EDU REKHA INTERNATIONAL JOURNAL OF ARTS, LAW AND SOCIAL SCIENCE

Journal Homepage: https://edurekhapublisher.com/erijalss/

Volume- 2 Issue – 4 (July-August) 2026

ISSN: 3107-5169 (Online)

Frequency: Bimonthly

PAGES: 164-171

ARTICLE TITLE:

"Deep Learning for Avatar Facial Emotion Recognition in the Metaverse"

Basma Mohamed[1*] & Mahmoud Almashad[2]

[1]Department of Information Systems, Giza Higher Institute for Managerial Sciences, Giza, Egypt

[2]Department of Accounting, Giza Higher Institute for Managerial Sciences, Giza, Egypt

ARTICLE HISTORY

RECEIVED
16-07-2026

ACCEPTED
20-07-2026

PUBLISHED
08-08-2026

Corresponding author:

Basma Mohamed

Department of Information Systems, Giza Higher Institute for Managerial Sciences, Giza, Egypt

Abstract

This paper proposes a deep learning-based method for real-time facial emotion recognition and classification of avatars, which is essential for immersive virtual environments, especially in the metaverse, where avatars are digital representations of users. The proposed system uses convolutional neural networks (CNNs) and transfer learning techniques to analyze avatar facial expressions and detect emotions like happiness, sadness, anger, surprise, fear, and disgust. The model is trained on a combination of real-world and synthetic datasets, which ensures robust performance across a variety of virtual environments. The results show high accuracy in emotion classification, with potential applications in e-commerce, gaming, mental health, education, and e-commerce. The paper offers a foundation for further research in this developing subject and tackles issues including dataset constraints, real-time processing, and ethical implications. By improving user connection and engagement in the metaverse, this effort advances the creation of emotionally intelligent avatars.

Keywords: Metaverse; Convolutional Neural Networks; Avatar Facial Emotion Recognition; Deep Learning

1. Introduction

Deep learning-based avatar facial emotion identification is a state-of-the-art usage of artificial intelligence (AI) that focuses on examining and deciphering the facial emotions of virtual characters. With avatars acting as digital representations of people in the metaverse, virtual reality (VR), augmented reality (AR), and gaming, this technology is very pertinent. The system can precisely identify and categorize emotions including joy, sorrow, rage, surprise, fear, and disgust by utilizing deep learning algorithms. Yang et al. [1] identified each frame in relation to an Avatar reference face model using the recently released SIFT flow technique. A new image-based representation and related reference image, known as the emotion avatar image (EAI) and the avatar reference, respectively, were introduced by Bhanu et al. [2]. The findings of a study conducted on individuals with schizophrenia that assessed facial recognition of emotions using a new set of dynamic virtual people that the research team had previously created were presented by Muros et al. [3].

The ideal interpersonal distance (IPD) between individuals and their affective avatars in facial affect recognition in immersive virtual reality (IVR) was established by Aguila et al. [4]. Using the active appearance model (AAM), k-nearest neighbor (k-NN), and the suggested classification model in mobile contexts, Lee [5] presented a novel multiple emotion detection system using facial expressions that can comprehend a combination of diverse emotions. A unique real-time face feature extraction approach was introduced by Bellenger et al. [6], yielding a tiny feature set that may be used to implement emotion recognition using avatars from online games and the metaverse. By comparing emotion recognition across a VR, video, and photo challenge, examining variables of recognition, and examining visual attention in VR, Geraets et al. [7] investigated a novel VR emotion recognition task. Mumenthaler et al. [8] examined the impact of socioaffective inferential mechanisms on social emotion recognition using artificial facial expressions. The validity of employing extra visual attributes in the avatars' faces to help identify emotions was proposed by Hube et al. [9]. Monferrer et al. [10] used a new dynamic virtual face (DVF) collection to evaluate facial emotion recognition in patients with depression. In order to assess the impact of four expression conditions—positive, neutral, negative, and no expressions and lip-syncing—on participants in an immersive virtual reality environment, Weng et al. [11] created a VR "trust game" setting. Using the depth and RGB data obtained from Microsoft's Kinect sensor, Seddik et al. [12] demonstrated a method that can identify the facial expressions made by a person's face and transfer them to a 3D face virtual model. The "Face and Voice Recognition-based Emotion Analysis System (EAS)" was proposed by Son et al. [13] to close this gap by evaluating emotions from both speech and face expressions. According to Arabian et al. [14], there was a favorable relationship between the participants' identified emotions and the projected facial expressions.

Navarro et al. [15] showed how the GAN architecture might be adjusted for applications that need more accurate and efficient emotional connection, greatly enhancing user experience in a variety of fields. Using the Chat GPT language model, Mullangi et al. [16] presented a novel approach to sentiment and emotion modeling in text-based interactions. In the context of metaverse games, Chen et al. [17] presented a theoretical framework and explained how the sophisticated multimodal interaction design can lead to overuse. The basic cognitive function of physical distance estimation and our social propensity toward others, as reflected by psychopathic traits, which are divided into three aspects: Coldheartedness, Self-Centered Impulsivity, and Fearless Dominance, were examined by Michalareas et al. [18].

