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Facial expression recognition for wild dataset using LBP features and Random Forest Classifier

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ABSTRACT

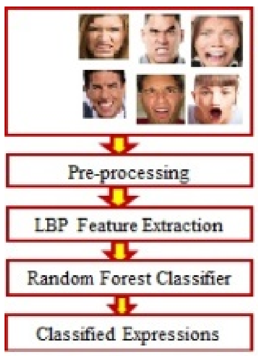
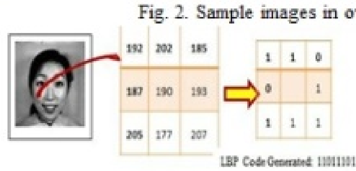
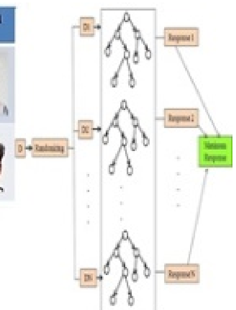


Fig.1. Basic Steps used in FERS

Fig. 2. Sample images in own dataset





Face expressions play major in communication. If machines are facilitated with expression recognition then humans can interact with machines same as humans. A lot of research is carried out in last forty years to find best algorithm for face expression recognition. Good recognition accuracy is achieved for posed images captured in controlled scenario. In this research paper a novel method is proposed for real time images. All the images in dataset are preprocessed before feature extraction. Texture information of images is obtained by using LBP features and random forest classifier is applied on the features extracted. The algorithm is tested by using four datasets and good recognition accuracy is achieved with real time dataset also.

Keywords: Facial Expression Recognition, LBP, Random Forest classifier, wild dataset, pre-processing, feature extraction

INTRODUCTION

Facial expressions plays vital role in interpersonal communication of human. According to research of psychologist Mehrabian in 1978 shows that face expressions and body language conveys 58% information in communication. Expressions are reflected on face during communication.[1] These expressions help to understand emotions of other persons. It is a easiest task for all human beings. In computer vision, face expression recognition system (FERS) is one of the difficult tasks. If digital computers will be able to recognize the face expression then it will be mile stone in human machine interaction. Research in human facial expression recognition is going on since last four decades, but still it is an unsolved problem. FER has a lot of applications in different fields like customer services, online study classes, lie detection and medical treatment etc. Ekman and W. Friesen defined six basic expressions as happy, sad, disgust, surprise, fear and angry.[2] Face without any expression is considered as neutral. These six expressions are considered as reference in almost all FERS.

FERS is multiclass supervised learning classification problem. During expressions, shape and size of different face components like eyes, eye brows, lips, cheeks changes and some wrinkles also appears on face region due to movement of muscles. These changes can be extracted by using different feature extraction algorithms. Every expression has particular changes on face, from which expressions can be identified. For example open lips with raised corner and wrinkles on the cheeks indicate happy expression. Up pulled lips with wrinkled nose and asymmetric nose indicated disgust expression. By identifying these changes expressions can be classified into seven classes as happy, sad, angry, surprised, disgust, fear and neutral.

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Literature Survey

Research is being conducted on FERS from last forty years. First FERS was proposed by Suwaet et. al. in 1978. In this work they traced 20 landmarks in motion frames to predict the expression. The research is going on for real time and low resolution images by using different pre-processing, feature extraction algorithms and classifiers.[3]

Different pre-processing techniques are applied by T. K. Arora et al.[4] To remove noise and detected face area from the image pre-processing is useful. First they converted image to grey scale. To remove noise, background and to decrease the dimensions Median and Gaussian filters are applied. Then edges of image are also smoothened by using three different kernel functions. After preprocessing features are extracted by geometric method using holistic approach. By using pertinent points in face image expression vector is formed. Convolution Neural Network (CNN) is applied for classification. To discover pattern in image and to find shape, edge and texture four different filters are used in the first part of convolution layer of CNN. In the second part, face components like eyes, lips, nose, eye brows are identified. In the final layer nonconventional perceptron layer is applied for classification.

