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STUDY ON DEEP LEARNING MODELS FOR VR SICKNESS LEVELS CLASSIFICATION

Abstract

Virtual Reality (VR) sickness is often accompanied by symptoms such as nausea and dizziness, and a prominent theory explaining this phenomenon is the sensory conflict theory. Recently, studies have used Deep Learning to classify VR sickness levels; however, there is a paucity of research on Deep Learning models that utilize both visual information and motion data based on sensory conflict theory. In this paper, the authors propose a parallel merging of a Deep Learning model (4bay) to classify the level of VR sickness by utilizing the user's motion data (HMD, controller data) and visual data (rendered image, depth image) based on sensory conflict theory. The proposed model consists of a visual processing module, a motion processing module, and an FC-based VR sickness level classification module. The performance of the proposed model was compared with that of the developed models at the time of design. As a result of the comparison, it was confirmed that the proposed model performed better than the single model and the merged (2bay) model in classifying the user's VR sickness level.

1. INTRODUCTION

Virtual Reality (VR) technology is used in various fields as it provides users with a realistic experience or a sense of immersion beyond it. VR technology has proven useful in various fields, such as education, healthcare, and entertainment. It aids in understanding complex concepts through simulations, enables the practice of high-risk surgeries, and provides immersive gaming and virtual environments.

In 2024, Merketsandmerkets, a global market research firm, forecasted that the virtual reality market size will grow to $39 billion by 2029. In addition, IMARC Group, the international market analysis research and consulting group, forecasted in 2023 that the virtual reality market size will grow to $82.3 billion by 2032.

However, despite advances in VR technology, VR sickness remains a significant problem for users. VR sickness occurs primarily in virtual reality environments using head-mounted displays (HMDs) and is accompanied by symptoms such as nausea and dizziness, causing great discomfort to users. Sensory conflict theory is a popular theory that explains VR sickness. The sensory conflict theory explains that VR sickness is caused by a sensory

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mismatch between the visual and vestibular systems (Ng et al., 2020; LaViola, 2000). In highly immersive environments, such as virtual reality, VR sickness is caused by a discrepancy between the visual motion perceived by the user through the HMD and the actual motion perceived by the vestibular system.

The measurement of user VR sickness is mainly carried out by qualitative methods, such as questionnaires and verbal reports (Lim et al., 2021). However, these qualitative methods are subjective assessments of individuals and have the limitation of being variable (Ree & Yoon, 2024). Therefore, there is a need for a quantitative measurement method for assessing VR sickness.

Machine Learning and Deep Learning have long been employed across various fields for tasks such as prediction and classification. With the rapid advancements in AI, these technologies are increasingly applied to analyze the complex relationships between data in non-linear and dynamic systems, where traditional methods often fall short.

These technologies are particularly widespread in complex simulation environments such as large-scale medical datasets, materials engineering, energy engineering, and computer science. Younis (2024) proposed a Machine Learning approach to predict patients' willingness to treat psychiatric disorders. Karpiński et al. (2023) proposed a diagnostic method using MLP (Multilayer perceptron), RBF (radial basis function) models for cartilage evaluation in vibroarthrography. Falkowicz and Kulisz (2024) combined numerical analysis and artificial neural networks to predict the buckling morphology and critical loads of thin plate elements made of composite materials for design optimisation and structural monitoring of composite structures. Kulisz et al. (2024) conducted a study to predict and optimize energy recovery from waste using a Machine Learning model trained on a dataset incorporating environmental indicators from European countries from 2013 to 2020.

In this way, Machine Learning has been used in a variety of fields to analyze and predict correlations between complex data. Particularly in virtual reality (VR) environments, motion sickness (hereafter referred to as VR sickness) is difficult to predict due to its non-linear nature, which arises from the complex interaction between user motions and visual elements. Therefore, studies utilizing Machine Learning (including Deep Learning) models to predict VR sickness have been actively conducted (Yang et al., 2020). In this paper, the authors propose a Deep Learning model based on sensory conflict theory to predict VR sickness.

