International Journal of
Intelligent Engineering & Systems

http://www.inass.org/

A Systematic Pelican Optimization based Weight Extreme Learning Machine Algorithm for Face Emotion Recognition

M. Sumithra[1]* **N. Rajkumar[1]**

[1]*Department of Computer Science and Engineering,*
Vel Tech Rangarajan Dr.Sagunthala Institute of Science and Technology,
Avadi, Chennai -600062, Tamilnadu, India
* Corresponding author's Email: blessfulsumi@gmail.com

Abstract: Recognizing the facial expressions from the given input is one of the challenging and demanding tasks in recent days owing to the low-resolution images and different backgrounds. Also, the facial emotional/expression recognition system has gained a significant attention in the field of computer vision. The conventional works implemented a variety of machine learning algorithms for face emotion recognition, but higher computation costs, decreased reliability, redundant information, and increased computational time requirement are still only a few of the issues. In this case, an image face filtering method is employed in the beginning to produce a normalized output image with high contrast and quality, which is used to increase the classifier's overall rate of emotion recognition. Then, the novel pelican optimization algorithm (POA) is used to optimize the feature set in order to guarantee the success of classifier training and testing. Prior to emotion recognition, this technique is used to reduce the dimensionality of information. Based on the given face image's optimized attributes, the weight optimized extreme learning machine (WOELM) algorithm is used to reliably identify the emotions. By using well-known datasets like CK+ and MMI, a wide range of factors are taken into consideration for study in order to compare and evaluate the outcomes of the proposed POA-WOELM face emotion identification system. The obtained results reveal that the combination of POA-WOELM provides an increased 99% of emotion recognition accuracy to all kinds of emotions, with the sensitivity of 98.8% and specificity of 98.9%.

Keywords: Face emotion recognition, Computer vision, Machine learning, Classification, Face detection, Pelican optimization algorithm (POA), Weight optimized extreme learning machine (WOELM).

1. Introduction

One of the most fundamental nonverbal expressions of human emotions and aspirations is facial expression. An automatic facial expression recognition system helps to evaluate and comprehend the human emotional actions [1, 2], hence it has recently attracted a lot of attention from researchers in the field of computer vision. In addition, it plays a vital role in the applications of emotion perception, healthcare system, social robotics and many others. Typically, the face emotion recognition system is classified into the two major categories such as image-based and video-based, in which the image-based approaches are widely used in the real-time environment [3-5]. In order to prevent crimes, it can be useful to keep an eye out for any unusual facial expressions among the population in public areas. By observing the patient's in-hospital expressions in real-time, it is possible to treat patients promptly in the service industry and to timely collect consumer feedback. Since, it provides an effective spatial information obtained from the given human face images [6, 7]. But, it is difficult to capture the temporal features from the video-sequences, and also it is highly required to encode the input video-sequences for recognition. So, the majority of the application system could use the image-based recognition systems [8-10]. Numerous facial expression recognition algorithms have been investigated in the fields of computer vision and machine learning [11-13] to extract emotion information from facial images.

According to a recent study, it is analyzed that people across nations interpret some fundamental emotions in the same manner [14, 15]. Moreover, anger, contempt, fear, happiness, sadness, and surprise are examples of normal facial expressions. The ability of machines to automatically recognize facial expressions might be extremely advantageous for a number of automated systems to enable direct interaction with users. Numerous scholars have extensively researched the recognition of facial expressions. Despite the existing research [16-18], developing robust face emotion recognition remains an incomplete and difficult undertaking. The majority of recognition algorithms, however, did not take into account inter-class variations brought on by variations in a single person's face features. Therefore, facial expression information and identity-related information are mostly used for emotion classification. Its primary flaw is that it impairs FER systems' capacity to extrapolate in general, which lowers their effectiveness when dealing with hidden identities [19, 20]. There are still just a few problems with higher computation cost, lowered reliability, redundant information, and more computational time demand. The level of sensitivity, specificity, precision, and detection rate of the face emotion recognition system may all be significantly impacted by these issues [21-23]. Therefore, the goal of this study is to create a classification model based on artificial intelligence that accurately detects facial expressions from images of human faces. The following are the main research goals of the proposed work:

•Here, an image face filtering approach is applied at the beginning for producing the normalized output image with high contrast and quality, which is used for improving the overall emotion recognition rate of the classifier.
•To ensure that the training and testing of a classifier are successful, the feature set is optimized using the recently developed pelican optimization algorithm (POA). This technique is mainly used to squeeze the dimensionality of features before emotion recognition.
•The weight optimized extreme learning machine (WOELM) algorithm is employed to accurately recognize the emotions from the given face image based on their optimized features.
•For analysis, a wide range of parameters are considered to validate and compare the results of proposed POA-WOELM face emotion recognition system by using the well-known datasets like CK+ and MMI.

The remaining part of the study is divided into the following sections: The machine learning approaches currently in use for the face emotion recognition system are reviewed in section 2 along with their benefits and drawbacks. The functional processes and flow of the suggested approach are then thoroughly described in section 3. The experimental and comparison findings of both the existing and proposed recognition systems are validated in section 4 using a variety of performance measures. In section 5, the entire paper's conclusion is presented together with the findings and future work.

2. Related works

This section explores various machine learning-based frameworks for recognizing facial emotions, along with their positives and negatives.

Jain, et al [24] deployed a hybrid deep learning technique for face emotion recognition. Here, the standard CNN and RNN techniques are integrated together for accurately predicting face emotions. Before classification, the image preprocessing is carried out to crop the face region for improving the recognition rate. *Mellouk, et al* [25] presented a comprehensive review to examine the different types of deep learning techniques used in the field of face emotion recognition. The authors of this paper intend to develop an automated recognition system for predicting human emotions with better performance outcomes. Typically, the spatio-temporal features are extracted from the face images with the use of deep learning techniques such as CNN-LSTM, 3DCNN, and deep CNN models. The study indicates that the deep learning-based emotion detection techniques provides an increased recognition rate. But a complex computational process and mathematical operations could maximize the complexity of recognition. *Ninaus, et al* [26] deployed a game based learning approach for effectively predicting emotions from human face images. Here, the positive and negative emotions for improving the face emotion recognition. *Zhang, et al* [27] utilized a hybrid deep learning algorithm for an effective facial expression recognition system. Here, the deep fusion network is constructed to extract the spatio-temporal features from the face image. During this process, the average pooling operation is performed to obtain the segment level features for improving the recognition performance. In this model, the supervised leaning model is used to tune the network parameters according to the back propagation function. This kind of prediction model helps to reduce the reconstruction error and better recognition performance.

Canal, et al [28] conducted a detailed survey to examine the recent state-of-the-art model approaches used for face emotion recognition. The main scope of this paper is to analyze the recent techniques that are published in the past few decades for developing an efficient and automated face emotion recognition framework. *Hayes, et al* [29] conducted a meta-analytical review for recognizing emotions from the face image according to its task characteristics. The purpose of this paper is to analyse the pattern of aging effects for categorizing different face emotions. *Chowdary, et al* [30] designed an emotion detection system by using enhanced pre-trained deep neural architectures. Here, the data augmentation, normalization, and scaling operations are applied to image enhancement. Then, a standard CNN technique is deployed for an automatic feature extraction, which helps to save the time of processing with better accuracy. In addition, the VGG 19, ResNet, MobileNet, and Inception V3 architecture models are used for emotion prediction. Moreover, the performance of these approaches is compared based on the parameters of number of epochs, dropout factor, weight value, and optimization function. The final prediction outcomes indicate that the Inception V3 overwhelms the other deep neural architectures with improved performance results.

