Utilizing virtual reality for real-time emotion recognition with artificial intelligence: a systematic literature review

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Article Info

Article history:

Received Jun 11, 2024
Revised Aug 27, 2024
Accepted Sep 4, 2024

Keywords:

Algorithms
Classifications
Electroencephalogram
Emotional
Virtual reality

ABSTRACT

Efficiency and optimization in virtual reality (VR) technology is an urgent need, especially in the context of optimizing algorithms to recognize user emotions while using VR. Efficient VR technology can improve user experience and enable more immersive and responsive interactions. This study adopts the preferred reporting items for systematic reviews and meta-analyses (PRISMA) (2020) method to identify and analyze gaps in the existing literature, focusing on the optimization of electroencephalogram (EEG) signal classification algorithms to recognize VR users' emotions. The literature search was conducted through the Scopus database, with article selection based on the type of emotion classified, the classification method used, the limitations of the research, and the results obtained. Of the 1478 articles found, 74 articles passed the initial selection stage, and the final stage 13 articles were selected for further analysis. The selected articles provide important insights into the development of EEG classification algorithms for VR users, especially in multi-user settings. The findings identify potential and opportunities in the development of more efficient and accurate EEG signal classification algorithms for VR users. By focusing on emotion classification in a multi-user VR environment, this research contributes to improving the efficiency of VR technology and supporting a better and more responsive user experience.

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1. INTRODUCTION

Virtual reality (VR) technology has experienced rapid development over the past decade, becoming a leading innovation in digital interaction and immersive experiences. The development of VR for multiple users is primarily driven by the desire to create more inclusive, dynamic, and collaborative virtual environments. In this context, VR serves not only as a medium for individual experiences but also as a platform for unprecedented social interaction and collaboration.

With advancements in VR hardware and software, the focus has shifted to virtual environments that allow users to interact with each other in VR, expanding VR applications beyond entertainment to education [1], [2], training [3], [4], teamwork [5], [6], and even tourism in VR museums [7]. This trend drives research and development of VR technology that supports multi-user activities, leveraging VR's potential to enhance collaborative learning, simulate teamwork in controlled risk conditions, and create other social experiences [8]-[10].

Studies by [11], [12] demonstrate the significant potential of VR in enhancing user collaboration, but research by [13] reveals the need for further investigation, particularly in the aspects of collaborative activities and their effectiveness. While VR offers a more immersive environment, there is still a lack of research on how this technology can be effectively used to maximize knowledge retention, such as in the healthcare field to prepare users for real clinical practice. Research on multi-user VR technology has been developed by several researchers, with issues that need further exploration including the need to increase the number of users to provide significant test results [14]–[17]. Additionally, conditioning users' health status before using VR applications is necessary [1], and early detection of user motion sickness is essential [18]. Previous review studies on the optimization of emotion classification have focused on facial emotion recognition for positive and negative emotions [19], [20], emotion analysis based on media [21], emotion analysis for individuals with autism [22], and electroencephalogram (EEG) feature extraction reviews using machine learning and deep learning [23].

The integration of technologies such as EEG in VR applications introduces additional complexity. EEG is a technique for recording the brain's electrical activity used in various applications involving emotional research. According to Prabowo *et al*. [24] EEG is a primary choice in emotion recognition research due to its unique capability to directly reflect central nervous system activity with high temporal resolution, allowing real-time observation of dynamic changes in brain activity associated with emotional processes. Its non-invasive nature and relatively low cost make EEG widely accessible and facilitate its use in diverse settings, including real-time studies that approximate natural conditions. Additionally, the characteristic of EEG being difficult to be modified by research subjects makes it an objective and reliable method for measuring emotional responses, offering more dynamic insights that complement or overcome the limitations of other emotion measurement methods. EEG works on the principle that neurons in the brain generate electrical activity when users communicate with each other. This technique enables researchers to monitor and analyze patterns of brain electrical activity, providing valuable insights into an individual's neurological and cognitive conditions. Further technical development and understanding of the differences in brain activity between VR and real environments require additional research to maximize the potential of developed VR applications [25].

