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Performance Evaluation of Fusion Based Efficient Algorithm for Facial Expression Recognition

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Abstract

Objectives: To develop face expression recognition system using JAFFE database and to evaluate the performance of the face expression recognition models. **Methods:** This study used the FER model based on modified-HoG (Histogram of oriented gradient), LBP (Local Binary Patterns) and Fast Key point detector and BRIEF descriptor (FKBD) to extract the significant features of JAFFE dataset. The features extracted using HoG, LBP and FKBD techniques form a feature vector. Then, the fusion of all the features is carried out at the feature level. The multiclass SVM and KNN classifiers are used to recognize the facial expressions, effectively. **Findings:** In this work, an effort is made to develop a robust FER model using JAFFE database. It is recorded that, based on the experimental results, the proposed model suits better with a performance rate of 98.26% for SVM and 96.51% for KNN, when compared with the different state-of-the-art methods. **Novelty:** Many FER models have been developed and adopted for enhancing their quality and to extract the facial features using transform and frequency domains. It is observed that, maximum approaches are based on generating the texture features. The fusion at the feature level using modified HoG, LBP and FKBD is performed and the SVM model is more compatible when compared with other classifiers and it supports one-to-one and one-to-many comparisons' technique.

Keywords: Face Expression Recognition; Local Binary Pattern; Emotions; Nearest Neighbor; Histogram of Gradients

1 Introduction

Face Expression Recognition (FER) is very crucial stage in feature extraction and classification of facial samples. The features of the face for different expressions may be expressed using the two approaches based on geometric or appearance. Based on the features extraction, the classification technique is used to classify the face samples for different expressions. The features of primary regions of face like eye, mouth and nose components can be considered for geometrically based features and the features extracted using the exact face can be considered to appearance model. Generally, the face offers (i) static, (ii) slow, and (iii) rapid signals. In static, the color of the skin is taken into the account which includes characteristics like pigmentation, greasy deposits, shapes, and location of facial information. In case of slow signals, the permanent wrinkles in facial appearance in addition with data related to muscle and skin changes over the time. Finally, in case of rapid signals which are nothing but raising the eyebrows containing of face muscles movement. As face is considered as proper message system, the information can be shared through a face. The different emotions of the human face are shown in Figure 1.

Fig 1. Different Facial expressions

The key elements of Face are used for the prediction of face emotions. The detection of the face emotion is done using SVM classifier. The CK and CK+ database is used to test the system. The app was developed that recognizes the seven emotions and then classify them into positive, negative, and neutral emotions[1]. Elliptical boundary model used for skin recognition and feature detection was performed. The geometric and anthropometric features are extracted using SVM, k-NN and decision tree classifiers. The publicly available KDEF dataset was used to test the model[2]. How AI can be used to recognition the emotion. The DNN is used for feature extraction in FER system[3]. An emotion recognition system was evaluated using FERC2013[4] dataset. Tanya developed a feature-level fused FER[5]. The system is based on two different modalities (expressions and body gesture). The HOG is used for face detection. The AED-2 is used for testing the model. Automatic facial emotion classification system using CNN is performed[6]. The SURF was used features extraction. The experiments were conducted on own local dataset of 200 individual people's images of faces[7]. The BPNN and CNN are used to evaluate the facial model. The use of physiological signals from physiological modalities is carried out in the research[8]. The SVM classifier is used to detect the various states of emotions. DEAP, MAHNOB-HCI datasets were used for training and testing the model. How to classify physically disabled and ACE expressions based on facial landmarks. The CNN and LSTM classifiers are used for real-time emotion recognition[9]. The local dataset considering of data having 10 virtual and 14 EEG raw data was used to test the model[10]. The enhanced face and eye detection technique using Cascaded multi-task convolutional network is performed[11]. The MTCNN and Haar-based Cascade classifier is used to detect the face and eyes. Own database was created for 100 videos consisting of 18265 images. Akriti[12] describes DL based emotion detection model where CNN classifier[13] is used for emotion detection from images. The FERC and JAFFE database are used to test the model. Sun[14] describes the facial features using LDA and Facial Landmark Detection. The SVM classifier is used for emotions recognition. Cohn-Kanda+ dataset are used for face emotion recognition. FER model based on face and brain signals. Feature extraction is done using wavelet Daubechies 4 transform and RNN. The system was tested using publicly available datasets called the DEAP dataset[15]. The architecture of the FER is discussed as shown in Figure 2. It includes preprocessing, feature extraction and classification mechanisms to recognize the different expressions of face[4].

