

A Comprehensive Review of AI-Based Real-Time Facial Expression Recognition

Muskan¹ and Dr. Poonam²

¹Research Scholar, Geeta University Panipat, India

²Associate Professor, CSE, Geeta University Panipat, India

¹muskanvats40@gmail.com, ²poonam.1520jp@gmail.com

Abstract

Facial Expression Recognition (FER) plays a crucial role in human-computer interaction, with applications spanning healthcare, security, entertainment, and education. The growing interest in real-time FER stems from its ability to create systems capable of interpreting human emotions instantly, facilitating more responsive and adaptive technologies. This paper provides a comprehensive examination of the latest advancements in real-time FER, particularly focusing on artificial intelligence (AI) techniques. The machine learning methods and modern deep learning architectures, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and hybrid models. Additionally, the challenges inherent in real-time FER, including computational complexity, occlusions, lighting variations, and cross-subject variability. The key aspects such as dataset evaluation, preprocessing methods, and deployment on edge devices are discussed, highlighting the importance of optimizing FER systems for real-world applications. It also investigates emerging trends such as transfer learning, attention mechanisms, and the integration of multimodal emotion recognition, which offer promising directions for improving FER performance. The study provides valuable insights for future developments aimed at building efficient, accurate, and robust real-time FER systems. Ultimately, it emphasizes the transformative potential of AI-driven FER in creating more intuitive and emotionally aware computing systems, while stressing the need for continued progress in overcoming challenges related to real-time processing, generalization, and ethical concerns.

Keywords: Real-time, Facial Expression Recognition, Artificial Intelligence, Emotion Recognition, Feature Extraction

1. Introduction

Facial expressions serve as one of the most powerful, natural, and universal modes of human communication. They effectively convey emotions, intentions, and reactions without the use of spoken language, playing a crucial role in everyday interpersonal interactions [1]. The accurate recognition and interpretation of facial expressions are essential across a wide range of applications, including human-computer interaction (HCI), psychological diagnostics, driver monitoring systems, virtual assistants, and security surveillance systems [2]. With the rapid advancement of artificial intelligence (AI)—particularly in machine learning (ML) and deep learning (DL)—significant strides have been made toward automating facial expression recognition (FER), especially in real-time environments [3]. However, real-time facial expression recognition (RT-FER) remains a challenging task due to factors such as dynamic facial variations, lighting inconsistencies, occlusions, aging effects, and the demand for low-latency processing. Facial expressions are key indicators of an individual's emotional state, making FER an essential tool in emotionally intelligent systems, healthcare monitoring, robotics, and human-computer interaction [4–6]. Despite the remarkable progress enabled by modern technology, achieving high accuracy in FER continues to be a complex and resource-intensive endeavor [7]. Commonly recognized emotional states include anger, joy, sorrow, fear, and surprise, with some studies also identifying hatred as a relevant emotional category [8]. Various obstacles—such as facial occlusions (e.g., hands, sunglasses), age-related changes, or pose variations—can significantly impact the accuracy and robustness of FER systems [9]. The FER process typically involves three main stages. The first stage focuses on detecting the face and extracting primary facial features, such as the eyes, eyebrows, nose, mouth, and chin, from static images or video frames [10]. The second stage refines this process by isolating more detailed characteristics from specific facial regions, enhancing the descriptive quality of the features. Finally, in the third stage, a classifier is trained using labeled data to identify and assign emotions to the extracted features. This pipeline has proven valuable in domains such as intelligent robotics, telemedicine, Internet of Things (IoT), fatigue detection, and forensic psychology.

The field of FER has attracted substantial academic attention, especially in the context of computer vision [11-12]. As people increasingly share their lives through digital images and videos, the demand for user-centric, emotion-aware systems has grown. The evolution of FER began with traditional image processing methods, which relied on handcrafted features and statistical classifiers. These early techniques were often constrained by their dependence on the quality of the input data and the manual effort required for feature design [13]. The emergence of machine learning marked a transformative shift, enabling the development of data-driven models that could learn patterns directly from examples. The subsequent adoption of deep learning—particularly convolutional neural networks (CNNs)—revolutionized FER by enabling automatic extraction of hierarchical features, greatly improving accuracy and scalability [14]. Recurrent neural networks (RNNs), including Long Short-Term Memory (LSTM) networks, further enhanced FER systems by enabling the modeling of temporal dynamics in facial expressions—an essential component for understanding evolving emotional states. Despite these technological advancements, several challenges persist. Variability in facial expressions across individuals, cultures, and environmental conditions remains a critical issue [15]. Real-time performance requirements further complicate model deployment, particularly in scenarios demanding immediate emotional response. Moreover, the ethical implications of FER cannot be ignored. Issues related to privacy, consent, data security, and algorithmic bias raise important questions about responsible development and deployment of such systems [16]. This review aims to provide a comprehensive overview of the current state-of-the-art in real-time facial expression recognition using AI-based techniques.

