

EEG-Based Cybersickness Classification Using Hjorth Parameters and Random Forest During 3D Gaming Exposure

Alfi Zuhriya Khoirunnisaa*, Misbah

Department of Electrical Engineering, Faculty of Engineering, Universitas Muhammadiyah Gresik, Indonesia

*Corresponding author, e-mail: alfi.zuhriya@umg.ac.id

Abstract— This study presents an efficient EEG-based framework for cybersickness classification utilizing Hjorth parameter features under a 3D immersive video game stimulus (*Mirror Edge*). Multimodal data acquisition was performed using a 14-channel Emotiv EEG system for objective measurement and the Simulator Sickness Questionnaire (SSQ) for subjective validation. The EEG signals were subjected to comprehensive preprocessing procedures, including band pass filtering and Independent Component Analysis (ICA) to eliminate artifacts. Then, using Discrete Wavelet Transform (DWT) to isolate theta, alpha, and beta bands. Hjorth parameters: activity, mobility, and complexity were subsequently extracted to capture the temporal dynamics of neural activity with low computational overhead. To mitigate feature redundancy and dimensionality, Correlation Feature Selection reduced the feature space from 126 to 9 salient features. Classification performance was evaluated using Random Forest, Support Vector Machine, and K-Nearest Neighbor. Experimental results indicate a consistent increase in SSQ scores across participants, with disorientation emerging as the predominant symptom. Random Forest achieved superior performance with an accuracy of 82%, outperforming K-NN (72.72%) and SVM (59.09%). Notably, feature reduction preserved Random Forest performance while enhancing alternative classifiers. These findings highlight the robustness and computational efficiency of the proposed approach, demonstrating its potential for real-time EEG-based cybersickness detection.

Keywords: Cybersickness, EEG, hjorth parameter, Random Forest, 3D game

This article is licensed under the [CC-BY-SA](#) license.

1. Introduction

The rapid advancement of digital technology, particularly in the three dimensional (3D) video game industry, has progressed significantly over recent decades. 3D games provide immersive experiences through realistic and interactive virtual environment visualizations. However, despite these advantages, a health-related issue known as *cybersickness* has emerged. Cybersickness refers to a physiological discomfort experienced during interaction with virtual environments, characterized by symptoms including dizziness, nausea, visual fatigue and spatial disorientation [1],[2]. Although cybersickness is often considered similar to motion sickness due to their comparable clinical symptoms, both conditions are conceptually different. Cybersickness is triggered by exposure to virtual environments that create conflicts between visual perception and the vestibular system without actual physical movement, for example when individuals play 3D video games using Virtual Reality (VR). In contrast, motion sickness occurs due to sensory conflicts caused by real physical body movement, resulting in inconsistencies among the visual, vestibular, and proprioceptive systems, such as those experienced by passengers in vehicles, buses, or airplanes [3].

Cybersickness may negatively affect user comfort, reduce both physical and psychological performance, and limit the duration of interaction with virtual reality technologies and 3D video games. Therefore, there is a need to increase awareness regarding the importance of early and objective cybersickness detection and monitoring, particularly for users interacting with virtual environments in both online and offline 3D gaming applications.

Along with the development of Brain-Computer Interface (BCI) technology, Electroencephalography (EEG) signals have emerged as a promising approach for the objective detection of physiological conditions such as cybersickness. EEG is capable of recording brain electrical activity with high temporal resolution, making it suitable for detecting cognitive and physiological changes associated with cybersickness. Numerous studies have explored the utilization of EEG signals for cybersickness detection and classification from various perspectives, including feature extraction methods, optimal EEG channel selection, stimulus objects, and brain mapping analysis [4].

A study conducted in [5] classified cybersickness and normal conditions using time-domain features and the 3D video game *Mirror's Edge* as the stimulus. The study identified three optimal features for cybersickness classification, namely standard deviation, variance, and number of peaks, achieving an accuracy of 83.3%. The EEG signals analyzed consisted of alpha (α) and beta (β) waves. In addition to physiological measurements, the study also employed subjective assessment using the Simulator Sickness Questionnaire (SSQ) developed by [1]. The combination of subjective (SSQ) and objective (EEG) measurements for cybersickness detection was also investigated by Naqvi *et al.* [6] using 2D and 3D movie stimuli for approximately 10 minutes. The results indicated that participants experiencing cybersickness obtained higher SSQ scores after watching 3D movies and exhibited decreased beta (β) wave power in the temporal brain region as well as decreased theta (θ) wave power in the frontal region based on EEG brain activity mapping. Meanwhile, the study conducted by [7] combined SSQ and eye-tracking methods for cybersickness detection. Participants were exposed to a driving simulator for approximately 10 minutes. The findings revealed that participants experiencing cybersickness showed high SSQ scores and tended to lose focus, as observed from the eye-tracking results.

