VIRTUAL REALITY SICKNESS PREDICTION MODEL

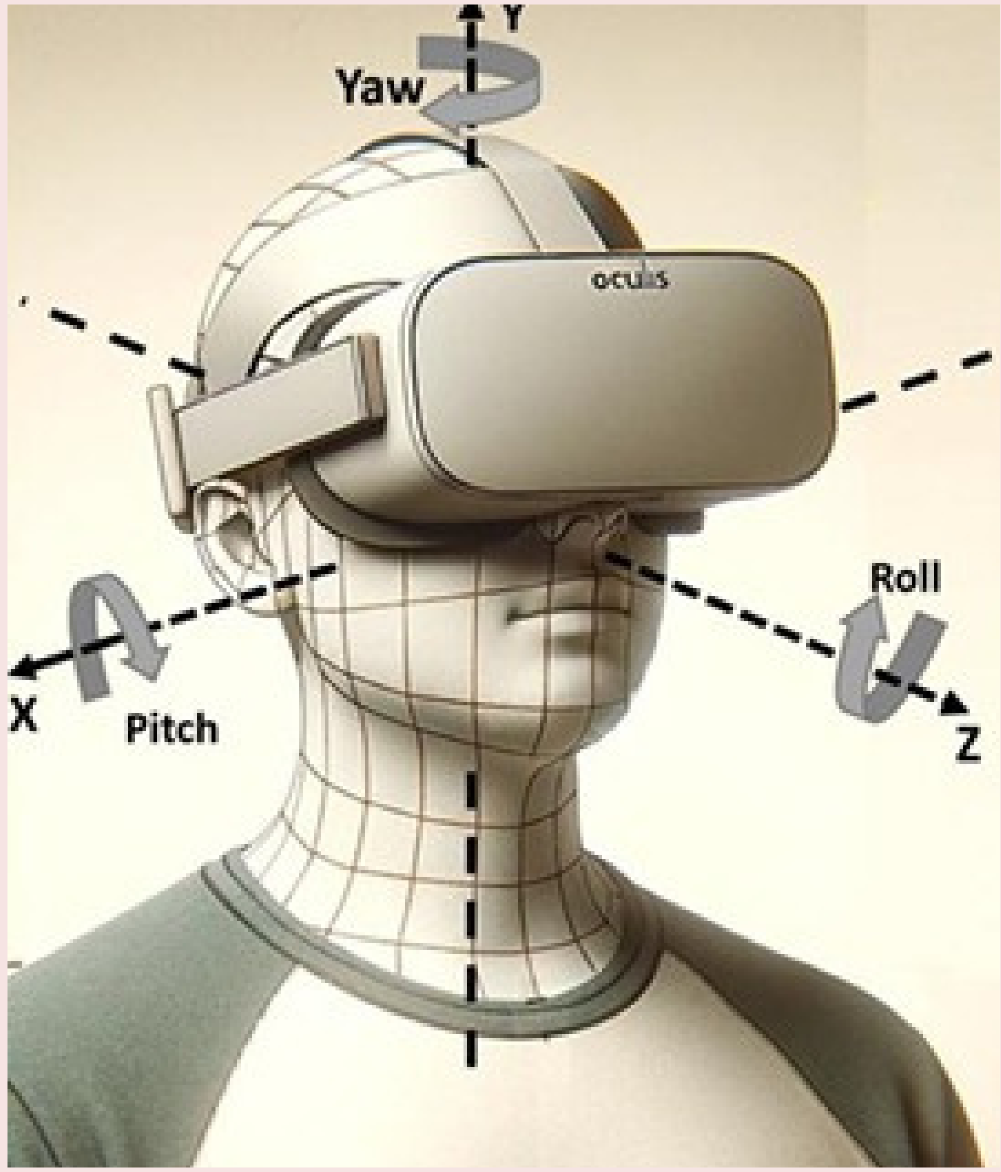
Team member : Rishitha Thoka , Afrin Banu R

OVERVIEW

The project “Virtual Reality Sickness Reduction Model" involves predicting cybersickness using head movement data captured by VR headsets. It encompasses the full lifecycle from data collection to feature extraction, model training, and evaluation. The target variable is the Indicated_Sick_SSQ2(Sickness Symptom Questionnaire) score, indicating whether a subject feels "sick" or "not sick,"which serves as the dependent variable applying feature extraction methods, and using machine learning models like Random forest, linear SVM, Logistic regression ,XG Boost and Adaboost . Extensive testing ensures accurate and timely prediction of cybersickness, enhancing user experience in VRenvironments.

INTRODUCTION

Virtual reality (VR) has gained popularity as a technology that can provide users with immersive, interactive experiences. Despite the benefits of VR, it has some limitations including the experience of cybersickness, a form of motion sickness, that may occur in virtual environments. Cybersickness prevents people from widely embracing and enjoying VR experiences due to symptoms such as nausea, dizziness, disorientation, and fatigue . Therefore, in this project we aim to use the head movements signals as a potential identifier for cybersickness. Head movements data can be a reliable, cheap, and easy to access source of data . By identifying patterns and appropriate identifiers extracted from physiological data; machine learning models can be trained to predict cybersickness .



PROBLEM STATEMENT

With the increasing adoption of Virtual Reality (VR) technologies, one of the main barriers to widespread usage is the occurrence of cybersickness, a form of motion sickness that can cause discomfort and limit users' ability to engage with VR environments for extended periods. Traditional detection methods of cybersickness are often subjective and not suitable for real-time monitoring, making it challenging to provide timely intervention. This project aims to develop a machine learning-based approach to predict cybersickness in real-time by analyzing head movement data fromVR headsets, offering an efficient, non-invasive solution to enhance user comfort and optimize VR experiences.

OBJECTIVES

•Develop Cybersickness Detection Model:
Create a machine learning model using VR head movement data to predict cybersickness in real-time.