The research on the effects of highly realistic avatars and AI-led co-creation on Metaverse hospitality services was lacking until Ramadan et al. [19] filled it. The dynamics of the N170 amplitude were determined by Kirasirova et al. [20] to be: The N170 amplitude was decreased by active attention to neutral virtual agent facial emotions; there was no signaling effect from either passive or active attention; there were significant interactions between the factors "emotion × attention" and "environment × attention," but none between the three. An emotion detection model based on EEG signals was proposed by Cruz-Vazquez et al. [21] utilizing deep learning techniques on a proprietary database. Wang et al. [22] looked into the potential impact of virtual interpersonal hugs on reducing depressive symptoms in individuals. With underrepresentations of 40.59% and 52.48%, respectively, compared to the average number of all deepfake avatars, Kaate et al. [23] indicated that current deepfake technology lacks diversity, primarily favoring young white individuals while neglecting older demographics, Asians, and Middle Eastern populations. Purnomo et al. [24] focused on optimizing electroencephalogram (EEG) signal classification algorithms to identify VR users' emotions by using the preferred reporting items for systematic reviews and meta-analyses (PRISMA) (2020) method to find and examine gaps in the literature. A dataset of 256 subjects was presented by Martinez et al. [25] and was obtained using two modalities: video from a headset's internal cameras and high resolution multi-view scans of the subjects' heads. A deep CNN-based emotion detection model for the metaverse was presented by Gupta et al. [26].

Cha et al. [27] used novel signal processing methods, such as covariate shift adaption approaches in the feature and classifier domains, to create a fEMG-based FER system that is resistant to electrode changes. NO2GESNet is a nonlinear model of an octonion ESN for SER that was proposed by Daneshfar et al. [28]. Li et al. [29] laid the groundwork for the establishment of a technology-driven metaverse and envision a time when digital interactions will reflect the intricacies of human communication. Three layers of perception, cognition and decision-making, and interaction make up the intelligent cockpit composition paradigm that Wu et al. [30] suggested.

In order to classify different negative feelings, Ham et al. [31] suggested a negative emotion detection system that gathers multimodal biosignal data, including skin temperature, galvanic skin reaction, and five EEG signals from an EEG headset and heart rate from a smart band. Assuming a commercial VR HMD equipment, Kim et al. [32] used ten electrodes placed around the eyes to build a FER system based on fEMG and EOG. A three-layer approach for studying emotions in conjunction with new technologies—like AI, GIS, and XR—was proposed by Rokhsaritalemi et al. [33]. A 3D picture technology animation character modeling system was proposed by Yan et al. [34] against the backdrop of the Metaverse.

The advantages of applying emotion prediction in the metaverse were investigated by Bellenger et al. [35]. Regardless of the presence of facial emotions, Kim et al. [36] shown that participants tend to look at the face region for the bulk of the time when conversing or attempting to predict emotion-related terms when playing charades. The symbiotic design of affective computing and the metaverse was promoted by Coutinho et al. [37]. By gathering information from the Internet, Lu et al. [38] suggested a way to create a sizable collection of facial expressions. Strong ethical frameworks and legal regulations are desperately needed to address these hazards while advancing fair access, privacy, autonomy, and mental health, according to Kourtesis et al. [39].

In order to perform a thorough analysis, Park et al. [40] separated the ideas and fundamental methods required to realize the Metaverse into three components (hardware, software, and contents) and three approaches (user interaction, implementation, and application), as opposed to marketing or hardware approach. Additional details may be found in the literature [41–56].

This study investigates real-time facial emotion recognition in metaverse avatars using deep learning, specifically Convolutional Neural Networks (CNNs). By correctly categorizing emotions such as surprise, rage, grief, and happiness, it seeks to improve user interaction. To guarantee reliable performance, the model is trained on a variety of datasets, including both synthetic and real-world data. The technology's wide range of applications is demonstrated by its use in gaming, virtual meetings, and mental health. Future developments in emotionally intelligent avatars are made possible by addressing issues like dataset constraints and ethical problems.

2. Key Steps in Avatar Facial Emotion Recognition Using Deep Learning

Here is a thorough explanation of this technology's operation, the deep learning techniques used, and some possible uses:

a. **Data Collection:**

Compile facial expression datasets for avatars. These can come from real-world facial expression databases modified for avatars, or they can be synthetic (created with 3D modeling tools) [57].

Examples of datasets:

- **FER-2013** (Facial Expression Recognition)
- **CK+** (Extended Cohn-Kanade)
- **AffectNet**
- Custom datasets created using avatar animation tools like **BlendShape** or **Faceware**.

b. **Preprocessing**:

Normalize and preprocess the data to ensure consistency [58].

