

Micro Expression with EEG and Face Emotion: Challenges and Opportunities

Bhavya N¹ and V. N. Manjunath Aradhya²

^{1,2}Department of Computer Applications, JSS Science and Technology University, Mysuru, 570006

Abstract—Emotion recognition through Brain-Computer Interface (BCI) technology has gained considerable attention due to its potential applications in human-computer interaction, healthcare, and entertainment. Electroencephalography (EEG) plays a pivotal role in capturing real-time brain activity associated with emotional states, providing insights into both cognitive and affective responses. This review paper presents a comprehensive analysis of EEG-based emotion recognition research from 2014 to 2024, emphasizing the role of both micro and macro expressions in decoding emotional nuances. Micro-expressions, which are brief and involuntary, offer a window into subtle emotional changes, while macro-expressions reveal more overt emotional reactions. By integrating EEG signals with advanced facial analysis methods, particularly in scenarios with occluded or ambiguous facial cues, this paper explores the methodologies, datasets, and feature extraction techniques used to classify emotions in real time. Key challenges and advancements are discussed, including issues related to data variability, classification accuracy, and the integration of BCI systems with emotion recognition frameworks. This review aims to identify emerging trends and propose future research directions to enhance the precision and applicability of emotion recognition technologies in BCI contexts.

Keywords— EEG-based emotion recognition, micro-expressions, macro-expressions, Brain-Computer Interface (BCI), real-time emotion detection.

I. INTRODUCTION

In the field of brain-computer interfaces (BCI), the use of EEG signals in combination with micro expressions represents a novel, multidisciplinary approach to emotional recognition. Additionally, by combining facial expressions with EEG data, traditional visual cues can be supplemented with this information to decode more subtle and spontaneous changes in emotional state.

For instance, improvements in hierarchical transformer networks (HTNet) for the coordinated subtle movements of facial muscles have greatly improve the recognition performance of micro expressions, addressing challenges related to facial action unit interactions [15].

EEG-based micro expression recognition holds particular promise in real-world applications such as security screening, psychological diagnostics, and improving human-computer interaction [1]. However, combining EEG and micro expression data presents distinct challenges, including the need for sophisticated signal processing techniques and large, multimodal datasets [2]. Additionally, utilizing transfer learning strategies from macro-expressions to micro-expressions can improve model accuracy, though the significant differences in facial patterns require further research [16].

Micro expressions are small but powerful involuntary facial expressions that help a person communicate their true emotions but will be suppressed by the person in question to hide an emotion. Such fleeting expressions can have a big impact across numerous domains including behavioural analysis psychology, security, and healthcare. Micro expressions might allow for crucial insights on emotional states, however their recognition is a difficult task due to a large number of challenges, namely their short time duration and sublimity. Traditionally, methods for micro expression recognition have predominantly relied on computer vision technologies, such as video-based approaches and facial landmark tracking [2]. While these methods have demonstrated progress, they still encounter limitations in accurately identifying and interpreting micro expressions in dynamic and ambiguous scenarios [7]. For instance, facial expressions in extended reality (XR) are often occluded by head-mounted displays (HMDs), hindering emotion recognition [14].

A promising direction for overcoming these obstacles is integrating electroencephalography (EEG) signals into micro expression detection. Electroencephalography (EEG), which measures the electrical activity of the brain through non-invasive electrodes placed on the scalp, providing direct insight into neurological processes and emotional responses. Instead of relying on visual-based methods, EEG is unique in that it captures electrical activity in the brain that seems to correlate with cognitive and emotional states, providing a complementary data input that is orthogonal to facial recognition. Recognizing micro expressions through EEG signals allows researchers to tap into deeper, subconscious emotional reactions, providing an additional layer of analysis for more accurate emotion detection [5][2]. Furthermore, integrating physiological signals with occluded facial expressions has shown promising improvements in emotion recognition accuracy in partial occlusion scenarios [14].

The Integration of EEG and micro expression recognition to enhance emotion recognition systems. It addresses challenges in data fusion, classification, and performance evaluation while highlighting potential applications in psychology, affective computing, and real-time emotion analysis [17][18].

