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CLASSIFICATION OF LEVELS OF VIRTUAL REALITY MOTION SICKNESS USING MACHINE LEARNING – ASSESSMENT AND MITIGATION

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Abstract

Virtual Reality applications are getting attention in fields like industry, education, healthcare, manufacturing, training etc. Engaging people in a 360-degree world with a head-mounted device may cause physical and health problems. Many people cannot use Virtual Reality devices seamlessly because of motion sickness problems. Complex graphical properties included in the scene make to feel more sickness for Virtual Reality users. Virtual Reality movements include various types of geometrical transformations such as yaw, pitch, roll, rotation, translation, scaling, shearing and transformation. Study shows that continuous involvement in a VR environment starts to show symptoms of motion sickness. The motion sickness can be measured using EEG signals. Many researchers contributed to the motion sickness detection for binary classification but there are few numbers on multi-level classification and the existing has less accuracy too. Our proposed model did multi-level classification on standard EEG data and got an accuracy of 98.82% and lime local explanation has also done in this paper.

Keywords: Classification, EEG, Lime, Machine Learning, Motion Sickness, Virtual Reality.

1. INTRODUCTION

Virtual Reality (VR) service providers are growing fast in making improved Head Mounted Displays. Quality devices give more immersion and interactivity feeling in the VR environment. Also, there arises motion sickness to some extent. Previous researches have shown that there are concerns for the continuous usage of VR. Different types of motion sickness are found in VR users, called it as cyber sickness. Cyber sickness causes discomfort in VR uses and discourages the spreading of VR among children [1].

Motion sickness is a crucial problem for VR users that needs to be analyzed properly. Safeties of VR users need to be ensured by the authority, especially in the education sector since children are the end beneficiaries of VR systems. Previous research on VR motion sickness consists of gender-wise impact on motion sickness, experience with hardware devices and the kind of artificially created virtual environments and the inclusion of graphical properties. Motion sickness may vary from person to person. Motion sickness has a negative impact on work with VR devices. Mostly found motion sickness for VR users are dizziness, nauseous feeling, vomiting and cold sweats. The severity causes vertigo and disorientation [2].

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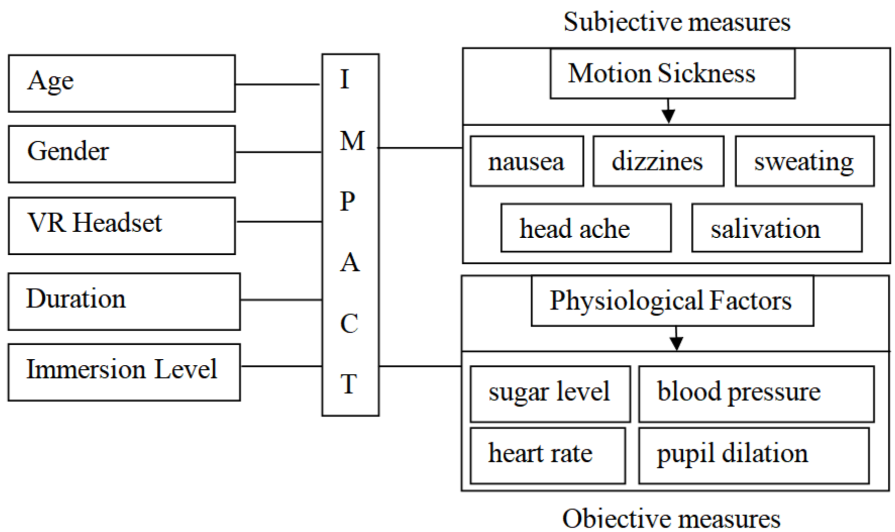
Motion Sickness related to Virtual Reality mainly consists of vertigo, blurred vision, increased salivation, nausea, headache, etc. Often, motion sickness reduces the immersiveness and interactivity of the VR experience. More generally adopted and simplest way to measure motion sickness is using electroencephalogram (EEG) signals, which reflect human emotions easily. Previous research shows there was a higher accuracy level for single evaluation with comparatively lower accuracy for multiple feature evaluation. EEG can effectively monitor and estimate cognitive workload, which could be useful in applications like adaptive training systems, cognitive assessments, and human-computer interaction. The study suggests that increasing immersion in VR leads to higher engagement and increases the user's cognitive demands [3].



This experiment uses two standard datasets for analysis. The first VR dataset has 1000 records with 7 features namely UserID, age, gender, VR Headset type, Duration, Immersion level and Motion sickness level, and the second is an EEG dataset with 2132 rows and 2549 columns. The second section of this study deals with reviewing existing literature. The third section contains the methodology and models conducting for the experiment. Fourth section contains the results and discussion and comparison with the existing methods. The conclusion and future scope of the work are reported in the fifth section.

2. LITERATURE REVIEW

Heeseaok et. al. [4] designed a protocol for evaluating cybersickness. They collected information from 154 members for their study. The study concentrated on VR both subjectively and objectively. Subjective data contains 52 VR scenes with subjective scenes and biological signals. They made a statistical analysis of data to examine the severity and it shows that both biological features, age, and susceptibility are correlated with motion sickness severity. They proposed a data set for fellow researchers to study motion sickness-related areas.

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Chatta et. al.[5] proposed a conceptual framework with two different VR environments, one designed for a pleasant theme and the other, for a horror genre. The pleasant environment consists of various outdoor scenes in daylight illumination, sea shore, and butterfly movements filled with good graphics and colors. It covers the entire VR space area with a fence boundary. On the other hand, a horror environment was created in an indoor area with a hospital background, a boundary with barren walls and misty windows. They experimented with 51 participants (23 F and 28M) aged 18-28 years. Pre-measurements and post-measurements were recorded both subjectively and objectively. 16 Simulator Sickness Questionnaire (SSQ) based subjective measurement was taken and included 5 features for objective measurement consisting of normal, elevated, hypertension 1,2 and 3 stages. They observed that people indulged in the VR experience undertaken in a pleasant environment had less motion sickness than the horror environment. Both blood pressure and heart rate were found to increase for 46 participants after experiencing a horror environment through VR devices. Sugar level decreased after watching the horror scene. Depending on the gender case, they analyzed that men have less motion sickness than the female. They experimented using ANOVA with Green house-Geisser correlation analysis.

Chang et. al. [6] conducted a comprehensive review of motion sickness, its main causes depicting machine factors as well as user-related factors. Hardware factors include frame rates, latency between user request and VR response, lower display resolution, and unfair field of view design whereas user factors pointed out that age, gender and current emotions. They used Simulated Sickness Questionnaires for their study for subjective answer representation and heart rate, eye-tracking and skin conductance for objective value measurement. The authors critically examined previous research in the field and highlighted the importance of optimizing both hardware and software for reducing VR sickness symptoms.

