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Facial Emotional State Recognition Inspired by the Human Brain

A. Kulkarni [1], N. Rajput [2,*]

[1] Department of Computer Science and Automation, Indian Institute of Science (IISc), Bengaluru, India
[2] Department of Electronics and Communication Engineering, National Institute of Technology Tiruchirappalli (NIT Trichy), Tiruchirappalli, India

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ABSTRACT

Facial emotional expressions play a fundamental role in conveying intentions and enhancing the quality of human communication. With the rapid advancement of facial recognition technologies and the increasing importance of emotion recognition, this study investigates facial emotional expression recognition using a Brain Emotional Learning (BEL) model. The Brain Emotional Learning model is inspired by the human brain's limbic system, which is responsible for processing emotional stimuli. The primary objective of this study is to improve the recognition rate of facial emotional expressions. The input to the proposed model is the standard Cohn–Kanade (CK) dataset, which contains six emotional states: happiness, sadness, anger, surprise, fear, and disgust. Image features are extracted using Principal Component Analysis (PCA) and subsequently fed into the classification stage of the Brain Emotional Learning model to determine the recognition rate of facial emotional expressions. In addition, a correlation matrix comprising the eyebrow, eye, and mouth features is constructed, and facial emotional states are identified through an averaging process. The correlation matrix is capable of recognizing facial emotional states when only one of these features is provided as input to the system. The analysis of the dataset demonstrates a facial emotion recognition rate of 95.81%**.** The findings indicate that the proposed Brain Emotional Learning model achieves a high level of accuracy in recognizing facial emotional expressions.

1. INTRODUCTION

The human face is a unique characteristic of human beings. Facial expressions are changes that appear on the face in response to an individual's emotional states or social interactions. Facial Expression Recognition (FER) [1] is one of the major research areas in computer vision, focusing on identifying individuals' facial expressions. In facial expression recognition systems, the emotional state of an individual is typically classified into categories such as happiness [2], sadness [3], anger [4], surprise [5], fear [6], and disgust [7] [1]. Accordingly, this study focuses on the recognition of facial emotional states.

The proposed model is inspired by the limbic system [8] of the human brain, which plays a fundamental role in emotional processing. This model is employed to improve the recognition rate of facial emotional states. The earliest

[*] Corresponding Author: NikhilRajput@gmail.com
Department of Electronics and Communication Engineering, National Institute of Technology Tiruchirappalli (NIT Trichy), Tiruchirappalli, India

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documented studies on the recognition of emotional states can be attributed to Charles Darwin [9], whose work was published in 1872. Darwin described in detail the facial expressions associated with emotions in both humans and animals [2].

Numerous studies have been conducted since Darwin's pioneering work. In 1994, Damasio [10] stated that one of the earliest interests in this field was the generation and recognition of facial emotional states. Emotional states play an important role in human recognition and are therefore essential in cognitive science, neuroscience, and social psychology studies [3]. Similarly, Cohn [11] concluded in 2001 that facial expressions can play a fundamental role in human communication [1]. In 2011, Wilbur [12] and colleagues used linguistic cues from facial expressions for encoding in grammar [4]. Therefore, models for understanding facial emotional states are important for the advancement of numerous scientific disciplines [1].

In 2008, Lekshmi [13] and colleagues investigated the recognition of emotional states in video sequences. They used skin color to detect the facial region and employed Principal Component Analysis (PCA) [14] for feature extraction. Following the face detection stage, their system effectively recognized the corresponding emotions [5].

In 2009, Murthy [15] and colleagues proposed a method for recognizing emotional states using eigenfaces and employed PCA to extract features from the input images. In this approach, the training dataset was divided into six basic classes happiness, sadness, anger, surprise, fear, and disgust and the output was evaluated based on these six classes. The Cohn–Kanade and Japanese Female Facial Expression (JAFFE) [16] datasets were used. The recognition rates achieved were 75% on the JAFFE dataset and 77.5% on the Cohn–Kanade dataset [6].