To improve accuracy of FERS, feature extracted using high variance LBP pixel selection. LBP pixels having low variance does not carry any information regarding expression changes and remains almost static. But pixels having high variance are very informative and useful. In pre-processing they converted 512 X 512 resolution colour image to 64 X 64 grey scales. After pre-processing LBP features are computed and features having high variance are selected for expression classification using distance. To recognize real time spontaneous expressions Nazil et al. proposed novel method.[5] Images from video are used as uncontrolled input. They trained Gaussian model on muscles movement. By concatenating the features, high dimension super vector is formed. To reduce its dimensions of super vector it is factorized. For spontaneous face expression recognition S L Happy et al. created dataset of real time spontaneous face expressions.[7] They collected 428 video clips from 50 Indian male and females. The dataset contains labeled face images for training, validation and testing of system. The images are labeled by using four decoders and these are validated by using self report by the subjects.

LBP based features extraction method is proposed by S. L. Happy et al. for FERS.[8] They extracted appearance features from salient patches. The most expressive face patches are decided from movement of face components and these called salient patches. These features contain information useful for the classification. Automated landmark detection decreases the execution time. To detect the position of landmarks, they proposed two different algorithms using Discriminative Response Map Fitting. The proposed method is applicable to low resolution images also.The recognition accuracy of FERS depends on the dataset used, pre-processing, feature extraction and classification algorithm.[9] For different datasets, we get different recognition results due to different characteristics of images. Texture, colour of skin, face shape, location of facial components like lips, eyebrows, nose eyes etc. varies for every individual.[10] Intensity of expression also changes as per situation for same individual also. Background, illumination variation, head movement occlusion are also affect on the accuracy of recognition. These are the challenge for design of robust FERS. For the dataset containing posed images captured in controlled scenario very good recognition accuracy is achieved by most of the algorithms. But for wild datasets having real time images still accuracy is poor and more research is required.[11]

Methodology

Basically there are three major steps in FER as pre-processing of dataset, feature extraction and classification into one of the seven classes. Figure. 1 shows basic steps applied in FERS

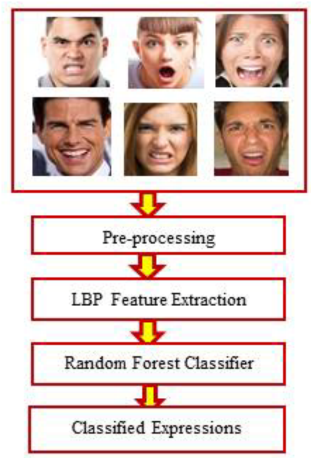

Figure 1. Basic Steps used in FERS

Four different datasets are used for the experimentation as input. To remove noise and to make all images of same size preprocessing is used. Then features are extracted by using Local Binary Pattern (LBP) algorithm. The extracted features are classified by using Random Forest (RF) classifier .[11] The format and size of images and total number of images in each dataset are different. 80 % images in each dataset are used for training and 20 % are used for testing purpose. Japanese Female Facial Expression (JAFFE) dataset contains two to four images of every expressions of Cohn Kanade (CK+) contain images captured in controlled environment of laboratory by using same camera. So illumination and background is same for all images. every subject. 593 images stored in CK+ dataset are captured from 123 subjects of 18 to 30 years age group. There are 213 images stored in grey scale having 256 X 256 resolution and TIFF format. The images are captured from 10

Figure 2. Sample images in own dataset

female subjects and have all seven expressions. The These grey scale images have resolution 640 X 490 resolutions and 8 bit precision. All these images are wild in nature as back ground, illumination, distance between subject and camera is not same for all the images. Figure 2 shows sample images in own dataset.

Experiment is performed using MATLAB 18. 70 % images in each dataset were applied for the training and 30 % were used for testing of proposed model. Table 1 shows actual number of images from each dataset used for training and testing.