Given the challenges of effectively managing multi-user VR environments under varying clinical conditions, further research is necessary to monitor real-time user conditions while using VR applications [26], [27]. The integration of EEG in VR applications offers significant potential for enhancing understanding and development across various fields, including rehabilitation and neural studies [1], [28]. However, there are technical and methodological challenges that must be addressed to maximize the synergy between these two technologies. This research focuses on improving system reliability, understanding the differences in brain activity between VR and real environments, and integrating VR and EEG more effectively, particularly for multi-user scenarios. This understanding will pave the way for developing more immersive and responsive VR applications that cater to the mental states of users [29].

In the development of recent VR applications, a significant advancement is the ability to measure and analyze user emotions using EEG signals. This technology allows researchers to classify users' emotional responses to virtual stimuli. A study by Marín-Morales *et al*. [30] utilizing the support vector machine (SVM) algorithm to recognize emotions from brain and heart dynamics in VR achieved an algorithm effectiveness of 73%. Furthermore, research by Moghimi *et al*. [31] used k-nearest neighbors (KNN) and SVM algorithms in VR environments, successfully enhancing human-machine interaction with classification accuracies of 87% and 92%, respectively. These studies demonstrate the substantial potential in developing VR applications that are responsive and adaptive to users' emotional states. The use of VR technology, combined with EEG data collection and other physiological metrics in well-controlled settings, will enable in-depth research into emotional dynamics and their impact on user experience in virtual environments.

Despite significant advancements in VR research and EEG signal classification, challenges remain in optimizing algorithms to enhance emotion classification for users. The main challenges include the complexity of EEG data, variability among users, and the need for more efficient and accurate algorithms. Further research is needed to deeply explore how user comfort can be measured and improved through the optimization of EEG classification algorithms. Focusing on developing more accurate and efficient algorithms can help overcome these challenges and provide better solutions for multi-user VR applications [32], [33].

This study adopts the preferred reporting items for systematic reviews and meta-analyses (PRISMA) (2020) method [34] to review the existing literature, focusing on optimizing EEG signal classification algorithms to recognize VR user emotions. This approach will help identify gaps in the literature and provide insights into the potential and opportunities for developing more efficient and user-friendly VR technology. Out of 1478 articles found, 74 articles passed the initial selection stage and finally, 13 articles were selected for further analysis, providing a strong foundation for the development of EEG classification algorithms in a multi-user VR setting.

2. METHOD

This research follows the PRISMA concept in conducting a systematic literature review (SLR), as illustrated in Figure 1. PRISMA is a reporting standard designed to help researchers conduct systematic reviews transparently and comprehensively. PRISMA provides guidelines that ensure all steps in the systematic review process are reported in detail, from literature search to data analysis, facilitating reproducibility, and clarity in research.

