International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online) Volume 14, Issue 7, July 2025)

Humans Facial Express Emotions Recognition using AI Techniques: A Review

[1]Sarthak Gupta, [2]Devendra Singh Rathore

[1]M.Tech Scholar, Department of CSE, LNCT, Bhopal, India
[2]Assistant Professor, Department of CSE, LNCT, Bhopal, India

Abstract— **Facial expressions are among the most direct and natural ways through which humans convey emotions. With the evolution of Artificial Intelligence (AI), recognizing these expressions has become a key research focus in emotion-aware computing. This review explores the spectrum of AI-based methods applied to the recognition of human facial emotions. From early machine learning approaches to contemporary deep learning frameworks, the paper highlights the technical progress, underlying models, and real-world applications. The findings suggest that AI holds vast potential to interpret emotional states from facial cues with increasing precision, benefiting areas like interactive systems, psychological assessment, and smart surveillance.**

Keywords—Recognition, Machine, Deep, AI, Facial expression.

I. INTRODUCTION

Facial expression is one of the most prominent and immediate forms of emotional communication in human interactions. The ability to understand and respond to facial cues is fundamental in social contexts and plays a critical role in shaping relationships, decision-making, and behavioral responses [1]. Over the years, Artificial Intelligence (AI) has shown great potential in replicating this human ability, allowing machines to detect, analyze, and classify emotional states from facial expressions. Facial Emotion Recognition (FER) using AI techniques is now an active and rapidly growing field of research, combining elements of computer vision, machine learning, and psychological science [2]. With the help of advanced algorithms and powerful computational models, it is now possible to process facial images and extract emotional information in real time. These advancements are being applied in diverse sectors such as intelligent surveillance, education, virtual reality, mental health diagnostics, and human-computer interaction. This review aims to comprehensively examine the various AI-driven techniques used for facial emotion recognition, assess their effectiveness, explore datasets and evaluation methods, and highlight future opportunities and unresolved challenges in this domain[3].

Facial expressions are a universal language of emotion, transcending linguistic and cultural barriers. A smile, a frown, or a raised eyebrow can speak volumes without a single word being uttered. For centuries, psychologists and social scientists have explored how human emotions are conveyed through the face. Today, this interest has extended into the digital world, where Artificial Intelligence (AI) is being trained to understand and interpret the subtleties of human emotions by analyzing facial expressions[4]. This capability, known as Facial Emotion Recognition (FER), is revolutionizing how machines interact with people[5]. AI-powered emotion recognition is not just about reading a happy or sad face—it involves learning complex facial patterns, interpreting micro-expressions, and understanding the emotional context behind facial movements. With the growth of deep learning, particularly neural network architectures like CNNs and RNNs, FER systems have become more intelligent, adaptive, and accurate. These technologies are now being integrated into daily life—from enhancing user experience in smart devices to monitoring mental well-being, and even aiding law enforcement in behavior analysis[6]. As we move further into an age where human and machine collaboration is becoming increasingly seamless, the ability of machines to understand our emotions could reshape the way we live, learn, and connect. This review delves into the AI techniques powering facial emotion recognition, highlighting the state-of-the-art approaches, current applications, limitations, and the path forward[7].

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online) Volume 14, Issue 7, July 2025)

