Indonesian Journal of Electrical Engineering and Computer Science
Vol. 31, No. 3, September 2023, pp. 1754-1762
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v31.i3.pp1754-1762

Investigation into facial expression recognition methods: a review

Ajaykumar Devarapalli[1,2], Jora M Gonda[1]
[1]Department of Electrical and Electronics Engineering, National Institute of Technology Karnataka, Surathkal, India
[2]Department of Electronics and Instrumentation Engineering, BMS College of Engineering, Bangalore, India

Article Info

Article history:

Received Mar 25, 2023
Revised May 3, 2023
Accepted May 6, 2023

Keywords:

Computer vision
Convolution neural network
Facial expression recognition
Human-computer interaction
Machine learning

ABSTRACT

Facial expression recognition (FER) is a rapidly emerging topic in computer vision that has gotten a lot of interest because of its numerous applications in fields including psychology, sociology, human-computer interaction (HCI), and security. FER seeks to recognise and analyse human facial expressions in order to determine emotions and other mental states. Several strategies, including feature-based, kernel-based, and deep learning-based methods, have been developed and implemented in FER in recent years. FER's major goal is to extract and identify the most discriminating elements that accurately represent the emotions expressed by facial expressions. The literature reviewed in this field shows that deep learning-based methods have outperformed traditional feature-based and kernel-based methods in terms of accuracy and robustness in recognizing facial expressions. However, these deep learning-based methods also pose several challenges, such as the need for large labeled-data-sets, robustness to different facial poses and illumination conditions, and generalization to unseen data. Despite these challenges, the field of FER is expected to continue growing, and future research will likely focus on addressing these challenges and improving the accuracy and robustness of FER systems.

Corresponding Author:

Ajaykumar Devarapalli
Department of Electrical and Electronics Engineering, National Institute of Technology Karnataka
Surathkal, India
Email: d.ajay402@gmail.com

1. INTRODUCTION

Recent studies indicate that each facet of the face conveys specific affective information. And also, the verbal mode communicates a third of the information while the non-verbal mode expresses two-thirds of the information [1]. Facial expression offers a resourceful technique of emotion identification that fosters human-computer interaction (HCI). It denotes decision, and in a social environment, facial expressions initiate social exchanges or responses to others. They can be analyzed through action units (AU) or by openly considering facial emotion interpretations acquired from facial expressions [2]. As an important technique of communication of human emotions, facial expressions have been explored in several fields, including deception detection, driver protection, monitoring, HCI, health, and others. Pranathi *et al.* [3] argue that facial expression recognition (FER) is a common examination phenomenon that has led to several computational vision tasks like super-resolution reconstruction, image generation, image translation, and video generation. Some of the common constitutes of facial expressions include fear, happiness, rage, sorrow, disgust, and surprise [4]. Expressions vary from one individual to another and with time, appearance, and intensity [5]. Furthermore, facial expressions differ with gender, and age and variations of the face such as rotation, change of illumination, accessories, and occlusions can degrade the performance of recognition systems. Therefore, FER has led to many challenges, which have resulted in numerous technological advances in AI and computer vision [6]. Such developments have encouraged the advent of automated systems that can precisely scrutinize and assess the reactions of people through facial expressions [4]. The present study concentrates on FER and the paper presents a wide-ranging review of emerging advances in algorithms and methods used for FER.

The paper is organized as follows. In section 2, we discuss the FER techniques, which include face detection, feature extraction, and classification. In section 3, we provide a comprehensive comparison of various FER methods available in the literature. In section 4 discusses the challenges faced in FER, including subjectivity, illumination, occlusion, and pose variations. Finally, section 5 provides a summary of the paper and future directions for research in this area.

2. FACIAL EXPRESSION RECOGNITION

FER can be formulated as a system, including various steps as depicted in Figure 1. The major steps of FER include-preprocessing, feature extraction, and classification [7]–[9]. Li and Jain [10] described three FER stages: face detection, facial feature extraction, and expression categorization.

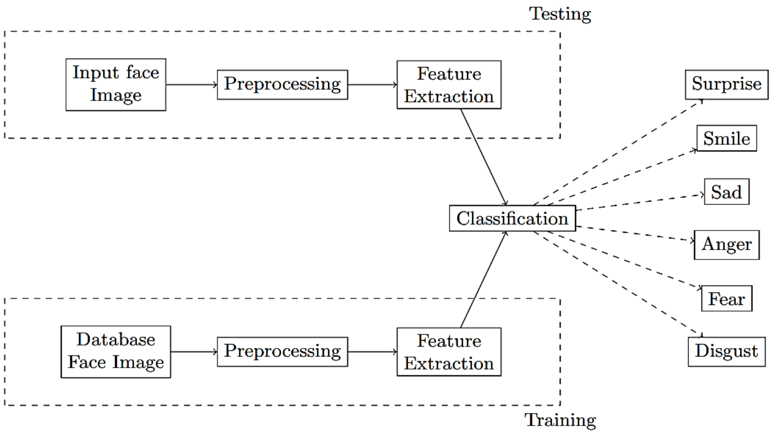

Figure 1. Illustration of the FER system

2.1. Face detection

Face detection is a necessary stage in FER. The face region in photos or videos can be automatically recognised by a powerful automated system. The face region in an image-sequence can be identified using facial traits like-edges, skin-colour, texture, and facial muscle movements. The facial region may be easily distinguished from the background because of these characteristics. The input image is divided into the face region and the non-face region during this stage. The eigenspace approach, adaptive skin colour method, and Viola-Jones method are among the few face identification techniques that are well-known. These techniques are based on algorithms like the haar classifier, adaboost, and contour points [8]. The goal of this survey is to evaluate the accuracy of face detection methods and their performance under different conditions. Table 1 provides an overview of the different face detection methods.