Pranav, et al [31] utilized a Deep Convolutional Neural Network (DCNN) technique for formulating an efficient emotion recognition framework. *Hassouneh, et al* [32] deployed a CNN based LSTM classification algorithm for face emotion recognition. In this framework, the haar like features are extracted from the input video sequence image frame, and based on these features, the CNN model predicts the type of emotion. *Li, et al* [33] conducted a detailed literature survey to investigate the different types of deep learning techniques for face emotion recognition. In this framework, the face alignment is performed as the preprocessing step, where the background elimination and non-face area removal have been performed to generate an enhanced image. Here, pre-training and parameter fine-tuning processes are carried out to analyse the face expressions with reduced overfitting. *Wang, et al* [34] deployed a CNN model for an accurate and efficient face emotion recognition. Here, some of the standard activation functions are computed to simplify the process of classification, which includes sigmoid function, tanh function, ReLu function, and softmax. Back propagation is the process of reducing the error between the real output and desired output in order to obtain an actual outcome nearer to the expected value. The significance that the activation function played in the convolutional neural network's training process was determined by looking at the forward and backward propagation processes. *Abdullah, et al* [35] utilized a multi-modal emotion recognition system with the use of deep learning technique for facial emotion recognition. The authors indicated that the multi-modal learning has gained a significant attention in present times, especially it is well-suited for face emotion recognition. *Jeong, et al* [36] used a Deep Joint Spatiotemporal Network (DJSTN) model for categorizing the type of face emotion according to the spatial and temporal features. Here, a 3D-CNN model is used to obtain the accurate recognition results, where the two distinct appearance network structures are integrated together to form the deep architecture.

It is determined from the literature study that the main issues of increased training complexity, lack of precision, and low system efficiency are where the existing research is limited. So, the proposed work intends to put into practice a new machine learning-based framework for facial emotion recognition.

3. Proposed methodology

A. Datasets used

The well-known benchmarking datasets, like CK+ and MMI have been used for system implementation and analysis. Extended Cohn-Kanade Dataset (CK+) [36] (CK+ Dataset | Kaggle) consists of 920 images in 6 emotion categories of basic facial expressions. The resolution of the image is 48x48 pixel and they are specified in a .csv file. MMI human face expressions database consists of high resolution still images and videos in 75 categories. More than 2900 videos and images from this database are encoded in various frame level for analyzing the onset, offset, apex and offset modes.

B. FER system

The proposed pelican optimization (PO) based weighted optimized extreme learning machine (WOELM) algorithm for facial emotion recognition is fully explained in this part. The main objective of this work is to use a better deep learning model to accurately recognize facial expressions of people's emotions. As can be seen in Fig. 1, the proposed facial emotion recognition system comprises the following operations:

- Image obtainment
- Face detection
- Preprocessing & normalization
- Feature selection using POA

Received: May 21, 2023. Revised: July 26, 2023.

- Emotion recognition using WOELM

Table 1. Advantages and limitations of the existing methodologies

Ref	Methods	Advantages	Drawbacks
[24]	Hybrid CNN -RNN	Increased recognition rate and accuracy	It requires more time to train the samples, and high system processing complexity.
[25]	CNN-LSTM, 3DCNN, and deep CNN models	It supports an effective emotion identification.	It requires hyper-parameter tuning for maximizing accuracy, overhead and high time complexity.
[26]	Game based learning model	Easy to implement.	Lack of efficiency and training complexity with increased number of features.
[27]	Deep fusion network	Reduced reconstruction error and better recognition performance.	The performance of classifier highly depends on the selection and computation of hyper-parameter.
[30]	Augmentation based CNN model	Better performance results.	Increased computational burden and time consumption.
[31]	Deep Convolutional Neural Network (DCNN)	It has better ability to handle complex datasets.	Computational and time complexities are high.
[32]	CNN based LSTM	High classification accuracy, and faster in process.	Overfitting, and it requires lot of time.
[34]	CNN	Higher accuracy.	Not suited for small datasets and high computational requirements.
[35]	Multi-modal emotion recognition system	Simple to understand the system model.	Increased error rate.
[36]	Deep Joint Spatiotemporal Network (DJSTN)	Automated feature learning.	Lack of interpretability, and high computational cost.

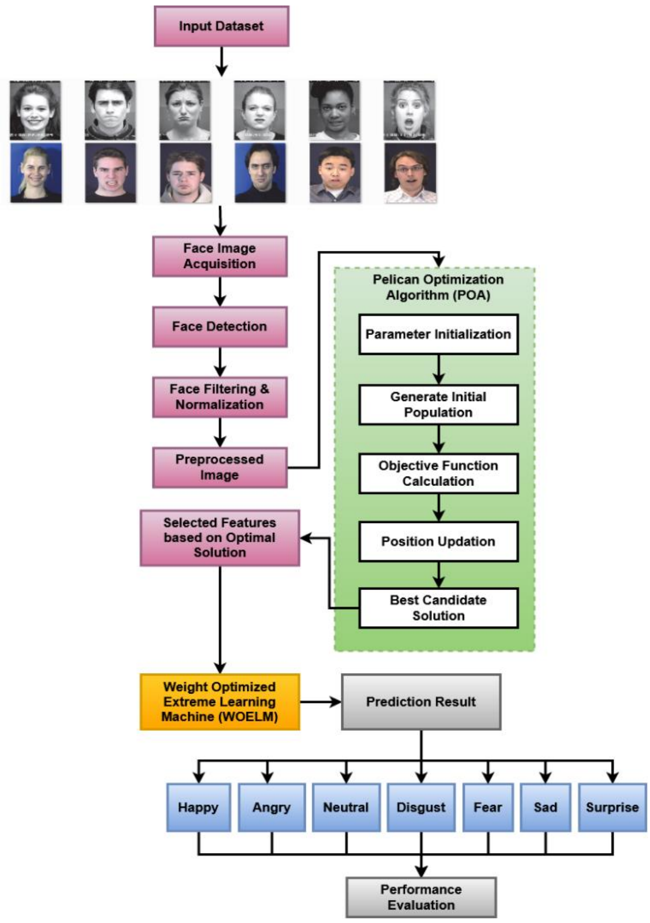


Figure. 1 Proposed facial emotion recognition system

- Performance evaluation

To detect the face from the given input image, the Haar feature extraction algorithm is utilized in this stage, which is one the extensively used detection algorithm due to its simplicity and efficiency. In this technique, the average of two values with its difference are estimated based on the elements of rows and columns in the image matrix. Typically, image preparation constitutes one of the fundamental and essential steps in the image processing systems. Since it is essential to ensure the better accuracy rate of the subsequent processes. Furthermore, it decreases the impact of artefacts that could impair classification accuracy. After the face region has been extracted, the image's noise is removed and its brightness is adjusted for generating an enhanced image. The output pre-processed and quality enhanced face image is considered as the input for classification.