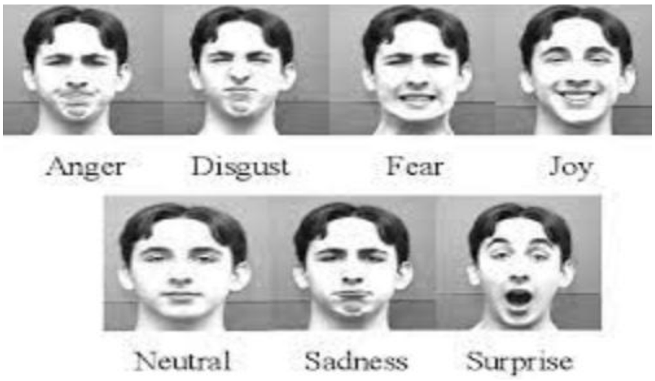

Figure 1: Facial Expression Recognition

Emotion recognition from facial expressions has become a central research theme in the domain of Artificial Intelligence (AI), driven by the need for more intuitive and emotionally aware human-computer interactions. The human face is a rich source of emotional information, capable of conveying subtle feelings through a combination of muscle movements and expressions[8]. The development of systems that can automatically detect and interpret these expressions has seen significant progress with the integration of AI techniques, particularly in the areas of computer vision and deep learning. The objective of Facial Emotion Recognition (FER) is to simulate the human cognitive ability to understand emotional expressions, enabling machines to function more effectively in emotionally sensitive environments. The evolution of FER techniques—from early rule-based and statistical approaches to sophisticated deep learning models—has led to improved accuracy and real-world applicability[9]. Convolutional Neural Networks (CNNs), for instance, have become the standard for spatial feature extraction from facial images, while Recurrent Neural Networks (RNNs) and attention-based mechanisms have been utilized for modeling temporal dynamics in video-based emotion recognition. Despite these advances, challenges such as inter-person variability, occlusions, illumination changes, and the recognition of spontaneous emotions remain open problems. This review aims to consolidate the progress made in AI-driven facial emotion recognition, critically evaluate various algorithms and frameworks, explore publicly available datasets, and identify future research directions that can address current limitations and improve the robustness and generalization of FER systems[10].

II. LITERATURE SURVEY

Yang et al. (2021) introduced a real-time facial expression recognition model that utilizes edge computing to reduce latency and improve system responsiveness. Their approach processes facial data locally rather than sending it to cloud servers, significantly enhancing speed and privacy. By deploying a hybrid model that combines convolutional neural networks (CNNs) with real-time edge inference, the system achieves high accuracy in emotion recognition without depending heavily on centralized infrastructure. The authors emphasized the importance of reducing bandwidth consumption and computational delay, especially in time-critical applications like surveillance and human-computer interaction. They tested the model on various edge devices and demonstrated robust performance, making it suitable for real-world deployment. This work highlights the growing relevance of edge AI in deploying responsive FER systems. It also addresses energy efficiency and scalability—two major concerns in remote and mobile environments. The paper sets a benchmark for deploying lightweight, real-time FER models in decentralized architectures[1].

Zhang et al. (2022) proposed a federated learning framework using a Graph Ensemble Autoencoder with Gaussian Mixture Modeling (GMM) for emotion recognition across multiple domains. Their method allows emotion models to be trained collaboratively across different environments while preserving user privacy, a key requirement in transportation systems and smart cities. The architecture integrates multidomain graph learning to handle data heterogeneity, thereby improving model generalization across unseen environments. This paper contributes to the field by overcoming the challenges of data privacy and distribution disparity in FER datasets. The use of graph structures also allows the model to understand the inter-relationships among different data sources, enhancing emotion prediction accuracy. The system outperforms several baselines in terms of robustness and flexibility, especially in real-world, federated settings. The work paves the way for scalable, privacy-preserving emotion recognition solutions in distributed environments like autonomous vehicles and smart surveillance networks[2].

In their 2022 study, Hwooi et al. developed a deep learning framework for continuous affect prediction using facial expression images, mapped within the valence-arousal emotional space. Unlike traditional models that categorize emotions into discrete classes, this model captures the subtle gradations of human emotion through continuous labeling. They employed convolutional neural networks (CNNs) and attention mechanisms to extract nuanced facial features and mapped emotional intensity dynamically. The system demonstrates superior performance in real-time emotion tracking applications, making it well-suited for adaptive systems in healthcare, education, and entertainment. Their experimental evaluation showed that the continuous prediction model better reflects the complexity of human emotions than categorical approaches. Furthermore, they emphasized the importance of temporal context and facial dynamics in improving emotion recognition performance. This study broadens the scope of FER research by incorporating affective computing principles for a more holistic understanding of emotions[3].

