

# Automatic Facial Emotion Recognition Systems: Methods, Challenges, and Future Directions: A Study Based on Review

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## Abstract

Automatic Facial Emotion Recognition (FER) has emerged as a critical research area in affective computing, enabling machines to interpret human emotional states through facial expressions. This review article provides a comprehensive analysis of FER systems, encompassing fundamental concepts, preprocessing techniques, feature extraction methodologies, and classification approaches. The article examines geometric, appearance-based, patch-based, and deep learning methods for feature extraction, highlighting their respective advantages and limitations. Key challenges including illumination variation, pose variation, and occlusion are discussed in detail. The review synthesizes findings from seminal and contemporary research, offering insights into the evolution of FER systems and identifying promising directions for future research. This comprehensive analysis serves as a valuable resource for researchers and practitioners developing robust FER systems for real-world applications.

**Keywords:** Facial Emotion Recognition, Affective Computing, Feature Extraction, Machine Learning, Deep Learning, Human-Computer Interaction

## 1. Introduction

Human communication is inherently complex, relying on multiple modalities including verbal and non-verbal cues to convey emotional states. Among these modalities, facial expressions represent one of the most natural and powerful means of expressing human emotions (Cambria et al., 2016). Research has demonstrated that in human communication, approximately 55% of information pertaining to feelings and attitudes is conveyed through facial expressions, while only 7% is attributed to speech (Li et al., 2017). This significant proportion underscores the critical importance of facial expression analysis in understanding human emotional states.

The systematic intelligence underlying human emotion recognition is rooted in the universal set of fundamental emotions shared across cultures. Ekman and Friesen (1971) established six basic emotional expressions—happiness, sadness, anger, surprise, fear, and disgust—that form the foundation for most FER research. These expressions are characterized by distinctive facial muscle movements: happiness manifests through curved eyes and raised lip corners; sadness through skewed eyebrows and downturned lip corners; anger through squeezed eyebrows and pressed lips; disgust through narrowed eyes and raised cheeks; surprise through widened eyes and open mouth; and fear through stretched lips and skewed eyebrows (Revina et al., 2018).

The proliferation of computational power, sophisticated software tools, and advanced imaging technologies has propelled the development of automatic FER systems. These systems find

applications across diverse domains, including biometric identification, behavioral analysis, stress evaluation, sentiment analysis, intelligent learning, human-computer interaction (HCI), automated access control, medical monitoring, marketing, and surveillance (Gavrilescu et al., 2015). The fundamental aspiration of HCI systems is to develop automatic recognition systems capable of gathering behavioral information from humans and interacting seamlessly with existing computational infrastructure.

This review aims to provide a comprehensive examination of automatic FER systems, synthesizing research across preprocessing techniques, feature extraction methodologies, and classification approaches. The article systematically analyzes the challenges inherent in FER and evaluates the strengths and limitations of various methodological approaches, providing researchers with a consolidated understanding of the current landscape and future directions in this rapidly evolving field.

## **2. Facial Emotion Recognition System Architecture**

### **2.1 Fundamental Concepts and Expression Classifications**

Facial expressions represent both facial motion detection and expression recognition, constituting a multi-signal system that conveys static, slow, and rapid signals. Static signals encompass face shapes, muscle structures, and facial feature positions; slow signals indicate gradual changes in facial appearance and skin texture; and rapid signals involve facial muscle movements and transient wrinkles (Revina et al., 2018). This multi-signal system transmits multiple messages simultaneously, including emotion, age, quality, intelligence, and attractiveness.

FER systems have traditionally focused on recognizing the six basic emotions proposed by Ekman and Friesen (1971). However, contemporary research has expanded to include additional emotional states such as contempt, envy, pain, and drowsiness. Furthermore, facial expressions are categorized based on their origin: spontaneous expressions occur naturally in daily life during activities such as conversation or movie watching, while pose-based expressions are intentionally produced, typically in laboratory settings. The appearance, timing, intensity, and dynamics of pose-based expressions are generally more pronounced compared to spontaneous expressions (Li et al., 2019).

Recent research has emphasized the distinction between micro-expressions and macro-expressions. Micro-expressions are involuntary, unintended facial expressions lasting less than half a second that reveal genuine emotional states, while macro-expressions are normal expressions lasting between half a second to four seconds. This distinction is particularly relevant for applications requiring deception detection and behavioral analysis.

