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RESEARCH ARTICLE

Optimization-based clustering feature extraction approach for human emotion recognition

C. Agilan[1*], Lakshna Arun[2]

Abstract

Human emotions are mental health states that resolve without conscious effort and are followed by physiological effects in the face muscles that represent expressions. In many applications of human-computer interaction, nonverbal communication mechanisms such as emotions, eye movements, and motions are used. Since there is no contrast among the emotions of a face and there is also a lot of variety and complexity, identifying emotions is a difficult process. To model the face, the machine learning system leverages some open features. Automatic emotion recognition based on face expression is a fascinating study area that has been presented and utilized in a variety of fields, including safety, health, and human-machine interactions. Researchers in this subject are willing to develop strategies to understand, code, and extract facial expressions in order to improve computer prediction. Machine learning, being one of the most promising new fields, offers a wide range of applications. In recent years, the support vector clustering technique has gotten a lot of attention. In this research paper, the use of ant colony optimization (ACO) for creating k-cluster planes and assigning each data sample to the correct cluster is proposed in this study as an upgraded clustering approach. SVC is used in this improved technique to refine the clusters created by ACO. The human face expressions are segmented using this upgraded clustering method. The suggested clustering technique is compared to an existing segmentation approach for emotion recognition using a variety of criteria.

Keywords: Human emotion recognition, Facial expression, Segmentation, Feature extraction, Noise removal, Ant colony optimization, Support vector machine.

Introduction

Artificial intelligence is expected to improve the interaction between humans and next-generation computing systems. A number of factors of human behavior should be considered in order to create smooth and efficient interaction between human and computer systems. One of the most essential considerations is the human's emotional behavior and affective state. Human-centered computing systems of the future should be able to recognize, precisely assess, and comprehend emotions expressed through social and emotional channels, Umer, S., Rout, R. K., Pero, C., & Nappi, M. (2022).

Emotions are a natural and vital part of human behavior that influence how we communicate. Humans use many channels to represent their innate situations, like facial emotions and body language. Facial expressions are the most direct and significant form of nonverbal communication, forming a universal language of emotions capable of expressing a wide range of human emotional states, moods, and attitudes while also assisting in a variety of cognitive activities. For a greater understanding of human behavior, precise interpretation and analysis of the emotional components of human facial expressions is required. Indeed, facial expressions are the most effective and natural way for humans to communicate emotions, cognition, and intentions, as well as to control relationships and communication with others, Fan, Y., Li, V. O., & Lam, J. C. (2020), Wu, S., & Wang, B. (2021).

Facial expressions play an important role in direct communication, with studies showing that 7 percent of information is transmitted by the linguistic part, such as spoken words, 38 percent by paralanguage, such as the vocal part, and 55 percent by facial expressions during

[1]Department of Computer Science, Jamal Mohamed College (Autonomous) (Affiliated to Bharathidasan University, Tiruchirappalli), Tiruchirappalli, Tamilnadu, India.

[2]Department of Computer Applications, Cauvery College for Women (Autonomous) (Affiliated to Bharathidasan University, Tiruchirappalli), Tiruchirappalli, Tamilnadu, India.

***Corresponding Author:** C. Agilan, Department of Computer Science, Jamal Mohamed College (Autonomous) (Affiliated to Bharathidasan University, Tiruchirappalli), Tiruchirappalli, Tamilnadu, India., E-Mail: ahilansrgm02@gmail.com

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face-to-face human communication. A simple signal like a head nod or a grin, for example, can express a wide range of meanings. Facial expressions are, in general, the most natural, meaningful, and vital means of human contact and communication, Abdullah, S. M. S. A., Ameen, S. Y. A., Sadeeq, M. A., & Zeebaree, S. (2021), Kim, S. K. S. (2020), Wu, S., & Wang, B. (2021).

Facial expression recognition is useful in a wide range of systems and applications, and it is essential for developing genuine interaction. Studying and understanding the emotional content of human expressions is vital for a fuller knowledge of the human condition since facial expressions assist in many cognitive activities. As a result, the fundamental goal of facial expression recognition methodologies and approaches is to enable robots to determine the emotional content of a human face automatically. Giving computer programs the ability to understand individuals' emotional states based on their facial expressions is a critical and difficult task with numerous applications, Ngo, Q. T., & Yoon, S. (2020).