Galea and Seychell (2022) focused on improving the training of FER models by optimizing dataset configurations, particularly in unconstrained, "in-the-wild" environments. Their research highlighted how variations in lighting, pose, occlusion, and resolution significantly impact the performance of emotion recognition systems. By experimenting with different dataset preprocessing techniques and augmentation strategies, they demonstrated noticeable improvements in model generalization and robustness. Their paper underscores the critical role of data quality and diversity in training effective AI systems for facial emotion recognition. The authors also provided recommendations for designing more balanced and representative datasets that better reflect real-world conditions. This work is particularly valuable for researchers aiming to create scalable, deployable FER systems that function reliably across various environmental and demographic contexts[4].

Priya et al. (2021) explored the application of deep learning techniques in emotion recognition and emphasized the potential of convolutional architectures in capturing complex facial features. Their model employed multiple convolutional and pooling layers to extract hierarchical facial representations, followed by dense layers for classification. The researchers tested their model on standard facial expression datasets and achieved competitive accuracy in recognizing key emotions. They discussed various hyperparameter tuning methods and the importance of dropout and batch normalization in stabilizing training. The paper contributes to the growing body of research validating the effectiveness of deep neural networks in FER tasks. Additionally, the authors highlighted the system's potential use cases in healthcare, security, and human-computer interaction. Their findings support the scalability of deep learning-based FER solutions in real-world applications, particularly those requiring high reliability and real-time inference[5].

Ganesh Babu and colleagues (2021) investigated the integration of classical image processing methods with machine learning algorithms for facial recognition and emotion classification. They explored techniques such as histogram equalization, edge detection, and feature scaling as preprocessing steps before feeding data into classifiers like Support Vector Machines (SVM) and Random Forest. The study demonstrated that preprocessing significantly enhances the feature extraction phase, leading to better emotion classification results. This hybrid approach bridges the gap between traditional image analysis and modern AI algorithms, making it suitable for environments with limited computational resources. The authors emphasized the importance of image clarity and feature enhancement, especially in low-resolution video feeds. Their method serves as a foundation for lightweight FER systems that do not require heavy computational infrastructure but still deliver competitive performance[6].

Li et al. (2021) introduced a novel Disentanglement Learning Generative Adversarial Network (DL-GAN) aimed at improving facial expression recognition. Their approach separates identity-related features from emotion-specific ones to ensure that the model focuses solely on expressions, irrespective of individual facial characteristics. This separation is particularly useful for FER systems that must operate across diverse populations with varying facial structures. The DL-GAN model demonstrated superior accuracy and generalization compared to conventional CNN-based approaches. Moreover, the generative model produced high-quality synthetic facial images, enhancing the training dataset and addressing data imbalance. The study provides a creative solution to the problem of inter-subject variability and opens new avenues for FER research using GAN-based data augmentation and disentangled representation learning[7].

Tiwari et al. (2021) developed a facial expression recognition system using Keras, a high-level neural network API built on top of TensorFlow. Their model leveraged convolutional layers for feature extraction and dense layers for emotion classification across standard datasets like FER2013. By utilizing Keras's modularity and GPU acceleration, the authors rapidly prototyped and tested their architecture, which achieved commendable accuracy in classifying six basic emotions. The study emphasized the accessibility and efficiency of building deep learning-based FER systems using open-source frameworks. It also detailed the preprocessing pipeline including grayscale conversion, normalization, and resizing of facial images. Their implementation showcases how accessible tools can be employed to develop scalable FER solutions suitable for deployment in consumer-grade hardware and educational settings[8].

Fan et al. (2020) proposed a Hybrid Separable Convolutional Inception Residual Network (HSCIRNet) for high-accuracy facial emotion recognition. The architecture integrates elements from the Inception and Residual networks with separable convolutions, aiming to reduce computational complexity while preserving performance. Their approach benefits from deep hierarchical learning and multi-scale feature extraction, which enhances the model's ability to detect fine-grained emotional cues. The network was trained and validated on multiple benchmark datasets, showing improved results compared to several standard deep learning models. This study offers a balanced approach that addresses the trade-off between model complexity and recognition accuracy. The innovative use of separable convolutions significantly reduces memory usage and inference time, making it feasible for real-time applications in embedded systems[9].