Foxman et. al [7] proposed a classification framework based on factors like spatial immersion, agency, embodiment, temporal structure and social presence. Spatial immersion refers to the ability to embed in a virtual environment and provide ambient navigability in VR space. The degree of reliability of an avatar interaction, the sense of togetherness, and the capability of real-time interaction play a constant role in the VR environment. This information is particularly useful for Game developers, designers, and researchers for accurate involvement. They pointed out the challenge being posed for the design of a universally accepted VR system because of the rapid changes that occurred in VR technology in various fields.

Kim et. al. [8] proposed a CNN that grasps the most relevant patterns leading to motion sickness from a VR environment by focusing on visual stimuli. The features include camera movement, speed of motion, field of view, and the complexity of the graphics. According to them, the mismatch occurring in visual stimuli and the vestibular system of the body causes motion sickness.

Martirosov et. al. [9] emphasizes the level of immersion in a VR environment and their impact on motion sickness. They categorized the level as low immersive, semi-immersive

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and fully immersive depending on the involvement and the hardware used for engagement and accessibility. A study was conducted and the participants answered the SSQ and physiological measurements such as heart rate, and skin conductance are also taken. The results show that all the categories felt discomfort and eye strain and are increasing on immersiveness and duration.

E Gupta et. al. [10] developed a dataset aiming for the motion sickness study. It has real-world physiological and subjective data that are collected from different VR users. Authors claim for the usability of dataset in machine learning models for motion sickness as it has feature measurements on skin conductance, heart rate, nausea, dizziness, and discomfort. The concept of Virtual Reality carries us to a new digitally created interactive world. Due the involvement of Artificial Intelligence and high computing resources, VR became a buzz word in the industry. Advancement technology aims to work with cheap and lightweight VR systems where people can program it in an easy way [22-23]. Robertson et. al. [11] took the factors of anxiety and depression levels rather than heart rate and blood pressure for their study of 60 participants divided into three groups. They claimed that experiencing VR had no added advantage on iPad use.

Gradl et. al. [12] proposed biosensors to measure heart rate and monitor it in real-time to manage stress. Wearable sensors take feedback from VR users and visualize it directly will help to control accordingly.

Li, Xiaolu et. al. [13] evaluated motion sickness using KNN, Polynomial SVM and Radial Basis Function SVM. They got an average accuracy for a single object of 92.85% and for 18 subjectsacuuracy of 79.25%. They used the feature extraction method WPT(Wavelet Packet Transform) in their work and alpha, beta, delta and theta rhythms to recognize VR motion sickness. Shen et. al. [14] developed classification models for both binary and ternary classification using EEG data from 25 participants using phase-locked value and CNN LSTM. They got an accuracy of 99.56% for binary classification and 86.94% for ternary classification. Functional connectivity matrix derived from six frequency bands and inputted into CNN-LSTM for the detection of visually induced motion detection.

Tremmel et. al. [15] estimated the cognitive workload of users (mental effort needed to perform a task) who are indulging in VR tasks using key features of EEG signals and how they perform during different difficulty levels of VR interaction environments.Extraction of frequency bands of alpha, beta, theta waves are done with the help of power spectral density analysis. They collected specific data consisting of 64 channel EEG system for their study. The tasks performed by participants includes different level of cognitive workload and the researchers collected EEG data on varying conditions making to classify appropriately. The multi-class classification for low, Medium and high level of cognitive workload is performed using machine learning algorithm with an accuracy of 75%.

Hell et. al. [15] made a recurrent neural network based framework for predicting motion sickness in rollercoaster environment by capturing real-time data, sickness felt with the help of SSQ (Simulator Sickness Questionnaire). The datset is RCVR, having parameters of position, gravitational forces exerted, speed, rollercoaster characteristics, motion

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sickness level ratings etc. It comprises of 23 users, 100 ratings on 33 roller coasters. The output is the nausea level prediction and they did not explicitly mentioned accuracy. They concentrated on how to handle variability in data for th prediction of different nausea levels.

Li et al. [16] calculated the score of VIMS depends on the content. They proposed two networks of neurological representation and for spatio temporal. Neurological mechanism has been followed in the first stage and features of spatial and temporal domains are expressed.

Hua et. Al [18] proposed amodel where the decomposition of EEG signals is done by using Variational mode decomposition for finding out resting time VIMS. A machine learning model was applied for the binary classification of motion sickness and got an accuracy of 98.3%.

Li, Yan et. al. [19] developed a model that took multiple biosignals such as respiration patterns, heart rate and skin conductance for VIMS classification purposes with the help of machine learning algorithms SVM and KNN got an accuracy of 76.3% for binary classification.

Lin et. al. [20] Demonstrated a moving vehicle-based online motion detection system with the aid of EEG signal analysis. They took both subjective reports as well as motion data for their analysis, combining neuroscience, machine learning and adaptive system applications.

Liu et. al. [21] put forward a deep learning model for VIMS in real-time detection and prediction, namely VIMSNet. They collected both subjective reports for their study and heart rate and galvanic skin response physiological responses. They got 96.7 % accuracy for the binary classification.

The induced sickness tends to be activated in a similar tendency, as done in clinical studies to visualize the cognitive response [22-26].

Table1 shows the analysis report summarizing the findings, methods used by authors, and key features related to VIMS.

Table 1: Summary of previous studies based on Motion sickness.

Author(s)	Participants	Study Focus	Data Collected	Findings	Methodology
Heeseaok et al. [4]	154 participants	Evaluating cybersickness in VR, subjective and objective data collection	52 VR scenes, biological signals	Both biological features and susceptibility correlated with motion sickness severity.	Statistical analysis on severity and correlation factors.
Chatta et al. [5]	51 participants (23 F, 28 M, aged 18-28)	Motion sickness in pleasant vs. horror VR environments	SSQ, blood pressure, heart rate, sugar levels (pre/post measurements)	Horror environments induced more motion sickness, and increased heart rate and blood pressure in	ANOVA, Greenhouse-Geisser correlation analysis