1.1 Database

The samples of face using various publicly available databases are used to conduct the experiments for FER which includes JAFFE, Cohn – Kanade, Extended Cohn – Kanade, MMI, MUG, Taiwanese Facial Expression, Yale, AR face database[16].

1.2 Preprocessing

It is a technique which helps to enhance the quality of image samples and it will be carried out prior to FE approaches. It includes image clarity and scaling etc., to improve the facial expression frames. The Cropping and scaling[17] on the face image is done by considering the nose as a midpoint from the face. In addition, scaling refers to size reduction of the facial image, but it protects the original aspects of the image. Resizing the image samples will improve the smoothness level of the images.

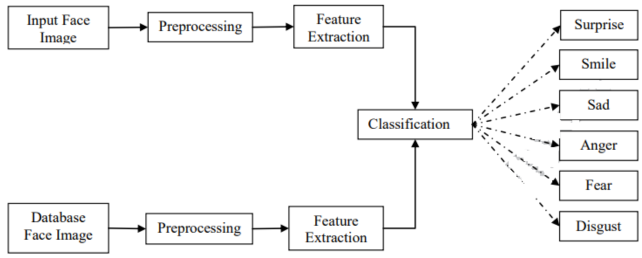

Fig 2. Block diagram of Face Expression Recognition System

Also, Normalization is used for the reduction of illumination to improve the facial quality with the consideration of medial filter when there are variations in the facial samples. In normalization, the extraction of eye positions results in robust nature for the FER system which intern provides more clarity to the facial samples. Segmentation is performed by regulating the face dimensions. In segmentation, ROI performs better and seems to provide for maximum information from the face images[18].

1.3 Feature Extraction

It provides the significant features within a facial sample for next stage in FER. The significant features are extracted from the facial samples. Next, the depiction data will be used for classification stage[19]. The feature extraction approaches are categorized into texture feature, edge based global and local feature-based, geometric feature and patch-based approaches. The texture feature-based methods are Gabor filter (magnitude and phase information), Gaussian Laguerre (GL) pyramidal structure, Vertical Time Backward (VTB), Weber Local Descriptor (WLD), which extracts the positive features[16]. The FE is performed using Supervised Descent Method (SDM) in three stages which include extraction of main positions of face, related positions are selected in next stage and finally, estimation of the distance will be carried out in the face sample[17].

1.4 Classification

Finally, the features extracted using various feature extraction models are classified to recognition of facial expressions. Few classification techniques include directed Line segment Hausdorff Distance dLHD method, ED metric considers normalized and similarity scores to estimate ED. The Minimum Distance Classifier (MDC) finds the distance between the features obtained and stored in the vector form. The KNN (k–Nearest Neighbors) relates among the assessment models[20]. Support Vector Machine (SVM) constructs the one subject sample (class A and B). The SVM technique gives better accuracy compared with other classification models. The NN model results in better performance rate than other NN models. Based on the above discussions, it is observed that, SVM model is more compatible when compared with others for FER[18].

Many FER models have been developed and adopted for enhancing their quality and to extract the facial features using transform and frequency domains. But most of the FER models faces the issues of variations due to the factors like illumination, pose, lighting. So, the model based on the fusion at the feature level using modified HoG, LBP and FKBD is performed.

The paper is organized as follows. The proposed model and its algorithm are discussed in section 2. The Performance metrics are described in section 3. The result analysis of the proposed model is done in section 4. The conclusion and future research of FER is addressed in Section 5.

