Enhancing Virtual Reality Immersion through Physiological and Emotional Analysis Using Machine Learning

MSc Research Project
MSc in Data Analytics

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MSc Project Submission Sheet

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Enhancing Virtual Reality Immersion through Physiological and Emotional Analysis Using Machine Learning

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Abstract

This dissertation concerns the concept, development, evaluation, and deployment of an emotion recognition system powered by machine learning to boost Virtual Reality (VR) experiences in educational and interaction spaces. Applying three distinct datasets, data preprocessing, feature extraction, and state-of-the-art approaches to the classification of emotional states provides high accuracy of the research. The study covers the design, implementation, and dynamic assessment of a model working within the system, as well as data complexity issues, the choice of an optimal model, and its application in real-world conditions. Further it focuses on the specification of the system architecture, data management, processing approach, and models for classifying emotions an incorporating Virtual Reality component. In the implementation, it describes countless techniques, employed five machine learning models, and five-fold cross-validation for doubling our accuracy rates.

This study serves as a groundwork towards developing more immersive, tailored, and hyper-realistic virtual interactions and discusses ways forward in accommodating new data, including, but not limited to, diversely sized and deep learning implementations across the data-sensor display pipeline.

1 Introduction

1. Introduction and background

Engagement in virtual reality (VR) situations has emerged as a major factor of research interest, especially in how users appreciate spaces within virtual computers. This dissertation presents how machine learning could improve immersion by analysing the user's physiological responses, emotional states, and preferences. Virtual Reality (VR), a cutting-edge technology developed in the recent past, has made remarkable impacts in diverse fields including gaming, E-commerce, health, education, etc., that delivered the User Interface. The utility and the success of VR are highly related to the immersion or the extent to which it elicits users' affective and somatic responses. Such responses are the ability to measure heart rate, skin conductance, and brainwaves and they affect the utilization and the pleasure the users derive from the virtual environment (Marín-Morales *et al.* 2020).

2. Rationale

The problem discussed in this dissertation is how to improve immersion in VR through the identification and modelling of the user's emotions and their physiological responses. Investing in truly engaging experiences using the current state-of-the-art VR devoting maximum share appeals is a considerable challenge. This issue occurs because emotional interaction is essential for enhancing user experience, satisfaction, and outcomes of VR solutions. Previous techniques of user engagement in VR settings often do not consider the multifaceted and complex nature of human emotion limiting the opportunities.

3. Problem Statement

The issue under focus in this dissertation is the attempt to express interaction improvements in a VR environment through accurate emotion recognition. Although present-day technological VR systems bear potential, current systems are typically unable to monitor and in turn adapt to the user's affective and physiological feedback, and as such, minimal affective immersion. Typically, existing approaches to recognizing emotions provide data constructs and simple models, which do not suffice in enabling the recognition of emotions in a highly complex VR setting, where these aspects are dynamic (Abd-Alhamid *et al.* 2020).

4. Research Aim

The aim of the research is to explore and analyse data based on feedback received from the user's human body signals, sound, or natural statistics, and improve Virtual Reality using machine learning algorithms that will classify the emotions of a person.

5. Research Objectives

a. To identify the classification of users' state of mind in virtual reality using physiological data and machine learning analyses.

b. To determine the use of various machine learning algorithms including Random Forest, Support Vector Classifier, and Decision Tree we shall be comparing the ability to classify the emotions based on different datasets.

c. To determine the most relevant features out of audio, physiological, as well as statistical data to enhance the mean classification of emotion accurately.

6. Research Questions

a. What sorts of phenomena and conditions of users in virtual reality can be investigated, and how, by employing the methods of machine learning?
b. With which of the algorithms, such as Random Forest, Support Vector Classifier, and Decision Trees, is higher accuracy achieved concerning the classification of the emotions due to the usage of which datasets?
c. Which aspects from the audio, physiological, and statistical data domains are most relevant to enhancing the VR-based emotion classification performance?

7. Summary

In this chapter context, there is literature review research about improving immersion in VR by computing users' emotional and physiological data with machine learning approaches. The introduction highlighted the importance of developing more emotionally enabling VR, as well as the calls for enhancing VR experiences through ways of recognizing people's emotional states.