Table 1. Face detection method

Technique	Accuracy	Description
Eigenspace [11]	Offers high precision in face detection in different pose conditions	Allows head movements in a horizontal path, making the system comprehensive
Haar classifier [12]	High precision due to haar attributes	Little computational intricacy because of minimal features
Adaptive skin color [13]	Good precision since it can identify skin color easily but can fail because of illumination	Employs adaptive gamma correction to overcome illumination challenges
Contours [14]	Good accuracy since it employs contour points	Because of a few features, the method reduces the computational cost
Adaboost classifier [15]	Achieves high accuracy due to strong classifier and can detect a single face	Employed trained model and hence minimal computational cost

2.2. Feature extraction

When face detection is completed, the subsequent process involves feature extraction. This process entails discovering and illustrating positive features in images [16], [17]. In image processing and computer vision, this step is important in identifying the transition from graphics to implied data representation [7]. Subsequently, the data representation is utilized as input for classification. The key methods used in feature extraction include principal component analysis (PCA), gabor features, local binary patterns (LBP), and active appearance models. These feature extraction techniques can be classified into five categories: patch, feature, geometric, textual, and edge-based techniques [18], [19].

Texture feature-based approaches encompass various methods for extracting features, such as the gabor filter, which captures phase and size information. Gabor filters with size features are commonly used for face image organization, while the phase feature accounts for the overall magnitude features [20]–[22]. Another widely used texture descriptor is the LBP, which generates binary codes to represent local image patterns. LBP features are obtained by applying a threshold between the neighboring pixels and the central pixel [23], [24]. Additionally, the gaussian laguerre (GL) algorithm provides a pyramidal structure for facial texture extraction, utilizing a single filter as compared to the gabor filter function [25]. The vertical time backward (VTB) method has also been proposed to extract textural features from facial images, and the moment descriptor is effective for extracting shape-based features in spatiotemporal planes [25]. The weber local descriptor (WLD) extracts discriminant texture features from subdivided facial images using the supervised descent method (SDM) [26], [27]. The weighted projection LBP (WPLBP) focuses on capturing intrusive elements during LBP feature extraction, while the discrete contourlet transform (DCT) decomposes data using the laplacian pyramid (LP), and directional filter bank (DFB) [28], [29].

In the realm of edge-based feature extraction, techniques such as line edge map (LEM), graphics processing unit-based active shape model (GASM), and histogram of oriented gradients (HOG) are employed [30]–[32]. The PCA and stepwise linear discriminant analysis (SWLDA) are global and local feature-centric extraction methods that have been developed [33], [34]. Geometric feature-based extraction techniques, including local curvelet transform (LCT), capture statistical properties such as standard deviation, mean, and entropy [35]. Patch-based feature extraction approaches consider facial movement and extract patches based on distance attributes, enabling localized analysis of facial expressions [36].

Overall, texture feature-based descriptors offer resourceful methods for capturing appearance-related textual features, providing essential feature vectors for FER systems. Additionally, discrete wavelet transforms (DWT), local directional number (LDN), KL-transform extended LBP (K-ELBP), and local directional ternary pattern (LDTP) are commonly deployed for texture feature extraction [37]–[39]. Table 2 provides a summarized overview of these techniques for easy reference.

Table 2. Feature extraction techniques

Category	Techniques
Texture	LBP [23], [24], GL algorithm [25], VTB method [25], WLD [26], WPLBP [28], DCT [29], DWT [37], gabor filter [20]–[22], K-ELBP [39], LDTP [39]
Geometric	Moment descriptor [25], LCT [35], GASM [31], SDM [27]
Feature-based	PCA [33], SWLDA [34]
Edge-based	HOG [32], LEM [30]

2.3. Classification

A supervised learning strategy called classification is used to forecast outcomes based on observed values. Classifiers are crucial in pattern recognition because they can predict class labels for unknown data based on training images. To achieve the highest recognition rates, a variety of categorization algorithms have been created [7]. But not all strategies are suitable for analysing various facial feature extraction techniques. A real-time FER system needs a dataset containing a wide range of spontaneous expressions in order to function properly. Classifiers categorise expressions including disgust, smile, fear, sad, anger, neutral, and surprise throughout the feature extraction process, which is regarded as the last phase in FER [40], [41]. Several classification methods are utilised in this phase, including the minimum distance classifier (MDC), a distance-based classifier that is used to calculate the distance between two feature vectors, and the dual local histogram descriptor (dLHD) [42], [43], which is used to recognise expressions. The K-nearest neighbours (KNN) approach is also used for classification, where the training phase involves estimating the relationship between the evaluation models [44]. support vector machine (SVM) is another classification method involving two types of techniques: one against one and one against all [45]–[47]. SVM encompasses a supervised machine learning approach that employs four kernels to ensure superior processes: sigmoid, linear, radial basis function (RBF), and polynomial [48]. Another classification approach involves the hidden markov model

(HMM), which is a statistical scheme that classifies expressions into various types. Hidden conditional random fields (HCRF) are also employed as a classifier of facial expressions. Other facial classification methods include online sequential extreme learning machine (OSELM) [49], learning vector quantization (LVQ) [35], [50], ID3 decision tree (DT) [51], [52], multilayer feed forward neural network (MFFNN) [53], [54], bayesian neural network, convolutional neural network (CNN) [55], deep neural network (DNN) [56], [57], and deep belief network (DBN) [58]. SVM has been found to offer superior recognition accuracy in facial classification approaches when compared to other classification methods [59]–[61]. The neural network-based classifier CNN offers higher precision than other neural network classification functions. Generally, in FER, SVM method is more commonly used than other classifiers [12].