Techniques include:

- Resizing images to a fixed resolution.
- Converting images to grayscale (if color is not essential).
- Augmenting data (e.g., rotation, flipping, scaling) to improve model robustness.

c. **Facial Landmark Detection**:

- Use deep learning models to detect key facial landmarks (e.g., eyes, mouth, eyebrows) on avatars [59].
- Tools like **Dlib** or **MediaPipe** can be used for this purpose.

d. **Feature Extraction**:

- Extract relevant features from the avatar's facial expressions using deep learning models.
- Convolutional Neural Networks (CNNs) are commonly used for this task [60,61].

e. **Emotion Classification**:

- Train a deep learning model to classify the extracted features into specific emotion categories [62].
- Common architectures include:
  - Convolutional Neural Networks (CNNs)
  - Recurrent Neural Networks (RNNs) for temporal data (e.g., video sequences)
  - Transformers for advanced feature learning.
  - Pre-trained models like VGG, ResNet, or EfficientNet can be fine-tuned for this task.

f. **Real-Time Emotion Recognition**:

- Deploy the trained model in a real-time system to analyze avatar facial expressions as users interact in the metaverse or virtual environments.
- Integration with VR/AR devices (e.g., Oculus Quest, HTC Vive) for seamless emotion tracking [63,64].

3. Deep Learning Architectures for Avatar Facial Emotion Recognition

a. **Convolutional Neural Networks (CNNs) [65]**:

- CNNs are the most common architecture for image-based emotion recognition.
- They excel at extracting spatial features from facial images.
- **Example:** A CNN model with multiple convolutional layers, pooling layers, and fully connected layers.

b. **Recurrent Neural Networks (RNNs)**:

- RNNs are useful for analyzing temporal data, such as video sequences of avatar expressions [66].
- Variants like **LSTM (Long Short-Term Memory)** or **GRU (Gated Recurrent Units)** can capture temporal dependencies.

c. **Hybrid Models**:

- Combine CNNs for spatial feature extraction and RNNs for temporal analysis [67].
- **Example:** A CNN-LSTM model for video-based emotion recognition.

d. **Transformers**:

- Transformers, originally designed for natural language processing (NLP), are increasingly used for computer vision tasks [68].
- Models like **Vision Transformers (ViT)** can be adapted for facial emotion recognition.

e. **Transfer Learning**:

- Use pre-trained models (e.g., VGG, Res Net, Efficient Net) and fine-tune them on avatar-specific datasets [69].

- This approach reduces training time and improves performance, especially with limited data.

4. Applications of Avatar Facial Emotion Recognition

a. **Gaming**:

- Enhance player immersion by enabling avatars to reflect real-time emotions.
- Adaptive gameplay based on the player's emotional state [70].

b. **Virtual Meetings and Social Interactions**:

- Improve communication in virtual meetings by making avatars more expressive.
- Social platforms in the metaverse can use emotion recognition to create more engaging interactions [71].

c. **Mental Health and Therapy**:

- Virtual therapists can detect users' emotions and provide personalized support.
- Emotion-aware avatars can help users practice emotional regulation [72].

d. **Education and Training**:

- Virtual teachers can gauge students' engagement and adjust their teaching methods.
- Emotion recognition can be used in training simulations (e.g., customer service, public speaking) [73,74].

e. **E-Commerce and Marketing**:

- Virtual shopping assistants can detect customer emotions and tailor recommendations [75].
- Analyze emotional reactions to virtual advertisements or product displays [76].

5. Challenges and Solutions

a. Dataset Limitations:

- **Challenge:** Lack of diverse and high-quality datasets for avatar facial expressions [77].
- **Solution:** Generate synthetic datasets using 3D modeling tools or adapt real-world datasets.

b. Real-Time Processing:

- **Challenge:** Real-time emotion recognition requires high computational resources [78].
- **Solution:** Optimize models for efficiency and use hardware acceleration (e.g., GPUs, TPUs).

c. Cross-Platform Compatibility:

- **Challenge:** Ensuring emotion recognition works across different metaverse platforms [79].
- **Solution:** Develop standardized APIs and frameworks for integration.

d. Privacy and Ethics:

- **Challenge:** Collecting and analyzing facial data raises privacy concerns [80-83].
- **Solution:** Implement robust data anonymization and user consent mechanisms.