2 Methodology

The proposed FER model is based on modified HoG, LBP and FKBD algorithms. The features are extracted, and the fusion is performed at the feature level. The multiclass SVM and NN are used to classify the image samples. The subjects of image/video are chosen, the advantages and performance analysis of proposed model is addressed to recognize the emotions of human face. The objective of the proposed work is as follows

- To develop the efficient algorithm for facial emotion recognition on JAFFE dataset.
- To increase the performance rate of the model.
- To decrease the error rate of the proposed algorithm.

Finally, the proposed model suggests the working idea in the domain of FER.

Table 1. State-of-the-art methods

Author	Preprocessing/ Feature Extraction/Classifier	Dataset	Results
Hyeon-Jung et al., [1]	CNN	Own Dataset	Accuracy of 51.2% was obtained for recognition of seven emotions.
Marcin et al., [2]	SVM, k-NN and decision tree classifiers	KDEF dataset	An accuracy of 57.7% was obtained for 6 different emotions
Vibha et al., [3]	DNN	FERC2013 dataset	68% accuracy is obtained
Tanya Keshar et al., [6]	HOG	Amrita Emotion Database-2	Facial expression accuracy of 86%, Body gesture 83.57%, Bimodal 94%
Ram Kumar et al., [9]	SURF	Own database	BPNN achieves an accuracy of 88%.
Cynthia J et al., [10]	The SVM classifier is used to detect the various states of emotions	DEAP MAHNOB HCI	75%

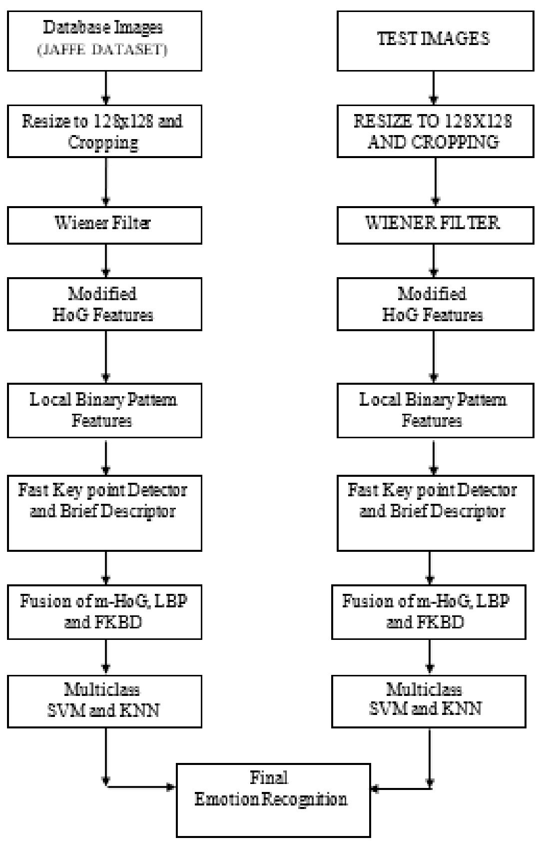

Fig 3. Block diagram of Face Expression Recognition System

2.1 Image Acquisition

The samples of face using JAFFE publicly available database is used to conduct the experiments for FER and is shown in Figure 3. The JAFFE contains 10 Japanese female's expressions and having 07 facial expressions of 213 image samples. Here, each image contains 256 × 256-pixel resolution [16]. Figure 2 shows few of the samples from JAFFE database. The resize of 128x128 will be carried out for the database samples to make all the image with equal size. Then cropping of samples is performed. The wiener filter is applying on the normalized image to enhance the quality of the image is shown in Figure 5.