2. Literature Review

Bode et.al (2026) [17] ensured that assessments of candidates are fair, consistent and equitable as virtual interviews and assessments are increasingly used. In this context, we propose a real-time face emotion detection software solution that uses computer vision and deep learning techniques to generate a measurement of candidate confidence in AI-conducted interviews. The Confidence Estimation Module relates this emotional data to different parts of an interview and gives useful behavioral insights. Face detection is done using OpenCV's Haar Cascade and a Convolutional Neural Network (CNN) is trained on FER-2013 dataset to recognize five different facial expressions (Happy, Neutral, Sad, Angry and Surprise). The system is running in real-time during trials, showing latency between 60 and 80 milliseconds and a satisfactory correlation coefficient value (0.71) between the confidence metrics of the system and confidence values supplied by the user. As such this methodology is a helpful method to improve overall fairness in virtual evaluations while maintaining human oversight and ethical behaviors.

Dey, K et.al [18] recognized human various facial emotions at any time from different resources like static photographs or a sequence of images is become a tough issue during the previous two decades in computer vision-based human computer interaction process. The human facial emotion requires higher-level expertise. Facial expression can be expressed in numerous ways of social behavior through unimodal, bio modal or multi modal. In recent utilization of Deep Learning (DL) and the results attained in their trials are highly encouraging. Though from last few years several researches have been given effectively using several conventional methodologies. In this literature review, we present a brief overview of the conventional methods in Facial Emotion Recognition (FER), its applications, and the rapid progress of deep learning techniques in FER to obtain superior performance on publically available heterogeneous datasets. In this paper we describe the usual pipelining of a deep FER system, with background information and recommendations for potential implementations at each phase. The deep FER has been introduced by new deep neural networks and associated training strategies for FER employing both static and dynamic image sequences and the merits and cons of each have been discussed.

Haq et al. (2024) [19] studied the recognition and categorization of seven universal emotional states—surprise, disgust, fear, happiness, neutrality, anger, and contempt—are explored in the context of facial expression recognition (FER). The emphasize the significance of convolutional neural networks (CNNs) in extracting and classifying facial expressions, as CNNs are particularly effective at learning features compared to previous methods. As a result, CNNs have become central to research in human-computer interaction. While existing FER algorithms perform well in controlled lab environments, their performance suffers in real-world, uncontrolled settings, which often feature challenges such as poor image quality, occlusions, fluctuating lighting, and changes in head posture. The deep learning approaches to improve FER accuracy in real-time applications, specifically under challenging conditions such as low-

resolution images and uncontrolled datasets. It evaluates the effectiveness of deep learning-based methods for emotion detection, demonstrating their ability to accurately identify emotions in both laboratory and real-world environments.

Dukić and Sovic Krzic (2022) [20] discussed the potential of facial expressions as indicators of students' emotional responses to teaching strategies in the classroom. The Facial Expression Recognition (FER) to automate the analysis of emotions during lectures, offering teachers insights into how students feel about specific teaching activities. The real-time emotion prediction of students engaged in various tasks with an educational robot, using models like ResNet-34 and Inception-v3. The analysis reveals that, in most activities, female students exhibited more visible emotions, while enjoyment was largely gender-neutral. The FER in providing educators with valuable feedback to enhance their instructional methods.

Yang et al. (2021) [21] addressed the challenge of real-time facial expression recognition in distributed environments, particularly due to the high network overhead required for transmitting facial action unit features. To mitigate this, the authors propose the use of a lightweight distributed system based on edge computing, specifically utilizing Raspberry Pi. By separating front-end and back-end processing locally, the system reduces latency and ensures high reliability. The solution is particularly suited for Internet of Things (IoT) and smart city applications, where large-scale, low-latency connection services are essential.

Chetan (2020) [22] studied real-time facial expression detection system using machine learning. The system employs the AdaBoost algorithm and Haar cascade classifier to identify faces, and deep learning techniques, particularly (CNNs), to recognize emotions. The model processes 15 frames per second and classifies various emotions based on facial features extracted in real time. The approach is designed to enable robots to interact more dynamically with humans, using the data to tailor responses according to detected emotional states, and fostering innovative applications in human-robot interaction.

Sang and Van Dat (2017) [23] proposed a deep learning approach to facial expression recognition that eliminates the need for manually designed feature descriptors. By applying Convolutional Neural Networks (CNNs), their method automatically interprets semantic information from facial expressions. Their results, tested on the FER-2013 dataset, demonstrate the effectiveness of their proposed networks, which outperform state-of-the-art methods. Additionally, their model offers improved performance speed, making it well-suited for real-time systems.