C. Pelican optimization algorithm (POA) based feature selection

The best features from the pre-processed image are selected using an innovative POA [37, 38] after preprocessing. It is one of the recently developed stochastic nature-inspired optimization algorithm especially developed for resolving multiple objective functions. The giant pelican has a long snout and a wide pouch in its throat, which uses it to grab and swallow prey. This bird thrives in social situations and flocks of up to a thousand pelicans. They have become skilled hunters as a result of their intelligent hunting behaviour and tactics. The modelling of the aforementioned strategy served as the primary source of inspiration for the design of the planned POA. It is a population-based algorithm that includes pelicans as members of its population.

In this technique, every member of the population is a candidate solution in population-specific algorithms. Depending on where they are in the search space, every member of the population offers values for the optimization problem parameters. As shown in Eq. (1), the population members are firstly assigned at random to coincide with the problem's lower bound and upper bound.

$$P_{i,j} = Lb_j + \delta \times (Ub_j - Lb_j) \tag{1}$$

Where, $i = 1, 2, 3 \dots n$ and $j = 1,2,3 \dots m$, $P_{i,j}$ indicates the population with candidate solution i , and variable j, then the parameters m, n indicates the count of population members and problem variables respectively, δ indicates the random variable, Lb_j and Ub_j are the lower and upper bound values respectively. Consequently, the matrix is constructed with the set of population members as shown in the following model:

$$P = \begin{bmatrix} P_1 \\ \vdots \\ P_i \\ \vdots \\ P_n \end{bmatrix}_{n \times m} = \begin{bmatrix} p_{1,1} & \cdots & p_{1,j} & \cdots & p_{1,m} \\ \vdots & & \vdots & & \vdots \\ p_{i,1} & \vdots & p_{i,j} & \cdots & p_{i,m} \\ \vdots & \cdots & \vdots & \cdots & \vdots \\ p_{n,1} & \cdots & p_{n,j} & \cdots & p_{n,m} \end{bmatrix}_{n \times m} \tag{2}$$

Where, P indicates the population matrix. According to this matrix, the objective function O is formulated as shown in the following equation:

$$O = \begin{bmatrix} O_1 \\ \vdots \\ O_i \\ \vdots \\ O_n \end{bmatrix}_{n \times 1} = \begin{bmatrix} O(P_1) \\ \vdots \\ O(P_i) \\ \vdots \\ O(P_n) \end{bmatrix}_{n \times 1} \tag{3}$$

The modified candidate solutions use the proposed POA, which mimics pelicans' behaviour and tactics when pursuing and hunting prey. This hunting tactic is mimicked in a couple of stages:

- Approaching prey while in the exploring phase.
- Winging on the surface of the water in the exploitation phase.

The pelicans locate the prey's position and then head in that direction. The scanning of the search space and the exploratory power of the suggested POA are made possible by imitating the pelican's tactical approach. The crucial aspect of POA is that the prey's position is produced at random within the field of search space. This strengthens POA's ability to explore the problem-solving domain precisely. The aforementioned ideas and the pelican's approach to its target prey are mathematically represented in the following equation:

$$p_{i,j}^{k_1} = \begin{cases} p_{i,j} + \delta \times (k_j - \beta \times p_{i,j}), O_k < O_i \\ p_{i,j} + \delta \times (p_{i,j} - k_j), \; else \end{cases} \tag{4}$$

Where, $p_{i,j}^{k_1}$ represents the status of pelican i in dimension j, δ and β are the random numbers ranging from 0 to 1, O_k represents the value of objective function. For each iteration and each member, this parameter is chosen at random. When this parameter's value is two, a member experiences more displacement, which may take them to fresh regions of the search space. As a result, a parameter can determine how well a POA can explore the search space. If the value of the objective function is enhanced at the new position, the pelican will accept it. The algorithm is stopped from moving to suboptimal locations during this kind of modifications also known to be successful updating. Moreover, the following Eq. (5) serves as the model for this procedure.

$$P_i = \begin{cases} P_i^{k_1}, O_i^{k_1} < O_i \\ P_i, else \end{cases} \tag{5}$$

Where, $P_i^{k_1}$ indicates the updated status of pelican, and $O_i^{k_1}$ is the updated objective function value. When the pelicans reach the water's surface, they expand their wings to lift the fish forward and then scoop them up in their throat pouches. More fish in the attacked region have been captured by pelicans as a result of this tactic. The proposed POA converges on more efficient spots in the hunting area as a result of mimicking the actions of pelicans. In order to converge to a good selection, the algorithm needs mathematically investigate the locations nearby the pelican site. The following Eq. (6) simulates this behavior of pelicans during their hunting season:

Received: May 21, 2023. Revised: July 26, 2023.

$$p_{i,j}^{k_2} = p_{i,j} + \text{C} \times (1 - \frac{y}{Y}) \times (2 \times \delta - 1) \times p_{i,j} \quad (6)$$

Where, $p_{i,j}^{k_2}$ indicates the updated status, C represents the constant value, y is the count of iterations, and Y is the maximum number of iterations. During this exploitation stage, the pelicans' new position is updated as shown in the following model:

$$P_i = \begin{cases} P_i^{k_2}, O_i^{k_2} < O_i \\ P_i \quad else \end{cases} \quad (7)$$

Where, $P_i^{k_2}$ is the newly updated status. According to this value, the best optimal solution is computed that is used for choosing the features from the preprocessed face image.

D. Weight optimized extreme learning machine (WOELM) classification

After feature selection, the WOELM technique is applied to predict the emotion from the given face image based on its selected attributes. When compared to the other classification techniques, the primary reasons of using this classification model are simplicity, easy to understand the system function, lower complexity, time efficiency and accurate recognition rate. Similar to the other machine learning models, the WOELM comprises the input, hidden and output layers. In this model, the number of neurons in the network are separately determined in the layers. Then, the connection weight is computed with the use of hidden and output layers. At first, the connection weight is estimated as shown in the following model:

$$\varphi = \begin{bmatrix} \varphi_{11} & \varphi_{12} & \cdots & \varphi_{1n} \\ \varphi_{21} & \varphi_{22} & \cdots & \varphi_{21} \\ \vdots & \vdots & \cdots & \vdots \\ \varphi_{h1} & \varphi_{h2} & \cdots & \varphi_{1n} \end{bmatrix}_{h \times n} \quad (8)$$

$$\Psi = \begin{bmatrix} \Psi_{11} & \Psi_{12} & \cdots & \Psi_{1m} \\ \Psi_{21} & \Psi_{22} & \cdots & \Psi_{2m} \\ \vdots & \vdots & \cdots & \vdots \\ \Psi_{h1} & \Psi_{h2} & \cdots & \Psi_{1m} \end{bmatrix}_{h \times m} \quad (9)$$

$$\beta = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_h \end{bmatrix}_{h \times 1} \quad (10)$$

Where, φ is the connection weight value between the hidden and input layers, Ψ represents the connection weight value between the hidden and output layers, β is the bias value. Based on this, the final output is predicted as shown in below:

Table 2. List of symbols and descriptions

Symbols	Descriptions
$P_{i,j}$	Set of population
m, n	Count of population members and problem variables respectively
Lb_j and Ub_j	Lower and upper bound values
P	Population matrix
O	Objective function
$p_{i,j}^{k_1}$	Status of pelican
i	Pelican
j	Dimension
δ and β	Random numbers
$P_i^{k_1}$	Updated status of pelican
$O_i^{k_1}$	Updated objective function value
C	Constant value
y	Count of iterations
Y	Maximum number of iterations
φ	Connection weight value between the hidden and input layers
Ψ	Connection weight value between the hidden and output layers
β	Bias value
PC	Predicted class
a	Activation function
q_j	Hidden layer neuron
h	hidden layer
n and m	Input and output layers

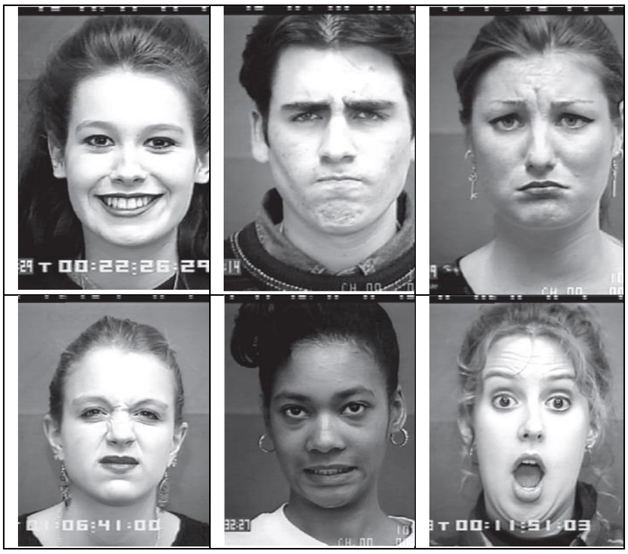
$$PC = \begin{bmatrix} \sum_{i=1}^{h} \Psi_{i1h} a(\varphi_i q_j + \beta_i) \\ \sum_{i=1}^{h} \Psi_{i2h} a(\varphi_i q_j + \beta_i) \\ \vdots \\ \sum_{i=1}^{h} \Psi_{im} a(\varphi_i q_j + \beta_i) \end{bmatrix}_{m \times h} \quad (11)$$

Where, PC indicates the predicted class, a is the activation function, q_j is the hidden layer neuron, h indicates the hidden layer, n and m are the input and output layers respectively. Based on this classification process, the recognized output is produced as the final result, which helps to categorize the emotion into the types of happy, sad, surprise, neutral, disgust, anger, or fear.

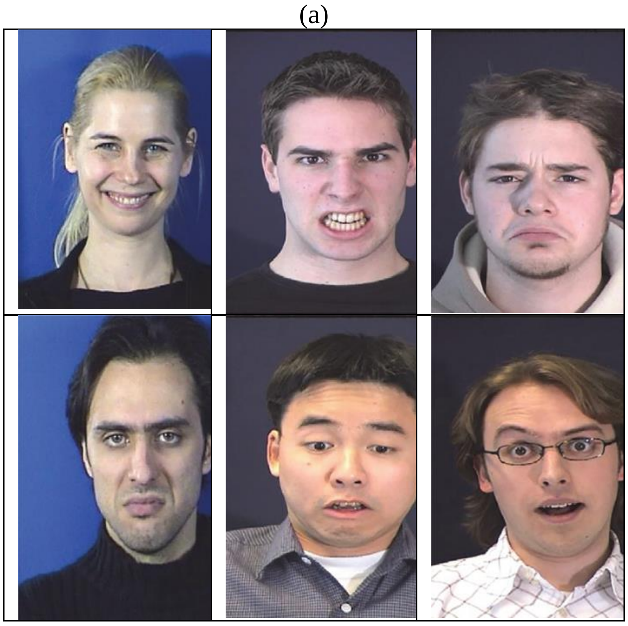
4. Results and discussion

In this section, the proposed POA-WOELM technique has been evaluated using a variety of well-known face image datasets, including CK+, JAFEE and MMI. Receiver operating characteristics (ROC) analysis, sensitivity, specificity, accuracy, and other performance metrics have all been used to assess the efficacy of both existing and new emotion

 DOI: 10.22266/ijies2023.1031.46

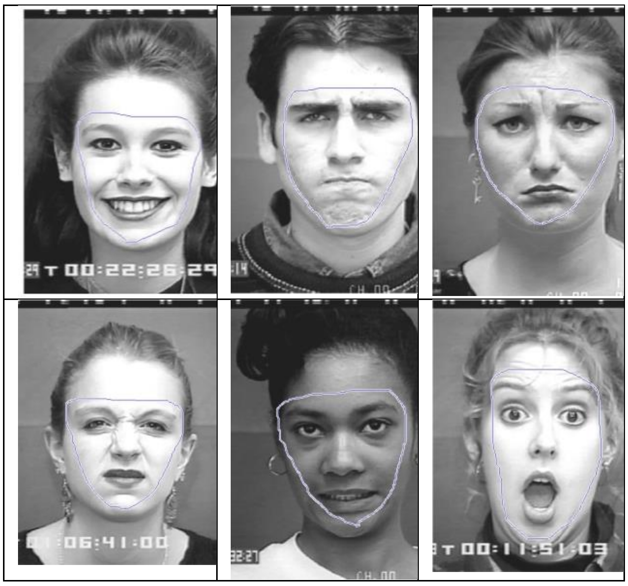


(a)

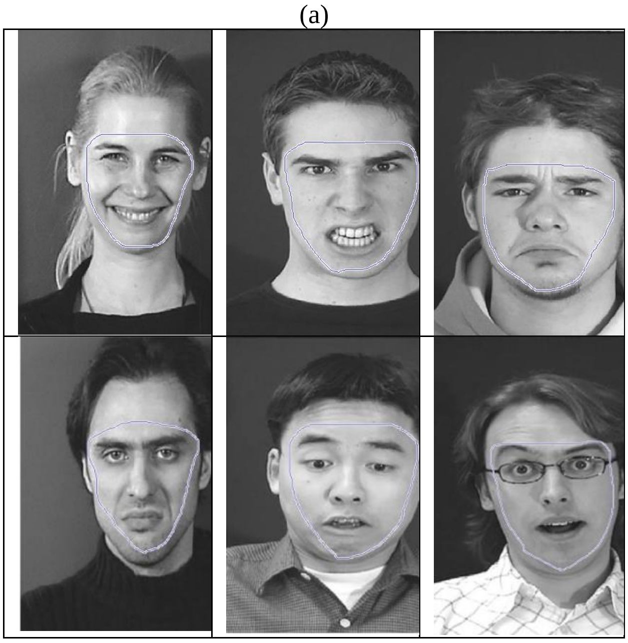


(b)

Figure. 2 (a) Sample input images from CK+ dataset (b) Sample input images from MMI dataset



(a)



(b)

Figure. 3 (a) Face detection for CK+ dataset (b) Face detection for MMI dataset

recognition systems. Along with their stated outcomes, each dataset also includes examples of the photos that they produced. Additionally, the various existing classification strategies have been compared with the POA-WOELM technique in order to show the superiority of the recommended method. Fig. 2 through Fig. 5 display some of the sample input and processed output images. The classifier's overall detection rate and efficiency are determined using the accuracy value. Additionally, the amount of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) that were really gathered during classification is used to make this decision. Then, it is mathematically represented as illustrated below.

$$Accuracy = \frac{Tp+Tn}{Tp+Tn+Fp+Fn} \tag{12}$$

$$Sensitivity = \frac{Tp}{Tp+Fn} \tag{13}$$

Sensitivity is commonly calculated as the ratio of the number of TP rate to the value of TP with FN.

$$Specificity = \frac{Tn}{Tn+Fp} \tag{14}$$

Specificity is also determined by the TN with FP ratio.

$$Precision = \frac{Tp}{Tp+Fp} \tag{15}$$

Received: May 21, 2023. Revised: July 26, 2023.