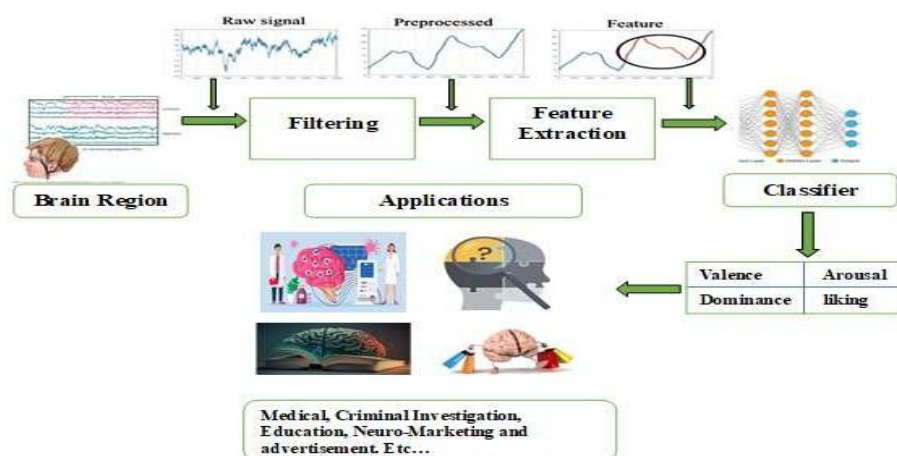


Fig 1: EEG-Based Emotion Recognition Pipeline.

The Fig 1 presented outlines the complete process of recognizing emotions through EEG, highlighting key stages of data analysis. It starts with the signals from brain regions captured as raw EEG data, which are then filtered to eliminate artifacts and noise. Following this, feature extraction is carried out to pinpoint relevant patterns from the cleaned signals. The features extracted are subsequently input into a classifier that predicts emotional states such as valence, arousal, dominance, and liking. The results have diverse applications across medical fields, criminal investigations, education, neuromarketing, and advertising. This structured approach emphasizes the significance of effective signal processing and classification methods in EEG-based emotion recognition systems.

This section underlines the growing relevance of EEG-based approaches in micro expression recognition, paving the way for real-time applications in fields like clinical psychology and human-computer interaction.

II. LITERATURE SURVEY

The literature review in Table 1 highlights EEG's potential in detecting micro-expression by analysis neural activity. Combining EEG signals with facial micro expressions enhances emotion recognition, as micro expressions can be faked in videos but not in EEG signals.

TABLE I: OVERVIEW OF LITERATURE ON EMOTION RECOGNITION USING EEG AND MICRO-EXPRESSIONS

Ref No	Year	Class	Methodology	Database + No. of Channels	Result
[1]	2022	Happiness, Sadness, Anger, Neutral	Fusion of EEG, facial, and physiological signals using decision-level integration	Custom dataset; 16 channels Participants: M - 12, F - 11, OpenBCI EEG soft headset	Arousal - 66.4% Valence - 70.2%
[2]	2022	Positive and negative emotions	This study used SEES to collect facial expression and EEG data, analyzing neural patterns for micro- and macro- expressions	Custom dataset; 128 channels Participants: M-20, F- 20; EEG data with 128 Biosemi electrodes	Micro- expressions have higher power in positive emotions
[3]	2022	Based On region: 13 ROIs	Artifact removal techniques and EEG signal enhancement	EEG with micro-ex- pression data; 16 channels Participants: M - 20, F- 20, EEG data with 128 Biosemi electrodes.	54%accuracy
[4]	2016	Joy, Anger, Surprise, Fear, Neutral, Contempt, Disgust, sadness, Positive, Negative	Sensor-based feature selection and classification	Sensor-specific dataset, 32 channels, Participants: M- 22, F - 18	Accuracy 94%
[5]	2022	Micro-Expressions	Graph-based functional network analysis	Functional EEG net- work dataset, 32 channels, Participants: M - 23, F - 42, 128 Bio- semi electrodes Functional network dataset; 32 channels	87% accuracy
[6]	2024	Micro-Expressions, Facial Expressions	Functional network efficiency metrics and classifiers	Participants: M-23, F - 42, 128 Biosemi elec- trodes	89.3% accuracy
[7]	2022	Emotional states (micro- and macro-expressions).	SWUME dataset created using emotion inhibition; EEG and video data from 68 participants analyzed with machine learning classifiers.	SWUME, Participants: M-30, F-48, EEG data with 128 Biosemi electrodes	90% accuracy for micro-expression
[8]	2021	6 emotions: happy, sad, angry, surprised, disgusted, fearful	16 participants; EEG and fEMG data collected during emotional video clips; SVM for classification	Video clips from Korean movies; Participants: M-13, F-3, 10 EEG channels using the 10-20 system	EEG accuracy 96.2%.
[9]	2024	happiness, sadness, anger, surprise, disgust, fear	Proposed PAFN framework with 3 modules 3DCM, PCP, PSAM	DEAP: 32 EEG channels. PEG: Facial data for micro-expressions.	Over 96% accuracy
[10]	2022	Focus on positive emotions, especially, laughter	EEG data with Tensor Component Analysis (TCA) and Physarum Network (PN); data from 70 subjects using a micro-expression elicitation paradigm	Participants M-20, F-20 no named public data base, participants: M - 23, F-42 using 128- channel Biosemi system	N/A