Halder et al. (2016) [24] focused on the integration of multiple channels—such as facial expressions, speech, and body language—in emotion recognition systems. The prototype system that uses a neural network-based solution combined with image processing techniques to classify universal emotions (happiness, sadness, anger, disgust, surprise, and fear). The system detects faces, extracts key feature points from the images, and inputs them into a neural network for emotion classification. It approached contributes to more accurate emotion recognition from facial expressions.

Deshmukh et al. (2016) [25] examined the challenges of real-time facial expression recognition, particularly in the context of varying factors like occlusions, pose, illumination, and low resolution. The advancements in algorithms and techniques used to address these challenges, noting the trade-offs between efficiency and accuracy in real-time systems. It improved strategies to overcome these obstacles without compromising performance, emphasizing the importance of developing more effective solutions for real-time FER applications.

Table 1: Comparison of Reviews

Author & Year	Focus	Findings
Bode et al. (2026)	Proposed a real-time facial emotion recognition system for AI-based virtual interviews using OpenCV Haar Cascade and CNN trained on the FER-2013 dataset to estimate candidate confidence.	Achieved real-time performance with 60–80 ms latency and a confidence correlation coefficient of 0.71. The framework improved fairness and behavioral assessment in virtual interviews while emphasizing ethical AI and human oversight.
K. Dey et al. (2025)	Comprehensive review of conventional and deep learning-based facial emotion recognition methods, including preprocessing, feature	Reported that deep learning approaches significantly outperform traditional methods for FER. Reviewed CNN-based and dynamic sequence models, discussed benchmark datasets, identified existing challenges, and highlighted future research directions for robust FER systems.

	extraction, expression classification, and benchmark datasets.	
Haq et al. (2024)	CNN-based FER in real-world settings	CNNs outperform traditional methods in FER. Accuracy drops in real-world data due to occlusions, lighting, and pose variations. Deep learning models improved real-time recognition on low-resolution images. Validated via comparison and subjective user evaluations.
Dukić & Sović Krzić (2022)	FER in active teaching environments	Applied FER in a robotics workshop setting. Inception-v3 and ResNet-34 were most effective. Found that emotion expression varied by activity type and gender. Happiness was the most common emotion. Programming evoked the most facial expressions.
Yang et al. (2021)	Real-time FER on edge devices	Developed a lightweight FER system using Raspberry Pi in a distributed edge computing setup. Reduced network overhead and latency, enhancing deployment in IoT and smart city scenarios.
Chetan (2020)	Real-time FER using Haar cascades and CNNs	Combined traditional image processing (Haar + AdaBoost) with CNN for real-time emotion recognition. Achieved 15 FPS and could classify multiple faces simultaneously. Trained on FER2013 dataset.
Sang & Van Dat (2017)	Improved CNNs for facial expression recognition	Proposed efficient CNNs with fewer parameters and improved training techniques. Outperformed the FER2013 competition winner model. Suitable for real-time use due to increased speed and accuracy.
Halder et al. (2016)	Emotion recognition using neural networks and feature point extraction	Used image processing for facial feature extraction and neural networks for classification. Successfully recognized six basic emotions using colored frontal images.
Deshmukh et al. (2016)	Review of real-time FER challenges and solutions	Highlighted common FER challenges like occlusion, pose, illumination, etc. Emphasized the trade-off between accuracy and efficiency in real-time FER systems. Suggested the need for new strategies to address these without compromising performance.

3. Facial Expression Recognition (FER) Architecture

The specific area focuses on systems that classify fundamental human emotions using modern artificial intelligence algorithms, particularly neural networks and the Facial Action Coding System (FACS) [26]. The general architecture of facial emotion recognition (FER) comprises three main phases: preprocessing, feature extraction, and classification [27].