Despite previous studies investigating EEG-based cybersickness detection using either subjective assessment, EEG feature extraction, or machine learning approaches, limited research has comprehensively integrated objective EEG measurements and subjective SSQ validation using Hjorth parameter features under immersive 3D gaming exposure. In addition, previous studies have rarely investigated the effectiveness of feature dimensionality reduction using Correlation-based Feature Selection (CFS) for improving computational efficiency in EEG-based cybersickness classification. Therefore, this study aims to fill this research gap by proposing an efficient cybersickness classification framework that combines EEG-based Hjorth parameters, SSQ validation, CFS-based feature reduction, and comparative machine learning analysis using an immersive 3D game stimulus.

The main contributions of this study are summarized as follows : (1) the integration of objective measurements (EEG) and subjective assessments (SSQ) for cybersickness classification using the 3D video game *Mirror's Edge* as the stimulus, thereby improving ground-truth validity; (2) the utilization of Hjorth parameters, including activity, mobility, and complexity features extracted from alpha (α), beta (β), and theta (θ) waves, to represent EEG signal characteristics in a compact yet informative time-domain representation; (3) the implementation of Correlation-based Feature Selection (CFS) to significantly reduce data dimensionality without decreasing classification accuracy; and (4) a comparative performance analysis of several machine learning algorithms for EEG-based cybersickness classification [8]. Therefore, this study contributes not only to classification accuracy improvement, but also to computational efficiency, measurement validity, and a deeper understanding of EEG feature characteristics for cybersickness detection, with the potential for implementation in real-time detection systems.

2. Method

2.1 Participant Profile

A total of nine participants were involved in the experimental study, consisting of seven males and two females aged between 19 and 22 years. All participants possessed normal or corrected to normal vision, were right-handed, and reported no history of chronic illness or medication dependence. To

ensure physiological consistency, participants were instructed to avoid caffeine consumption, obtain at least six hours of sleep, and have breakfast on the day prior to data acquisition. These requirements were enforced to ensure an optimal physiological condition during the experiment. Prior to data collection, participants were briefed regarding the experimental procedure and were informed about the potential effects that may occur during cybersickness induction.

This study involved human participants and was conducted in accordance with ethical standards for research involving human subjects. Prior to the experiment, all participants were informed about the experimental procedures, potential risks, and cybersickness symptoms that might occur during the gameplay session. Written informed consent was obtained from all participants before data acquisition. Participants were also allowed to withdraw from the experiment at any stage without any consequences. All collected data were anonymized and used solely for research purposes.

2.2 Selection of 3D Video Game

This study utilized the 3D video game *Mirror's Edge*, developed by EA Digital Illusions CE, as the experimental stimulus. The game was chosen based on recommendations from the Game Surabaya community (GADAS) and its previous application in cybersickness research conducted by Guo et al [9] for the detection of Visual Induced Motion Sickness (VIMS). *Mirror's Edge* is a first-person perspective (FPP) action-adventure game that focuses on parkour-based movement within a futuristic urban setting, as shown in Figure 1. The fast-paced motion and dynamic visual presentation make this game suitable as a cybersickness-inducing stimulus. In addition, its visual characteristics enable effective acquisition of physiological responses, EEG and eye-tracking signals.

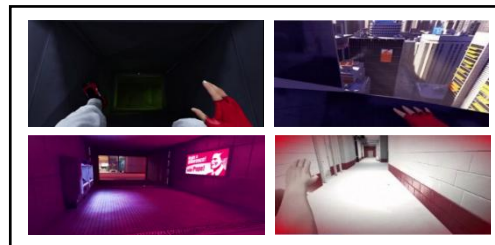


Figure 1. *Mirror Edge's* Game Stages [10]

2.3 Objective and Subjective Measurement Instruments

In this study, the Brain-Computer Interface (BCI) used for objective measurement was the Emotiv EPOC+ 14-channel EEG headset. This device is a non-invasive EEG system designed to record brain electrical activity from the scalp. The electrode placement follows the international 10–20 system, as illustrated in Figure. 2.

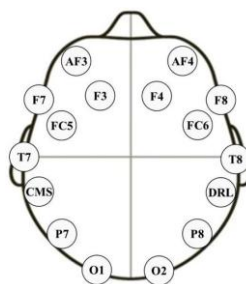


Figure 2. Emotiv EPOC+ 14-channel EEG headset

The subjective assessment instrument utilized in this study was the Sickness Questionnaire (SSQ), originally developed by Kennedy et al [3]. The SSQ is a standardized questionnaire designed to evaluate the severity of cybersickness symptoms after exposure to virtual environments or 3D visual stimuli. SSQ consist of 16 symptoms categorized into 3 subscales like Nausea, Oculomotor and Disorientation as presented in Tabel 1.