•Feature Extraction and Processing:
Extract velocity, acceleration, jerk, and other features to detect cybersickness-related patterns.

•Optimize Predictive Accuracy:
Apply feature selection and machine learning techniques (Random Forest, Logistic Regression ,XG Boost, Linear SVM,AdaBoost) to improve prediction accuracy.

•Real-time Monitoring:
Implement real-time tracking of head movements for early cybersickness detection.

•Improve VR User Experience:
Develop a scalable, non-invasive solution to enhance VR usability and reduce cybersickness risks

TOOLS

1.Python: Main programming language for data analysis and machine learning.

2.Pandas: For data manipulation and handling large datasets.

3.NumPy: For numerical computations and array handling.

4.Scikit-learn: Machine learning library for model training and evaluation.

6.Matplotlib: Data visualization library for plotting graphs.

7.Seaborn: Aesthetically pleasing statistical visualization library.

8.SciPy: Library for scientific computing and statistical analysis.

TECHNOLOGIES

•**Machine Learning Algorithms:** Algorithms like Logistic Regression, Random Forest, and SVM are used to build predictive models for cybersickness detection.

•**Feature Extraction Tools:** Libraries within scikit-learn are used to extract and engineer statistical, temporal, and spectral features from head movement data for model training.

•**Data Processing (Python, Pandas):** Python libraries such as Pandas are used for handling and processing large datasets, including data cleaning, transformation, and preparation for model training.

Driver vs. Passenger – Design & Data Sheet Date____________________

Name ____ Participant # _________

Driver **Passenger**

<u>**For Passengers**</u>: Driver's Subject Number: ___________; Driver Discontinued Time: ____________

A. Inspection Search **B. Search Inspection**

Age ______ Male Female Height (meters) ______________ Weight (lbs) ____________

Do you currently play video games? **Yes** **No**

At what age did you begin to play video games ______________

How many years have you played video games? __________

Currently, approximately how many hours do you play each week? ________________

Have you ever used a virtual reality headset such as the Oculus Rift? **Yes** **No**

Do you own a virtual reality headset? **Yes** **No**

Currently, approximately many hours per week do you use any virtual reality headset? _____________

Search Task # of R's found __________

Search Task end point: Line # _______ Word _____________________________

Extra credit for class ______________________________

DATASET:

Subject	Sex	Driving Status	Age	Height (cm)	Weight (lbs)	Weight(kg)	Do you currently play video games? (0: No; 1: Yes)	At what age did you begin to play video games? (0 = Nev	How many years have you played video games?	Currently, approximately how many hours do you play each week?	Have you ever used a virtual reality headset such as the oculus rift? (Yes: 1; No: 0	Do you own a virtual reality headset? (Yes:1, No:0)	Currently, approximately many hours do per week do you use any virtual reality headset	First Visual Task	Second Visual Task	Discont	ation Time (Secs)
3F	Female	Driver	21	163	145	65.77084	0	10	0	0	0	0	0	Inspection	Search		
4F	Female	Passenger	19	165	134	60.78133	0	7	12	0	0	0	0	Inspection	Search		
5F	Female	Driver	21	157	117	53.07026	0	9	10	0.5	1	0	0	Search	Inspection		
6F	Female	Passenger	20	158	163	73.9355	0	0	0	0	0	0	0	Search	Inspection		
7F	Female	Driver	21	162	158	71.66754	0	7	5	0	0	0	0	Inspection	Search		
8F	Female	Passenger	21	166	126	57.15259	0	12	1.5	0	1	0	0	Inspection	Search		
9F	Female	Driver	20	164	121	54.88463	0	10	6.5	0.5	0	0	0	Search	Inspection		
10F	Female	Passenger	21	168	169.5	76.88384	0	12	5	0	1	0	0	Search	Inspection		
11F	Female	Driver	21	179	200	90.7184	0	0	0	0	0	0	0	Inspection	Search	82.71	
12F	Female	Passenger	22	174	173	78.47142	0	9	13	1	0	0	0	Inspection	Search		
13F	Female	Driver	20	176	135	61.23492	0	8	12	0	0	0	0	Search	Inspection	538.97	
14F	Female	Passenger	20	177	180	81.64656	1	7	13	0	0	0	0	Search	Inspection	665	
15F	Female	Driver	21	170	143	64.86366	0	10	11	0	0	0	0	Inspection	Search		
16F	Female	Passenger	19	169	156	70.76035	0	8	11	0	1	0	0	Inspection	Search	413.33	
17F	Female	Driver	20	151	118	53.52386	0	0	0	0	1	0	0	Search	Inspection		
18F	Female	Passenger	24	161	148	67.13162	0	6	13	0	1	0	0	Search	Inspection		
19F	Female	Driver	20	160	127	57.60618	0	0	0	0	0	0	0	Inspection	Search		
20F	Female	Passenger	21	167	127	57.60618	0	8	4	0	0	0	0	Inspection	Search		
21F	Female	Driver	23	165	127	57.60618	0	10	13	0	0	0	0	Search	Inspection	270	
23F	Female	Driver	20	159	105	47.62716	0	8	3	0	1	0	0	Inspection	Search		
24F	Female	Passenger	19	160	134	60.78133	1	6	13	2	1	0	0	Inspection	Search		
25F	Female	Driver	21	165	134	60.78133	0	10	3	0	0	0	0	Search	Inspection	356	