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				46 participants, men had less motion sickness than women.	
Chang et al. [6]	Review	Causes of motion sickness in VR related to machine and user factors	Simulated Sickness Questionnaire, heart rate, eye tracking, skin conductance	Highlights optimization of both hardware and software to reduce VR sickness symptoms.	Comprehensive review, subjective and objective measures
Foxman et al. [7]	N/A	Classification framework for VR immersion and its effects on user experience	Spatial immersion, agency, embodiment, temporal structure, social presence	Key VR features like spatial immersion, narrative control, and real-time interaction impact user involvement and challenge universal VR system design due to technological changes.	Conceptual framework development for VR features
Kim et al. [8]	N/A	CNN-based motion sickness prediction based on visual stimuli in VR	Camera movement, speed, field of view, graphics complexity	A mismatch between visual stimuli and the vestibular system leads to motion sickness.	CNN analysis of visual stimuli
Martirosov et al. [9]	N/A	Impact of VR immersion levels (low, semi, full) on motion sickness	SSQ, heart rate, skin conductance	Increased discomfort and eye strain in higher immersive environments.	Physiological and subjective measures
E. Gupta et al. [10]	N/A	Motion sickness dataset creation	Skin conductance, heart rate, nausea, dizziness, discomfort	Provides data for machine learning models studying motion sickness.	Dataset development
Robertson et al. [11]	60 participants	Study anxiety and depression levels in VR	Anxiety and depression measurements	No advantage of VR over iPad use for mental health indicators.	Group study with subjective measurements
Gradl et al. [12]	N/A	Biosensors for real-time heart rate monitoring in VR	Real-time heart rate feedback	Wearable sensors to manage stress based on VR usage feedback.	Wearable biosensor technology
Li, Xiaolu et. al. [13]	N/A	Motion sickness evaluation using machine learning	WPT-based feature extraction (alpha, beta, delta, theta waves), KNN, SVM	Achieved 92.85% accuracy for single object detection, 79.25% for 18 subjects.	WPT feature extraction, KNN, Polynomial SVM, RBF-SVM

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Shen et al. [14]	25 participants	EEG-based classification of motion sickness (binary and ternary)	EEG data, phase-locked value, CNN-LSTM	Achieved 99.56% accuracy for binary classification, 86.94% for ternary classification.	EEG data analysis, CNN-LSTM
Tremmel et al. [15]	N/A	Cognitive workload in VR tasks based on EEG data	EEG signals, power spectral density analysis	Achieved 75% accuracy for multi-class classification of cognitive workload.	EEG signal analysis, power spectral density
Hell et al. [16]	23 participants	Predicting motion sickness in rollercoaster environments	SSQ, real-time data (position, speed, gravitational force, rollercoaster characteristics)	Nausea level prediction during rollercoaster VR experience, variability in data handling for nausea prediction.	Recurrent neural network (RNN) framework for real-time analysis
Hua C., Chai L., Zhou Z., Xu C., Liu J. [17]	Not explicitly mentioned	Automatic detection of VR motion sickness in a resting state using EEG data	EEG signals in resting state post-VR session	High accuracy in detecting motion sickness using resting state EEG. VMD effectively extracts motion sickness features.	Variational Mode Decomposition (VMD) to extract features from EEG data, followed by machine learning classification.
Li, Yan, Aie Liu, and Li Ding [18]	Not explicitly mentioned	Machine learning assessment of visually induced motion sickness levels based on multiple biosignals	Biosignals such as heart rate, skin conductance, and respiration patterns	Multiple biosignals are effective in predicting visually induced motion sickness levels, improving assessment accuracy.	Machine learning models (SVM, KNN) trained on biosignals to classify different levels of visually induced motion sickness.
Lin, Chin-Teng, Shu-Fang Tsai, and Li-Wei Ko [19]	16 participants in a dynamic vehicle environment	Estimation of motion sickness levels using EEG signals in real-time during vehicle motion	EEG signals, motion data (vehicle dynamics), subjective motion sickness reports	EEG signals can accurately estimate motion sickness levels in real-time in dynamic vehicle environments.	An EEG-based learning system with an adaptive algorithm to estimate motion sickness levels in real-time during vehicle movements.
Liu, Ran, et al. [20]	Participants exposed to visual stimuli inducing motion sickness.	Development of VIMSNet for real-time detection of motion sickness.	Visual stimuli, Physiological and subjective responses.	VIMSNet outperformed existing methods in accuracy.	VIMSNet architecture design, model training and performance evaluation.

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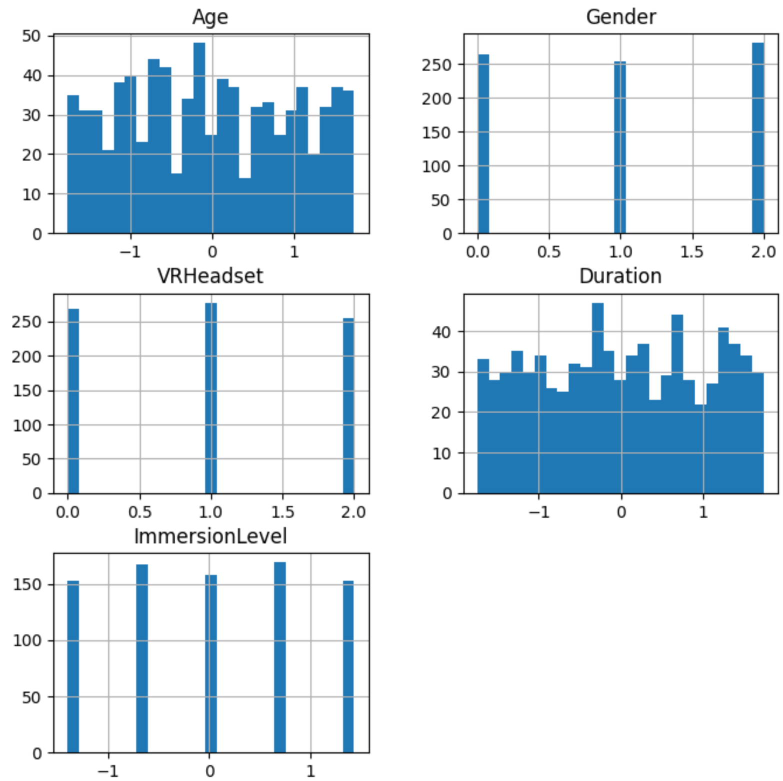

Fig 1: Distribution of Variables of VR Dataset (a)

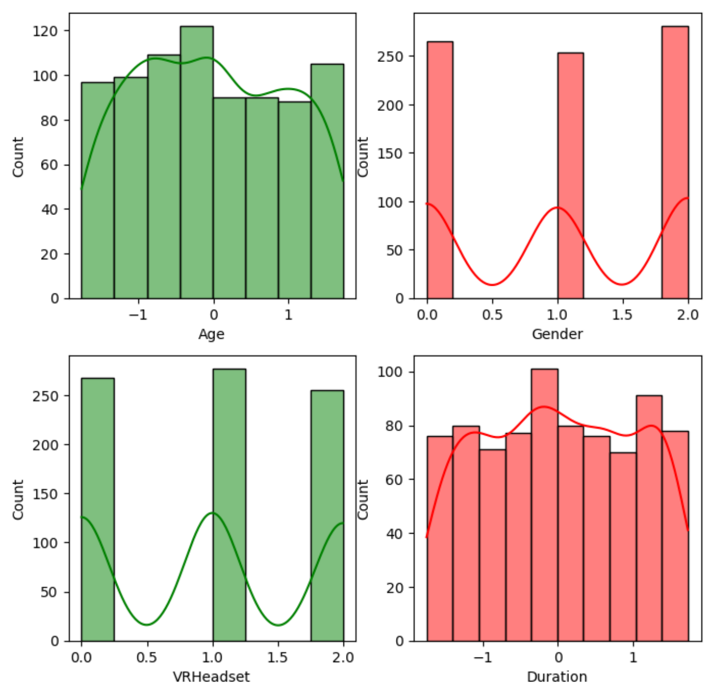

Fig 2: Distribution of Variables (b)

