

This is the author-created version of the following work:

Hag, Ala, Qazani, Mohammad Reza Chalak, and Asadi, Houshyar (2025)
Quantifying Motion Sickness in Virtual Reality Using a Multimodal 1CNN–GRU–
Attention Approach With GSR Data. IEEE Transactions on Intelligent
Transportation Systems, 26 (12) pp. 22003-22014.

Access to this file is available from:

<https://researchonline.jcu.edu.au/89010/>

© 2025 IEEE. All rights reserved, including rights for text and data mining, and training of artificial intelligence and similar technologies. Personal use is permitted, but republication/redistribution requires IEEE permission.

Please refer to the original source for the final version of this work:

<https://doi.org/10.1109/TITS.2025.3605372>

Quantifying Motion Sickness in Virtual Reality Using a Multimodal 1CNN–GRU–Attention Approach with GSR Data

Ala Hag¹, *Member, IEEE*, Mohammad Reza Chalak Qazani², *Senior Member, IEEE*, Houshyar Asadi¹, *Member, IEEE*

Abstract—Cybersickness remains a significant barrier to the widespread adoption of virtual reality (VR) and enhancing passenger comfort and safety in autonomous vehicles (AVs). Predicting and mitigating cybersickness is crucial for creating safer and more comfortable VR experiences. This study introduces a one-dimensional convolutional neural network-gated recurrent unit-attention (1CNN–GRU–Attention) model trained on galvanic skin response (GSR) data collected from 24 participants in VR under various weather conditions. Participants reported cybersickness severity on a 10-point scale every minute, providing real-time labels for evaluation. The model’s performance was compared with that of k-nearest neighbours (KNN) and support vector machine (SVM) classifiers in binary (two-class) and multi-class (four-class: none, low, acute, high) classification settings, both with and without class balancing using the synthetic minority oversampling technique (SMOTE). Evaluation metrics included accuracy (ACC), Matthews correlation coefficient (MCC), and unified performance metric (UPM), with performance assessed via 5-fold cross-validation and statistical t-tests. Results show that the 1CNN–GRU–Attention model significantly outperforms both SVM and KNN across all metrics. Applying SMOTE improved binary classification accuracy from 75.15% to 86.94% in binary classification and from 48.77% to 64.63% in multiclass classification, with notable improvements in MCC. These findings highlight the importance of balanced data and the effectiveness of the 1CNN–GRU–Attention model in assessing cybersickness severity, advancing physiological monitoring methods for VR, and facilitating broader VR adoption.

Index Terms—cybersickness, virtual reality, galvanic skin response (GSR), deep learning, attention mechanism, SMOTE, GRU.

I. INTRODUCTION

The rapid advancement of technologies in the 21st century has made virtual reality (VR) a transformative force, revolutionising various sectors, including healthcare, education, training, and entertainment. VR’s potential to create immersive, interactive experiences has opened new opportunities in these fields. However, the widespread adoption of VR remains constrained by the persistent challenge of cybersickness.

Current studies report that cybersickness affects a substantial proportion of users during or after VR immersion [1]–[4]. An estimated 30%–80% of VR users experience cybersickness symptoms [5], [6], depending on individual susceptibility and VR system characteristics. Cybersickness, which shares many symptoms with motion sickness, is characterised by nausea, headaches, dizziness, disorientation, and sweating [3], [7], [8].

When VR is used in mobile settings such as autonomous vehicles (AVs), motion-induced discomfort becomes a greater concern. Anwar et al. [9] highlighted the compounded risks of cybersickness in autonomous vehicles (AVs) and stressed the need for Quality of Experience (QoE) standards to ensure user comfort during in-car immersive media consumption. Cybersickness symptoms can range from mild to severe and may persist for minutes to several hours, occasionally lasting up to five hours after VR exposure [10]. This variability in symptom duration underscores the need for targeted mitigation strategies and accurate quantification of cybersickness severity to enhance user safety in immersive systems and autonomous vehicles [10], [11].

Several theories have been proposed to explain the occurrence of cybersickness, including the sensory conflict theory, postural instability theory [12], and poison theory [13]. Among these, the sensory conflict theory is the most widely accepted. It posits that cybersickness arises from a mismatch between the visual motion perceived in the VR environment and the absence of corresponding physical motion. This mismatch conflicts with sensory inputs—visual, vestibular, and somatosensory—during unexpected movements, causing discomfort in healthy individuals [14].

Unlike motion sickness, which is caused by real motion, such as car rides or flights, cybersickness is induced by VR environments. Terms like cybersickness, VR sickness, and visually induced motion sickness are often used interchangeably. Visually induced motion sickness is a broader term that refers to the sensation caused by visual stimuli in virtual environments, such as VR experiences, video games, or movie theatres. This condition is also known as digital or simulation sickness involving motion simulators [15]–[17].

Although considerable effort has been directed toward identifying and mitigating the causes of cybersickness, the condition remains prevalent. Studies have highlighted its correlation with factors such as user demographics (e.g., age, gender, motion sickness history), system properties (e.g., latency, field of view, frame rate), and VR content characteristics (e.g.,

¹A. Hag and H. Asadi are with the Institute for Intelligent Systems Research and Innovation (IISRI), Deakin University, Victoria, Australia. s222327138@deakin.edu.au, houshyar.asadi@deakin.edu.au

²M. R. C. Qazani is with the College of Science and Engineering, James Cook University, Townsville, QLD 4814, and Faculty of Computing and Information Technology (FCIT), Sohar University, Sohar 311, Oman. m.r.chalakqazani@gmail.com

motion type, exposure time) [18]–[22].

This ongoing challenge highlights the complexity of the issue. However, finding comprehensive solutions that address all these aspects remains challenging. As VR technology and intelligent transportation systems continue to evolve, there is a need to refine strategies to mitigate cybersickness and improve user comfort and safety. Accurate assessment and quantification of the severity level of cybersickness are crucial, as they are the first step in adjusting VR systems to mitigate this persistent issue.

To address this, researchers have proposed strategies such as modifying VR content, such as reducing field-of-view changes and implementing smooth locomotion techniques and user acclimatisation strategies, which involve gradually increasing exposure to VR [23], [24]. However, these often lack real-time adaptability and fail to personalise the VR experience [25]. Therefore, recent approaches, such as dynamic field-of-view adjustments and physiological biofeedback systems, offer a promising personalised, real-time solution for mitigating cybersickness [26], [27]. Additionally, a novel approach by Kooijman et al. [28] investigated the influence of neck muscle vibrations on the perception of illusory self-motion in VR. They found that while neck vibrations enhanced vection quality and presence, cybersickness was not strongly associated with either presence or vection.

Research highlights the importance of physiological signals and sensory feedback in managing discomfort. Buchheit [29] introduced the 6DOF-SVC model for motion sickness prediction in self-driving cars, emphasising the role of vehicle dynamics patterns and human factors response. Kim [30] linked visual-vestibular mismatches to simulator sickness, while Reza [31] optimised motion-cueing algorithms to reduce sensory conflicts in VR. Li Ma [32] advanced passenger task detection using lightweight neural networks with attention mechanisms, emphasising real-time adjustments. Together, these studies underscore the critical role of sensory feedback in mitigating cybersickness in immersive environments. Despite these advancements, cybersickness remains a pressing challenge for VR design and adoption [4], [33].

Traditionally, cybersickness has been assessed using subjective self-report methods such as the Simulator Sickness Questionnaire (SSQ) and the Virtual Reality Sickness Questionnaire (VRSQ). While these tools offer insights into nausea, oculomotor issues, and disorientation, they are limited in providing continuous or real-time feedback [1], [19], [21], [34]–[37]. Additionally, the fast motion sickness scale (FMS) is widely used in most current studies to evaluate the severity level of motion sickness [21]. Generally, subjective assessment methods rely on participants' subjective reports, which can vary widely and may not accurately reflect the physiological response.

To overcome the subjectivity and limitations of traditional assessment methods, researchers have increasingly adopted objective approaches that rely on physiological and behavioural signals. Common physiological signals include heart rate (HR), heart rate variability (HRV), electrodermal activity (EDA), blood volume pulse (BVP), respiration (RESP), photoplethysmography (PPG), galvanic skin response (GSR) [34],

[38], and eye movement are used to evaluate the severity of cybersickness [11], [39].

While these signals offer promising real-time insight into users' physiological states, each signal presents its challenge, for instance, electroencephalography (EEG) setups are complex and noise-sensitive [40], [41]; non-cybersickness factors like stress or exercise influence HRV; and GSR susceptible to environmental variations like temperature and humidity [38], [42], [43]. Eye-based metrics such as pupil dilation and gaze direction have shown potential, though they can be affected by lighting and user attention [10], [25].