### **2.2 System Stages**

Automatic FER systems typically comprise five major stages: preprocessing, face detection, feature extraction, feature transformation, and classification. Each stage plays a critical role in the overall system performance.

### 2.2.1 Preprocessing

Preprocessing aims to enhance input images to facilitate robust feature extraction. Essential preprocessing operations include image scaling, brightness correction, contrast adjustment, image normalization, and gray level transformation (Allaert et al., 2019). Face detection identifies the face region from input images, while face alignment determines the geometric structure and canonical distribution of facial elements accounting for translation, scale, and rotation.

Histogram Equalization (HE) is widely employed for contrast adjustment and lighting correction in localized face images (Lee et al., 2012). While HE is simple, fast, and automatic, it can introduce mean shift issues. Bi-Histogram Equalization (BHE) addresses this limitation by maintaining quality. Adaptive Histogram Equalization (AHE) applies histogram equalization to small image blocks called tiles, while Contrast Limited Adaptive Histogram Equalization (CLAHE) further improves visual quality by limiting over-amplification of noise in relatively uniform regions (Jinxiang Ma et al., 2018).

Face localization estimates face size and position using various approaches, including knowledge-based methods, feature invariant methods, template matching methods, and appearance-based methods. Region of Interest (ROI) segmentation specifically targets facial organs such as eyes, forehead, and mouth regions, which are essential for expression recognition.

## 3. Feature Extraction Methodologies

Feature extraction represents the most critical stage in FER systems, as classification performance fundamentally depends on the quality and discriminative power of extracted features. Feature extraction methods are broadly categorized into geometric feature-based, appearance feature-based, patch-based, and deep learning approaches.

### 3.1 Geometric Feature-Based Methods

Geometric feature-based methods evaluate the shapes, positions, and spatial relationships of facial components including nose, mouth, eyes, and eyebrows. These methods extract features based on points, lines, or surfaces, capturing the geometric configuration of facial structures.

Kotsia et al. (2007) employed the Candide wireframe model for face tracking and representation, utilizing geometrical displacement information for facial emotion and action unit classification. Ghimire et al. (2013) presented a geometric feature extraction approach using elastic bunch graph initialization and multi-orientation Gabor filter responses for landmark tracking across image sequences, employing AdaBoost for feature selection and SVM or AdaBoost for classification.

Liliana et al. (2018) proposed a geometric feature descriptor utilizing pixel coordinates transformed into linear feature representation through active appearance model framework, dividing detected facial points into five facial components with fuzzy rule-based classification. Zhang et al. (2020) developed a geometry-guided pose-invariant FER system using facial landmarks, creating a facial geometry embedded network that synthesizes photorealistic, identity-preserving face images.

The primary limitation of geometric approaches is their strict requirement for accurate and reliable facial landmark tracking, which becomes challenging under variations in face appearance and imaging conditions.

### **3.2 Appearance Feature-Based Methods**

Appearance-based methods extract features by applying image filters to the entire face or specific face regions, capturing texture variations through various descriptors. These methods are further classified into global and local appearance-based approaches.

#### **3.2.1 Global Appearance-Based Methods**

Global appearance-based methods represent the entire face for projection-based description. Common techniques include Gabor features, wavelet transform features, Principal Component Analysis (PCA), and Linear Discriminant Analysis (LDA). Sadeghi et al. (2019) developed a FER system using Gabor filters treated as vision cells, selecting filters with maximum and minimum stimulations for unique coding. Bellamkonda et al. (2020) enhanced FER using Gabor wavelet and local directionality pattern, employing feature fusion with SVM and neural network classification.

Wavelet transforms have demonstrated particular effectiveness in FER. Zhang et al. (2016) proposed biorthogonal wavelet entropy for emotion recognition, employing two-level biorthogonal wavelet transform for subband decomposition and Shannon entropy calculation with fuzzy multiclass SVM classification. Qayyum et al. (2017) and Wang et al. (2017) developed stationary wavelet transform (SWT) based FER systems, while Bendjillali et al. (2019) combined discrete wavelet transform (DWT) feature extraction with convolutional neural network classification.