2. RELATED WORKS

Studies to quantify a user's VR sickness mainly use Deep Learning techniques. These methods analyze patterns in the user's physiological indicators in order to evaluate VR sickness. In this section, studies that utilized Deep Learning to evaluate VR sickness are examined. To this end, literature collection was performed using Web of Science and IEEE search engines, and it was limited to literature published from 2020 to 2024 to analyze the latest related research. The search keywords were "VR sickness", "Cyber sickness", and "Simulator sickness". After removing duplicate papers, a total of 1,462 documents were collected after the primary literature collection. Then, the authors selected papers that included Machine Learning and Deep Learning in the abstract, and conducted a detailed review, and finally selected 31 papers. The overall process of literature collection is shown in Fig. 1.

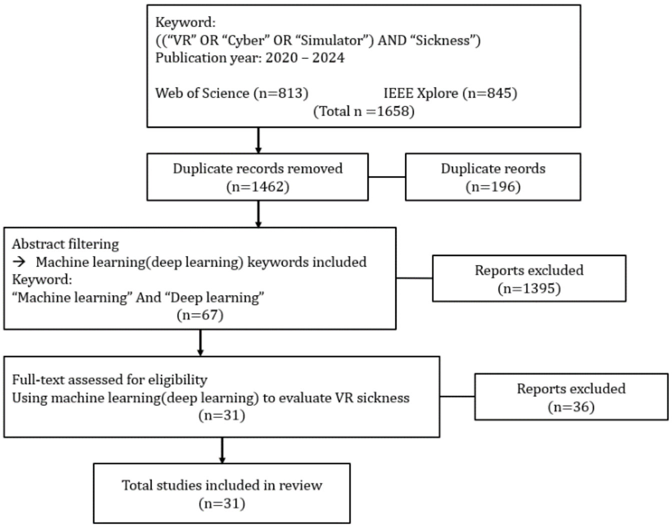


Fig. 1. Literature review process of studies using Machine Learning/Deep Learning to assess VR sickness

2.1. Input data used in the VR sickness Deep Learning model

The types of input data used in the 31 studies were broadly classified into physiological data and content data. Physiological data refers to a user's physiological responses measured through sensors, while content data refers to data on content output through the HMD. It was confirmed that 24 studies used only physiological data, 2 studies used only content data, and 3 studies used both data together. Two cases were classified as other cases. Therefore, it was found that the majority of prior research primarily used physiological data. The input data related to the sensory conflict theory can be defined as visual information (such as camera speed, rotation, and optical flow, Etc.) displayed according to the user's movements (head movements, body movements, and eye movements. Etc.).

Thus, five studies used movement-related data (Shodipe & Allison, 2023; Shimada et al., 2023a; Keshavarz et al., 2022; Shimada et al., 2023b; Kundu et al., 2023), three studies used visual data (Du et al., 2021; Monteiro et al., 2021; Zhao et al., 2023), and two studies used both types of data (Wang et al., 2020; Jeong et al., 2023). Consequently, it was confirmed that only 0.68% of the total 1,462 papers used both Deep Learning and sensory conflict theory related data to evaluate VR sickness. Table 1 shows the input data primarily used in Machine Learning in the previous studies.

Tab. 1. Types of input data commonly used in Machine Learning/Deep Learning

Score in percent				**Categories**	
1	Heart Rate	6	Respiratory Rate	11	Camera Speed
2	Galvanic Skin Response	7	Head Movement	12	Camera Rotation
3	Electroen	8	Body Movement	13	Optical Flow
4	Electroencephalogram	9	Eye Data	14	Field of View
5	Skin Temperature	10	Electromyography	15	Virtual Character Movement

2.2. Deep Learning models used to classify VR sickness

An analysis of the 31 selected papers revealed that the commonly used Machine Learning models were LSTM (10 papers), CNN (7 papers), SVM (4 papers), and RF models (3 papers). Among these, the studies relevant to this paper are as follows.

Du et al. (2021) proposed a 3D CNN model using optical flow and disparity features to classify the user's VR sickness level, and confirmed that the proposed model outperforms the existing models. Shimada et al. (2023b) proposed an ALSTM-FCN (Long Short-Term Memory Fully Convolutional Network) VR sickness level classification model using the user eye data, and the performance evaluation showed an accuracy of 71% in VR sickness severity classification. Kundu et al. (2023) also proposed a lightweight Lite VR framework that utilizes features from eye data to classify the user's VR sickness level. Lastly, Wang et al. (2020) proposed an LSTM-based model using eye movement data and virtual character movements to classify VR sickness level. As a result of performance evaluation of the proposed model, it was confirmed that the more sensitive users are to VR sickness, the better the performance of the model.