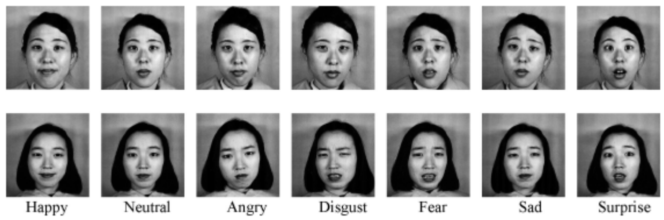

Fig 4. Samples of JAFFE

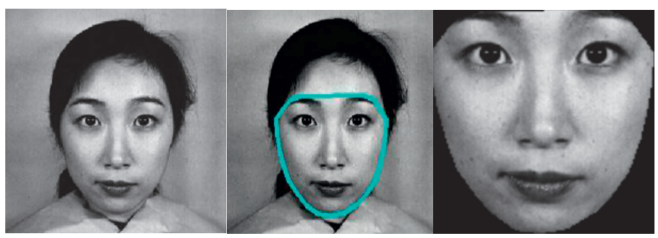

Fig 5. Preprocessing ofImage sample

2.2 Modified HoG Features

The known HoG descriptor was introduced where the image samples were divided into regions named as cell. The images of 8×8 pixel values are dominated in each cell. The HoG descriptor collects the gradient magnitude and orientation of cell [15]. The related HoG features include thirty-six vertical blocks and one vertical block. The features using HoG are extracted to improve FER accuracy. The computations of horizontal, vertical, diagonal gradient and orientation bring to make the modal with higher accuracy rate is shown in Figure 6.

The procedures for extracting the HoG features are as follows:

- Small adjacent cells were created and calculate the gradients of magnitude and directions of individual cell.
- Compute the "b_{in}" for the above cell using HoG and blocks are built.
- Feature vectors are created with the provision of block normalization.

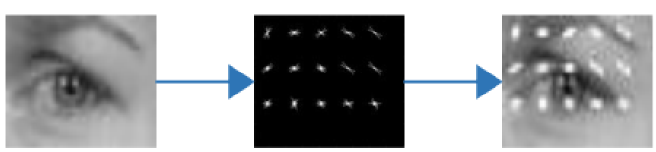

Fig 6. HOG features extracted from face/eye image

The gradient magnitude and orientation is calculated as follows
Gradient Vector,

$$\nabla f = G_x + G_y \tag{1}$$

Where Gx and Gy talks about horizontal and vertical gradient values.

$$\text{Gradient Magnitude } = \sqrt{G_x^2 + G_y^2} \tag{2}$$

$$\text{HoG Orientation } \theta = \tan^{-1}\left(\frac{G_y}{G_x}\right) \tag{3}$$

$$\text{Normalization } = \frac{\nabla_f}{|\nabla f|} \tag{4}$$

2.3 Local Binary Pattern

Local Binary Pattern will handle many occlusions and problems existing from handle illumination changes and used in many issues includes such as image/facial and motion analysis [15]. The procedures for extracting the LBP features are as follows:

- Creation of tiny cells with the provision of radius and number of neighbors.
- Thresholding with the consider of pixel existing in central position and its neighbor pixels. Binary number will be the outcome for thresholding and intern the same will be converting into decimal numbers.
- Each of the LBP will be store in 'count' and later, calculate the histogram for the frequency of each 'count'.
- Concatenation of the histograms to compute the feature vector is performed.

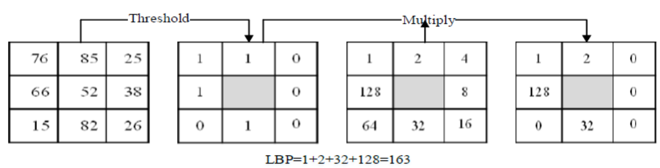

Fig 7. Local Binary Pattern Process

The process of LBP is shown in Figure 7. The input patterns having threshold and weight is addressed, a radius of 1 with 8 neighbors surrounding the center pixel is considered in the LBP process. The LBP equation is stated in equation in 5.

$$LBP_{P,R}(x,y) = \sum_{p=0}^{P-1} S(f(x,y))\, f(x_p, y_p)\, 2^p \tag{5}$$

Here, P and R represents neighborhood and radius of neighbors around the pixels. The f(xp,yp), f(x,y) and (x, y) indicates neighbourhood pixel, centre pixel and pixel respectively. The modified HoG and LBP features values helped to extract the gradient directions and properties of expressions of face and formed a feature vectors. The LBP samples are shown in Figure 8.