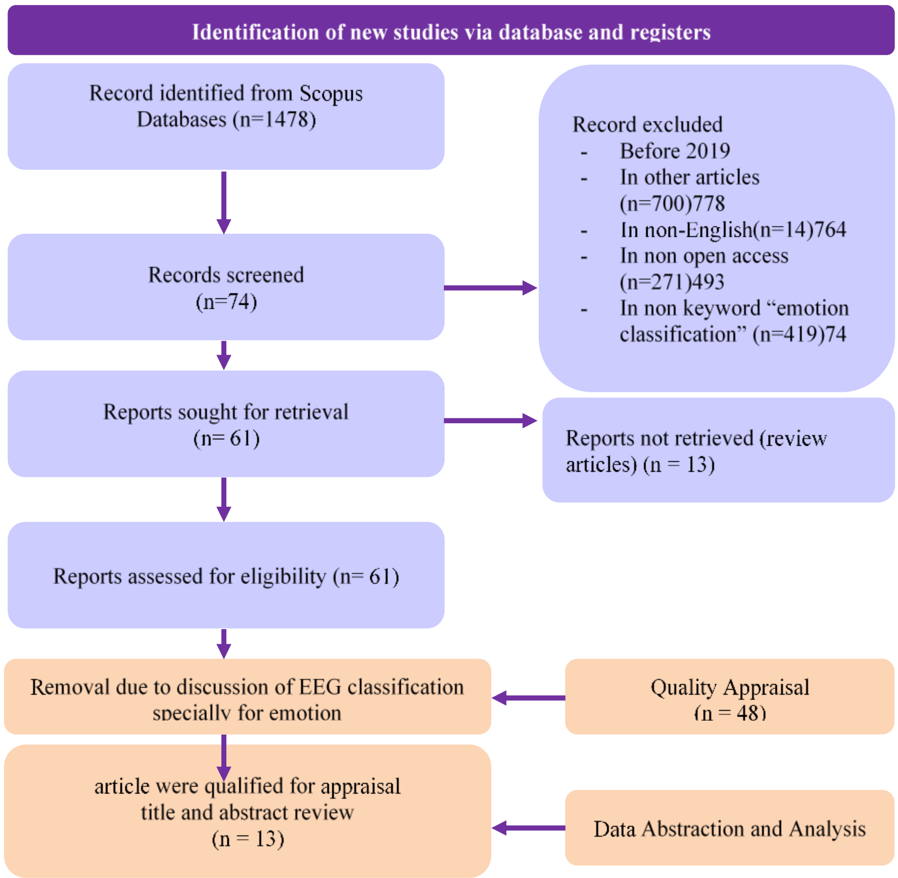

Figure 1. SLR process (adapted from PRISMA [34])

2.1. Formulation of research questions

In conducting this SLR, the first step is the formulation of clear and focused research questions. The main topic of this research is the optimization of algorithms for EEG signal classification. The research questions are formulated to explore how EEG classification algorithms can be improved to more accurately recognize user emotions in a multi-user VR environment.

2.2. Literature search strategy

The literature search strategy was conducted through the Scopus portal, one of the largest and most reputable academic databases. The search was performed using keywords relevant to the two main research topics. Table 1 shows the first set of keywords included "Virtual Reality", "Emotion Recognition", "Real-Time", and "Artificial Intelligence". Table 2 shows additional filters were applied to ensure that the selected articles were peer-reviewed and relevant to the research topics. Figure 1 shows the initial search results for the first set of keywords, with articles published after 2019, yielded 1,478 articles. These articles were further screened based on data abstraction and analysis, resulting in 13 articles that were deemed significant and contributed to an in-depth analysis of the development of algorithms for EEG signal classification.

Table 1. Keywords used for selecting the database in Scopus

Database	Search keywords
Scopus	"Virtual Reality" AND "Emotion Recognition" AND "Real-time" AND "Artificial Intelligence" AND PUBYEAR > 2019 AND PUBYEAR < 2025 AND (LIMIT-TO (SRCTYPE, "j")) AND (LIMIT-TO (OA, "all")) AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (EXACTKEYWORD, "Emotion Recognition")).

Table 2. Table of article groupings by experts

Code	Title	Year	Paper quality by expert 1			Paper quality by expert 2			Remarks
			High	Moderate	Low	High	Moderate	Low	
1	Simplified 2D CNN architecture with channel selection for emotion recognition using EEG spectrogram [35]	2023	√			√			
2	Physiological sensors based emotion recognition while experiencing tactile enhanced multimedia [36]	2020	√			√			
3	Online learning for wearable EEG-based emotion classification [37]	2023	√			√			
4	Nuclear norm regularized deep neural network for EEG-based emotion recognition [38]	2022		√			√		
5	Musical emotions recognition using entropy features and channel optimization based on EEG [39]	2022	√			√			
6	Multi-input CNN-LSTM deep learning model for fear level classification based on EEG and peripheral physiological signals [40]	2023	√			√			
7	M1M2: deep-learning-based real-time emotion recognition from neural activity [41]	2022	√			√			
8	Emotion-driven analysis and control of human-robot interactions in collaborative applications [42]	2021		√			√		
9	Emotion recognition with audio video EEG and EMG a dataset and baseline approaches [43]	2022		√			√		
10	Cross-subject channel selection using modified relief and simplified CNN-based deep learning for EEG-based emotion recognition [44]	2023		√			√		
11	Analysis of personality and EEG features in emotion recognition using machine learning techniques to classify arousal and valence labels [45]	2020		√			√		
12	Affective computing on machine learning-based emotion recognition using a self-made EEG device [46]	2021	√			√			
13	A hybrid hand-crafted and deep neural spatio-temporal EEG features clustering framework for precise emotional status recognition [47]	2022	√			√			

2.2.1. Screening strategy of articles

The selection process, as illustrated in Figure 1, began with the given keywords "Virtual reality", "Emotion recognition", "Real-time", and "Artificial intelligence" for articles published after 2019, yielding 1,478 articles. The initial filter was applied to include only articles and exclude conference papers, review papers, and short surveys, resulting in 778 articles. Further, articles not in English were excluded, reducing the count to 764 articles. Next, a filter was applied to include only open-access articles, resulting in 493 articles. Lastly, articles with the keyword "emotion classification" were excluded, narrowing the count to 74 articles. A brief review of the article titles and abstracts was then conducted, resulting in 13 review articles. Finally, articles were assessed for eligibility, focusing on those that reviewed emotional classification using EEG signals, culminating in 13 eligible articles [48]–[50].