CYBERSICKNESS DEMOGRAPHICS DATA

1	Subject	SSQ1 Tc	Indicate	SSQ2 Tc	Indicate	Did Part	SSQ3 Tc	Indicate	Post-Exposure Score Used in Analysis (SSQ2 for Every Participant Except 34M, who indicated they were sick on the SSQ3)
2	3F	0	0	0	0	1	0	0	0
3	4F	7.48	0	14.96	0	1	0	0	14.96
4	5F	0	0	56.1	1	0			56.1
5	6F	3.74	0	29.92	0	1	48.62	0	29.92
6	7F	0	0	3.74	0	1	0	0	3.74
7	8F	0	0	7.48	0	1	0	0	7.48
8	9F	0	0	11.22	0	1	0	0	11.22
9	10F	7.48	0	22.44	0	1	3.74	0	22.44
10	11F	0	0	115.94	1	0			115.94
11	12F	7.48	0	52.36	0	1	3.74	0	52.36
12	13F	0	0	82.28	1	0			82.28
13	14F	14.96	0	63.58	1	0			63.58
14	15F	0	0	7.48	0	1	0	0	7.48
15	16F	0	0	18.7	1	0			18.7
16	17F	7.48	0	3.74	0	1	0	0	3.74
17	18F	0	0	33.66	0	1	97.24	0	33.66
18	19F	0	0	3.74	0	1	0	0	3.74
19	20F	0	0	11.22	0	1	0	0	11.22
20	21F	3.74	0	97.24	1	0			97.24
21	23F	18.7	0	7.48	0	1	0	0	7.48
22	24F	22.44	0	11.22	0	1	0	0	11.22
23	25F	0	0	67.32	1	0			67.32
24	26F	29.92	0	26.18	0	1	37.4	0	26.18
25	27F	0	0	82.28	1	0			82.28
26	28F	3.74	0	74.8	1	0			74.8
27	29F	0	0	7.48	0	1	0	0	7.48
28	30F	11.22	0	29.92	0	1	0	0	29.92

SIMULATOR SICKNESS QUESTIONARE (SSQ) DATA

Subject: 1I	Mediolate	Anterior Posterior
Condition:	-0.959	-2.745
	-0.938	-2.742
	-0.938	-2.742
	-0.948	-2.734
	-0.947	-2.711
	-0.958	-2.722
	-0.959	-2.745
	-0.979	-2.725
	-0.989	-2.717
	-0.988	-2.733
	-0.997	-2.738
	-1.007	-2.73
	-1.038	-2.721
	-1.05	-2.717
	-1.05	-2.697
	-1.051	-2.681
	-1.061	-2.689
	-1.08	-2.685
	-1.089	-2.674
	-1.109	-2.673
	-1.107	-2.67
	-1.128	-2.67
	-1.149	-2.653
	-1.15	-2.634
	-1.169	-2.634
	-1.159	-2.603
	-1.161	-2.609
	-1.171	-2.597

INSPECTION TASK

Subject_1M_Inspection_Task	18-09-2024 13:33	Microsoft Excel W...	56 KB
Subject_1M_Search_Task	18-09-2024 13:33	Microsoft Excel W...	55 KB
Subject_2M_Inspection_Task	18-09-2024 13:33	Microsoft Excel W...	58 KB
Subject_2M_Search_Task	18-09-2024 13:33	Microsoft Excel W...	57 KB
Subject_3F_Inspection_Task	18-09-2024 13:33	Microsoft Excel W...	55 KB
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Subject_3M_Inspection_Task	18-09-2024 13:33	Microsoft Excel W...	59 KB
Subject_3M_Search_Task	18-09-2024 13:33	Microsoft Excel W...	59 KB
Subject_4F_Inspection_Task	18-09-2024 13:33	Microsoft Excel W...	56 KB
Subject_4F_Search_Task	18-09-2024 13:33	Microsoft Excel W...	56 KB
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Subject_4M_Search_Task	18-09-2024 13:33	Microsoft Excel W...	57 KB
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Subject_7F_Search_Task	18-09-2024 13:33	Microsoft Excel W...	57 KB
Subject_7M_Inspection_Task	18-09-2024 13:33	Microsoft Excel W...	60 KB

SIMULATOR SICKNESS QUESTIONNAIRE(SSQ)

A brief explanation of the Simulator Sickness Questionnaire (SSQ)

Each item is rated with the scale from none, slight, moderate to severe. Through some calculations, four representative scores can be found. Nausea-related subscore (N), Oculomotor-related subscore (O), Disorientation-related subscore (D) are the scores for the symptoms for the specific aspects. Total Score (TS) is the score representing the overall severity of cybersickness experienced by the users of virtual reality systems.

The calculations in the Simulator Sickness Questionnaire

None = 0
Slight = 1
Moderate = 2
Severe = 3

Symptoms	Weights for Symptoms Nausea	Oculomotor	Disorientation
General discomfort	1	1	
Fatigue		1	
Headache		1	
Eye strain		1	
Difficulty focusing		1	1
Increased salivation	1		
Sweating	1		
Nausea	1		1
Difficulty concentrating	1	1	
Fullness of head			1
Blurred vision		1	1
Dizzy (eyes open)			1
Dizzy (eyes closed)			1
Vertigo			1
Stomach awareness	1		
Burping	1		
Total*	[1]	[2]	[3]

Score
Nausea = [1] × 9.54
Oculomotor = [2] × 7.58
Disorientation = [3] × 13.92
Total Score = ([1] + [2] + [3]) *3.74

* Total is the sum obtained by adding the symptoms scores. Omitted scores are zero

Date ________ Simulator Sickness Questionnaire Participant ________

SSQ-X

Are you motion sick now? Circle YES or NO

Circle how much each symptom below is affecting you now.
0 = "not at all" 1 = "mild" 2 = "moderate" 3 = "severe"

1. General discomfort	0	1	2	3
2. Fatigue	0	1	2	3
3. Headache	0	1	2	3
4. Eyestrain	0	1	2	3
5. Difficulty focusing	0	1	2	3
6. Increased salivation	0	1	2	3
7. Sweating	0	1	2	3
8. Nausea	0	1	2	3
9. Difficulty concentrating	0	1	2	3
10. Fullness of head	0	1	2	3
11. Blurred vision	0	1	2	3
12. Dizziness (eyes open)	0	1	2	3
13. Dizziness (eyes closed)	0	1	2	3
14. Vertigo*	0	1	2	3
15. Stomach awareness**	0	1	2	3
16. Burping	0	1	2	3

*Vertigo is experienced as loss of orientation with respect to vertical upright
**Stomach awareness is usually used to indicate a feeling of discomfort that is just short of nausea.