3. COMPARISON OF FER TECHNIQUES

In Figure 2 shows a comparison of FER methods based on their recognition accuracy. The x-axis represents various FER approaches, while the y-axis shows the accuracy of FER techniques. The accuracy has been evaluated based on different studies and databases utilized. Classification techniques such as the gabor function, SVM, and DCT have been found to offer better accuracy [62]–[64]. On the other hand, WLD and LBP descriptors have been found to offer better accuracy with pair-wise classifiers. Table 3 in the Appendix presents a comparison of the performance of FER methods, including the recognition accuracy, database name, advantages of the methods, number of expressions recognized, and other parameters. The databases used include KDEF, JAFFE, Yale, CK+, AR, MMI, TFEID, and MUG [65]–[69].

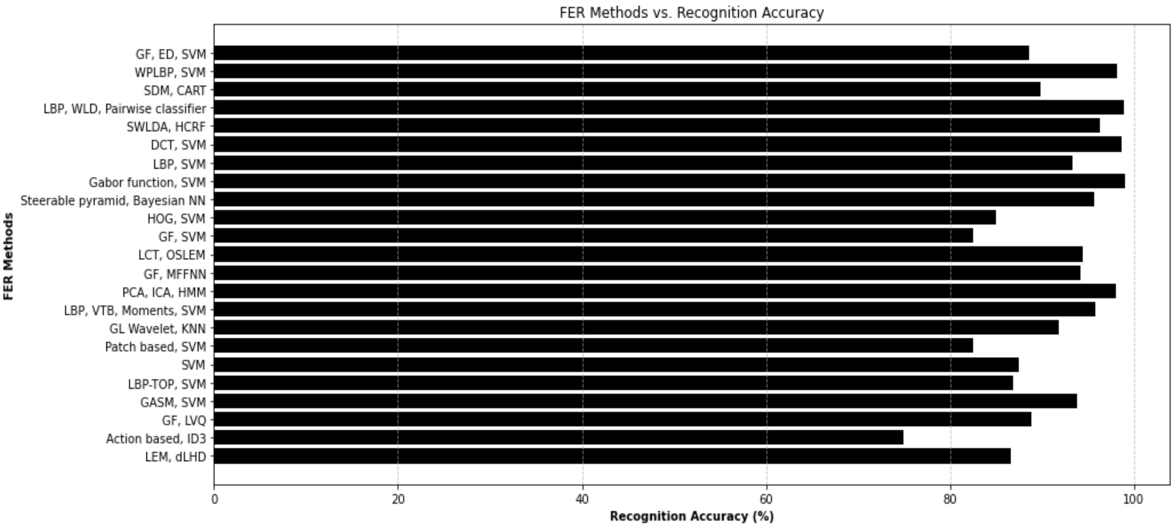

Figure 1. Comparison of accuracy of various FER approaches

4. CHALLENGES

FER faces a number of difficulties that impair its performance in real-world situations. With regard to position variation, illumination, subjectivity, and occlusion, FER presents specific issues. To overcome these obstacles, dependable and robust FER systems need complex algorithms and robust feature extraction approaches that can adapt to changes in position, lighting, subjectivity, and occlusion. The following subsections will explain them in brief.

4.1. Subjectivity

To develop a subjective representation of a person's face, it is important to identify elusive disparities beyond the prototypical reactions like curiosity, disapproval, and attention [2], [70]. Expression predictions are commonly individual-dependent, where a trained face of a person is employed to recognize the facial expression [71]. Subject-independent or individual-independent recognition of expressions is an increasingly multifaceted process since there is a considerable difference in the actual context of facial information and hence requires robust classifiers [72], [73]. Algorithms like PCA and LBP are usually individual-dependent, while haar classifier and PPBTF are individual-independent algorithms that build on typical facial feature models for recognizing expressions.

4.2. Illumination
Differences in illumination can influence feature extraction and lead to misclassification as well as inefficient feature analysis [74]. Various methods have been proposed to overcome this challenge, including LBP maps suggested by Ouyang [75], [76]. Additionally, PPBTF is being used as a PCA training model that can map 5-pixel facial expressions to achieve high computational speed and robust illumination

4.3. Occlusion
The occurrence of occlusion results in inaccurate emotional labeling among humans. Changes in the appearance of a face due to the overlapping of various entities might result in the loss of useful facial attributes [77], [78]. The occluded region is increasingly hard to detect its predominant visual features, making it difficult to track the face region and can degrade FER performance. Obtaining prior knowledge of the occlusion can assist in forecasting the appearance, time, type, shape, and location of occlusion [79].

4.4. Pose variations
Pose variations are a self-occlusion associated with the change in head pose, which occurs regularly in the image series [80]. The majority of automatic FER apps are designed to recognize anterior face expression outlooks [81]. However, the lack of front outlooks can cause variations. FER systems perform poorly due to the loss of informative face regions across different views.

5. CONCLUSION AND FUTURE DIRECTION
FER is an emerging research field with several real-time applications. Scholars have developed and adopted a variety of face detection, feature extraction, and classification approaches, as outlined in this paper. However, face expression detection is still a challenging task influenced by several factors such as pose variation, multifaceted background, illumination, and occlusion. In the future, there is a need to extend the advancement of FER systems to recognize various signs and facial expressions beyond elementary expressions. For example, FER systems should focus on detecting exhaustion, aggressiveness, frustration, and expectation expressions in real-time. Robust algorithms must be created in order to handle complicated face expressions and fluctuations in lighting, occlusion, and position. To enhance the precision and dependability of FER systems in practical contexts, additional research is also required.