6. Future Directions

a. Multimodal Emotion Recognition

Future advancements in multimodal emotion recognition will focus on:

- **Advanced AI Models:** Leveraging deep learning and attention mechanisms for better cross-modal integration.
- **Real-time Processing:** Implementing edge computing and low-latency systems for live applications.
- **Personalization:** Developing adaptive, user-specific models for accurate emotion detection.
- **Ethics & Privacy:** Ensuring privacy-preserving techniques and mitigating biases for fair systems.
- **Multimodal Fusion:** Exploring early, late, and hybrid fusion techniques for robust emotion analysis.
- **Diverse Applications:** Expanding into healthcare, education, and human-computer interaction.
- **Cross-cultural Adaptation:** Building models that recognize emotions across cultures and languages.
- **Explainability:** Creating transparent and interpretable models for user trust.
- **Robustness:** Enhancing systems to handle noisy data and contextual variability.
- **Integration with AI:** Combining emotion recognition with other AI systems for smarter, emotion-aware solutions.

These directions aim to make emotion recognition more accurate, inclusive, and applicable in real-world scenarios.

b. Personalized Avatars:

Future directions for **personalized avatars** include:

- **Customizable Emotions**: Let users design avatars with unique emotional expressions or sync real-time emotions via facial/voice recognition.
- **AI Personalization**: Use AI to tailor avatars to users' personalities and adapt over time.
- **Real-time Interaction**: Enable live emotion sync for virtual meetings, gaming, or social platforms.
- **Cross-platform Use**: Develop avatars that work seamlessly across apps, games, and VR.
- **Enhanced Realism**: Improve graphics and add haptic feedback for more immersive experiences.
- **Ethical Design**: Ensure inclusivity, avoid biases, and protect user privacy.
- **Applications**: Use avatars in mental health therapy, education, and entertainment for better emotional engagement.

DOI: 10.5281/zenodo.21849079

These advancements will make avatars more expressive, realistic, and versatile for digital interactions.

c. Emotion-Driven Content:

Dynamic Metaverse Environments: Future directions for **emotion-driven metaverse environments** include:

- **Real-time Adaptation**: Use emotion recognition (facial, voice, physiological) to adjust lighting, music, and visuals based on users' emotions.
- **Personalized Content**: Deliver tailored experiences, like adaptive narratives or games, that align with users' moods.
- **Immersive Tech**: Integrate VR/AR and haptic feedback for emotionally responsive, lifelike environments.
- **AI Systems**: Develop emotion-aware AI to predict and enhance user experiences over time.
- **Applications**: Use in gaming, social interactions, and therapy for engaging, emotionally resonant experiences.
- **Ethics**: Ensure privacy, consent, and bias-free systems.

These advancements will create immersive, adaptive metaverse environments that respond to users' emotions in real-time.

d. Ethical AI Frameworks:

- **Ethical Use of Emotion Recognition in the Metaverse**

Key guidelines for ethical emotion recognition in the metaverse include:

- **Transparency**: Clearly explain how emotional data is collected and used.
- **Privacy**: Obtain informed consent, minimize data collection, and ensure secure storage.
- **Bias Mitigation**: Address biases and ensure fairness across diverse demographics.
- **User Control**: Allow users to opt out, delete data, and maintain ownership.
- **Accountability**: Define clear roles and comply with regulations.
- **Ethical Use**: Ban harmful applications and promote positive use cases like mental health support.
- **Collaboration**: Involve experts and the public in developing guidelines.

These frameworks ensure responsible, fair, and trustworthy use of emotion recognition in the metaverse.

7. Conclusion

Deep learning holds significant promise for advancing avatar facial emotion recognition in the Metaverse. By leveraging state-of-the-art techniques and addressing key challenges, developers can create more immersive, empathetic, and engaging virtual experiences. As the Metaverse evolves, emotion-aware systems will play a pivotal role in shaping the future of human-computer interaction.