In 2012, Manal Abdullah [17] and colleagues proposed an improved method for recognizing digital facial images using PCA. In this method, images were decomposed into smaller sets of features or eigenfaces. Compared with conventional PCA, the proposed approach reduced the processing time by approximately 35% while achieving a high recognition accuracy [7].

In 2013, Murtaza [18] and colleagues identified automatic facial expression recognition as one of the most emphasized problems in security systems, identity verification, and authentication applications, including forensic applications. Facial expressions not only convey emotional information but can also be used to assess subjective attitudes and psychological or psychiatric aspects [8].

In 2015, Kumari [19] and her colleagues stated that facial expression recognition systems have numerous applications and are not limited to understanding human behavior, detecting mental disorders, or representing human structure [9].

In 2010, Beheshti and colleagues described the major components of the limbic system involved in emotional processing and investigated a computational model of the limbic system based on these concepts [10]. The Brain Emotional Learning (BEL) model [20] is a powerful approach for real-time control and decision-making systems. Consequently, it can be considered an appropriate model for recognizing facial emotional states. Furthermore, the biological system of the human brain is highly effective in processing emotional information and constitutes a fundamental mechanism for emotion recognition. Therefore, the BEL model is employed in this study for facial emotional state recognition.

The objective of the present study is to recognize facial emotional states using the Brain Emotional Learning (BEL) model. The BEL model is one of the emerging approaches in the field of cognitive science [21]. The Brain Emotional Learning model provides a computational framework for modeling emotional states and can therefore be applied to facial expression recognition.

In this study, a proposed model based on BEL is presented for recognizing facial emotional states. Subsequently, the proposed model is evaluated through a series of experiments. Finally, the findings and conclusions of the study are presented.

2. PROPOSED METHOD

The proposed method in this study is based on the Brain Emotional Learning (BEL) model, which operates according to the principles of the mammalian brain's limbic system. For a more detailed description, it should be noted that the limbic system of the human brain is responsible for emotional processing and consists of four major components: the sensory cortex [1], thalamus [2], amygdala [3], and orbitofrontal cortex [4] [11].

To the best of our knowledge, no previous study has investigated facial expression recognition using a model inspired by the biological mechanisms of the human brain. Therefore, this study proposes a model that incorporates this characteristic and is capable of recognizing human emotional states based on the biological mechanisms of the human brain.

In the proposed approach, facial images of individuals are first loaded, and their quality is enhanced by applying appropriate image preprocessing techniques. Subsequently, the principal facial components are extracted using Principal Component Analysis (PCA). The extracted components are then localized, and a communication matrix [5] is constructed for the facial components. This matrix can contain information such as the spatial distances between facial components or the degree of similarity among their features. Consequently, a communication matrix is generated for each facial image, and the corresponding matrix is stored for subsequent processing.

Next, the weights of the BEL algorithm are initialized. In the following stage, the dataset is divided into subsets to prepare the data for input into the BEL network. In this study, data partitioning is performed using the k-fold cross-validation method. In k-fold data partitioning, one subset is used for testing the system, while the remaining k − 1 subsets are used for training the system.

In the next stage, the BEL algorithm begins the learning process. Its coefficients and weights are iteratively updated, and the performance of the system is evaluated. This learning process continues until the optimal value of k for facial expression recognition is determined. The overall simulation procedure is illustrated in Figure 1.

