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Facial Emotion Recognition Using Convolutional Brain Emotional Learning (CBEL) Model

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ABSTRACT

Facial expression is considered one of the most important ways of communication and human response to its environment. Recognition of facial emotional expression is used in many research fields, such as psychological studies, robotics, identity recognition, disease diagnosis, etc. This paper, due to the importance of recognition of facial emotional expression, presents a new and efficient method based on learning and recognition of facial emotional expression, which is a combination of the limbic system of the human brain and the convolutional neural network. In the proposed model, first, the facial emotional expression images are normalized, and after reducing the dimensions of implicit features, proper and practical features are classified using the convolutional brain emotional learning (CBEL) model, and facial emotional expressions are recognized. Moreover, the performance of the proposed model is compared with BEL, CNN, SVM, MLP, and KNN models. After examining the results, it is concluded that the accuracy of facial emotional expression recognition rate is higher in the CBEL learning model.

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1. Introduction

Emotion is a mental and physiological state including much behavior, actions, thoughts, and feelings. Emotional expressions play an important role in human cognition, therefore, cognitive science, neuroscience, and social psychology studies are necessary [1]. Also facial expressions play a significant role in human communication [2]. Therefore, understanding models of facial emotional expressions is essential for the progress of many scientific fields [3]. The first reason for machine learning and computational investigations is to provide computational models to understand facial expressions, which are useful for cognitive science studies [4]. In addition, computational models of facial expressions are important for developing artificial intelligence and are essential in Human-Computer Interaction (HCI) systems [5]. Martinez and Du (2011) provided a computational model of human understanding of facial emotional expression, which is a review of cognitive science. The model can be useful in studies of visual perception, social interactions, and disorders such as schizophrenia and autism. According to the dimensions of the computational space in this model, humans mostly in this part use shapes to understand and recognize facial expressions and configuration features [6]. The vertical distance between the eyebrows and the mouth can be one of the configuration features, as a constant non-rotating discrete modeling between the facial components. This area, to overcome recent problems in face recognition algorithms (including recognition and expressions), should move towards shape-based modeling. According to this model, the main concern of designing computer systems and machine learning systems is the accurate detection of features and classification [7].

The human face is an amazing piece of engineering. There are many muscles under the skin that allow many configurations. Facial muscles can be considered as Action units (AU) that define the positions of facial expressions [8]. These facial muscles are connected to the cortex neural network through the medulla oblongata. The upper muscles are connected on both sides, while the lower muscles are connected to the opposite hemisphere on one side. Through proper training, a person can learn to move most of these muscles independently. Otherwise, the facial expressions are a predefined configuration. Learning emotional expressions is controversial because it seems that they are innate. Moreover, class understanding of emotion is considered. There is a definite set of predefined classes of expressions, including happiness, sadness, anger, surprise, fear, and disgust, and this is known as the classification model [9]. In addition, according to neuroscience studies, separate paths in the brain are used to detect different emotional expressions [10]. The continuous model is another way for the categorical model [11]. In this model, each expression is an analytical feature in multidimensional space with some common features for all emotional s expressions. Russell's two-dimensional circular complex model is of this category, whose basic criteria are pleasure-displeasure and secondary arousal [12]. Explicit feature extraction is suggested to avoid the complicated process, manipulation of low-level data is suggested in traditional facial expression recognition and the use of fast R-CNN to recognize facial expressions [13]. Trainable convolution kernel and max-pooling are extracted in order to extract implicit features and to reduce the dimension of implicit features, respectively [14]. In [15], an efficient method to reduce feature redundancy was presented by a convolutional neural network (FRR-CNN). In contrast with the traditional Convolutional neural network

(CNN), the divergent FRR-CNN convolutional kernel is more compact due to the more discriminative differences between feature maps at the same level, and as a result fewer redundant features, and more compact images representation. In addition, the invariant pool strategy is used to extract cross-transform features. In [16], a gesture-based Bayesian hierarchical model was presented to solve the challenging problem of multi-user facial expression recognition. The model was a combination of local appearance features, general geometric information, and average learning before recognition. As a result of sharing a set of functions with different situations, and bypassing individual training and parameter setting from each situation, a single solution was created for multi-functional facial expression recognition. Therefore, it can be extended to a large number of expressions. Although the performance of the CNN algorithm has been very successful in recognizing facial expressions, there are still problems such as long training time and low recognition rate in complex backgrounds.