III. DATA ANALYSIS

Micro expression recognition using EEG data demands synchronized datasets and innovative experimental designs. Across the reviewed literature, various approaches were explored to elicit and record micro expressions and the corresponding neural signals. In [7] introduced the SWUME dataset, combining EEG and micro expression video data from 68 participants, collected using emotionally charged stimuli. In [10] applied an ME elicitation paradigm with 70 participants, using emotional images to induce concealed emotions while employing tensor component analysis (TCA) and the Physarum network algorithm. In [3] involved datasets capturing brain activity during emotion elicitation in controlled settings, recording neural responses alongside facial expressions. Table 2 summarizes key characteristics of experimental setups in these studies, demonstrating the diverse approaches and data modalities involved.

The datasets examined in the Table 2 differ in terms of stimuli, participant characteristics, and methods of data collection. Below is a summary table that compares the key features of each dataset utilized in the studies.

TABLE II: OVERVIEW OF EXPERIMENTAL SETUPS IN REVIEWED STUDIES

Dataset and ref number	Participants	Stimuli	EEG Channels	Synchronization Modality
Not explicitly mentioned but refers to the dataset constructed for the micro-expressions and EEG study.[3]	68 right-handed individuals (23 males, 45 females, aged 17–22), excluding 10 ineligible participants	Seven positive-emotion video clips (~2 minutes each).	Recorded using a Biosemi Active Two system with 128 electrodes.	EEG signals and facial images with shared triggers for timestamps
SWUME [7]	68 undergraduate students (48 females, 30 males), aged 17–22	Seven 2-minute video clips from movies and TV shows evoking target emotions, arranged to ensure natural responses	Exact details of channels are unspecified, but signals were collected in synchronization with video data	High-speed camera and EEG acquisition system were synchronized for simultaneous collection of micro-expression videos and EEG signals.
Video clips from Korean movies, categorized into four emotion types via a survey by the Korea Institute of Science and Technology.[8]	16 participants (13 males, 3 females, avg. age 23.25 ± 3.40 years), with 2 excluded for missing facial expression data.	20 two-minute video clips in four emotional categories: High/Low Valence and High/Low Arousal (5 clips per category).	Recorded with 10 electrodes (Fp1, Fp2, F7, F8, T7, T8, P7, P8, O1, O2) using the 10–20 system.	Aligned using a “beep” tone before each video playback.
Dataset collected for this study, referred to as the EEG micro-expression dataset.[10]	65 right-handed individuals (23 men, 42 women, aged 17–26); 5 excluded for no micro-expressions.	Three <3-minute Chinese comedy clips eliciting laughter, validated by 20 subjects.	128 active electrodes for comprehensive scalp coverage.	LabView system synchronized EEG with a high-speed camera.
Study-specific dataset on EEG-based micro-expression recognition.[6]	70 participants, with positive emotions as the study focus.	Three video clips (selected from 15) eliciting intense delight (average rating >6 on a 7-point scale).	128 active electrodes mapped to functional brain regions (frontal, parietal, temporal, occipital).	LabView system synchronized EEG and video data with shared timestamps.