Table 1. SSQ Symptom Categories

Nausea	Oculomotor	Disorientation
General discomfort	General discomfort	Difficulty focusing
Increased Salivation	Fatigue	Nausea
Sweating	Headache	Fullness of head
Nausea	Eye strain	Blurred vision
Difficulty concentrating	Difficulty focusing	Dizzy (eyes open)
Stomach awareness	Blurred vision	Dizzy (closed open)
Burping	Difficulty concentrating	Vertigo

The Nausea subscale is associated with gastrointestinal discomfort and general autonomic imbalance. The Oculomotor subscale reflects visual strain and eye-related fatigue, while the Disorientation subscale is related to vestibular dysfunction and spatial disorientation. Each symptom is rated using a four-point Likert scale: 0 (none), 1 (slight), 2 (moderate), and 3 (severe). The weighted SSQ score, referred to as Total Severity Cybersickness (TSC), is calculated using the following equation:

$$TSC = (([1] \times 9.54) + ([2] \times 7.58) + ([3] \times 13.92)) \times 3.74 \quad (1)$$

Where N, O and D represent the total score of the Nausea, Oculomotor and Disorientation subscales, respectively. The resulting TSC score is used to determine the severity level of cybersickness experienced by participants after exposure to the virtual reality stimulus.

2.4 Data Acquisition Using Emotiv EPOC+

The data acquisition scenario in this study consisted of four stages, as illustrated in Figure. 3. The initial stage involved a pre-SSQ assessment, during which participants completed the SSQ to evaluate their baseline condition before EEG acquisition was conducted using the Emotiv EPOC+ device. The second stage involved EEG data recording using the Emotiv EPOC+ 14-channel headset.

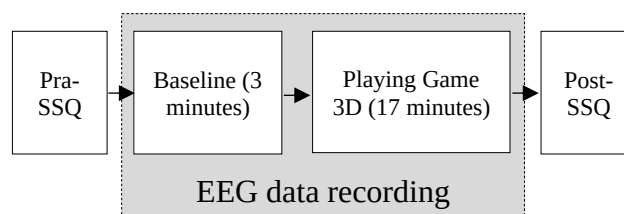


Figure 3. Data acquisition

EEG recording was conducted for a total duration of 20 minutes, consisting of a 3-minute baseline period and a 17-minute gameplay session. During the baseline phase, participants were instructed to remain seated in a stationary position, keep their eyes closed, stay relaxed and minimize all bodily movements.

Following the baseline recording, participants proceeded to the gameplay phase, in which they played the 3D video game *Mirror's Edge* for 17 minutes using a keyboard and mouse, as shown in Figure. 4. The game was displayed on a 47-inch television monitor with a resolution of 1366×768 pixels. The distance between the participant and the display screen was maintained at approximately 50 cm. A webcam was positioned in front of the participant to record all behavioral activities during the gameplay session for further analysis.

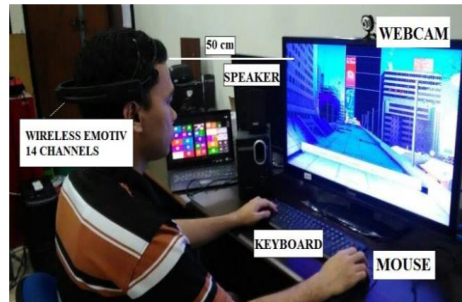


Figure 4. EEG Data Recording Using Emotiv Epoc+[10]

Following the EEG recording session, participants were given a 2 minute rest period to reduce potential residual effects induced by gameplay exposure. Subsequently, they were instructed to complete the post-SSQ questionnaire (post-exposure SSQ) to evaluate their cybersickness condition after interacting with the 3D video game stimulus.

2.5 EEG Signal Processing Method

The EEG signal processing pipeline in this study consists of five main stages, namely EEG preprocessing, time-frequency analysis, feature extraction (Hjorth parameters), feature selection, and classification, as illustrated in Figure. 5.

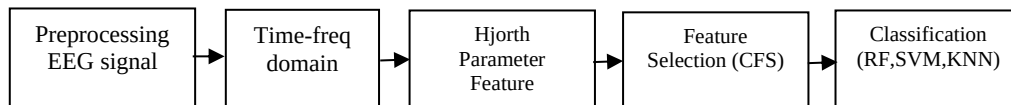


Figure 5. EEG Signal Processing Pipeline

2.5.1 Preprocessing

Signal preprocessing was conducted to minimize noise interference and eliminate artifact that could affect EEG analysis quality. One of the most significant artifacts is the Electrooculography (EOG) signal, which is caused by eye blinks and eye movements.

In this study, EOG artifact removal was conducted using EEGLAB toolbox. The raw EEG data were initially imported into EEGLAB and subsequently processed using a Finite Impulse Response (FIR) band pass filter within the frequency range of 1-40 Hz to preserve the relevant EEG components. Furthermore, Independent Component Analysis (ICA) was employed to separate neural EEG activity from noise components, particularly ocular artifacts [11], [12].