However, these prior studies primarily utilized individual physiological data (e.g., eye data) to evaluate user VR sickness, which may not fully reflect the comprehensive factors based on sensory conflict theory. Additionally, while studies have focused on the simple classification of VR sickness presence (i.e., VR sickness, none VR sickness), there is a lack of research on the detailed classification of VR sickness level.

Therefore, this paper proposes a Deep Learning model using user motion-related data and visual-related data based on sensory conflict theory to quantitatively evaluate user VR sickness. In this paper, HMD and controller data are used as motion-related data, and rendered images and depth images are used as visual-related data. The proposed model consists of a motion processing module, a visual processing module, and an FC (Fully Connected Layer)-based VR sickness classification module, and finally classifies the user VR sickness level into FMS (Fast Motion Sickness) scores (1-5). The performance of the proposed model is compared with that of a single model and a merged model (2bay) developed during the design phase.

3. MATERIALS AND METHODS

This section describes the proposed Deep Learning model in detail. The proposed model is composed of three main modules: A) Motion Processing Module, B) Visual Processing Module, and C) FC-based VR Sickness Classification Module. The composition of the proposed model is shown in Fig. 2. The details are described below.

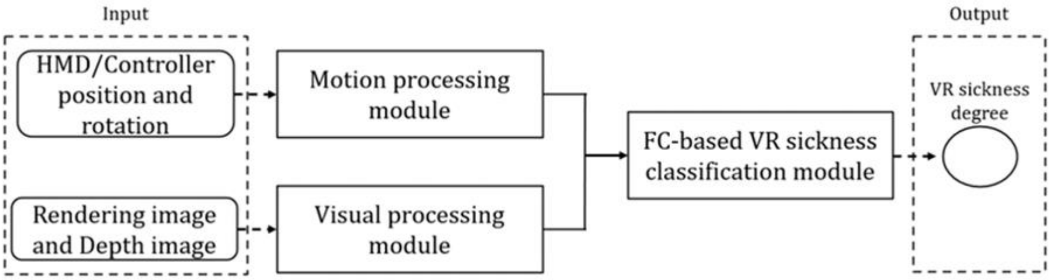


Fig. 2. An architecture of the Proposed model

3.1. Dataset for experiment

In this paper, the authors utilize the VR sickness open dataset provided by Wen et al. (2024) to train the Deep Learning model. VR net is a large-scale dataset with a total of 165 hours of data collected from 500 participants in 10 representative genres, of which data acquired from 46 participants in 8 types of content is publicly available. VR net includes various types of data, such as HMD, controller, gaze, virtual camera, and rendered images. Based on the dual sensory conflict theory, we use HMD data and controller data as motion data, and rendered images and corresponding depth images as visual data. Figure 3 shows an overview of the dataset in VR net.