2 Related Work

2.1 Introduction

The literature review reviews prior works and research done on increasing immersion in Virtual Reality (VR) based on Emotion Recognition and Machine Learning. Facial emotion recognition has attracted much research interest in recent years because of its importance in modelling human behaviour and decisions. Technological enhancements in VR have made it possible not only to investigate feelings with relative clarity but also to provoke certain emotions at various rates by creating situations that may be encountered in ordinary life.

2.2 Physiological Responses and Emotional States in Virtual Reality

Automated detection of subject physiological activity and identification of subject emotional state in VR environments has emerged as a significant focus of study given the relevance of physiological response profiles for designing VR interfaces which can provide higher levels of user immersion. Being inherent components of people's interactions, emotions widely affect cognitive activities, decisions, and experiences in virtual spaces (Suhaimi *et al.* 2022).

However, the studies have also analysed the feelings with which the subjects wearing the VR headsets and other bio signals including the EEG have been provided using cheap and compact EEG helmets (Saeed *et al.* 2024). Measurement of physiological responses as a way of identifying emotions in VR is not only limited to measurement but is inclusive of application in the improvement of user experiences. The systematic review on VR-based emotion recognition identified an interaction between VR and physiological methodologies as a revolutionary step in affective computing (Bobade and Vani, 2020). Thus, VR provides opportunities for reproducing actual and complex scenes to evoke. This form of simulation is more intense as compared to the traditional methods of exposing participants to media content hence the natural physiology is more evident (Geraets *et al.* 2021).

2.3 Machine Learning Algorithms for Emotion Classification in Virtual Reality

The use of machine learning algorithms for emotion classification in virtual reality has become one of the most important trends in affective computing. For example, one of the works used emotion induction in VR and analysed the data of the EEG signals using a low-cost wearable EEG headset (Bibri, 2022). The researchers used four basic emotions, happiness, fear, calm, and boredom, and SVMs as classifiers to classify the data with intra-subject and inter-subjects' classification accuracies being above 85% (Ahmad and Khan, 2022).

2.4 Feature Selection and Data Preprocessing for Enhanced Emotion Recognition

Feature selection targets the methods for selecting the desirable subset of attributes from datasets that might incorporate physiological signals, behavioural measurements, and loudness information (Salur and Aydin, 2020). In all these studies, several sophisticated preprocessing techniques for emotion recognition in VR have been suggested (Tao *et al.* 2020).

2.5 Literature gap

Although there has been a remarkable amount of progress in both emotion recognition using physiological signals and machine learning, there are still some important research gaps. Firstly, although numerous works examine emotion recognition in VR, the majority of these works are based on transferring the same participants using a small number of emotional datasets or on utilizing only a few bio signals, including EEG or EDA (Zyphur *et al.* 2020).

2.6 Summary

This chapter brought together the current state of literature involving emotion recognition in virtual reality (VR) employing physiological signals and machine learning algorithms. The discussion started with the presentation of the basic distinction between physiological reactions and emotional experiences in the context of an IVR environment, with a special focus on the benefits of VR technology in the elicitation and investigation of emotions.

3 Research Methodology

3.1 Introduction

This chapter presents the study method that has been used to examine the ability to recognize emotions in VR based on physiologic signals, and machine learning algorithms. The goal of the current work is to identify the emotions of the users in different VR environments and assess the performance of various machine learning algorithms for emotion classification by using physiological signals.

3.2 Research philosophy

The research for this dissertation relies on positivism as its research paradigm This research paradigm presupposes that knowing occurs when studying facts. It depends on the assembly of facts that may be quantified with the help of accurate scientific parameters and numerators and outcomes can be predicted using the results obtained through data accumulation (Doyle *et al.* 2020).

3.3 Research approach

The deductive approach of this dissertation means that it tests existing theories and hypotheses with empirical data. This one is where the researcher sets out with a theory or framework in mind and tests it against a set of specific data. Such a method benefits from the development of clear hypotheses at its beginning to make the whole process more goal-oriented (Morgenstern *et al.* 2021).

3.4 Data sources

All the datasets for this dissertation are sourced from Kaggle, an international repository of datasets with no restrictions on usage and are largely popular, lar, especially in establishing links with datasets from different fields such as emotion recognition and physiological signals. Kaggle has an array of datasets that are well documented and available for use hence a good source of secondary data collection (Dozio *et al.* 2022).