References

1. Yang, S., & Bhanu, B. (2011, March). Facial expression recognition using emotion avatar image. In *2011 IEEE International Conference on Automatic Face & Gesture Recognition (FG)* (pp. 866-871). IEEE.
2. Yang, S., & Bhanu, B. (2012). Understanding discrete facial expressions in video using an emotion avatar image. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, *42*(4), 980-992.
3. Muros, N. I., García, A. S., Forner, C., López-Arcas, P., Lahera, G., Rodriguez-Jimenez, R., ... & Fernández-Sotos, P. (2021). Facial affect recognition by patients with schizophrenia using human avatars. *Journal of Clinical Medicine*, *10*(9), 1904.
4. Del Aguila, J., González-Gualda, L. M., Játiva, M. A., Fernández-Sotos, P., Fernández-Caballero, A., & García, A. S. (2021). How interpersonal distance between avatar and human influences facial affect recognition in immersive virtual reality. *Frontiers in Psychology*, *12*, 675515.
5. Lee, Y. H. (2017). Virtual representation of facial avatar through weighted emotional recognition. *International Journal of Internet Protocol Technology*, *10*(1), 30-35.
6. Bellenger, D., Chen, M., & Xu, Z. (2024). Facial emotion recognition with a reduced feature set for video game and metaverse avatars. *Computer Animation and Virtual Worlds*, *35*(2), e2230.
7. Geraets, C. N., Tuente, S. K., Lestestuiver, B. P., van Beilen, M., Nijman, S. A., Marsman, J. B. C., & Veling, W. (2021). Virtual reality facial emotion recognition in social environments: An eye-tracking study. *Internet interventions*, *25*, 100432.
8. Mumenthaler, C., Sander, D., & Manstead, A. S. (2018). Emotion recognition in simulated social interactions. *IEEE Transactions on Affective computing*, *11*(2), 308-312.
9. Hube, N., Vidackovic, K., & Sedlmair, M. (2022, April). Using expressive avatars to increase emotion recognition: a pilot study. In *CHI Conference on Human Factors in Computing Systems Extended Abstracts* (pp. 1-7).
10. Monferrer, M., García, A. S., Ricarte, J. J., Montes, M. J., Fernández-Sotos, P., & Fernández-Caballero, A. (2023). Facial affect recognition in depression using human avatars. *Applied Sciences*, *13*(3), 1609.
11. Luo, L., Weng, D., Ding, N., Hao, J., & Tu, Z. (2023). The effect of avatar facial expressions on trust building in social virtual reality. *The Visual Computer*, *39*(11), 5869-5882.
12. Seddik, B., Maamatou, H., Gazzah, S., Chateau, T., & Amara, N. E. B. (2013, March). Unsupervised facial expressions recognition and avatar reconstruction from Kinect. In *10th International Multi-Conferences on Systems, Signals & Devices 2013 (SSD13)* (pp. 1-6). IEEE.
13. Son, S., & Jeong, Y. (2025). Face and Voice Recognition-Based Emotion Analysis System (EAS) to Minimize Heterogeneity in the Metaverse. *Applied Sciences*, *15*(2), 845.
14. Arabian, H., Alshirbaji, T. A., Bhave, A., Wagner-Hartl, V., Igel, M., Chase, J. G., & Moeller, K. (2025). Feasibility study of emotion mimicry analysis in human–machine interaction. *Scientific reports*, *15*(1), 3859.
15. Villegas-Ch, W., Navarro, A. M., & Mera-Navarrete, A. (2025). Using Generative Adversarial Networks for the synthesis of emotional facial expressions in virtual educational environments. *Intelligent Systems with Applications*, 200479.

