Int. J. Fuzzy Syst.
https://doi.org/10.1007/s40815-022-01402-z

Optimized Anfis Model with Hybrid Metaheuristic Algorithms for Facial Emotion Recognition

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Received: 22 December 2021 / Revised: 1 August 2022 / Accepted: 4 September 2022

Abstract Emotion recognition from facial images is an important and active area of research. Facial features are widely used in computer vision for emotion interpretation, cognitive science, and social interaction. To obtain accurate analysis of facial expressions (happy, angry, sad, surprised, disgusted, fearful, and neutral), a complex method based on human–computer interaction and data is required. It is still difficult to develop an effective and computationally simple mechanism for feature selection and emotion classification. In this paper, an emotion recognition model using adaptive neuro-fuzzy inference system optimized with particle swarm optimization is proposed. The proposed model was compared with many classification algorithms (ANNs, SVMs, and k-Nearest Neighbor (k-NN) and their subcomponents). The confusion matrix was used to evaluate the performance of these classifiers. The proposed model was evaluated using the MUG database. The model achieved a prediction accuracy of 99.6%.

Keywords Facial expression · Emotion recognition (ER) · Adaptive neuro-fuzzy inference system (ANFIS) · Machine learning (ML) · Particle swarm optimization (PSO)

1 Introduction

Facial expressions are one of the most effective nonverbal means by which people communicate their feelings and intentions. Automated facial expression analysis is a fascinating and challenging topic that has significant implications for several industries, including human–computer interaction and data-driven animation. In recent years, automated facial expression recognition has attracted considerable attention due to its wide range of applications [1–4] Despite significant progress [5–18], recognizing facial expressions with high accuracy remains challenging due to the subtlety, complexity, and diversity of facial expressions. Obtaining an accurate facial representation from original facial images is a crucial step for successful facial expression recognition. There are two basic methods for extracting facial features: methods based on geometric features and methods based on appearance [19]. The shape and position of the retrieved facial components are represented by geometric features to produce a feature vector that reflects the facial geometry [20, 21]. Mouth, nose, etc. are structural geometric features. They are derived from the measurements used to create the organ movement points. Ekman and Friesen [22] used the Facial Action Coding System (FACS) to create derived geometric features. This is a recognition technique that relies on human observers to detect minute changes in facial features. Face Action Units (FAUs) are fully controlled face models that can be used to assign specific facial movements. FAU has gained acceptance as the basis for recognizing seven different emotional facial expressions (happy, angry, sad, surprised, disgusted, fearful, and neutral) and has contributed to the development of intelligent systems in this area [23, 24]. It is based on the fact that vectors constructed from landmark coordinates belong to different expressions. The machine learning approach (ML) is used for emotion categorization and prediction [25–27]. This strategy involves the developing algorithms that can extract patterns from known data to create a model, which is then applied to unknown data to predict the outcome [28].

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Published online: 21 October 2022

In this paper, facial emotions are studied objectively by using the properties of FAUs to identify facial expressions independent of the person. The most important properties of FAUs are their adaptability to changing lighting conditions and their computational simplicity. The approach proposed in this study attempts to classify emotions based on facial movements, known as Action Units (AUs), described with the FACS [11]. FACS is the most popular and well-known technique developed for human observers to characterize facial activity based on visually visible facial muscle movements (AUs) [29, 30]. To evaluate a facial expression, we use four machine learning classifiers including ANFIS [31–36], ANNs [28, 37], SVMs [38, 39], and k-nearest neighbors (k-NN) [40].

The emotion recognition process consists of three steps: face tracking and identification, facial feature extraction, and facial feature classification [26]. Here, we focus on the process of facial feature classification. The first two processes are obviously very important to improve the accuracy of classification [41–43]. Conditions such as face recognition and feature extraction, application conditions, changing facial expressions over time, and environmental factors such as light intensity have a significant impact on accurate emotion recognition. For the first two processes and their implementation, there are some databases that are publicly available. One of them is the database MUG [44]. This dataset was used in this study. Developing robust and automated facial emotion estimation with a high degree of accuracy and minimal processing complexity is critical. Based on this logic, we propose the ANFISPSO classification model to improve classification performance, which is the third component of accurate emotion recognition. The proposed model was used with different classification techniques such as ANN, SVM, and k-NN and their subcomponents. ANFIS is a soft computing technique that combines fuzzy inference mechanisms with the capabilities of ANN to enable fast and accurate learning and a high degree of generalization [45]. Although conventional ANFIS techniques perform well, they have the problem of overfitting and parameter optimization. Therefore, it was used with PSO to improve the prediction accuracy and compensate for the limitations of the model [31, 33, 46, 47].

Numerous methods have been developed to properly train the parameters [48–51]. These approaches can update the parameters deterministically or probabilistically. Unlike deterministic techniques, which are inertial and do not converge under certain circumstances, metaheuristic algorithms are population based, so anyone capable of performing a global search could be a candidate solution. Since standard ANFIS training techniques use the gradient descent method (GD), there are multiple local optima at each step due to the calculation of the gradient by the chain rule. Numerous optimization solutions have been developed to solve these problems [52–54].