3.5 Data Analysis

In this dissertation, some important data analysis steps are followed to properly handle and extract useful information from datasets. First, if there are any gaps in the physiological, and/or emotional data sets obtained from Kaggle, then pre-processing using feature removal powered by missing value imputation; utilization of IQR to remove outliers; and normalization of data cleaning techniques are undergone. This safeguards the data before the next steps are taken in data analysis.

4 Design Specification

4.1 Introduction

"Design Specification," presents the particular design procedure of the emotion recognition system set up in a virtual reality environment. This chapter presents the core components of the system, data acquisition, data pre-processing, classification techniques, machine learning algorithms, and system design.

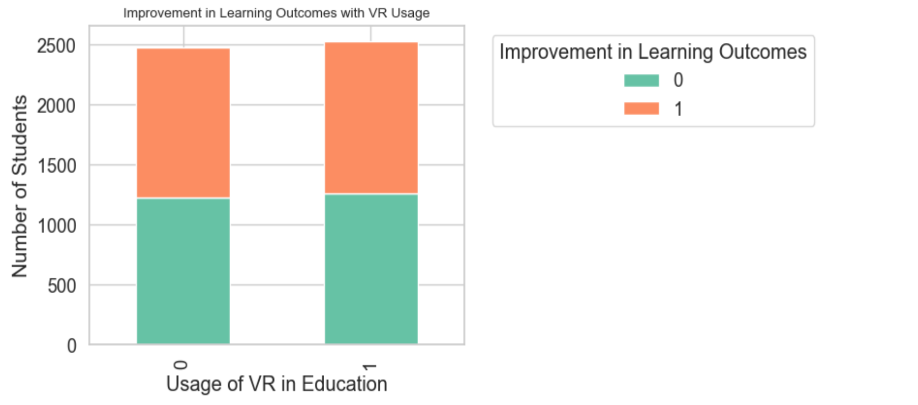

Figure 1: Stacked Bar Chart for Improvement with VR Usage

(Source: Implemented in Jupyter Notebook)

The data is then pre-processed through several methods to make the result accurate and relevant. Regarding the analysis and classification of the expressions based on the physiological signals, the Machine learning models that include Support Vector Machine (SVM), Random Forest, and Decision Trees are used.

4.2 Data Collection and Preprocessing Design

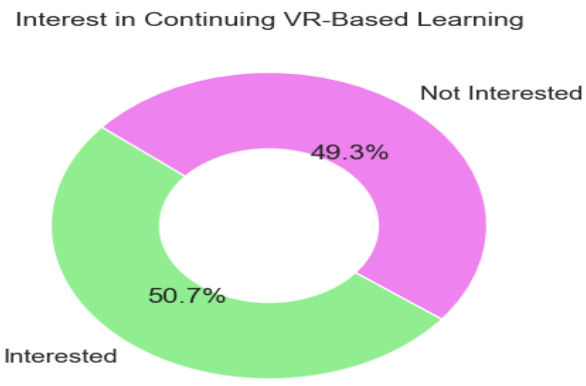

Figure 2: Donut Chart

(Source: Implemented in Jupyter Notebook)

Following this, there is the cleaning exercise with the aim of eliminating information that cannot be beneficial in analysis (Domínguez-Jiménez *et al.* 2020). Cleaning is a process of; handling missing or noisy data points, removal of noises from natural data, and normalizing of the signals.

4.3 Machine Learning Model Design

The process of selecting correct algorithms that can be used to classify users' emotions based on the physiological signals in context to design Machine Learning Model for emotion recognition in Virtual Reality can be described as follows.

Table 1: Output for Classification Report for the Random Forest Model

Class	Precision	Recall	F1-score	Support
0	0.97	0.99	0.98	143
1	1	1	1	148
2	0.99	0.97	0.98	136
Accuracy			0.99	427
Macro avg	0.99	0.99	0.99	427
Weighted avg	0.99	0.99	0.99	427

4.4 Summary

The chapter in the book that deals with the design specification focuses on what constitutes the architecture and part of building the emotion recognition system in virtual reality. This paper describes the overall framework of the system, how the data is collected and pre-processed, the architecture used for emotion recognition, and how the machine learning model is developed.

5 Implementation

The machine learning models are depicted in the implementation chapter indicating how the datasets for this research were analysed. It only covers the pre-processing of data, choice of classifiers and learners, model building and training, and testing/ validating phase. This chapter describes the particular models to recognize emotions, and the strategies applied to increase the model performance.