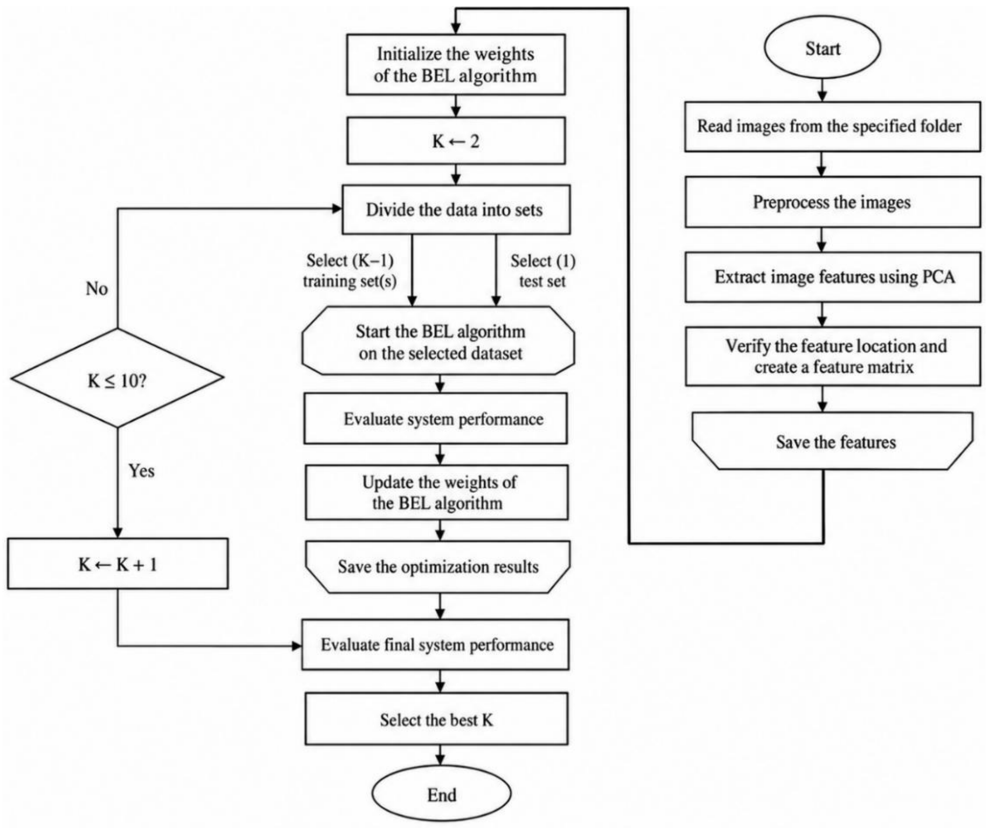

Fig. 1. Block Diagram of the Proposed Method

As shown in Figure 1, the overall workflow of the proposed study is presented. All the aforementioned stages were implemented and experimentally evaluated in the MATLAB programming environment. The BEL model was implemented as a function and evaluated based on the parameters defined for facial expressions in the proposed system. The facial emotional recognition rate was then assessed across six emotional states: happiness, sadness, anger, surprise, fear, and disgust.

2.1. Dataset

The development of a high-quality dataset requires considerable expertise, time, and system training. In this study, the well-known Cohn–Kanade dataset, which is widely used in facial expression recognition research, was employed.

The Cohn–Kanade dataset contains 500 image sequences obtained from 100 subjects, of whom approximately 65% are female. The subjects are between 18 and 30 years of age. The images were collected from individuals from different geographical regions, including Africa, America, and Asia.

This database focuses specifically on emotional facial expressions. Six basic emotional states happiness, sadness, anger, surprise, fear, and disgust are represented in the dataset [12]. Figure 2 presents representative images from the dataset corresponding to these six emotional states.

Fig. 2. Sample images from the Cohn–Kanade dataset

As shown in Figure 2, six emotional states are presented, with one image of an individual representing each state. In the first step of the proposed method, all images in the dataset are loaded using the appropriate image-reading commands in the MATLAB environment. The images are then transferred to the next stage, where their quality is enhanced.

2.2. Image Quality Enhancement

To improve the performance of the system, the images in the dataset are subjected to quality enhancement. In this study, morphological image processing [1] was employed to improve image quality. These operations are applied to images to enhance their quality and remove unwanted noise.