2.4 Fast Key point Detector and Brief Descriptor

Due to the limitations of SIRF and SURF, Oriented FAST and Rotated BRIEF performs magnitude faster and better [19]. It builds using FAST key point detector and the BRIEF descriptor techniques due to their good performance and low cost. The OBRIEF features are computed, variance and correlation are analyzed. The reduction in the dimensionality of the features produced by the image samples is carried out by Principal Component Analysis [17].

The concept of feature normalization is performed to increase the rate of facial image before fusion scheme is applied on the samples. The normalization of LBP features is carried out within the range of 0-1. Finally, the modified HoG, LBP and Fast Key point Detector and Brief Descriptors features are fused by Z-score method [20]. The ORB samples are shown in Figure 9.

2.5 Multiclass SVM and KNN

The Multi class SVM is use a classifier to recognize the different emotions of the human image samples [18]. Also, it is proved that it is an efficient and effective classifier in the facial expression recognition. Here, the extracted features from the proposed

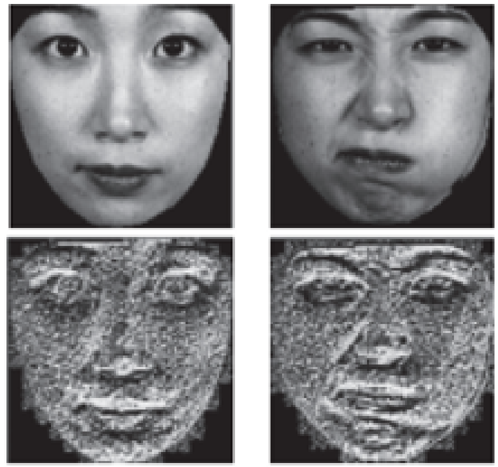

Fig 8. Local Binary Pattern Samples

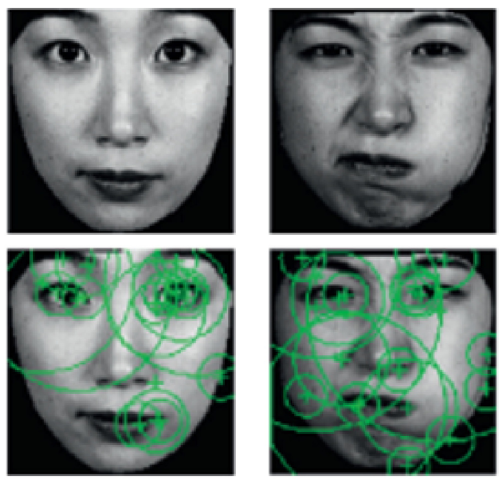

Fig 9. ORB samples

feature extraction techniques (m-HoG, LBP, Fast Key point Detector and Brief Descriptor and PCA) is classified using SVM classifier and the process of classification is shown in Figure 10.

The training and testing phase of the proposed model will be carried out in considering few of the things which is described here. In training, there will be existence of many hyper planes in SVM, and the classifier learns the hyper plane. The optimal hyper plane will be chosen to train the data with greater margin by the hyper plane generated by SVM for different categories.

$$f(x) = \sum_{i=1}^{L} \alpha i \; yik \, (xi - x) + b \tag{6}$$

Whereas in testing phase, the f(x) given in equation 6 is used to classify the test subject x. where x_i, $y_{i,}$ k, represents support vector, labels and k refers kernel function of SVM from the value 'α' obtained from the training phase. The most used K-NN classification[14] is the Euclidian distance metric, which is defined based on the feature vectors x and y and is given in equation 7.

$$euc = (\vec{x}, \vec{y}) = \sqrt{\sum_{i=1}^{f} (x_i - y_i)^2} \tag{7}$$

The 'f' indicates the number of features, and it is observed that the smaller distance values represent larger similarity. The proposed algorithm is tabulated in Table 2.