2.5.2 Time-Frequency Analysis Using Discrete Wavelet Transform

EEG signals are non-stationary and dynamic in nature, meaning their frequency characteristics vary over time. Therefore, time–frequency analysis is highly suitable for EEG signal processing. In this study, the Discrete Wavelet Transform (DWT) was applied to decompose EEG signals into three frequency bands, namely theta (4–8 Hz), alpha (8–16 Hz), and beta (16–32 Hz), using a sampling frequency of 256 Hz. The signal decomposition process was conducted up to level 6 employing the

Daubechies 4 (db4) mother wavelet. This process resulted in a feature matrix of size 14 electrodes $\times$ 3 frequency bands for each participant. However, only two segments of the EEG data were analyzed using wavelet decomposition: the baseline condition (3 minutes) and the last 3 minutes of the cybersickness induction phase, as illustrated in Figure. 6.

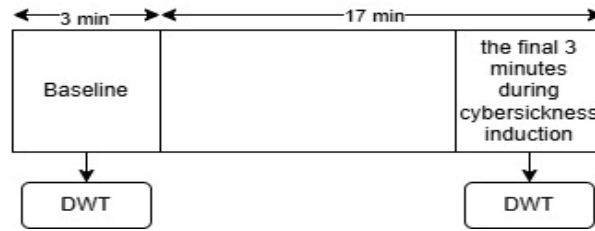


Figure 6. EEG Segments used for DWT Analysis
 (baseline vs final 3 minutes of cybersickness induction)

2.5.3 Hjorth Features

Hjorth descriptors are commonly utilized in EEG feature extraction since they effectively describe temporal characteristics of brain signals with low computational complexity. Yuri *et al.*[13] applied Hjorth parameters for detecting fatigue in Search and Rescue (SAR) teams using a Bagged Tree machine learning algorithm, achieving an accuracy of 94.8%. Similarly, Asyraf *et al.*[14] utilized Hjorth parameters to identify brain regions associated with chronic neuropathic pain. In this study, Hjorth parameters are also employed, consisting of three features: activity, mobility, and complexity.

a. Activity

Activity represents the signal variance in the time domain and reflects the overall energy of the EEG signal. A higher activity value indicates higher signal energy and increased brain activity:

$$Activity = var(y(t)) \quad (1)$$

b. Mobility

Mobility reflects the mean frequency or the proportion of standard deviation of the power spectrum, representing how fast the EEG signal changes over time:

$$Mobility = \sqrt{\frac{var\left(\frac{dy(t)}{dt}\right)}{var(y(t))}} \quad (2)$$

c. Complexity

Complexity measures the similarity of the signal to a pure sine wave and reflects the signal's irregularity or structural complexity:

$$Complexity = \frac{Mobility\left(\frac{dy(t)}{dt}\right)}{Mobility(y(t))} \quad (3)$$

Where $y(t)$ represents the EEG signal in the domain, and $\frac{dy(t)}{dt}$ denotes its first derivative. Higher complexity values indicate more irregular and less predictable brain activity

2.5.4 Feature Selection

The EEG acquisition system used in this study employs 14 channels, resulting in a large number of extracted features. Specifically, each participant generates: 14 electrodes $\times$ 3 frequency bands $\times$ 3 Hjorth parameters = 126 features. The high dimensionality of the feature space increases computational complexity and may degrade classification performance. Therefore, Correlation-based Feature Selection (CFS) is applied to select the most relevant features for cybersickness detection. CFS, proposed by Hall [15], has also been applied in previous studies, such as channel selection optimization in EEG-based systems by Khoirunnisaa *et al.* This method assumes that an optimal feature subset consists of features that exhibit strong correlation with the target class while maintaining minimal correlation among the features themselves. The CFS merit function is defined as:

$$Merits = \frac{k\bar{r}_{cf}}{\sqrt{k+k(k-1)\bar{r}_{ff}}} \quad (4)$$

where:

- k : number of feature in the subset
- $\bar{r}_{cf}$: average feature-class correlation
- $\bar{r}_{ff}$: average inter-feature correlation

2.5.5 Classification Using Machine Learning

Random Forest is a supervised machine learning algorithm that has been extensively utilized for prediction and pattern recognition in EEG-based application[16][17][18]. This approach is frequently employed because of this robust ability to manage nonlinear data characteristics and the high variability commonly observed in EEG signals.

Random Forest is an ensemble learning technique composed of multiple decision trees constructed using the bagging (bootstrap aggregating) approach. In this method, each decision trees is trained on a randomly selected subset of data and features, while the final classification outcome is determined through a majority voting mechanism [19][20]. The advantages of Random Forest include robustness to noise, minimal parameter tuning requirements, ability to handle high-dimensional data, and generally high classification accuracy compared to other machine learning algorithms. However, its limitations include high computational cost and relatively low interpretability. To address the high dimensionality problem in this study, CFS-based feature selection is applied prior to classification.