In addition to physiological measures, recent research has highlighted behavioural markers as valuable tools for detecting cybersickness. For instance, Kinsella et al. [44] found that the use of head-mounted displays (HMDs) significantly increased postural sway, which not only impaired task performance but also served as an indicator of user discomfort. Similarly, Smart et al. [45] demonstrated that nonlinear kinematic parameters could be employed in real-time to predict motion sickness, suggesting that behavioural features offer a valuable complement to physiological measures in immersive environments.

Among physiological signals, GSR stands out for its practicality as it is cost-effective, easy to deploy, and closely linked with sympathetic nervous system arousal. These properties make it particularly suitable for real-time detection of cybersickness in both lab and field settings.

To model these physiological and behavioural inputs, researchers have employed machine learning (ML) approaches. These models often integrate multi-sensor data streams, including VR content, head and torso movements, eye-tracking, and GSR, to predict cybersickness [29], [46], [47]. While promising, many existing studies still rely on conventional ML classifiers or sequential hybrid models like CNN-LSTM architectures [38], [48], [49].

However, sequential models present certain drawbacks. By processing data in a chained fashion—where CNN outputs are passed into LSTM or GRU units—they risk losing valuable spatial-temporal information at transition stages. This issue is especially critical when dealing with physiological signals like GSR, which require fine-grained temporal analysis [5], [17], [38], [50], [51]. This loss of crucial information could potentially impair the accuracy of quantifying cybersickness. Additionally, these models assume continuous input from all sensors, making them vulnerable to sensor dropout, which can interrupt the entire prediction pipeline.

To address these issues, this study proposes a non-sequential multimodal architecture—1CNN–GRU–Attention—that processes spatial and temporal data in parallel rather than sequentially. This model is trained using only GSR data collected under varied environmental conditions, including different weather states that introduce visual oscillations in the aircraft simulator. The novelty of our approach lies in:

- Using a single, lightweight physiological modality (GSR) under real-world conditions,
- Employing a non-sequential fusion architecture that preserves spatial-temporal dependencies without the limitations of chaining models,

- Leveraging an attention mechanism to dynamically prioritise relevant signal components, thus mitigating GSR's inherent latency.

In this structure, the 1D-CNN extracts spatial features from tonic and phasic GSR signals, the GRU captures temporal dependencies, and the attention layer dynamically weights important patterns. This architecture enhances the model's ability to detect cybersickness severity with improved accuracy and generalisability.

We hypothesise that this model will outperform traditional classifiers, such as SVM and KNN, which struggle to capture complex nonlinear dependencies in physiological time-series data.

The rest of the paper is structured as follows: Section II reviews related work, Section III outlines the methodology and proposed model, Section IV presents the model performance results, Section V discusses the findings and limitations, and Section VI concludes with the key contributions of this study.

II. RELATED WORK

This section provides a detailed review of existing studies relevant to our research. It focuses on GSR-based cybersickness studies and reviews the performance of various AI models used for these tasks, highlighting their limitations and motivating our proposed non-sequential attention-based approach.

1) *GSR-based Cybersickness Studies*: Previous studies have found a direct association between sweating and motion sickness, making it a well-documented physiological response [38], [52], [53].

GSR is particularly suited for detecting cybersickness, as it measures changes in skin conductivity caused by sweat gland activity triggered by autonomic nervous system (ANS) arousal, providing a direct correlation to these symptoms [39]. Cybersickness often induces nausea, dizziness, and sweating, which are direct manifestations of ANS activation. Researchers have shown that cybersickness and motion sickness can increase both tonic and phasic GSR components, reflecting the body's fight-or-flight response. For example, Wan et al. [54] demonstrated that tonic and phasic skin conductance correlated with motion sickness severity, with forehead measurements proving more accurate than palmar finger measurements.

Also, Gavvani et al. [55] confirmed that tonic and phasic GSR readings from the forehead and fingers increased with nausea levels. Similarly, Irmak et al. [53] found tonic and phasic GSR levels escalated in response to motion sickness. However, they also noted that GSR increased over time independently of motion sickness, suggesting the influence of external factors. Another study by Kim et al. [6] observed a significant increase in skin conductance levels (SCL) during the final minute of navigation in a simulator, correlating with increased simulator sickness symptoms. In contrast, Jäger et al. [56] observed a decrease in SCL in participants using a driving simulator, indicating that SCL responses may not consistently increase with motion sickness symptoms under specific conditions or environments. While most studies

find a positive correlation between SCL and motion sickness/cybersickness score [6], [53], [55], some report weak or no correlations [57].

Although GSR has shown promise, limitations remain. Being a distal measure of brain activity, it introduces latency due to signal propagation time through the central and peripheral nervous systems. This delay complicates data synchronisation, reducing real-time detection performance. Our study addresses this limitation by applying attention mechanisms to dynamically prioritise time-sensitive features in GSR signals.

2) *Prediction of Cybersickness Based on Machine Learning*: The use of machine learning (ML) to predict cybersickness has gained traction in recent years. Studies have leveraged data from physiological signals, VR content, eye-tracking, and head and body movements to build predictive models. For instance, Hwang et al. [38] compared six unimodal classification models and four multimodal fusion methods in a real driving scenario, where participants reported their actions every minute using a keypad, revealing that GSR performance had lower accuracy than EEG and HR. Another study by Dennison et al. [39] showed that EEG and electrocardiography (ECG) features were effective in modelling cybersickness.

Similarly, Dayoung et al. [58] utilised eye-tracking and head movement data to predict VR sickness, highlighting the potential of visual and vestibular cues in these models. The multimodal learning approach has been a focus due to its ability to fuse multiple sensors, such as EEG, HR, and GSR data, thereby enhancing synchronisation and robustness. Almost all multimodal studies report higher accuracy than unimodal models [38], [48], [50], [59].

Therefore, recent studies have highlighted the importance of multimodal learning, which involves multiple forms of sensory input. multimodal analysis using machine learning leverages data from various sources, such as EEG, HR, and GSR, to provide a comprehensive understanding of motion sickness. This approach not only improves data synchronisation and detection accuracy but also compensates for the weaknesses of individual modalities [38], [60]. However, multi-method approaches offer potential for assessing cybersickness but present several limitations. These include extensive setup time—particularly for EEG—limited real-life applicability, high data dimensionality, challenges in sensor integration, and the cost and complexity of using multiple sensors. Such issues complicate the practical deployment of multimodal methods in real-world scenarios, making efficient and cost-effective solutions challenging to achieve [38], [60], [61].

To mitigate high dimensionality—commonly referred to as the "curse of dimensionality"—researchers have employed feature selection techniques. For instance, Li et al. [62] employed principal component analysis (PCA) to reduce the dimensions of EEG data, thereby enhancing classification accuracy. Colmenares et al. [63] applied recursive feature elimination to physiological signals, boosting deep learning performance. Wang et al. [64] employed a mutual information-based selection approach for multimodal data, thereby improving accuracy and robustness. Hadadi et al. [50] employed persistent entropy and empirical mode decomposition in VR studies, achieving higher classification accuracy. These

works underscore the promise of multimodal systems while highlighting ongoing challenges such as data quality, sensor synchronisation, and individual variability.

However, traditional feature selection methods, such as PCA and recursive elimination, are typically static and struggle to capture contextual dependencies, nonlinear relationships, and scalability [65]. Attention mechanisms perform context-aware, dynamic feature weighting, which is better suited to non-stationary, high-dimensional signals than static selection [66]. These limitations motivate a non-sequential architecture that fuses spatial and temporal cues in parallel and uses attention to focus on informative segments.

Recent studies have explored hybrid AI models for quantifying cybersickness, demonstrating improved performance over single-model approaches [38], [48], [49]. Yet, many rely on sequential architectures such as CNN-LSTM, where a convolutional neural network processes spatial features before passing them to an LSTM for temporal analysis. While effective, this step-wise structure can lead to information loss, reducing the model's accuracy in assessing cybersickness severity.

Additionally, these models depend on continuous data streams from all sensors, meaning that a failure in any single sensor can disrupt predictions and compromise system robustness. For example, Islam et al. [48] used a CNN-LSTM model for binary classification of cybersickness severity based on the Fast Motion Sickness (FMS) scale.

Hwang et al. [38] classified motion sickness levels using bio-signals collected during real driving. Their framework compared six unimodal and four multimodal fusion methods, finding that combining self-attention with tensor fusion achieved 76.26%.