2.2.2. Eligibility of articles for synthesis

Once the articles were deemed eligible in the SLR process, several crucial steps followed. First, data extraction was conducted by designing a form to record key information from each article, including authors, publication year, methods, main findings, contributions, and research limitations. This was followed by systematic data extraction. Second, the data was analyzed through categorization and grouping based on themes, methods, or main findings, followed by narrative synthesis. Third, the quality of the articles was grouped. Fourth, the results were interpreted and presented, with a discussion of findings in the context of the research questions, identification of gaps and research opportunities, and clear conclusions. Lastly, the SLR report was compiled according to PRISMA guidelines, ensuring transparency and reproducibility, allowing the research to be replicated by other researchers.

2.3. Quality apprasial of articles

After the eligibility process, the quality of the articles will be assessed. The quality assessment of the articles is classified into three levels: high, medium, and low. Only articles with high and medium-quality ratings will be considered for inclusion. The assessment includes the algorithms used, classification results, and the focus on the physiological EEG signals utilized. Table 2 shows the expert evaluations in categorizing the articles as high, medium, or low quality [51].

2.4. Data abstraction and analysis on article

Thematic analysis is used to identify, analyze, and report sub-themes within the research. An initial understanding of the data through article reviews allows for the identification and categorization of themes. Category creation is represented by coding each article. This analysis process resulted in 13 articles being categorized at high and moderate levels.

3. RESULTS AND DISCUSSION

Based on the stages of identification, screening, eligibility, quality assessment, and data abstraction, several algorithms for classifying EEG signals for user emotions were identified. The analysis stage can be mapped to the types of emotion recognition and the use of classification algorithms according to the accuracy results produced for EEG classification. The grouping results of emotion recognition types are presented in Table 3 and the types of algorithms and the accuracy achieved for classifying EEG emotional signals are shown in Table 4.

Table 3. Categories of emotion recognition

Emotion recognition group	References
General emotion recognition	[35]-[37]
Specific emotion recognition	[38], [40], [41]
Special methods and techniques of emotion recognition	[39], [43], [47]
Implementation and validation of emotion recognition algorithms	[42], [45], [46], [52]

3.1. General emotion recognition

Farokhah *et al*. [35] proposed a simplified 2D convolutional neural network (CNN) model for EEG-based emotion recognition using a channel selection method. This study achieved an increase in inter-subject emotion recognition accuracy by 9.73% and 11.7% for valence and arousal using 32 channels, and by 3.53% and 7.2% with only 10 channels. This model helps reduce computational load while maintaining high accuracy, although inter-subject accuracy remains lower.

Raheel *et al*. [36] conducted research on emotion recognition using EEG, galvanic skin response (GSR), and photoplethysmography (PPG) in tactile multimedia. The results showed that the fusion of features from various modalities increased classification accuracy up to 79.76% for four emotions. The KNN method was used for emotion recognition and demonstrated a significant improvement in accuracy; however, there were limitations regarding privacy and camera positioning in conventional methods. Moontaha *et al*. [37] developed a real-time EEG emotion classification pipeline with an average F1 score of

87% for arousal and 82% for valence in a live labeling setup. This pipeline is fast enough for real-time prediction; however, class imbalance in arousal ratings needs to be addressed with up-sampling for training.

3.2. Specific emotion recognition

Liang *et al*. [38] proposed the norm regularized deep neural network (NRDNN) for EEG-based emotion recognition. This model captures structural information among various brain regions, achieving state-of-the-art performance in emotion recognition by leveraging structural information within the feature matrix. Although NRDNN improves average classification results compared to other methods, the study is limited to EEG-based emotion recognition.