3. Result and Discussion

3.1 Subjective Measurement of Cybersickness

All participants involved in the cybersickness experimental scenario completed the Simulator Sickness Questionnaire (SSQ) twice: before cybersickness induction (pre-SSQ) and after the induction process (post-SSQ). The two scores were subsequently compared to evaluate changes in cybersickness severity. According to previous studies [7][21], participants are considered to experience cybersickness when the Total Severity Cybersickness (TSC) score obtained from the post-SSQ assessment is higher than that of the pre-SSQ assessment. The results of the TSC score calculation for all participants are presented in Figure. 7.

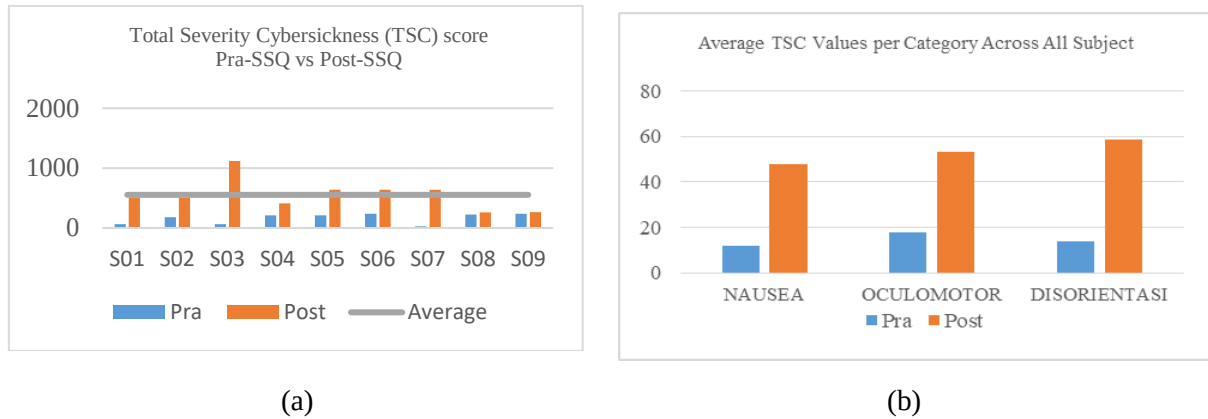


Figure 7a. Comparison of pre-SSQ and post-SSQ TSC Scores, **7b.** Average Scores for Each SSQ Category Across Nine Participants

The graph in Figure. 7 shows that all nine participants involved in the cybersickness experimental scenario exhibited higher post-SSQ TSC scores compared to pre-SSQ scores, although the magnitude of the score increase varied among participants. This finding indicates that the 3D game stimulus successfully induced cybersickness symptoms in all participants.

Based on the average threshold represented by the green line, four participants (S03, S05, S06, and S07) obtained post-SSQ scores above the average value, indicating a higher level of cybersickness severity. In contrast, the remaining five participants showed post-SSQ scores below the average threshold, suggesting relatively lower cybersickness levels.

Participants S08 and S09 demonstrated the smallest difference between pre-SSQ and post-SSQ scores. This condition is presumed to be associated with their prior experience in playing 3D video games, which may have enabled them to adapt more effectively to the *Mirror's Edge* gameplay environment and character movement mechanisms. Consequently, their perceived cybersickness symptoms were relatively lower compared to the other participants. This finding is consistent with previous studiws reporting that experienced gamers tend to exhibit greater adaptation to visually induced motion environments.

To evaluate the effect of the 3D game stimulus on cybersickness severity, a statistical comparison between pre-SSQ and post-SSQ scores was conducted. Since the measurements were obtained from the same participants before and after the cybersickness induction, a paired statistical analysis was performed. The normality of the data distribution was initially evaluated using the Shapiro-Wilk test. When the data satisfied the normality assumption ($p > 0.05$), a paired t -test was subsequently performed to examine whether a statistically significant difference existed between the pre-SSQ and post-SSQ scores. Otherwise, the non-parametric Wilcoxon signed-rank test was employed.

The significance level was set at 0.05. Statistical analysis was conducted to determine whether exposure to the 3D video game stimulus significantly increased the Total Severity Cybersickness (TSC) score. The results demonstrated that the post-SSQ scores were generally higher than the pre-SSQ scores for most participants, indicating an increase in cybersickness symptoms after gameplay exposure. This finding suggests that the 3D game stimulus successfully induced cybersickness conditions during the experiment. The paired t -test revealed a statistically significant difference between the pre-SSQ and post-SSQ scores ($p = 0.012 < 0.05$), indicating that exposure to the gameplay significantly increased the severity of cybersickness.

In addition to the comparison between pre-SSQ and post-SSQ scores, this study also analyzed the increase in each SSQ subscale category, as presented in Figure. 8. The graph illustrates the average scores of the nine participants for the three SSQ categories, namely Nausea, Oculomotor, and Disorientation, before and after cybersickness induction. The results indicate that the Disorientation

category exhibited the highest increase, with an average increment of 44.86 points, followed by Oculomotor with 35.39 points and Nausea with 36.11 points. These findings suggest that disorientation-related symptoms were the most dominant effects experienced by participants during exposure to the 3D video game stimulus.