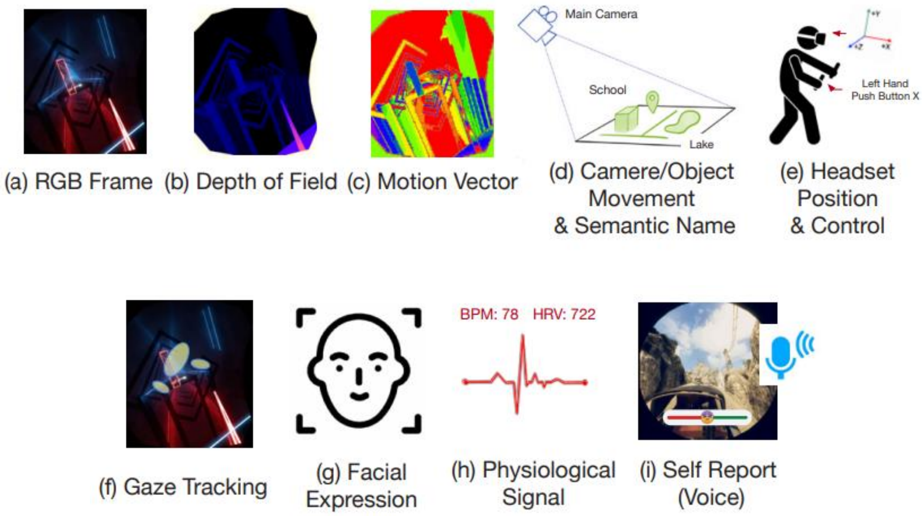


Fig. 3. An architecture of the proposed model

1. Data preprocessing

Since the total number of frames measured for each participant varies, the authors unify the data to have the same number of frames for all participants. The number of frames is unified to the minimum number of all subjects' frames, and because the FMS in the VR net dataset is labeled in 3-minute intervals, preprocessing is performed with the minimum number of frames among subjects measured for more than 10 min to utilize at least three

FMS scores. The number of frames set to match the data of all subjects to the same length is calculated as Equation (1).

$$FN_{list} = [fn_{s1}, fn_{s2}, fn_{s3} \cdots, fn_{sn}]$$
$$Frame_{total} = \min(FN_{list}) \tag{1}$$
$$Subject_{frame} = \text{Data}[1: Frame_{total}]$$

where: FN_{list} – the number of frames in the subjects,
$Frame_{total}$ – the minimum frame among subjects measured over 10 minutes,
$Subject_{frame}$ – the range of frames in the subjects.

The input data for all subjects are then interpolated using CubicSpline, as the data for some frames from the subjects' time series data are incomplete. In addition, in order to label all measured data according to the frame, CubicSpline is also applied to the FMS score. Since the FMS score has a range from 1 to 5 (where 1 means no VR disease and 5 means severe VR disease), the label value interpolated with CubicSpline is limited to 1 to 5. Figure 4 shows an example of CubieSpline interpolation of FMS scores on frames.

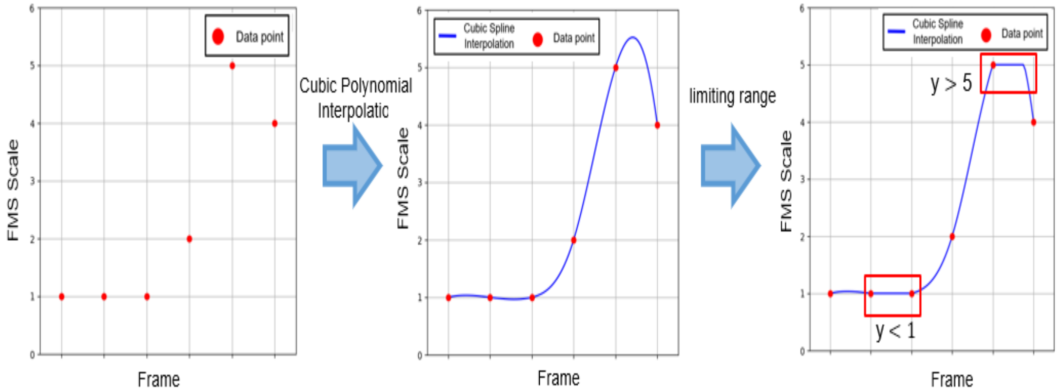


Fig. 4. Example CubicSpline interpolation of FMS score

Then, the HMD data and controller data are normalized using Equation (2), and the render image and depth image are resized to 224*224 and normalized using Equation (3).

$$Normalized\ Data = \frac{Data - \min(Data)}{\max(Data) - \min(Data)} \tag{2}$$

$$x' = \frac{x - \mu}{\sigma} \tag{3}$$

where: x – the original pixel value,
x' – the normalized pixel value,
μ – the mean of the pixel values,
σ – the standard deviation of the pixel values.

3.2. Design of Deep Learning model

1. Motion processing module

The motion processing module (hereafter referred to as M_{motion}) uses two types of input data (HMD and Controller) to output a motion-based FMS score. These input data are time-series data related to user motions, and the module is designed based on the LSTM model, which is specialized for time-series analysis. It is composed of two LSTM models (HMD-based LSTM: M_{head}, Controller-based LSTM: $M_{controller}$) that are merged in parallel. The outputs of each LSTM model are merged through a FC layer. In addition, the output value of a single model is designed to be exported as it is, so that the output value can be maintained even if the HMD data or controller data are not measured in a particular frame. The detailed structure of M_{motion} is shown in Fig. 5. The hyperparameters of each LSTM model are designed with optimal hyperparameters using a random search method, and the hyperparameters of each model are as follows: M_{head} 1) Hidden size: 128, 2) Num layer: 1, 3) Learning rate: 0.001; $M_{controller}$ 1) Hidden size: 128, 2) Num layer: 4, 3) Drop out: 0.5, 4) Learning rate: 0.001.