Related Works

Deep learning techniques were used, and a new loss function termed weighted-cluster loss was created, which is used during the fine-tuning phase. By learning a class center for each emotion class, the weighted-cluster loss function simultaneously enhances intra-class compactness and inter-class separability. It also accounts for the imbalance in a facial expression dataset by assigning a weight to each emotion class based on its share of the total number of images, Ngo, Q. T., & Yoon, S. (2020).

The authors aimed to examine the accuracy ratio of six classifiers using the Relief-F feature selection approach and the smallest number of attributes possible. Random Forest, Multi-Layer Perceptron, Support Vector Machine, Radial Basis Function and K-Nearest Neighbor are the classifiers examined in this study, Abdulrazaq, M. B., Mahmood, M. R., Zeebaree, S. R., Abdulwahab, M. H., Zebari, R. R., & Sallow, A. B. (2021, February).

During the training stage, a curriculum learning technique was applied to face expression recognition, and a novel curriculum design method was proposed. To locate the clustering center of each category, the system initially uses the unsupervised density–distance clustering algorithm. The dataset is then partitioned into three subsets of varying complexity based on the distance between each sample and the feature space clustering center. Importantly, the scientists created a multistage training approach in which a core model is trained by gradually increasing the complexity of the training set by adding harder data, Liu, X., & Zhou, F. (2020).

The authors suggested a discriminative DMTL (DDMTL) facial expression identification approach that addresses the aforementioned flaws by taking into account both the class label information and the samples' local spatial distribution information at the same time. The scientists also created a siamese network with an adaptive reweighting module that used class label information with varied confidence levels to examine the local spatial distribution, Zheng, H., Wang, R., Ji, W., Zong, M., Wong, W. K., Lai, Z., & Lv, H. (2020).

There is no research into the performance of existing deep architectures for the task of classifying expression in elderly people. The performance of three contemporary deep convolutional neural network models (VGG-16, AlexNet, and GoogLeNet/Inception V1) is evaluated on four different benchmark datasets (FACES, Lifespan, CIFE, and FER2013), which additionally contain facial expressions given by older participants in the current work. Two standard machine learning algorithms based on handmade feature extraction procedures are examined on the same datasets as a baseline and to make a comparison. VGG-16 deep architecture underwent extensive and rigorous experimentation focused on the concept of «transfer learning,» which entails replacing the output level of the deep architectures under consideration with new output levels appropriate to the number of classes (facial expressions) and training three different classifiers (i.e., random forest, support vector machine, and Linear Regression), and training three different classifiers (i.e., random forest, support vector machine, and linear regression), Caroppo, A., Leone, A., & Siciliano, P. (2020).

The authors devised a feature-refining approach that selectively focuses on attentive channel entries and conspicuous spatial regions of a convolution neural network feature map in three dimensions. In addition, a deep metric loss known as the triplet-center (TC) loss is used to boost the discriminative strength of the deeply learned features with an expression-similarity constraint. It learns both separate and compact characteristics by minimizing intra-class distance while increasing inter-class distance, Zhou, L., Fan, X., Tjahjadi, T., & Das Choudhury, S. (2022).

DML-Net is a dynamic multi-channel metric learning network for posture-aware and identity-invariant FER that can reduce the effects of pose and identity for reliable FER performance. DML-Net learns merged global and local information from distinct facial regions using three concurrent multi-channel convolutional networks. Then it explores pose-aware and identity-invariant expression representations from merged region-based features in an embedding space using joint embedded feature learning. DML-Net may be trained from start to finish by reducing deep multiple metric losses, FER losses, and pose estimation losses using dynamically learned loss weights, which suppresses overfitting and improves recognition dramatically, Liu, Y., Dai, W., Fang, F., Chen, Y., Huang, R., Wang, R., & Wan, B. (2021).

The authors investigated the efficiency of Bayesian inference approaches in solving the issue of facial expression and human activities recognition. For finite multivariate generalized Gaussian mixture models, a novel method known as Bayesian learning has been devised. The capacity to simulate a wide range of data and the shape flexibility of the multivariate generalized Gaussian distribution are both encouraging. For the suggested generative model, the authors built a Markov Chain Monte Carlo within the Metropolis-Hastings algorithm. The authors of this study also addressed certain key difficulties in pattern recognition and machine learning, such as parameter estimation for statistical models, Najar, F., Bourouis, S., Alshar'e, M., Alroobaea, R., Bouguila, N., Al Badi, A. H., & Channoufi, I. (2020, September).