In order to avoid the complex process of explicit feature extraction in the traditional recognition of facial expressions, this paper proposes a suitable cognitive science method to recognize facial expressions based on the CNN model, image edge detection, and the BEL model. The main sections of the article are organized as follows: section 2 relates to literature review, section 3 is the definition of the BEL cognitive science model. Section 4 of the proposed model is fully explained. Sections 5 and 6 are related to the analysis of experimental results and conclusions, respectively.

2. Literature review

The identification of facial expressions began radically in the 19th century. Then, in 1971, Friesen and Ekman identified six distinct emotional categories, each of which was characterized by a special facial expression. These six categories: happiness, discomfort, anger, surprise, fear and hatred, are shared among all human beings of any nationality and are called basic excitement [17]. Although facial expression analysis was initially conducted only in the field of psychology, in 1978, Ekman and his colleagues conducted preliminary research on automating facial expression recognition in a sequence of images. As a result of their research, a new system was known as face movement coding system. In 2012, Manal Abdullah et al. presented an improved method for detecting digital facial images using PCA. In this method, images were decomposed into small sets of special features or faces. At the beginning of the work, the set of educational images are made to compare the results. The image of the entry face is preprocessed and compared with the training data set. The highest conformity with the images of multiple faces identified the person's face. It requires a lot of time. In this method, 35% of the time compared to PCA has been reduced and the accuracy of diagnosis has been high [18]. In 2013, Murtaza and his colleagues called automatic facial expression recognition one of the most emphasized issues in security systems, authentication or authentication such as criminology. Facial expressions not only show emotions, but can also be used to judge mental views and psychiatric aspects. This study was based on a complete study of different facial expressions diagnosis. Considering that the human face has changes in different situations and conditions, it has evaluated the combined methods in four models of feature extraction method: evaluation based on facial movements, evaluation of facial expressions model, assessment based on muscle facial expressions [19]. In 2015, Kumari and his group stated that the facial expression system has many applications and is not limited to understanding human behavior, revealing mental disorders and expressing human structure. Two famous methods in this field for face expression recognition automated systems are based on geometry and appearance. Emotional states of the face are divided into six categories: anger (combination of lower eyebrows, upper eyelid rise, narrowing of eyelids, narrowing of lips), hate (combination of nasal folds, lower lip corner, bottom Upper lip coming), fear (combination of eyebrow raising, upper lip rise, narrowing of eyelids, loosening of lips, jaw drop), happiness (combination of chin elevation, lip corner retracement), discomfort (combination from eyebrow raising, retracing of the lip corner, surprise (combination of eyebrow rise, upper eyelid rise, jaw drop [20]. Ekman et al. defined seven expressions (anger, fear, happiness, sad, contempt, disgust, and surprise) and study on face emotion identification base on machine learning models [21,22]. Martin compared 6 CNN studies of depths 5 to 11 against VGG, Inception, ResNet and an ensemble [23]. Zhang discussed a few deep belief networks and CNNs [24]. Ko describes a number of long short term memory CNN approaches [25].

3. Brain emotional learning (BEL) model

Since the human brain is the core of neuroscience, the models inspired by it are also assumed to be efficient. On the other hand, many models inspired by the limbic system have been proposed for emotion speech recognition. According to studies, the most comprehensive and most practical of them for emotional speech recognition, the BEL model, consists of four main parts: the Thalamus, Sensory Cortex, Amygdala, and Orbitofrontal, each of which is responsible for performing a series of tasks. The thalamus, for example, is responsible for receiving input and sending it to the sensory cortex and amygdala. The sensory cortex preprocesses and analyzes the received signals. The amygdala learns to anticipate and respond to a particular amplifier. It is also responsible for emotional learning. The orbitofrontal system learns to control the output of the system against non-compliance. Noncompliance means calculating between predicting the base system and receiving the actual amplifiers [18–20]. Fig 1. refers to the BEL model components.