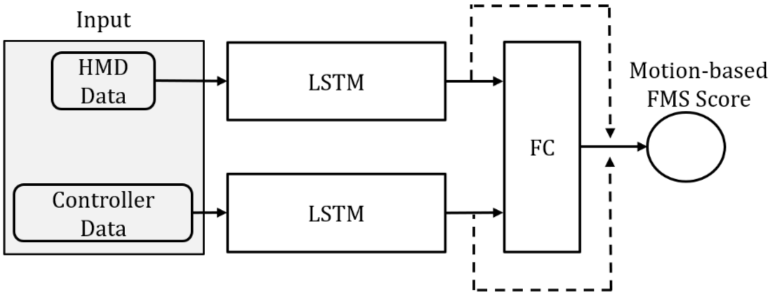


Fig. 5. An architecture of the motion processing module (Dashed lines indicate FMS output when one input attribute is missing)

2. Visual processing module

The visual processing module (hereafter referred to as M_{visual}) uses two input data (rendering image and depth image) to output a visual-based FMS score. The input data is image data, which is designed based on the ResNet model (He et al., 2016), a neural network architecture widely used in the field of image recognition. The ResNet model can effectively train very Deep neural networks through skip connection, a process of adding input values to output values in residual blocks.

M_{visual} is specifically composed of two ResNet18 models (rendering image-based ResNet18: M_{image}, depth image-based ResNet18: M_{depth}) that are merged in parallel, with their outputs merged through a Fully Connected (FC) layer. Additionally, similar to M_{motion}, the model is designed to export the output value of a single model as it is so that the output value can be maintained even if the data for certain frames is incomplete. The detailed structure of M_{visual} is shown in Fig. 6.

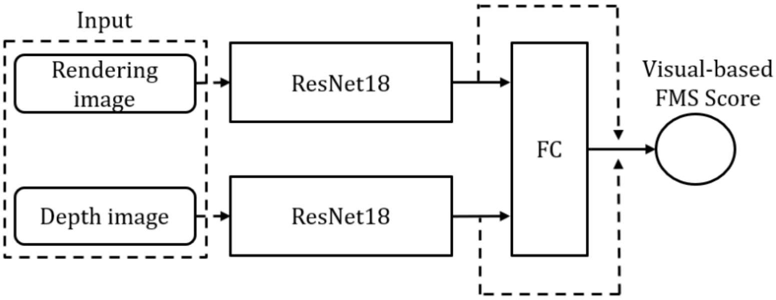


Fig. 6. An architecture of the visual processing module (Dashed lines indicate FMS output when one input attribute is missing)

3. FC-based VR sickness classification module

The FC-based VR Sickness Classification Module utilizes M_{motion} and M_{visual} as input data for the MLP (Multi-Layer Perceptron) to classify the FMS score. The output size of the final proposed model (hereafter referred to as $M_{proposed}$) is 1, producing a real number between 1 and 5. The MLP is composed of 4 layers, each being a Fully Connected layer with ReLU activation functions, and the loss function used is Mean Squared Error (MSE). The final designed Deep Learning model architecture is shown in Fig. 7.