METHODOLOGY

1.Requirements Analysis and Planning

• The project began by analyzing the specific needs for predicting cybersickness in VR environments and determining the hardware and software requirements.
• Google Colab was selected as the cloud-based platform for data analysis due to its compatibility with Python libraries and ease of access to Google Drive for dataset management.

2.Virtual Environment Setup

• Google Drive Integration: The project commenced by mounting Google Drive within Google Colab to facilitate access to the dataset files required for analysis.
• Data File Path Definition: The file path for the Excel files containing the head movement and SSQ data was defined, along with the relevant sheet names for male subjects.

3.Model Development:
Train various machine learning models, including Random Forest, XGBoost, Linear SVM, and AdaBoost, using the selected features derived from the head movement data.

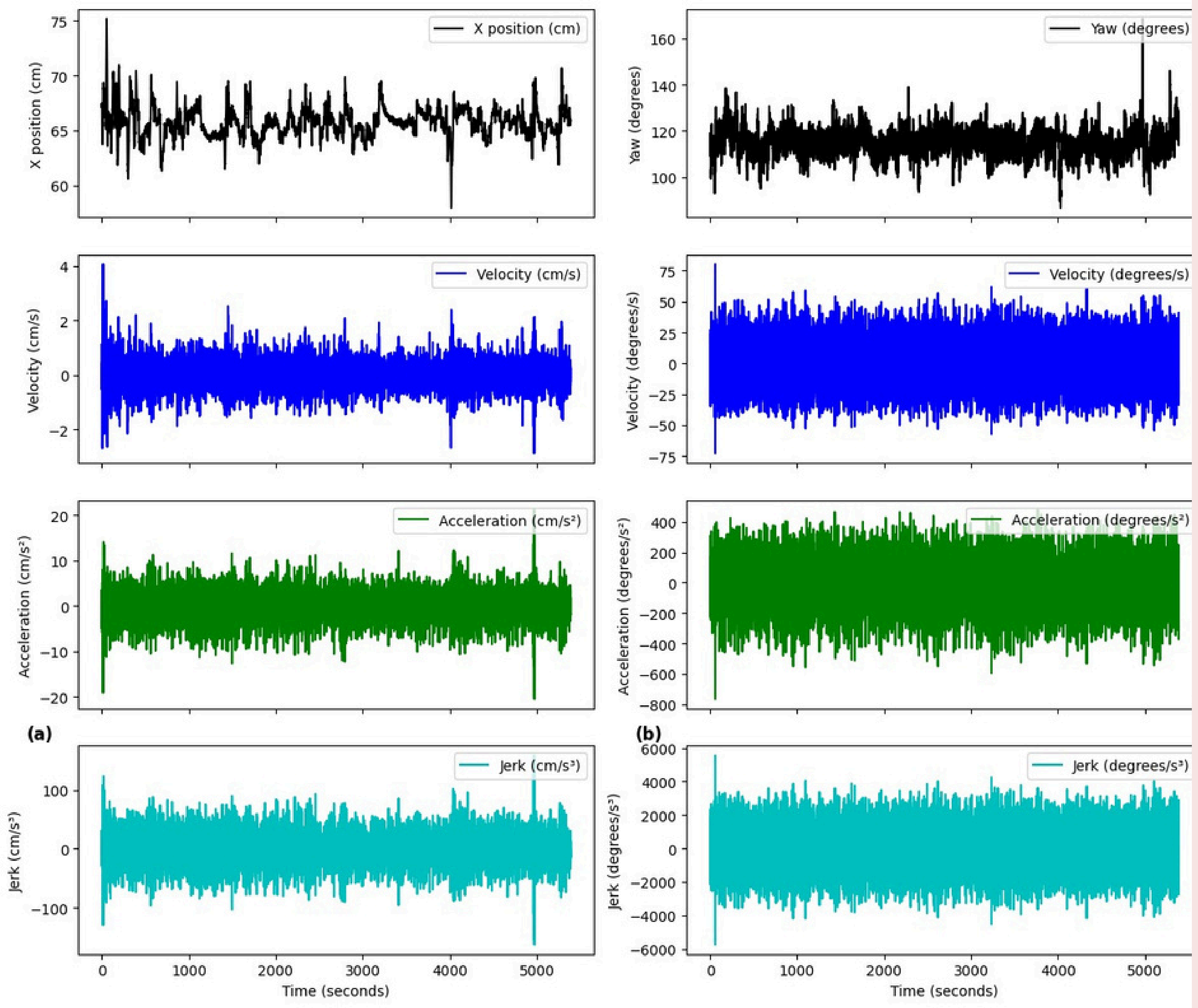
4.Model Evaluation:
Use evaluation metrics such as accuracy, precision, recall, and F1 score to assess each model's effectiveness in predicting cybersickness.