A. Feature Extraction

Feature extraction is essential for interpreting EEG signals. Across studies shown in Table 3, preprocessing involved filtering to eliminate noise, removing ocular and muscle artifacts, and normalizing data for consistency. In [3][7] and [10] applied similar preprocessing steps to enhance signal quality, including band-pass filtering to isolate frequency bands associated with cognitive and emotional processing.

Temporal and spectral characteristics formed the cornerstone of feature extraction methods. In [7] utilized statistical and spectral analyses to extract 21 features per channel. In [9] applied advanced modules like Three-Dimensional Construction (3DCM) to derive rich temporal features. IN [8] emphasized time-frequency analysis using a support vector machine (SVM) framework, achieving an F1 score of 0.971. In [4] incorporated Fast Fourier Transform (FFT) to analyze frequency-domain EEG signals.

TABLE III. OVERVIEW OF FEATURE EXTRACTION TECHNIQUES USED IN EEG-BASED EMOTION RECOGNITION

Ref	Feature Types	Methodology	Key Outcomes
[3]	Facial: MDMO from 13 ROIs. EEG: 512 PSD features (theta, alpha, beta, gamma bands).	68 participants, positive videos, facial suppression. Data: 100 fps camera, 128-channel EEG. Analysis: Optical flow (facial), Granger causality (EEG).	Artifacts: Reduced from 11.5% to 3.7%. Causality: Micro-expressions influence EEG. Novelty: First study linking facial artifacts to EEG.
[7]	EEG: Alpha, beta, gamma band power; statistical features (means, differences); wavelet entropy Total Features: 21 per channel.	Dataset: SWUME developed using EEIPS, synchronizing EEG and high-speed video. Data Collection: 68 participants watched emotional videos while suppressing expressions. Analysis: Classifiers (KNN, SVM, XGB, BP Neural Network) with 10-fold cross-validation.	SWUME Dataset: 806 micro and 393 macro-expression samples. Accuracy: 90% with XGBoost for micro vs. macro-expression. Insights: EEG reliably distinguishes micro-expressions, useful in security and crime investigations.
[8]	fEMG: Facial muscle signals, amplitude, frequency. EEG: Power in Delta, Theta, Alpha, Beta, Gamma bands.	Participants: 16. Stimuli: 20 emotion clips, synced audio. Data Collection: fEMG & EEG simultaneously. Classification: SVM, F1 score.	Detection: High accuracy. Emotion Recognition: F1 = 0.971. EEG vs fEMG: EEG better (F1: 0.962 vs 0.797).

[9]	Facial Expressions: 64×64 images of facial movements. EEG Signals: 9×9 matrix of brain activity, covering key frequency bands	PAFN Modules: 3D Construction (EEG), Convolutional Preprocessing (facial features), Self-Attention (LSTM & encoding).	Accuracy: 96% on DEAP and PEG. Comparison: Multimodal outperforms unimodal. Training: Faster convergence with better accuracy
[4]	Time-domain: Min, Max, Mean, Sum; Frequency-domain: FFT for Delta, Theta, Alpha, Beta, Gamma	Recording: EEG (Emotiv) & facial expressions (FACET) during IAPS stimuli. Extraction: Java program for time-frequency features. Classification: Machine learning predicts emotions	Accuracy: High prediction accuracy with EEG. Sensor Identification: Key electrodes for emotion detection. VR Application: Works in VR where webcams fail.

B. Fusion Strategies and Classification

Combining EEG signals with other modalities is a dominant theme in achieving higher accuracy in micro expression recognition.

In [7] achieved 90% accuracy by utilizing XGBoost to classify micro expressions based on EEG-video fusion. In [9] Periphery Attention Fusion Network (PAFN) leveraged multimodal data, reaching an accuracy of 96%. In [5] explored multimodal fusion by integrating facial features with EEG signals, highlighting that multimodal systems significantly outperform unimodal systems in emotion recognition tasks.

Fusion Approaches

- Feature-Level Fusion: In [3] proposed combining EEG features with facial data to construct a holistic feature set.
- Decision-Level Fusion: In [5] employed ensemble methods where decisions from individual modalities were combined for robust classification.

C. Evaluation and Performance Metrics

Performance evaluation is vital to gauge the robustness of these systems. In [7],[9], and [8] employed metrics such as accuracy, precision, recall, and F1 scores.