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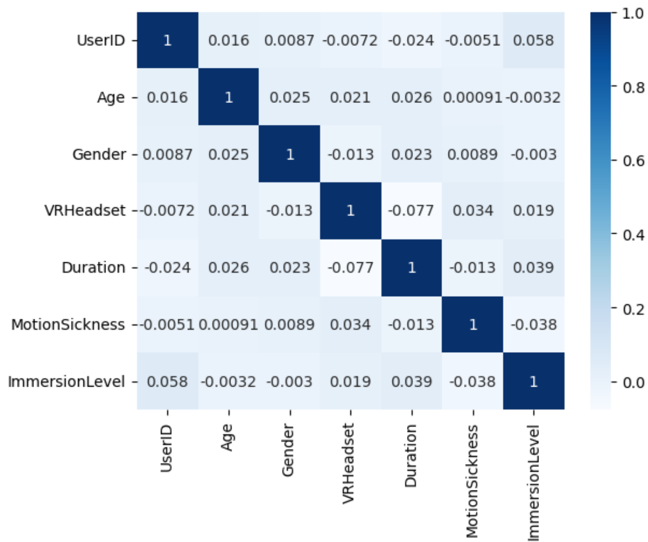


Fig 3: Heat map of the VR Dataset

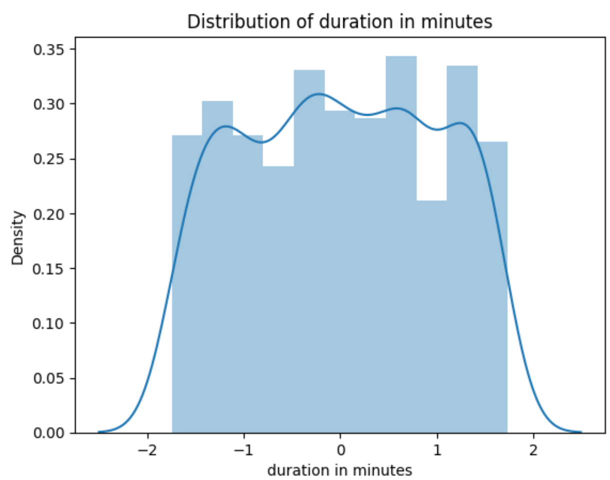
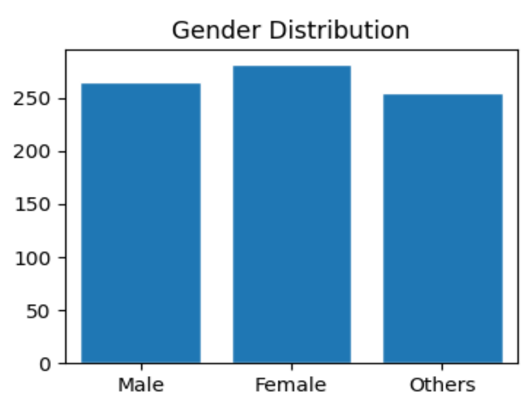


Fig 4: Distribution of duration in minutes

Gender distribution



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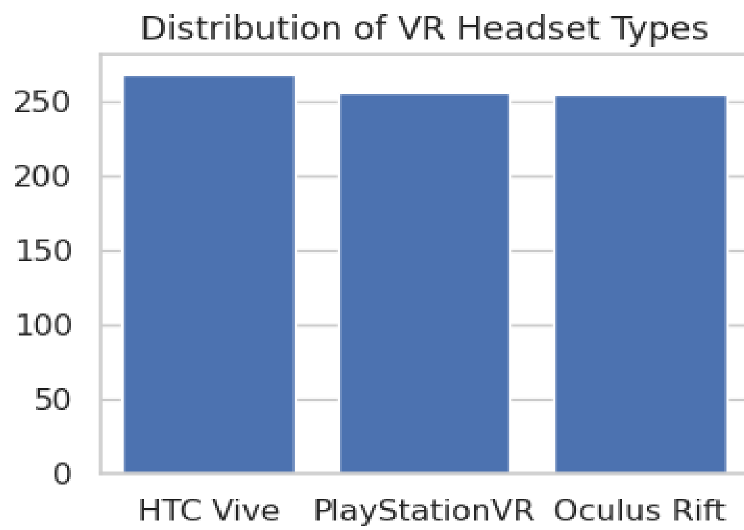
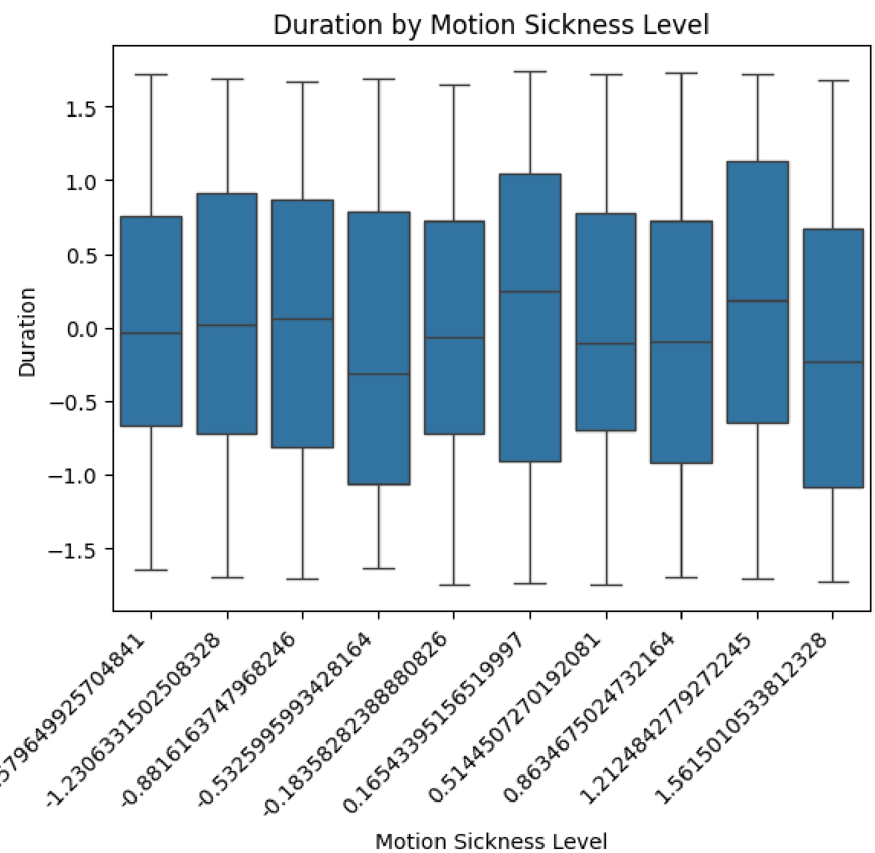
VR Headset distribution