Pre-processing is one of the major step in FER. It includes face detection, resizing, noise cancellation, horizontal alignment and normalization. Viola-Jones algorithm is used to detect the face in the image.[12] It is fast and efficient algorithm used for object detection. Only face part from image is selected by using this algorithm and remaining part is removed by using this algorithm. Gaussian normalization function and standard deviation is used is used for normalization. It is useful to reduce feature mismatch in the same class. Impulse noise is removed by using median filters. These filters are very effective to remove noise and decreases intensity variation. It preserves the edge information, so it is useful for FERS. Bessesl's down sampling is applied on own dataset to resize all the images without affecting the aspect ratio. All images in own dataset are stored in JPEG format with resolution 256 X 256.

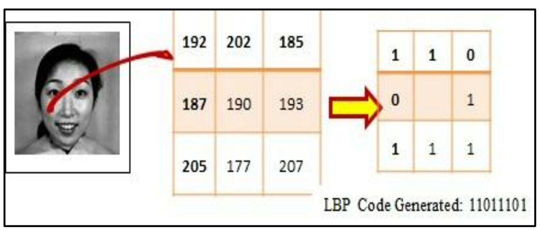

Figure 3. LBP Calculation procedure

To detect direction, pattern, texture and fine edges LBP feature extraction method is used.[13] LBP is simplest way of features calculation. LBP features captures texture information like wrinkles and shape of face. These features are robust to illumination variation and are able to handle head pose variation.[14] Due to these characteristics LBP features are selected for the experimentation and features calculation of real time images. For calculation procedure of LBP is shown in Figure 3. From each pixel LBP features are calculated using matrix of size 3 X 3. In this matrix, intensity of central pixel is considered as threshold value. It is compared with neighboring eight pixels. If neighboring pixel has value less than threshold then it is replaced by zero or otherwise by one. Let grey value of central pixel is denoted by Gc and gery value of neighboring pixel is Gp. The LBP code of central pixel is calculated by using equation (1).

$$LBP(XC, YC) = \sum S(Gp - Gc)2P, \qquad S(X) = \begin{cases} 1, & X \geq 0 \\ 0, & X < 0 \end{cases} \quad \ldots (1)$$

For 3X3 matrix, every central pixel has eight neighbor and so 256 different grey intensity values are possible. The weighted cumulative sum of 0's and 1's of eight neighbors is considered as LBP value of central pixel of 3 X 3 matrix.

LBP values calculated at different regions are concatenated to form feature vector. It helps to find local intensity variation pattern and texture information. Figure 4 shows LBP features vector calculation method.

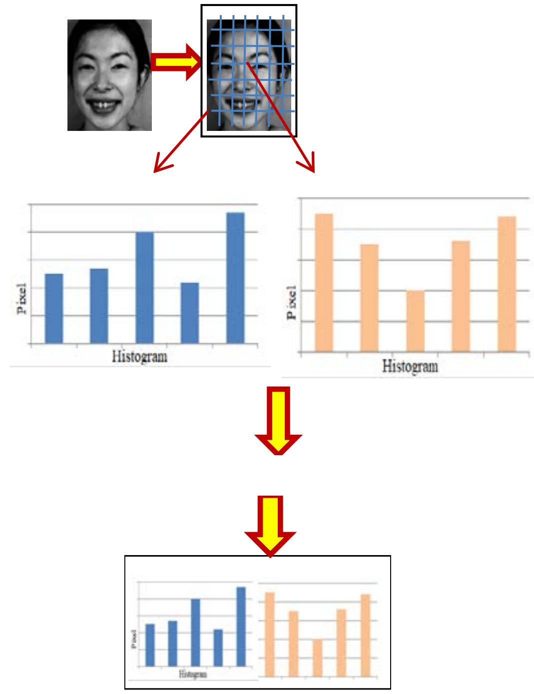

Figure 4. LBP feature calculation

Random Forest Classifier: Random Forest (RF) is an ensemble learning algorithm having simple model and regression task. The features are selected randomly. So it is called as random forest. It is a robust algorithm and has generalization ability. This classifier is able to handle noisy, high-dimensional, non-linear input data. So it is suitable for face expression recognition as input data has illumination and pose variation. The nodes of tree represents feature test and the outcome of test is represented by branch. The structure of RF classifier is shown in Figure 5. Multiple prediction decision trees are combined in the RF classifier. Weak learners of decision tree are collected together to form strong learner.