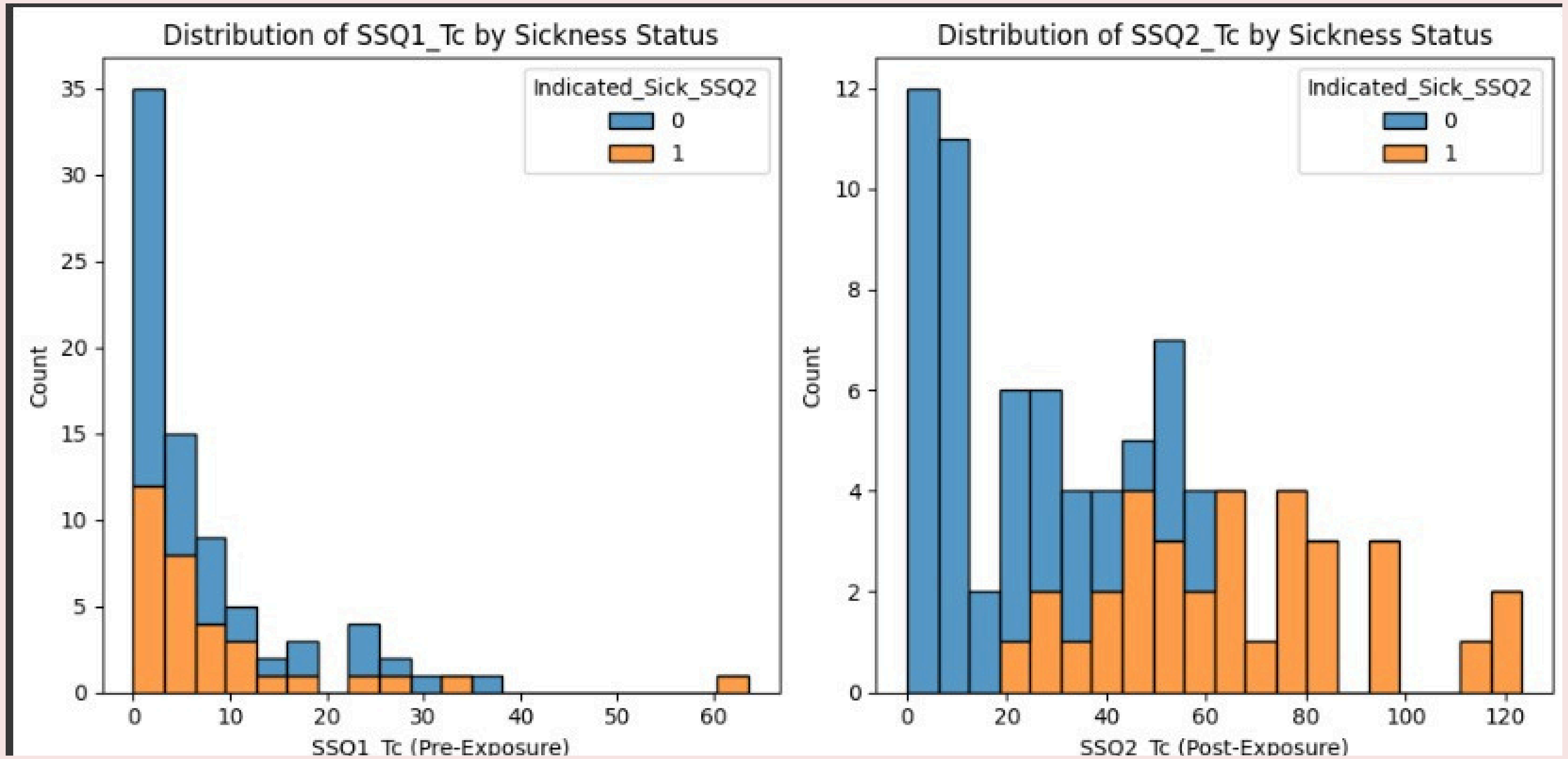
5.Real-time Prediction:
Implement the trained model to enable real-time detection of cybersickness by continuously monitoring head movements within VR environments.

6.Testing and Validation:
Conduct tests to evaluate the model's performance in real-time scenarios, focusing on accuracy, false positives, and false negatives.

7.Deployment:
Deploy the model within a scalable, non-invasive system designed for continuous cybersickness detection in VR applications. Monitor system performance and gather user feedback to make iterative improvements, enhancing the overall user experience in VR environments.