Similarly, Hadadi et al. [50] investigated VR navigation using physiological signals (GSR, BVP, HR, temperature), analysed through persistent entropy and empirical mode decomposition. Using a dataset from 53 participants, they achieved 71% accuracy with an SVM-RBF classifier and topological data analysis. Despite promising outcomes, these approaches rely on sequential processing pipelines that may not effectively preserve spatial and temporal dependencies. Furthermore, the need for real-time, robust, and low-cost solutions remains unmet.

In response, we propose a novel non-sequential model architecture, 1CNN-GRU-Attention, trained solely on GSR signals. Unlike sequential models, our architecture processes spatial and temporal features in parallel, reducing information loss and enhancing model robustness. The attention mechanism prioritises informative segments in the GSR time series, compensating for inherent delays and environmental variability.

This work addresses key gaps in current literature by: (1) removing reliance on expensive or complex multimodal setups, (2) introducing a robust fusion mechanism via attention, and (3) demonstrating the generalisability of a GSR-only approach in real-world conditions.

III. METHODOLOGY

This section outlines the methodology employed to develop and evaluate the proposed 1CNN-GRU-Attention model for

quantifying the severity level of cybersickness in virtual reality (VR). The methodology is designed to address the limitations of using GSR data alone (collected from different weather conditions) by integrating advanced non-sequential AI models to improve the accuracy and reliability of cybersickness detection.

A. Participants

The VR experiment was conducted at Deakin University. A total of 24 volunteers participated in this study, mainly students and staff of the Institute for Intelligent Systems Research and Innovation (IISRI) at Deakin University. All participants were male (mean age 29.0 ± 3.9 years), reported good health, and had no reported visual or vestibular dysfunction. Before the experiment began, participants completed informed consent and pre-study questionnaires. All participants had no prior VR experience, ensuring their responses were not influenced by familiarity or habituation effects.

B. Experiment Procedure

The VR experiment was structured into three phases: briefing, training, and main flight scenarios. Each experimental session lasted approximately 70 minutes. Participants were informed about the study's objectives and procedures during the 13-minute briefing, followed by completion of consent forms and the pre-experiment Simulator Sickness Questionnaire (pre-SSQ). COVID-19 screening was conducted before entry and took approximately 5 minutes. Physiological sensors were then attached to their bodies, a process that required approximately 15 minutes.

During the 10-minute training phase, participants practised flying simulators using both a flat screen and a VR headset (HMD), as shown in Fig. 1. All scenarios were conducted at Avalon Airport following a predetermined flight path, as illustrated in Fig. 2. The main flight scenarios involved navigating a virtual environment under either "clear" or "stormy" weather conditions, presented in a randomised order. Each scenario lasted approximately 7 minutes, followed by a 1-minute post-SSQ and a 2-minute break.

Participants were informed that they could stop at any point if they felt unwell and were asked about their well-being every minute. The simulated weather conditions were: "clear," with good visibility and no wind, and "stormy," with strong winds and varying visibility (rain and dark clouds) to induce cybersickness.

C. Device and Equipment

The experiment was conducted using a high-performance computer that exceeded the recommended specifications of the Next Level Racing Motion Platform V3 (NLRMP V3). The VR setup consisted of an HTC Vive HMD with Tobii Pro eye tracking and an Equivital life monitor (ELM) for physiological data. The GSR was attached to fingers and connected to the ELM belt recorder, with a sampling rate of 16 Hz. The virtual environment was built in X-Plane 11 using a Cirrus SR22 aeroplane model. The scenarios were conducted using a



Fig. 1. Flying patterns and maps used in the flying simulator (Google Maps).



Fig. 2. Experiment set-up with attachment of HTC VIVE Pro Eye, and Equivalant EQ02 life monitor sensor belt and recording device. The experiment was performed using the Next Level Racing Motion Platform V3 (NLRMP V3).

predefined virtual path of Avalon Airport, incorporating the Next Level Racing Motion Platform V3 (NLRMP V3), as shown in Fig. 2.

D. Data Collection and Annotation

During the experiment, participants verbally reported the severity level of cybersickness every minute, using the FMS score, which ranged from 0 to 10 [21]. The physiological data of GSR were collected to correlate with FMS scores at each given time point. During the analysis phase, the cybersickness severity levels were categorised based on FMS scores into two scenarios: binary classification and multi-level severity classification. The binary classification divided the data into "No Sickness" and "cybersickness (CS)." The multi-level severity classification further divided the data into four categories: no sickness (NS), low sickness (LS), acute sickness (AS), and high sickness (HS). The grouping of cybersickness severity levels was formed according to the following rules:

$$\text{Cybersickness}_{\text{binary}} = \begin{cases} \text{NS}, & \text{if } 0 \leq FMS_t < 1, \\ \text{CS}, & \text{if } 1 \leq FMS_t \leq 10. \end{cases} \quad (1)$$

$$\text{Cybersickness}_{\text{multi}} = \begin{cases} \text{NS}, & \text{if } 0 \leq FMS_t < Q1, \\ \text{LS}, & \text{if } Q1 < FMS_t \leq Q2, \\ \text{AS}, & \text{if } Q2 < FMS_t \leq Q3, \\ \text{HS}, & \text{if } Q3 < FMS_t \leq 10. \end{cases} \quad (2)$$

where $Q1 = 1$, $Q2 = 4$, and $Q3 = 7$ represent quantiles of the FMS distribution. This rule ensured that the physiological signals were accurately labelled according to the severity of the reported cybersickness. For instance, if a participant rated their FMS score as 5 at a given time t , all GSR data recorded up to that time, based on a window size of one minute, were annotated with an "Acute Sickness" label.

E. Models for Quantifying Cybersickness Severity Level

SVM and KNN are used to quantify cybersickness effectively. The detailed architecture of SVM and KNN is shown in Table I. SVM employs an RBF kernel to separate instances of cybersickness levels. In contrast, KNN uses the majority class of the five nearest neighbours for classification. Both models undergo K-Fold cross-validation (CV) with standardised features. Performance metrics, such as accuracy, the unified performance metric (UPM), and the Matthews correlation coefficient (MCC), are used to evaluate their effectiveness. We also proposed a model called 1CNN-GRU-Attention, which aims to reliably identify patterns of cybersickness and enhance mitigation strategies in virtual environments.

TABLE I
HYPERPARAMETERS FOR SVM AND KNN.

Model	Hyperparameter	Value
SVM	Kernel Function	Radial Basis Function (RBF)
	Regularization Parameter (C)	1.0
	Kernel Coefficient (gamma)	'scale'
KNN	Number of Neighbours (k)	5
	Distance Metric	Euclidean distance

TABLE II
THE BEST HYPERPARAMETERS FOR THE 1CNN-GRU-ATTENTION MODEL SELECTED BASED ON A GRID SEARCH APPROACH WITH THE UPM AS THE EVALUATION CRITERION.

Hyperparameter	Value
L1 Regularization (ConvID)	0.001
L2 Regularization (Dense)	0.001
Dropout Rate	0.2
GRU Units	64
Convolutional Filters	128
Convolutional Kernel Size	3
Pooling Size	2
Dense Layer Units	64
Optimizer	AdamW
Learning Rate	0.001

F. 1CNN-GRU-Attention Model Architecture

Our proposed model employs a multimodal, non-sequential approach comprising three fusion modules: 1CNN, GRU, and an attention mechanism (Fig. 3). 1CNN aims to extract spatial features from the GSR data. It employs a 1D convolutional

layer with various filter sizes to capture the spatial and temporal patterns of cybersickness onset. These features represent the spatial characteristics of the physiological response [67]. The GRU layer extracts data in parallel with the 1CNN. The GRU focuses on capturing the temporal features of the GSR data, which is used to track the sequential changes in GSR over time and capture the evolving physiological response associated with motion sickness susceptibility [68]. These features represent the temporal characteristics of the response. The output of both 1CNN and GRU layers is fed into the attention mechanism, which acts as a memory feature selection mechanism, identifying the most relevant features related to motion sickness severity levels [69]. By focusing on informative areas for predicting susceptibility to motion sickness, the attention mechanism enhances the model's overall accuracy and interpretability. It assigns weights based on their importance, resulting in a weighted combination of features from both branches. The combined weighted features from the attention mechanism are fed into two fully connected (Softmax) layers with non-linear activation functions. These layers further enhance the model's learning capacity and ability to model complex relationships within the data. The final Softmax layer, with the number of units corresponding to the number of output classes, 0 to 3 classes corresponding to the quantification level of motion sickness severity (none, low, acute, and severe), utilises a Softmax activation function to produce the final prediction class. The detailed architecture of the 1CNN-GRU-Attention model is presented in Table III.

TABLE III
THE ARCHITECTURE DETAILS OF THE 1CNN-GRU-ATTENTION MODEL.