The main objective of this study is to categorize seven facial emotions (happy, angry, sad, surprised, disgusted, fearful, and neutral) using a model developed with the ANFISPSO method. The ANFIS models were developed using the Fuzzy C software (function FCM or genfis3). ANFIS applications use "and," "or," and "not" as logical operators. However, based on the generated fuzzy logic rules, any operator can be used to accommodate the structure of the input data. In this study, only the logical operator "and" was used.

In addition, PSO was used to improve the performance of the model. Several statistical criteria, including the complexity matrix, F-score, percentage of correctness, and ROC curve, were used to evaluate the performance of the developed models. The general view of the proposed architecture is shown in Fig. 1.

ANFIS is a very effective tool, but it is computationally intensive. This tool provides a solution to the problem of computational complexity by incorporating PSO in the estimation of the relevant parameters. With PSO, ANFIS can achieve a better result and converge faster. This study introduces the hybrid structure of ANFIS with PSO, a well-known metaheuristic optimization approach for describing facial emotions. To our knowledge, previous studies have not used the ANFISPSO framework for FER based on AUs. The proposed model is considered a new framework with a new hybrid approach used for FER using AUs.

These are the aims of this study:

- To experimentally analysis of the recognition properties of facial expressions in AUs and in-depth analysis of the facial features extracted from the database and application of different learning techniques for their classification.
- To build a fuzzy neural network-based FER model using AUs
- To explore the possibilities of improving the performance of the conventional ANFIS model, a nature-motivated metaheuristic optimization algorithm, the PSO algorithm, is used to fine tune the ANFIS parameters.
- To compare the performance of ANFISPSO with that of ANN, KNN, and the SVM model to determine its applicability in the FER estimation process.
- The proposed ANFISPSO classifier is intended to achieve better classification performance compared to the other classifiers.

The organization of this paper is covered in four different sections. Section 2 presents the materials and the method. This section discusses the different modeling techniques used, the selection of input data, and the process

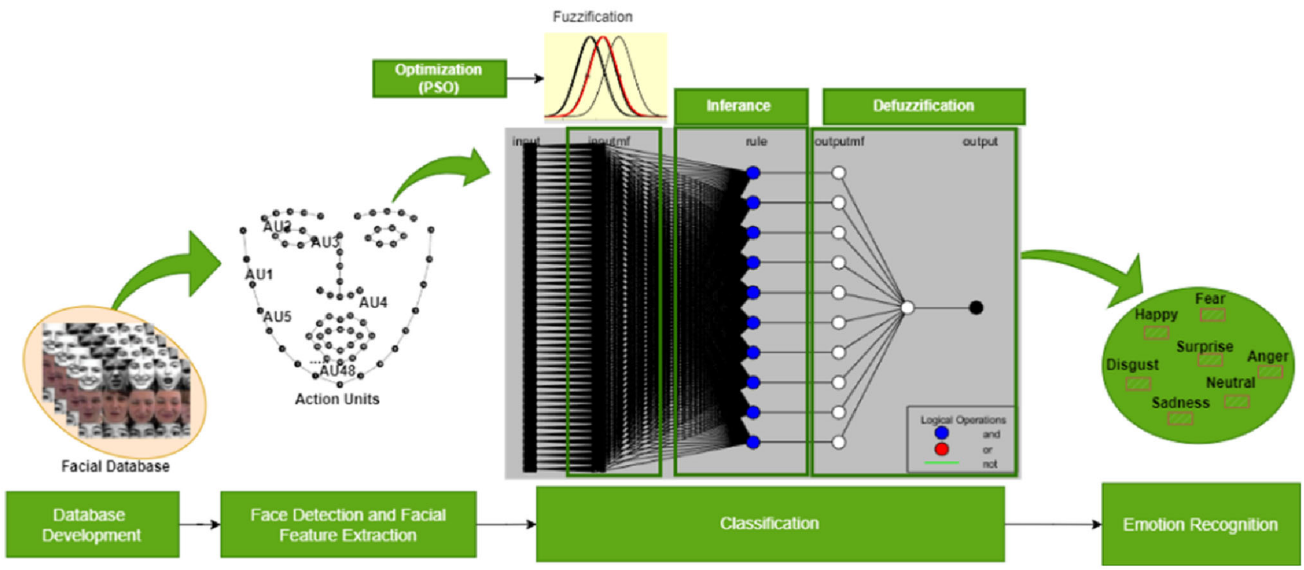


Fig. 1 The frame work of the proposed architecture

of model development. The experimental results are presented in Sect. 3. Finally, the conclusion is presented in Sect. 4.