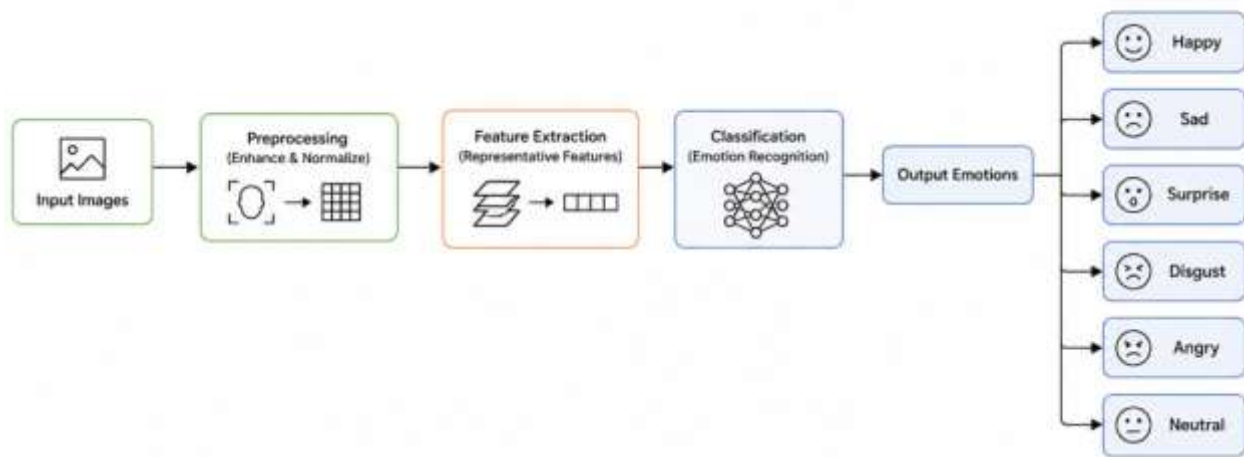


Figure 1: Three phases of the Facial Expression Recognition (FER) Architecture.

➤ **Preprocessing:** Preprocessing is a critical step in deep learning applications, especially in image and signal processing, to enhance system performance. This stage includes steps such as facial alignment, grayscale conversion, 2D adaptive noise filtering, image sharpening using unsharp masking, and data augmentation [28]. The goal is to enhance input image quality and reduce redundancy [29–30]. Initially, an RGB image of size $m \times n$ is read and converted to grayscale using a standard formula [31]. The facial region is detected using the Haar Cascade classifier from Open CV [32–34], then cropped and resized to a standard scale. Images are normalized to a 64×64 grayscale format to match the input requirements of neural networks, helping to avoid over fitting due to excessive input density [35]. In real-world scenarios, image data can be collected under varying conditions — including different angles, lighting, and facial poses. Therefore, preprocessing techniques such as normalization, cropping, and centralization are crucial to enhance facial recognition accuracy during experimentation [36].

➤ **Feature Extraction:** The focuses on identifying and extracting key facial features from images or videos [37]. The current research prioritizes extracting discriminative features capable of distinguishing the six basic emotions: anger, disgust, fear, sadness, happiness, and surprise [38]. Feature extraction reduces the data dimensionality while preserving critical information, thus optimizing computational resources [39]. During this process, the preprocessed data is transformed to highlight the most representative features [40]. These features form the basis for accurate classification. Traditional facial feature extraction techniques fall into two main categories:

Geometric-based methods, such as Active Appearance Models (AAM), rely on facial geometry including landmarks, angles, and distances. Appearance-based methods, such as Gabor wavelet representations and Local Binary Patterns (LBP), analyze texture patterns across the entire image [41–43]. Deep feature extractors are often used to identify high-level image characteristics. These extracted features are then used to train conventional classifiers like Support Vector Machines (SVM), Linear Discriminant Analysis (LDA), and K-Nearest Neighbors (K-NN) [44]. Complex descriptors can further represent facial form and texture variations. For instance, Supervised Descent Method (SDM) points track changes in facial shape, while texture descriptors like Local Directional Ternary Pattern (LDTP), Histogram of Oriented Gradients (HOG), Spatio-Temporal Texture Map (STTM), and LBP highlight variations in facial texture. These features play a vital role in identifying and classifying facial expressions [45].

➤ **Classification:** The final phase in the FER pipeline is classification, where the system maps extracted features to specific emotional labels. During this stage, various algorithms are trained on the extracted features to recognize facial expressions. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Deep Neural Networks (DNNs), have proven highly effective in image classification tasks [46–47]. An end-to-end deep learning model is often employed, capable of learning hierarchical features directly from raw data without relying on handcrafted inputs [48]. These learned features or "activations" can also be used with traditional classifiers [49–50]. Among conventional classifiers, SVM, K-NN, and LDA are widely adopted for their classification accuracy [51]. The overall performance of the classifier is largely dependent on the quality of the features extracted [52]. Each classification algorithm has unique strengths: for instance, SVM can utilize kernel functions to map features into higher-dimensional spaces, making it effective for complex classification tasks such as facial emotion recognition. LDA, in contrast, seeks optimal projection directions for

separating multiple classes. The combination of effective feature extraction methods and robust classifiers can significantly enhance emotion recognition accuracy.

4. Discussion

Facial expression recognition (FER) plays a crucial role in human-computer interaction, emotional intelligence applications, and various security systems. With the advancements in artificial intelligence (AI), especially deep learning techniques, real-time facial expression recognition has achieved significant progress in recent years. However, despite these advancements, challenges remain in optimizing these models for real-time applications.