Notably, [8] achieved an F1 score of 0.971 using SVM, while [9] reported a classification accuracy of 96% for its PAFN approach.

Evaluation metrics used:

- Accuracy: Measures the proportion of correct classifications [7][9] and
- F1 Score: Balances precision and recall, crucial for micro expression tasks [8]
- Precision and Recall: Critical in ensuring reliable classification in imbalanced datasets [6].

TABLE IV: FUSION STRATEGIES IN REVIEWED STUDIES

Ref	Fusion Approach	Data Modalities	Classification Method
[3]	Feature-level	EEG, facial expressions	Random Forest
[5]	Decision-level	EEG, facial expressions	Ensemble learning
[7]	Feature-level	EEG, micro expression video	XGBoost
[9]	Feature-level	EEG, facial data, peripheral cues	PAFN
[6]	N/A	EEG and physiological data	Neural Networks

Table 4 demonstrate that multimodal fusion consistently outperforms single-modality approaches, particularly when combining EEG with facial expressions and physiological data.

In [3], for instance, achieved a notable improvement in classification accuracy through the decision-level fusion of EEG, facial micro-expressions, and physiological signals.

Similarly, in [1] and [8] showed that combining facial expressions with EEG and PPG/GSR significantly improved accuracy in detecting emotional states across both valence and arousal dimensions.

D. Summary and Key Observations

The review highlights significant progress in micro expression recognition via EEG data analysis:

- Multimodal datasets like SWUME facilitate synchronized emotion recognition experiments [7].
- Advanced preprocessing and feature extraction techniques, such as dynamic convolution [9] and FFT [4], improve signal interpretation. Dynamic convolution adapts filter weights dynamically based on input variations, enabling more precise feature extraction by tailoring the convolutional process to the temporal and spatial complexities of EEG signals.

Similarly, FFT efficiently transforms signals into the frequency domain, providing valuable insights into neural oscillations and emotional state patterns. Fusion strategies and machine learning methods consistently

enhance recognition performance, with multimodal approaches achieving >95% accuracy in specific studies [7][9].

- Fusion strategies and machine learning methods consistently enhance recognition performance, with multimodal approaches achieving >95% accuracy in specific studies [7][9].

IV. DISCUSSION AND FUTURE DIRECTIONS

Integrating EEG signals with micro-expression recognition provides an innovative approach to understanding hidden emotions and subtle cognitive responses. However, several challenges must be addressed before achieving efficient, real-world applications. Noise in EEG signals, caused by environmental factors, muscle movements, or other artifacts, can severely impact data quality. Studies like [2] and [8] underscore the importance of advanced techniques, such as independent component analysis (ICA) and wavelet transforms, to reduce noise and improve signal clarity. Another hurdle lies in the limited availability of diverse datasets. Existing datasets, as noted in [5] and [7], often focus on narrow demographic groups, restricting model generalization to larger, diverse populations. Furthermore, aligning the fleeting nature of micro-expressions, which last mere milliseconds, with EEG data is no small feat. Research from [3] highlights this difficulty, pointing to methods like dynamic time warping (DTW) as promising solutions.

Progress in feature extraction and data fusion has shown potential, with models like Periphery Attention Fusion Networks (PAFN) [9] demonstrating success in combining EEG with facial video data. PAFN leverages attention mechanisms to focus on the most relevant peripheral features from both modalities, improving the model's ability to capture subtle correlations between brain activity and facial expressions. Yet, computational demands and scalability remain issues, particularly in real-time applications, as noted in [1]. Additionally, variations in EEG signals across individuals pose challenges for generalizing models, with [4] and [6] recommending strategies like transfer learning and domain adaptation.

Looking ahead, interdisciplinary approaches integrating EEG with other physiological signals, alongside advancements in hardware, preprocessing, and experimental design, hold promise for breaking these barriers. The continued refinement of multimodal frameworks and temporal synchronization strategies will be pivotal for advancing emotion recognition systems in real-world contexts [19]–[23].

Extracting meaningful features from EEG signals is fundamental to advancing systems for emotion recognition, BCIs, and medical diagnostics. Feature extraction methods like Fourier Transform, Power Spectral Density (PSD), and Band Power are widely used to manage the complexity and non-stationary nature of EEG data, each offering unique advantages and facing specific challenges.