APPENDIX

Table 3. Comparison of the performance of FER methods

FER method	Database used	Difficulty	Recognition accuracy	Number of expressions recognized	Key contributions	Benefits
dLHD	AR	Less complicated	86.6%	Three	Can extract oriented structural features	Can be deployed in real-time apps
GL Wavelet	JAFFE, MMI, and CK	Medium complexity	92%	Six	Can extract texture and geometric data	Offers rich capabilities for textual analysis
Steerable pyramid, and Bayesian NN	CK and Jaffee	Less complex	95.7%	Seven	Obtains statistical features from steerable representations	Effective for robust extraction and providing outstanding results
LBP-TOP, SVM	JAFFE, CK	Less	86.9%	Seven	Detects facial features point of motion as well as image ratio features	It is increasingly robust for lighting differences
Gabor filter function	KDEF	Less complex	99%	Does not support	Segments the face into two sections	Achieve high performance and low cost
LBT, VBT Moments, and SVM	Own	Medium complexity	95.8%	Six	Extract spatial temporal features	Effective in image recognition
LBP	JAFFE	Less complex	93.3%	Six	Can detect landmarks, eyebrow corners, and lips	Less complex in terms of computational.
Action-based, ID3 DT	JAFFE	Less	88.9%	Does not support	Effective in recognizing fear expressions	Outstanding precision for fear emotions
SWLDA	Yale, JAFFE, MMI, and CK	Very complex	96.4%	Six	Categories expressions into three classes	Achieves high accuracy

Table 3. Comparison of the performance of FER methods (continued)

FER method	Database used	Difficulty	Recognition accuracy	Number of expressions recognized	Key contributions	Benefits
HMM, PCA and ICA	Own	Less complicated	98%	Six	Multilayer model to avoid similarity challenges	Achieves high accuracy based on its dataset
WPLBP	MMI, JAFFE, and CK+	Medium complexity	98.2%	Seven	Extracts discriminative features from informative face sections	Minimal misclassifications
SVM	JAFFE	Less complicated	87.5%	It is not supported	Offers DKFER for detecting emotions	It is efficient for emotion detection
GF, MFFNN	Yale and JAFFE	High complexity	94.1%	Seven	Offers feature selection using adaboost	Offer the least computational cost
GASM, SVM	CK	High	93.9%	Six	Undertakes adaboost learning from multi-resolution attributes	Offers flexibility in terms of methods utilized for feature selection
OSLEM	CK and JAFFE	Very complicated	94.4%	Seven	Can extract statistical features such as standard deviation, mean, and entropy	offers an approach that is trustworthy for identifying facial expressions
GF	Yale and JAFFE	Less complex	88.6%	Six	Possibility of projecting feature vector space to dimension space	Enhances recognition proficiency
SVM Patch based	JAFFE and CK	Less complex	83%	Six	Can capture face motions depending on distance features	Outstanding recognition computation
HOG, SVM	JAFFE	Very complex	85%	Seven	Offers a SIFT flow algorithm for aligning faces	Goof for rotation, clutter, and occlusion

REFERENCES

[1] B. C. Ko, "A brief review of facial emotion recognition based on visual information," *Sensors (Switzerland)*, vol. 18, no. 2, p. 401, Jan. 2018, doi: 10.3390/s18020401.

[2] M. F. Valstar, B. Jiang, M. Mehu, M. Pantic, and K. Scherer, "The first facial expression recognition and analysis challenge," in *2011 IEEE International Conference on Automatic Face and Gesture Recognition and Workshops, FG 2011*, Mar. 2011, pp. 921–926, doi: 10.1109/FG.2011.5771374.

[3] P. Pranathi, C. Lakshmi, and M. Suneetha, "A review on various facial expression recognition techniques," in *Proceedings of the 5th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud), I-SMAC 2021*, Nov. 2021, pp. 1246–1254, doi: 10.1109/I-SMAC52330.2021.9640733.

[4] R. R. Adyapady and B. Annappa, "A comprehensive review of facial expression recognition techniques," *Multimedia Systems*, vol. 29, no. 1, pp. 73–103, 2023, doi: 10.1007/s00530-022-00984-w.

[5] D. H. Kim, W. J. Baddar, J. Jang, and Y. M. Ro, "Multi-objective based spatio-temporal feature representation learning robust to expression intensity variations for facial expression recognition," *IEEE Transactions on Affective Computing*, vol. 10, no. 2, pp. 223–236, 2019, doi: 10.1109/TAFFC.2017.2695999.

[6] V. Jacintha, J. Simon, S. Tamilarasu, R. Thamizhmani, K. T. Yogesh, and J. Nagarajan, "A review on facial emotion recognition techniques," *Proceedings of the 2019 IEEE International Conference on Communication and Signal Processing, ICCSP 2019*, 2019, pp. 517–521, doi: 10.1109/ICCSP.2019.8698067.

[7] Y. Tian, T. Kanade, and J. F. Cohn, "Facial expression recognition," *Handbook of Face Recognition*, pp. 487–519, 2011, doi: 10.1007/978-0-85729-932-1_19.

[8] S. Li and W. Deng, "Deep facial expression recognition: a survey," *IEEE Transactions on Affective Computing*, vol. 13, no. 3, pp. 1195–1215, 2022, doi: 10.1109/TAFFC.2020.2981446.