Table 4. Classification algorithms and accuracy results

No	Classification algorithm	Reference/accuracy	Emotion recognition
1	CNN	[35] CNN and STFT (73.53%)	EEG
		[37] CNN and FFT (F1 score 87% for passion, 82% for valence)	EEG
		[41] CNN, FFT (99.89% (M1), 99.22% (M2))	EEG
		[44] CNN, RELIEF, and Morlet (high accuracy for valence and arousal)	EEG
		[47] Hybrid CNN, wavelet transform, and BoDF (96.7%)	EEG
2	KNN	[36] KNN (79.76%)	EEG, GSR, PPG
		[39] KNN, particle swarm optimization (PSO) (68.84-84.66%)	EEG (musical emotions)
		[43] KNN, SVM, RF, MLP, CNN, and LSTM (KNN significant)	Audio, video, EEG, and EMG
3	LSTM	[40] CNN and LSTM (98.79%, F1 score 99.01%)	EEG, peripheral physiological signals
		[43] KNN, SVM, RF, MLP, CNN, and LSTM (LSTM significant)	Emotion recognition with audio, video, EEG, and EMG
		[52] RF, SVM, gaussian Naive Bayes, k-NN, 1D-CNN, and LSTM (LSTM significant)	EEG (360 VR videos)
4	Adaptive random forest (ARF) and streaming random patches (SRP)	[37] ARF, SRP, and LR (F1 score 87% for passion, 82% for valence)	EEG
5	NRDNN	[38] NRDNN (91.2%)	EEG
6	Random forest (RF)	[52] RF, SVM, Gaussian Naive Bayes, k-NN, 1D-CNN, and LSTM (RF shows the best performance)	EEG (360 VR Videos)
7	Naive Bayes, random forest, and artificial neural network (ANN)	[45] Naive Bayes, RF, and ANN (<70% for arousal and valence)	EEG
8	SVM	[46] SVM, MLP, 1D-CNN 85.81% (subject-dependent), and 78.52% (subject-independent)	EEG
		[52] RF, SVM, Gaussian Naive Bayes, k-NN, 1D-CNN, and LSTM (RF shows the best performance)	EEG (360 VR videos)
		[47] Hybrid CNN, wavelet transform, and BoDF (96.7%)	EEG

Masuda and Yairi [40] developed a long short term memory (CNN-LSTM) multi-input deep learning model for classifying3 fear levels based on EEG and physiological signals. This model achieved 98.79% accuracy and a 99.01% F1 score in cross-validation, demonstrating effectiveness in recognizing fear. However, the classification of fear levels beyond four categories was not explored due to dataset constraints.

Akter *et al*. [41] used M1 and M2 CNN models for EEG-based emotion recognition. The M2 model required only 2 seconds of EEG signal to achieve 99.22% accuracy and over 96% accuracy with just 125 milliseconds of EEG data for valence classification. This model shows enhanced emotional recognition with minimal EEG data, but the research is limited to the DEAP dataset and subject-dependent recognition.

3.3. Special methods and techniques for emotion recognition

Xie *et al.* [39] used the KNN method for EEG-based emotion recognition with entropy features. This study employed long-term dynamic stimulus materials to evoke emotions and analyzed EEG signals using approximate entropy (ApEn) and sample entropy (SamPen). The study showed that emotion recognition accuracy ranged from 68.84% to 84.66%, with common channels reflecting universal features, although accuracy for the common channel set was about 10% lower.

Chen *et al*. [43] presented a new dataset comparing human emotion classification based on audio, video, EEG, and EMG modalities. This study demonstrated that bootstrapping biosensor signals (EMG and EEG) significantly improved emotion classification performance. The LSTM model was identified as suitable for classifying sequences of audio and human emotion images, outperforming other traditional classifiers in emotion classification.

Haq *et al*. [47] used continuous wavelet transform and deep neural networks for emotion detection from EEG signals. This study achieved 96.7% accuracy on the SEED dataset using continuous wavelet transform and differential entropy-based feature selection techniques. Although the results are promising, the discussion on the generalization of the proposed model is limited.

3.4. Implementation and validation of emotion recognition algorithms

Eyam *et al*. [42] developed a system to adapt cobot parameters based on human emotions using EEG technology. The study demonstrated that engagement emotions were higher when working with a cobot that adjusted based on human emotional states. However, the accuracy of emotion measurement and the limitations of repetition were highlighted as challenges.

Mai *et al*. [46] developed an affective computing method based on EEG for emotion recognition. The study achieved the highest average accuracy of 85.81% in subject-dependent cases and 78.52% in subject-independent cases using a combination of SamPen measures and 1D-CNN. However, limitations not explicitly mentioned in the provided context need to be addressed.