Using random sampling multiple samples of random data are created. Every subset is trained on one decision tree. By this process diversity is introduced in the individual trees. At every node of decision tree randomness is introduced by considering the subset of random features. It de-correlates tree and improves the performance of classifier. It makes classifier robust and avoids overfitting problem. In RF classifier every tree produces prediction output. Depending on maximum predictions, inputs are classified. RF is splitted depending on different parameters like number of parameters to be considered for classification, depth and number of trees.

To get optimum performance, these parameters are tuned. In RF classifier output of decision trees is ensemble. It can interpret about which features are important for a specific expression. The algorithm of proposed RF classifier is divided in two parts as code to create RF and code to predict decision. Initially 'k' random features are selected for 'm' input features. These features are divided into nodes and daughter nodes by considering splitting point. The procedure is repeated until last node is reached. From this RF tree is generated. To predict about decision of classification, every randomly created decision tree is applied on the test features. The output decision is stored as target. The highest voted decision is called as classified output of RF.

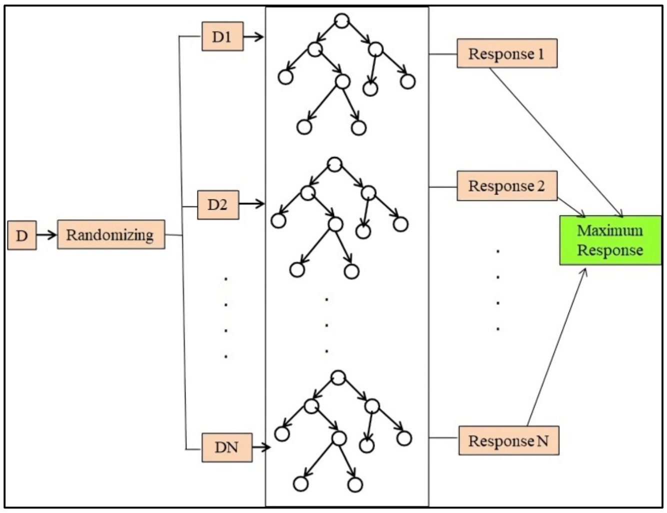

Figure 5. Structure of Random Forest Classifier

EXPERIMENTAL RESULTS

The experiments are carried out on 4 datasets as elaborated in section III. Only recognition accuracy is not sufficient to measure effectiveness of any system. The performance of proposed system is measured with the help of following parameters.[15]

- Recognition Accuracy
- Sensitivity (Recall)
- Specificity
- False Acceptance Rate (FAR)
- False Recognition Rate (FRR)
- Precision
- F1-Score

These parameters are calculated using confusion matrix. The performance of classification model is evaluated using confusion matrix.[16] In confusion matrix true values are represented in rows and predicted values in columns. The numbers of correctly classified expressions we get from upper left to lower write diagonal of confusion matrix A confusion matrix represents values in four categories as True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN). TP indicates correctly predicted instances. TN indicates correctly predicted non-expressions. FP indicates the incorrectly classified instances as positive. FN indicates the incorrectly classified instances as negative. Accuracy is defined as the overall correctness of predictions. To calculate accuracy formula given by equation (2) is used.

$$\text{Accuracy} = \frac{\sum \text{number of correctly classified expressions}}{\text{Total number of images in dataset}}$$

$$\therefore \quad \text{Accuracy} = \frac{(\text{TP+TN})}{(\text{TP+TN+FP+FN})} \qquad (2)$$

Sensitivity is defined as the proportion of true positive predictions out of all actual positive instances. It represents the model's ability to capture all instances of a particular expression. The formula to calculate sensitivity is given by equation (3). It is also called as Recall or True Positive Rate.