2 Material and Methods

In this section, an overview of the database used in this study is provided, followed by a detailed description of the classifiers proposed to classify the extracted features from facial images to apply the emotion estimation system. Then, the metrics used to evaluate the performance of the classifiers, the confusion matrix technique, are evaluated. Figure 2 shows the primary flowchart of the model, the graphical representation of the algorithms working together, and the interaction between the data processing operations required to achieve the desired result. The following sections provide information about each phase.

2.1 Database

The database MUG was used for this research [44]. This database contains 86 subjects (51 males and 35 females). All subjects are between 20 and 35 years old. There are only 52 subjects accessible to Internet researchers. The images were taken with a camera and two 300 W light sources. The subject is sitting on a chair in front of a blue background. 19 frames per second were taken with a resolution of 896 $\times$ 896 pixels in JPEG format. Each subject has seven facial expressions, and each emotion is stored in many image sequences (often three to five), with 50–160 photos per sequence. Each subject contains an average of over 1462 photos. This database contains 260 angry, 255 disgusted, 240 fear, 260 happy, 260 neutral, 2445 sad, and 260 surprised images. In total, there are 1780 images.

2.2 Adaptive Neuro-Fuzzy Inference System (Anfis)

ANFIS is a practical artificial intelligence method developed by Jang [34] that mimics human reasoning. The philosophy of the structure is based on how neurons work in the human brain. The studies of these neurons are transferred to computers and converted into algorithmic models. Using fuzzy “IF THEN” principles and specified inputs and outputs, it converts the inputs and information links from highly interconnected neural networks into the desired output. Inputs and outputs are used to generate the membership function of ANFIS, which is then combined with the database through a rule-based combination. ANFIS can manage nonlinear and complex problems in a unique structure by using both ANN and fuzzy inference methods. As shown in Fig. 3, ANFIS consists of nodes and routed paths, and all input–output values can be adjusted by varying the parameters described in the network design. ANFIS systems can be used with various optimization algorithms to reduce the final errors in the training phase. The situation implemented in this study also served this goal [55].

The ANFIS is divided into two phases, each with its own learning algorithm: The first phase uses offline learning, often known as Forward Least Squares, while the second phase uses gradient descent. The FIS structure consists of five layers of sensory neurons. The sensory neurons in each layer are identical and their functions are shown below [56–58].

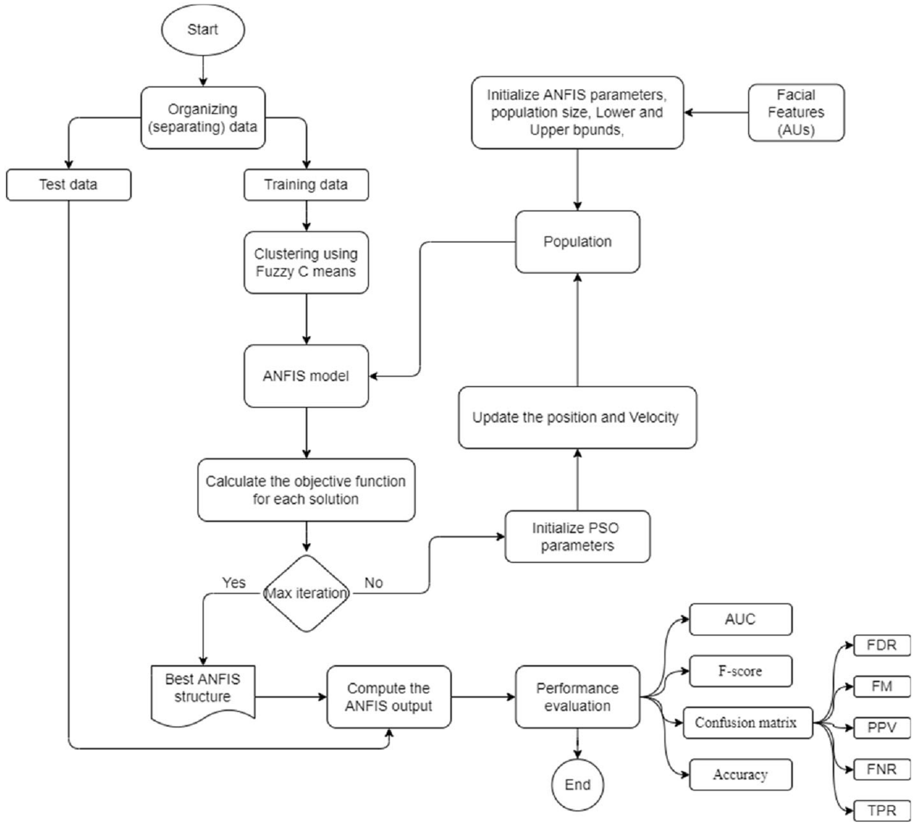


Fig. 2 The flowchart of the proposed structure: (ACC (accuracy), F-score, TPR (true-positive rate), FM (Fowlkes–Mallows index), PPV (positive predictive value), FNR (false-negative rate), FDR (false discovery rate), and area under the ROC curve (AUC))