16. Mullangi, P., Dimmita, N., Supriya, M., Murty, P. S. C., Nirmala, G. V., Palagan, C. A., ... & Rajeswaran, N. (2025). Sentiment and Emotion Modeling in Text-based Conversations utilizing ChatGPT. *Engineering, Technology & Applied Science Research*, *15*(1), 20042-20048.
17. Chen, C., Wang, Y. Y., Zhang, K. Z., & Xie, F. (2025). Excessive use in the metaverse: The role of multisensory interaction. *Decision Support Systems*, *190*, 114390.
18. Michalareas, G., Lehr, C., Grabenhorst, M., & Hecht, H. (2025). Social processing distorts physical distance perception. *Scientific Reports*, *15*(1), 5669.
19. Ramadan, Z., & Ramadan, J. (2025). AI avatars and co-creation in the metaverse. *Consumer Behavior in Tourism and Hospitality*, *20*(1), 131-147.
20. Kirasirova, L., Maslova, O., & Pyatin, V. (2025). Impact of virtual agent facial emotions and attention on N170 ERP amplitude: comparative study. *Frontiers in Behavioral Neuroscience*, *19*, 1523705.
21. Cruz-Vazquez, J. A., Montiel-Pérez, J. Y., Romero-Herrera, R., & Rubio-Espino, E. (2025). Emotion recognition from EEG signals using advanced transformations and deep learning. *Mathematics*, *13*(2), 254.
22. Wang, X., Liu, Q., Li, X., Zheng, X., Hommel, B., & Ma, K. (2025). Sadness is reduced by virtual hugging. *Applied Psychology: Health and Well-Being*, *17*(1), e70007.
23. Kaate, I., Salminen, J., Al Tamime, R., Jung, S. G., & Jansen, B. J. (2025). Is Deepfake Diversity Real? Analyzing the Diversity of Deepfake Avatars. *Expert Systems with Applications*, *269*, 126382.
24. Purnomo, F. A., Arifin, F., & Surjono, H. D. (2025). Utilizing virtual reality for real-time emotion recognition with artificial intelligence: a systematic literature review. *Bulletin of Electrical Engineering and Informatics*, *14*(1), 447-456.
25. Martinez, J., Kim, E., Romero, J., Bagautdinov, T., Saito, S., Yu, S. I., ... & Sheikh, Y. (2025). Codec Avatar Studio: Paired Human Captures for Complete, Driveable, and Generalizable Avatars. *Advances in Neural Information Processing Systems*, *37*, 83008-83023.
26. Gupta, B. B., Gaurav, A., Chui, K. T., & Arya, V. (2024, January). Deep learning-based facial emotion detection in the metaverse. In *2024 IEEE International Conference on Consumer Electronics (ICCE)* (pp. 1-6). IEEE.
27. Cha, H. S., & Im, C. H. (2023). Improvement of robustness against electrode shift for facial electromyogram-based facial expression recognition using domain adaptation in VR-based metaverse applications. *Virtual Reality*, *27*(3), 1685-1696.
28. Daneshfar, F., & Jamshidi, M. B. (2023). An octonion-based nonlinear echo state network for speech emotion recognition in Metaverse. *Neural Networks*, *163*, 108-121.
29. Li, Y., Hashim, A. S., Lin, Y., Nohuddin, P. N., Venkatachalam, K., & Ahmadian, A. (2024). AI-based visual speech recognition towards realistic avatars and lip-reading applications in the metaverse. *Applied Soft Computing*, *164*, 111906.
30. Li, W., Wu, L., Wang, C., Xue, J., Hu, W., Li, S., ... & Cao, D. (2022). Intelligent cockpit for intelligent vehicle in metaverse: A case study of empathetic auditory regulation of human emotion. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *53*(4), 2173-2187.
31. Ham, S. M., Lee, H. M., Lim, J. H., & Seo, J. (2023). A negative emotion recognition system with internet of things-based multimodal biosignal data. *Electronics*, *12*(20), 4321.
32. Kim, C., Cha, H. S., Kim, J., Kwak, H., Lee, W., & Im, C. H. (2023). Facial motion capture system based on facial electromyogram and electrooculogram for immersive social virtual reality applications. *Sensors*, *23*(7), 3580.
33. Rokhsaritalemi, S., Sadeghi-Niaraki, A., & Choi, S. M. (2023). Exploring emotion analysis using artificial intelligence, geospatial information systems, and extended reality for urban services. *IEEE Access*, *11*, 92478-92495.
34. Yan, G., Xin, H., & Kuan, Z. (2024). Application of three-dimensional image technology in the context of the metaverse in the production of emotional contrast and special effects in animation. *Multimedia Tools and Applications*, *83*(14), 40857-40872.
35. Bellenger, D., Chen, M., & Xu, Z. (2024). The emotional metaverse: exploring the benefits of predicting emotion from 3D avatars. *Procedia Computer Science*, *232*, 183-190.
36. Kim, K., Joh, H., Kim, Y., Park, S., & Oh, U. (2022). Understanding the Importance of Presenting Facial Expressions of an Avatar in Virtual Reality. *International journal of advanced smart convergence*, *11*(4), 120-128.
37. Coutinho, R. W., & Boukerche, A. (2023). When smart metaverse meets affective computing: Opportunities and design guidelines. *IEEE Communications Magazine*, *61*(10), 46-52.
38. Lu, J., & Wan, X. (2023). RETRACTED ARTICLE: Affective computing model for natural interaction based on large-scale self-built dataset. *SN Applied Sciences*, *5*(2), 53.
39. Kourtesis, P. (2024). A Comprehensive Review of Multimodal XR Applications, Risks, and Ethical Challenges in the Metaverse. Multimodal Technologies and Interaction, 8(11), 98.
40. Park, S. M., & Kim, Y. G. (2022). A metaverse: Taxonomy, components, applications, and open challenges. *IEEE access*, *10*, 4209-4251.
41. Ibrahim, D. R., Shehadeh, H. A., Aladaileh, M. A., Alieyan, K., Jaradat, G. M., Telfah, W. A., & Wang, X. (2023, October). A hybrid facial recognition approach based on grasshopper optimization method. In *AIP Conference Proceedings* (Vol. 2979, No. 1). AIP Publishing.
42. Alzoubi, S., Abualigah, L., Sharaf, M., Daoud, M. S., Khodadadi, N., & Jia, H. (2024). Synergistic Swarm Optimization Algorithm. *CMES-Computer Modeling in Engineering & Sciences*, *139*(3).
43. Alshinwan, M., Khashan, O. A., Khader, M., Tarawneh, O., Shdefat, A., Mostafa, N., & AbdElminaam, D. S. (2024). Enhanced Prairie Dog Optimization with Differential Evolution for solving engineering design problems and network intrusion detection system. *Heliyon*, *10*(17).
44. Shehadeh, H. A., Jebril, I. H., Jaradat, G. M., Ibrahim, D., Sihwail, R., Al Hamad, H., ... & Alia, M. A. (2023). Intelligent Diagnostic Prediction and Classification System for Parkinson's Disease by Incorporating Sperm

Swarm Optimization (SSO) and Density-Based Feature Selection Methods. *International Journal of Advances in Soft Computing & Its Applications*, *15*(3).