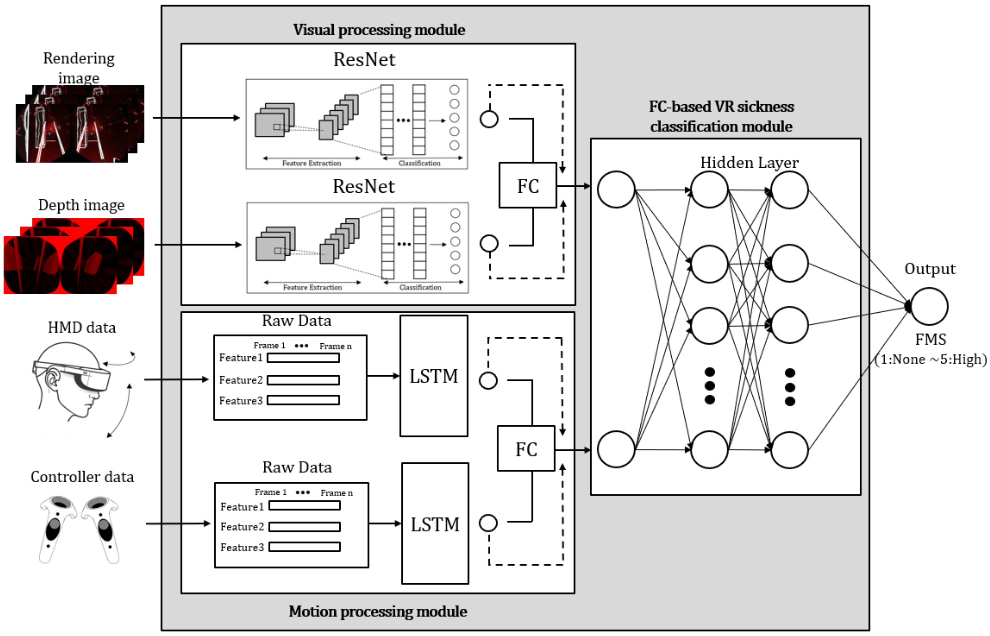
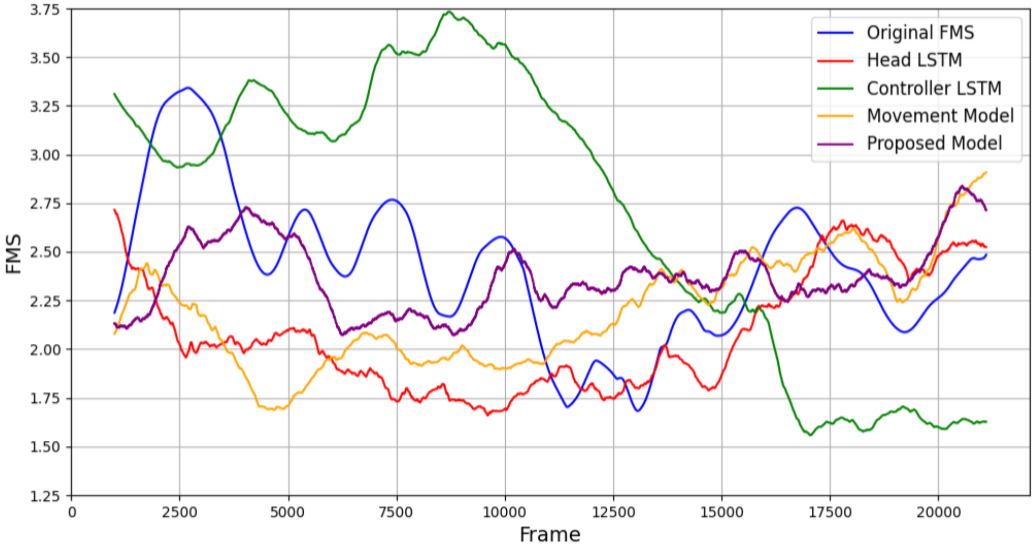


Fig. 7. An architecture of the proposed Deep Learning model

4. RESULTS

The performance of the proposed Deep Learning model ($M_{proposed}$) was compared with the existing models developed during the design phase (single models: M_{head}, $M_{controller}$, merged model: M_{motion}). First, the FMS score outputs by M_{head}, $M_{controller}$, M_{motion} and $M_{proposed}$ were compared to the actual FMS scores using the same test set. The test set was constructed by randomly selecting one subject per each of the 8 content types in advance. The visualization result of the FMS classification scores for each model compared to the actual FMS score is shown in Fig. 8. Upon examining the errors (MAE, MSE, RMSE) between each model's FMS scores and the actual FMS scores, it was confirmed that the proposed model had the lowest errors. The error results between each model and the actual FMS scores are shown in Tab. 2.