(a)

(b)

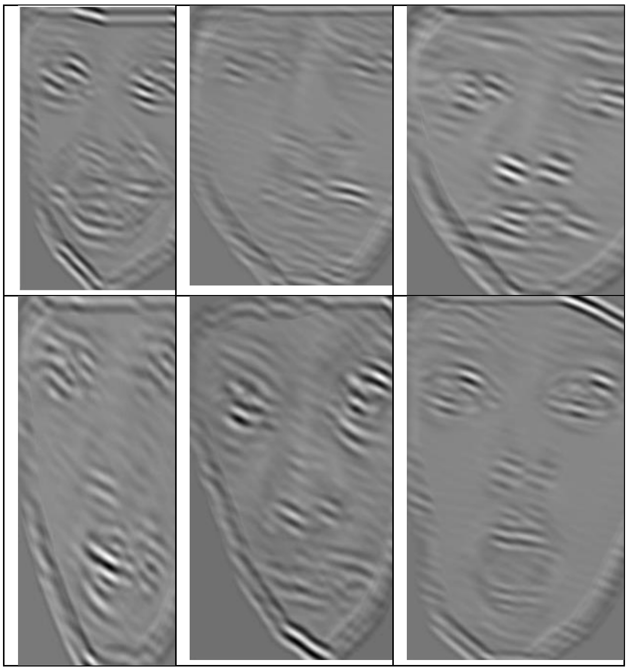
Figure. 4 (a) Face region cropped CK+ dataset (b) Face region cropped for MMI dataset

Precision is calculated in terms of True positive values proportional to the total true positives and false positive values.

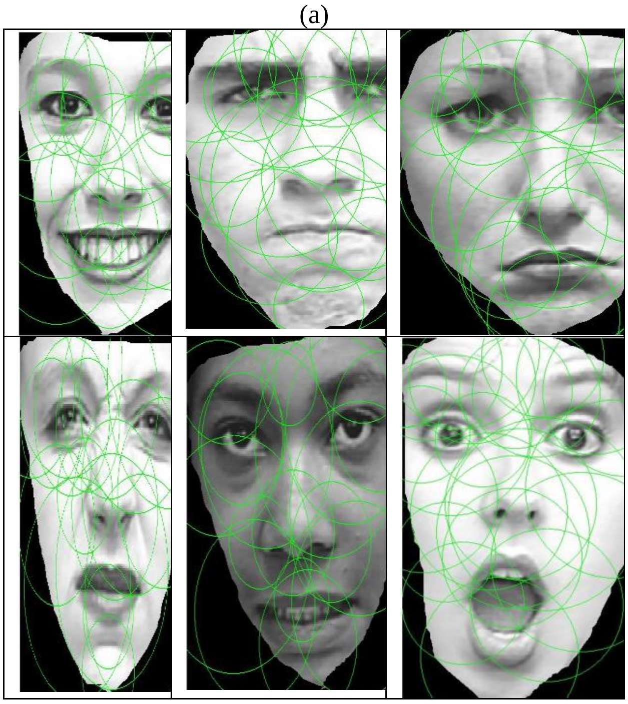
$$F1 - Score = \frac{2*Precision*Recall}{Precision+Recall} \quad (16)$$

To assess how successfully the classifier was able to anticipate the precise values throughout the recognition phase, other metrics like as accuracy, recall, F1 score, and error rate are used.

Fig. 6 validates the ROC of proposed emotion recognition system with and without optimization techniques. The TPR and FPR correlation is often examined using the ROC curve, and the prediction



(a)



(b)

Fig 5. Feature extraction

rate is calculated using the level of ROC, which offers insights on recall and precision. It is expected that TPR and FPR will determine how accurately emotion recognition is carried out in this scenario. Given the low threshold in this case, we can enhance the TPR and FPR. Due to proper face detection, normalization, and classifier training operations with the right features, the findings demonstrate that the proposed WOELM classification mechanism gives improved ROC values when it integrates with the POA. Moreover, the confusion matrices are generated for

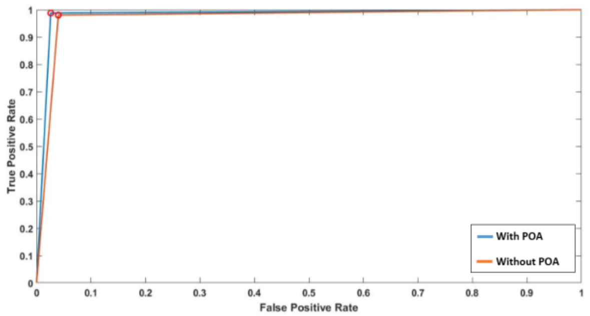


Figure. 6 ROC analysis with and without ROA

Emotion	Angry	Disgust	Fear	Happy	Sad	Neutral
Angry	99	0	0	0	0	0
Disgust	0.75	98.9	0	0	0.51	0
Fear	0	0	99.3	0.35	0	0.33
Happy	0	1.05	0	98.95	0	0
Sad	0.17	0	0.63	0	99.3	0
Neutral	0	0	0	0	0	100

Figure. 7 Confusion matrix for CK+ dataset

Emotion	Angry	Disgust	Fear	Happy	Sad	Neutral
Angry	99.35	0	0	0	0	0
Disgust	0.5	99.1	0	0	0.5	0
Fear	0	0	99	0.2	0	0.3
Happy	0	1	0	98.95	0	0
Sad	0.2	0	0.5	0	99.2	0
Neutral	0	0	0	0	0	99.4

Figure. 8 Confusion matrix for MMI dataset

CK+ and MMI datasets with respect to different emotions as shown in Figs. 7 and 8 respectively.

Figs. 9 to 11 validates the overall performance analysis of the proposed POA-WOELM based face emotion recognition system using MMI, CK+ and JAFEE datasets respectively. For this analysis, the different types of emotions such as surprise, sad, fear, disgust, angry, neutral and happy. The accuracy of the emotion recognition system is determined based on these parameters. The estimated results show that the proposed POA-WOELM mechanism provides high performance results for all datasets [39]. Since, the face features are optimally selected by using the POA, which helps to obtain the better results in the proposed emotion recognition system.