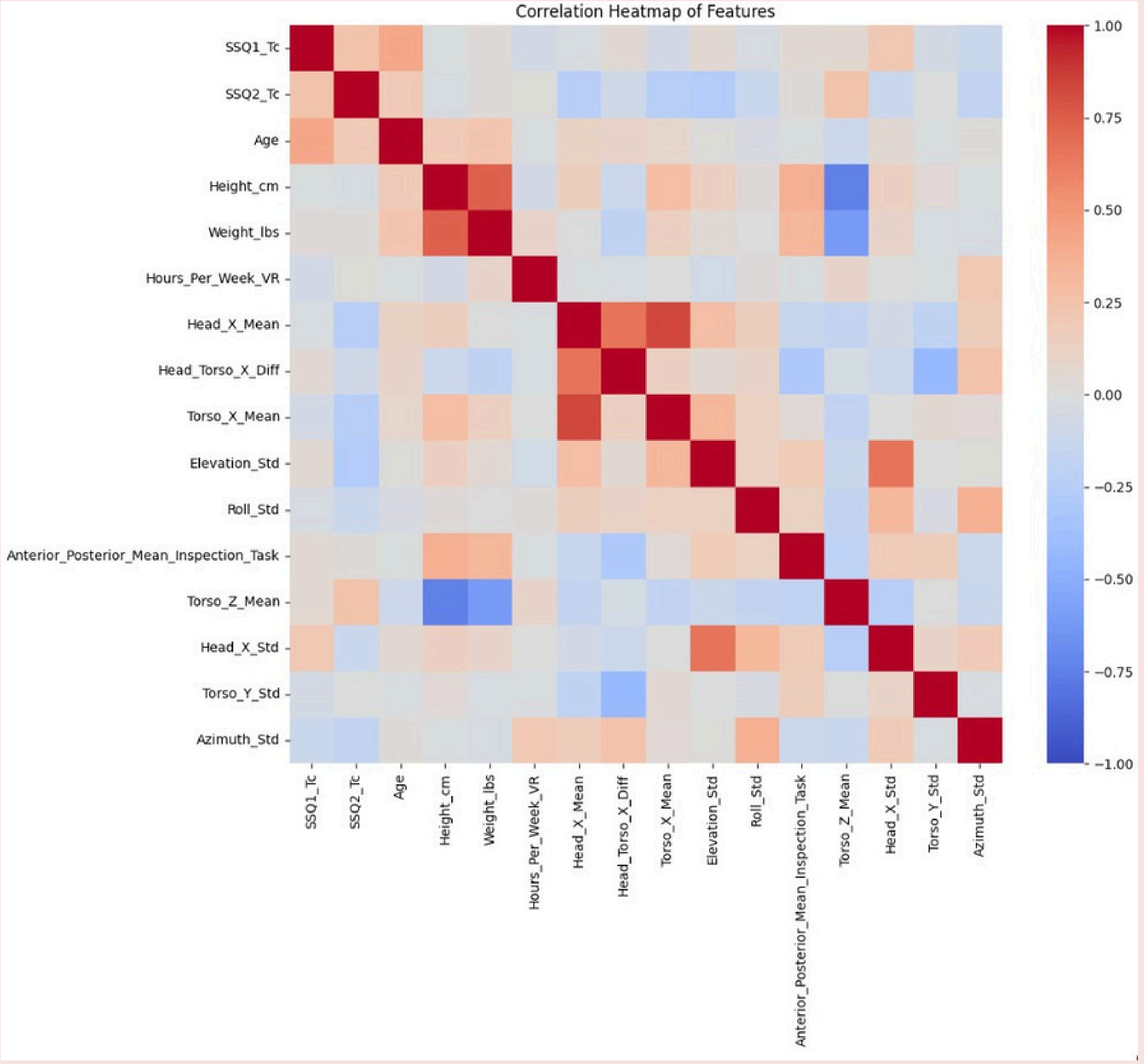
VISUALIZATION:



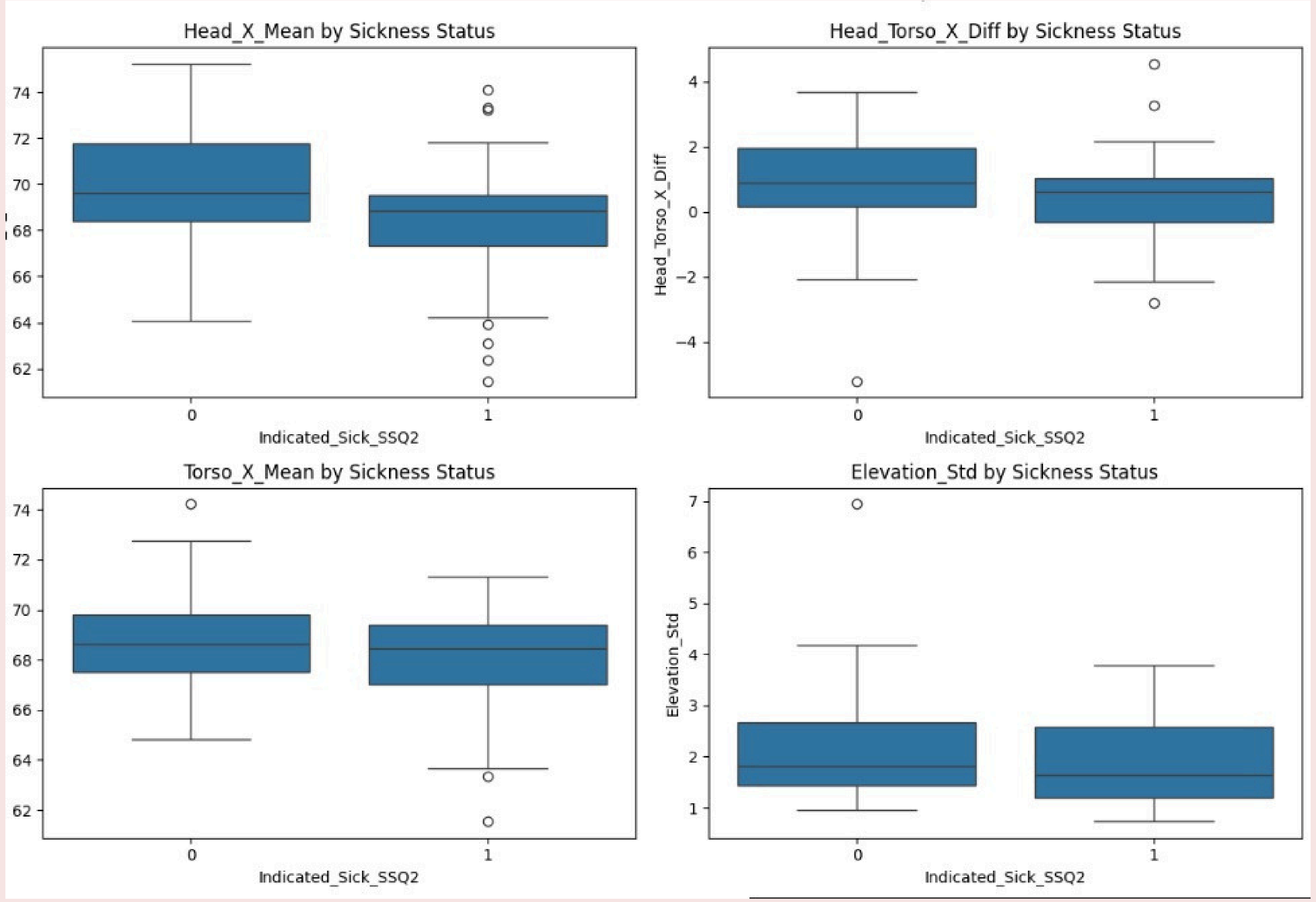


Pre-Exposure **Post-Exposure**

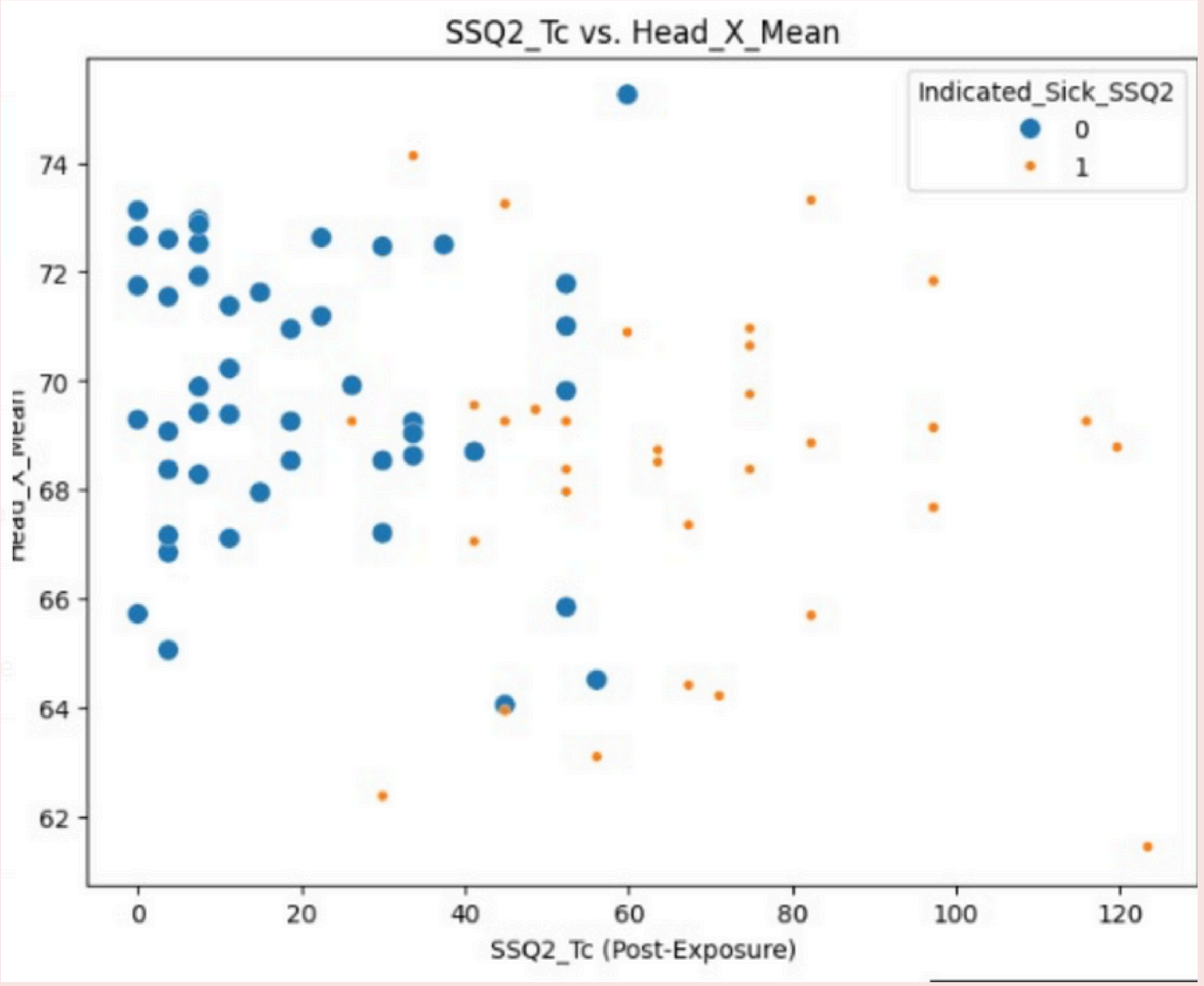
Time-Series Motion Data Plots



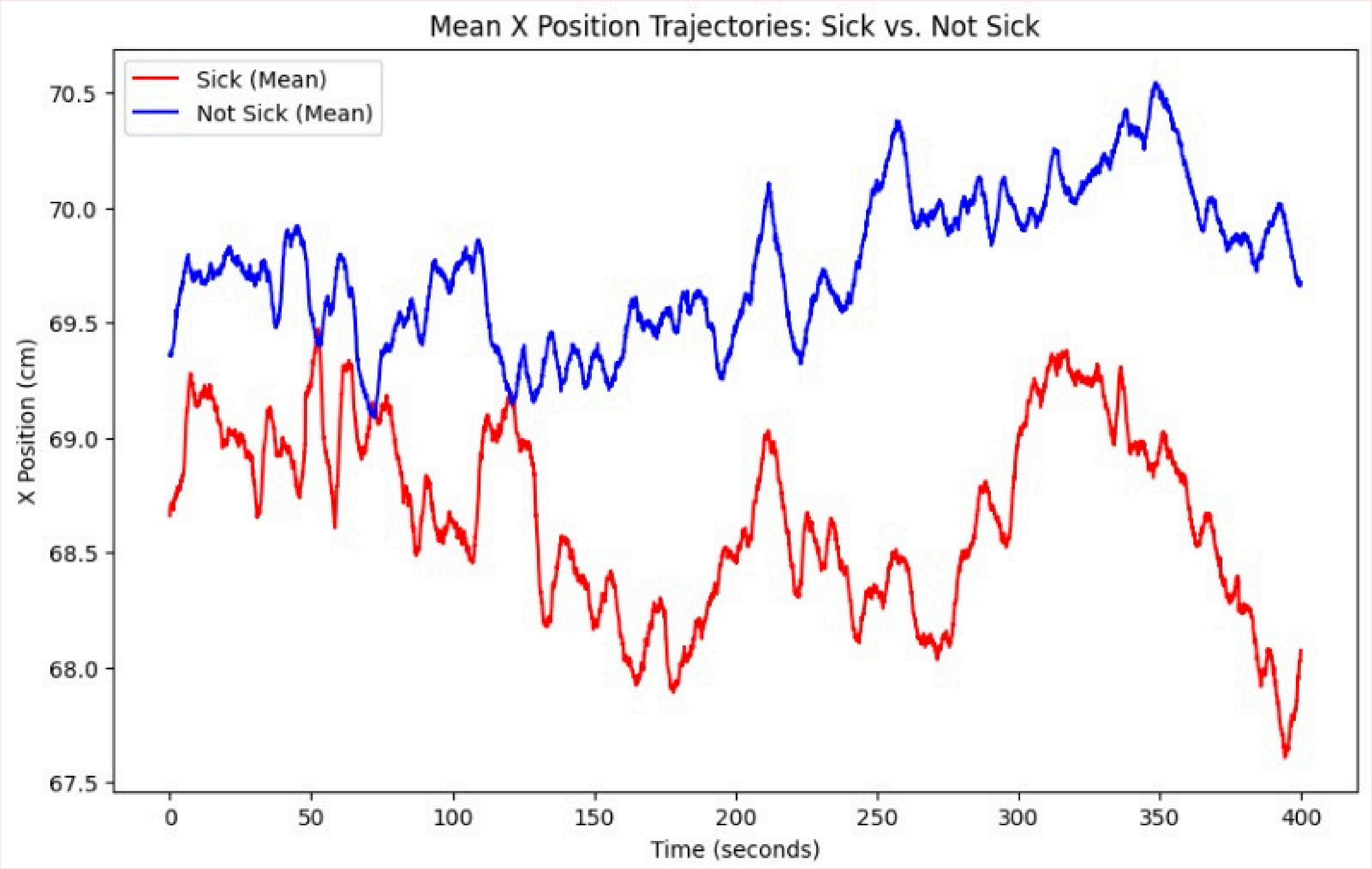
Correlation Heatmap of Features



Boxplots of Key Kinematic Features by Sickness Status



Scatter Plot of SSQ2



Mean X Position Trajectories: Sick vs. Not Sick

APPLICATIONS

1.Virtual Reality Training:

Detects and mitigates cybersickness during training simulations for military, aviation, and industrial sectors, ensuring trainee comfort and performance.

2.Healthcare and Rehabilitation:

Monitors and reduces cybersickness symptoms in virtual therapy or rehabilitation environments, improving patient outcomes during VR-assisted treatments.

3.VR Gaming and Entertainment:

Enhances user experience by minimizing cybersickness in immersive VR games and entertainment applications, leading to longer play sessions and higher engagement.

4.Education and Remote Learning:

Facilitates smoother virtual learning experiences for students and educators by reducing discomfort during extended VR classroom or remote learning

CONCLUSION

In conclusion, this project uses machine learning to analyze VR head movement data and introduces a novel approach to addressing the persistent issue of cybersickness in Virtual Reality (VR) environments. The performance of the XGBoost, Random Forest, Linear SVM, and AdaBoost models was compared to determine the most effective model for predicting cybersickness based on head movement and Simulator Sickness Questionnaire (SSQ) scores. Understanding these thresholds could inform the design of VR environments to mitigate discomfort and enhance user experience. The XGBoost model achieved the highest accuracy making it the most accurate in detecting cybersickness. Therefore, the overall accuracy would vary depending on which model is chosen for final deployment, but XGBoost at 90% can be considered the best-performing model.