- The primary AI techniques employed in real-time facial expression recognition are deep learning-based models, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer-based architectures. CNNs have proven to be particularly effective in feature extraction from facial images, as they can automatically learn hierarchical representations.
- Despite advancements, several challenges persist in real-time FER. One of the primary challenges is the trade-off between accuracy and processing speed. Real-time systems require a delicate balance where facial expression models must make accurate predictions while maintaining low latency. This is particularly difficult in resource-constrained environments, such as mobile devices or embedded systems.
- The potential applications of real-time FER are vast and varied, spanning from healthcare (e.g., detecting emotional states in patients with neurological disorders) to interactive gaming, smart assistants, and security systems. For instance, real-time FER can enhance user experience in customer service by enabling adaptive responses based on emotional states. However, the deployment of these systems in the real world necessitates addressing issues like privacy concerns, data security, and ethical implications, particularly when it comes to sensitive emotional data.
- To improve the robustness and accuracy of real-time FER systems, future research should focus on several key areas. First, developing lightweight models that maintain high accuracy while being computationally efficient is critical for real-time applications.

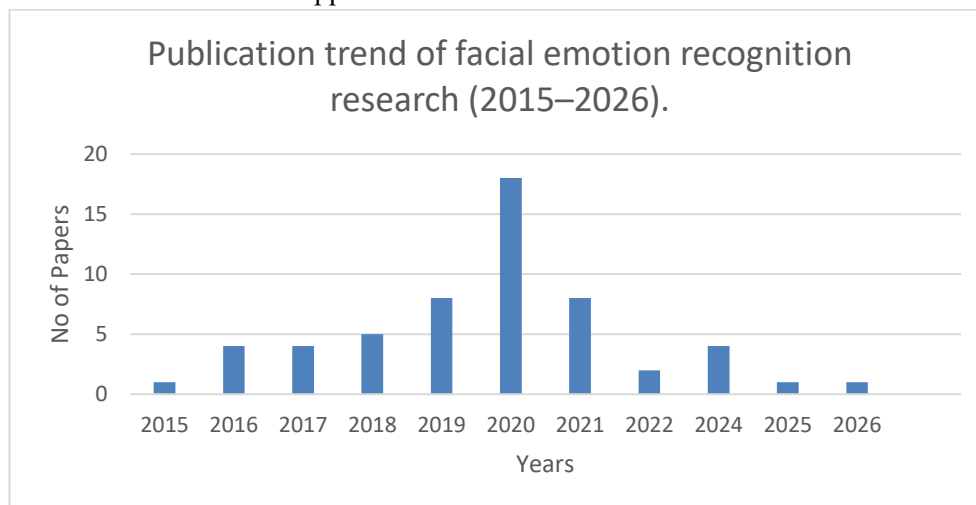


Figure 2: Publication trend of facial emotion recognition research (2015–2026).

In Figure 2 illustrates the publication trend in review paper of taken facial emotion recognition (FER) research from 2015 to 2026. A significant increase in publications can be observed after 2018, with the highest research activity occurring during 2020. This growth reflects the rapid adoption of deep learning techniques, especially Convolutional Neural Networks (CNNs), attention mechanisms, and transfer learning for robust emotion recognition. Recent studies further emphasize real-time FER, explainable AI, and ethical considerations.

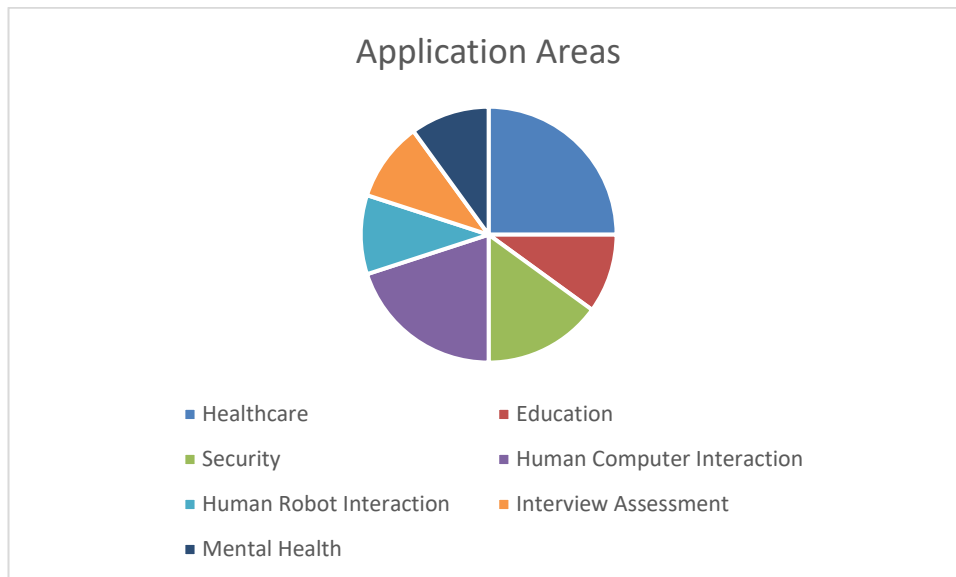


Figure 3: Major application domains of facial emotion recognition.