Duration by motion sickness level



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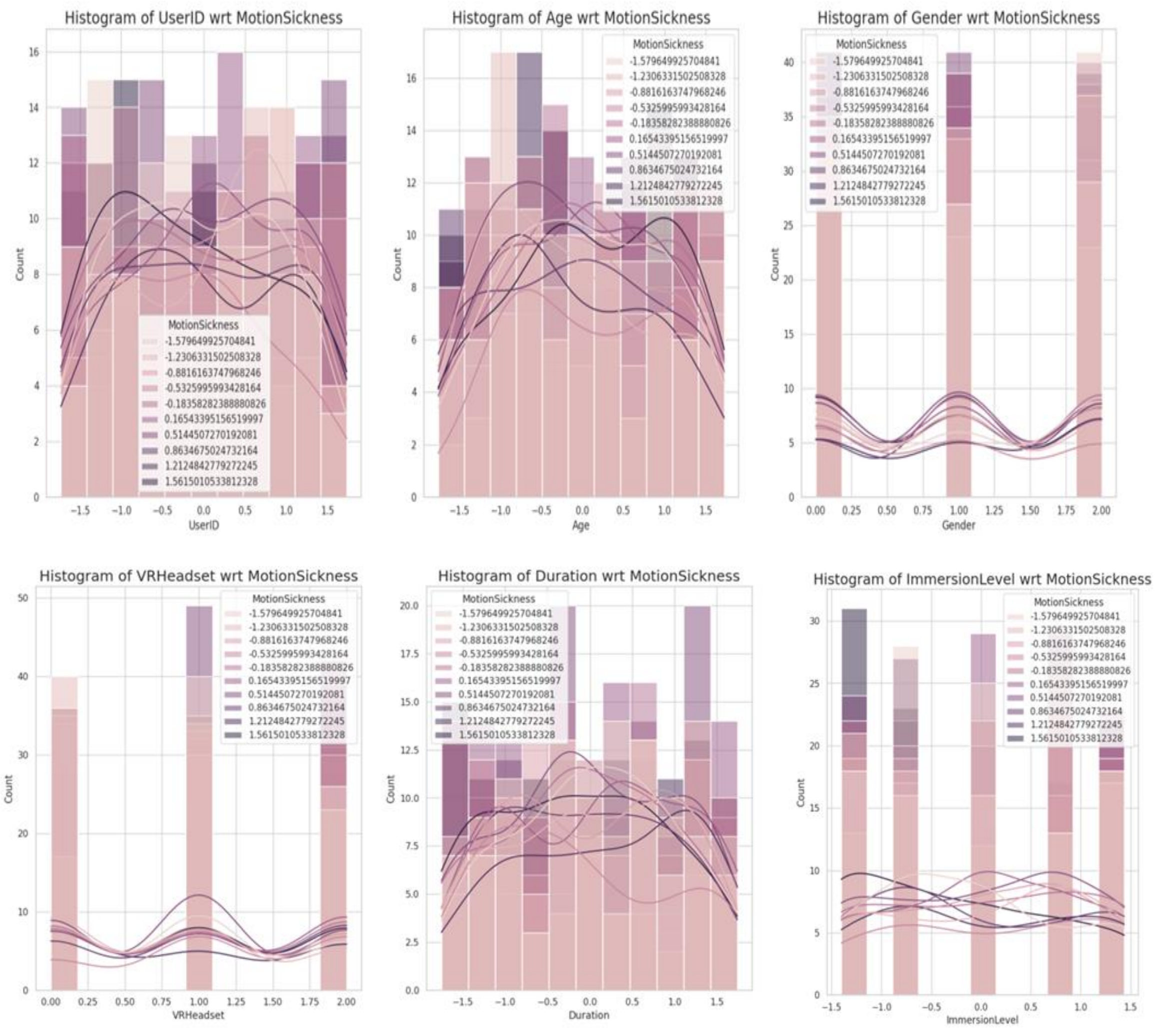

Fig: Histogram of different variables with respect to Motion Sickness on VR dataset

3. METHODOLOGY

Most users in the data set belong to the 30-40 age groups. Immersion level is almost balanced but the increase in age is dependent on higher motion sickness. Duration and Age appear to have the most significant influence. The majority of the male participants have 4 immersion levels and females are found to be balanced. Most of the VR headsets used are Oculus Rift. Experience below 20 minutes has a low immersion level and is found increasing gradually for longer usage. Also, higher motion sickness gives lower immersion rates. The study found from this data set that people of age between 34 and 44 have lower motion sickness with best experience. A convenient duration is 31minutes is found for the best experience and lower motion sickness.

Experiment

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3.1 Regression algorithms performed on VR dataset

Experiment was done with a standard VRdataset, downloaded from Kaggle [18]. Dataset consists of 7 features User ID, Age, Gender, VRHeadset, Duration, Motion Sickness and Immersion Level and 1000 instances. Gender distribution in the dataset is [265, 281, 254] and VR Headset distribution is [268, 255, 254]. Oculus Rift34%, HTC Vive33% and Other 32%. Seven Regression analysis techniques applied for the VR dataset. They consists of Linear Regression, SVR(Support Vector Regression), Random Forest, Ordinal Regression, Gradient Boosting, KNN(K-Nearest Neighbour) and Decision Tree. It is found that all the models perform poor predictive performance on this dataset. Average value of MAE as 2.7 indicates small deviation in motion sickness for VR users. Also low values on RMSE, MAE and MedAE signify little motion sickness according to the VR dataset. Table 2 represents the name of the model and corresponding evaluation metrics on regression techniques respectively for MSE, RMSE, MAE, MedAE, R-squared and Explained variance.