Blue: Actual FMS Score
Red: FMS Classification Score of M_{head}
Green: FMS Classification Score of $M_{controller}$
Yellow: FMS Classification Score of M_{motion}
Purple: FMS Classification Score of $M_{proposed}$

Fig. 8. Visualization of each model's FMS classification scores compared to actual FMS score

Tab. 2. Error results between each model and actual FMS score

Model evaluation metrics	M_{head}	$M_{controller}$	M_{motion}	$M_{proposed}$
MAE	0.442	0.723	0.435	0.333
MSE	0.310	0.670	0.272	0.155
RMSE	0.557	0.819	0.522	0.393

Subsequently, a paired t-test was conducted to determine if there were significant differences between the errors of the FMS score from each model and the actual FMS score.

The results indicated that the proposed $M_{proposed}$ showed a 50% reduction in MSE (p-value: 0.036) and a 29% reduction in RMSE (p-value: 0.034) compared to M_{head}, both reductions being statistically significant at the 0.05 significance level. However, no significance was confirmed in the MAE error. In $M_{proposed}$ and $M_{controller}$, the MSE was significantly reduced by 76% (p-value: 0.032) and the RMSE was also reduced by 52% (p-value: 0.037); however, the MAE was not confirmed to be significant. Finally, for $M_{proposed}$ and M_{motion}, all errors were reduced by at least 20%, however, only the RMSE was confirmed to be significant (p-value: 0.044). The error comparison results for $M_{proposed}$ and each model are shown in Fig. 9-11.

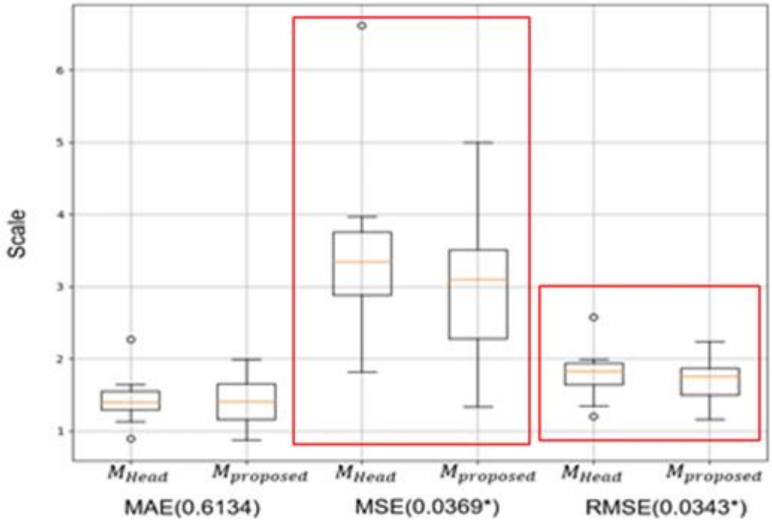


Fig. 9. Visualization of the FMS score error for $M_{proposed}$ and M_{head}. (p<0.05)

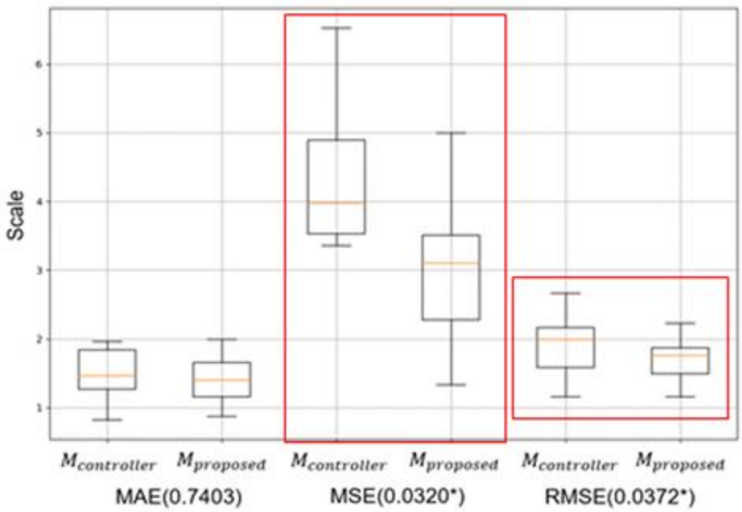


Fig. 10. Visualization of the FMS score error for $M_{proposed}$ and $M_{controller}$. (p<0.05)