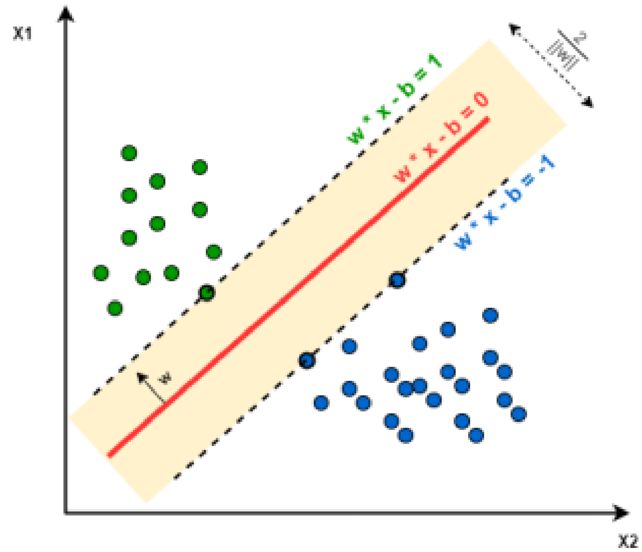

Fig 10. SVM operation

Table 2. Proposed algorithm

Input: Read the images from JAFFE Dataset
Output: Facial emotion recognition
Step 1: The images from the JAFFE dataset is taken and resized to 128X128, followed by cropping the sample.
Step 2: The wiener filter is applied on the samples to remove the noises.
Step 3: The features of the image will be extracted in three phases. Firstly, the significant local and statistical features of filtered sample/image will be extracted using modified HoG technique.
Step 4: Next, the Local Binary Pattern approach is applied on the samples to extract the informative features. Finally, the Fast Keypoint detector and BRIEF descriptor is applied to fetch the informative sections of the image.
Step 5: The fusion of features produced by modified-HoG, LBP and FKDBD will be carried out.
Step 6: Multiclass SVM and KNN are used to classify the facial expressions.
Step 7: Performance of the proposed model is computed and evaluated.

3 Result and Discussion

The Precision (P) and Recall (R) curve and the ROC curve are considered to plot the graphical representation of the proposed model. The PR tells about the precision and recall, where as the TPR and FPR relation will be brought by ploting the ROC curve[15]. Here, TPR and FPR are considered to know the images either genuine or imposter. By considering the low threshold, we can achieve more TP and FPR. The evalaution parameters are given in equation 8, 9, 10.

$$TPR = Recall = \frac{Tp}{Tp + FN} \tag{8}$$

$$FPR = \frac{Fp}{Fp + TN} \tag{9}$$

$$P = \frac{Tp}{Tp + Fp} \tag{10}$$

For desired face sample, True positive (TP) is accepted (positive) and False Positive negative (FN) is rejected. Whereas, for Undesired face sample, False positive (FP) is accepted (positive) and True negative (TN) is rejected. The experiments were conducted in MATLAB tool for the FER model based on modified HoG, LBP and FKBD. The samples of the JAFFE database for different facial expressions are considered to validate the proposed model. The statistical features of the proposed model is extarcted and is shown in Figure 11. Here, the various values of Kurtois, mean, moment etc., are recorded for different expressions.