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}} \qquad (3)$$

Specificity indicates the proportion of TN predictions out of all actual negative instances. It represents the model's ability to correctly classify non-expressions. Formula used to find specificity is given by equation (4). It is also called as True Negative Rate.

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}} \qquad (4)$$

FAR is a fraction of imposters accepted by system as authorized. It is calculated by dividing the number of false acceptances by the total number of log in attempts. The formula used to calculate FAR is (5)

$$\text{FAR} = \frac{\text{FP}}{\text{TN+FP}}\ \text{X}\ 100 \qquad (5)$$

False Recognition Rate (FRR): Fraction of genuine rejected by system. It measures how well a binary classification test properly identifies negative cases. It is calculated by using formula 7.5

$$\text{FRR} = \frac{\text{TN}}{\text{TN+FP}}\ \text{X}\ 100 \qquad (6)$$

Precision is called as positive prediction value. It is calculated by using equation (7). It is also called as Positive Predictive Value.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \qquad (7)$$

F1-Score: It is a harmonic mean of precision and recall. It is calculated by using equation (8). It balances the trade-off between precision and recall.

$$\text{F1} - \text{Score} = \frac{2(\text{Precision X Recall})}{(\text{Precision+Recall})} \qquad (8)$$

Confusion matrix is calculated for every combination of input dataset, feature extraction and classifier used to find the ambiguous results. For seven expressions 7 X 7 confusion matrix is required. In confusion matrix, classified labels are compared with true labels. It gives detail information about errors occurred in classification.

Only accuracy is not sufficient to find overall performance of classification model. Sensitivity defines correctly identified images. From specificity we get correctly identified negative images. From precision and recall actual percentage of false positive and false negative is calculated. F1-score value finds balance in precision and recall value. All these parameters are calculated using confusion matrix. Table 2 shows confusion matrix obtained on JAFFE dataset and corresponding TP, TN, FP, FN values calculated from confusion matrix. Table 3 shows various performance parameters calculated for JAFFE dataset using proposed methodology. Table 4 shows confusion matrix obtained on CK+ dataset and corresponding TP, TN, FP, FN values calculated from confusion matrix. Table 5 shows various performance parameters calculated for CK+ dataset using proposed methodology.

Table 1. Number of Images used for Experiment

	JAFFE Dataset			CK+ Dataset			FER 2013			Own dataset		
	Train	**Test**	**Total**	**Train**	**Test**	**Total**	**Train**	**Test**	**Total**	**Train**	**Test**	**Total**
Angry	25	6	31	68	17	85	400	80	480	240	60	300
Disgust	25	6	31	68	17	85	400	80	480	240	60	300
Fear	25	6	31	68	17	85	400	80	480	240	60	300
Happy	25	5	30	68	16	84	400	80	480	240	60	300
Neutral	25	5	30	68	16	84	400	80	480	240	60	300
Sad	25	5	30	68	17	85	400	80	480	240	60	300
Surprise	25	5	30	68	17	85	400	80	480	240	60	300
Total	175	38	213	476	117	593	2800	560	3360	1680	420	2100

Table 2. Confusion matrix on JAFFE dataset

Confusion Matrix		**Actual Values**							**Values calculated from Confusion Matrix**			
		Angry	**Disgust**	**Fear**	**Happy**	**Neutral**	**Sad**	**Surprise**	**TP**	**TN**	**FP**	**FN**
Predicted Values	**Angry**	5	1	0	0	0	0	0	5	31	0	1
	Disgust	0	5	0	0	0	1	0	5	31	1	1
	Fear	0	0	4	0	0	0	1	4	32	0	1
	Happy	0	0	0	4	0	0	1	4	31	1	1
	Neutral	0	0	0	0	5	0	0	5	31	1	0
	Sad	0	0	0	0	1	4	0	4	31	1	1
	Surprise	0	0	0	1	0	0	4	4	30	2	1