Morphological image processing primarily involves two basic operators: erosion [2] and dilation [3]. Erosion is an operation that causes the thinning of objects in an image, whereas dilation expands or thickens image objects [13]. Applying these operations to the images improves their clarity and visual quality. Figure 3 illustrates the result of this processing stage for an image from the Cohn–Kanade dataset.

(b) (a)

Fig. 3. (a) Original Image**; (b)** Image Enhanced Using Morphological Operations

As shown in Figure 3, part (a) presents the original image, whereas part (b) shows the same image after applying morphological operations, resulting in enhanced image quality.

2.3. Facial Component Extraction

Facial components are among the most important features for facial expression recognition. Therefore, accurately extracting these components and determining their precise locations within the face is essential. In this study, facial components are identified using edge detection techniques. One of the commonly used methods for edge extraction is the Sobel filter [1]. This section provides a brief description of how the Sobel filter operates for facial component extraction.

2.3.1. Sobel Filter

The Sobel edge detection method was introduced by Sobel in 1970. The Sobel edge detector identifies edges for image segmentation based on an approximation of the image derivative. It detects edges by following points with relatively high gradient magnitudes.

The Sobel method provides a two-dimensional spatial gradient magnitude for an image. Consequently, it emphasizes regions with high spatial frequencies, which generally correspond to image edges. In general, this method is used to estimate the absolute gradient at each point in an n-dimensional input grayscale image.

In its simplest formulation, the operator consists of a pair of 3 × 3 convolution kernels, as presented in Table 1. One kernel is given as the reference kernel, while the other is obtained by rotating the first kernel by 90 degrees. The Sobel method is closely related to the Roberts cross operator [14].

Table 1. Sobel Operator Matrices: (a) (G_y); (b) (G_x)

-1	**-2**	**-1**
0	**0**	**0**
+1	**+2**	**+1**

b

-1	**0**	**+1**
-2	**0**	**+2**
-1	**0**	**+1**

a

As shown in Table 1, part (a) presents the Sobel (G_y) matrix, while part (b) presents the Sobel (G_x) matrix. These matrices were used to perform edge detection on the images in the dataset.

Image Filtered Using the Sobel Operator

Original Image

Fig. 4. Output of Applying the Sobel Filter to the Image

Figure 4 illustrates the output obtained by applying the Sobel filter to an image from the Cohn–Kanade dataset. By applying 3 × 3 windows in both the horizontal and vertical directions across the image, the Sobel operator effectively identifies and highlights the facial components and their corresponding edges.

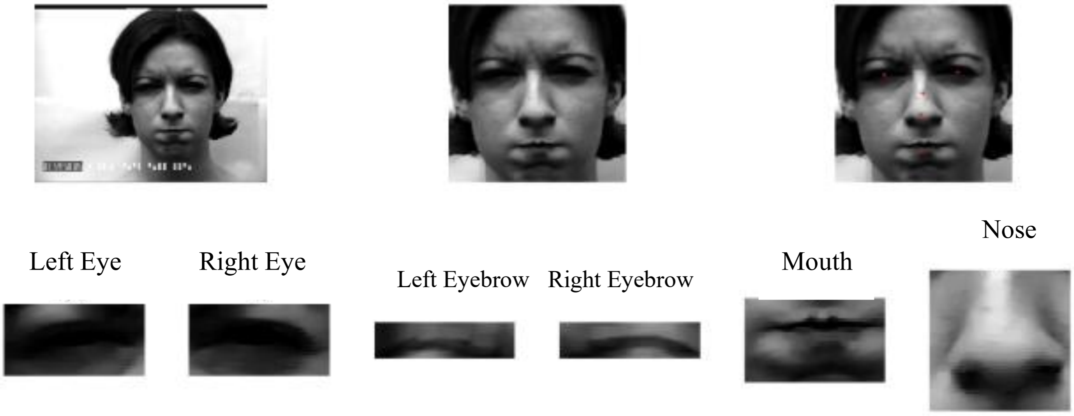

Fig. 5. Extraction of Facial Components from an Image in the Cohn–Kanade Dataset

Figure 5 shows an image representing the anger emotion of a subject from the Cohn–Kanade dataset. The facial components have been effectively extracted by identifying their central points. In this figure, the nose, left and right eyebrows, left and right eyes, and mouth can be clearly observed.