Layer	Output Shape	Parameter	Dropout Rate	Activation Function
Conv1D	(287, 128)	512	-	ReLU
MaxPooling1D	(143, 128)	0	-	-
Dropout	(143, 128)	0	0.2	-
Bidirectional (GRU)	(289, 128)	99328	-	ReLU
Dropout (GRU branch)	(289, 128)	0	0.2	-
GlobalAveragePooling1D	128	0	-	-
Attention	(287, 128)	0	-	-
Layer Normalization	(287, 128)	0	-	-
Flatten	36656	0	-	-
Dense	64	2346048	-	ReLU
Dropout	64	0	0.2	-
Dense	4	260	-	Softmax

G. Data Preprocessing

Before training, the GSR data undergoes several preprocessing steps to ensure high-quality input and enhance model performance. First, the data is split into training and testing sets (80/20 split) to evaluate performance. Missing values in the window size are removed to maintain consistency across all windows. Outliers are removed using z-score analysis, which eliminates data points that are far away from the mean. Normalisation is applied to scale the data between 0 and 1. At the same time, standard scaling ensures that features have a mean of 0 and a standard deviation of 1, which aids models that are sensitive to data scale. To address the class imbalance, we employ the synthetic minority over-sampling

technique (SMOTE) [70], which generates synthetic samples for minority classes, ensuring a balanced representation. These preprocessing steps collectively improve the accuracy and robustness of the models in predicting cybersickness severity levels.

H. Model Training, Optimisation, and Evaluation

A subject-independent approach was employed for model development, using an 80/20 split for training and testing. Early stopping (patience = 10) was applied during training to prevent overfitting. Model performance was assessed using 5-fold cross-validation (CV) on the training set, reporting mean accuracy (ACC), unified performance metric (UPM), and Matthews correlation coefficient (MCC). The accuracy for both binary and multiclass classification was calculated as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

where TP represents true positives, TN represents true negatives, FP represents false positives, and FN represents false negatives.

The UPM has been proposed as an alternative to MCC, especially in imbalanced datasets [71]. UPM comprises the harmonic mean of F_1^+ and F_1^- scores and is calculated as:

$$\text{UPM} = \frac{4 \times TP \times TN}{(4 \times TP \times TN) + (TP + TN) \times (FP + FN)} \quad (4)$$

where N is the number of classes, TP_i , FP_i , and FN_i are the true positives, false positives, and false negatives for class i .

For binary classification, the MCC is calculated as:

$$\text{MCC} = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (5)$$

For multiclass classification, MCC is generalised as:

$$\text{MCC} = \frac{c \times s - \sum_k p_k \times t_k}{\sqrt{(c^2 - \sum_k p_k^2)(c^2 - \sum_k t_k^2)}} \quad (6)$$

where c is the total number of samples, s is the sum of the product of the confusion matrix diagonal elements, p_k is the sum of the k th row of the confusion matrix, and t_k is the sum of the k th column of the confusion matrix.

We also employed UPM to search for the optimal parameters of the proposed model, which yielded a robust evaluation and interpretation, as shown in Table II.

IV. RESULTS

This section presents the performance of the 1CNN-GRU-Attention model in quantifying the severity levels of cybersickness in VR environments with varying weather conditions. A previous study found significantly higher GSR levels during stormy weather compared to clear weather [52]. We evaluated the model's effectiveness with and without SMOTE for class balancing, considering two classification scenarios: binary (2 cybersickness classes) and multiclass (4 cybersickness severity levels: none, low,

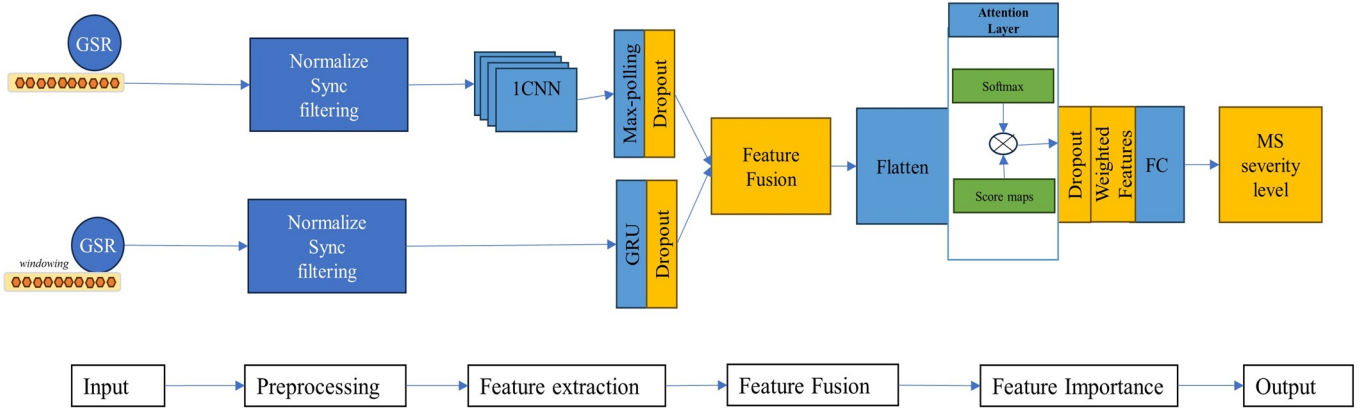


Fig. 3. The 1CNN-GRU-Attention model architecture for cybersickness quantification level using GSR.

acute, and high). A 5-fold CV was used, and Accuracy (ACC), MCC, and UPM performance metrics were utilised to evaluate the models. Statistical t-tests were conducted to assess the significance of differences between models. The statistical analysis using t-tests provided significant insights into model performance and the impact of SMOTE. Detailed analytics for each scenario are provided below:

A. Statistical Analysis for Binary Classification

Significant differences were observed between the models in the scenario without the balancing technique (SMOTE) (Table IV). SVM exhibited statistically lower ACC (71.03%) compared to both KNN (75.2%, $p < 0.05$) and 1CNN-GRU-Attention (75.17%, $p < 0.01$). Similarly, SVM achieved a lower MCC (59.25%) compared to 1CNN-GRU-Attention (64.1%, $p < 0.01$). However, no significant difference was found between KNN (55.98%) and SVM ($p > 0.05$) in terms of MCC. UPM also revealed significant differences, with SVM (28.79%) performing worse than both KNN (22.21%, $p > 0.05$) and 1CNN-GRU-Attention (55.82%, $p < 0.001$). However, when applying SMOTE in binary classification, the results are similar to those of the non-SMOTE scenario. All comparisons yielded statistically significant differences (Table IV).

The 1CNN-GRU-Attention model achieved the highest accuracy of 86.94%, significantly outperforming SVM (68.73%, $p < 0.001$) and KNN (73.91%, $p < 0.001$). A similar pattern was observed for the MCC, with 1CNN-GRU-Attention (87.01%) exceeding both SVM (75.58%, $p < 0.001$) and KNN (70.61%, $p < 0.001$). The UPM also followed this trend, with 1CNN-GRU-Attention (86.84%) surpassing SVM (71.41%, $p < 0.001$) and KNN (68.71%, $p < 0.001$).

Comparing SMOTE versus non-SMOTE configurations for each model in binary classification revealed no significant improvements for SVM and KNN; however, 1CNN-GRU-Attention benefited significantly from SMOTE. This enhancement can be attributed to the model's ability to leverage the additional synthetic samples generated by SMOTE, thereby learning the underlying patterns in the data more effectively and improving its performance.

B. Statistical Analysis for multiclassification

The findings for the multiclassification scenario without SMOTE reflected the binary classification results (Table V). All models exhibited significant differences in accuracy (ACC) ($p < 0.001$). The 1CNN-GRU-Attention model achieved the highest ACC of 48.77%, significantly outperforming SVM (28.90%, $p < 0.001$) and KNN (42.20%, $p < 0.001$). Similarly, the MCC showed significant differences ($p < 0.001$), with 1CNN-GRU-Attention (66.29%) outperforming SVM (59.97%, $p < 0.001$) and KNN (59.57%, $p < 0.001$). The UPM also revealed significant differences ($p < 0.001$), with 1CNN-GRU-Attention (59.70%) surpassing SVM (30.10%, $p < 0.001$) and KNN (38.92%, $p < 0.001$).