Table 3. Performance parameters calculated on JAFFE dataset

	Accuracy	**Sensitivity**	**Specificity**	**FAR**	**FRR**	**Precision**	**F1-score**	**Execution time**
Angry	97.30	0.83	1.00	0.00	100.00	1.00	0.91	5.82
Disgust	94.74	0.83	0.97	3.13	96.88	0.83	0.83	
Fear	97.30	0.80	1.00	0.00	100.00	1.00	0.89	
Happy	94.59	0.80	0.97	3.13	96.88	0.80	0.80	
Neutral	97.30	1.00	0.97	3.13	96.88	0.83	0.91	
Sad	94.59	0.80	0.97	3.13	96.88	0.80	0.80	
Surprise	91.89	0.80	0.94	6.25	93.75	0.67	0.73	
Average	95.39	0.84	0.97	2.68	97.32	0.85	0.84	

Table 4. Confusion matrix on CK+ dataset

Confusion Matrix		**Actual Values**							**Values calculated from Confusion Matrix**			
		Angry	**Disgust**	**Fear**	**Happy**	**Neutral**	**Sad**	**Surprise**	**TP**	**TN**	**FP**	**FN**
Predicted Values	**Angry**	14	2	0	0	0	1	0	14	99	1	3
	Disgust	1	12	0	0	0	4	0	12	100	4	5
	Fear	0	0	12	0	0	3	2	12	98	2	5
	Happy	0	0	0	12	2	0	2	12	96	5	4
	Neutral	0	0	0	3	10	3	0	10	96	5	6
	Sad	0	2	0	0	2	13	0	13	89	11	4
	Surprise	0	0	2	2	1	0	12	12	96	4	5

Table 5. Performance parameters calculated on CK+ dataset

	Accuracy	Sensitivity	Specificity	FAR	FRR	Precision	F1-score	Execution time
Angry	96.58	0.82	0.99	1.00	99.00	0.93	0.88	8.19
Disgust	92.56	0.71	0.96	3.85	96.15	0.75	0.73	
Fear	94.02	0.71	0.98	2.00	98.00	0.86	0.77	
Happy	92.31	0.75	0.95	4.95	95.05	0.71	0.73	
Neutral	90.60	0.63	0.95	4.95	95.05	0.67	0.65	
Sad	87.18	0.76	0.89	11.00	89.00	0.54	0.63	
Surprised	92.31	0.71	0.96	4.00	96.00	0.75	0.73	
Average	92.22	0.73	0.95	4.54	95.46	0.74	0.73	

Table 6. Performance parameters calculated on FER 2013 dataset

Confusion Matrix		**Actual Values**							**Values calculated from Confusion Matrix**			
		Angry	**Disgust**	**Fear**	**Happy**	**Neutral**	**Sad**	**Surprise**	**TP**	**TN**	**FP**	**FN**
Predicted Values	**Angry**	14	9	10	11	11	12	13	14	401	79	66
	Disgust	11	14	16	6	8	15	10	14	463	72	66
	Fear	13	15	14	6	6	12	14	14	435	71	66
	Happy	12	10	9	14	8	13	14	14	430	50	66
	Neutral	12	11	12	8	14	13	10	14	431	49	66
	Sad	15	13	11	7	9	14	11	14	410	70	66
	Surprise	16	14	13	12	7	5	13	13	408	72	67

Table 7. Performance parameters calculated on FER 2013 dataset

	Accuracy	Sensitivity	Specificity	FAR	FRR	Precision	F1-score	Execution time
Angry	74.11	0.18	0.84	16.46	83.54	0.15	0.16	15.44
Disgust	77.56	0.18	0.87	13.46	86.54	0.16	0.17	
Fear	76.62	0.18	0.86	14.03	85.97	0.16	0.17	
Happy	79.29	0.18	0.90	10.42	89.58	0.22	0.19	
Neutral	79.46	0.18	0.90	10.21	89.79	0.22	0.20	
Sad	75.71	0.18	0.85	14.58	85.42	0.17	0.17	
Surprise	75.18	0.16	0.85	15.00	85.00	0.15	0.16	
Average	76.85	0.17	0.87	13.45	86.55	0.18	0.17	