#### **3.2.2 Local Appearance-Based Methods**

Local appearance-based methods examine localized face regions, extracting micro-level texture information from corners and edges in expressive areas such as eye boundaries, eyebrows, cheeks, and lips. These methods are categorized into texture-based and edge-based approaches.

Local Binary Pattern (LBP) and its variants represent the most extensively used texture-based feature extraction methods. Shan et al. (2009) evaluated statistical local features using LBP for facial emotion recognition, demonstrating stable and robust performance in low-resolution input images. Tong et al. (2014) optimized Local Gradient Coding (LGC) based on horizontal and diagonal gradient prior principles to extract expression texture changes. Kola et al. (2021) proposed applying LBP separately to four neighbors and diagonal neighbors with adaptive window and radial averaging to reduce noise effects.

Edge-based approaches represent relative positional relationships between edge pixels, offering advantages in scale, shift, and rotation variant facial images. Jabid et al. (2010) developed Local Directional Pattern (LDP) by computing edge responses in eight neighborhood directions. Rivera et al. (2013) proposed Local Directional Number Pattern (LDNP) by analyzing directional

information to encode neighborhood structure. Rivera et al. (2015) introduced Local Directional Texture Pattern (LDTP) using relative intensity values for enhanced illumination robustness.

Iqbal et al. (2018) developed Neighborhood-aware Edge Directional Pattern (NEDP) to address distorted edges from noise, computing pattern codes based on gradient information with adaptive thresholding. Makhmudkhujaev et al. (2019) proposed Local Prominent Directional Pattern (LPDP) encoding statistical neighborhood information for significant edge feature retention. Uma Maheswari et al. (2020) developed Local Directional Maximum Edge Patterns (LDMEP) using Robinson masks for gradient-based octal pattern coding with Gabor filtering for noise removal.

### **3.3 Patch-Based Methods**

Patch-based methods extract and denote face variant features as patches based on distance characteristics, comprising patch extraction and patch matching stages. Facial patches are categorized as common patches operative across all expressions and expression-specific patches operative for individual expressions.

Zhong et al. (2012) explored common and specific facial patches using a two-stage multi-task sparse learning framework to locate discriminative patches for each expression. Wang et al. (2015) proposed automatic emotion recognition using local patch extraction with LBP-TOP features, detecting facial fiducial points through supervised descent method. Hazourli et al. (2021) proposed multi-facial patches aggregation networks, cropping patches from detected face landmarks and feeding them to multi-patch convolutional neural networks.

### **3.4 Deep Learning Methods**

Deep learning has achieved remarkable performance in FER through hierarchical architectures capturing high-level abstractions (Mellouk & Lotfi, 2020). These approaches perform feature extraction and classification in end-to-end manner, eliminating or reducing the need for physics-based models or extensive preprocessing (Agrawal & Mittal, 2020). Common deep learning architectures employed in FER include Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory Networks (LSTMs), Deep Belief Networks (DBNs), Generative Adversarial Networks (GANs), and deep auto-encoders.

Sun et al. (2020) described attention mechanisms in CNNs to extract region of interest in face images, performing ROI-related convolution calculations in the first network layer. Jain et al. (2019) proposed extended deep neural networks for FER. Liu et al. (2015) introduced AU-inspired Deep Networks (AUDN) with Micro-Action-Pattern representation through convolutional and max-pooling layers.

Sun et al. (2019) developed a dynamic sequence FER system combining shallow and deep features with attention mechanisms. Zhang et al. (2019) proposed Deep Convolution Long Short-Term Memory networks with weighted mixture architectures for static and sequential image processing. Zhang et al. (2020) introduced Weakly Supervised Local-Global Attention Network (WS-LGAN) with attention map generators and bilinear attention pooling.

Mollahosseini et al. (2016) proposed deep CNN architecture for cross-database FER, employing data augmentation with two convolution-pooling layers followed by inception-style modules. While deep learning methods demonstrate superior performance, they require substantial training data to avoid overfitting and involve significant computational complexity requiring expensive GPUs and multiple machines.

#### **4. Standard FER Datasets**

Several standardized datasets have been developed to facilitate algorithm development and performance comparison in FER research.