The Fourier Transform, for instance, is computationally efficient and well-suited for real-time applications like sleep monitoring but struggles with short EEG signals, limiting its precision [12]. PSD is similarly efficient and versatile for applications like BCI cursor control, but its inability to handle non-stationary signals limits its dynamic applications [11][13]. Meanwhile, Band Power demonstrates high accuracy in tasks like wheelchair control but requires intensive computational resources for real-time operation [12]. These techniques, when appropriately selected, play a crucial role in advancing EEG analytics, particularly for micro-expression detection, where high temporal precision is critical for capturing subtle, rapid changes in facial signals. Selecting the right combination of methods and architecture is vital to deploying these systems effectively in real-world applications. Future research must tackle several challenges to realize the full potential of EEG-based systems. Real-time capabilities, scalable designs, culturally adaptable models, and ethical considerations will be critical for integrating these technologies into healthcare, education, and beyond. Addressing these issues will pave the way for transformative applications, leveraging multimodal fusion to improve precision and uncover new possibilities in emotion recognition and micro-expression analysis.

V. CONCLUSION

Combining micro-expression recognition with EEG signals opens up exciting possibilities across various fields. From providing deeper insights through psychological testing to enhancing the way we interact with machines, this technology has the potential to make a meaningful impact in our daily lives and beyond. While significant progress has been made, substantial challenges remain to be overcome in order for this technology to realize its full potential. In the future, cross-disciplinary collaboration, innovative solutions in signal processing, more comprehensive and diverse datasets, and ethical considerations will be necessary to bring micro-expression recognition using EEG to practice. As advances continue in the methods and applications of this technology, the possibilities for enriching emotional communication, enhancing therapeutic processes, and improving human

understanding will continue to expand. By building upon the current body of research and addressing these key challenges, the field stands poised for significant breakthroughs that will impact a wide range of industries, from mental health care to AI-driven applications