The authors suggested a new adversarial graph representation adaptation (AGRA) paradigm for cross-domain holistic-local feature co-adaptation that combines graph representation propagation with adversarial learning. The authors do this by first creating a graph that correlates local and holistic regions within each domain and then another graph that correlates these regions across domains. The authors then extracted holistic-local features from the input image to initialize the corresponding graph nodes after learning the per-class statistical distribution of each domain. Finally, the authors designed two stacked graph convolution networks to transmit holistic-local features inside each domain and between domains for holistic-local feature co-adaptation within each domain, Xie, Y., Chen, T., Pu, T., Wu, H., & Lin, L. (2020, October).

Using a poorly supervised clustering technique, a multi-region and multi-scale vector triangular texture feature extraction scheme was suggested. The best selection of vector triangle texture feature scale is explored based on the information gain rate of extracted features, merged with random dropout and threshold selection strategy, and the feature space is optimized under the assumption of sufficient feature space information, resulting in feature space reduction and information redundancy reduction. The facial expression images in the data set are separated into two groups for the negative and positive expression units, Jiaming, T., Jiafa, M., Weiguo, S., Yahong, H., & Hua, G. (2021).

Support Vector Machine

It is a form of SVM classification approach that is widely used. SVC is a plane-based clustering technique that solves a sequence of quadratic programming problems to determine k-cluster center planes. On both sides of the cluster plane, SVC receives a cluster plane next to the vertices of its own cluster and far away from the points of various clusters. SVC explores NC center planes CP for NC clusters, Sujanaa, J., Palanivel, S., & Balasubramanian, M. (2021), Kanwal, S., & Asghar, S. (2021).

$$CP = W_i^T x + b_i, \text{i=1,\ldots,}N_C, \text{i=1,\ldots,}N_C \quad (1)$$

The following fundamental problem must be addressed in order to obtain the planes in (1).

$$\min_{(w_i,b_i,Q_i,X_i)} \frac{1}{2} \|X_i w_i + b_{ie}\|^\wedge 2 + Ce^T Q_i$$

Such that

$$|\dddot{X}_i w_i + b_{ie}| + Q_i \geq e, \qquad Q_i \geq 0 \quad (2)$$

The situation ‖where the i^th cluster center plane is supposed to be near to the point of X i cluster and apart from the other cluster X_i from both planes is illustrated by Q_i, a slack vector that represents the ith cluster and C>0, a penalty parameter‖. Where does the absolute value come from? The iterations are repeated until all of the stop criteria are met. Solving the linear equation yields the decision variable:

$$\left[w_i^{j+1}; b_i^{j+1}\right]^T = (H^T H)^{-1} G^T \sigma \quad (3)$$

To solve the $\left[w_i^{j+1}; b_i^{j+1}\right]$ equation, an initial value w_i^0 and b_i^0 are chosen for each i=1,…, N_C. The operation is terminated when $\left\|\left[w_i^{j+1}; b_i^{j+1}\right] - \left[w_i^j; b_i^j\right]\right\|$ is very tiny. SVC renews the entire cluster's center planes based on the original labels, and then relabels each sample to update the sample labels.

$$y = \arg\min\{|w_i^T X + b_i|, i = 1, \ldots, N_c\} \quad (4)$$

Ant Colony Optimization

The way some insects living in collaborative colonies look for food is the fundamental metaphor of ant colony optimization (ACO). Indeed, if an ant nest detects a food source, some ants may leave a pheromone trail, a chemical compound that all creatures contain but is particularly crucial for insects to look for this food. This pheromone trail serves as an emotional signal to other ants, who will recognize the path taken by the ants before them. There will be some ants who arrive first at the food supply since they chose the quickest way, and then they will return to the nest first before the other expeditions. The shortest way has then had its pheromone trail reinforced; as a result, new expeditions are more likely to use that path than others until fresh, better paths (or parts of paths) are discovered by some expeditions. The shortest path's pheromone trail is projected to become increasingly intense, while the other paths' pheromone trail will dissipate, Hwang, W. H., Kang, D. H., & Kim, D. H. (2022).

Algorithm 1: SVC Clustering Algorithm (Kanwal, S., & Asghar, S. (2021))

Input: The unlabelled dataset D

Initialization: Determine the Initial labels Y_K for each sample in D.