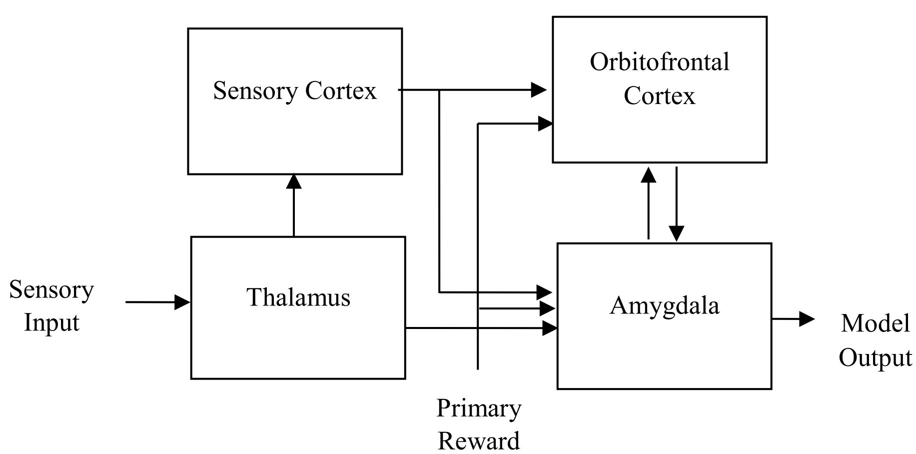

Fig. 1. The BEL model inspired by limbic system [20].

According to Fig 1, the input vector enters the thalamus. The thalamus should calculate the maximum stimulus, which is done by applying the max operator to all feature vectors. All stimuli, along with the most stimulus, enter the sensory cortex, and after simultaneous normalization, enter the amygdala and orbitofrontal. In the amygdala and orbitofrontal, there is an MLP network, which learns the weights of vectors.

Since a strong method for extracting features has not been specified in the sub-sections of the thalamus and sensory cortex of the BEL model, in this article convolutional neural network has been used in the sub-sections of the thalamus and the sensory cortex of the BEL model. The reason for using the convolutional neural network in the sub-sections of the thalamus and sensory cortex of the BEL model is that it displays better and more accurate results in the output, and by having a pooling layer, it preserves useful information and reduces the amount of data processing. Therefore, it is suitable for large datasets. But due to the many calculations that exist in the maxplool layer and the fully connected layer of convolutional neural networks, the combination of convolutional neural networks and the BEL model is used in the proposed model. That is, the output of the Pooling layers in the convolutional neural network is sent to the MLP networks in the amygdala and orbitofrontal from the BEL model. In the following, the sub-sections of the CBEL model are fully explained.

4. Convolutional brain emotional learning (CBEL) model

The input of the proposed model, CBEL, is the normalized images of different facial emotional expressions, next, using the convolutional neural network, the facial features are extracted, and then, the facial salient features are given to the BEL classification model to recognize the facial expressions. The reason for selecting the BEL model is that this model is inspired by the biological limbic system of the human brain. Of course, some changes have been made in this model, and the convolutional neural network has been used in the thalamus. One of the advantages of the convolutional neural network is the ability to adjust the network to achieve better and more accurate results. The better this network is adjusted and fed with a sufficient amount of data, it can provide better results compared to machine learning algorithms. Moreover, each neuron is not connected to all neurons in the previous layer, but only to a small number of neurons. Finally, it can be mentioned that the Pooling layer can reduce the amount of data processing by keeping useful data, and it is suitable for large datasets. Although Convolutional Neural Networks have many advantages, they are significantly slower due to a large number of calculations in the maxpool and the Fully Connected layers. To this end, in the proposed CBEL model, and to solve this problem, the output of the Pooling layers can be sent to the MLP networks in the amygdala and orbitofrontal, in the BEL model. The steps of the proposed model are such that, in the convolutional neural network, convolutional layers C1, C2, and C3 use 32, 64, and 128 convolutional kernels, respectively, for the convolution. The size of the convolutional kernels used in each convolution layer is 5×5, and the size of the sampling window used in the S1 and S2 layers is 2×2. The features extracted from the S2 layer will be obtained using a feature selection method to select the most distinctive features. We use a Correlation-Based Feature Selection (CFS) method in the thalamus, which selects distinctive features [21]. CFS evaluates the subset of features and selects only those features with the output class label that have a high correlation. The classification algorithm on these features increases the evaluation accuracy. The architecture of the proposed model is shown in Fig 2, and the explanation of each part and step is given below, respectively:

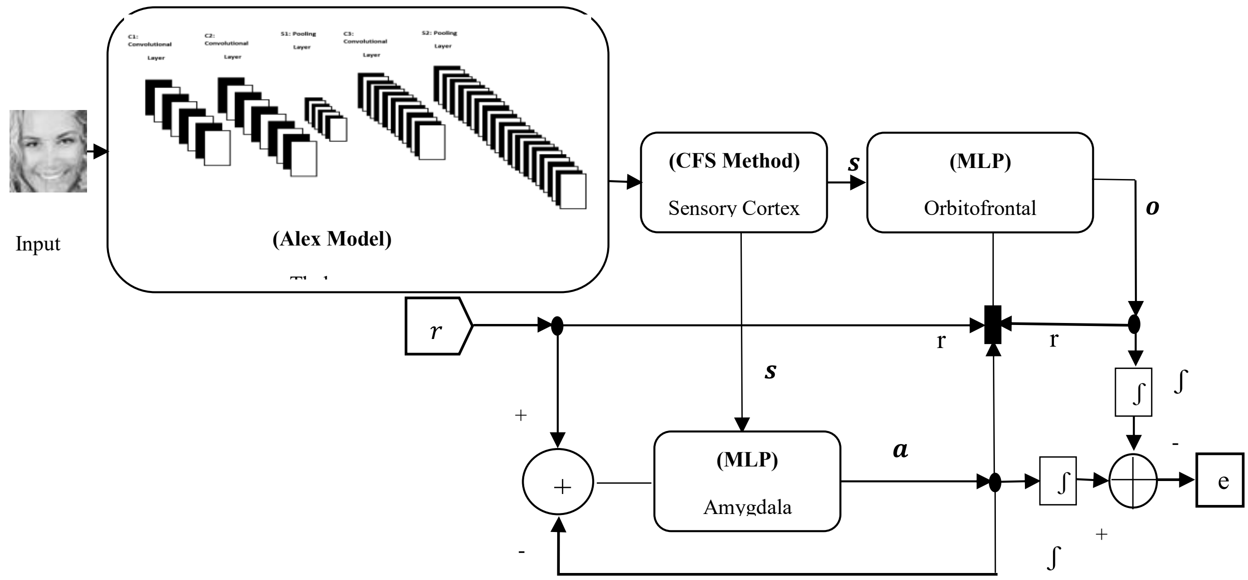

Fig. 2. CBEL Model.

4.1. The input of the BEL model in the thalamus

All input signals in the first layer are pre-processed and resized to sizes 277 × 227 × 3 to be compatible with the size of the speech signal in the input layer. In this section, the AlexNet model is used and this model includes five convolutional layers: Conv1, Conv2, Conv3, Conv4 and Conv5. The ReLU activation function is used to adapt to the training process at the output of each convolutional layer. In our proposed model, we use the properties extracted from the convolutional layer (Conv4) followed by the Correlation-Based Feature Selection (CFS) method to select the most distinctive features [22].

The CFS evaluates a subset of features and selects only distinctive features that are highly correlated with a class instance [22]. CFS rankings are features that will be calculated using a heuristic evaluation function, based on correlation and discards irrelevant features that are less relevant to the class label. The CFS is calculated using Eq. (1):

$$CFS = \max\left[r_c f_1 + r_c f_2 + .. + r_c f_k \,/\, \sqrt{k + 2\,(rf_1 f_2 + .. + rf_i f_j + .. + rf_k f_{k-1})}\right] \quad (1)$$

Where $r_c f_i$ is the feature classification correlation, k is the number of features, and $rf_i f_j$ is the correlation between the features. The obtained features are sent in parallel to the amygdala and orbitofrontal sub-sections of the proposed model; and in sub-sections of the amygdala and orbitofrontal, will apply to all obtained MLP network features to classify the features. The advantage of these networks is that they work well for inputs through matrix structure (2-D and 3-D). The MLP network changes the structure of the input data, converting a 100 x 100 2-D matrix to a 10,000 dimensions vector. In the following, the details of the feature classification calculations are fully explained in sub-sections of the amygdala and orbitofrontal.