Table 2: Evaluation metrics for different type of regression analysis on VR Dataset

Sl No	Model	MSE	RMSE	MAE	MedAE	R-squared	Explained Variance
1	Linear Regression	9.4325	3.0712	2.735	2.751	-0.0282	-0.0076
2	SVR	9.5399	3.0887	2.7225	2.6792	-0.0399	-0.011
3	Random Forest	9.6586	3.1078	2.6969	2.565	-0.0528	-0.0268
4	Ordinal Regression	9.67	3.1097	2.76	3	-0.0541	-0.029
5	Gradient Boosting	10.0398	3.1686	2.7989	2.8602	-0.0944	-0.057
6	KNN	11.1168	3.3342	2.866	2.8	-0.2118	-0.1781
7	Decision Tree	20.085	4.4816	3.645	3	-1.1893	-1.186

Figure compares different regression algorithms and their evaluation metrics.

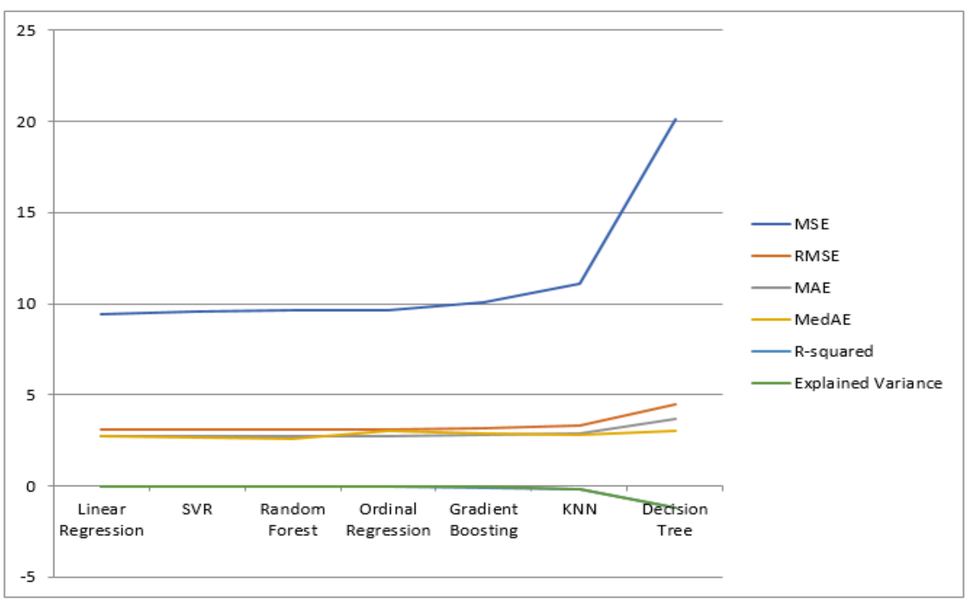

Fig: Regression algorithm vs evaluation metrics

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3.2 Classification algorithms performed on EEG dataset

EEG brain wave dataset used in classification consists of brain wave signals collected from EEG headset in temporal format. The standard EEG dataset [19] taken for visually induced motion sickness classification study consists of 2132 rows and 2549 columns. The target variables are positive, negative and neutral. The dataset created was with one male and one female subject with the experience of six video clips and the EEG signals was recorded with signals down sampled to 150Hz with data points of 324000 brain waves. Statistical measures applied for the data like mean, min, max, correlation, FFT and logarithmic measures calculated over data points with a sliding window of 1 second. The dataset is divided into 80:20 ratios for training and testing purpose in this study and the random state used is 42. LightGBM got an accuracy of 99.76% for three-class classification. Other evaluation metrics are displayed in the table. A confusion matrix is displayed in the figure. Lime explainer was used to explain the local explanation for the classes such as positive, negative and neutral. Table 3 show the accuracy, precision, recall, F1-score, MCC, Cohen's Kappa, Balanced Accuracy and Log loss on EEG dataset for 12 classification algorithms performed on python.

Table 3: Various evaluation metrics got on EEG dataset for classification algorithms

Sl No	Model	Accuracy	Precision	Recall	F1-score	MCC	Cohen's Kappa	Balanced Accuracy	Log Loss
1	SVM	0.384	0.3599	0.384	0.2504	0.1462	0.0582	0.3706	1.0456
2	Logistic Regression	0.384	0.5328	0.384	0.338	0.1298	0.0905	0.3936	0.9731
3	Gaussian Naive Bayes	0.4121	0.412	0.4121	0.3071	0.1364	0.1134	0.4022	18.1478
4	MLPClassifier	0.562	0.5772	0.562	0.4922	0.394	0.3496	0.5696	15.7849
5	Decision Tree	0.9531	0.954	0.9531	0.9531	0.93	0.9296	0.9519	1.6882
6	KNN	0.7611	0.7522	0.7611	0.7503	0.6456	0.6404	0.7557	0.0738
7	Multinominal Naïve Bayes	0.822	0.8342	0.822	0.8239	0.7374	0.7333	0.8208	1.5766
8	Balanced Bagging Classifier	0.9765	0.9768	0.9765	0.9765	0.9649	0.9648	0.9758	0.0732
9	Random Forest	0.9882	0.9884	0.9882	0.9882	0.9824	0.9824	0.9878	0.0822
10	Balanced Random Forest	0.9836	0.9837	0.9836	0.9836	0.97546	0.9753	0.983	0.0882
11	XGBoost	0.9976	0.9976	0.9976	0.9976	0.9964	0.9964	0.9975	0.0073
12	LightGBM	0.9976	0.9976	0.9976	0.9976	0.9964	0.9964	0.9976	0.0047

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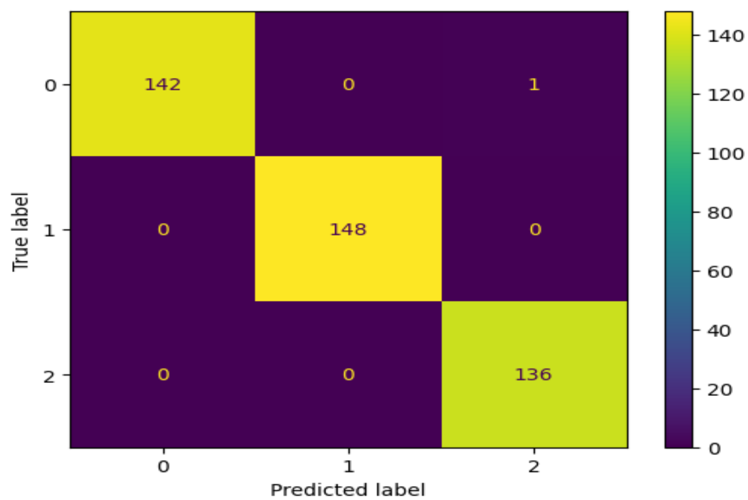