By using the MMI and CK+ datasets, respectively, Figs. 12 and 13 validate the average accuracy of the proposed and standard emotion recognition systems [40]. The results show that, when compared to the other classification models, the suggested POA-WOELM technique offers a higher average accuracy.

The total average accuracy of the suggested emotion identification system is significantly improved for the provided datasets by making use of appropriate face detection, normalization, and feature

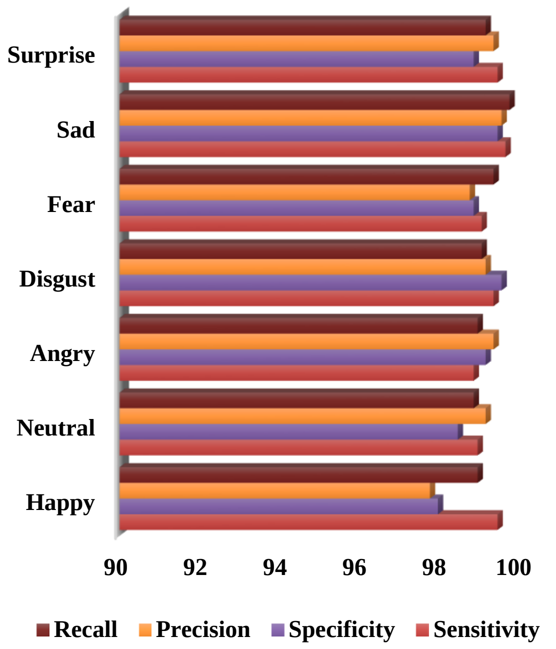


Figure. 9 Performance analysis using MMI dataset

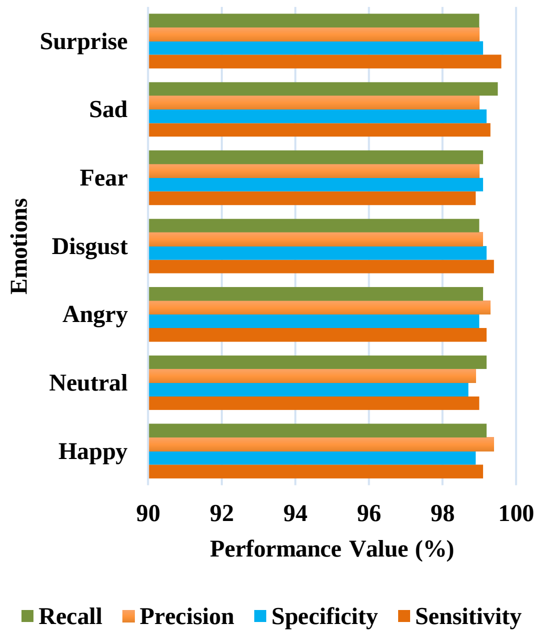


Figure. 10 Performance analysis using CK+ dataset

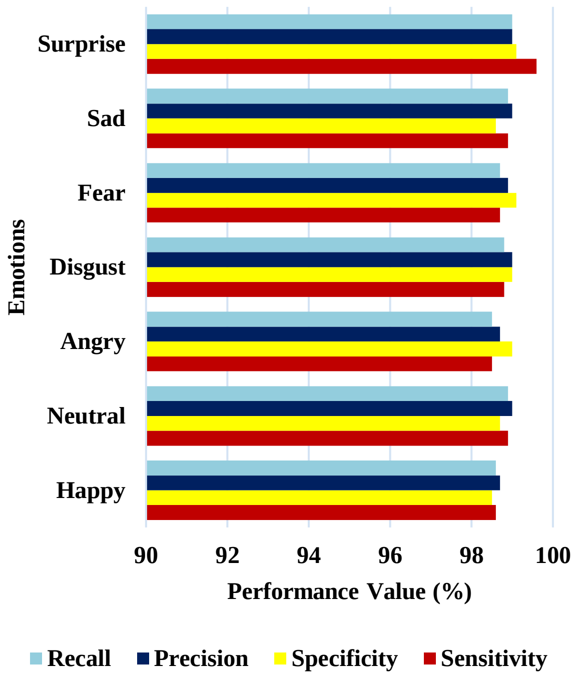


Figure. 11 Performance analysis using JAFEE dataset

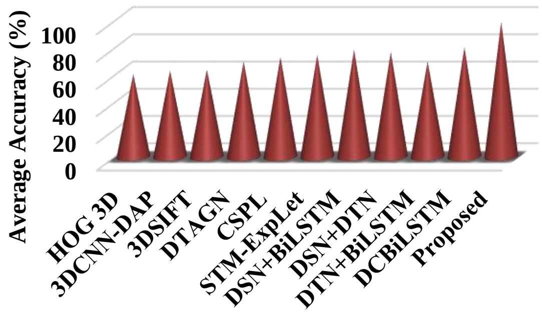


Figure. 12 Average accuracy using MMI dataset

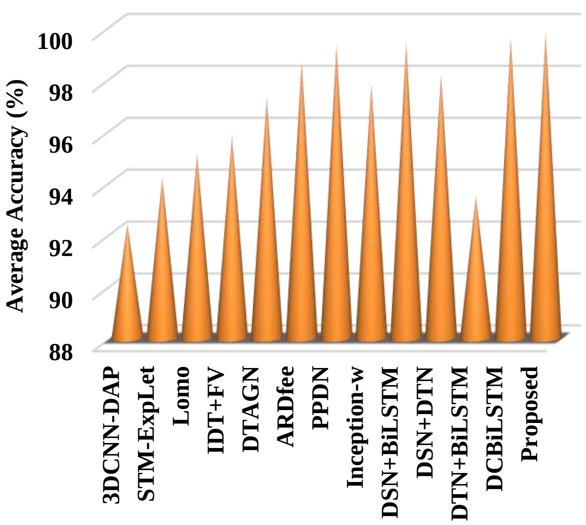


Figure. 13 Average accuracy using CK+ dataset

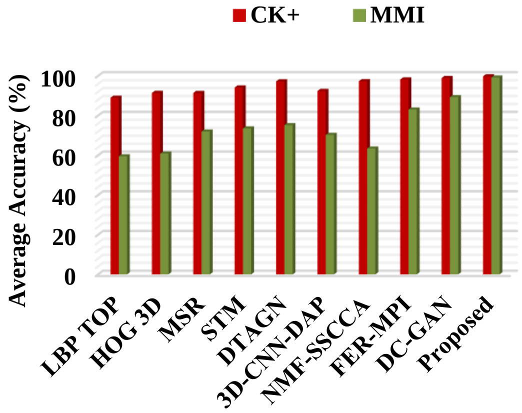


Figure. 14 Comparative analysis based on accuracy using CK+ and MMI datasets

optimization methods. Additionally, using the CK+ and MMI datasets, Fig. 14 compares the accuracy of current feature extraction-based classification and proposed face emotion recognition models. The results show the accuracy level is greatly increased by the proposed POA-WOELM technique.

As shown in Figs. 12 and 13, the average accuracy of the standard emotion recognition and proposed emotion techniques are validated and compared by using MMI and CK+ datasets respectively. Then, the overall comparison based on average accuracy for both datasets is represented in Fig. 14. Typically, the classifier's average accuracy is one of the essential parameters that is used to determine its overall effectiveness. In this study, some of the existing classification techniques are compared with the proposed model based on its average accuracy.