2.3.2. Dimensionality Reduction Using Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is one of the most successful methods used in recognition tasks and is a statistical technique based on the extraction of principal components. The use of PCA as a dimensionality reduction and feature extraction method has also received considerable attention in various pattern recognition and classification problems [18].

The primary objective of PCA is to reduce the dimensionality of the data space (observed variables) to a smaller-dimensional feature space consisting of independent variables. This method is particularly useful when strong correlations [1] exist among the observed variables. PCA is capable of addressing a range of problems within the linear domain and is therefore considered a classical dimensionality reduction technique. This theory is also associated with the concept of minimizing mean reconstruction error.

In general, PCA transforms a set of high-dimensional vectors into a set of lower-dimensional vectors while preserving the most important information contained in the original data. The original dataset can subsequently be reconstructed from the extracted principal components. Applications of PCA include signal processing, image processing, control systems, and communications. PCA, also referred to as principal component analysis, has been extensively used in facial recognition and related pattern recognition applications.

Previous studies have shown that this method is generally suitable for reducing the dimensionality of multivariate data. PCA is primarily employed for dimensionality reduction and is used during the feature extraction stage to decrease the dimensionality of the feature space [15, 16].

By extracting principal components, or vectors representing the most informative patterns within a dataset, relevant information can be extracted from image data. In this study, the extracted feature matrix initially has dimensions of 200 × 200. The PCA algorithm is then applied to eliminate redundant information. As a result, the feature vectors are reduced to 50 × 50, corresponding to a 75% reduction in dimensionality.

2.4. Brain Emotional Learning (BEL) Model

Several models have been proposed for emotional state recognition that are inspired by the biological structure and functions of the brain's limbic system. Examples include the Morén model [2], the Brain Emotional Learning (BEL) model, and the Balkenius model [3]. Among these approaches, the BEL model provides a comprehensive computational representation of the relevant emotional learning mechanisms. Therefore, this model is investigated in greater detail in this section.

In the BEL network, the weights are iteratively updated using the parameters α and β. In this model, reward and punishment play an important role in the learning process. As mentioned previously, the BEL model consists of four main components, each of which is responsible for specific functions.

The thalamus receives the input signals and transmits them to the sensory cortex and amygdala. The sensory cortex is responsible for preprocessing and analyzing the received signals. The amygdala learns to make predictions and responds to the reinforcement signal. It is also responsible for emotional learning. The orbitofrontal system learns to inhibit the system output when a mismatch occurs between the system's baseline prediction and the actual reinforcement signals received.

The reinforcement signal r is defined as a function of the other input signals. The parameter r represents a cost-related evaluation function. For example, reward and punishment can be determined based on a predefined cost function.

Accordingly, BEL learning, which is modeled after the limbic system, is adaptive in nature. In other words, during the training process, the network learns and adjusts its parameters in order to achieve the desired output. This process is performed through reinforcement based on a cost function, in which the reward signal guides the learning process, as illustrated in Figure 6.