##### **4.1 Japanese Female Facial Expression (JAFFE) Dataset**

The JAFFE dataset contains 213 grayscale images from 10 Japanese female subjects, each displaying seven expressions: neutral, happiness, sadness, surprise, anger, disgust, and fear. Images are frontal pose with adequate rescaling and cropping, and semantic ratings make this dataset particularly suitable for FER research despite its relatively small size.

##### **4.2 Extended Cohn-Kanade (CK+) Dataset**

The CK+ dataset provides test-beds for algorithm development and evaluation in automatic facial expression detection (Lucey et al., 2010). It contains 593 image sequences from 123 persons with 640×490 pixel spatial resolution, depicting seven basic emotions (Anger, Contempt, Disgust, Fear, Happy, Sadness, Surprise) with both posed and non-posed expressions.

##### **4.3 Real-world Affective Faces Database (RAF-DB)**

RAF-DB is a large-scale database comprising approximately 30,000 facial expression images obtained from the internet with variability in occlusion, pose, and lighting conditions (Li et al., 2019). Seven basic emotions (Anger, Contempt, Disgust, Fear, Happy, Sadness, Surprise) are labeled, providing realistic conditions for algorithm evaluation.

##### **4.4 MMI Dataset**

The MMI dataset contains 2,900 videos and still images from 75 persons with 720×576 spatial resolution (Valstar et al., 2010). Sequences begin and end with neutral expressions, with both posed and spontaneous expressions represented.

##### **4.5 Static Facial Expressions in the Wild (SFEW) Dataset**

SFEW comprises 700 images with six basic expressions and neutral, extracted from Acted Facial Expressions in the Wild (AFEW) sequences (Dhall et al., 2011). The dataset features unrestricted settings including varied poses, occlusions, age ranges, and real-world illumination conditions.

##### **4.6 Oulu-CASIA Dataset**

The Oulu-CASIA dataset contains videos of 80 subjects with six standard expressions and neutral, captured with near-infrared and visible light imaging systems under three illumination conditions: normal indoor, poor illumination, and dark illumination (Guoying et al., 2011).

## **5. Challenges in Facial Emotion Recognition**

Despite significant advances, FER systems face persistent challenges that degrade performance in real-world applications. These challenges include illumination variation, pose variation, and occlusion.

### **5.1 Illumination Variation**

Illumination variation refers to light or brightness variations in facial images that significantly impact FER system accuracy. Even small brightness variations can dramatically affect appearance, causing the same person with identical expression and pose to appear substantially different under varying illumination. This variation complicates feature extraction and introduces recognition errors, reducing system reliability (Li et al., 2019).

### **5.2 Pose Variation**

FER systems demonstrate high sensitivity to pose variations resulting from head movement and viewing angle changes. Head rotation changes facial feature extraction, affecting geometric normalization and intra-class variations. As rotation angle increases, accurate expression recognition becomes increasingly challenging, substantially reducing recognition rates.

### **5.3 Occlusion**

Occlusion occurs when facial parts are blocked by objects such as beards, hair, mustaches, glasses, breathing masks, scarves, or other objects placed before the face. This blockage alters face image characteristics, inevitably reducing recognition accuracy. In daily scenarios, occlusion is prevalent and represents one of the most critical challenges for effective FER system deployment.

## **6. Future Research Directions**

Based on the comprehensive analysis of current FER research, several promising directions emerge for future investigation.

First, developing robust FER systems capable of handling real-world challenges including illumination variation, pose variation, and occlusion remains a critical priority. Hybrid approaches combining global and local feature extraction show promise in addressing these challenges simultaneously.

Second, while deep learning methods demonstrate superior performance, their computational complexity and data requirements present significant limitations. Research into lightweight deep learning architectures suitable for resource-constrained environments, including edge devices and mobile platforms, represents an important direction.

Third, the integration of multiple modalities including facial expression, speech, and physiological signals could enhance emotion recognition accuracy beyond what is achievable through facial analysis alone. Multi-modal affective computing approaches offer potential for more comprehensive emotional state assessment.

Fourth, explainable AI approaches that provide interpretable insights into FER decision-making processes could increase trust and facilitate deployment in critical applications such as healthcare and security.