45. Abualigah, L., Al-Okbi, N. K., Mirjalili, S., Alshinwan, M., Al Hamad, H., Khasawneh, A. M., ... & Gandomi, A. H. (2022). Moth-Flame Optimization Algorithm, Arithmetic Optimization Algorithm, Aquila Optimizer, Gray Wolf Optimizer, and Sine Cosine Algorithm: A Comparative Analysis Using Multilevel Thresholding Image Segmentation Problems. In *Handbook of Moth-Flame Optimization Algorithm* (pp. 241-263). CRC Press.
46. Hausawi, Y. M., El-Meligy, M., Alzaid, Z., Alharbi, O., Almutairi, B., & Mohamed, B. (2025). ALGORITHM FOR FINDING CONNECTED RESOLVING NUMBER OF A GRAPH. *Advances and Applications in Discrete Mathematics*, *42*(1), 69-77.
47. Asiri, A., & Mohamed, B. (2024). Binary fruit fly optimization algorithm for counting the number of spanning trees in networks. *Advances and Applications in Discrete Mathematics*, *41*(8), 663-676.
48. Batiha, I. M., & Mohamed, B. (2024). Binary rat swarm optimizer algorithm for computing independent domination metric dimension problem. Mathematical Models in Engineering, 10(3), 119-132.
49. Mohamed, B., Mohaisen, L., & Amin, M. (2023). Binary Archimedes Optimization Algorithm for Computing Dominant Metric Dimension Problem. *Intelligent Automation & Soft Computing*, *38*(1).
50. Batiha, I. M., Anakira, N., & Mohamed, B. (2024). Algorithm for finding domination resolving number of a graph. *Journal of Mechanics of Continua and Mathematical Sciences*, *19*, 18-23.
51. Mohamed, B., & Amin, M. (2023). Hybridizing slime mould algorithm with simulated annealing for solving metric dimension problem. *Machine Learning Research*, *8*(1), 9-16.
52. Alrimawi, F. (2025). Numerical radius inequalities involving 2× 2 block matrices. *European Journal of Pure and Applied Mathematics*, *18*(1), 5597-5597.
53. Alrimawi, F. (2025). Some inner product inequalities with applications to numerical radius inequalities. *J. Math. Computer Sci*, *38*, 16-24.
54. Anakira, N., Oqilat, O., Almalki, A., Irianto, I., Meqdad, S., & Amourah, A. (2025). Numerical proceduers for computing the exact solutions to systems of ordinary differential equations. *Int. J. Neutrosophic Sci*, *2*, 165-65.
55. Hussain, A., Hammad, M., Rahimzai, A. A., Koh, W. S., & Khan, I. (2025). Dynamical analysis and soliton solutions of the space–time fractional Kaup-Boussinesq system. *Partial Differential Equations in Applied Mathematics*, 101205.
56. Okasha, M. M., Gubari, M. Q., Ameen, H. F. M., Abbas, M., Norberdiyeva, M., Koh, W. S., & Khan, I. (2025). Computational assessment of local thermal non-equilibrium effects on non-Darcy chemical reactive flow of Boger hybrid nanofluid with elastic deformation. *Partial Differential Equations in Applied Mathematics*, 101260.
57. Pourebadi, M., & Riek, L. D. (2022). Facial expression modeling and synthesis for patient simulator systems: Past, present, and future. *ACM Transactions on Computing for Healthcare (HEALTH)*, *3*(2), 1-32.
58. Ortiz, B. L., Gupta, V., Kumar, R., Jalin, A., Cao, X., Ziegenbein, C., ... & Choi, S. W. (2024). Data preprocessing techniques for ai and machine learning readiness: Scoping review of wearable sensor data in cancer care. *JMIR mHealth and uHealth*, *12*(1), e59587.
59. Li, Y., Wang, C., Xie, L., Jin, Q., Fan, L., Ning, J., & Lu, S. (2024). Facial Landmark Detection Based on High Precision Spatial Sampling via Millimeter-wave Radar. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *8*(4), 1-26.
60. Pereira, R., Mendes, C., Ribeiro, J., Ribeiro, R., Miragaia, R., Rodrigues, N., ... & Pereira, A. (2024). Systematic review of emotion detection with computer vision and deep learning. *Sensors*, *24*(11), 3484.
61. Karkuzhali, S., Murugeshwari, R., & Umadevi, V. (2024). Facial Emotion Recognition and Synthesis with Convolutional Neural Networks. *International Journal of Computer Applications*, *186*(11), 0975-8887.
62. Billah, M. M., Sarker, L., Akhand, M., & Kamal, M. S. (2024). Emotion recognition with intensity level from bangla speech using feature transformation and cascaded deep learning model. *International Journal of Advanced Computer Science & Applications*, *15*(4).
63. Hatami, M., Qu, Q., Chen, Y., Kholidy, H., Blasch, E., & Ardiles-Cruz, E. (2024). A Survey of the Real-Time Metaverse: Challenges and Opportunities. *Future Internet*, *16*(10), 379.
64. Rehman, M., Petrillo, A., Forcina, A., & De Felice, F. (2024). Metaverse Simulator for Emotional Understanding. *Procedia Computer Science*, *232*, 3216-3228.
65. Agung, E. S., Rifai, A. P., & Wijayanto, T. (2024). Image-based facial emotion recognition using convolutional neural network on emognition dataset. *Scientific reports*, *14*(1), 14429.
66. Jbene, M., Chehri, A., Saadane, R., Tigani, S., & Jeon, G. (2025). Intent detection for task-oriented conversational agents: A comparative study of recurrent neural networks and transformer models. *Expert Systems*, *42*(2), e13712.
67. Mahmoud, A., & Mohammed, A. (2024). Leveraging hybrid deep learning models for enhanced multivariate time series forecasting. *Neural Processing Letters*, *56*(5), 223.
68. Zhang, H., & Shafiq, M. O. (2024). Survey of transformers and towards ensemble learning using transformers for natural language processing. *Journal of big Data*, *11*(1), 25.
69. Mahmoud, K. A., Badr, M. M., Elmalhy, N. A., Hamdy, R. A., Ahmed, S., & Mordi, A. A. (2024). Transfer learning by fine-tuning pre-trained convolutional neural network architectures for switchgear fault detection using thermal imaging. *Alexandria Engineering Journal*, *103*, 327-342.
70. Mitsea, E., Drigas, A., & Skianis, C. (2025). A Systematic Review of Serious Games in the Era of Artificial Intelligence, Immersive Technologies, the Metaverse, and Neurotechnologies: Transformation Through Meta-Skills Training. *Electronics*, *14*(4), 649.
71. Lim, J., & Lee, M. (2024). The buffering effects of using avatars in synchronous video conference-based online learning on students' concerns about interaction and negative emotions. *Education and Information Technologies*, *29*(12), 16073-16096.