Although there are significant differences among the models, their overall performance remains low. It does not promise to quantify multiple classes of cybersickness. Therefore, SMOTE techniques were utilised to test if there was an improvement. Similar to the non-SMOTE scenario, all comparisons yielded statistically significant differences when SMOTE was applied (Table V). 1CNN-GRU-Attention achieved the highest ACC (64.63%) compared to both SVM (41.75%, $p < 0.001$) and KNN (44.53%, $p < 0.001$). The same trend was observed for MCC and UPM, with 1CNN-GRU-Attention outperforming both SVM and KNN ($p < 0.001$) for all comparisons. In general, SMOTE's impact on the accuracy of the proposed model is evident, as shown in Tables IV and V. For binary classification, accuracy increased from 75.15% (without SMOTE) to 86.94% (with SMOTE), suggesting that class imbalance limits the model's effectiveness. The SMOTE approach addresses this by generating synthetic samples, improving class representation and performance. In multiclass classification, accuracy rose from 48.77% to 64.63%, highlighting the model's enhanced learning capability across all cybersickness severity levels. Fig. 4 shows the comparison of 1CNN-GRU-Attention with KNN and SVM under balanced and imbalanced conditions for binary and multiclass cybersickness quantification. We observed less variation in binary classification but a significant drop in multiclass classification without SMOTE, indicating higher sensitivity to class imbalance. These findings suggest that the proposed

model achieves high performance when dealing with balanced data, but requires techniques such as SMOTE to effectively address class imbalance.

V. DISCUSSION

We proposed a non-sequential model for quantifying cybersickness levels in VR environments. The 1CNN-GRU-Attention model demonstrated superior performance compared to traditional methods, such as KNN and SVM, as shown in Fig. 4. This success is attributed to the model's ability to capture both temporal and spatial feature fusion, aligning with our hypothesis and existing literature that emphasises the importance of advanced architectures for enhanced cybersickness assessment. To evaluate the model, we examined the impact of class imbalance on the performance of the 1CNN-GRU-Attention model in quantifying cybersickness severity using different performance metrics and a 5-fold CV. Building upon previous research that identified significantly higher GSR levels during stormy weather compared to clear weather [52], its effectiveness was evaluated with and without SMOTE for class balancing in both binary and multiclass classifications.

The 1CNN-GRU-Attention model consistently outperformed both SVM and KNN across binary and multi-class classification tasks. These findings align with prior studies showing that deep neural architectures, particularly those integrating convolutional and recurrent layers, capture spatial-temporal dependencies in physiological data more effectively than traditional machine learning classifiers [49], [72], [73].

Unlike previous sequential hybrid architectures (e.g., CNN-LSTM), our non-sequential design enables parallel processing of features, thereby avoiding the information loss that often occurs in chained models.

The SMOTE balancing technique significantly improved the performance of the proposed 1CNN-GRU-Attention model. Accuracy rose from 75.15% to 86.94% for binary classification, and from 48.77% to 64.63% for multiclass classification. MCC and UPM scores showed similar gains. This enhancement can be attributed to the model's ability to leverage additional synthetic samples generated by SMOTE, which better represent the underlying patterns in the data [70].

Although SVM and KNN performed reasonably well, the 1CNN-GRU-Attention model outperformed them across all metrics. SVM, known for handling high-dimensional spaces and its robustness in preventing overfitting, performed better than KNN in some scenarios but still lagged behind the deep learning approach [74], [75]. KNN's simplicity and ease of implementation are advantageous. However, its performance highly depends on the choice of k and the distance metric, which may limit its effectiveness compared to more sophisticated models [76]. The study's context of varying weather conditions (clear vs. stormy) provided a realistic and challenging environment for evaluating the model. Significant performance differences observed across models and conditions underscore the importance of considering environmental factors in VR applications. Previous studies have also highlighted the influence

of external conditions on physiological responses, validating our approach [52].

This study advances the field in several key ways. First, it demonstrates that a single lightweight modality (GSR) can be used effectively under variable real-world conditions, which contrasts with previous works that rely on complex multimodal sensor setups. Second, the attention mechanism integrated in our model helps dynamically focus on the most informative segments of the signal, compensating for GSR's response latency—a challenge often overlooked in the literature. Third, by decoupling feature processing from sequential pipelines, our non-sequential design provides a more robust architecture that improves detection accuracy while minimising reliance on sensor synchrony.

Despite using only GSR data, our accuracy is competitive with that of multimodal approaches reported in prior works. Hadadi et al. [50] investigated VR navigation using multiple physiological signals (GSR, BVP, HR, and temperature), achieving 71% accuracy with an SVM-RBF classifier and topological data analysis. Hwang et al. [38] focused on real driving simulations using a combination of physiological data (EEG, ECG, RESP, PPG, GSR) and achieved 76.26% accuracy with a self-attention and tensor fusion model. Our model's higher accuracy can be attributed to the effective architecture of the non-sequential 1CNN-GRU-Attention model in capturing the dynamics of GSR data relevant to cybersickness assessment.

The superior performance of the 1CNN-GRU-Attention model suggests that incorporating advanced deep learning techniques can significantly enhance the accuracy and reliability of cybersickness prediction models. These models can effectively capture complex patterns in physiological data, making them suitable for real-time monitoring and intervention in VR environments.

The substantial improvements observed with SMOTE highlight the critical role of data balancing in training effective machine learning models. Addressing class imbalance ensures the model can generalise better and make accurate predictions across all severity levels of cybersickness. Deploying such techniques in practical VR applications can lead to improved user experiences by mitigating the incidence and severity of cybersickness, thereby facilitating broader adoption of VR technology in gaming, education, and healthcare.

Using MCC and UPM further validates the robustness of the 1CNN-GRU-Attention model. As a balanced metric, MCC comprehensively evaluates the model's performance by considering all elements of the confusion matrix. This is particularly important in imbalanced datasets where traditional metrics like accuracy might be misleading. UPM is also an alternative to MCC, offering an aggregated performance measure that incorporates various aspects, such as precision and recall, thereby providing a holistic view of the model [71].

It is important to acknowledge the study's limitations. Conducted in a controlled lab environment, the study may not fully replicate real-world VR experiences. Additional factors in real-world settings could affect GSR and potentially impact model performance. The study's sample size was limited; a larger and more diverse subject pool could enhance the