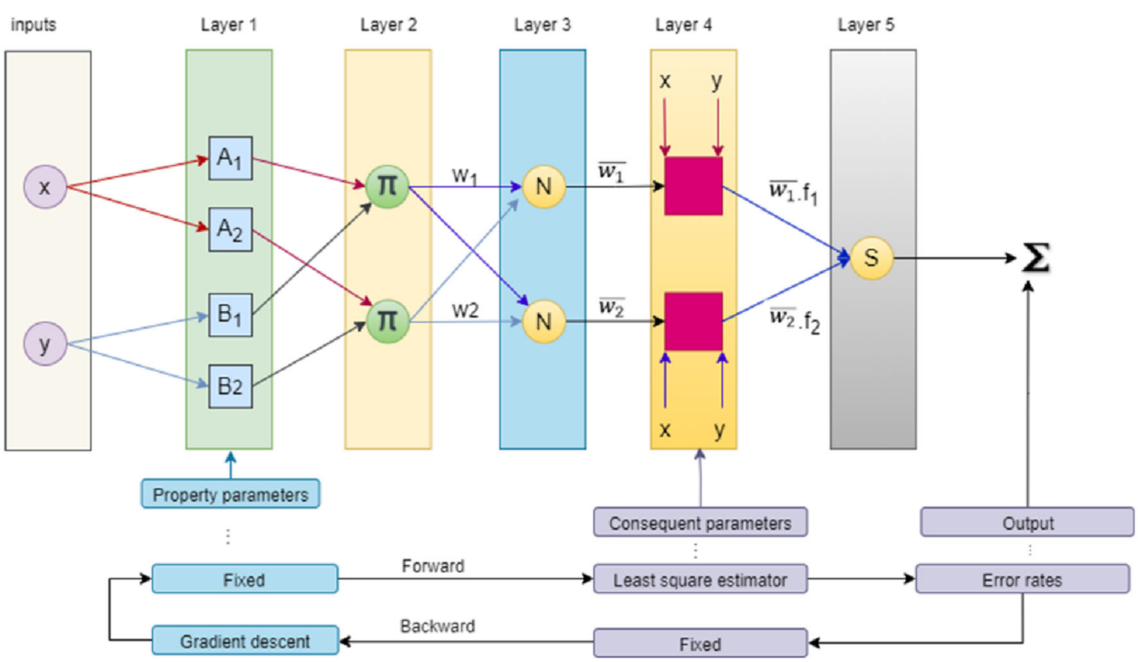
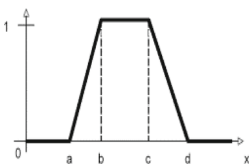


Fig. 3 ANFIS structure

Layer 1 (fuzzyifying layer): The neurons in this layer are adaptive membership functions containing antecedent parameters. A membership function, i.e., a linguistic label or fuzzy set, can be a generalized Bell, trapezoidal, triangular, or Gaussian function. The trapezoidal membership function is shown in the following figure.



$$O_i^{(1)} = T(x;a,b,c,d) = \begin{cases} 0, & x \le a \ \ or\ x \ \ge d \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ 1, & b \le x \le c \\ \dfrac{d-x}{d-c}, & c \le x \le d \end{cases} \quad (1)$$

Defined by its lower bound (a) and its upper bound (d), and the lower and upper bounds of its core, b and c respectively. $O_i^{(1)}$ represents the output of this layer.

Layer 2 is the product layer. Each node in this layer is denoted by π and represented by a circle. The nodes in this layer accept input from their respective fuzzy neurons and decide the firing intensity of the rule they represent depending on the incoming signals. The output value is calculated using Eq. (2).

$$O_i^{(2)} = \prod\nolimits_{i=1}^{r} x_{ji}^{(2)}. \quad (2)$$

Here $x_{ji}^{(2)}$ is the layer input from layer 1(j) to layer 2(i), and the output $O_i^{(2)}$ is for each neuron i in the product layer.

Layer 3 (normalization layer): Each neuron in this layer is denoted by a circle and labeled N. It receives feedback from all neurons. It receives feedback from all neurons in the product layer and measures the weighted firepower of a given rule. Equation (3) is used for the result of the neurons in this layer.

$$O_i^{(3)} = \frac{x_{ji}^{(3)}}{\sum_{j=1}^{n} x_{ji}^{(3)}} = \overline{w}_i, \quad (3)$$

where $x_{ji}^{(3)}$ represents the input to neuron i in the normalization layer from the product layer according to neuron j, while $O^{(3)}$ represents the output of layer 3.

Layer 4 (defuzzification layer): The neurons in this layer are actually adaptive or modifiable neurons that contain outcome parameters. The formula used for the defuzzification layer is shown in Eq. (4).

$$O_i^{(4)} = x_i^{(4)} f_i = \overline{w}_i [p_i \mathrm{x} + q_i \mathrm{y} + r_i]. \quad (4)$$

Here $x_i^{(4)}$ is the input of layer 4, while the output is $O_i^{(4)}$. p_i, q_i, r_i are parameter set.