Previous studies [2] reported that cybersickness symptoms generally follow the pattern Disorientation > Nausea > Oculomotor (D > N > O). However, this pattern is not consistently observed across all cybersickness detection studies [22]. A similar phenomenon was identified in the present study, where the average scores across all participants showed the pattern Disorientation > Oculomotor > Nausea (D > O > N) following cybersickness induction using the 3D video game stimulus.

The dominance of disorientation symptoms compared to oculomotor and nausea symptoms is likely caused by strong visual-vestibular conflicts resulting from dynamic first-person perspective movements within the virtual environment. This condition primarily affects spatial orientation and visual processing, thereby producing stronger disorientation and oculomotor responses among participants. Meanwhile, nausea symptoms tended to develop more gradually and were less dominant, particularly among participants with prior experience playing the 3D video game *Mirror's Edge*. Previous gaming experience may facilitate adaptive mechanisms that decrease susceptibility to cybersickness symptoms during exposure to virtual environments. This finding is consistent with the Sensory Conflict Theory, which proposes that cybersickness occurs due to discrepancies between visual motion perception and vestibular sensory feedback.

3.2 Objective Measurement of Cybersickness

The objective measurement of cybersickness in this study was conducted using the Emotiv EPOC+ 14-channel EEG system to record brain signals. EEG data were collected over a total duration of 20 minutes, consisting of baseline (pre-stimulus) and post-stimulus conditions after 3D video game exposure. Each condition had a duration of 3 minutes.

The EEG dataset was segmented per minute, resulting in 20 data segments per participant. Each segment consisted of 126 features, obtained from 14 EEG channels × 3 frequency bands × 3 Hjorth parameters. In this study, the first 4 minutes were used as baseline data and labeled as non-cybersickness, while the last 4 minutes were used as post-stimulus data and labeled as cybersickness. Consequently, each participant contributed 8 segments × 126 features, resulting in a total dataset of 72 × 126 features across nine participants.

3.3 Classification Using Random Forest

The classification model was implemented using the Random Forest algorithm with a test size of 0.3, where 70% of the data was used for training and 30% for testing. A fixed random state value of 42 was used to ensure reproducibility by controlling the data shuffling process. The Random Forest model achieved an overall classification accuracy of 82%. The detailed performance results are presented in Table 2.

Table 2. Random Forest Classification Performance

Class	Precision	Recall	F1-Score
Non Cybersickness	0.82	0.82	0.82
Cybersickness	0.82	0.82	0.82

3.4 Comparison with Other Machine Learning Methods

To further assess the effectiveness of the proposed approach, the performance of the Random Forest (RF) classifier was compared with that of Support Vector Machine (SVM) employing a linear kernel and K-Nearest Neighbor (K-NN) with $k = 5$. The comparative results are presented in Table 3.

Table 3. Comparison of Machine Learning Methods

Method	Accuracy (%)
SVM kernel linier	59.09%
K-NN (k=5)	72.72%
Random Forest	82%

The results indicate significant differences in classification performance among the evaluated methods. The SVM with a linear kernel achieved the lowest accuracy (59.09%), indicating limited capability in capturing the nonlinear patterns of EEG-based cybersickness data. This limitation is attributed to the linear decision boundary, which is not well-suited for complex EEG signal characteristics. The K-NN method achieved an accuracy of 72.72%, demonstrating improved performance compared to SVM. This suggests that cybersickness-related EEG features exhibit local similarity patterns that can be effectively captured using distance-based classification.

In contrast, Random Forest achieved the highest accuracy of 82.00%. This superior performance is attributed to its ensemble learning mechanism, which combines multiple decision trees using bagging. This approach enables the model to capture nonlinear relationships among Hjorth features while reducing the risk of overfitting. Additionally, Random Forest is more robust to noise and variability in EEG signals.

Overall, Random Forest is more effective for cybersickness classification compared to SVM and K-NN due to its ability to handle nonlinear and high-dimensional EEG data.

3.5 Feature Selection Using CFS

Despite demonstrating strong performance, Random Forest exhibits relatively high computational complexity, particularly when processing high-dimensional dataset (72x126 features). To mitigate this issue, Correlation based Feature Selection (CFS) was employed to reduce the dimensionality of the feature space. CFS identifies and selects features that exhibit strong correlation with the target class while maintaining minimal redundancy among feature. The selected features are presented in Table 4.

Table 4. Selected Features Using CFS

Selected Features	
1. Activity_theta4	6. Complexity_beta9
2. Complexity_alpha2	7. Activity_alpha9
3. Complexity_alpha10	8. Mobility_theta1
4. Complexity_beta14	9. Activity_theta1

5. Complexity_alpha11

After feature selection, the dataset dimension was reduced to 72×9 features. The reduced dataset was then used for classification using the same machine learning models. The comparative results before and after CFS are presented in Table 5.