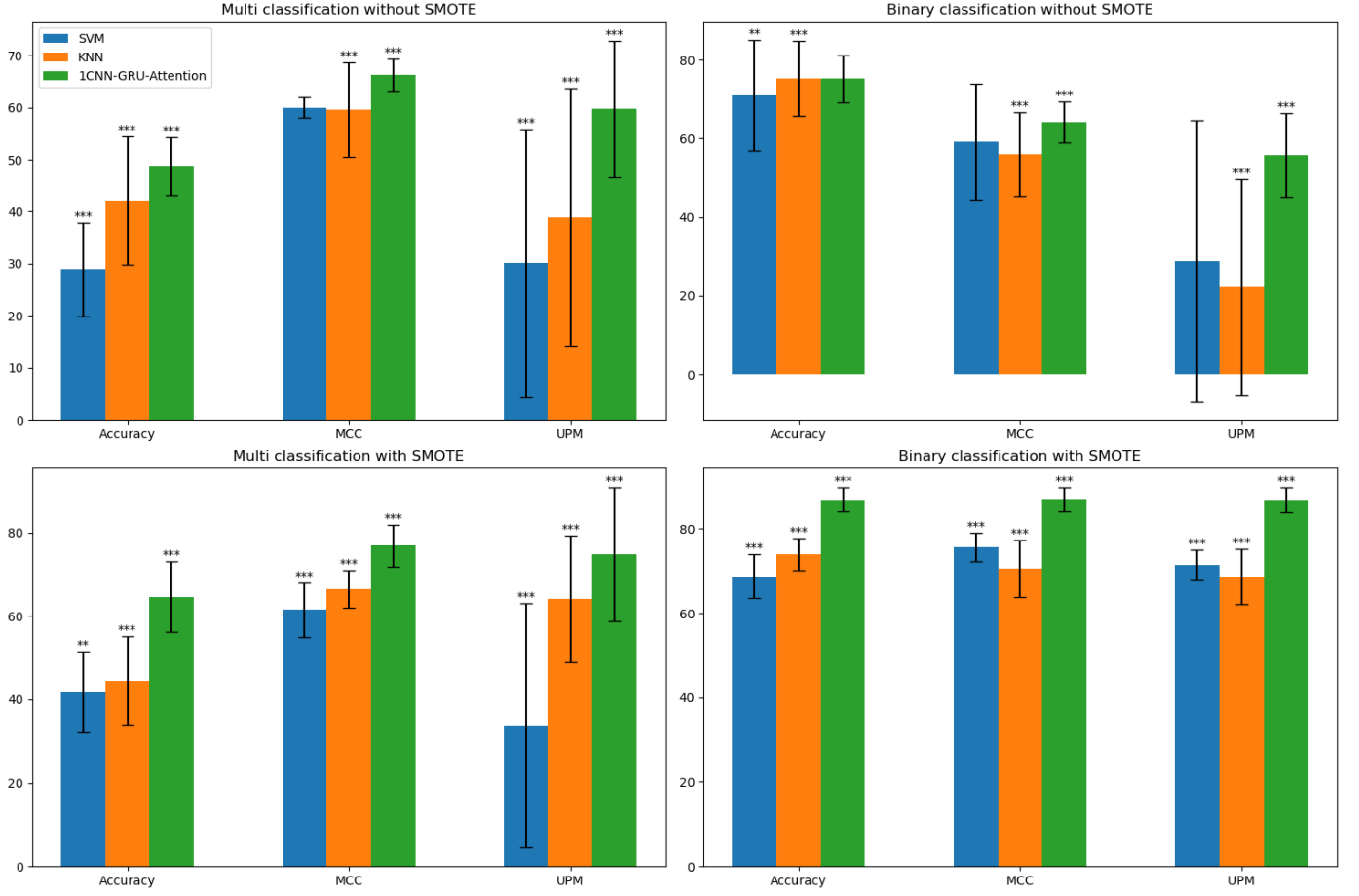


Fig. 4. Performance of 1CNN-GRU-Attention versus KNN and SVM with and without class balancing (SMOTE) for binary and four-class cybersickness classification.

TABLE IV
T-TEST RESULTS FOR QUANTIFYING CYBERSICKNESS IN BINARY CLASSIFICATION (WITH AND WITHOUT SMOTE).

Metric	Comparison	T-Statistic Non-SMOTE	P-Value Non-SMOTE	T-Statistic SMOTE	P-Value SMOTE
Acc	SVM vs KNN	-2.462674	1.4645e-02	-8.003430	1.0035e-13
Acc	SVM vs 1CNN-GRU-Attention	-2.714999	7.2131e-03	-30.564621	6.6981e-77
Acc	1CNN-GRU-Attention vs KNN	-0.026654	9.7876e-01	27.111906	1.4233e-68
MCC	SVM vs KNN	1.798130	7.3680e-02	6.525603	5.5467e-10
MCC	SVM vs 1CNN-GRU-Attention	-3.112992	2.1262e-03	-25.821823	2.6653e-65
MCC	1CNN-GRU-Attention vs KNN	6.817646	1.0926e-10	22.136749	1.8717e-55
UPM	SVM vs KNN	1.458141	1.4639e-01	3.637546	3.5105e-04
UPM	SVM vs 1CNN-GRU-Attention	-7.245780	9.3800e-12	-33.266055	5.3089e-83
UPM	1CNN-GRU-Attention vs KNN	11.373447	2.1595e-23	25.537643	1.4411e-64

TABLE V
T-TEST RESULTS FOR QUANTIFYING CYBERSICKNESS IN MULTICLASSIFICATION (WITH AND WITHOUT SMOTE).

Metric	Comparison	T-Statistic Non-SMOTE	P-Value Non-SMOTE	T-Statistic SMOTE	P-Value SMOTE
Acc	SVM vs KNN	-7.854571	2.4919e-13	-4.295277	2.7322e-05
Acc	SVM vs 1CNN-GRU-Attention	-13.030685	1.9626e-28	-38.402994	1.0697e-93
Acc	1CNN-GRU-Attention vs KNN	5.837279	2.1414e-08	41.822664	3.1314e-100
MCC	SVM vs KNN	0.219955	8.2613e-01	-6.670033	2.4968e-10
MCC	SVM vs 1CNN-GRU-Attention	-4.056518	7.1618e-05	-34.813149	2.4215e-86
MCC	1CNN-GRU-Attention vs KNN	5.642190	5.7478e-08	13.943453	3.1037e-31
UPM	SVM vs KNN	-1.954530	5.2046e-02	-40.996487	1.0831e-98
UPM	SVM vs 1CNN-GRU-Attention	-7.934705	1.5288e-13	-88.651990	2.6071e-161

model's generalisability.

To further improve practical applicability, future work should explore behavioural markers such as postural instabil-

ity, eye movement and head-body sway for added predictive power; also evaluate model deployment in real-world VR scenarios, such as educational simulators or automotive ap-

plications; and investigate reinforcement learning for adaptive cybersickness mitigation that adjusts VR content in real-time based on physiological feedback. These directions could strengthen model generalisation and effectiveness in diverse immersive contexts.

VI. CONCLUSION

This study demonstrates the effectiveness of the non-sequential ICNN-GRU-Attention model, which preserves spatial-temporal patterns in physiological data and outperforms SVM and KNN in predicting cybersickness severity. Using SMOTE to address class imbalance significantly improved the model's performance, resulting in higher accuracy, MCC, and UPM across binary and multiclass classification scenarios. Data Preprocessing and k-fold CV enhanced the model's robustness and reliability. Our model demonstrated superior performance using only GSR data, outperforming existing studies and validating its applicability in varied real-world conditions. Although the controlled lab setting and limited sample size are noted limitations, future research should focus on expanding the subject pool, incorporating additional physiological signals, and exploring multimodal machine learning architectures. In summary, the ICNN-GRU-Attention model, combined with SMOTE and rigorous preprocessing, provides a reliable approach for predicting cybersickness severity, supporting improved VR user experiences and broader adoption.

VII. ACKNOWLEDGMENT

The authors would like to acknowledge the support of the Australian Research Council (Project ID: DE210101623) and the Institute for Intelligent Systems Research and Innovation (IISRI) at Deakin University, which provided the necessary equipment and laboratory facilities crucial to the successful completion of this project. The authors also express their gratitude to Wadhah Al-Ashwal for sharing the datasets. Additionally, the authors extend their appreciation to Dr. Lars Kooijman for his valuable feedback and thorough review of the literature and statistical data analysis.