Layer 5 (combination layer): The output of this layer contains a single neuron that combines all the outputs of the previous layer. The formula used for the defuzzification layer is shown in Eq. (5).

$$O_i^{(5)} = \sum_i \overline{w}_i . f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}. \quad (5)$$

The ANFIS learning process is two-stage and includes hybrid gradient descent (GD) and least-squares error (LSE) method, changing parameters both forward and backward. The least-squares method is used to compute the result parameters in the forward pass of the node outputs from layer 1 to layer 4, which occurs between layers 1 and 4. During the backward pass, the error signals are sent from the output layer to the input layer, and the GD algorithm changes the values of the previous parameter values.

2.3 Particle Swarm Optimization (PSO)

PSO is a metaheuristic stochastic population-based evolutionary optimization algorithm developed by Eberhart and Kennedy [59]. The algorithm was developed by mimicking the movements of flocks of birds and fish to exploit the group intelligence of a group of particles moving at a given velocity in a search space. During each iteration, the velocity and position of each particle are updated along with the particle's current solution, the particle's individual best solution, and the global best solution obtained by all particles. Equations (6) and (7) were developed to perform these calculations. The lower and upper bounds of each particle size are represented by upper and lower in the algorithm.

$$X_i^{t+1} = X_i^t + V_i^{t+1}, \quad (7)$$

$$V_i^{t+1} = \underbrace{\overbrace{w * V_i^t}^{\substack{\textbf{Diversification}\\ \text{Searches new solutions,}\\ \text{finds the regions with}\\ \text{potencially the best}\\ \text{solutions}}}}_{\substack{\textbf{Inertia}\\ \text{Makes the particles move}\\ \text{in the same direction and}\\ \text{at the same velocity}}} + \overbrace{\underbrace{c_1 * r_1 \left(P^t{}_{b(i)} - X_i^t\right)}_{\substack{\textbf{Personal influence}\\ \text{improves the individual.}\\ \text{makes the particle return to}\\ \text{a previous position that is better}\\ \text{than the current one.}}} + \underbrace{c_2 * r_2 * \left(G^t{}_{b(i)} - X_i^t\right)}_{\substack{\textbf{Social Influence}\\ \text{makes the particle}\\ \text{follow the best neighbors direction.}}}}^{\substack{\textbf{Intensification}\\ \text{explores the previous solutions,}\\ \text{finds the best solution of given region}}} \tag{6}$$

where V_i is the velocity of the particle, w is the inertial weight, c_1 is a cognitive constant, r_1 and r_1 are random numbers, c_2 is a social constant, X_i is the position of the particle, P_b is the personal best and G_b is the global best, respectively. When particles interact, their motion is influenced by their social and cognitive behavior. The social behavior is determined by the best solution of the swarm (G_b), and the cognitive behavior indicates the best solution of the particles so far (P_b). As cognitive coefficients, these factors are used to balance the exploration and exploitation functions. The pseudocode is shown in Algorithm 1.

Algorithm 1 PSO

Input: ← size (**N**), position of particle swarm (**X**), inertia weight (**W**), and learning factors {**c1,c2**}, number of iteration (**Tmax**), and the solution dimension (**d**).

Output: ← Optimal solution (**gbest**)

Begin
while t < Tmax
Particle swarm fitness evaluation
  For i = 1: N
    Find **pbest**
    Find **gbest**
    For j = 1: d
      Adjust velocity by (6)
      Adjust all positions by (7)
    End for
    Update **W**
  End for
End
End

2.4 Model Structure

The proposed models optimize existing ANFIS algorithms using the PSO algorithm. The data file used was [44], a dataset with a total of 1780 images, the details of which are given in the database title. The inputs used for the system consist of a set of facial features (AUs). The output of the system consists of seven different emotion classes. The general architectural framework of the proposed system is shown in Fig. 4.

First, the training and testing data of the system are determined. The training data were used to build a model using FCM (genfis3) [60], and the mean and standard deviation for Gaussian membership function were optimized using PSO. The improved model was evaluated against the test data, and the output of the model was used to determine the emotion classes. The facial features (AUs) extracted from the dataset were used as training and test data for the classification algorithms presented. 70% of the data were randomly selected for training and 30% for testing. MATLAB program was used to simulate ANFIS models. Numerous tests were performed to determine whether the proposed ANFIS model provided an acceptable outcome without overfitting. Overfitting is a common phenomenon in ANFIS models [58, 61]. This is the result of excessive ANFIS data training. Each ANFIS-trained dataset can be constrained to a certain number of periods before overfitting kicks in and the estimated output exceeds precision. The optimum number of periods can only be determined through experimentation. Overfitting can be avoided by changing the number of training cycles in ANFIS modeling. The number of periods for basic ANFIS and iteration algorithms is 300. Table 1 shows the