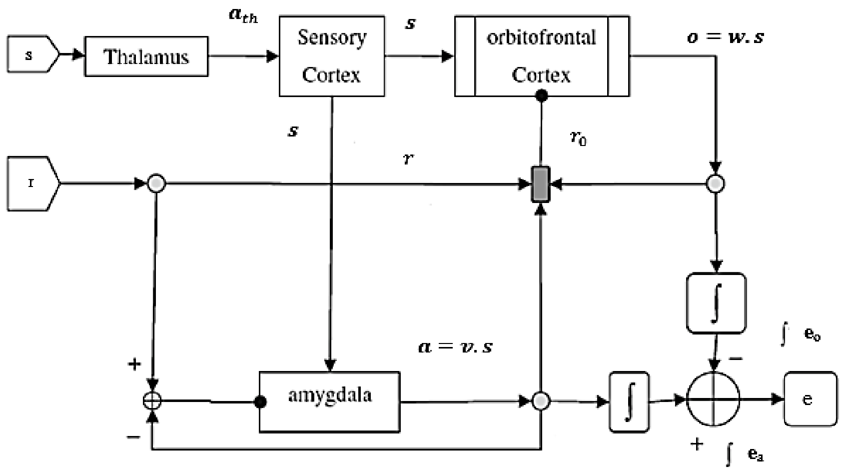

Fig. 6. BEL Model

As mentioned earlier, the BEL model is controlled and guided by reinforcement and reward signals. Therefore, in this study, the BEL approach is employed to improve the recognition rate of facial emotional states [17].

2.5. Communication Matrix

After extracting the facial components and applying the BEL method, a communication matrix is constructed to determine the relationships and dependencies among the facial components for each emotional state. The main facial components extracted in this study are the eyes, eyebrows, and mouth.

Six 3 × 3 matrices are constructed, corresponding to the six emotional categories. These matrices are subsequently used to recognize facial emotional states. The elements of each matrix represent the degree of relationship among the facial components for a particular emotional state.

In the communication matrix, the input image is compared with the six emotional categories in the dataset based on the learning process performed by the BEL model. The degree of membership of the input image in each emotional category is represented by the corresponding elements of the communication matrix. In other words, these values indicate which facial component contributes most strongly to assigning the input image to each emotional category.

By calculating the mean of all elements of the communication matrix, a numerical value representing the weights generated by the BEL model is obtained. A larger value indicates a stronger association between the input image and the emotional category represented by the corresponding matrix.

3. EVALUATION RESULTS OF THE PROPOSED METHOD

In this study, the k-fold cross-validation method was employed to evaluate the proposed model. In this type of data partitioning, the dataset is divided into k − 1 training subsets and one testing subset. In the present study, the system was evaluated for values of k ranging from 5 to 15, and the final system accuracy was calculated as the average performance obtained across all evaluation stages.

The results obtained using the Brain Emotional Learning model are presented in Figure 7. As illustrated in the figure, the proposed system achieves its highest recognition accuracy at k = 11.

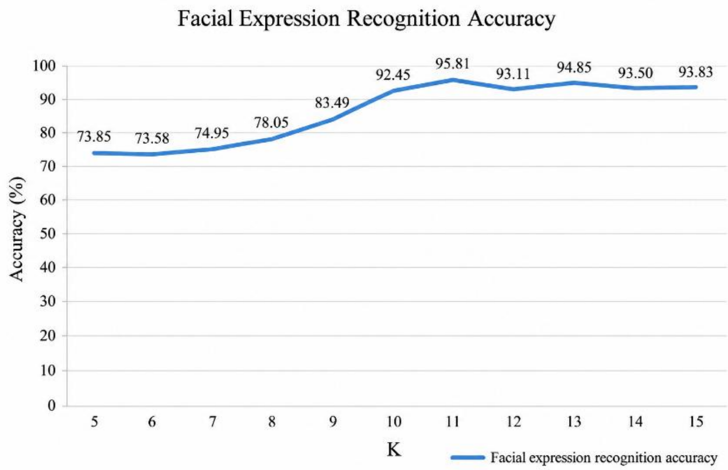

Fig. 7. Evaluation of the Proposed System on the Cohn–Kanade Dataset

Figure 7 presents the evaluation results of the proposed system on the Cohn–Kanade dataset. The highest accuracy was obtained at k = 11, with an overall system accuracy of 95.81%.