Table 8. Performance parameters calculated on Own dataset

Confusion Matrix		**Actual Values**							**Values calculated from Confusion Matrix**			
		Angry	**Disgust**	**Fear**	**Happy**	**Neutral**	**Sad**	**Surprise**	**TP**	**TN**	**FP**	**FN**
Predicted Values	**Angry**	12	14	8	5	6	8	7	12	323	39	48
	Disgust	11	13	14	6	7	5	4	13	345	53	47
	Fear	9	13	14	6	7	5	6	14	328	56	46
	Happy	8	4	12	14	10	4	10	14	317	43	48
	Neutral	1	6	8	16	13	12	4	13	308	54	47
	Sad	5	8	6	5	16	12	8	12	314	48	48
	Surprise	5	8	8	5	8	14	12	12	323	39	48

Table 9. Performance parameters calculated on Own dataset

	Accuracy	Sensitivity	Specificity	FAR	FRR	Precision	F1-score	Execution time
Angry	79.38	0.20	0.89	10.77	89.23	0.24	0.22	17.58
Disgust	78.17	0.22	0.87	13.32	86.68	0.20	0.21	
Fear	77.03	0.23	0.85	14.58	85.42	0.20	0.22	
Happy	78.44	0.23	0.88	11.94	88.06	0.25	0.24	
Neutral	76.07	0.22	0.85	14.92	85.08	0.19	0.20	
Sad	77.25	0.20	0.87	13.26	86.74	0.20	0.20	
Surprise	79.38	0.20	0.89	10.77	89.23	0.24	0.22	
Average	77.96	0.21	0.87	12.80	87.20	0.22	0.21	

Table 10. Results of LBP feature extraction and RF classifier

Dataset	Accuracy (%)	Sensitivity	Specificity	FAR	FRR	Precision	F1-Score	Execution time (sec)
JAFFE	95.39	0.84	0.97	2.68	97.32	0.85	0.84	5.82
CK+	92.22	0.73	0.95	4.54	95.46	0.74	0.73	8.19
FER 2013	76.85	0.17	0.87	13.45	86.55	0.18	0.17	15.44
Own	77.96	0.21	0.87	12.80	87.20	0.22	0.21	17.58

Table 6 shows confusion matrix obtained on FER 2013 dataset and corresponding TP, TN, FP, FN values calculated from confusion matrix. Table 7 shows various performance parameters calculated for FER 2013 dataset using proposed methodology. Table 8 shows confusion matrix obtained on own dataset and corresponding TP, TN, FP, FN values calculated from confusion matrix. Table 9 shows various performance parameters calculated for JAFFE dataset using proposed methodology. Table 10 summarizes the performance parameters obtained on four datasets using proposed algorithm.

Discussion

Performance on JAFEE dataset is best as compared to other three datasets. The recognition accuracy is highest and execution time required is also very less. The number of images in JAFFEE dataset are very less as compared to other dataset but the images are captured in controlled scenario. For CK+ dataset also accuracy is very good. Also it takes less time for execution of the algorithm. For real time datasets like FER 2013 and own, the recognition accuracy is less than JAFFE but still remarkable results are obtained. Also it takes more execution time. For FER 2013 and own dataset, false acceptance rate is also more than JAFFE and CK+. If it is reduced by careful algorithm design then accuracy will increase.

Conclusion

The recognition accuracy results for JAFFE and CK+ are very good as it contains images captured is controlled scenario of laboratory. For FER 2013 and own dataset also good recognition accuracy is obtained. Execution time required for real time images is more. LBP features captures texture information and are robust to head pose variation, illumination and noise. Execution time required for RF classifier is shortest also it can deal with high dimensional feature space. RF and LBP have low computational complexity. They are easy to implement and can handle large training dataset. The proposed algorithm can be effectively used for real time images.