In their 2020 research, K. V and C. H analyzed how the performance of facial emotion recognition systems depends on hyperparameters like dropout rate and learning rate. By systematically adjusting these values, they evaluated their impact on convergence speed, overfitting, and model stability. Using a deep learning framework, the authors trained CNN-based architectures across different configurations and datasets to find optimal combinations. Their results demonstrated that even minor changes in learning rate or dropout can drastically influence model accuracy and generalization. This study is particularly useful for developers and researchers seeking to fine-tune their FER systems for maximum performance. It emphasizes that beyond architecture design, proper hyperparameter optimization is equally critical in achieving state-of-the-art results [10].

III. CHALLENGES AND IMPACT

Challenges in Facial Expression Recognition Using AI

Despite significant advancements in artificial intelligence (AI) techniques for facial expression recognition (FER), several challenges remain that impact the performance, accuracy, and real-world applicability of these systems. Some of the key challenges include:

1. **Variability in Facial Expressions** Human facial expressions vary significantly across individuals due to differences in age, gender, ethnicity, and cultural background. Some emotions are expressed differently across cultures, making it difficult for AI models to generalize effectively. A model trained on one demographic may not perform well on another, leading to biased predictions.

2. **Occlusion and Partial Visibility** Facial expressions can be partially obstructed by accessories such as glasses, masks, beards, or hands. In real-world scenarios, occlusions can hinder the ability of AI models to detect emotions accurately. Addressing this challenge requires robust feature extraction techniques and occlusion-invariant models.

3. **Illumination and Pose Variations** Changes in lighting conditions and head positions significantly affect the accuracy of FER systems. Variations in illumination can alter facial features, making it difficult for deep learning models to extract

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online) Volume 14, Issue 7, July 2025)

meaningful patterns. Similarly, different head poses may distort facial expressions, leading to incorrect classification.

4. **Data Imbalance and Bias** Many FER datasets contain imbalanced distributions of facial expressions, with some emotions being overrepresented while others are underrepresented. This bias affects the model's ability to accurately recognize all emotions equally. Moreover, datasets may lack diversity in terms of ethnicity, age, and gender, leading to biased AI models that perform well only on certain populations.

5. **Real-Time Processing and Computational Complexity**
Implementing FER systems in real-time applications, such as human-computer interaction or surveillance, requires fast and efficient processing. However, deep learning models, especially complex architectures like transformers and CNNs, demand high computational resources. Deploying these models on edge devices or low-power systems remains a challenge.

Impact of AI-Based Facial Expression Recognition

Despite the challenges, AI-driven facial expression recognition has had a profound impact on various industries, enhancing applications in multiple domains:

1. **Healthcare and Mental Health Monitoring**
AI-powered FER systems are increasingly used in healthcare to monitor patient emotions, detect early signs of mental health disorders such as depression or anxiety, and provide personalized therapy. Emotion recognition can also aid in detecting neurological disorders such as Parkinson's disease or autism spectrum disorder, improving patient care.

2. **Human-Computer Interaction (HCI) and Virtual Assistants**
AI-driven FER enhances human-computer interaction by enabling machines to understand and respond to human emotions. Virtual assistants, customer service chatbots, and interactive learning platforms leverage FER to adapt responses based on user emotions, creating more engaging and personalized experiences.

3. **Security and Surveillance** Emotion recognition is used in security systems to identify suspicious behaviors in real-time. AI-based FER helps in detecting stress, fear, or nervousness in crowded areas, improving security measures in airports, public spaces, and law enforcement applications.

4. **Marketing and Customer Experience Enhancement**
Businesses leverage FER to analyze customer emotions and preferences, allowing brands to tailor advertisements and marketing strategies based on user responses. AI-powered emotion analysis enables companies to enhance customer experiences by personalizing products and services according to emotional feedback.