[9] S. Rajan, P. Chenniappan, S. Devaraj, and N. Madian, "Facial expression recognition techniques: a comprehensive survey," *IET Image Processing*, vol. 13, no. 7, pp. 1031–1040, 2019, doi: 10.1049/iet-ipr.2018.6647.

[10] S. Z. Li and A. K. Jain, "Handbook of face recognition," *Handbook of Face Recognition*. Springer-Verlag, 2005, doi: 10.1007/b138828.

[11] E. Kheirkhah and Z. S. Tabatabaie, "A hybrid face detection approach in color images with complex background," *Indian Journal of Science and Technology*, vol. 8, no. 1, pp. 49–60, 2015, doi: 10.17485/ijst/2015/v8i1/51337.

[12] I. M. Revina and W. R. S. Emmanuel, "A survey on human face expression recognition techniques," *Journal of King Saud University - Computer and Information Sciences*, vol. 33, no. 6, pp. 619–628, 2021, doi: 10.1016/j.jksuci.2018.09.002.

[13] M. Pantic and L. Ü. M. Rothkrantz, "Automatic analysis of facial expressions: the state of the art," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 22, no. 12, pp. 1424–1445, 2000, doi: 10.1109/34.895976.

[14] A. Dey, "A contour based procedure for face detection and tracking from video," in *2016 3rd International Conference on Recent Advances in Information Technology, RAIT 2016*, 2016, pp. 483–488, doi: 10.1109/RAIT.2016.7507949.

[15] W. Y. Lu and M. Yang, "Face detection based on viola-jones algorithm applying composite features," in *Proceedings - 2019 International Conference on Robots and Intelligent System, ICRIS 2019*, 2019, pp. 82–85, doi: 10.1109/ICRIS.2019.00029.

[16] S. M. Lajevardi and Z. M. Hussain, "Automatic facial expression recognition: feature extraction and selection," *Signal, Image and Video Processing*, vol. 6, no. 1, pp. 159–169, 2012, doi: 10.1007/s11760-010-0177-5.

[17] X. Zhao and S. Zhang, "A review on facial expression recognition: feature extraction and classification," *IETE Technical Review (Institution of Electronics and Telecommunication Engineers, India)*, vol. 33, no. 5, pp. 505–517, 2016, doi: 10.1080/02564602.2015.1117403.

[18] J. Anil and L. P. Suresh, "Literature survey on face and face expression recognition," in *Proceedings of IEEE International Conference on Circuit, Power and Computing Technologies, ICCPCT 2016*, 2016, doi: 10.1109/ICCPCT.2016.7530173.

[19] A. A. Chandio, M. Pickering, and K. Shafi, "Character classification and recognition for Urdu texts in natural scene images," *2018 International Conference on Computing, Mathematics and Engineering Technologies: Invent, Innovate and Integrate for Socioeconomic Development, iCoMET 2018 - Proceedings*, 2018, vol. 2018, pp. 1–6, doi: 10.1109/ICOMET.2018.8346341.

[20] G. P. Hegde, M. Seetha, and N. Hegde, "Accuracy analysis of expression recognition rates using subspace based approaches," *International Journal of Engineering Trends and Technology (IJETT)-Special Issue*, 2017.

[21] D. K. Bhadangkar, J. D. Pujari, and R. Yakkundimath, "Comparison of tuplet of techniques for facial emotion detection," in *Proceedings of the 4th International Conference on IoT in Social, Mobile, Analytics and Cloud, ISMAC 2020*, 2020, pp. 725–730, doi: 10.1109/I-SMAC49090.2020.9243439.

[22] P. Shanthi and S. Nickolas, "An efficient automatic facial expression recognition using local neighborhood feature fusion," *Multimedia Tools and Applications*, vol. 80, no. 7, pp. 10187–10212, 2021, doi: 10.1007/s11042-020-10105-2.

[23] H. Sikkandar and R. Thiyagarajan, "Deep learning based facial expression recognition using improved cat swarm optimization," *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, no. 2, pp. 3037–3053, 2021, doi: 10.1007/s12652-020-02463-4.

[24] M. Kas, Y. E. Merabet, Y. Ruichek, and R. Messoussi, "New framework for person-independent facial expression recognition combining textural and shape analysis through new feature extraction approach," *Information Sciences*, vol. 549, pp. 200–220, 2021, doi: 10.1016/j.ins.2020.10.065.

[25] D. Gera, S. Balasubramanian, and A. Jami, "CERN: Compact facial expression recognition net," *Pattern Recognition Letters*, vol. 155, pp. 9–18, 2022, doi: 10.1016/j.patrec.2022.01.013.

[26] A. Banerjee, N. Das, and K. C. Santosh, "Weber local descriptor for image analysis and recognition: a survey," *Visual Computer*, vol. 38, no. 1, pp. 321–343, 2022, doi: 10.1007/s00371-020-02017-x.

[27] F. Z. Salmam, A. Madani, and M. Kissi, "Fusing multi-stream deep neural networks for facial expression recognition," *Signal, Image and Video Processing*, vol. 13, no. 3, pp. 609–616, 2018, doi: 10.1007/s11760-018-1388-4.

[28] P. Babajee, G. Suddul, S. Armoogum, and R. Foogooa, "Identifying human emotions from facial expressions with deep learning," *2020 Zooming Innovation in Consumer Technologies Conference, ZINC 2020*, 2020, pp. 36–39, doi: 10.1109/ZINC50678.2020.9161445.