Fig: Confusion matrix of the proposed Light GBM model

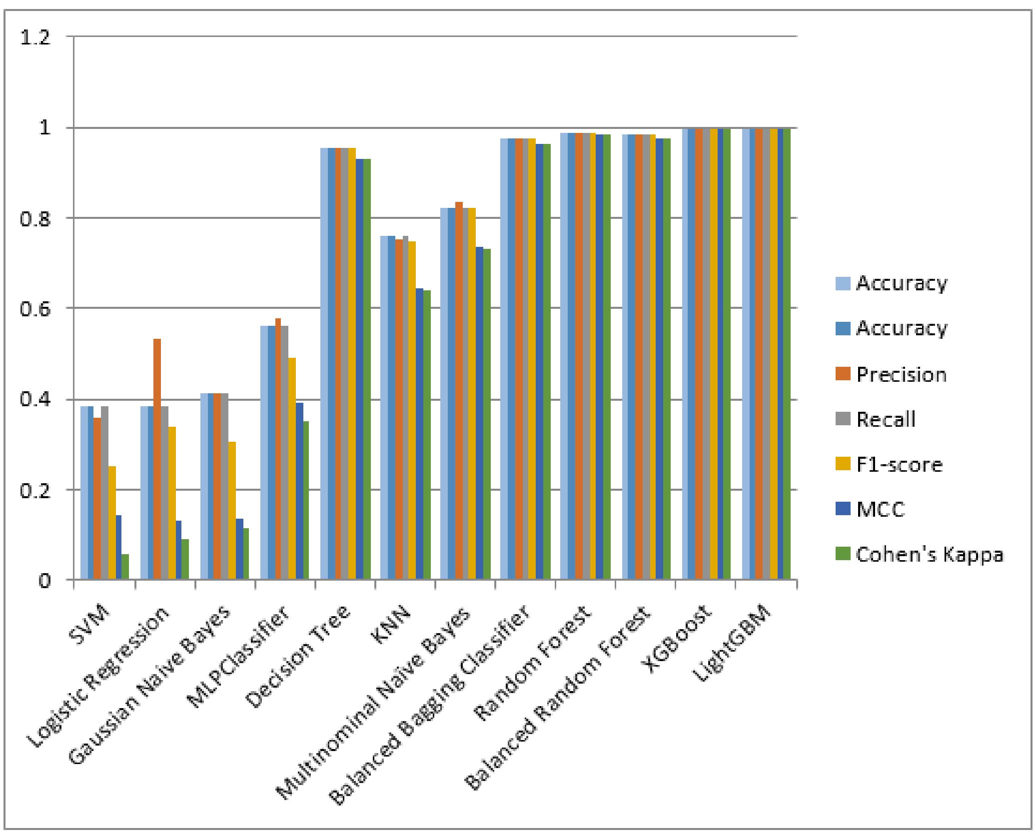

Fig: Bar chart on Classification algorithm vs evaluation metrics for EEG dataset

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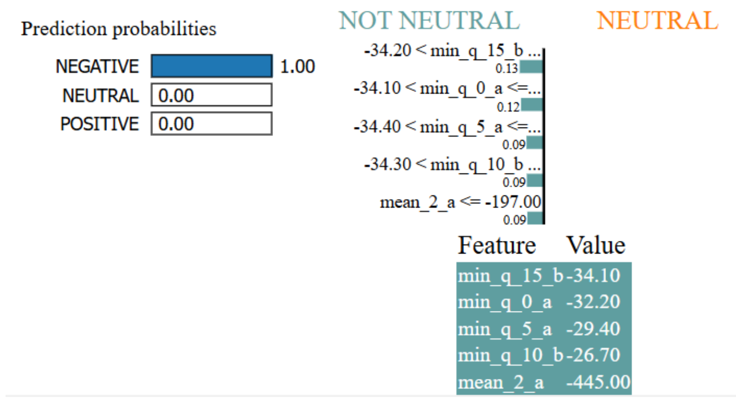
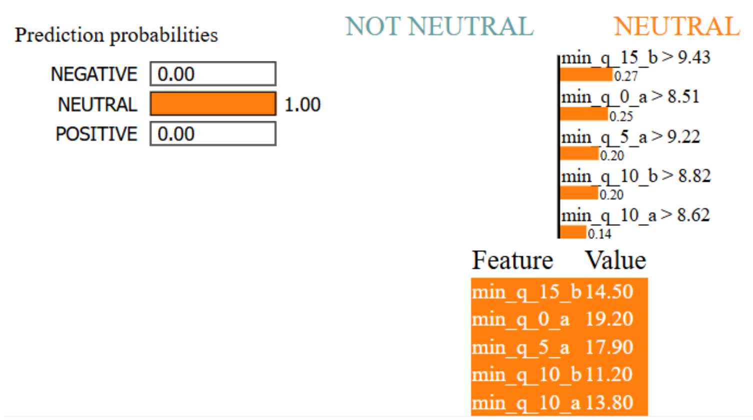
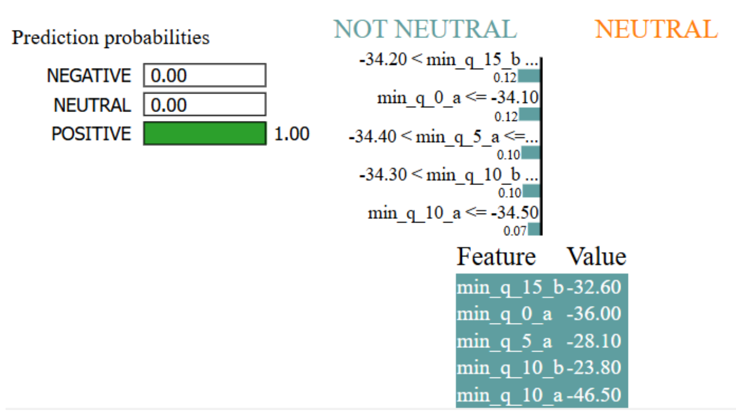
Local explanation helps to understand the behavior of model for a particular given instance. Figure shows the local instances of 2, 20 and 120 respectively respresenting negative, neutral and positive recognition of emotion using EEG dataset.



(a)



(b)



(c)

Fig: Local explanation of (a) negative class, (b) neutral class and (c) positive class

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The figure shows the lime local explanation for 8 features of instance 120, which belongs to the class of 'positive'. Horizontal bar plots of aggregated feature importance are shown in the figure by taking feature weight values (scores) on the x-axis and 8 feature weight keys (feature names) on the y-axis. It visualizes feature contribution of each feature to the model's prediction of the instance 120.

