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An Efficient Adaptive Network-Based Fuzzy Inference System with Mosquito Host-Seeking For Facial Expression Recognition

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ABSTRACT
In this paper, an efficient facial expression recognition system using ANFIS-MHS (Adaptive Network-based Fuzzy Inference System with Mosquito Host-Seeking) has been proposed. The features were extracted using MLDA (Modified Linear Discriminant Analysis) and then the optimized parameters are computed by using mGSO (modified Glow-worm Swarm Optimization).The proposed system recognizes the facial expressions using ANFIS-MHS. The experimental results demonstrate that the proposed technique is performed better than existing classification schemes like HAKELM (Hybridization of Adaptive Kernel based Extreme Learning Machine), Support Vector Machine (SVM) and Principal Component Analysis (PCA). The proposed approach is implemented in MATLAB.

KEY WORDS: Face recognition, Gaussian filter, Active contour, linear discriminant analysis, GSO, ANFIS, Mosquito host-seeking.

1 INTRODUCTION

IN human society, the facial expression is considered as a significant role for interpersonal communication. As indicated by Mehrabian (1968), the 55% of human expression is conveyed through facial expressions only. To develop an intelligent and user-friendly computer for facilitating HMI, the psychology of human beings from their emotions has been taught for computers and it provides efficient services to humans. At present, the computers are used as robots and these are interacting with people. But still, making computers to understand the human facial expression is much tedious. Due to this problem, the feature extraction and classification of human expression has been very difficult.

An effective FER- (Facial Expression Recognition) system development is still considered as a challenging task. Suwa et al. (1978) had taken the first attempt to develop an automatic facial expression system via analysing 20 known areas of image structure. As many attempts have been taken to develop automatic emotion expression recognition system. Generally, the FER system has 3 phases like face detection; facial tracking and emotion classification (1989). At first, the human faces have been detected by head pose estimation, head tracking and face recognition. The features are extracted in anatomical fashion or holistic fashion. In anatomical approach, sub-portions of the facial features are extracted based on the geometric transformations and distance measures (2017, 1990). On the other hand, whole face features are extracted based on the image transformation or textures (2001). Donato, et. al. (2003) have applied Gabor Wavelets as texture descriptors in-plane image transform with Nearest Neighbor (NN) classifier and evaluated in posed image of 24 subjects. In FER system, the feature extraction has a significant role to classify the emotions. But still, it has to be improved for effective performance. Generally, the features are based on the appearance (2009) or geometry (2015).Wang, et. al. (1998) analyzed emotions via using geometrical B spline curve and classified by Euclidean classifier. It was evaluated on data from eight different subjects. For studying FER, the Appearance-based features used skin texture variants such as wrinkles and furrows, which are applied the selected face as well as a completed face. Wu, et al. (2012) presented a Support Vector Machine (SVM) classifier for FER. Here, the Gabor motion energy used as a texture descriptor in-plane image transform and this was evaluated in Cohn-Kanade (CK) (2015) as a database. Valstar and Pantic (2017) presented an

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SVM and affine transformation applied in a registration technique on predefined MMI-(Maximization of Mutual Information) (2012) and CK databases through defining dynamics of 20 facial points. The hybrid approaches are based on both appearance and geometric based features. Yacoob and Davis (1996) presented a region based optical geometricschemes

With the rule-based classifier and applied on posed data of 32 subjects.

In this paper, the main aid of this to improve the performance of the FER system by extracting features. Here, Modified Linear Discriminant Analysis (MLDA) has been used for feature extraction because itremoved redundant information as well as retain useful information. For that reason, this system has been used less storage space and increased computing speed. To improve the classification accuracy, the feature selection scheme has been used. The simulation results show that this system efficiency compared than existing schemes. This paper contains four parts. In Section 2 describes the related work for facial expression. Section 3 presents the proposed scheme, Section 4 evaluate the performance results of the proposed scheme and section 5 concludes the paper.

2 RELATED WORK

IN this section, the existing research methods for facial expression are reported in the literature. A complete survey of existing FER methods is presented in (2006, 2014, 2007). Lopes, et. al. (2017) proposed a Convolution Neural Network (CNN) classifier for FER system. This scheme was evaluated in JAFFE, CK+ and BU-3DFE datasets. It has attained very aggressive results when compared to other schemes. But, it has complexity in accuracy and processing time. Wang, et al (2017) proposed a Bayesian network (BN) classifier, which trains the Action Unit (AU) using images with comprehensive labels. Here, to balance the missing AU labels, the expression labels have been used in a hidden knowledge. The interaction between expression and AUs has been captured by BN. While the AU labels have been missed, a Structural Expectation Maximization (SEM) was to learn the structure of the parameters of BN. This scheme was evaluated in ISL (1993) CK+ (1978) and BP4D-Spontaneous(2015) databases. The results show that this scheme attained better performance for both classification and intensity estimation of AU. But AU prediction was less difficult.

Ali, et. al. (2016) presented a new scheme for efficient multispectral FER systems based on the boosted Neural Network Ensemble (NNE) scheme. It has three steps to process the expressions and classify the emotions. Here, the first step was training the BNN (i.e. binary neural network). Second, the BNN combined to the prediction to form NNE and then the final step, to integrate the predictions of NNE sets in order to find the occurrence of an expression. The BNN outcomes are combined to the NNE probability collection. The NNE was worked based on the Bayes classifier. Here, three feature extraction schemes have been used like Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP) and Principle Component Analysis (PCA). The scheme was evaluated in four available datasets. The experimental results show that this scheme attained efficient performance compared than other schemes. But, the computational time and accuracy were not attained good performance. Wang, et. al. (2017) presented a Sparse Local Fisher Discriminate

Analysis (SLFDA) based on the Local Fisher Discriminant Analysis (LFDA) for efficient FER. It has been proposed to solve the sparse problem minimization one. Here, the linearized Bargeman iteration has been introduced to obtain the sparse solution. It has been solved the multi-modal troubles due to their more discriminate power than LFDA since the non-zero elements in the basis images are selected from the mainly the important factors or regions. This scheme was evaluated on several benchmark datasets. The experimental results show that the effectiveness of this scheme. The system stability and reliability were not up to the mark.