[29] S. Kumar, M. K. Bhuyan, and Y. Iwahori, "Multi-level uncorrelated discriminative shared Gaussian process for multi-view facial expression recognition," *Visual Computer*, vol. 37, no. 1, pp. 143–159, 2021, doi: 10.1007/s00371-019-01788-2.

[30] S. Noh, H. Park, Y. Jin, and J. Il Park, "Feature-adaptive motion energy analysis for facial expression recognition," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 4841 LNCS, no. PART 1, pp. 452–463, 2007, doi: 10.1007/978-3-540-76858-6_45.

[31] S. Zhang *et al.*, "Combining cross-modal knowledge transfer and semi-supervised learning for speech emotion recognition," *Knowledge-Based Systems*, vol. 229, p. 107340, 2021, doi: 10.1016/j.knosys.2021.107340.

[32] A. Bhandari and N. R. Pal, "Can edges help convolution neural networks in emotion recognition?," *Neurocomputing*, vol. 433, pp. 162–168, 2021, doi: 10.1016/j.neucom.2020.12.092.

[33] M. H. Siddiqi, R. Ali, A. Sattar, A. M. Khan, and S. Lee, "Depth camera-based facial expression recognition system using multilayer scheme," *IETE Technical Review (Institution of Electronics and Telecommunication Engineers, India)*, vol. 31, no. 4, pp. 277–286, 2014, doi: 10.1080/02564602.2014.944588.

[34] M. H. Siddiqi, R. Ali, A. M. Khan, Y. T. Park, and S. Lee, "Human facial expression recognition using stepwise linear discriminant analysis and hidden conditional random fields," *IEEE Transactions on Image Processing*, vol. 24, no. 4, pp. 1386–1398, 2015, doi: 10.1109/TIP.2015.2405346.

[35] A. Uçar, Y. Demir, and C. Güzeliş, "A new facial expression recognition based on curvelet transform and online sequential extreme learning machine initialized with spherical clustering," *Neural Computing and Applications*, vol. 27, no. 1, pp. 131–142, 2016, doi: 10.1007/s00521-014-1569-1.

[36] S. Nigam, R. Singh, and A. K. Misra, "Efficient facial expression recognition using histogram of oriented gradients in wavelet domain," *Multimedia Tools and Applications*, vol. 77, no. 21, pp. 28725–28747, 2018, doi: 10.1007/s11042-018-6040-3.

[37] R. C. Rahul and M. Cherian, "Facial expression recognition using PCA and texture-based LDN descriptor," *Advances in Intelligent Systems and Computing*, vol. 398. Springer India, pp. 113–122, 2016, doi: 10.1007/978-81-322-2674-1_11.

[38] M. Guo, X. Hou, Y. Ma, and X. Wu, "Facial expression recognition using ELBP based on covariance matrix transform in KLT," *Multimedia Tools and Applications*, vol. 76, no. 2, pp. 2995–3010, 2017, doi: 10.1007/s11042-016-3282-9.

[39] L. Zhang and D. Tjondronegoro, "Facial expression recognition using facial movement features," *IEEE Transactions on Affective Computing*, vol. 2, no. 4, pp. 219–229, 2011, doi: 10.1109/T-AFFC.2011.13.

[40] H. Li and H. Xu, "Deep reinforcement learning for robust emotional classification in facial expression recognition," *Knowledge-Based Systems*, vol. 204, p. 106172, 2020, doi: 10.1016/j.knosys.2020.106172.

[41] O. Ekundayo and S. Viriri, "Facial expression recognition: a review of methods, performances and limitations," in *2019 Conference on Information Communications Technology and Society, ICTAS 2019*, 2019, doi: 10.1109/ICTAS.2019.8703619.

[42] Y. Gao, M. K. H. Leung, S. C. Hui, and M. W. Tananda, "Facial expression recognition from line-based caricatures," *IEEE Transactions on Systems, Man, and Cybernetics Part A:Systems and Humans.*, vol. 33, no. 3, pp. 407–412, 2003, doi: 10.1109/TSMCA.2003.817057.

[43] D. I. Islam, S. R. N. Anal, and A. Datta, "Facial expression recognition using 2DPCA on segmented images," *Advances in Intelligent Systems and Computing*, vol. 706, pp. 289–297, 2018, doi: 10.1007/978-981-10-8237-5_28.

[44] S. Biswas and J. Sil, "An efficient expression recognition method using Contourlet transform," *ACM International Conference Proceeding Series*, vol. 26-27-Febr. ACM, pp. 167–174, 2015, doi: 10.1145/2708463.2709036.

[45] A. Poursaberi, H. A. Noubari, M. Gavrilova, and S. N. Yanushkevich, "Gauss-Laguerre wavelet textural feature fusion with geometrical information for facial expression identification," *Eurasip Journal on Image and Video Processing*, vol. 2012, no. 1, 2012, doi: 10.1186/1687-5281-2012-17.

[46] G. P. Hegde, M. Seetha, and N. Hegde, "Kernel locality preserving symmetrical weighted fisher discriminant analysis based subspace approach for expression recognition," *Engineering Science and Technology, an International Journal*, vol. 19, no. 3, pp. 1321–1333, 2016, doi: 10.1016/j.jestch.2016.03.005.

[47] L. Zhang, D. Tjondronegoro, and V. Chandran, "Random Gabor based templates for facial expression recognition in images with facial occlusion," *Neurocomputing*, vol. 145, pp. 451–464, 2014, doi: 10.1016/j.neucom.2014.05.008.