Author Contributions

All the authors contributed in the study of concept and design methodology. Data collection, literature study and analysis were performed by Shubhangi Patil-Kashid, Anandrao Kashid. The manuscript was written by Shubhangi Patil-Kashid. The manuscript was read critically and approved for publication by Dr. Y. M. Patil.

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Conflict of Interest

Authors declare no conflict of interest is there for publication of this work.

References

1. A. Mehrabian. Communication without words. *Commun. Theory Second Ed.* **2017**, 9 (2), 193–200.
2. P. Ekman, W. Friesen. Unmasking the face: A guide to recognizing emotions from facial clues; Prentice Hall, Englewood Cliffs, **2003**.
3. A.A. Pise, M.A. Alqahtani, P. Verma, et al. Methods for Facial Expression Recognition with Applications in Challenging Situations. *Comput. Intell. Neurosci.* **2022**, 2022, 17.
4. T. Kumar Arora, P. Kumar Chaubey, M. Shree Raman, et al. Optimal Facial Feature Based Emotional Recognition Using Deep Learning Algorithm. *Comput. Intell. Neurosci.* **2022**, 2022, 10 10 1155 2022 8379202.
5. N. Perveen, D. Roy, C.K. Mohan. Spontaneous Expression Recognition Using Universal Attribute Model. *IEEE Trans. Image Process.* **2018**, 27 (11), 5575–5584.

6. S.L. Happy, P. Patnaik, A. Routray, R. Guha. The Indian Spontaneous Expression Database for Emotion Recognition. *IEEE Trans. Affect. Comput.* **2017**, 8 (1), 131–142.
7. S. Patil, Y.M. Patil. Face Expression Recognition Using SVM and KNN Classifier with HOG Features. In *Smart Innovation, Systems and Technologies*; Iyer, B., Crick, T., Peng, S. L., Eds.; **2022**; Vol. 303 SIST, pp 416–424.
8. S.L. Happy, A. Routray. Automatic facial expression recognition using features of salient facial patches. *IEEE Trans. Affect. Comput.* **2015**, 6 (1), 1–12.
9. X. Zhao, S. Zhang. A review on facial expression recognition: Feature extraction and classification. *IETE Tech. Rev. (Institution Electron. Telecommun. Eng. India)* **2016**, 33 (5), 505–517.
10. S. Patil, Y.M. Patil. A Review of Human Facial Expression Recognition Systems Applied For Wild Dataset in Last Decade. In *AIP Conference Proceedings*; **2022**; Vol. 2494, p 10.
11. M.K. Abd El Meguid, M.D. Levine. Fully automated recognition of spontaneous facial expressions in videos using random forest classifiers. *IEEE Trans. Affect. Comput.* **2014**, 5 (2), 141–154.
12. P. Viola, M. Jones. Rapid object detection using a boosted cascade of simple features. In *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*; Kauai, HI, USA, **2001**; Vol. 1, pp 511–518,.
13. S. Patil-Kashid, Y.M. Patil, V.R. Pawar, A.S. Kashid. Facial Expression Recognition for Low Resolution Images using Local and Global Features with SVM Classifier. *SSRG Int. J. Electr. Electron. Eng.* **2023**, 10 (7), 181–187.
14. C. Shan, S. Gong, P.W. McOwan. Facial expression recognition based on Local Binary Patterns: A comprehensive study. *Image Vis. Comput.* **2009**, 27 (6), 803–816.
15. M.P. Sunil, S.A. Hariprasad. Facial Emotion Recognition using a Modified Deep Convolutional Neural Network Based on the Concatenation of XCEPTION and RESNET50 V2. *SSRG Int. J. Electr. Electron. Eng.* **2023**, 10 (6), 94–105.
16. I. Markoulidakis, I. Rallis, I. Georgoulas, et al. Multiclass Confusion Matrix Reduction Method and Its Application on Net Promoter Score Classification Problem. *Technologies* **2021**, 9 (4), 81.