Yan (2016) presented a Biased Linear Discriminant Analysis (BLDA) scheme for misalignment-robust FER. To attain a well-aligned face images for FER in computer vision, this scheme has been used. In the testing phase, different weights have been allocated for facial expression samples, which are virtually misaligned. The Weighted BLDA (WBLDA) attribute space has been extracted discriminative features for recognition. Then, Weighted Biased Margin Fisher Analysis (WBMFA) has been introduced for improving the geometrical information's via using a graph embedding criterion to extract discriminative information. The simulation results show that the two methods obtained good performance results compared than other schemes.

Li, et. al. (2015) proposed an incremental Parallel Cascade of Linear Regression (PCLR) scheme for FER based on full automatic multimodal 2D and 3D feature. It has been working based on the shape and texture features. At first, the 2D and 3D based set of fiduciary facial landmarks have been localized through PCLR. After that, to extract the local texture approximately, a novel Histogram of Second Order Gradients (HSOG) has been used with each 2D landmark. Simultaneously, the first and second order surface differential geometry quantities are extracted to obtain the local geometry approximately each 3D landmark. The complete simulation results show that the proposed multimodal feature based scheme outperforms than other schemes.

Pu, et. al. (2015) presented a Twofold Random Forest (TFR) classifier for FER through recognizing

Action Units (AUs) from image sequences. To track the facial points, the Active Appearance Model (AAM) focal points by through Lucas–Kanade (LK) optical flow tracker. The LK has been estimated the displacements of the feature points. To attain motion feature of facial expression, the displacement vector has been connected the neutral expression frame. These are transmitted to the random forest input and verify the Aus. of equivalent expression sequences. This scheme was evaluated in CK+ database and the experimental results show that it has attained higher performance compared with the existing schemes. Wang, et. al. (2015) proposed a Fuzzy Support Vector Machine (FSVM) and K-Nearest Neighbour (KNN) for efficient FER. Initially, the Principle Component Analysis (PCA) has been removed the static facial expression image, and then the regions are split and merged with FSVM and KNN attributes. After that, it switches to the classifier, and the simulation results show that the computational complexity and system reliability was not good.Chang and Hsieh (2011) applied the Enhanced Bayesian Matting Algorithm for image forgery detection (2011). Khazaee and Ebrahimzadeh (2013) presented the premature ventricular contraction with the support vector machine (SVM) and genetic algorithm (GA).Velagic and Osmic (2013) presented the genetic algorithm and fuzzy logic based model.

3 PROPOSED METHODOLOGY

IN this paper, the proposed ANFIS-MHS based FER has been discussed. The step by step process of the proposed FER system has been explained below.

3.1 System overview

The proposed scheme has been illustrated in Figure 1. At first, the input image is pre-processed to reduce the salt and pepper noise. Then, to improve emotion expression prediction accuracy, the edge detection scheme has been introduced. After that, the face is identified by Gabor Local Binary Pattern (GLBP) and then features are extracted by using MLDA. Extracted feature parameters are optimized to reduce the processing time by using mGSO. At last, the emotional expressions are classified by using ANFIS with MHS algorithm. The performance results show that the proposed system attained good results compared than existing schemes.

3.2 Pre-processing using Gaussian filter

The input image has been pre-processed by using a Gaussian filter to reduce the impulsive noise like salt and pepper and Gaussian noise from the image for improving the quality of the image. The Gaussian filter is applied to the image to enhance its boundaries and make the image gradients stronger. Compared than other filtering schemes, the Gaussian smoothing is very effectual for removing Gaussian noise and computationally efficient. In this filtering, the weights give higher consequence to pixels near the edge and it can be reduced the edge blurring. For the above reasons, the Gaussian filter has been used in this proposed system. The main purpose of this filtering is to remove the unwanted information and noises. It has been used the kernel, which denoted the shape of the Gaussian (i.e bell-shaped) hump. Circularity symmetric (i.e. an isotropic) Gaussian has the form as

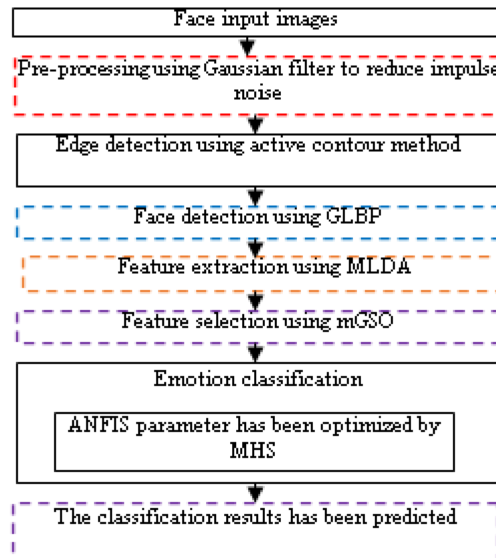

Figure 1. The proposed ANFIS-MHS based FER system

$$G(i,j) = \frac{1}{2\pi\sigma^2} e^{-\frac{i^2+j^2}{2\sigma^2}} \tag{1}$$

where (i, j) representing an image pixel, σ defined standard deviation. In this Gaussian smoothing, the 2-D distribution has been used as a point-spread function and it attained by convolution. The convolution has been performed by a discrete estimation to the Gaussian function while the image is saved as a gathering of discrete pixels. Here, the kernel can be shortened at 3σ limits from the mean. Based on this function the noises are reduced in this step.