5. **Education and E-Learning** In online education, FER helps analyze students' engagement levels and emotional states during virtual classes. AI-based systems can provide real-time feedback to educators, allowing them to modify teaching strategies and improve learning outcomes.

6. **Gaming and Entertainment** The gaming industry incorporates AI-based FER to create more immersive and interactive experiences. Emotion-aware gaming systems adjust gameplay based on players' facial expressions, enhancing user engagement and entertainment value.

IV. CONCLUSION

AI-based facial expression recognition has made remarkable strides, enabling applications across healthcare, human-computer interaction, security, marketing, and education. Despite its potential, challenges such as dataset biases, occlusions, illumination variations, real-time processing limitations, and ethical concerns remain significant hurdles. Addressing these issues requires advancements in model architectures, diverse and unbiased datasets, and the integration of explainable AI for transparency and fairness.

REFERENCES

1. J. Yang, T. Qian, F. Zhang and S. U. Khan, "Real-Time Facial Expression Recognition Based on Edge Computing," in IEEE Access, vol. 9, pp. 76178-76190, 2021, doi: 10.1109/ACCESS.2021.3082641.
2. C. Zhang, M. Li and D. Wu, "Federated Multidomain Learning With Graph Ensemble Autoencoder GMM for Emotion Recognition," in IEEE Transactions on Intelligent Transportation Systems, 2022, doi: 10.1109/TITS.2022.3203800.
3. S. K. W. Hwooi, A. Othmani and A. Q. M. Sabri, "Deep Learning-Based Approach for Continuous Affect Prediction From Facial Expression Images in Valence-Arousal Space," in IEEE Access, vol. 10, pp. 96053-96065, 2022, doi: 10.1109/ACCESS.2022.3205018.
4. N. Galea and D. Seychell, "Facial Expression Recognition in the Wild: Dataset Configurations," 2022 IEEE 5th International Conference on Multimedia Information Processing and Retrieval (MIPR), 2022, pp. 216-219, doi: 10.1109/MIPR54900.2022.00045.
5. R. N. B. Priya, M. Hanmandlu and S. Vasikarla, "Emotion Recognition Using Deep Learning," 2021 IEEE Applied Imagery Pattern Recognition Workshop (AIPR), 2021, pp. 1-5, doi: 10.1109/AIPR52630.2021.9762207.
6. T. R. Ganesh Babu, K. Shenbagadevi, V. S. Shoba, S. Shrinidhi, J. Sabitha and U. Saravanakumar, "Image Processing Methods for Face Recognition using Machine Learning Techniques," 2021 International Conference on Computational Performance Evaluation (ComPE), 2021, pp. 519-523, doi: 10.1109/ComPE53109.2021.9752410.
7. L. Li, H. Yan and M. Li, "Disentanglement Learning Generative Adversarial Network for Facial Expression Recognition," 2021 5th Asian Conference on Artificial Intelligence Technology (ACAIT), 2021, pp. 515-521, doi: 10.1109/ACAIT53529.2021.9731242.
8. T. Tiwari, V. Bharti, Srishti and S. K. Vishwakarma, "Facial Expression Recognition Using Keras in Machine Learning," 2021 3rd International Conference on Advances in Computing, Communication Control and Networking (ICAC3N), 2021, pp. 466-471, doi: 10.1109/ICAC3N53548.2021.9725756.
9. X. Fan, R. Qureshi, A. R. Shahid, J. Cao, L. Yang and H. Yan, "Hybrid Separable Convolutional Inception Residual Network for Human Facial Expression Recognition," 2020 International Conference on Machine Learning and Cybernetics (ICMLC), 2020, pp. 21-26, doi: 10.1109/ICMLC51923.2020.9469558.
10. K. V and C. H, "Performance Dependency of Facial Emotion Recognition System on Dropout and Learning Rate," 2020 3rd International Conference on Intelligent Sustainable Systems (ICISS), 2020, pp. 71-81, doi: 10.1109/ICISS49785.2020.9316077.