Table 5. Classification Performance Before and After CFS

Machine Learning	Before CFS (126 x 72)	After CFS (9 x 72)
Random Forest	82%	82%
SVM	59.0%	61%
K-NN	72.7%	77.27%

The results show that SVM improved slightly from 59.09% to 61%, while K-NN improved from 72.72% to 77.27% after feature selection. However, Random Forest did not show any improvement in accuracy after CFS. This is because Random Forest inherently performs implicit feature selection during tree construction by randomly selecting feature subsets at each split. Therefore, irrelevant features are naturally mitigated within the ensemble process. Additionally, features removed by CFS may have contributed minimally to classification performance, resulting in no significant impact on accuracy. Furthermore, the characteristics of the dataset, which exhibit relatively clear class separability, may also contribute to the stability of Random Forest performance even after dimensionality reduction. These findings indicate that feature selection does not always improve classification accuracy. However, it remains important for reducing computational complexity and improving model efficiency by reducing feature dimensionality.

4. Conclusion

This study presented an EEG-based cybersickness detection framework using a combination of objective and subjective measurements. Subjective assessment using the Simulator Sickness Questionnaire (SSQ) confirmed that all participants experienced an increase in Total Severity Cybersickness (TSC) scores after exposure to the 3D video game stimulus, indicating successful induction of cybersickness conditions. From the objective measurement perspective, EEG signals recorded using the Emotiv EPOC+ 14-channel system were processed using Hjorth parameters, feature selection, and machine learning classification. Among the evaluated models, Random Forest achieved the highest performance with an accuracy of 82%, outperforming K-NN (72.72%) and SVM with a linear kernel (59.09%). These results demonstrate that ensemble-based learning methods are more effective in capturing nonlinear patterns in EEG signals related to cybersickness.

Furthermore, the application of Correlation-based Feature Selection (CFS) reduced the feature dimensionality from 126 to 9 features per sample. Although feature reduction did not improve Random Forest accuracy, it enhanced computational efficiency and reduced model complexity. The stability of Random Forest performance after dimensionality reduction indicates its robustness to irrelevant or redundant features. Overall, the integration of EEG-based objective measurement and SSQ-based subjective assessment provides a more reliable framework for cybersickness detection. The findings confirm that EEG signals combined with machine learning techniques can effectively classify cybersickness conditions induced by 3D virtual environments.

Despite the promising results, several limitations remain in this study. First, the number of participants is relatively small, which may limit the generalizability of the model. Future studies should involve a larger and more diverse population to improve statistical validity and model robustness. Second, this study only utilized Hjorth parameters as feature descriptors. Future research may explore additional feature extraction techniques such as entropy-based features, connectivity analysis, or deep learning-based feature representation to capture more complex EEG patterns. Third, this study utilized conventional machine learning algorithms. Future research may explore advanced deep learning architectures, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), to enhance classification performance and facilitate end-to-end learning directly from raw EEG signals. Finally, real-time implementation of the proposed system should be explored to enable online cybersickness detection in practical virtual reality applications. This would allow adaptive VR systems to dynamically adjust visual stimuli based on user physiological responses, thereby minimizing cybersickness effects.