3.3 Edge detection using active contour method

Identify sudden changes or discontinuities in an image. It can be used to improve image quality and identify clear edges on images and has the enviable performance for images with weak object boundaries. Here, the Active Contour Method (ACM) has been used for efficient edge detection. Here, a heuristic snake initialization method has been used to choose the nearest edge point from the origin as the face boundary in each direction. Then, the longest continuous edge has been chosen as one part of face boundary. Then, the selected boundary has been segmented and the continuity property has been directing the heuristic initialization of face boundary. Here, the ACM (1990) has been used to arrange the contour to energy minima in the face image. A finite number of iterations, the time delayed the discrete dynamic programming formulation has been assured the convergence of the active contour while the total energy is monotonically reducing the number of iterations. Edge detection of face image has been efficiently identified from pre-processed images.

3.4 Face recognition using GLBP

For reducing the process time, the face region has been recognized by GLBP. It is a combination of Gabor wavelet function and Local Binary Operator (1996)]. The face can be recognized by following those two functions and it can describe as

$$GLBP_{s,o}(z_{cp}) = \sum_{p=0}^{7} S\left(\alpha_{s,o}(z_p) - \alpha_{s,o}(z_{cp})\right) 2^p \quad (2)$$

where $z\ is\ defined\ (i,j)$, $\alpha_{s,o}(z_{cp})$ is defined the ith element of $A_{s,o}(z) = f(z) * \psi_{s,o}(z)$ and it described the convolution of image $f(z)$ with $\psi_{s,o}(z)$- Gabor wavelet function (1996) s,oHave represented the scale and orientation of the Gabor wavelets and here 5 scales and 8 orientations are used. In this face recognition, at first, the GLBP operators are conducted on the face to build multi-scale and multi-orientation GLBP images. Then, the histogram is extracted from each local region of GLBP images to build the local representation of the face. Finally, all the histograms are concatenated into One feature vector to build the global representation. The tolerance of local histogram to puzzle-like movement implies that face representation with GLBP is insensitive to shape variation, such as expression and aging.

3.5 Feature extraction using MLDA

The main aid of LDA is reducing the dimensionality and the complexity of space through reducing the time of machine training. It has been found the projection direction, where the images belong different classes (i.e. labels) are separated maximally. The projection matrix (i.e. weight) has been computed mathematically, and it represented the ratio of the within class scatters matrix and between- class scatter matrix of projected image has been maximized (2009). This approach tries to find the projection direction where images belonged to different classes are separated maximally. Mathematically, it tries to find the projection matrix (the weights) in such a way that the ratio of the between-class scatter matrix and the within class scatter matrix of projected images is maximized (2009). It has been mainly used to solve an optimal discrimination projection matrix W_{0P} (2009) and it can be defined as

$$W_{op} = arg \underset{w}{max} \frac{|W^T S_B W|}{|W^T S_W W|} \quad (3)$$

The basic steps in LDA are as follows:

a) within-class scatter matrix, S_W can be calculated as

$$S_W = \sum_{i=1}^{c} (x_i - \mu_{k_i})(x_i - \mu_{k_i})^T \quad (4)$$

b) between-class scatter matrix, S_B can be computed as

$$S_B = \sum_{i=1}^{c} n_i(\mu_i - \mu)(\mu_i - \mu)^T \quad (5)$$

where c is representing the total number of samples in the whole image set, x is defined as the feature vector of a sample and μ_k is representing the vector of image class that X belongs to μ and is defined the mean feature vector of class i, and n is a number of samples in image class i.

c) the eigenvectors of the projection matrix can be estimated as

$$W = eig(S_T^{-1} S_B) \quad (6)$$

where $S_T = S_B + S_w$ represented a the total scatter matrix

d) The test image's projection matrix has been compared with the projection matrix of each training image through using a similarity measure. Finally, the training image has been computed, which is the closest to the test image.

In this MLDA, the Raleigh quotient has been maximized to minimize the misclassification error and it can be defined as

$$J(Z) = \frac{z^T S_B z}{z^T S_W z} \text{ over Z} \quad (7)$$

where z is a new space linearly spanned and this Raleigh quotient has been used to solve the following generalized eigenvalue difficulty and can be defined as

$$S_B v_i = \lambda_i S_W v_i \quad (8)$$

where $\lambda_i$represented as the variance when data scheme onw_i and w_i is represented as a corresponding Eigen vector for class i, the i[th] Fisher's linear discriminant or Eigen vector defined asv_i. Here, the linear discriminant features like Contrast, Energy, Homogeneity, Mean, Correlation, Entropy and Variance, etc., are extracted. Totally, 28 features have been extracted from this MLDA. It has more time for training process. So, reduce the time consumption, the important features have been selected from this MLDA by using mGSO.

3.6 Optimal feature selection using mGSO

The GSO has been worked based on the natural behaviour of glow-worms (2013).It has higher coverage rate and simultaneously worked for multiple functions compared than other swarm algorithms. For that reason, the features are selected by this algorithm due to their efficient performance. Generally, this function has 4 steps like deployment of glow-worms, luciferin-update, movement and decision step. The step by step process has been given below

Step 1: Initialize the glow-worms randomly in the entire objective space. In mGSO, to attain better randomness, Tent map of chaos n has been introduced into this stage. The chaos has been represented as a universal non-linear phenomenon, which has better periodicity and randomness. It can be enabled the glow-worms to search the optimal value accurately and is defined as

$$x_{k+1} = \begin{cases} 2x_k, 0 \leq x_k \leq 0.5 \\ 2(1 - x_k), 0.5 \leq x_k \leq 1 \end{cases} \tag{9}$$

Step 2: Each and every swarms have equal quantity of luciferin and sensor range. The Luciferin value has been represented based on the objective function value and it can be represented as

$$l_i(t+1) = (1-\rho)l_i(t) + \gamma j_i(t+1) \tag{10}$$

where ρ is represented as luciferin decay constant and it has value$(0 < \rho < 1)$, $j_i(t)$ is defined the luciferin enhancement constant and $\gamma j_i\ (t)$has been *indicated* the objective function value at glow-worm *i*'s location at time t. In mGSO, to improve the convergence speed the movement rule has been presented. While the iteration number is >10, the glow-worms positions of the worst fitness of 5% have been replaced by the average position of all glow-worm and it can be increased the speed of search the optimal value.