In Figure 3 summarizes the major application domains of facial emotion recognition identified in the reviewed literature. Healthcare and human-computer interaction represents the most extensively explored application areas. Emerging domains such as AI-driven interviews, mental health monitoring, and intelligent educational systems have also gained increasing research attention due to advancements in deep learning and computer vision technologies.

Conclusion

Facial Expression Recognition (FER) has emerged as a vital component in bridging the gap between human emotions and machine understanding, driven by the rapid progress in artificial intelligence, particularly in machine learning and deep learning. Through a structured pipeline comprising preprocessing, feature extraction, and classification, modern FER systems are increasingly capable of recognizing and interpreting facial expressions in real-time, enabling their application across diverse domains such as healthcare, driver monitoring, virtual assistants, and security. Advanced neural network models like CNNs and RNNs have greatly enhanced the ability to extract meaningful patterns from facial data, even under challenging conditions involving occlusions, lighting variations, and pose changes. However, despite these advancements, the field still faces significant hurdles related to data diversity, model generalizability, computational efficiency, and ethical considerations surrounding privacy and bias. Addressing these issues through inclusive dataset development, lightweight model architectures, and ethical safeguards will be crucial for the continued evolution and responsible deployment of FER technologies. As research continues to refine both the accuracy and accessibility of FER systems, their potential to create emotionally intelligent machines capable of empathetic interaction with humans becomes increasingly attainable.

Reference

1. Hwang, H. C., & Matsumoto, D. (2016). Facial expressions.
2. Esposito, A., Esposito, A. M., & Vogel, C. (2015). Needs and challenges in human computer interaction for processing social emotional information. *Pattern Recognition Letters*, 66, 41- 51.
3. Dalvi, C., Rathod, M., Patil, S., Gite, S., & Kotecha, K. (2021). A survey of ai-based facial emotion recognition: Features, ml & dl techniques, age-wise datasets and future directions. *Ieee Access*, 9, 165806-165840.
4. Kumari, A., Tanwar, S., Tyagi, S., & Kumar, N. (2018). Fog computing for Healthcare 4.0 environment: Opportunities and challenges. *Computers & Electrical Engineering*, 72, 1-13.
5. Hathaliya, J., Sharma, P., Tanwar, S., & Gupta, R. (2019, December). Blockchain-based remote patient monitoring in healthcare 4.0. In *2019 IEEE 9th international conference on advanced computing (IACC)* (pp. 87-91). IEEE.
6. Vora, J., DevMurari, P., Tanwar, S., Tyagi, S., Kumar, N., & Obaidat, M. S. (2018, July). Blind signatures based secured e-healthcare system. In *2018 International conference on computer, information and telecommunication systems (CITS)* (pp. 1-5). IEEE.