REFERENCES

- [1] R. S. Kennedy, J. Drexler, and R. C. Kennedy, "Research in visually induced motion sickness," *Appl. Ergon.*, vol. 41, no. 4, pp. 494–503, 2010, doi: 10.1016/j.apergo.2009.11.006.
- [2] L. Rebenitsch and C. Owen, "Virtual Reality Review on Cybersickness in Applications and Visual Displays." *Virtual Reality*, vol. 20, no. 2, pp. 101–125, 2016.
- [3] R. S. Kennedy, N. E. Lane, K. S. Berbaum, and M. G. Lilienthal, "Simulator Sickness Questionnaire: An Enhanced Method for Quantifying Simulator Sickness," *Int. J. Aviat. Psychol.*, vol. 3, no. 3, pp. 203–220, 1993, doi: 10.1207/s15327108ijap0303_3.
- [4] E. Chang, M. Billingham, and B. Yoo, "Brain activity during cybersickness: a scoping review," *Virtual Real.*, vol. 27, no. 3, pp. 2073–2097, 2023, doi: 10.1007/s10055-023-00795-y.
- [5] M. A. Mawalid, A. Z. Khoirunnisa, M. H. Purnomo, and A. D. Wibawa, "Classification of EEG Signal for Detecting Cybersickness through Time Domain Feature Extraction using Naïve Bayes," *2018 Int. Conf. Comput. Eng. Netw. Intell. Multimedia, CENIM 2018 - Proceeding*, pp. 29–34, 2018, doi: 10.1109/CENIM.2018.8711320.
- [6] S. A. A. Naqvi, N. Badruddin, M. A. Jatoy, A. S. Malik, W. Hazabbah, and B. Abdullah, "EEG based time and frequency dynamics analysis of visually induced motion sickness (VIMS)," *Australas. Phys. Eng. Sci. Med.*, vol. 38, no. 4, pp. 721–729, Dec. 2015, doi: 10.1007/s13246-015-0379-9.
- [7] M. Bahit, S. Wibirama, H. A. Nugroho, T. Wijayanto, and M. N. Winadi, "Investigation of visual attention in day-night driving simulator during cybersickness occurrence," *Proc. 2016 8th Int. Conf. Inf. Technol. Electr. Eng. Empower. Technol. Better Futur. ICITEE 2016*, no. October, 2017, doi: 10.1109/ICITEED.2016.7863260.
- [8] A. H. X. Yang, N. Kasabov, and Y. O. Cakmak, "Machine learning methods for the study of cybersickness: a systematic review," *Brain Informatics*, vol. 9, no. 1, 2022, doi: 10.1186/s40708-022-00172-6.
- [9] "Active playing and passive watching." [Online]. Available: <http://forums.steampowered.com/forums/showthread.php?t=>
- [10] A. Z. Khoirunnisa, "Seleksi Kanal Pada Electroencephalograph (Eeg) Menggunakan Metode Correlation Feature Selection (Cfs) Untuk Identifikasi Cybersickness." CA: Institut Teknologi Sepuluh Nopember. 2018. pp : 32
- [11] C. Y. Sai, N. Mokhtar, H. Arof, P. Cumming, and M. Iwahashi, "Automated classification and removal of EEG artifacts with SVM and wavelet-ICA," *IEEE J. Biomed. Heal. Informatics*, vol. 22, no. 3, pp. 664–670, 2018, doi: 10.1109/JBHI.2017.2723420.
- [12] R. M. Mehmood and H. J. Lee, "Towards human brain signal preprocessing and artifact rejection methods," *Int'l Conf. Biomed. Eng. Sci.*, no. July, pp. 26–31, 2016.
- [13] Y. Pamungkas, R. D. Indriani, P. N. Crisnapati, and Y. Thwe, "Work Fatigue Detection of Search and Rescue Officers Based on Hjorth EEG Parameters," *J. Robot. Control*, vol. 5, no. 6, pp. 1836–1844, 2024, doi: 10.18196/jrc.v5i6.23511.
- [14] H. Asyrafi, N. Handayani, L. B. Ilmawan, F. Shabir, R. Jamal, and M. Jannah, "Jurnal Fisika

- Identification of Brain Areas Associated with Chronic Neuropathic Pain through Hjorth Parameter Analysis of EEG Signals,” vol. 15, no. 2, pp. 8–24, 2025.
- [15] M. A. Hall, “Correlation-based Feature Selection for Machine Learning,” PhD dissertation, Dept. Computer Science, University of Waikato. April, 1999.
 - [16] T. C. de Brito Guerra, T. Nóbrega, E. Morya, A. de M. Martins, and V. A. de Sousa, “Electroencephalography Signal Analysis for Human Activities Classification: A Solution Based on Machine Learning and Motor Imagery,” *Sensors*, vol. 23, no. 9, 2023, doi: 10.3390/s23094277.
 - [17] R. B. Jadekar, P. Basavaraju, S. B. S. Kumar, and M. Rafi, “Emotion Recognition from EEG Signals Using Principal Component Analysis and Random Forest Classifier,” *Eng. Technol. Appl. Sci. Res.*, vol. 15, no. 5, pp. 27300–27305, 2025, doi: 10.48084/etasr.12301.
 - [18] Y. Wang, W. Chen, K. Huang, and Q. Gu, “Classification of neonatal amplitude-integrated EEG using random forest model with combined feature,” *Proc. - 2013 IEEE Int. Conf. Bioinforma. Biomed. IEEE BIBM 2013*, vol. 13, no. Suppl 2, pp. 285–290, 2013, doi: 10.1109/BIBM.2013.6732504.
 - [19] C. Strobl, J. Malley, and G. Tutz, “An Introduction to Recursive Partitioning: Rationale, Application, and Characteristics of Classification and Regression Trees, Bagging, and Random Forests,” *Psychol. Methods*, vol. 14, no. 4, pp. 323–348, 2009, doi: 10.1037/a0016973.
 - [20] T. Hengl, M. Nussbaum, M. N. Wright, G. B. M. Heuvelink, and B. Gräler, “Random forest as a generic framework for predictive modeling of spatial and spatio-temporal variables,” *PeerJ*, vol. 2018, no. 8, 2018, doi: 10.7717/peerj.5518.
 - [21] S. Davis, K. Nesbitt, and E. Nalivaiko, “Comparing the onset of cybersickness using the Oculus Rift and two virtual roller coasters,” 2015.
 - [22] S. V. G. Cobb and J. R. Wilson, “Virtual Reality-Induced Symptoms and Effects,” pp. 169–186, 1996.