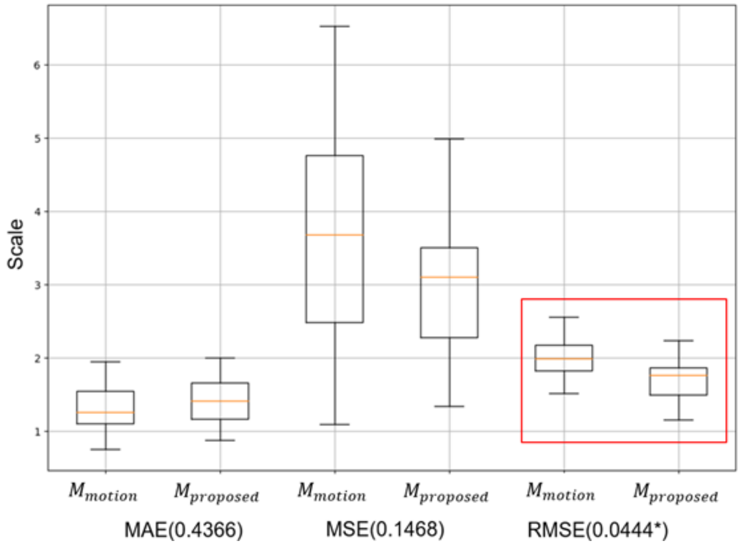


Fig. 11. Visualization of the FMS score error for $M_{proposed}$ and M_{motion}. (p<0.05)

5. CONCLUSION

In this paper, the authors proposed a Deep Learning model to classify the level of user VR sickness. The proposed model consists of three main modules: 1) Motion processing module, 2) Visual processing module, and 3) FC-based VR sickness classification module. The Motion Processing Module is designed by merging two individual LSTM models that use HMD data and controller data respectively, to output a FMS score based on motion information. The Visual Processing Module is designed by merging two individual ResNet models that use rendering images and depth images respectively, to output a FMS score based on visual information. Finally, the FC-based VR Sickness Classification Module merges the outputs from the two processing modules to calculate the final FMS score.

The performance of the proposed model was compared with the single models (M_{head}, $M_{controller}$) and the 2bay merged model (M_{motion}) which were developed during the design phase. Comparing the errors (MAE, MSE, RMSE) between the actual FMS scores and the FMS scores output by each model, the proposed model reduced all errors by at least 20% compared to M_{head}. Significant differences were observed in MSE (p-value: 0.036) and RMSE (p-value: 0.034). In comparison with $M_{controller}$, the proposed model significantly reduced all the errors by at least 52%. Significant differences were confirmed in MSE (p-value: 0.032) and RMSE (p-value: 0.037). Lastly, when comparing the errors of the proposed model to M_{motion}, MAE decreased by 23%, MSE by 43%, and RMSE by 24%, with a significant difference observed only in RMSE (p-value: 0.044).

From these results, it was confirmed that the proposed model had better classification performance than the existing single models and merged models.

This paper proposed a 4bay parallel model to classify VR sickness levels, with the following main contributions:

1) Based on the sensory conflict theory, the most representative theory to explain motion sickness, the authors selected input data (motion data and visual data) and designed a parallel integrated model to process them.

2) Unlike previous studies that classified VR sickness using a simple binary approach (sickness or non-sickness), this paper further refined the classification of VR sickness by dividing it into five levels.

3) The proposed model is capable of predicting a user's VR sickness level in real-time, making it applicable for real-time monitoring and content adjustments in various VR content such as gaming, education, and simulation. This feature is particularly useful in VR-based education, training, and therapeutic programs, as it can provide personalized experiences tailored to the user's specific needs.

However, this study had several limitations. First, the dataset was limited to a specific genre of content and a restricted group of users, necessitating further validation with datasets that incorporate measurements from more diverse environments. Second, although this paper utilized motion data and visual data, it is necessary to consider incorporating physiological data for a more comprehensive analysis. Third, experiments involving real subjects must be conducted to assess the model's applicability to VR content and evaluate its commercialization potential.

In future work, the authors will conduct tests in different VR environments and additional datasets to validate the generality of the model and examine real-time applicability.

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