7. Zhang, L., Verma, B., Tjondronegoro, D., & Chandran, V. (2018). Facial expression analysis under partial occlusion: A survey. *ACM Computing Surveys (CSUR)*, 51(2), 1-49.
8. Uma Maheswari, V., Aluvalu, R., & Chennam, K. K. (2021). Application of machine learning algorithms for facial expression analysis. *Mach. Learn. Sustain. Dev*, 9, 77.
9. Swapna, M., Viswanadhula, U. M., Aluvalu, R., Vardharajan, V., & Kotecha, K. (2022). Bio- signals in medical applications and challenges using artificial intelligence. *Journal of Sensor and Actuator Networks*, 11(1), 17.
10. Spezialetti, M., Placidi, G., & Rossi, S. (2020). Emotion recognition for human-robot interaction: Recent advances and future perspectives. *Frontiers in Robotics and AI*, 7, 532279.
11. Ramis, S., Buades, J. M., & Perales, F. J. (2020). Using a social robot to evaluate facial expressions in the wild. *Sensors*, 20(23), 6716.
12. Bhatti, Y. K., Jamil, A., Nida, N., Yousaf, M. H., Viriri, S., & Velastin, S. A. (2021). Facial expression recognition of instructor using deep features and extreme learning machine. *Computational Intelligence and Neuroscience*, 2021(1), 5570870.
13. Kopalidis, T., Solachidis, V., Vretos, N., & Daras, P. (2024). Advances in facial expression recognition: A survey of methods, benchmarks, models, and datasets. *Information*, 15(3), 135.
14. Liu, Y., Pu, H., & Sun, D. W. (2021). Efficient extraction of deep image features using convolutional neural network (CNN) for applications in detecting and analysing complex food matrices. *Trends in Food Science & Technology*, 113, 193-204.
15. Zhang, L., Verma, B., Tjondronegoro, D., & Chandran, V. (2018). Facial expression analysis under partial occlusion: A survey. *ACM Computing Surveys (CSUR)*, 51(2), 1-49.
16. Katirai, A. (2024). Ethical considerations in emotion recognition technologies: a review of the literature. *AI and Ethics*, 4(4), 927-948.
17. Bode, A., Ambule, A., Khandale, G., Malekar, N., & Dange, B. (2026). Facial Human Analysis for AI-Driven Interviews.
18. Dey, K., Roy, S., Jana, B., & Dhar, P. (2025). Recent advancements in facial emotion recognition using conventional and deep neural network: a comprehensive review. *Smart Science*, 13(4), 431-444.
19. Haq, H. B. U., Akram, W., Irshad, M. N., Kosar, A., & Abid, M. (2024). Enhanced real-time facial expression recognition using deep learning. *Acadlore Transactions on AI and Machine Learning*, 3(1), 24-35.
20. Dukić, D., & Sovic Krzic, A. (2022). Real-time facial expression recognition using deep learning with application in the active classroom environment. *Electronics*, 11(8), 1240.
21. Yang, J., Qian, T., Zhang, F., & Khan, S. U. (2021). Real-time facial expression recognition based on edge computing. *IEEE Access*, 9, 76178-76190.
22. Chetan, H. (2020, December). Performance dependency of facial emotion recognition system on dropout and learning rate. In *2020 3rd International Conference on Intelligent Sustainable Systems (ICISS)* (pp. 71-81). IEEE.
23. Sang, D. V., & Van Dat, N. (2017, October). Facial expression recognition using deep convolutional neural networks. In *2017 9th International Conference on Knowledge and Systems Engineering (KSE)* (pp. 130-135). IEEE.
24. Halder, Rituparna & Sengupta, Sushmit & Pal, Arnab & Ghosh, Sudipta & Kundu, Debashish. (2016). Real Time Facial Emotion Recognition based on Image Processing and Machine Learning. *International Journal of Computer Applications*. 139. 16-19. 10.5120/ijca2016908707.
25. Deshmukh, S. P., Patwardhan, M. S., & Mahajan, A. (2016). Survey on real-time facial expression recognition techniques. *IET Biometrics*, 5(3), 155–163. <https://doi.org/10.1049/IET-BMT.2014.0104>
26. Babajee, P., Suddul, G., Armoogum, S. and Foogooa, R. (2020). Identifying Human Emotions from Facial Expressions with Deep Learning. *2020 Zooming Innovation in Consumer Technologies Conference (ZINC)*, 36- 39
27. Chen, J., Lv, Y., Xu, R. and Xu, C. (2019). Automatic social signal analysis: Facial expression recognition using difference convolution neural network. *Journal of Parallel and Distributed Computing*, 131, 97-102