72. Jelassi, M., Matteli, K., Ben Khalfallah, H., & Demongeot, J. (2024). Enhancing Personalized Mental Health Support Through Artificial Intelligence: Advances in Speech and Text Analysis Within Online Therapy Platforms. *Information*, *15*(12), 813.
73. El-Sabagh, H. A. (2021). Adaptive e-learning environment based on learning styles and its impact on development students' engagement. *International Journal of Educational Technology in Higher Education*, *18*(1), 53.
74. Ong, S. G. T., & Quek, G. C. L. (2023). Enhancing teacher–student interactions and student online engagement in an online learning environment. *Learning environments research*, *26*(3), 681-707.
75. Raji, M. A., Olodo, H. B., Oke, T. T., Addy, W. A., Ofodile, O. C., & Oyewole, A. T. (2024). E-commerce and consumer behavior: A review of AI-powered personalization and market trends. *GSC Advanced Research and Reviews*, *18*(3), 066-077.
76. Zimmermann, R., Mora, D., Cirqueira, D., Helfert, M., Bezbradica, M., Werth, D., ... & Auinger, A. (2023). Enhancing brick-and-mortar store shopping experience with an augmented reality shopping assistant application using personalized recommendations and explainable artificial intelligence. *Journal of Research in Interactive Marketing*, *17*(2), 273-298.
77. Liu, Y. J., Wang, B., Gao, L., Zhao, J., Yi, R., Yu, M., ... & Gu, X. (2023). 4D facial analysis: A survey of datasets, algorithms and applications. *Computers & Graphics*, *115*, 423-445.
78. Canal, F. Z., Müller, T. R., Matias, J. C., Scotton, G. G., de Sa Junior, A. R., Pozzebon, E., & Sobieranski, A. C. (2022). A survey on facial emotion recognition techniques: A state-of-the-art literature review. *Information Sciences*, *582*, 593-617.
79. Abilkaiyrkyzy, A., Elhagry, A., Laamarti, F., & El Saddik, A. (2023). Metaverse key requirements and platforms survey. *IEEE Access*, *11*, 117765-117787.
80. Slade, S., & Prinsloo, P. (2013). Learning analytics: Ethical issues and dilemmas. *American Behavioral Scientist*, *57*(10), 1510-1529.
81. Shehab, M., Shambour, M. K. Y., Abu Hashem, M. A., Al Hamad, H. A., Shannaq, F., Mizher, M., ... & Abualigah, L. (2024). A survey and recent advances in black widow optimization: variants and applications. Neural Computing and Applications, 1-21.
82. Mohammad Abualigah, L., Al-diabat, M., Al Shinwan, M., Dhou, K., Alsalibi, B., Said Hanandeh, E., & Shehab, M. (2020). Hybrid harmony search algorithm to solve the feature selection for data mining applications. Recent advances in hybrid metaheuristics for data clustering, 19-37.
83. Almodfer, R., Mudhsh, M., Chelloug, S., Shehab, M., Abualigah, L., & Abd Elaziz, M. (2022). Quantum mutation reptile search algorithm for global optimization and data clustering. Hum-Centr Comput Inf Sci, 12.