Martínez-Tejada *et al*. [45] analyzed the contribution of EEG data, age, gender, and personality traits in emotion recognition. The study showed that EEG features increased classification accuracy for arousal and valence labels. However, age, gender, and personality traits did not significantly influence emotion classification.

Xue *et al*. [52] introduced the CEAP-360VR dataset for continuous emotion annotation in 360 VR videos. The study demonstrated that the CEAP-360VR dataset enables immersive QoE assessment and momentary affective state evaluation. However, the selection of 360 video stimuli was limited due to the lack of a database.

3.5. Types of algorithms for emotion classification based on electroencephalogram

The types of algorithms and the accuracy achieved for classifying EEG emotional signals aim to evaluate the extent to which these algorithms play a role in classification and their future potential in research development. Based on Table 4, research on EEG-based emotion recognition using various methods and algorithms shows very promising results. CNN and LSTM, either separately or combined, achieve very high accuracy, with some studies reaching up to 99.89%. Other algorithms like KNN, RF, and SVM also perform well in certain contexts. Hybrid and optimized approaches, such as using wavelet techniques and channel selection, provide significant results with accuracy reaching 96.7%. Further research can focus on optimizing algorithms, using larger and more diverse datasets, and integrating with the latest technology to enhance the accuracy and efficiency of emotion recognition, especially in the context of multi-user VR applications.

3.6. New proposals electroencephalogram emotion classification algorithms for virtual reality

Based on the SLR conducted, the following recommendations are proposed for further research topics (see Table 5).

Table 5. Proposals for new developments in EEG emotion classification algorithms for VR

No	Recommendation	Description	Proposed innovation	References
1	Use of machine learning algorithms	Implement deep learning and hybrid models to improve classification accuracy	Develop a new hybrid model combining CNN and LSTM specifically for emotion classification in multi-user VR	[40], [53]
2	Optimization of Feature extraction techniques	Develop better feature extraction techniques and multimodal data fusion	Create a new feature extraction algorithm utilizing continuous wavelet transform and multimodal data fusion	[45], [46]
3	Development of EEG signals for multi-user	Manage signal interference and build individually adjustable models	Develop innovative interference management techniques and personalization models for EEG-based multi-user VR	[37], [41]
4	Real-time processing implementation	Use edge computing and optimize algorithms for real-time processing	Design a new, efficient edge computing architecture for real-time EEG classification in multi-user VR	[42], [37]
5	Better validation and evaluation	Use robust cross-validation techniques and larger datasets for evaluation	Develop stronger cross-validation methods and create a new, rich multi-user VR EEG dataset	[38], [52]
6	Hardware infrastructure enhancement	Use high-density EEG caps and comfortable EEG devices	Design and test new comfortable and efficient wearable EEG devices for long-term VR use	[46], [42]
7	Use of other supporting technologies	Combine AR technology and haptic feedback systems to enhance user experience	Develop new haptic feedback systems integrated with EEG emotion classification for multi-user VR	[42], [43]

4. CONCLUSION

Based on the conducted SLR, research on EEG-based emotion recognition has shown that algorithm optimization plays a crucial role in improving the accuracy and efficiency of emotion classification, especially in the context of VR users with diverse conditions, including multi-user settings. CNN and LSTM methods, both separately and combined, have shown very high results, with accuracy reaching up to 99.89%, making them the top choice for real-time applications in VR. Additionally, hybrid approaches combining CNN with wavelet techniques and channel selection have proven effective, achieving accuracy up to 96.7%. Algorithms like KNN, RF, and SVM also show significant potential, especially when used in combination with feature optimization techniques such as particle swarm optimization (PSO) and nuclear norm regularization. However, challenges remain in ensuring the generalization of these models to various user conditions, including individual variability and multi-user dynamics. Further research is needed to develop adaptive and robust algorithms capable of handling the complexity and diversity of EEG signals in dynamic VR environments. These efforts should include the development of larger and more diverse datasets, the integration of superior deep learning techniques, and extensive validation in real multi-user situations to ensure the success of applications in practical scenarios.

ACKNOWLEDGEMENTS

This research was funded by Universitas Sebelas Maret with contract number 356/UN27/KP/2024 to complete further studies in the Doctoral Program in Engineering Science, Faculty of Engineering, Universitas Negeri Yogyakarta.

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