28. Ozcan, T. and Basturk, A. (2020). Static facial expression recognition using convolutional neural networks based on transfer learning and hyperparameter optimization. *Multimedia Tools and Applications*, 79, 26587-26604
29. Ekundayo, O. and Viriri, S. (2019). Facial expression recognition: a review of methods, performances and limitations. *2019 Conference on Information Communications Technology and Society (ICTAS)*, 1-6
30. Ganapathy, N., Veeranki, Y. R. and Swaminathan, R. (2020). Convolutional Neural Network based Emotion Classification using Electrodermal Activity Signals and Time-Frequency Features. *Expert Systems with Applications*, 113571
31. Kaviya, P. and Arumugaprakash, T. (2020). Group Facial Emotion Analysis System Using Convolutional Neural Network. *2020 4th International Conference on Trends in Electronics and Informatics (ICOEI)*, 643-647
32. Mohan, K., Seal, A., Krejcar, O. and Yazidi, A. (2020). Facial Expression Recognition using Local Gravitational Force Descriptor based Deep Convolution Neural Networks. *IEEE Transactions on Instrumentation and Measurement*, 70, 1-12
33. Sulaiman, D. M., Abdulazeez, A. M., Haron, H. and Sadiq, S. S. (2019). Unsupervised Learning Approach-Based New Optimization K-Means Clustering for Finger Vein Image Localization. *2019 International Conference on Advanced Science and Engineering (ICOASE)*, 82-87
34. Othman, G. and Zeebaree, D. Q. (2020). The Applications of Discrete Wavelet Transform in Image Processing: A Review. *Journal of Soft Computing and Data Mining*, 1, 31-43
35. Ozdemir, M. A., Elagoz, B., Alaybeyoglu, A., Sadighzadeh, R. and Akan, A. (2019). Real Time Emotion Recognition from Facial Expressions Using CNN Architecture. *Medical Technologies Congress (TIPTEKNO)*, 1- 4
36. Bargshady, G., Zhou, X., Deo, R. C., Soar, J., Whittaker, F. and Wang, H. (2020). Enhanced deep learning algorithm development to detect pain intensity from facial expression images. *Expert Systems with Applications*, 149, 113305
37. Lee, J. R. H. and Wong, A. (2020). TimeConvNets: A Deep Time Windowed Convolution Neural Network Design for Real-time Video Facial Expression Recognition. *17th Conference on Computer and Robot Vision (CRV)*, 9-16
38. Xue, M., Mian, A., Duan, X. and Liu, W. Learning Interpretable Expression-sensitive Features for 3D Dynamic Facial Expression Recognition. *2019 14th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2019)*, 1-7
39. Zebari, R., Abdulazeez, A., Zeebaree, D., Zebari, D. and Saeed, J. (2020). A Comprehensive Review of Dimensionality Reduction Techniques for Feature Selection and Feature Extraction. *Journal of Applied Science and Technology Trends*, 1. 1, 56-70
40. Le, T. T. Q., Tran, T.-K. and Rege, M. (2020). Dynamic image for micro-expression recognition on region-based framework. *2020 IEEE 21st International Conference on Information Reuse and Integration for Data Science (IRI)*, 75-81 Abdullah et al., *Journal of Soft Computing and Data Mining* Vol. 2 No. 1 (2021) pp. 54-65 64
41. Li, J., Jin, Zhou, K., Kubota, N. and Ju, Z. (2020). Attention Mechanism-based CNN for Facial Expression Recognition. *Neurocomputing*, 411, 340-350
42. Chincharikar, N. A. (2019). Facial Expression Recognition Using Deep Learning: A Review. *International Research Journal of Engineering and Technology (IRJET)*, 6, 3274-3281
43. Hussein, E. S., Qidwai, U. and Al-Meer, M. Emotional Stability Detection Using Convolutional Neural Networks, *2020 IEEE International Conference on Informatics, IoT, and Enabling Technologies (ICIoT)*, 136-140
44. Fei, Z., Yang, E., Li, D. D.-U., Butler, S., Ijomah, W., Li, X., et al. (2020). Deep convolution network based emotion analysis towards mental health care. *Neurocomputing*, 388, 212-227, 2020
45. Baddar, W. J., Lee, S. and Ro, Y. M. (2019). On-the-Fly Facial Expression Prediction using LSTM Encoded Appearance-Suppressed Dynamics. *IEEE Transactions on Affective Computing*, doi: 10.1109/TAFFC.2019.2957465

46. Najat, N. and Abdulazeez, A. M. (2017). Gene clustering with partition around mediods algorithm based on weighted and normalized Mahalanobis distance. 2017 International Conference on Intelligent Informatics and Biomedical Sciences (ICIIBMS), 140-145
47. Lopes, A. T., de Aguiar, E., De Souza, A. F. and Oliveira-Santos, T. (2017). Facial expression recognition with convolutional neural networks: coping with few data and the training sample order. Pattern Recognition, 61, 610- 628
48. Zeebaree, D. Q., Abdulazeez, A. M., Hassan, O. M. S., Zebari, D. A. and Saeed, J. N. (2020). Hiding Image by Using Contourlet Transform, The Mattingley Publishing Co., Inc 83, 16979 – 16990
49. Sulaiman, M. A. (2020). Evaluating Data Mining Classification Methods Performance in Internet of Things Applications. Journal of Soft Computing and Data Mining, 1, 11-25
50. Zeebaree, D. Q., Haron, H. and Abdulazeez, A. M. (2018). Gene selection and classification of microarray data using convolutional neural network. 2018 International Conference on Advanced Science and Engineering (ICOASE), 145-150
51. Zebari, D. A., Zeebaree, D. Q., Abdulazeez, A. M., Haron, H. and Hamed, H. N. A. (2020). Improved Threshold Based and Trainable Fully Automated Segmentation for Breast Cancer Boundary and Pectoral Muscle in Mammogram Images. IEEE Access, 8, 203097-203116
52. Deng, L., Wang, Q. and Yuan, D. (2019). Dynamic Facial Expression Recognition Based on Deep Learning. 2019 14th International Conference on Computer Science & Education (ICCSE), 32-37