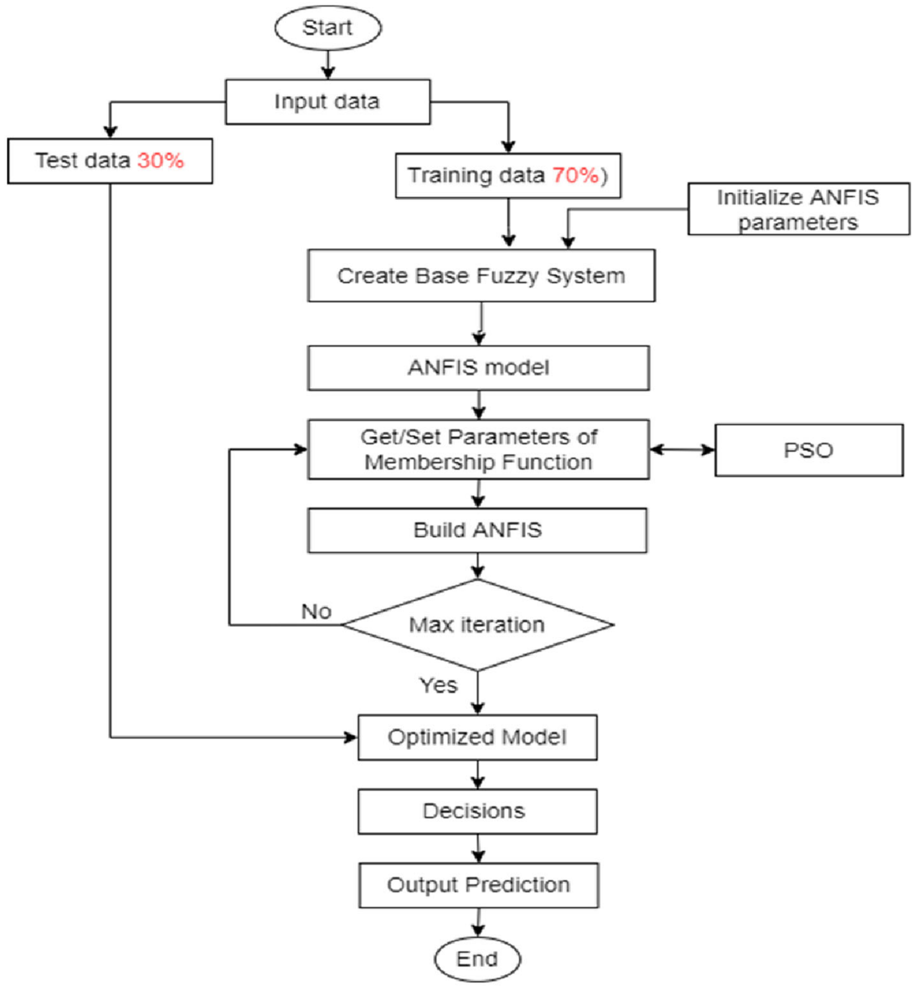


Fig. 4 Flowchart of ANFISPSO

parameters of the algorithms used. Finally, clasification performance was determined using test data.

In neuro-fuzzy networks, it is important to define the appropriate network topology and to choose the parameters of the membership functions. Moreover, the effectiveness of these networks depends on the precision and efficiency of the learning algorithms. Most learning techniques for neural networks are gradient-based, especially post-propagation error and least squares. Algorithms such as Hybrid and Backpropagation Error are used for training neuro-fuzzy networks. Although these algorithms are very promising, the presence of significant errors in certain cases can complicate the training process. Gradient-based algorithms use local search strategies and are, therefore, prone to trapping local optimal positions. Moreover, algorithms such as the Levenberg–Marquardt algorithm (LM) and hybrids have very high computational complexity. Therefore, the use of gradient-based algorithms for problem solving has been discussed for a long time. To train the network, evolutionary algorithms such as PSO are the most suitable. Evolutionary algorithms are very good at performing exhaustive search and avoiding localized locations.

3 Experiments

Different strategies allow to predict a related variable based on one or more independent factors and to establish a relationship between several variables. Linear regression, neural networks, fuzzy inference systems, and a mixture of fuzzy inference systems and neural networks are some examples (called ANFIS). Based on the particle swarm optimization (PSO) algorithm and adaptive neuro-fuzzy inference system (ANFIS) for prediction, the performance of the combined technique is investigated in this paper. The method consists of using various machine learning algorithms to investigate whether the face correctly classifies the emotion class according to the emotion features.