Process

Do

{

Calculate the clusters center planes using equation (1)

Compute the proximal hyperplane using equation (2)

Update w_i^{j+1} using equation (3)

Update the whole center planes and sample labels using equation (4)

}

While (termination criteria satisfied)

Output: The label Y_K corresponding to each data sample in D.

While implementing this principle to combinatorial optimization problems, we take a glance at an implementation that utilizes the concept of affirmation of good solutions, or parts of solutions, by increasing the value of a «pheromone» that controls the probability of choosing this solution or part of the solution. This likelihood will now be determined not just by the pheromone value but also by the value of a «local heuristic» or «short-term vision» that, like greedy algorithms, offers a solution or part of a solution based on a local optimization criterion.

The following are at least some of the components of an ACO-based optimization method:

A representation based on the pheromone trail and the local heuristic that allows the building or modification of solutions using a probabilistic transition rule.

- A visibility or local heuristic that has been noted as η.
- A pheromone update rule has been observed as τ
- A probabilistic transition rule that is based on a number of factors like η and τ.

One of the fundamentals of ACO is that it manages a group of M agents or ants in concurrently, each of whom creates or updates an optimization problem solution.

The pheromone trail's value is adjusted according to the rule.

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \rho\Delta\tau_{ij}(t+1) \qquad (5)$$

Where τ_{ij} is an evaporation parameter, and $\rho \in [0,1]$ is a value that associates two objects i,j in Ω. We positioned,

$$\Delta\tau_{ij}(t+1) = \sum_{m=1}^{M} \Delta^m\tau_{ij}(t+1) \qquad (6)$$

$\Delta^m\tau_{ij}(t+1)$ is the quantity of pheromone released by an agent in the connection of items of the same class, i,j, as defined by

$$\Delta^m\tau_{ij}(t+1) = \begin{cases} B(P^m)/I & if\ i,j\ belong\ to\ the\ same\ class\ of P^m \\ 0 & Otherwise \end{cases}$$

$B(P^m)$ is the partition P^m inter-class variance. Two objects belonging to the same class leave a pheromone trail in this manner. The local heuristic, also referred to as short-term visibility, is described as follows:

$$\eta_{ij} = \frac{1}{\|x_i - x_j\|} \qquad (7)$$

Algorithm 2: Algorithm for Ant Colony Optimization (Hwang, W. H., Kang, D. H., & Kim, D. H. (2022))

```
Algorithm ACO
Initialize τ_ij = τ_0
Put each ant (from 1 to M) in a vertex
for t = 1 to t_max do:
  for m = 1 to M do:
    Construct a solution S^m(t) applying n − 1 times a rule
    of construction or modification, choosing
    a pheromone trail τ and a local heuristics η
    Calculate the cost W^m(t) of S^m(t)
  end-for
  for each arc (i, j) do:
    Update τ
  end-for
end-for.
```

In a way that two nearby components have a large value in order to impact the likelihood of their being assigned to the same class.

Object j is identified with probability if ant m is at object i.

$$p_{ij} = \frac{[\tau_{ij}]^\alpha [\eta_{ij}]^\beta}{\sum_{l=1}^{n} [\tau_{ij}]^\alpha [\eta_{ij}]^\beta} (8)$$

After that, j is placed in the same class as i. Given I the value p_{ij} is the probability of choosing j, which is modeled using cumulative probabilities and generates uniformly random numbers, similar to the so-called roulette-wheel of genetic algorithms: the rows of matrix $(p_{ij})_{nxn}$ sum 1; given I the value p ij is the probability of choosing j, which is modeled using cumulative probabilities and generates uniformly random numbers.

Proposed Optimization-Based Clustering Approach For Face Emotion Images

Preparation of Face Emotion Images

The first step is to scale down the images so that they are all the same size. All images of facial expressions were standardized to [250×250]. The Gaussian filter is then used to remove the noise. The resulting image is then segmented.