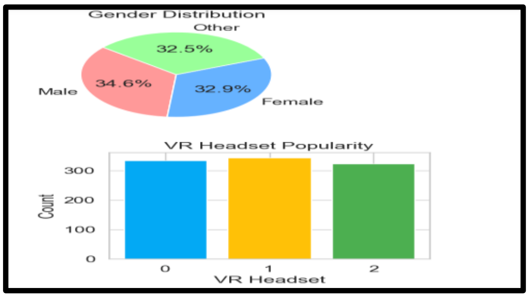

Figure 3: Pie Chart and Bar Chart

(Source: Implemented in Jupyter Notebook)

This was done to some extent to have some level of fairness and not to interfere with other libraries as an environment was simulated virtually (Seo et al. 2020).

5.1 Data Collection and Preprocessing Implementation

The approach for data gathering for this dissertation involves the use of three different datasets found on Kaggle. The first data set is called "Virtual_Reality_in_Education_Impact.csv and is concerned with the effectiveness of VR applications in education and includes variables like student characteristics, use of VR, and results of learning fairs.

In each case of two datasets for the models, the preprocessing of data was done such that the models could use the data effectively. First, the data was read into the environment through Panda and NumPy.

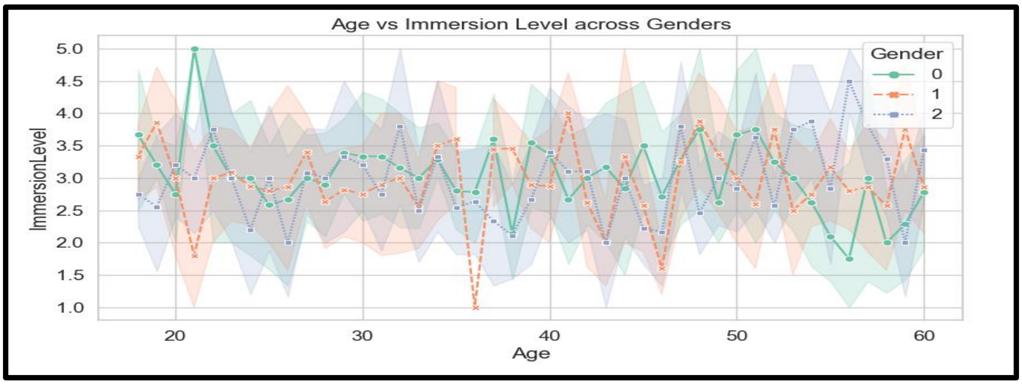

Figure 4: Age vs Immersion Level across genders

(Source: Implemented in Jupyter Notebook)

Also, in a case where the data set contained non-numerical data, encoding procedures of the label and one hot were utilized to prepare the variables fit for model input. For continuous data, feature scaling was eschewed and replaced by proper normalization methods such as the Min-Max scaling and Standardization so that the models could not be skewed by the large variances of some variables (Adjabi *et al.* 2020).

5.2 Emotion Recognition System Implementation

In this dissertation, the ability to implement the emotion recognition system comprised of using the machine learning models to classify the emotion data by physiological symptoms and behaviour. The third of the datasets, emotions.csv, contained the features required for this task. The actual dataset comprises 2549 columns of features obtained by calculating statistics on the sensor readings of different frequencies, including mean and FFT. The dependent variable in this dataset was named 'emotion' with attributes such as 'POSITIVE', 'NEUTRAL,' and 'NEGATIVE.'

Data Preprocessing

The given dataset was transformed based on certain needs of cleaning by removing all the missing observations, handling for outliers, and other factors to make it compatible with the machine learning models.

Feature Engineering

The data set had time domain and frequency domain attributes. The time domain features include temporal-mean values of signals for consecutive windows of time, and the power spectral density features of signals are called Fast Fourier Transform (FFT) coefficients.