Table 1 Parameter setting for the selected ANFISPSO structure in predicting facial emotion recognition

Algorithm	Parameters	Values/types
ANFIS	Error goal	0
	Input membership function	Gaussian
	Output membership shape	Linear
	Max. Iteration	300
	Minimum improvement	1e-5
	FIS generation	FCM
	Step size Decrease Rate	0.9
	Initial Step Size	0.01
	Step Size Increase Rate	1.1
PSO	w	1
	wdamp (Inertia Weight Damping Ratio)	0.99
	c1	1
	c2	2
	number of population	50
	Max iterations	1000

Table 2 Confusion matrix

Predicted value	Actual value	
	Positive	Negative
Positive	TP (true positive)	FN (false negative)
Negative	FP (false positive)	TN (true negative)

3.1 Performance Evaluation

In this subtitle, we will discuss how to evaluate the proposed model. The goal of the performance evaluation is to assess the effectiveness of the algorithms used and to validate the usability of the system. To validate a categorization approach, output values must be compared to observed values. The confusion matrix [62] is a performance metric for the classification problem in machine learning. The confusion matrix is shown in Table 2. There are four different combinations of expected and actual values in this table. Table 3 shows the formulas that can be derived from the complexity matrix. The performance evaluation was performed using these measures.

In the confusion matrix: TP (True Positive) represents the number of correctly classified positive data, FP (False Positive) represents the number of misclassified positive data, TN (True Negative) represents the number of correctly classified negative data, and FN (False Negative) represents the number of misclassified negative data (False Positive). In addition, statistics on the sensitivity, specificity, accuracy, F-measure, and area under the curve

Table 3 Performance metrics [63–65]

Abbreviations	Description	Formula
ACC	*Accuracy*	$ACC = \frac{TP+TN}{TP+FP+TN+FN}$
FSC	F-1 score	$\mathrm{FSC} = 2 * \frac{PRE.RCL}{PRE+RCL}$
AUC	Area under the curve	$\mathrm{AUC} = \frac{1}{2}.(RCL + SPC)$
TPR	True positive rate	$TPR = \frac{TP}{P} = \frac{TP}{TP+FN} = 1 - FNR$
PPV	Positive predictive value	$PPV = \frac{TP}{TP+FP} = 1 - FDR$
FM	Fowlkes–Mallows index	$FM = \sqrt{PPV + TPR}$
FNR	False-negative rate	$FNR = \frac{FN}{P} = \frac{FN}{FN+TP} = 1 - TPR$
FDR	False discovery rate	$FDR = \frac{FP}{FP+TP} = 1 - PPV$

(AUC) of the proposed techniques were used. The formulas for the performance criteria used in this study can be found in Table 3.

Key performance indicators consisting of ACC (accuracy), F-score, terminology, and derivatives of the confusion matrix with TPR (true-positive rate), FM (Fowlkes–Mallows index), PPV (positive predictive value), FNR (false-negative rate), FDR (false discovery rate), and area under the ROC curve (AUC). These are scoring metrics that subtract the desired number from the classifier's results and report the result as a percentage of the classifier's number. In a classifier, the ROC curve can be used to evaluate the tradeoff between the rates of true positives and false positives. AUC is a graphical representation of the false-positive rate (FPR) and the true-positive rate (TPR) at different confidence levels.

3.2 Experimental Results

This research paper presents a hybrid classifier for emotion classification and a performance comparison between this hybrid classifier and machine learning-based classifiers. The proposed approach consists of three main steps: facial emotion dataset (MUG), feature normalization with Procrustes analysis (GPA), proposed ANFISPSO, and 18 other different classifiers. Emotion recognition accuracy, ACC, F-score, ROC area (AUC), FM, TPR, FNR, PPV, and FDR statistics were used to systematically evaluate the effectiveness of the proposed technique. The results obtained are presented in Table 4.

Table 4 shows the results of the different classifiers. The tests were performed 10 times and the average values of all measurements were taken into account. Figure 5 shows the result data obtained visually.

Table 4 The criteria and results for evaluating facial emotion recognition performance

		ACC (%)	F-score	ROC area (AUC)	FM	TPR	FNR	PPV	FDR
Neural network classifiers	Narrow neural network	99.3	96.4571	0.99	13.8893	96.4285	3.5714285	96.4857	3.51428
	Medium neural network	88.3	96.6928	0.99	13.9063	96.6714	3.3285714	96.7142	3.28571
	Wide neural network	89.5	97.0357	0.99	13.9309	97.0285	2.3285714	97.0428	2.95714
	Bilayered Neural Network	93	96.7928	1.00	13.9135	96.7857	3.2142857	96.8	3.2
	Trilayered Neural Network	94.3	96.5642	0.99	13.8970	96.5428	3.4571428	96.5857	3.41428
Nearest neighbor classifiers	Fine KNN	64.5	87.2498	0.91	13.2098	87.1428	12.857142	87.3571	12.6428
	Medium KNN	72.1	78.6177	0.97	12.5396	78.0857	21.914285	79.1571	20.8571
	Coarse KNN	60.7	65.7313	0.95	11.4673	64.6428	35.357142	66.8571	33.1428
	Cosine KNN	65.5	71.2424	0.96	11.9367	71.0714	28.928571	71.4142	28.6
	Cubic KNN	68.6	78.4767	0.97	12.5282	78.1	21.9	78.8571	21.1428
	Weighted KNN	72.1	84.8637	0.98	13.0279	84.6428	15.357142	85.0857	14.9142
Support vector machines (SVM) classifiers	Linear SVM	95.546	97.9999	1.00	14	97.9857	2.0142857	98.0142	1.98571
	Quadratic SVM	95.51	98.4571	0.99	14.0326	98.4571	1.5428571	98.4571	1.54285
	Cubic SVM	91.7	97.2928	0.99	13.9493	97.2714	2.7285714	97.3142	2.68571
	Fine Gaussian SVM	71.1	76.7724	0.96	12.4309	71.1	28.9	83.4285	16.5714
	Medium Gaussian SVM	81.4	93.0855	0.99	13.6444	92.9571	7.0428571	93.2142	6.78571
	Coarse Gaussian SVM	80.7	85.6044675	0.98	13.0848	85.1285	14.871428	86.0857	13.9142
ANFISPSO		**99.6**	**99.5570**	**1.00**	**14.1107**	**99.4714**	**0.5285714**	99.6428	**0.35714**