4.2. Brain emotional learning (BEL) model

The vector obtained from the feature selection from the previous step (s) enters the amygdala and the orbitofrontal simultaneously. There is a node a for each stimulus s, in the amygdala network model [26–28]. There is also a weight plastic connection of v_i to s_i. The output of each node is obtained by multiplying each input by weight v through Eq. (2) [23].

$$a = s.v \tag{2}$$

In Eq. (3), the e_a is the output vector of the amygdala node, and the sum of the output is a simple sum of its elements:

$$e_a = \sum_i a(i) \tag{3}$$

To adjust the variable v_i, the difference between nodes a and the amplification signal r is calculated (Eq. (4)) [23]:

$$\Delta v = diag(y.\max(r - e_a, 0).s) \tag{4}$$

In Eq. (4), the max operator results in uniform learning between the input stimuli, and the information formed in the learning weights. The amygdala outlets go to the inputs of the orbitofrontal cortex. Weight v can not be reduced, because after training the emotional response, the result of the training must be constant, which is manipulated by the orbitofrontal and at the appropriate response time. The behavior of node o is a behavior similar to Eq. (2) with weight w, and is calculated by Eq. (5). Moreover, the sum output of all output nodes from the orbitofrontal is obtained by Eq. (6) [23]:

$$o = w.s \tag{5}$$

$$e_o = \sum_j o(j) \tag{6}$$

The connection of weights w has been updated in proportion to the sensor inputs, and the internal amplification signal r_0. In Eq. (7), β is the orbitofrontal learning rate and r_0 is the input amplification signal of the orbitofrontal cortex. The exact value of $r_0$is calculated in Eq. (8):

$$\Delta w = diag(\beta.r_0.s) \tag{7}$$

$$r_0 = \begin{cases} \max(e_a - r, 0) - e_o & if\ r \neq 0 \\ \max(e_a - e_o, 0) & Otherwise \end{cases} \tag{8}$$

According to Eq. (8), r_0 is the internal reward, and r is the input amplification signal. In the training phase, if $r \neq 0$ then $\max(e_a - r.0) - e_o$is used to calculate the internal reward, otherwise $\max(e_a - e_o.0)$ is used. The learning rules of the amygdala and orbitofrontal are very similar, except that the weight of the orbitofrontal w changes while increasing and decreasing and acts as an inhibition. The final output e is obtained by Eq. (9) by subtracting the outputs of node a and node o [23].

$$e = e_a - e_o \tag{9}$$

5. Analyzing experiments results

All experiments in this part have been applied to the FER-2013 emotional facial expressions database [24]. The images of seven emotional expressions of anger, disgust, fear, happiness, sadness, surprise, and neutral are stored in this database. The FER-2013 emotional facial expressions database contains 28,709 training images and 7,178 experiment images, and all images are gray and 48 × 48 in dimensions [29,30]. Most of the images are centered, so no special pre-processing is required. Therefore, all images are entered into the CBEL model for reading, feature extraction, and finally, classification. Table 1 shows the list of abbreviations of expressions.

Table 1
List of abbreviations of states.

1	Anger	An
2	Disgust	Di
3	Fear	Fe
4	Happiness	Ha
5	Sadness	Sa
6	Surprise	Su
7	Neutral	Ne

Table 2 shows the recognition rate of emotional expressions from five classifications using SVM, KNN, MLP, BEL, and CBEL models on the FER-2013 dataset.

Table 2
Results obtained from f classifications using KNN, SVM, MLP, BEL and CBEL models without using feature selection.

Method	CBEL	BEL	MLP	SVM	KNN
Rate of Recognition	91.22 ± 2.24	88.10 ± 1.03	85.10 ± 1.22	86.90 ±1.25	83.01 ± 1.06

According to examining Table 2, the highest recognition rate is related to the recognition of facial emotional expressions, using the CBEL model, and the recognition rate of 91.22 ± 2.24. Furthermore, the lowest recognition rate is related to MLP.

In the following, Table 3 shows the obtained results from feature extraction, and then feature selection using permutation, and after that, applying different classifications to classify facial emotional expressions.

Table 3
Results obtained from five classifications using KNN, SVM, MLP, BEL and CBEL models using feature selection.

Dataset	CBEL	BEL	MLP	SVM	KNN
FER-2013	94.32 ± 1.04	90.33 ± 1.07	85.22 ± 1.45	88.70 ±1.08	85.10 ± 2.01

Examining the results of Table 3 shows that BEL and CBEL cognitive science models have high performance.