REFERENCES

- [1] K. M. Jang, M. Kwon, S. G. Nam, D. M. Kim, and H. K. Lim, "Estimating objective (eeg) and subjective (ssq) cybersickness in people with susceptibility to motion sickness," *Applied Ergonomics*, vol. 102, p. 103731, 2022.
- [2] H. Kim *et al.*, "Effect of virtual reality on stress reduction and change of physiological parameters including heart rate variability in people with high stress: An open randomized crossover trial," *Frontiers in Psychiatry*, vol. 12, p. 614539, 2021.
- [3] U. Laessoe, S. Abrahamsen, S. Zepernick, A. Raunsbaek, and C. Stensen, "Motion sickness and cybersickness—sensory mismatch," *Physiology & Behavior*, vol. 258, p. 114015, 2023.
- [4] L. M. Prinz, T. Mathew, and B. Weyers, "A systematic literature review of virtual reality locomotion taxonomies," *IEEE Transactions on Visualization and Computer Graphics*, vol. 29, no. 12, pp. 5208–5223, 2023.
- [5] W. Jin, J. Fan, D. Gromala, and P. Pasquier, "Automatic prediction of cybersickness for virtual reality games," in *2018 IEEE Games, Entertainment, Media Conference (GEM)*, 2018, pp. 1–9.
- [6] Y. Y. Kim, H. J. Kim, E. N. Kim, H. D. Ko, and H. T. Kim, "Characteristic changes in the physiological components of cybersickness," *Psychophysiology*, vol. 42, no. 5, pp. 616–625, 2005.
- [7] R. S. Kennedy, N. E. Lane, K. S. Berbaum, and M. G. Lilienthal, "Simulator sickness questionnaire: An enhanced method for quantifying simulator sickness," *International Journal of Aviation Psychology*, vol. 3, no. 3, pp. 203–220, 1993.
- [8] J. R. Lackner, "Motion sickness: More than nausea and vomiting," *Experimental Brain Research*, vol. 232, no. 8, pp. 2493–2510, 2014.
- [9] M. S. Anwar, A. Choi, S. Ahmad, K. Aurangzeb, A. A. Laghari, T. R. Gadekallu, and A. Hines, "A moving metaverse: Qoe challenges and standards requirements for immersive media consumption in autonomous vehicles," *Appl. Soft Comput.*, vol. 159, no. C, Jul. 2024.
- [10] E. Chang, H. T. Kim, and B. Yoo, "Predicting cybersickness based on user's gaze behaviors in hmd-based virtual reality," *Journal of Computational Design and Engineering*, vol. 8, no. 2, pp. 728–739, 2021.
- [11] Y. Zhang, H. Zhao, C. Hu, Y. Tian, Y. Li, X. Jiao, and G. Wen, "Mitigation of motion sickness and optimization of motion comfort in autonomous vehicles: Systematic survey," *IEEE Transactions on Intelligent Transportation Systems*, vol. 25, no. 12, pp. 21 737–21 756, 2024.
- [12] G. E. Riccio and T. A. Stoffregen, "An ecological theory of motion sickness and postural instability," *Ecological Psychology*, vol. 3, no. 3, pp. 195–240, 1991.
- [13] M. Treisman, "Motion sickness: An evolutionary hypothesis," *Science*, vol. 197, no. 4302, pp. 493–495, 1977.
- [14] J. T. Reason, "Motion sickness adaptation: A neural mismatch model," *Journal of the Royal Society of Medicine*, vol. 71, no. 11, pp. 819–829, 1978.
- [15] J. E. Bos, W. Bles, and E. L. Groen, "A theory on visually induced motion sickness," *Displays*, vol. 29, no. 2, pp. 47–57, 2008.
- [16] R. S. Kennedy, J. Drexler, and R. C. Kennedy, "Research in visually induced motion sickness," *Applied Ergonomics*, vol. 41, no. 4, pp. 494–503, 2010.
- [17] B. Keshavarz, K. Peck, S. Rezaei, and B. Taati, "Detecting and predicting visually induced motion sickness with physiological measures in combination with machine learning techniques," *International Journal of Psychophysiology*, vol. 176, pp. 14–26, 2022.
- [18] L. Rebenitsch and C. Owen, "Review on cybersickness in applications and visual displays," *Virtual Reality*, vol. 20, no. 2, pp. 101–125, 2016.
- [19] J. J. W. Lin, H. B. L. Duh, D. E. Parker, H. Abi-Rached, and T. A. Furness, "Effects of field of view on presence, enjoyment, memory, and simulator sickness in a virtual environment," in *Proceedings of the Virtual Reality Annual International Symposium*, 2002, pp. 164–171.
- [20] K. Stanney *et al.*, "Identifying causes of and solutions for cybersickness in immersive technology: Reformulation of a research and development agenda," *International Journal of Human-Computer Interaction*, vol. 36, no. 19, pp. 1783–1803, 2020.
- [21] B. Keshavarz and H. Hecht, "Validating an efficient method to quantify motion sickness," *Human Factors*, vol. 53, no. 4, pp. 415–426, 2011.
- [22] A. Jasper, N. C. Sepich, S. B. Gilbert, J. W. Kelly, and M. C. Dorneich, "Predicting cybersickness using individual and task characteristics," *Computers in Human Behavior*, vol. 146, p. 107800, 2023.
- [23] Z. Lu, M. Yu, G. Jiang, B. Chi, and Q. Dong, "Prediction of motion sickness degree of stereoscopic panoramic videos based on content perception and binocular characteristics," *Digital Signal Processing*, vol. 132, p. 103787, 2023.
- [24] T. Porcino, E. O. Rodrigues, A. Silva, E. Clua, and D. Trevisan, "Using the gameplay and user data to predict and identify causes of cybersickness manifestation in virtual reality games," in *2020 IEEE 8th International Conference on Serious Games and Applications for Health (SeGAH)*, 2020, pp. 1–8.
- [25] M. Vinnikov, R. S. Allison, and S. Fernandes, "Impact of depth of field simulation on visual fatigue: Who are impacted? and how?" *International Journal of Human-Computer Studies*, vol. 91, pp. 37–51, 2016.
- [26] J. Teixeira and S. Palmisano, "Effects of dynamic field-of-view restriction on cybersickness and presence in hmd-based virtual reality," *Virtual Reality*, vol. 25, no. 2, pp. 433–445, 2021.
- [27] K. Lim, J. Lee, K. Won, N. Kala, and T. Lee, "A novel method for vr sickness reduction based on dynamic field of view processing," *Virtual Reality*, vol. 25, no. 2, pp. 331–340, 2021.
- [28] L. Kooijman, H. Asadi, C. Gonzalez Arango, S. Mohamed, and S. Nahavandi, "Investigating the influence of neck muscle vibration on illusory self-motion in virtual reality," *Virtual Reality*, vol. 28, no. 2, p. 76, 2024.
- [29] B. Buchheit, E. N. Schneider, M. Alayan, F. Dauth, and D. J. Strauss, "Motion sickness prediction in self-driving cars using the 6dof-svc model," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 8, pp. 13 582–13 591, 2022.