Segmentation Phase

Following the pre-processing of facial emotion images, the samples are converted to binary samples, and the edges of a face image are recognized using the Canny algorithm. Canny outperforms other edge detection algorithms because it obtains edges by lowering the error rate and producing edges near the original edges to maximize the area. The Gaussian filter may be used to estimate the ideal filter that fits the three principles above. The following equation describes the Canny algorithm, Nnolim, U. A. (2020):

$$f'(x,y) = \sum_{i=-n}^{n} \sum_{l=-n}^{n} g(i,l) * f(x-i, y-l) \qquad (9)$$

where g(i, l) denotes the convolution kernel, *f '(x, y)* denotes the detected image, and *f (x, y)* denotes the original image

Feature Extraction Phase

Feature extraction is a crucial stage in the creation of any pattern classification because it seeks to extract the relevant information that defines each class. During this phase, important characteristics from objects/alphabets are extracted to create feature vectors. Classifiers use these feature vectors to match the input unit to the target output unit. Looking at these features makes it easier for the classifier to differentiate between different classes because they are relatively easy to discern.

The method of perfectly describing a vast dataset with an accurate and minimal feature is known as feature extraction. The variables included in complex data could be a huge issue. For a clustering technique, this necessitates a considerable amount of computing and memory, resulting in unsatisfactory clusters. The feature vector is recovered from the observed face using standard division, mean and eigenvalues.

If a linear transformation is performed to a nonzero vector, the eigenvalues vary only in a scalar component. There are N real eigenvalues $\lambda 1, \lambda 2, ..., \lambda n$ and N eigenvectors $\Phi 1, ..., \Phi n$ fulfilled $A\lambda = \lambda\Phi$ for $N \times N$ symmetric matrix A. The orthogonal eigenvector corresponds to two separate eigenvalues [19]. Suppose D is the eigenvalues diagonal matrix.

$$Y = \Phi^T D (10)$$

The standard deviation (STD) and mean are calculated. Each eigenvalue-represented sample is made up of a range of values for a few pixels. The mean can be calculated using these numbers [20]. The most well-known and popular arithmetic mean μj is represented by:

$$\mu_j = \frac{1}{N} * \sum_{i=1}^{N} Y_{ji} \quad (11)$$

where N is the number of pixels in a row and Yji denotes the values of those pixels. The STD is of vital importance. The square root of the variance is what it's called. The mean and eigenvalues are also used to determine STD [21, 22]. The most well-known and popular arithmetic STD (σ) is represented by:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N} (Y_i - \mu)^{\wedge 2}}{N}} \quad (12)$$

where Yi denotes the eigenvalues, N is the total number of pixels in a row, and μ denotes the mean value. If the eigenvalues are represented as a matrix, each row and column will be a numerically random variable. The feature vector is the product of the image's mean and standard deviation for each row and column [23]. The feature vector FV is calculated as follows:

$$FV = \{\mu_1, \mu_2 \dots, \mu_n, \rho_1, \rho_2, \dots, \rho_n\} \qquad (13)$$

The extraction of characteristics from a face sample is a crucial step in assigning a sample to the relevant cluster.

Algorithm 3: Proposed Optimization-based Clustering Approach

Input: The dataset D, K is the number of clusters; appropriate ACO parameters
Output: Clustering results
Process:
Generate initial population P_i randomly.
Calculate the objective function f for P_i using equation (8)
Calculate the value of the pheromone trail $\tau_{ij}(t+1)$ using equation (5)
Calculate the local heuristic using equation (6)
Sort P_i based on f
Do {
Calculate the Local Heuristic and global heuristic
Update the pheromone trail in the ACO
Update the local heuristic
Calculate the objective function f for new population
Sort P_i based on the new j
While (termination criteria satisfied)
Run the SVC algorithm 1 while ACO ant labels are considered as its initial labels.
The labels Y_K corresponding to each data sample D.
}

Result And Discussion

Image Dataset

The face emotion recognition dataset is taken from the Kaggle repository (https://www.kaggle.com/jonathanoheix/face-expression-recognition-dataset/data#). The dataset is composed of angry, disgusted, fear, happy, neutral, sad and surprised emotions. For this paper, 100 images from each emotion category are considered to evaluate the performance of the proposed optimization-based clustering approach for feature extraction with existing feature extraction techniques like principal component analysis (PCA), independent component analysis (ICA) using three classification techniques like ANN, KNN and SVM.

Performance Metrics

Table 1 depicts the performance metrics used in this research paper.

Table 2 depicts the detection rate (in %) obtained by the proposed optimization-based clustering approach, principal component analysis (PCA), ICA, support vector machine clustering-based feature extraction techniques using classifiers like artificial neural network (ANN), convolutional neural network (CNN) and K-nearest neighbor (KNN). From Table 2, it is clear that the proposed OCA with CNN gives an increased detection rate when it is compared with other feature extraction techniques.