Examining Tables 2 and 3 show that the recognition rate of the SVM learning model is better than MLP and KNN. In addition, the examination results of these two tables concluded that selecting the feature increases the recognition accuracy and also the recognition rate. According to Fig 3., the evaluation in this paper is done for the number of features k=5 to k=15, and the final accuracy of the system is obtained from the average of all steps.

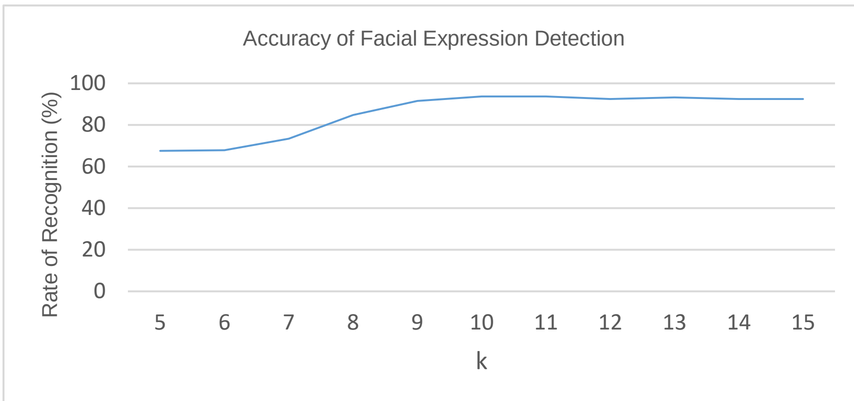

Fig. 3. Evaluation of the proposed system for k=5 to k=15.

Moreover, the accuracy analysis of the recognition of facial expressions from single emotion classes, using the CBEL Confusion Matrix model of seven facial expressions, is presented in Table 4.

Table 4
Confusion matrix for recognizing facial emotional states using the CBEL model.

CBEL model	An	Di	Fe	Ha	Sa	Su
An	95	1.7	0.3	2.3	0	0.5
Di	0	98	0.3	0.3	1.4	0
Fe	0.3	0	84.7	5.7	7	2.3
Ha	3.1	2.6	1.7	88.6	2.3	1.7
Sa	0.3	0	2.7	0	92	5
Su	1.7	0	6	2.3	0	90

According to the results of Table 4, the highest recognition rate is related to disgust, and after that, the highest recognition rate of facial emotional expression is related to anger. On the other hand, the lowest recognition rate of facial emotional expression is related to fear.

6. Conclusions and suggestions

Emotion is a mental and physiological state that includes many behaviors, actions, thoughts and feelings. Emotional state plays an important role in human diagnosis and therefore, it is necessary in studies of cognitive science, neurology and social psychology. The first reason for machine learning and computational studies is the creation of computational models of understanding facial expressions that help studies in cognitive sciences. This article introduces the CBEL cognitive science model to recognize facial emotional expressions on the FER-2013 dataset. Our main purpose is to provide a cognitive science model inspired by a similar function of the human brain, which works as well as, or even better than machine learning models. So, the BEL cognitive science model inspired by the limbic system of the brain has been used to recognize facial emotional expressions. However, the reason for changing the BEL model in the thalamus is the need for a strong method to extract the features of emotional images. To this end, the CNN is used in this part. In order to increase the processing speed, changes have been made in the pooling layer of this neural network. Finally, in order to more accurately classify each basic emotional state, the output of the pooling layers from the CNN neural network has been sent to the MLP networks in the amygdala and orbitofrontal in the CBEL model. Moreover, the CRF feature selection technique has been used in order to increase the accuracy of facial expression recognition, select effective features and remove additional features. One of the advantages of the proposed model is that this model is inspired by the biological system of the brain, and also, the method of selecting effective features in this model, and reducing the number of ineffective features, has increased the processing speed and recognition accuracy. Examining the results of the experiments shows that the recognition rate in identifying the seven emotional expressions of anger, disgust, fear, happiness, sadness, surprise, and normal from the proposed CBEL model is at the highest accuracy and is equal to 94.32 ± 1.04 %, and the performance of this model is better than MLP, KNN, and SVM. Therefore, it can be concluded that the CBEL cognitive classification model has a higher rate of recognizing facial emotional expressions than machine learning models.

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