After completing the evaluations and selecting the optimal k-fold value, Table 3 was generated for k = 11 to compare the recognition performance across the six emotional states. Table 2 presents the abbreviations used for the emotional states in Table 3.

The first column of Table 2 lists the facial emotional states, while the first row indicates the emotional state of the test image.

Table 2. List of Abbreviations for Emotional States

No.	Emotional State	Abbreviation
1	Anger	An
2	Disgust	Di
3	Fear	Fe
4	Happiness	Ha
5	Sadness	Sa
6	Surprise	Su

Table 3. System Evaluation Using 11-Fold Cross-Validation on the Cohn–Kanade Dataset

Su	Sa	Ha	Fe	Di	An	Cohn-Kanade
0	0	0	0	0	%100	**An**
0	0	4/%20	2/%53	%100	0	**Di**
0	0	0	97/%47	0	0	**Fe**
0	0	95/%80	0	0	0	**Ha**
0	%100	0	0	0	0	**Sa**
100%	0	0	0	0	0	**Su**

As shown in Table 3, a high recognition accuracy was achieved on the dataset. In particular, the emotional states of anger, disgust, sadness, and surprise were recognized with 100% accuracy. However, the recognition of fear and happiness involved a potential error rate, as both emotions were classified as disgust in some cases. In addition, Figure 8 presents a comparison of the six emotional categories obtained using the Brain Emotional Learning (BEL) method.

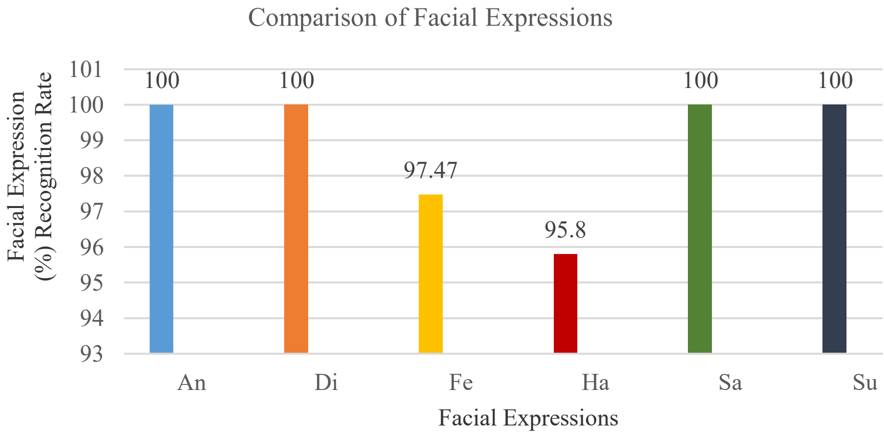

Fig. 8. Comparison of Emotional States on the Cohn–Kanade Dataset

4. CONCLUSION

In this study, facial emotional responses were analyzed with a particular focus on the eyebrows, eyes, and mouth. To detect emotional states, a BEL-based classification approach, inspired by the brain's limbic system, was employed.

The limbic system plays a fundamental role in emotional processing. To date, limited research has investigated facial emotional state recognition using a computational model inspired by the limbic system. Therefore, the main contribution of the present study can be considered the application of the Brain Emotional Learning (BEL) model and the construction of a communication matrix that enables facial emotional states to be recognized even when only some of the relevant facial features are available.

The proposed BEL model was evaluated using the Cohn–Kanade dataset, and the performance of the proposed method was experimentally assessed. The six emotional states were recognized with a high overall recognition rate. In particular, the anger, disgust, sadness, and surprise categories achieved a 100% recognition rate compared with the other emotional states. However, the fear and happiness categories were associated with a certain degree of misclassification.

It is hoped that the proposed approach can contribute to a better understanding of emotional and psychological disorders and ultimately assist researchers in developing more effective methods for their diagnosis and treatment.

Declaration

We acknowledge that we used ChatGPT to enhance the academic writing of our manuscript while ensuring the originality and integrity of our work.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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