Step 3: in this step, the glow-worms are move towards their neighbours, which one has high luciferin value by using probabilistic mechanism. The $p_j(t)$ defined probability of glow-worms moving towards a neighbour j can be defined as

$$p_j(t) = \frac{(l_j(t) - l_i(t))}{\sum_{k\epsilon n_i(T)}(l_k(t) - l_i(t))} \tag{11}$$

where the luciferin value of glow-worm is represented as $l_i(t)$and the movement of glow-worms '*i*' can be followed as

$$x_i(t+1) = x_i(t) + s\left(\frac{x_j(t) - x_i(t)}{\left\|x_j(t) - x_i(t)\right\|}\right) \tag{12}$$

where *s* is the step-size.

Step 4: finally, the luciferin rule has been updated, while the number of neighbour changes and it can be defined as

$$r_d^i(t+1) = min\{r_s, max\{0, r_d^i(t) + \beta(n_t - |N_i(t)|)\}\} \tag{13}$$

where $r_d^i(t+1)$ is represented as the local-decision domain of 'i' at the t+1 iteration, $'\beta'$ denoted as constant parameter , which affects the speed of change of the neighbor domain and $'n_t'$ is denoted as a threshold that is used to control the number of neighbours. From this scheme, the optimal features have been selected and these are switch to Hybrid algorithm of ANFIS (HANFIS) classification.

3.7 Classification of emotion expression by using ANFIS

The combination of ANFIS and the optimal process of MHS have been named as HANFIS. The ANFIS model has been used to detect the emotion expression for each extraction results from mGSO. Generally, the ANFIS system contains five layers like input, fuzzy, product, de fuzzily and output is predicted in (2012) for several classification tasks. In this system, the training and testing of the parameters selection is an important issue in expression detection task, because these parameters are mentioned the on gradient function, but it's hard to update in the each step of expression detection task. So, to solve the above problem, the swarm intelligence based scheme of Mosquito Host-Seeking algorithm has been introduced to optimise the parameters to improve the detection accuracy. In this work, Takagi-Sugeno-Kang type fuzzy model (2006) has been used for expression detection and classification. It has two major parts like antecedent and consequent parts and the ANFIS model whole structure is shown in Figure2.

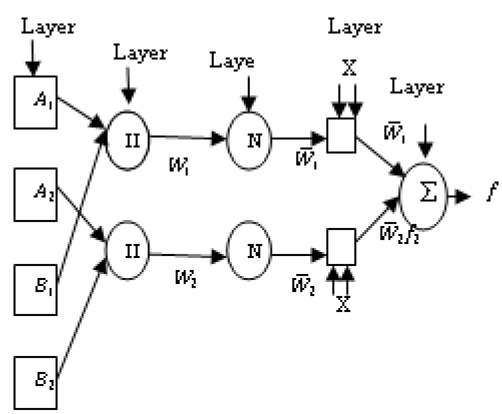

Figure 2. Structure of ANFIS model

Initially, the feature vectors are given as input layer and then the fuzzy if-then rules has been formed in fuzzy layer. The rule is given as below

$$\mathrm{R_i - rule\ if\ x_1\ is\ A_{i1}\ and\ x_2\ is\ A_{i2}\ then\ x_1\ is\ y_i\ is\ f_i(x)} \tag{14}$$

where x_1 and x_2 are the input feature vectors. $A_{i1}, \ldots A_{in}$Be the fuzzy membership set function to each rule $(i = 1, 2, \ldots, n)$ and y_i is the expression detection emotion classification results for Ith rule. Fuzzy set A_{ij} at layer for each feature vector has been represented as

$$A_{ij}(x) = exp\left\{-\left(\frac{x_j - m_{ij}}{\sigma_{ij}}\right)^2\right\} \tag{15}$$

where m_{ij}represents the centre and σ_{ij}be the measurement of A_{ij} to detect the results of emotion expression. These parameters are represented as antecedent parameters. Emotion expression recognition results of ANFIS is attained through weighting the parameters values of consequent parts of n rules by the equivalent membership evaluation as

$$\hat{y} = \sum_{i=1}^{n} \bar{w}_i f_i = \frac{w_i}{\sum_{i=1}^{n} w_i} \tag{16}$$

where

$$w_i = \prod_{j=1}^{n} A_{ij}(x_i) \tag{17}$$

$$y_i = f_i(x) = (a_i x_1 + b_i x_2 + c_i) \tag{18}$$

where $(a_i, b_i, c_i)$the parameter is set of ANFIS objective function and is known as consequent parameters. These parameters are optimized by using MHS. The weight values of layer 2 and layer 3 are decreased linearly starting 0.9 to 0.4 during the face emotion expression detection process. Since the appropriate choice of the weight value only provides the best detection results among six types of emotions.