According to the comparison, it is noted that the proposed model provides high average accuracy by properly recognizing the emotions with reduced false predictions. Moreover, the proper learning and training of features is also one of the main reasons for obtaining greater accuracy.

Table 3 compares the literature models with the proposed technique based on the classification performance measures. From the above results, it is observed that the proposed technique outperforms other classifiers with superior results. Consequently, the proposed model is compared with the standard machine learning techniques by using JAFEE dataset. In order to determine the overall efficacy of the proposed emotion recognition system, the recent state-of-the-art model approaches are compared in this study. With proper training and testing of optimized feature set, the overall classifier's performance is greatly improved in the proposed system.

Received: May 21, 2023. Revised: July 26, 2023.

Table 3. Comparative study with the literature work [30]

Techniques	Sensitivity	Specificity	Precision	F1-Score	Accuracy
VGG 19	**82**	**98**	**84**	**83**	**96**
ResNet	**92**	**98**	**92**	**91**	**97**
MobileNet	**94**	**99**	**94**	**93**	**98**
Inception V3	**79**	**96**	**78**	**75**	**94**
Proposed	**98**	**99**	**98**	**98.5**	**98.9**

Table 4. Comparison with JAFEE dataset [17]

Methods	Accuracy	Precision	Recall	F1-score	Training time (s)
NB	**90**	**93**	**90**	**91**	**0.005**
QDA	**79**	**80**	**79**	**79**	**0.005**
DT	**90**	**91**	**90**	**90**	**0.005**
LR	**86**	**90**	**86**	**86**	**0.09**
RF	**93**	**94**	**93**	**93**	**0.33**
MLP	**90**	**94**	**90**	**91**	**0.41**
SVM	**88**	**91**	**88**	**88**	**0.008**
KNN	**95**	**97**	**95**	**95**	**0.002**
Proposed	**98.8**	**98.5**	**98**	**98.7**	**0.0018**

5. Conclusion

Even though the study of emotion identification is still challenging, communication depends on it. Facial expressions can convey sensations and provide crucial emotional information. As a result, one can instantaneously interpret another person's emotional state based on their facial expression. Therefore, information on face expressions is commonly incorporated into automated emotion recognition systems. Because of technological advancements, we can now address problems with automated methods, such as the capacity to identify an individual's emotion from a face image. This study uses the POA-WOELM mechanism to create a facial emotion recognition system that is automated and computationally efficient. This study makes a contribution by employing machine learning to develop a straightforward and precise face emotion identification system. The Haar feature extraction approach, one of the most widely used detection algorithms because of its simplicity and effectiveness, is employed in this stage to detect the face from the input image. In this method, the elements of the rows and columns in the image matrix are used to estimate the average of two values with their difference. Following that, image preprocessing is completed to produce the output normalized image. In order to choose the important features from the pre-processed dataset with the most optimal solution, the POA technique is used. Finally, the WOELM can reliably identify the emotion according to the chosen attributes. By using well-known datasets including CK+, MMI, and JAFEE, the performance of the proposed POA-WOELM approach is assessed and contrasted for validation. The results show that the proposed POA-WOELM performs better than the current emotion recognition models with better prediction outcomes.

In future, an advanced deep learning algorithm can be used to predict the type of emotion from the given face image with low system complexity.

Conflicts of interest (Mandatory)

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author contributions (Mandatory)

"Conceptualization, M.S.; methodology, M.S.; software, M.S.; validation, M.S., and N.R.; formal analysis, M.S.; investigation, M.S.; resources, M.S.; data curation, M.S.; writing—original draft preparation, M.S.; writing—review and editing, N.R.; visualization, M.S.; supervision, N.R.;

References

[1] İ. SAYIN and B. AKSOY, "Proposal of New Dataset for Child Face Expression Recognition and Comparison of Deep Learning Models on The Proposed Dataset", *Türk Doğa Ve Fen Dergisi*, Vol. 12, No. 1, pp. 12-20, 2023.

[2] A. Sultana, S. K. Dey, and M. A. Rahman, "Facial emotion recognition based on deep transfer learning approach", *Multimedia Tools and Applications*, pp. 1-15, 2023.

[3] N. Khan, A. V. Singh, and R. Agrawal, "Enhancing Feature Extraction Technique Through Spatial Deep Learning Model for Facial Emotion Detection", *Annals of Emerging Technologies in Computing (AETiC)*, Vol. 7, No. 2, 2023.

[4] A. I. Jabbooree, L. M. Khanli, P. Salehpour, and S. Pourbahrami, "A novel facial expression recognition algorithm using geometry β–

skeleton in fusion based on deep CNN", *Image and Vision Computing*, Vol. 134, pp. 104677, 2023.

[5] S. B. Punuri, S. K. Kuanar, M. Kolhar, T. K. Mishra, A. Alameen, H. Mohapatra, and S. R. Mishra, "Efficient Net-XGBoost: An Implementation for Facial Emotion Recognition Using Transfer Learning", *Mathematics*, Vol. 11, No. 3, pp. 776, 2023.

[6] T. Ghosh, M. H. A. Banna, M. J. A. Nahian, M. S. Kaiser, M. Mahmud, S. Li, and N. Pillay, "A Privacy-Preserving Federated-MobileNet for Facial Expression Detection from Images", In: *Proc. of International Conference on Applied Intelligence and Informatics*, pp. 277–292, 2022, doi: 10.1007/978-3-031-24801-6_20.

[7] S. A. Sumaidaee, M. Abdullah, R. A. Nima, S. Dlay, and J. Chambers, "Spatio-Temporal Modelling with Multi-Gradient Features and Elongated Quinary Pattern Descriptor for Dynamic Facial Expression Recognition", *Pattern Recognition*, pp. 109647, 2023.

[8] R. G. Abd, A. W. S. Ibrahim, and A. A. Noor, "Facial Emotion Recognition Using HOG and Convolution Neural Network", *Ingénierie Des Systèmes D'Information*, Vol. 28, No. 1, 2023.

[9] K. Vasudeva, A. Dubey, and S. Chandran, "SCL-FExR: supervised contrastive learning approach for facial expression Recognition", *Multimedia Tools and Applications*, pp. 1-21, 2023.

[10] N. Churamani, T. Dimlioglu, G. I. Parisi, and H. Gunes, "Continual Facial Expression Recognition: A Benchmark", *ArXiv Preprint ArXiv:2305.06448*, 2023.

[11] P. D. Kusuma and F. C. Hasibuan, "Attack-Leave Optimizer: A New Metaheuristic that Focuses on The Guided Search and Performs Random Search as Alternative", *International Journal of Intelligent Engineering & Systems*, Vol. 16, No. 3, 2023, doi: 10.22266/ijies2023.0630.19.

[12] P. D. Kusuma and M. Kallista, "Quad Tournament Optimizer: A Novel Metaheuristic Based on Tournament Among Four Strategies", *International Journal of Intelligent Engineering & Systems*, Vol. 16, No. 2, 2023, doi: 10.22266/ijies2023.0430.22.