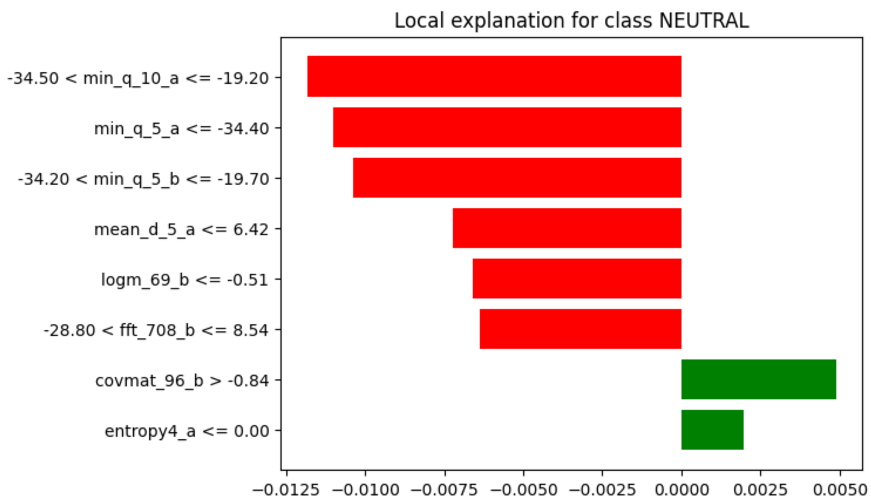

Fig: Horizontal bar plot showing aggregate 8 feature importance

A 3D scatter plot of 3 most relevant features identified by LIME is shown in the figure. PCA is used to reduce the dimensionality of the features to 3D.

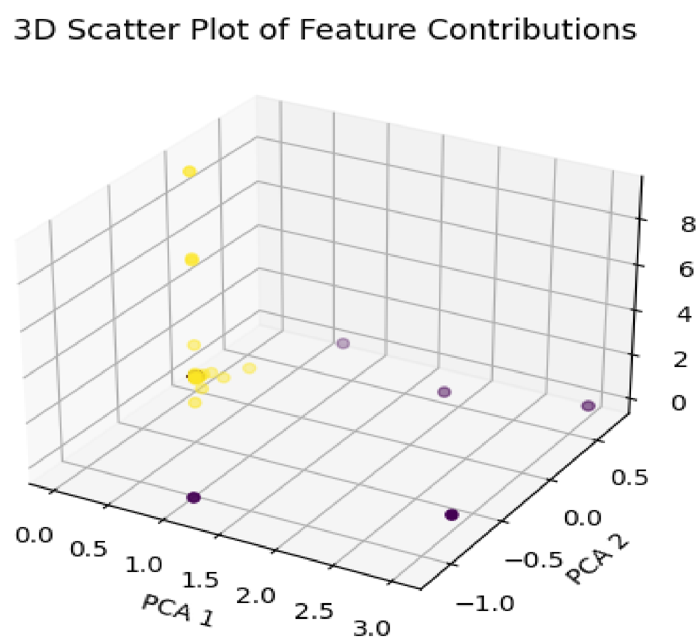

Fig: 3D scatter plot of the feature contributions

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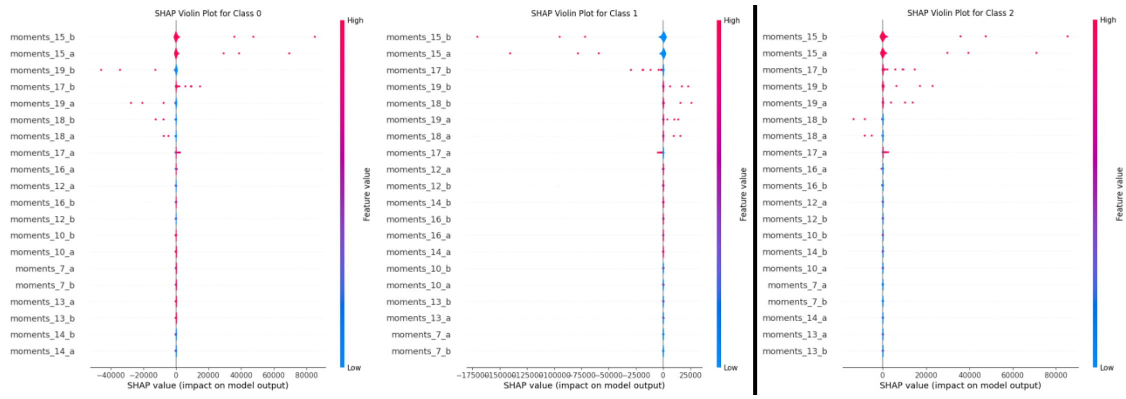
SHAP violin plots of the three output classes are drawn in the figure. Table2 lists the accuracy of the binary as well as multi-class classification of the state-of-the-art methods based on the EEG datasets. Our proposed method outperforms well for the ternary classification compared to other methods. Figures show the violin plots of output class0, outputclass1 and output class 2 respectively corresponding to the shap value indicating the impact of model output.



4. RESULTS AND DISCUSSION

We analyzed two different datasets for our study. VR dataset contains 7 features and 1000 instances while EEG dataset have 2132 records with 2549 features. 7 regression algorithms are performed on the VR dataset and 12 classifications done on EEG dataset. Light GBM has got highest accuracy of 99.76% which out performs the state-of-the-art methods that are shown in table 4. Previous studies have shown that there is a significant improvement in the classification of binary data rather than multi-level classification. Our proposed algorithm performs ternary classification for the EEG dataset for positive, neutral and negative classification target variables.

Table 4: Classification accuracy of VIMS recognition on EEG dataset for the state-of-the-art methods

Author	Binary classification accuracy	Multi-class classification accuracy
Tremmal et. al [15]	75	-
Li, Yan et. al. [20]	76.3	-
Lin et. al. [21]	82	-
Liu et. al. [22]	96.7	-
Hua et. al [18]	98.3	-
Li, Xiaolu et. al. [13]	92.85	79.25
Shen et. al. [14]	99.56	86.94
Proposed method	**-**	**99.76**

5. CONCLUSION

Motion sickness felt in Virtual Reality negatively influences the adoption of VR in many fields. Motion sickness comprises of various health discomforts in humans like nausea, dizziness and discomfort. It creates a conflict between the vestibular system and eye vision for humans. An EEG-based emotion based ternary classification has developed with an accuracy of 99.76% and corresponding lime local explanation has been done. Also using another VR data set, we visualize the feature relationship, heat map and various plots. Many previous researches got good accuracy in binary classification where whereas less accuracy in multi-class classification for motion sickness. The proposed model classifies the standard dataset of EEG ternary classification of positive, negative, and neutral classification. The dataset contains EEG of one male and one female subjects evaluated for six videos. More analysis can be done using more subjects in the future.

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