3.8 Mosquito Host-Seeking (MHS) for parameter optimization

The MHS algorithm has been developed based on the host-seeking of mosquito's behaviours. This algorithm has advantages like: it can be performed large-scale dispersed parallel optimization, it has a complete optimization capability for multiple objectives, and converges speed is high and it doesn't depend on any prior knowledge. Due to these merits, the algorithm has attained better performance. The illustration of MHS to optimize consequent parts of ANFIS is mathematically specified as following steps

Step 1: The n-vector values for every parameter has been given and initialized the number of artificial mosquitoes to be $n \times n$ as well as the sex of all artificial mosquitoes has been initialized and denoted asx_{ij}. Then, the gray scale values r_{ij} has been initialized for artificial mosquitoes m_{ij} can be defined as the average values. The weight values also initialized and selected the related coefficients a $\epsilon = 0.8$, $\lambda_1 = 0.05$, $\lambda_2 = 0.05, \lambda_3 = 0.9$,
$\lambda_4 = 0.9$.

Step 2: Then, the radial distance $u_{ij}(t)$between an artificial mosquitosm_{ij} with host at time t using given below equation

$$u_{ij}(t) = \exp\left(-c_{ij}(t) r_{ij}(t) x_{ij}(t)\right) \tag{19}$$

As well as $\frac{du_{ij}(t)}{dt}$ has been computed by using the formula in [41].

Step 3: Computed the $dr_{ij}(t)$ for each artificial mosquito using the given formula

$$dr_{ij}(t)\big/_{dt} = -\lambda_1 \frac{\partial u_{ij}(t)}{\partial r_{ij}(t)} - \lambda_2 \frac{\partial J(t)}{\partial r_{ij}(t)} - \lambda_3 \frac{\partial P(t)}{\partial r_{ij}(t)} - \lambda_4 \frac{\partial Q(t)}{\partial r_{ij}(t)} \tag{20}$$

where $J(t) = \sum_{i=1}^{n} \sum_{j=1}^{n} u_{ij}(t)$ is defined the utility sum of all artificial mosquitoes,

$$P(t) = \epsilon^2 \ln \sum_{i=1}^{n} \sum_{j=1}^{n} \exp\left[-\frac{u_{ij}^2(t)}{2\epsilon^2}\right] - \epsilon^2 \ln nn$$

Is represented the attraction function,
$Q(t) = \sum_{i=1}^{n} |\sum_{j=1}^{n} r_{ij}(t) x_{ij}(t) - 2|^2 - \sum_{i,j} \int_0^{u_{ij}} \{[1 + \exp(-10x)]^{-1} - 0.5\} dx$ Is represented as

Interaction behaviour function.

Step 4: The gray scale value of all mosquitoes has been updated by using given formula

$$r_{ij}(t+1) = r_{ij}(t) + dr_{ij}(t)/dt \tag{21}$$

As well as the parallel weight has been updated by

$$c_{ij}(t+1) = c_{ij}(t) + dc_{ij}(t)/dt \tag{22}$$

Step 5: Check if all $du_{ij}(t)/dt$=0, then the highest value has been updated, otherwise it goes step 2.

where x_{ij}vector values for every parameters of ANFIS model through d-dimensional investigates space correspondingly. In equation (19,20) represents the update value of grey and weight of each parameter in ANFIS models, which give sufficient information to optimize ANFIS parameters by the examination in solution search space.

There are two major parts presented in equation (20, 21), there are first and second parts. The initial part of the equation is used for the approximation of the result of current feature vectors for expression recognition, and the second parts move towards to achieve best optimized ANFIS parameters for entire training samples. From this optimized parameters face emotion detection accuracy is enhanced in terms of parameters like sensitivity, specificity, and detection accuracy. The optimized ANFIS parameters result from MFO are measured using spread factor with improved face emotion detection rate than the normal ANFIS model.

4 RESULTS AND DISCUSSION

HERE, the performance of proposed HANFIS-MHS have been evaluated and the results are compared with existing emotion expression recognition schemes like HAKELM, SVM (2014) and PCA (2014) in terms of accuracy, processing time, ROC, sensitivity and specificity.

4.1 Dataset description

The proposed method has been evaluated in three dataset images like ORL database, Indian Face Database (2009) and JAFFE (Japanese Female Face expression) Database (2009).

Dataset 1: ORL database- this database has 40 subjects of images, which each one contains 10 images. So, total, 400 images have been taken for this scheme evaluation. The images are based on the open or close eyes, smiling or non-smiling, etc., there are 10 different images of 40 distinct subjects.

Dataset 2: Indian Face Database-it contains one Indian person expressions of images, contains 6 types of emotion images with 6 angles, so tally contains 36 images for each person. Here 3 subjects have been considered.

Dataset 3: JAFFE Database- it contains 10 female subjects and each one has 7 facial expressions, so totally 213 images have been there in this. Each person has 2-4 images for a single expression. In this system, 400 images were taken and 250 images are trained and 150 images are tested. The sample image for three data sets with six and seven types of emotion expressions is shown in Figures 3, 4 and 5.