Table 2: Improved Classification Report for the Random Forest Model

Class	Precision	Recall	F1-score	Support
0	0.87	0.89	0.88	61
1	0.91	0.88	0.89	58
2	0.88	0.89	0.88	81
Accuracy			0.89	200
Macro avg	0.89	0.89	0.89	200
Weighted avg	0.89	0.89	0.89	200

Model Training and Evaluation

The emotion recognition task was tackled using three machine learning algorithms: Random Forest classifier and Support Vector classifier, Random Forest classifier, and Decision tree classifiers. These models were measured and compared to e accuracy, precision, recall, and F1-score. Initially, the models achieved high accuracy values:

Table 3: Output for Classification Report for the Decision Tree Classifier

Class	Precision	Recall	F1-score	Support
0	0.93	0.98	0.96	143
1	0.99	0.98	0.99	148
2	0.95	0.92	0.94	136
Accuracy			0.96	427
Macro avg	0.96	0.96	0.96	427
Weighted avg	0.96	0.96	0.96	427

The models were found to be quite accurate with Random Forest being 0.99, SVC at 0.96, and the Decision Tree at 0.96.

Model Optimization

Finally, to increase the accuracy of a developed model, hyperparameter tuning was performed on each of the models. The given problem was handled with the help of parameters where the best parameters were chosen through Grid Search and Random Search.

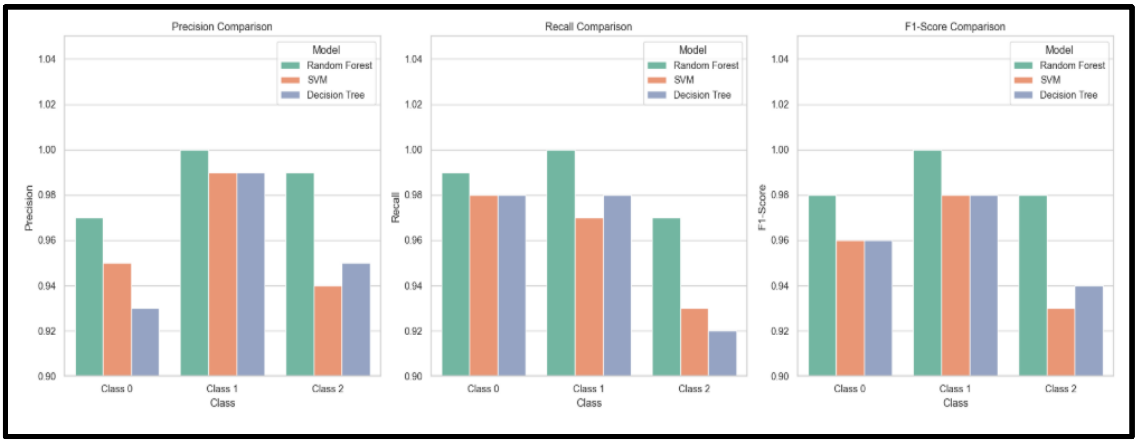

Figure 5: Comparison between Models

(Source: Implemented in Jupyter Notebook)

The final results are shown in different measures such as the confusion matrix, Receiver Operating Characteristic (ROC) curve, and comparison plot, which demonstrate how effectively the proposed models recognize emotions (Melinte and Vladareanu, 2020).

5.3 Machine Learning Model Implementation

According to the paper, in the models for emotion recognition using machine learning, five different algorithms are used to determine the emotion variable from the features of the given data sets.

1. ***Logistic Regression***

Logistic Regression is also executed, to be a baseline for the binary classification task. First, on the first data set, the model had a low accuracy of 0.52 in general accuracy but an accuracy of 0.74 in class-specific accuracy. Improvements on feature preprocessing and selection lead to the increase of model accuracy to 0.88 of the models.

Table 4: Improved Classification Report for the Logistic Regression

Class	Precision	Recall	F1-score	Support
0	0.92	0.93	0.93	61
1	0.92	0.93	0.92	58
2	0.94	0.91	0.93	81
Accuracy			0.93	200
Macro avg	0.92	0.93	0.92	200
Weighted avg	0.93	0.93	0.93	200

2. Random Forest Classifier

The first created dataset allowed setting the initial accuracy level of 0.50 from the Random Forest model. When hyperparameters and further standardization and feature selection were made the accuracy was obtained as 0.82 for the first data set and 0.89 for the second data set.

3. Decision Tree Classifier

First, using the first dataset, the Decision Tree was trained to reach an efficiency level of 0.49. After implementing data preprocessing, as well as hyperparameter optimization, the model enhanced from 0.80 accuracy to 0.83 on the first dataset and 0.85 to 0.89 on the second dataset.