[48] A. Hernandez-Matamoros, A. Bonarini, E. Escamilla-Hernandez, M. Nakano-Miyatake, and H. Perez-Meana, "Facial expression recognition with automatic segmentation of face regions using a fuzzy based classification approach," *Knowledge-Based Systems*, vol. 110, pp. 1–14, 2016, doi: 10.1016/j.knosys.2016.07.011.

[49] G. J. de Vries, S. Pauws, and M. Biehl, "Facial expression recognition using learning vector quantization," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 9257. Springer International Publishing, pp. 760–771, 2015, doi: 10.1007/978-3-319-23117-4_65.
[50] N. Sebe, M. S. Lew, Y. Sun, I. Cohen, T. Gevers, and T. S. Huang, "Authentic facial expression analysis," *Image and Vision Computing*, vol. 25, no. 12, pp. 1856–1863, 2007, doi: 10.1016/j.imavis.2005.12.021.
[51] S. Bashyal and G. K. Venayagamoorthy, "Recognition of facial expressions using Gabor wavelets and learning vector quantization," *Engineering Applications of Artificial Intelligence*, vol. 21, no. 7, pp. 1056–1064, 2008, doi: 10.1016/j.engappai.2007.11.010.
[52] S. Gupta, K. Verma, and N. Perveen, "Facial expression recognition system using facial characteristic points And ID3," *International Journal of Computer and Communication Technology*, pp. 109–113, 2014, doi: 10.47893/ijcct.2014.1229.
[53] H. Kishan Kondaveeti and M. Vishal Goud, "Emotion detection using deep facial features," in *Proceedings of IEEE International Conference on Advent Trends in Multidisciplinary Research and Innovation, ICATMRI 2020*, 2020, doi: 10.1109/ICATMRI51801.2020.9398439.
[54] E. Owusu, Y. Zhan, and Q. R. Mao, "A neural-adaBoost based facial expression recognition system," *Expert Systems with Applications*, vol. 41, no. 7, pp. 3383–3390, 2014, doi: 10.1016/j.eswa.2013.11.041.
[55] S. Xie and H. Hu, "Facial expression recognition with FRR-CNN," *Electronics Letters*, vol. 53, no. 4, pp. 235–237, 2017, doi: 10.1049/el.2016.4328.
[56] T. Zhang, W. Zheng, Z. Cui, Y. Zong, J. Yan, and K. Yan, "A deep neural network-driven feature learning method for multi-view facial expression recognition," *IEEE Transactions on Multimedia*, vol. 18, no. 12, pp. 2528–2536, 2016, doi: 10.1109/TMM.2016.2598092.
[57] H. Jung *et al.*, "Development of deep learning-based facial expression recognition system," in *2015 Frontiers of Computer Vision, FCV 2015*, 2015, doi: 10.1109/FCV.2015.7103729.
[58] S. A. Khan, S. Shabbir, R. Akram, N. Altaf, M. O. Ghafoor, and M. Shaheen, "Brief review of facial expression recognition techniques," *International Journal of Advanced and Applied Sciences*, vol. 4, no. 4, pp. 27–32, 2017, doi: 10.21833/ijaas.2017.04.005.
[59] Y. Luo, C. M. Wu, and Y. Zhang, "Facial expression recognition based on fusion feature of PCA and LBP with SVM," *Optik*, vol. 124, no. 17, pp. 2767–2770, 2013, doi: 10.1016/j.ijleo.2012.08.040.
[60] P. Michel and R. E. Kaliouby, "Real time facial expression recognition in video using support vector machines," in *Proceedings of the 5th international conference on Multimodal interfaces*, 2003, pp. 258–264, doi: 10.1145/958432.958479.
[61] E. Owusu, Y. Zhan, and Q. R. Mao, "An SVM-AdaBoost facial expression recognition system," *Applied Intelligence*, vol. 40, no. 3, pp. 536–545, 2013, doi: 10.1007/s10489-013-0478-9.
[62] M. Kaur and R. Vashisht, "Comparative study of facial expression recognition techniques," *International Journal of Computer Applications*, vol. 13, no. 1, pp. 43–50, 2011, doi: 10.5120/1741-2368.
[63] S. Saeed, M. K. Mahmood, and Y. D. Khan, "An exposition of facial expression recognition techniques," *Neural Computing and Applications*, vol. 29, no. 9, pp. 425–443, 2016, doi: 10.1007/s00521-016-2522-2.
[64] C. Shi, C. Tan, and L. Wang, "A facial expression recognition method based on a multibranch cross-connection convolutional neural network," *IEEE Access*, vol. 9, pp. 39255–39274, 2021, doi: 10.1109/ACCESS.2021.3063493.
[65] M. Abdulrahman and A. Eleyan, "Facial expression recognition using support vector machines," in *2015 23rd Signal Processing and Communications Applications Conference, SIU 2015 - Proceedings*, 2015, pp. 276–279, doi: 10.1109/SIU.2015.7129813.
[66] I. M. Revina and W. R. S. Emmanuel, "Face expression recognition using weber local descriptor and F-RBFNN," in *Proceedings of the 2nd International Conference on Intelligent Computing and Control Systems, ICICCS 2018*, 2019, pp. 196–199, doi: 10.1109/ICCONS.2018.8662891.
[67] S. Gaur, M. Dixit, S. N. Hasan, A. Wani, T. Kazi, A. Z. Rizvi, "Comparative studies for the human facial expressions recognition techniques," *International Journal of Trend in Scientific Research and Development (IJTSRD)*, vol. 3, no. 5, pp. 2421–2442, 2019, doi: 10.31142/ijtsrd28027.
[68] A. N. Dixit and T. Kasbe, "A survey on facial expression recognition using machine learning techniques," in *2nd International Conference on Data, Engineering and Applications, IDEA 2020*, 2020, doi: 10.1109/IDEA49133.2020.9170706.
[69] S. Wang *et al.*, "A natural visible and infrared facial expression database for expression recognition and emotion inference," *IEEE Transactions on Multimedia*, vol. 12, no. 7, pp. 682–691, 2010, doi: 10.1109/TMM.2010.2060716.
[70] T. M. Luhrmann, "Subjectivity," *Anthropological Theory*, vol. 6, no. 3, pp. 345–361, 2006, doi: 10.1177/1463499606066892.
[71] S. Chen, J. Wang, Y. Chen, Z. Shi, X. Geng, and Y. Rui, "Label distribution learning on auxiliary label space graphs for facial expression recognition," in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2020, pp. 13981–13990, doi: 10.1109/CVPR42600.2020.01400.
[72] W.-J. Yan, S. Li, C. Que, J. Pei, and W. Deng, "RAF-AU database: in-the-wild facial expressions with subjective emotion judgement and objective AU annotations," *Computer Vision – ACCV 2020*, pp. 68–82, 2021, doi: 10.1007/978-3-030-69544-6_5.
[73] S. L. Happy, A. George, and A. Routray, "A real time facial expression classification system using local binary patterns," in *4th International Conference on Intelligent Human Computer Interaction: Advancing Technology for Humanity, IHCI 2012*, 2012, doi: 10.1109/IHCI.2012.6481802.
[74] S. Singh and F. Nasoz, "Facial expression recognition with convolutional neural networks," in *2020 10th Annual Computing and Communication Workshop and Conference, CCWC 2020*, 2020, pp. 324–328, doi: 10.1109/CCWC47524.2020.9031283.
[75] B. Martinez and M. F. Valstar, "Advances, challenges, and opportunities in automatic facial expression recognition," *Advances in Face Detection and Facial Image Analysis*, pp. 63–100, 2016, doi: 10.1007/978-3-319-25958-1_4.
[76] Y. Ouyang, N. Sang, and R. Huang, "Robust automatic facial expression detection method based on sparse representation plus LBP map," *Optik*, vol. 124, no. 24, pp. 6827–6833, 2013, doi: 10.1016/j.ijleo.2013.05.076.
[77] Y. Li, J. Zeng, S. Shan, and X. Chen, "Occlusion aware facial expression recognition using CNN with attention mechanism," *IEEE Transactions on Image Processing*, vol. 28, no. 5, pp. 2439–2450, 2019, doi: 10.1109/TIP.2018.2886767.
[78] L. Zhuang, T. H. Chan, A. Y. Yang, S. S. Sastry, and Y. Ma, "Sparse illumination learning and transfer for single-sample face recognition with image corruption and misalignment," *International Journal of Computer Vision*, vol. 114, no. 2–3, pp. 272–287, 2015, doi: 10.1007/s11263-014-0749-x.
[79] H. Ding, P. Zhou, and R. Chellappa, "Occlusion-adaptive deep network for robust facial expression recognition," *IJCB 2020 - IEEE/IAPR International Joint Conference on Biometrics*, 2020, doi: 10.1109/IJCB48548.2020.9304923.
[80] Z. Chen, Y. Wang, D. Huang, and L. Chen, "Fast and light manifold CNN based 3D facial expression recognition across pose variations," *MM 2018 - Proceedings of the 2018 ACM Multimedia Conference*, 2018, pp. 229–238, doi: 10.1145/3240508.3240568.
[81] F. Zhang, T. Zhang, Q. Mao, and C. Xu, "Geometry guided pose-invariant facial expression recognition," *IEEE Transactions on Image Processing*, vol. 29, pp. 4445–4460, 2020, doi: 10.1109/TIP.2020.2972114.