Face Expression for JAFFE Dataset		Kurtosis	Mean	Moment	Standard Deviation	Variance
	Anger	2.471	2880	129.33	52.6633	2770.33
	Disgust	2.562	3316.33	142.23	57.3658	3324.53
	Fear	2.893	3073.56	152.32	55.2389	3046.56
	Happiness	3.115	2356.12	154.43	57.2356	2636.25
	Sad	3.256	2942.36	156.32	58.2165	3024.62
	Surpise	3.456	3025.23	158.26	55.3654	3078.23

Fig 11. Statistical Measures

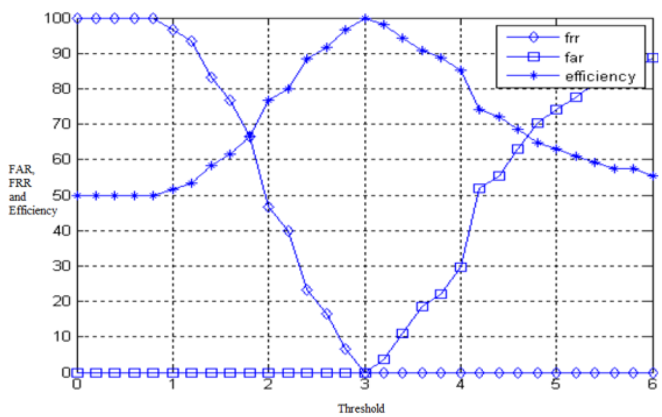

Fig 12. FAR, FRR and Efficiency on JAFFE

The FAR, FRR and Efficeiency of the proposed model for the low threshod on JAFFE face samples is shown in Figure 10, it is observaed the recognition rate is 100%. The recognition rate for different expresions on JAFFE dataset for SVM and KNN is tabulated in the Table 3. The average rate for SVM is 98.26% and 96.51% for KNN reported respectively. The classifications results for JAFFE datasets, considering the different face expressions are shown in Figure 13.

The existing approaches of feature extraction techniques and classifiers for facial emotion recognition are compared with the proposed FER. The recognition rates for SVM and KNN classifiers of the proposed feature level fusion is tabulated in Table

Table 3. Recognition rate for SVM and KNN

Face Expression for JAFFE Dataset	Recognition Accuracy (%) for SVM classifier	Recognition Accuracy (%) for KNN during K=3
Anger	96.78	93.56
Disgust	96.75	94.65
Fear	98.6	96.45
Happiness	99.42	98.63
Sad	98.67	98.26
Surpise	99.35	97.56
Average	98.26	96.51

Fig 13. Classification Results

6 and the performance rate for the proposed model seems better when compared with the different state-of-the-art methods.

Table 4. Comparison of existing algorithms for FER

Authors	Model Descriptions	Recogniton rate (%)
Aya Hassouneh et al.,[9]	The CNN and LSTM classifiers are used for real-time emotion recognition.	Emotion recognition in 99.81% and 87.25% EEG
Mahmudul et al.,[11]	MTCNN and Haar-based Cascade classifiesr	For MTCNN classifier 98% percent and for Haar Cascade classifier 68.16%.
Akriti Jaiswal et al.,[12]	DL based emotion detection and CNN classifier.	An accuracy of 70.14 and 98.65 was obtained
Adrian et al.,[17]	wavelet Daubechies transform and RNN.	Average recognition rate of 89.6%
Lanxin Sun et al.,[20]	LDA and Facial Landmark Detection. SVM classifier	73.9% was obtained fo LDA and for Facial Landmark 84.5%
Proposed Model	mHoG+LBP+PCA with SVM and KNN	98.26% for SVM and 96.51% for KNN

In recent year, the various methods are adopted for enhancing their quality and to extract the facial features using transform and frequency domains. It is observed that, maximum approaches are based on generating the texture features. The features extracted are classified using classification techniques discussed above. The SVM model is more compatible when compared with other classifiers and it supports one-to-one and one to many comparisons' technique.

4 Conclusion

The feature level fusion performed using multiple descriptors is carried out in this research work. The multiclass SVM and KNN classifiers are used to recognize the facial expressions effectively. The JAFFE database is used to evaluate the performance of the FER model. Based on the experimental results, the proposed model suits better with a performance rate of 98.26% for SVM and 96.51% for KNN, when compared with the different state-of-the-art methods. In the future, the FER model can be tested using fusion algorithms on standard databases to evaluate the performance rate.

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