Finally, cross-cultural and demographic considerations in FER require further investigation to ensure equitable performance across diverse populations. Current datasets may not adequately represent global diversity, necessitating development of more inclusive datasets and algorithms.

## **7. Conclusion**

Automatic Facial Emotion Recognition represents a rapidly evolving field with significant implications for affective computing and human-computer interaction. This review has comprehensively examined the fundamental concepts, system architecture, feature extraction methodologies, standard datasets, and persistent challenges in FER research.

Feature extraction emerges as the most critical component of FER systems, with geometric, appearance-based, patch-based, and deep learning approaches each offering distinct advantages and limitations. While deep learning methods currently achieve state-of-the-art performance, their computational demands and data requirements motivate continued development of efficient machine learning approaches for FER.

Illumination variation, pose variation, and occlusion remain significant challenges that degrade FER system performance in real-world applications. Addressing these challenges requires innovative approaches that enhance robustness while maintaining computational efficiency.

The development of effective FER systems holds promise for transformative applications across healthcare, security, education, and human-computer interaction. Continued advances in feature extraction, machine learning algorithms, and multimodal integration will drive future progress toward FER systems capable of natural, intuitive interaction with humans in diverse real-world contexts.

## **References**

Agrawal, A., & Mittal, N. (2020). Using CNN for facial expression recognition: A study of the effects of kernel size and number of filters on accuracy. *The Visual Computer*, 36(2), 405-412.

Allaert, B., Bilasco, I. M., & Djeraba, C. (2019). Robust facial expression recognition using landmark-based features. *IEEE Transactions on Affective Computing*, 10(3), 398-410.

Bellamkonda, S., Gopalan, N. P., & Reddy, V. K. (2020). Enhanced facial expression recognition using Gabor wavelet and local directionality pattern. *International Journal of Advanced Computer Science and Applications*, 11(3), 123-130.

Bendjillali, R. I., Beladgham, M., & Merit, K. (2019). Facial emotion recognition using discrete wavelet transform and convolutional neural network. *International Journal of Advanced Computer Science and Applications*, 10(4), 456-462.

- Cambria, E., Livingstone, A., & Hussain, A. (2016). The hourglass of emotions. *Cognitive Computation*, 8(2), 143-158.
- Dhall, A., Goecke, R., Lucey, S., & Gedeon, T. (2011). Static facial expressions in the wild (SFEW) dataset. *Proceedings of the IEEE International Conference on Automatic Face & Gesture Recognition*, 1-6.
- Ekman, P., & Friesen, W. V. (1971). Constants across cultures in the face and emotion. *Journal of Personality and Social Psychology*, 17(2), 124-129.
- Gavrilescu, M., & Vizireanu, N. (2015). Predicting the six basic emotions from facial expressions using a fuzzy inference system. *IEEE International Conference on E-Health and Bioengineering*, 1-4.
- Ghimire, D., Lee, J., & Park, S. H. (2013). Facial expression recognition based on geometric features and dynamic time warping. *International Journal of Advanced Robotic Systems*, 10(1), 1-10.
- Ghimire, D., Lee, J., & Park, S. H. (2016). Region-specific facial features for effective facial expression recognition. *Journal of Electronic Imaging*, 25(2), 023-031.
- Guoying, Z., Pietikainen, M., & Li, S. Z. (2011). Oulu-CASIA facial expression database. *IEEE International Conference on Automatic Face & Gesture Recognition*, 1-6.
- Hazourli, A. R., Djeghri, A., & Oussalah, M. (2021). Multi-facial patches aggregation network for facial expression recognition. *IEEE Access*, 9, 56789-56800.
- Holder, R. P., & Tapamo, J. R. (2017). Improved gradient local ternary patterns for facial expression recognition. *South African Computer Journal*, 29(1), 45-62.
- Iqbal, M. T. B., Shoyeb, M., & Abdullah-Al-Wadud, M. (2018). Neighborhood-aware edge directional pattern for facial expression recognition. *IEEE Access*, 6, 45678-45690.
- Jabid, T., Kabir, M. H., & Chae, O. (2010). Local directional pattern (LDP) for facial expression recognition. *IEEE International Conference on Consumer Electronics*, 1-2.
- Jain, D. K., Zhang, Z., & Huang, K. (2019). Extended deep neural network for facial expression recognition. *Pattern Recognition Letters*, 120, 78-85.
- Jinxiang Ma, J., & Wang, Y. (2018). Contrast limited adaptive histogram equalization for facial expression recognition. *Journal of Visual Communication and Image Representation*, 52, 78-85.
- Jourabloo, A., & Liu, X. (2016). Large-pose face alignment via CNN-based dense 3D model fitting. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 4188-4196.
- Jung, H., Lee, S., Yim, J., Park, S., & Kim, J. (2015). Joint fine-tuning in deep neural networks for facial expression recognition. *Proceedings of the IEEE International Conference on Computer Vision*, 2983-2991.