- [30] J. Kim, S. M. Lee, H. Son, and T. Park, "Effects of unlimited angular motion cue and cue discrepancy on simulator sickness," *Expert Systems with Applications*, vol. 213, p. 119196, 2023.
- [31] M. R. Chalak Qazani, H. Asadi, L. Zhang, F. Tabarsinezhad, S. Mohamed, C. P. Lim, and S. Nahavandi, "A new prepositioning technique of a motion simulator platform using nonlinear model predictive control and recurrent neural network," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 12, pp. 23 268–23 277, 2022.
- [32] L. Ma, Y. Guo, R. Fu, and Q. Sun, "Passenger non-driving related tasks detection using a light weight neural network based on human prior knowledge and soft-hard feature constraints," *Expert Systems with Applications*, vol. 219, 2023.
- [33] T. Porcino, E. O. Rodrigues, F. Bernardini, D. Trevisan, and E. Clua, "Identifying cybersickness causes in virtual reality games using symbolic machine learning algorithms," *Entertainment Computing*, vol. 41, p. 100473, 2022.
- [34] M. Kaufeld, J. Bourdeinik, L. M. Prinz, M. Mundt, and H. Hecht, "Emotions are associated with the genesis of visually induced motion sickness in virtual reality," *Experimental Brain Research*, vol. 240, no. 10, pp. 2757–2771, 2022.
- [35] N. C. Sepich, A. Jasper, S. Fieffer, S. B. Gilbert, M. C. Dorneich, and J. W. Kelly, "The impact of task workload on cybersickness," *Frontiers in Virtual Reality*, vol. 3, p. 943409, 2022.
- [36] J. Y. Chun *et al.*, "Prediction of specific anxiety symptoms and virtual reality sickness using in situ autonomic physiological signals during virtual reality treatment in patients with social anxiety disorder: Mixed methods study," *JMIR Serious Games*, vol. 10, no. 3, p. 38284, 2022.
- [37] N. Tian and R. Boulic, "Who says you are so sick? an investigation on individual susceptibility to cybersickness triggers using eeg, egg and ecg," *IEEE Transactions on Visualization and Computer Graphics*, vol. 30, no. 5, pp. 2379–2389, 2024.
- [38] J. U. Hwang, J. S. Bang, and S. W. Lee, "Classification of motion sickness levels using multimodal biosignals in real driving conditions," in *2022 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, 2022, pp. 1304–1309.
- [39] M. S. Dennison, A. Z. Wisti, and M. D'Zmura, "Use of physiological signals to predict cybersickness," *Displays*, vol. 44, pp. 42–52, 2016.
- [40] A. Hag *et al.*, "Eeg mental stress assessment using hybrid multi-domain feature sets of functional connectivity network and time-frequency features," *Sensors*, vol. 21, no. 18, p. 6300, 2021.
- [41] R. Katmah, F. Al-Shargie, U. Tariq, F. Babiloni, F. Al-Mughairbi, and H. Al-Nashash, "A review on mental stress assessment methods using eeg signals," *Sensors*, vol. 21, no. 15, p. 5043, 2021.
- [42] S. Lee, S. Kim, H. G. Kim, and Y. M. Ro, "Assessing individual vr sickness through deep feature fusion of vr video and physiological response," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 32, no. 5, pp. 2895–2907, 2022.
- [43] J. Smyth, S. Birrell, R. Woodman, and P. Jennings, "Exploring the utility of eda and skin temperature as individual physiological correlates of motion sickness," *Applied Ergonomics*, vol. 92, p. 103315, 2021.
- [44] A. Kinsella, S. Beadle, M. Wilson, L. J. Smart Jr., and E. Muth, "Measuring user experience with postural sway and performance in a head-mounted display," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 61, no. 1, pp. 2062–2066, 2017.
- [45] L. J. Smart, A. Drew, T. Hadidon, M. Teaford, and E. Bachmann, "Using nonlinear kinematic parameters as a means of predicting motion sickness in real-time in virtual environments," *Human Factors*, vol. 65, no. 8, pp. 1830–1840, 2023.
- [46] P. Kourtesis, R. Amir, J. Linnell, F. Argelaguet, and S. E. MacPherson, "Cybersickness, cognition, & motor skills: The effects of music, gender, and gaming experience," *IEEE Transactions on Visualization and Computer Graphics*, vol. 29, no. 5, pp. 2326–2336, 2023.
- [47] N. Padmanaban, T. Ruban, V. Sitzmann, A. M. Norcia, and G. Wetzstein, "Towards a machine-learning approach for sickness prediction in 360° stereoscopic videos," *IEEE Transactions on Visualization and Computer Graphics*, vol. 24, no. 4, pp. 1594–1603, 2018.
- [48] R. Islam *et al.*, "Automatic detection and prediction of cybersickness severity using deep neural networks from user's physiological signals," in *2020 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)*, 2020, pp. 400–411.
- [49] R. Islam, K. Desai, and J. Quarles, "Cybersickness prediction from integrated hmd's sensors: A multimodal deep fusion approach using eye-tracking and head-tracking data," in *2021 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)*, 2021, pp. 31–40.
- [50] A. Hadadi, C. Guillet, J.-R. R. Chardonnet, M. Langovoy, Y. Wang, and J. Ovtcharova, "Prediction of cybersickness in virtual environments using topological data analysis and machine learning," *Frontiers in Virtual Reality*, vol. 3, p. 973236, 2022.
- [51] M. Recenti *et al.*, "Toward predicting motion sickness using virtual reality and a moving platform assessing brain, muscles, and heart signals," *Frontiers in Bioengineering and Biotechnology*, vol. 9, p. 635661, 2021.
- [52] W. Al-Ashwal *et al.*, "Cybersickness measurement and evaluation during flying a helicopter in different weather conditions in virtual reality," in *IEEE International Conference on Systems, Man and Cybernetics*, 2021, pp. 2152–2157.
- [53] T. Irmak, D. M. Pool, and R. Happee, "Objective and subjective responses to motion sickness: the group and the individual," *Experimental Brain Research*, vol. 239, no. 2, pp. 515–531, 2021.
- [54] H. Wan, S. Hu, and J. Wang, "Correlation of phasic and tonic skin conductance responses with severity of motion sickness induced by viewing an optokinetic rotating drum," *Perceptual and Motor Skills*, vol. 97, no. 3, pp. 1051–1057, 2003.
- [55] A. M. Gavgani, K. V. Nesbitt, K. L. Blackmore, and E. Nalivaiko, "Profiling subjective symptoms and autonomic changes associated with cybersickness," *Autonomic Neuroscience*, vol. 203, pp. 41–50, 2017.
- [56] M. Jäger, N. Gruber, R. Müri, U. P. Mosimann, and T. Nef, "Manipulations to reduce simulator-related transient adverse health effects during simulated driving," *Medical & Biological Engineering & Computing*, vol. 52, no. 7, pp. 601–610, 2014.
- [57] B. C. Min, S. C. Chung, Y. K. Min, and K. Sakamoto, "Psychophysiological evaluation of simulator sickness evoked by a graphic simulator," *Applied Ergonomics*, vol. 35, no. 6, pp. 549–556, 2004.
- [58] D. Jeong and K. Han, "Leveraging multimodal sensory information in cybersickness prediction," in *Proceedings of the 28th ACM Symposium on Virtual Reality Software and Technology*, 2022, pp. 1–2.
- [59] R. Islam, K. Desai, and J. Quarles, "Towards forecasting the onset of cybersickness by fusing physiological, head-tracking and eye-tracking with multimodal deep fusion network," in *2022 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)*, 2022, pp. 121–130.
- [60] 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.
- [61] U. Tasnim, R. Islam, K. Desai, and J. Quarles, "Investigating personalization techniques for improved cybersickness prediction in virtual reality environments," *IEEE Transactions on Visualization and Computer Graphics*, vol. 30, no. 5, pp. 2368–2378, 2024.
- [62] Y. Li, A. Liu, and L. Ding, "Machine learning assessment of visually induced motion sickness levels based on multiple biosignals," *Biomedical Signal Processing and Control*, vol. 49, pp. 202–211, 2019.
- [63] J. A. Ruiz Colmenares, E. Asua Uriarte, and I. del Campo, "Driving-style assessment from a motion sickness perspective based on machine learning techniques," *Applied Sciences*, vol. 13, no. 3, p. 1510, 2023.
- [64] Y. Wang, J.-R. R. Chardonnet, and F. Merienne, "Vr sickness prediction for navigation in immersive virtual environments using a deep long short term memory model," in *2019 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, 2019, pp. 1874–1881.
- [65] B. Venkatesh and J. Anuradha, "A review of feature selection and its methods," *Cybernetics and Information Technologies*, vol. 19, no. 1, pp. 3–26, 2019.
- [66] A. Vaswani *et al.*, "Attention is all you need," *Advances in Neural Information Processing Systems*, vol. 30, 2017.
- [67] I. Ullah, M. Hussain, E. u. H. Qazi, and H. Aboalsamh, "An automated system for epilepsy detection using eeg brain signals based on deep learning approach," *Expert Systems with Applications*, vol. 107, pp. 61–71, 2018.
- [68] K. Cho, B. van Merriënboer, D. Bahdanau, and Y. Bengio, "On the properties of neural machine translation: Encoder-decoder approaches," in *Proceedings of the 8th Workshop on Syntax, Semantics and Structure in Statistical Translation*, 2014, pp. 103–111.
- [69] D. Bahdanau, K. Cho, and Y. Bengio, "Neural machine translation by jointly learning to align and translate," *3rd International Conference on Learning Representations (ICLR)*, 2015, available at <http://arxiv.org/abs/1409.0473>.
- [70] N. V. Chawla, K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer, "Smote: Synthetic minority over-sampling technique," *Journal of Artificial Intelligence Research*, vol. 16, pp. 321–357, 2002.
- [71] A. R. Redondo, J. Navarro, R. R. Fernández, I. M. de Diego, J. M. Moguerza, and J. J. Fernández-Muñoz, "Unified performance measure for binary classification problems," in *Intelligent Data Engineering and Automated Learning—IDEAL 2020*, 2020, pp. 104–112.

- [72] D. Jeong, S. Yoo, and J. Yun, "Cybersickness analysis with eeg using deep learning algorithms," in *2019 IEEE Conference on Virtual Reality and 3D User Interfaces*, 2019, pp. 827–835.
- [73] J. Kim, W. Kim, H. Oh, S. Lee, and S. Lee, "A deep cybersickness predictor based on brain signal analysis for virtual reality contents," in *2019 IEEE/CVF International Conference on Computer Vision (ICCV)*, 2019, pp. 10 579–10 588.
- [74] A. Halbouni, T. S. Gunawan, M. H. Habaebi, M. Halbouni, M. Kartiwi, and R. Ahmad, "Machine learning and deep learning approaches for cybersecurity: A review," *IEEE Access*, 2022.
- [75] S. Sharma, G. Singh, and M. Sharma, "A comprehensive review and analysis of supervised-learning and soft computing techniques for stress diagnosis in humans," *Computers in Biology and Medicine*, vol. 134, p. 104450, 2021.
- [76] N. S. Altman, "An introduction to kernel and nearest-neighbor non-parametric regression," *The American Statistician*, vol. 46, no. 3, pp. 175–185, 1992.



Ala Hag received his B.S. and M.S. degrees in Computer Science from the International Islamic University Malaysia (IIUM). Currently a Ph.D. candidate at Deakin University. His research focuses on motion sickness prediction using physiological data. His previous work at Taylor's University focused on mental stress assessment using EEG signals using machine learning and deep learning modeling.



Mohammad Reza Chalak Qazani (Senior Member, IEEE) Received the Bachelor of Engineering in manufacturing and production from the University of Tabriz, Tabriz, Iran, in 2010 and the master's degree in robotic and mechanical engineering from Tarbiat Modares University, Tehran, Iran, in 2013. He received the Ph.D. degree in modelling and simulation of a motion cueing algorithm using prediction and computational intelligence techniques from the Institute for Intelligent Systems Research and Innovation (IISRI), Deakin University, Australia, in 2021. He was an Alfred Deakin Postdoctoral Research Fellow in the IISRI for two years, working in the areas of model predictive control, motion cueing algorithms, and soft computing controllers. He is currently a Lecturer in the College of Science and Engineering, James Cook University. His Teaching areas are Dynamics of Machines, Mechanical Design, Introduction to Artificial Intelligence, and Advanced Machine Learning.



Houshyar Asadi (Member, IEEE) received the Bachelor of Engineering degree (Hons.) in electrical control systems, in 2008, the master's degree in industrial electronic and control engineering from the University of Malaya, in 2012, and the Ph.D. degree in human perception-based washout filtering using artificial intelligence (AI) from the Institute for Intelligent Systems Research and Innovation (IISRI), Deakin University, Australia, in 2015. He is currently an Associate Professor with IISRI and leads the research area of motion simulator technologies. His current research interests include AI, motion simulator technologies, motion cueing algorithms, control, and human factors in virtual environments.