BIOGRAPHIES OF AUTHORS

Ajaykumar Devarapalli received his B.Tech. Electronics and Communications Engineering) from JNTU, Hyderabad, Andhra Pradesh, and M.Tech. Integrated Circuit Technology from University of Hyderabad, Hyderabad, Andhra Pradesh. He is persuing Ph.D. degree from department of Electrical and Electronics Engineering, National Institute of Technology Karnataka, Surathkal, India. He has 2 years of experience in the industry and 13 years in teaching. He is an active IEEE member and has published 5 international, 5 national and 5 international journal papers, filed 03 indian patents. He has been a reviewer, program committee member, coordinator, organiser and guest speaker for technical conferences/contests/workshops in the domain of VLSI and SoC. He can be contacted at email: d.ajay402@gmail.com.

Jora M Gonda obtained B.E. degree in Electrical Engineering in June 1986, securing 7^{th} rank in the University. Later he obtained his M.E. degree in Electrical Engineering from IISc. Bangalore in the year 1993 and Ph.D. degree from the department of E&C, NITK Surathkal in the year 2017. He joined NITK Surathkal in the year 1987 and currently holds a position of Associate Professor in the Department. He has been focussing on meeting the needs of the students of the department in the fast-changing world and that motivated him to author and offer several courses-in the area of electric circuit theory, power electronics and drives, power system operation and control, power quality, digital signal processing, optimization, control systems, machine learning. He has been a reviewer of research thesis, books, and research publications. He is a senior member of IEEE (USA), life member of institution of engineers (India), Indian society for technical education, and systems society of India. He has been interacting with several industries in the form of-collaboration for students' projects, training, and testing and consultancy activities. He can be contacted at email: gonda@nitk.edu.in.