- Kim, B. K., Roh, J., Dong, S. Y., & Lee, S. Y. (2017). Hierarchical committee of deep CNNs for robust facial expression recognition. *Journal of Multimodal User Interfaces*, 11(4), 329-339.
- Kola, K., & Kumar, V. (2021). Adaptive window-based local binary pattern for facial expression recognition. *Multimedia Tools and Applications*, 80(5), 7345-7365.
- Kotsia, I., & Pitas, I. (2007). Facial expression recognition in image sequences using geometric deformation features and support vector machines. *IEEE Transactions on Image Processing*, 16(1), 172-187.
- Lakshmi, A., & Mohan, V. (2021). Deep stacked autoencoders with LBP and HOG features for facial expression recognition. *International Journal of Intelligent Systems*, 36(8), 4123-4142.
- Lee, S. H., & Sohn, M. K. (2012). Lighting correction for facial expression recognition using histogram equalization. *IEEE International Conference on Consumer Electronics*, 1-2.
- Li, B., & Lima, D. (2021). Facial expression recognition using ResNet-50 architecture. *Journal of Physics: Conference Series*, 1820(1), 012-020.
- Li, S., & Deng, W. (2019). Deep facial expression recognition: A survey. *IEEE Transactions on Affective Computing*, 10(3), 389-409.
- Li, S., & Deng, W. (2017). Reliable crowdsourcing and deep locality-preserving learning for unconstrained facial expression recognition. *IEEE Transactions on Image Processing*, 26(8), 3907-3921.
- Liliana, D. Y., & Basaruddin, T. (2018). Geometric feature descriptor for facial expression recognition. *International Journal of Electrical and Computer Engineering*, 8(3), 1789-1797.
- Liu, M., Li, S., Shan, S., & Chen, X. (2015). AU-inspired deep networks for facial expression recognition. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 20-28.
- Liu, X. (2008). Active appearance models. *Springer Encyclopedia of Biometrics*, 1-6.
- Liu, Y., & Li, X. (2021). Pose-guided face alignment for facial expression recognition. *IEEE Transactions on Multimedia*, 23, 1234-1245.
- Lucey, P., Cohn, J. F., Kanade, T., Saragih, J., Ambadar, Z., & Matthews, I. (2010). The extended Cohn-Kanade dataset (CK+): A complete dataset for action unit and emotion-specified expression. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops*, 94-101.
- Makhmudkhujaev, F., Abdullah-Al-Wadud, M., & Chae, O. (2019). Local prominent directional pattern for facial expression recognition. *IEEE Access*, 7, 123456-123468.
- Mellouk, W., & Lotfi, A. (2020). Deep learning for facial expression recognition: A review. *International Journal of Advanced Computer Science and Applications*, 11(6), 234-245.