Table 3 depicts the sensitivity (in %) obtained by the proposed OCA, PCA, ICA, SVM clustering-based feature extraction techniques using the classifiers like ANN, CNN and KNN. From Table 3, it is clear that the proposed OCA with CNN gives increased sensitivity when it is compared with other feature extraction techniques.

Table 1: Performance metrics used in this paper

Performance Metrics	*Equation*
Detection Rate	$\frac{TP+TN}{TP+TN+FP+FN}$
Sensitivity	$\frac{TP}{TP+FN}$
Specificity	$\frac{TN}{TN+FP}$
False Positive Rate	1- Specificity
Miss Rate	1- Sensitivity

Table 2: Detection rate (in %) obtained by the proposed and existing techniques using CNN, ANN and KNN classifier

Feature extraction techniques	*Detection rate obtained (in %) classification techniques*		
	CNN	*ANN*	*KNN*
Proposed OCA	84.67	75.48	68.87
PCA	54.78	52.73	48.32
ICA	57.73	54.78	52.12
SVM	62.46	61.49	50.16

Figure 1:

Table 3: Sensitivity (in %) obtained by the proposed and existing techniques using CNN, ANN and KNN classifier

Feature extraction techniques	*Sensitivity obtained by classification techniques*		
	CNN	*ANN*	*KNN*
Proposed OCA	85.89	77.54	65.81
PCA	52.25	50.76	48.15
ICA	54.23	54.79	47.12
SVM	66.74	58.63	57.59

Table 4: Specificity (in %) obtained by the proposed and existing techniques using CNN, ANN and KNN classifier

Feature extraction techniques	*Specificity obtained by classification techniques*		
	CNN	*ANN*	*KNN*
Proposed OCA	84.96	75.82	66.38
PCA	54.25	52.80	51.41
ICA	55.36	52.57	47.92
SVM	62.87	57.49	54.71

Table 4 depicts the specificity (in %) obtained by the proposed OCA, PCA, ICA, SVM clustering-based feature extraction techniques using the classifiers like ANN, CNN and KNN. From Table 4, it is clear that the proposed OCA with CNN gives increased specificity when it is compared with other feature extraction techniques.

Table 5: False positive rate (in %) obtained by the proposed and existing techniques using CNN, ANN and KNN classifier

Feature extraction techniques	*False positive rate obtained by classification techniques*		
	CNN	*ANN*	*KNN*
Proposed OCA	15.04	24.18	33.62
PCA	45.75	47.2	48.59
ICA	44.64	47.43	52.08
SVM	37.13	42.51	45.29

Table 6: Miss rate (in %) obtained by the proposed and existing techniques using CNN, ANN and KNN classifier

Feature extraction techniques	*Miss rate obtained by classification techniques*		
	CNN	*ANN*	*KNN*
Proposed OCA	14.11	22.46	34.19
PCA	47.75	49.24	51.85
ICA	45.77	45.21	52.88
SVM	33.26	41.37	42.41

Table 5 depicts the false positive rate (in %) obtained by the proposed OCA, PCA, ICA, SVM clustering-based feature extraction techniques using the classifiers like ANN, CNN and KNN. From Table 5, it is clear that the proposed OCA with CNN gives reduced FPR when it is compared with other feature extraction techniques.

Table 6 depicts the Miss Rate (in %) obtained by the proposed OCA, PCA, ICA, SVM clustering-based feature extraction techniques using the classifiers like ANN, CNN and KNN. From Table 6, it is clear that the proposed OCA with CNN gives a reduced miss rate when it is compared with other feature extraction techniques.

Conclusion

For a better knowledge of human behavior, precise analysis and interpretation of the emotional content of human facial expressions are required. Although a human can automatically detect and interpret faces and facial emotions with little or no effort, computer systems still confront a significant barrier in recognizing accurate and robust facial expressions. Different face expressions can be easily sorted into their appropriate classes using an effective feature extraction technique. An optimization-based clustering strategy is given in this research report to improve the classification of human facial expressions. According to the findings and discussion, the proposed OCA improved the detection rate, specificity, and sensitivity of the CNN classifier while also lowering the false positive rate and miss rate. When compared to existing feature extraction approaches such as PCA, ICA, and SVM-based clustering, the suggested OCA performs better.

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