[13] P. D. Kusuma and A. Novianty, "Multiple Interaction Optimizer: A Novel Metaheuristic and Its Application to Solve Order Allocation Problem", *International Journal of Intelligent Engineering & Systems*, Vol. 16, No. 2, 2023, doi: 10.22266/ijies2023.0430.35.

[14] H. Zhang, A. Jolfaei, and M. Alazab, "A face emotion recognition method using convolutional neural network and image edge computing", *IEEE Access*, Vol. 7, pp. 159081-159089, 2019.

[15] M. B. Harms, A. Martin, and G. L. Wallace, "Facial emotion recognition in autism spectrum disorders: a review of behavioral and neuroimaging studies", *Neuropsychology Review*, Vol. 20, pp. 290-322, 2010.

[16] M. Bentoumi, M. Daoud, M. Benaouali, and A. T. Ahmed, "Improvement of emotion recognition from facial images using deep learning and early stopping cross validation", *Multimedia Tools and Applications*, Vol. 81, No. 21, pp. 29887-29917, 2022.

[17] A. I. Siam, N. F. Soliman, A. D. Algarni, A. E. Samie, E. Fathi, and A. Sedik, "Deploying machine learning techniques for human emotion detection", *Computational Intelligence and Neuroscience*, Vol. 2022, 2022.

[18] S. Eluri, "A novel Leaky Rectified Triangle Linear Unit based Deep Convolutional Neural Network for facial emotion recognition", *Multimedia Tools and Applications*, pp. 1-21, 2022.

[19] I. Bah and Y. Xue, "Facial expression recognition using adapted residual based deep neural network", *Intelligence & Robotics*, Vol. 2, No. 1, pp. 72-88, 2022.

[20] W. M. Alenazy and A. S. Alqahtani, "An automatic facial expression recognition system employing convolutional neural network with multi-strategy gravitational search algorithm", *IETE Technical Review*, Vol. 39, No. 1, pp. 72-85, 2022.

[21] N. B. Kar, K. S. Babu, and S. Bakshi, "Facial expression recognition system based on variational mode decomposition and whale optimized KELM", *Image and Vision Computing*, Vol. 123, p. 104445, 2022.

[22] S. R, S. G and A. V, "Facial Emotion Recognition using Deep Learning Approach", In: *Proc. of 2022 International Conference on Automation, Computing and Renewable Systems (ICACRS)*, Pudukkottai, India, pp. 1064-1069, 2022, doi: 10.1109/ICACRS55517.2022.10029092.

[23] A. Dixit and T. Kasbe, "Multi-feature based automatic facial expression recognition using deep convolutional neural network", *Indonesian Journal of Electrical Engineering and Computer Science*, Vol. 25, No. 3, pp. 1406-1419, 2022.

[24] N. Jain, S. Kumar, A. Kumar, P. Shamsolmoali, and M. Zareapoor, "Hybrid deep neural networks for face emotion recognition", *Pattern Recognition Letters*, Vol. 115, pp. 101-106,

2018.

[25] W. Mellouk and W. Handouzi, “Facial emotion recognition using deep learning: review and insights”, *Procedia Computer Science*, Vol. 175, pp. 689-694, 2020.

[26] M. Ninaus, S. Greipl, K. Kiili, A. Lindstedt, S. Huber, E. Klein, H. O. Karnath, and K. Moeller, “Increased emotional engagement in game-based learning–A machine learning approach on facial emotion detection data”, *Computers & Education*, Vol. 142, p. 103641, 2019.

[27] S. Zhang, X. Pan, Y. Cui, X. Zhao, and L. Liu, “Learning affective video features for facial expression recognition via hybrid deep learning”, *IEEE Access*, Vol. 7, pp. 32297-32304, 2019.

[28] F. Z. Canal, T. R. Müller, J. C. Matias, G. G. Scotton, A. R. D. S. Junior, E. Pozzebon, and A. C. Sobieranski, “A survey on facial emotion recognition techniques: A state-of-the-art literature review”, *Information Sciences*, Vol. 582, pp. 593-617, 2022/01/01/, 2022.

[29] G. S. Hayes, S. N. M. Lennan, J. D. Henry, L. H. Phillips, G. Terrett, P. G. Rendell, R. M. Pelly, and I. Labuschagne, “Task characteristics influence facial emotion recognition age-effects: A meta-analytic review”, *Psychology and Aging*, Vol. 35, No. 2, p. 295, 2020.

[30] M. K. Chowdary, T. N. Nguyen, and D. J. Hemanth, “Deep learning-based facial emotion recognition for human–computer interaction applications”, *Neural Computing and Applications*, pp. 1-18, 2021.

[31] E. Pranav, S. Kamal, C. Satheesh Chandran, and M. H. Supriya, "Facial Emotion Recognition Using Deep Convolutional Neural Network", In: *Proc. of 2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS)*, Coimbatore, India, pp. 317-320, 2020, doi: 10.1109/ICACCS48705.2020.9074302.

[32] A. Hassouneh, A. M. Mutawa, and M. Murugappan, “Development of a Real-Time Emotion Recognition System Using Facial Expressions and EEG based on machine learning and deep neural network methods”, *Informatics in Medicine Unlocked*, Vol. 20, p. 100372, 2020/01/01/, 2020.

[33] S. Li and W. Deng, “Deep facial expression recognition: A survey”, *IEEE Transactions on Affective Computing*, Vol. 13, No. 3, pp. 1195-1215, 2020.

[34] Y. Wang, Y. Li, Y. Song, and X. Rong, “The influence of the activation function in a convolution neural network model of facial expression recognition”, *Applied Sciences*, Vol. 10, No. 5, p. 1897, 2020.

[35] S. M. S. A. Abdullah, S. Y. A. Ameen, M. A. Sadeeq, and S. Zeebaree, “Multimodal emotion recognition using deep learning”, *Journal of Applied Science and Technology Trends*, Vol. 2, No. 02, pp. 52-58, 2021.

[36] D. Jeong, B. G. Kim, and S. Y. Dong, “Deep joint spatiotemporal network (DJSTN) for efficient facial expression recognition”, *Sensors*, Vol. 20, No. 7, p. 1936, 2020.

[37] P. D. Kusuma and A. L. Prasasti, “Guided Pelican Algorithm”, *International Journal of Intelligent Engineering and Systems*, Vol. 15, No. 6, pp. 179-190, 2022, doi: 10.22266/ijies2022.1231.18.

[38] P. D. Kusuma and M. Kallista, “Stochastic Komodo Algorithm”, *International Journal of Intelligent Engineering & Systems*, Vol. 15, No. 4, 2022, doi: 10.22266/ijies2022.0831.15.

[39] S. Porcu, A. Floris, and L. Atzori, “Evaluation of data augmentation techniques for facial expression recognition systems”, *Electronics*, Vol. 9, No. 11, pp. 1892, 2020.

[40] A. Ullah, J. Wang, M. S. Anwar, T. K. Whangbo, and Y. Zhu, “Empirical investigation of multimodal sensors in novel deep facial expression recognition in-the-wild”, *Journal of Sensors*, Vol. 2021, pp. 1-13, 2021.