FUTURE SCOPE

Personalized Sickness Prediction:
By collecting more data (e.g., physiological signals like heart rate, eye tracking), you can build more accurate models to predict sickness for individual users.

Real-Time Sickness Detection:
Integrate your model into VR systems to monitor kinematic data in real-time and predict sickness during a session. If sickness is likely, the system can alert the user or adjust settings (e.g., reduce motion intensity).

Sickness Reduction Strategies:
Individualized Interventions: Use model insights (e.g., SHAP values) to identify which factors (e.g., high head velocity) contribute most to sickness for a specific user. Then, recommend personalized adjustments, such as:

- Reducing field of view (FOV) to minimize motion sickness.
- Slowing down head movement through VR feedback (e.g., haptic cues).
- Adjusting VR content (e.g., reducing acceleration in virtual environments).

REFERENCES

Journal References:

[1] A. Fernández, F. Martín-Gutiérrez, J. M. Fernández and C. Rodríguez, "Effect of Virtual Reality Sickness on User Experience in Interactive Virtual Environments," IEEE Access, vol. 8, pp. 149318-149327, 2020.

[2] Y. Kim, D. Cho, B. Kim and Y. Cho, "Deep Learning-Based Cybersickness Prediction Model in Virtual Reality Environment," IEEE Access,vol. 9, pp. 53719-53731, 2021.

[3] A. Shafer and P. R. Almeida, "Detecting Cybersickness in Virtual Reality Systems Using Machine Learning Techniques," IEEE Transactions on Visualization and Computer Graphics, vol. 27, no. 9, pp. 3883-3893, 2021.

[4] C. Yao, Z. Huang, Z. Li and H. Chen, "Real-time VR Sickness Detection for Immersive Virtual Experiences," IEEE Access, vol. 10, pp. 19928-19936, 2022.

[5] K. Munafo, M. J. Diedrick and S. J. Stoffregen, "The Virtual Reality Head-Mounted Display Oculus Rift Induces Motion Sickness and is Sexually Dimorphic in its Effects," IEEE Transactions on Visualization and Computer Graphics, vol. 21, no. 4, pp. 535-542, 2015.