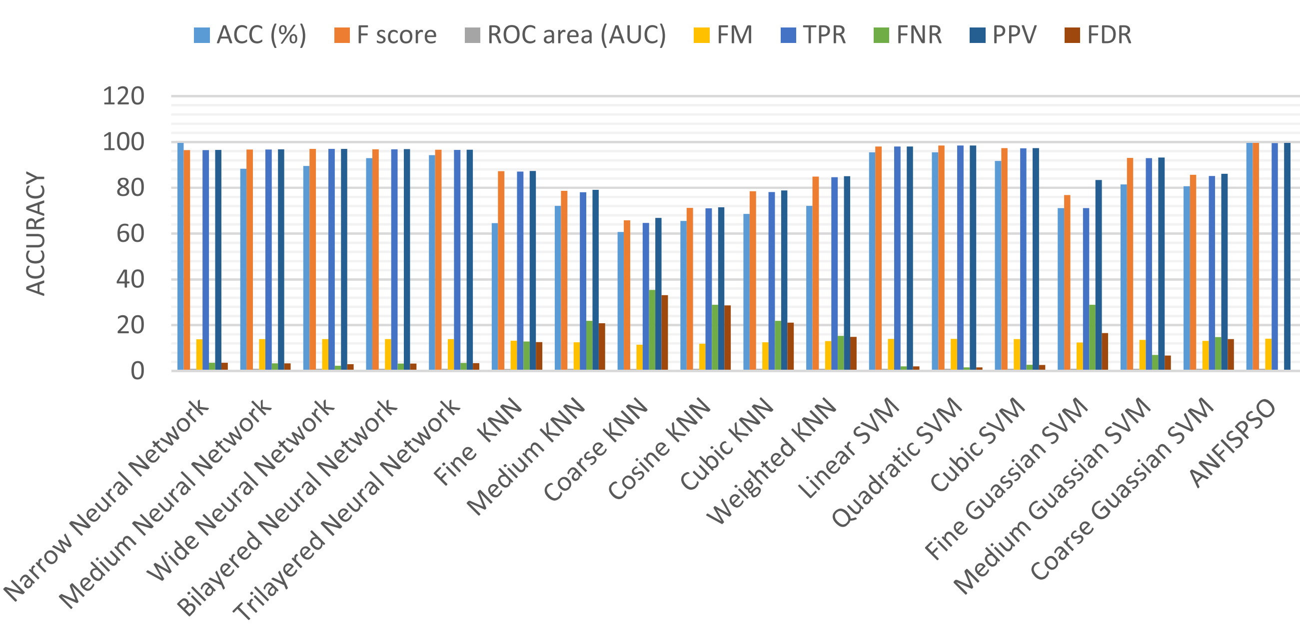


Fig. 5 The Performance of classifier with different emotions

The proposed model performs well in terms of accurate emotion recognition. The results where ANFISPSO outperformed the other classifiers used are shown in bold in Table 4.These results show the feasibility of the proposed approach.

4 Conclusion and Future Work

In this paper, we propose a study on automatic analysis of facial expressions from facial images. An ANFISPSO classifier recognition model is used to develop reliable decision support systems with fully automatic, fast, and robust face recognition from facial images. Using the proposed approach, GPA-based normalization and a variety of classifiers based on AU features, the performance of the classifiers was compared. The ANFISPSO algorithm combines the detection and exploitation capabilities of particle swarm optimization (PSO) with the ANFIS algorithm. The proposed ANFISPSO-based classifier achieved a classification accuracy of 99.6%. In summary, this study proposes a novel framework and highly accurate classification algorithm based on AUs for emotion recognition. The effectiveness of the proposed model was evaluated using several criteria. Compared to previous methods, the proposed model showed superior performance (99.6%). This research has the disadvantage that face recognition is performed on static images without considering the temporal behavior of facial emotions. We can currently only detect and track facial features in frontal images. We have not considered changes in head position and occlusions, which we will investigate in future research. We will also investigate the effects of ambiguous facial poses on face recognition results.

Funding No financial support was received for this work.

Declarations

Conflict of interest The authors declared no conflict of interest.

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