Figure 3. **ORL database training samples**

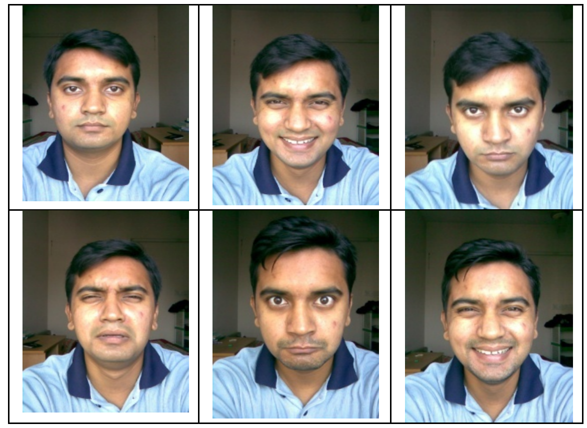

Figure 4. **Indian images training samples**

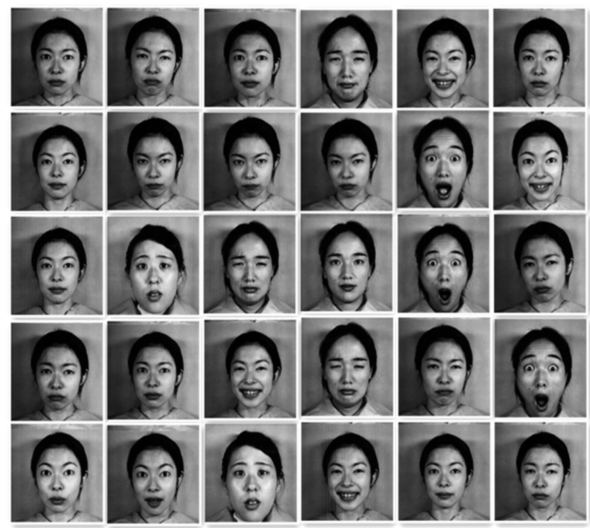

Figure 5. **JAFFE sample images for training**

In the training process, initially, the input image has been pre-processed for removing noise. Then, the edges are detected and face has been identified. From this, the MLDA features are extracted. In that, efficient features are selected by mGSO. Finally, the ANFIS has trained the features and classify the emotions.

In that process, the high consequent parameter values are attained by using MHS. Based on these training values, the query images are tested and classified with high accuracy and less processing time.

The evaluation metrics are referred from this paper (2012). The sensitivity refers the true positive rates, and specificity refers the true negative rates.

The metrics results show that the proposed scheme has less false error rate compared than other algorithms.

The step by step processing results is showed in Figures 6 to 9. The Figure 6 illustrates the pre-processing outcome of the three datasets based sample image. Figure 7 shows the ACM based

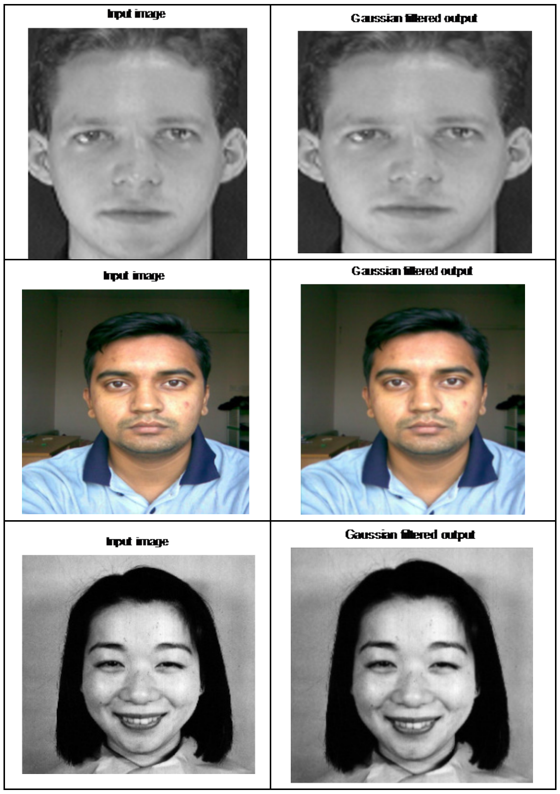

Figure 6. Pre-processing result for sample faces

segmentation outcome from the pre-processed image. Then, GLBP based face expression has been recognized from the segmented image and its illustrated in Figure 8. Finally, the facial expressions are classified from face recognized image and it's illustrated in Figure 9

4.2 ROC performance comparison

The Receiver Operating Characteristic (ROC) curve has been measured to predict the accuracy of face expression recognition. In this, the proposed ANFIS-MHS scheme results have been evaluated between existing schemes like HAKELM, PCA and SVM. The ROC curve, x- axis contains the false positive rate and Y-axis contains true positive rate. The performance comparison is illustrated in Figure 10. It shows the ANFIS-MHS has attained high true positive rate when increased the false positive rate compared than existing schemes. Due to the efficient edge detection and feature selection process, the anticipated scheme has a high accurate prediction of true and positive rates. These are increased the classification accuracy. The numerical evaluation performance values are shown in table 1.

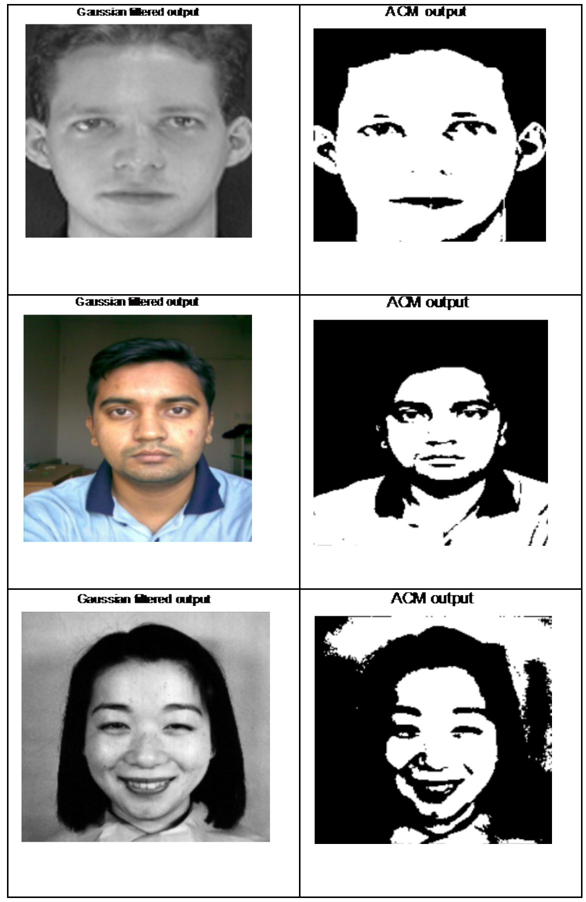

Figure7. ACM based edge detection

4.3 Processing Time performance comparison

How much time has to be taken for doing this evolution is predicted by processing time and is shown in Figure 11 for proposed ANFIS-MHS and existing schemes like HAKELM, PCA and SVM. It shows that the ANFIS-

MHS has obtained less time compared than other schemes. Because the efficient feature extraction and selection processes have been reduced the processing time. When increased the number of images, the processing time also increased. The numerical processing time results are shown in table 2.