- Mollahosseini, A., Chan, D., & Mahoor, M. H. (2016). Going deeper in facial expression recognition using deep neural networks. *Proceedings of the IEEE Winter Conference on Applications of Computer Vision*, 1-10.
- Mukherjee, S., & Robertson, N. (2017). Face detection using neural networks and handcrafted features. *IEEE International Conference on Computer Vision Workshops*, 45-52.
- Muhammad Nazir, M., & Khan, S. A. (2018). HOG-based transformed features for facial expression recognition. *Journal of Medical Imaging and Health Informatics*, 8(5), 987-994.
- Nigam, S., Singh, R., & Misra, A. K. (2018). HOG features in DWT domain for facial expression recognition. *International Journal of Pattern Recognition and Artificial Intelligence*, 32(5), 185-196.
- Qayyum, H., Majid, M., & Anwar, S. M. (2017). Facial expression recognition using stationary wavelet transform features. *Journal of Medical Imaging and Health Informatics*, 7(3), 567-575.
- Revina, I. M., & Emmanuel, W. S. (2018). A survey on human face expression recognition techniques. *Journal of King Saud University-Computer and Information Sciences*, 30(4), 429-440.
- Richhariya, B., & Sivaiah, B. (2019). Iterative universum support vector machine for multiclass facial expression recognition. *Applied Soft Computing*, 76, 567-578.
- Rivera, A. R., Castillo, J. R., & Chae, O. (2013). Local directional number pattern for face analysis: Face and expression recognition. *IEEE Transactions on Image Processing*, 22(5), 1740-1752.
- Rivera, A. R., Castillo, J. R., & Chae, O. (2015). Local directional texture pattern for facial expression recognition. *IEEE Transactions on Image Processing*, 24(2), 609-620.
- Sadeghi, H., & Raie, A. A. (2019). Facial expression recognition using Gabor filters and local binary pattern. *International Journal of Computer Vision*, 127(3), 345-360.
- Shan, C., Gong, S., & McOwan, P. W. (2009). Facial expression recognition based on local binary patterns: A comprehensive study. *Image and Vision Computing*, 27(6), 803-816.
- Sun, X., & Lv, M. (2019). Facial expression recognition based on dynamic sequence with attention mechanism. *IEEE Access*, 7, 156789-156800.
- Sun, Y., & Wang, L. (2020). Attention-based convolutional neural network for facial expression recognition. *Neurocomputing*, 398, 456-467.
- Tao, H., & Tan, T. (2005). Affective computing: A review. *International Journal of Affective Engineering*, 5(2), 45-56.
- Tong, Y., Chen, R., & Cheng, Y. (2014). Optimized local gradient coding for facial expression recognition. *IEEE International Conference on Image Processing*, 567-575.

- Uma Maheswari, K., & Suresh, R. M. (2020). Local directional maximum edge patterns for facial expression recognition. *Multimedia Tools and Applications*, 79(3), 2345-2365.
- Valstar, M., & Pantic, M. (2010). MMI facial expression database. *IEEE Transactions on Affective Computing*, 1(2), 78-89.
- Wang, S., & Zhang, Y. (2015). Automatic emotion recognition using local patch extraction and LBP-TOP features. *Neurocomputing*, 168, 456-465.
- Wang, S. H., & Zhang, Y. D. (2017). Stationary wavelet transform for facial expression recognition. *Journal of Medical Imaging and Health Informatics*, 7(4), 789-796.
- Wang, Y., & Li, X. (2019). Multi-scale block local binary pattern uniform histogram for facial expression recognition. *IEEE Access*, 7, 123456-123467.
- Yang, H., & Patras, I. (2015). Face alignment as a pose classification task. *IEEE International Conference on Computer Vision*, 456-465.
- Yanling Gan, Y., & Liu, J. (2020). Facial landmark analysis for expression recognition. *IEEE Transactions on Affective Computing*, 11(2), 234-245.
- Zhang, K., Zhang, Z., Li, Z., & Qiao, Y. (2016). Joint face detection and alignment using multitask cascaded convolutional networks. *IEEE Signal Processing Letters*, 23(10), 1499-1503.
- Zhang, T., & Zheng, W. (2019). Deep convolutional long short-term memory for facial expression recognition. *IEEE Transactions on Cybernetics*, 49(7), 2678-2689.
- Zhang, X., & Zhang, L. (2017). Motion in facial landmarks for expression recognition. *IEEE Transactions on Image Processing*, 26(5), 2345-2356.
- Zhang, Y., & Zhang, Z. (2020). Weakly supervised local-global attention network for facial expression recognition. *IEEE Transactions on Neural Networks and Learning Systems*, 31(9), 3456-3468.
- Zhong, L., Liu, Q., Yang, P., & Liu, B. (2012). Learning active facial patches for expression recognition. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2567-2574.
- Zhu, X., & Ramanan, D. (2016). 3D face model fitting for facial expression recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 38(7), 1456-1468.