REFERENCES

- [1] Saffaryazdi, N., Wasim, S. T., Dileep, K., Nia, A. F., Nanayakkara, S., Broadbent, E., & Billinghurst, M. (2022). Using Facial Micro-Expressions in Combination With EEG and Physiological Signals for Emotion Recognition. *Frontiers in Psychology*, 13, 864047.
- [2] Zhao, X., Liu, Y., Chen, T., Wang, S., Chen, J., Wang, L., & Liu, G. (2022). Differences in brain activations between micro- and macro-expressions based on electroencephalography. *Frontiers in Neuroscience*, 16, 903448. <https://doi.org/10.3389/fnins.2022.903448>
- [3] Zeng, X., Zhao, X., Wang, S., Qin, J., Xie, J., Zhong, X., Chen, J., & Liu, G. (2022). Affection of facial artifacts caused by micro-expressions on electroencephalography signals. *Frontiers in Neuroscience*, 16, 1048199. <https://doi.org/10.3389/fnins.2022.1048199>
- [4] Benlamine, M. S., Chaouachi, M., Frasson, C., & Dufresne, A. (2016). Physiology-based Recognition of Facial Micro-expressions using EEG and Identification of the Relevant Sensors by Emotion: Proceedings of the 3rd International Conference on Physiological Computing Systems, 130–137.
- [5] Zhao, X., Chen, J., Chen, T., Wang, S., Liu, Y., Zeng, X., & Liu, G. (2022). Responses of functional brain networks in micro-expressions: An EEG study. *Frontiers in Psychology*, 13, 996905.
- [6] Zhao, X., Chen, J., Chen, T., Liu, Y., Wang, S., Zeng, X., Yan, J., & Liu, G. (2024). Micro-Expression Recognition Based on Nodal Efficiency in the EEG Functional Networks. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 32, 887–894. <https://doi.org/10.1109/TNSRE.2023.3347601>
- [7] Wang, S., Zhao, X., Yuan, G., Li, W., & Liu, G. (2022). The Establishment and Application of a Micro-expression Dataset with EEG Signals. *Proceedings of the 8th International Conference on Computing and Artificial Intelligence*, 726–729. <https://doi.org/10.1145/3532213.3532323>
- [8] Kim, H., Zhang, D., Kim, L., & Im, C.-H. (2022). Classification of Individual's discrete emotions reflected in facial microexpressions using electroencephalogram and facial electromyogram. *Expert Systems with Applications*, 188, 116101. <https://doi.org/10.1016/j.eswa.2021.116101>
- [9] Zhang, Y., & Chen, W. (2025). A multimodal emotion classification method considering micro-expression information and simulating human visual attention mechanism. *Biomedical Signal Processing and Control*, 100, 107036. <https://doi.org/10.1016/j.bspc.2024.107036>
- [10] Zhao, X., Chen, J., Liu, Y., Chen, T., Wang, S., Zeng, X., & Liu, G. (2022). Electrophysiological evidence for inhibition hypothesis of micro-expressions based on tensor component analysis and Physarum network algorithm. *Neuroscience Letters*, 790, 136897.
- [11] Islam, Md. K., & Rastegarnia, A. (2023). Editorial: Recent advances in EEG (non-invasive) based BCI applications. *Frontiers in Computational Neuroscience*, 17, 1151852.
- [12] Maiseli, B., Abdalla, A. T., Massawe, L. V., Mbise, M., Mkocha, K., Nassor, N. A., Ismail, M., Michael, J., & Kimambo, S. (2023). Brain-computer interface: Trend, challenges, and threats. *Brain Informatics*, 10(1), 20.
- [13] Singh, A. K., & Krishnan, S. (2023). Trends in EEG signal feature extraction applications. *Frontiers in Artificial Intelligence*, 5, 1072801. <https://doi.org/10.3389/frai.2022.1072801>
- [14] Pei, Y., Tang, J., Tang, Q., Zha, M., Xie, D., Wang, G., Liu, Z., Xie, N., Wang, P., Yang, Y., & Shen, H. (2024). Emotion Recognition in HMDs: A Multi-task Approach Using Physiological Signals and Occluded Faces. *Proceedings of the 32nd ACM International Conference on Multimedia*,
- [15] Wang, Z., Zhang, K., Luo, W., & Sankaranarayanan, R. (2024). HTNet for micro-expression recognition. *Neurocomputing*, 602, 128196. <https://doi.org/10.1016/j.neucom.2024.128196>
- [16] Li, H., Niu, H., & Zhao, F. (2024). From Macro to Micro: Boosting micro-expression recognition via pre-training on macro-expression videos (No. arXiv:2405.16451). *arXiv*.
- [17] Yang, H., Xie, L., Pan, H., Li, C., Wang, Z., & Zhong, J. (2023). Multimodal Attention Dynamic Fusion Network for Facial Micro-Expression Recognition. *Entropy*, 25(9), 1246.
- [18] Wang, F., Li, J., Qi, C., Wang, L., & Wang, P. (2024). A 4D spontaneous micro-expression database: Establishment and evaluation. *IET Image Processing*, 18(10), 2584–2601.
- [19] Wezowski, K., & Penton-Voak, I. S. (2024). Relationship between low mood and micro-expression processing: Evidence of negative bias in interpreting fleeting facial expressions. *Royal Society Open Science*, 11(7), 231944. <https://doi.org/10.1098/rsos.231944>
- [20] Bai, M., & Goecke, R. (2024). Can Expression Sensitivity Improve Macro- and Micro-Expression Spotting in Long Videos? *Proceedings of the 2nd International Workshop on Multimodal and Responsible Affective Computing*, 30–38. <https://doi.org/10.1145/3689092.3689396>
- [21] Döllinger, L., Laukka, P., Högman, L. B., Bänziger, T., Makower, I., Fischer, H., & Hau, S. (2021). Training Emotion Recognition Accuracy: Results for Multimodal Expressions and Facial Micro Expressions. *Frontiers in Psychology*, 12, 708867. <https://doi.org/10.3389/fpsyg.2021.708867>

- [22] Fan, X., Chen, X., Jiang, M., Shahid, A. R., & Yan, H. (2023). SelfME: Self-Supervised Motion Learning for Micro-Expression Recognition. 2023 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 13834–13843. <https://doi.org/10.1109/CVPR52729.2023.01329>
- [23] Liu, X., Shi, H., Chen, H., Yu, Z., Li, X., & Zhao, G. (2021). iMiGUE: An Identity-free Video Dataset for Micro-Gesture Understanding and Emotion Analysis. 2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 10626–10637.