4.4 Accuracy, sensitivity, specificity performance comparison for all classifiers

The performance comparison of sensitivity, specificity Accuracy results are shown in Figure 12 for proposed ANFIS-MHS and existing HAKELM, PCA and SVM. It shows the high accuracy rate attained by proposed scheme compared than other schemes. As well as the sensitivity and specificity also improved in proposed scheme due to the efficient pre-processing and feature extraction and selection with optimal parameters of ANFIS. Numerical evaluation results of Accuracy, sensitivity, specificity for all classifiers are shown in Table 3.

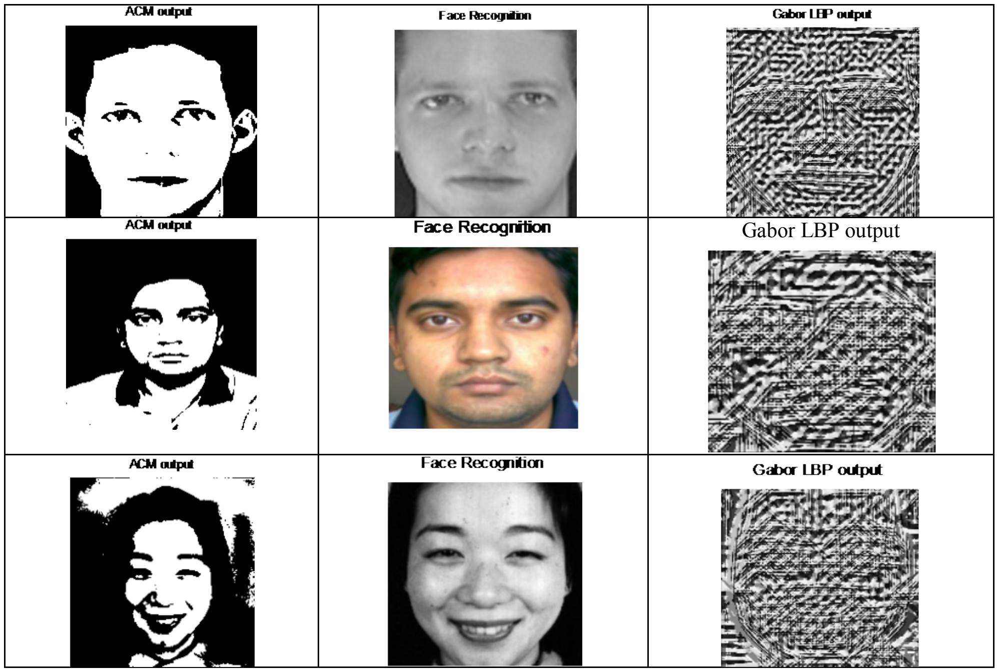

Figure 8. GLBP based face expression reorganisation

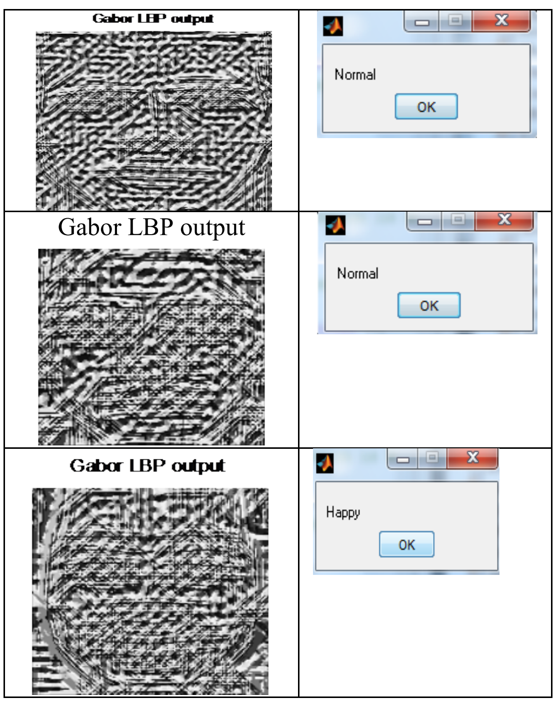

Figure 9. Facial expression classification result of proposed FER system

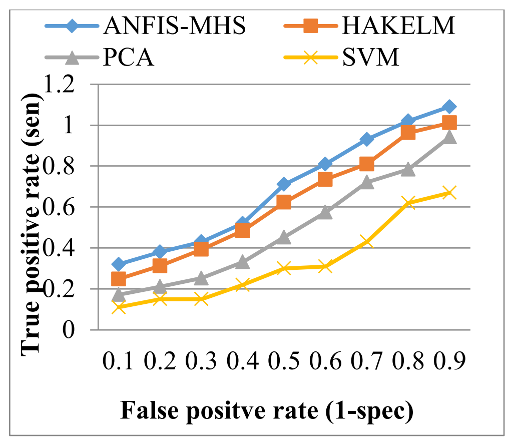

Figure 10. ROC curve performance comparison

Table 1. Numerical evaluation performance values of ROC for all classifiers

(1-spec)	ANFIS-MHS	HAKELM	PCA	SVM
0.1	0.32	0.248	0.172	0.11
0.2	0.38	0.312	0.211	0.15
0.3	0.43	0.393	0.253	0.15
0.4	0.52	0.484	0.332	0.22
0.5	0.71	0.623	0.453	0.3
0.6	0.81	0.735	0.574	0.31
0.7	0.93	0.81	0.721	0.43
0.8	1.02	0.962	0.784	0.62
0.9	1.09	1.011	0.942	0.67

