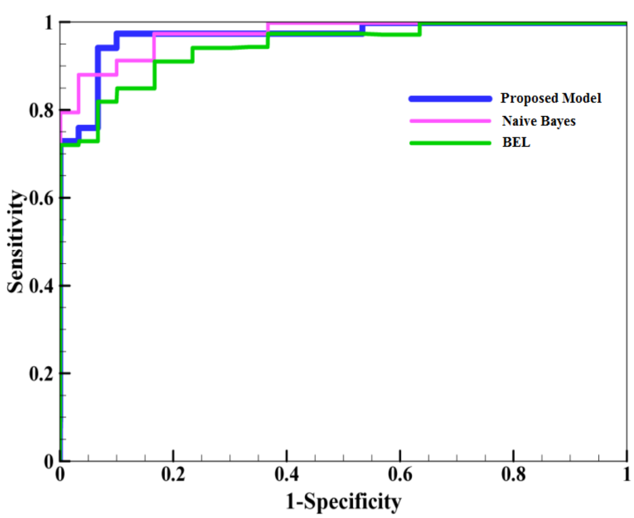

Fig. 3. ROC diagram for three methods

As shown in Figure (3), classification with the proposed model and based on SVM works better than other methods. Figure (4) shows the accuracy of the proposed method using the number of different images and EBIF features, compared to Naive Bayes and BEL methods with the same features.

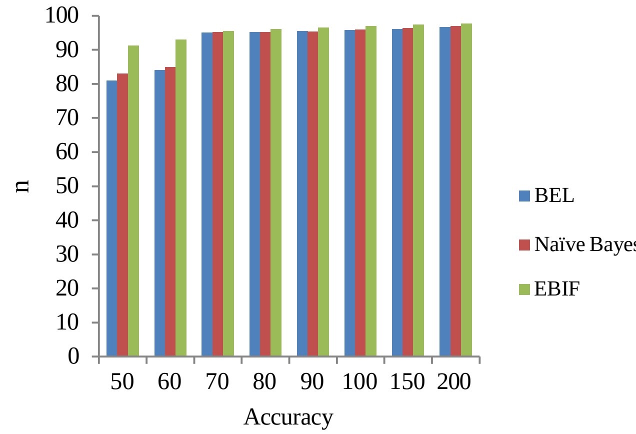

Fig.4. accuracy chart of the proposed method using the number of different images

As can be seen, the proposed model has shown better accuracy in each step. In Table (1), the proposed model was compared with the results of previous researches that used Naive Bayes and BEL classification using Gaussian distribution, mean, variance and PCA features, and the results are given below [11 and 32].

Table 1: comparing the accuracy of the proposed model with two competing models

model	Naive Bayes	BEL	EBIF
Accuracy	77.09	96.57	99.33
Precision	81.00	96.1	99.71
Recall	79.30	95.9	99.5

As can be seen, the proposed model is in the first place with 98.32% accuracy, the BEL model is in the second place with 96.57% accuracy, and the Naive Bayes model is in the third place with 77.09% accuracy. The accuracy of the proposed method when detecting anger, happiness and surprise has also been compared and its results are shown in Table (2).

Table 2: comparing the accuracy of the proposed model with two competing models in different states

State	Naive Bayes	BEL	EBIF
angry	59.27	98.2	99.1
happiness	81.16	92.16	99.2
surprise	68.15	96.5	99.03

As can be seen, the proposed model performs better than the competing models in other facial states. In anger mode, the proposed model has performed better with 99.1% accuracy compared to BEL and Naïve Bayes models, which are 98.25% and 59.27% accuracies, respectively. Also, in the state of happiness, the proposed model has performed better with an accuracy of 99.2% compared to the BEL and Naïve Bayes models, which are 92.16% and 81.16%, respectively. In addition, it can be seen that, in surprise state, the proposed model has performed better with 99.03% accuracy compared to BEL and Naïve Bayes models.
The precision of the proposed model when detecting anger, happiness and surprise has also been compared and the results are shown in Table (3).

Table 3: comparing the precision of the proposed model with two competing models in different states

State	Naive Bayes	BEL	EBIF
angry	57.3	97.1	98.7
happiness	83.7	94.2	99.1
surprise	69.04	95.7	98.2

As can be seen in table (3), the proposed model has shown better precision in all states. The recall of the proposed model when detecting anger, happiness and surprise are shown in Table (4).

Table 4: comparing the recall of the proposed model with two competing models in different states

State	Naive Bayes	BEL	EBIF
angry	54.1	94.9	98.1
happiness	81.2	91.1	98.9
surprise	65.3	94.2	98.4

As can be seen in table (4), the proposed model has shown better recall in all states.
The obtained results in the above tables show that the proposed model has performed better in all evaluation criteria compared to the other two methods.

Conclusions

In this article, the recognition of the emotional state of fear was discussed. The high accuracy of recognizing the emotional state of fear helps doctors in the treatment of many diseases, including schizophrenia, phobia, etc. Here, the early biological model was used for the first time to identify the emotional state of fear, which was observed to perform the recognition process with high accuracy. Four computational layers were used in the proposed model. In the first layer, the input images were pyramided in six scales from large to small. Then the whole pyramid was entered into the next layer and the Gabor filter was applied to each image and the result was given to the next layer. In the third layer, dimension reduction was done in feature extraction. In the last layer, normalization was done on the images and finally the results were entered into the SVM category because the use of this category increases efficiency.
The proposed method was applied on the JAFFE dataset to test the accuracy of the proposed method. The results of the proposed model showed that the accuracy of recognizing the emotional state of fear is 99.33%. Also, in order to evaluate, the proposed method was compared with two models, BEL and Naive Bayes, and by analyzing the information output, it was concluded that the proposed model has a higher identification accuracy and the BEL method performs better in the second place.

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