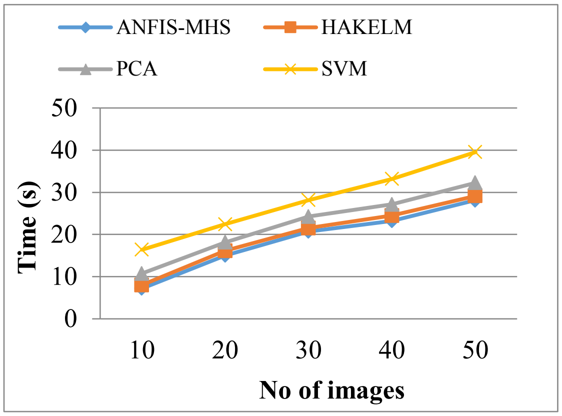

Figure 11. Processing time performance comparison for all expression recognition classifier schemes

Table 2. Numerical evaluation results of Processing Time for all classifiers

No of images	ANFIS-MHS	HAKE LM	PCA	SVM
10	7.213	8.0121	10.745	16.417
20	15.032	16.141	18.147	22.417
30	20.743	21.522	24.254	28.154
40	23.234	24.473	27.147	33.177
50	28.123	29.144	32.257	39.5412

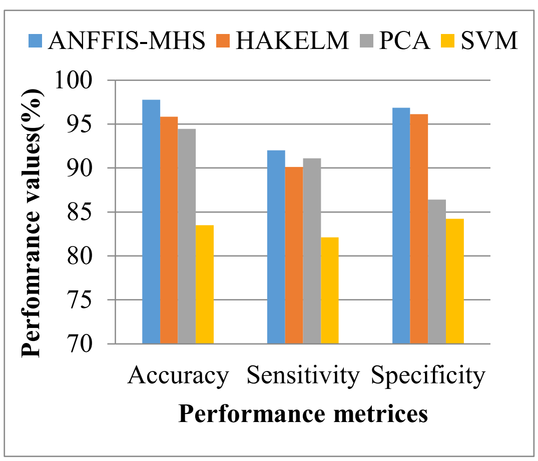

Figure12. Performance comparison for all expression recognition classifier schemes

Table 3. Numerical evaluation results of Accuracy, sensitivity, specificity for all classifiers

Performance matrices	ANFFIS-MHS	HAKELM	PCA	SVM
Accuracy	97.78	95.83	94.46	83.51
Sensitivity	92.01	90.14	91.12	82.12
Specificity	96.87	96.13	86.41	84.24

4.5 *Performance comparison of precision, recall and F-measure*

The performance comparison of precision, recall and F-measure results are shown in Figure 13 for proposed ANFIS-MHS and existing HAKELM, PCA and SVM. It shows the high F-measure rate attained by proposed scheme compared than other schemes. As well as the precision and recall also improved in proposed scheme due to the high true positive rate and less false negative rate. Numerical evaluation results of Precision, recall and F-measure are shown in Table 4.

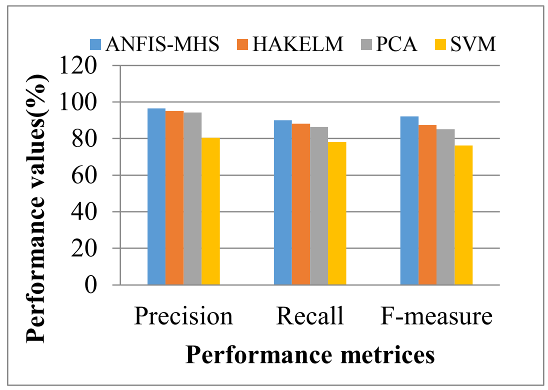

Figure 13. Performance comparison of precision, recall and F-measure for all expression recognition classifier schemes

Table 4. Numerical evaluation results of Precision, recall and F-measure for all classifiers

Performance matrices	ANFIS -MHS	HAKE LM	PCA	SVM
Precision	96.54	95.12	94.33	80.43
Recall	90.12	88.13	86.34	78.12
F-measure	92.15	87.45	85.15	76.13

5 CONCLUSION

For efficient facial emotion expression recognition, this paper proposed an Adaptive Network-Based Fuzzy Inference System With Mosquito Host-Seeking (ANFIS-MHS) algorithm. It has been efficiently detected the emotions and classifies them in high accuracy rate of 97.78% for three available datasets. The Gaussian filter and ACM have been used in this system for efficient image quality and reducing the processing time. Then, the face is detected by the GLBP function for effectual classification and MLDA features has been extracted for reducing the storage space. After that, the eye, mouth, nose point of features has been selected by using mGSO and it has the high computational speed for local and global search. Finally, the emotions are classified by using ANFIS and their consequent parameters are optimized by MHS for achieving a high detection rate. The experimental results demonstrate that the proposed

ANFIS-MHS obtained a high accuracy rate of 97.78%, sensitivity of 92.01%, precision 96.54%, specificity 96.87%, recall of 90.12 % and F-measure of 92.15% compared than existing FER schemes like HAKELM, PCA and SVM. Examine new techniques in the future to cope with various expressions and more depth to investigate the face expression detection and classification problem.

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