Table 5: Improved Classification Report for the Decision Tree Model

Class	Precision	Recall	F1-score	Support
0	0.87	0.89	0.88	61
1	0.91	0.88	0.89	58
2	0.88	0.89	0.88	81
Accuracy			0.89	200
Macro avg	0.89	0.89	0.89	200
Weighted avg	0.89	0.89	0.89	200

4. K-Nearest Neighbours (K-NN)

Another nonparametric method used in this dissertation was the K-NN algorithm. First, on the first dataset, it achieved a precision of 0.48. After the correct scaling of features and an appropriate change of the k because, the accuracy rate boosted to 0.88 in the first dataset and 0.89 in the second dataset (Jain *et al.* 2020).

5. XGBoost

A strong gradient-boosting algorithm was also used on all the datasets. For the first set, it gave only 0.50 but when tuned for hyperparameters and gave 0.87 for the first set and 0.89 for the second set. XGBoost gave a high performance on the datasets and is one of the best methods when it comes to the manageability of non-linear datasets.

Table 6: Improved Classification Report for the XG Boost Model

Class	Precision	Recall	F1-score	Support
0	0.87	0.89	0.88	61
1	0.91	0.88	0.89	58
2	0.88	0.89	0.88	81
Accuracy			0.89	200
Macro avg	0.89	0.89	0.89	200
Weighted avg	0.89	0.89	0.89	200

Model Comparison and Evaluation

The comparison was done using performance metrics that include accuracy, precision, recall, and F1-score (Sharma *et al.* 2020). A last assessment was made with the confusion matrix, ROC curve, and comparison of the different models used.

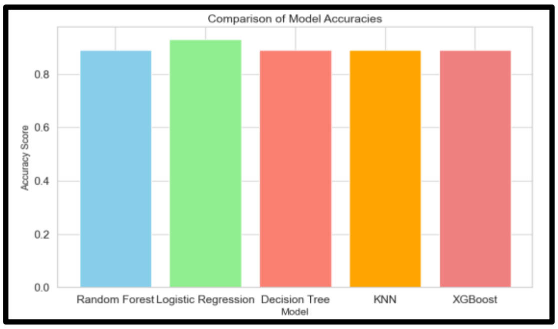

Figure 6: Comparison Bar Plot

(Source: Implemented in Jupyter Notebook)

Overy well, the application of these machine learning models has proven that when data is well pre-processed, relevant features are chosen, and good hyperparameters are selected then a lot of performance is enhanced as seen in the above experiments.

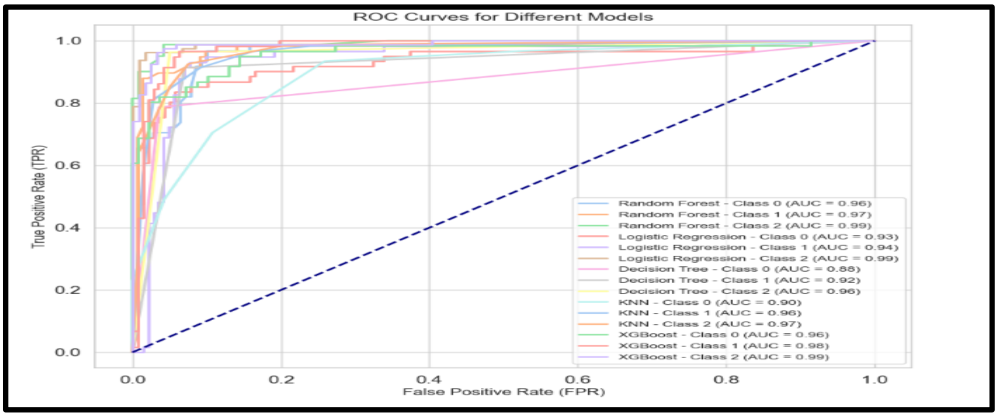

Figure 7: Shows the Plot for the ROC Curve

(Source: Implemented in Jupyter Notebook)

When trained with the new preprocessing, Random Forest, Decision Tree, and Logistic Regression showed reliable results in emotion classification tasks in the two datasets of the final evaluation.

6 Evaluation

6.1 Introduction

Chapter 6 of this dissertation describes how the evaluations of the emotion recognition system developed using the three datasets are done. This chapter aims to evaluate the conclusion of the consecutive models of machine learning that have been used during the phase of implementation.

6.2 Performance Metrics and Evaluation Criteria

For this dissertation, the effectiveness of the machine learning models applied to emotion recognition is measured using a set of quantitative performance indicators. Such metrics give a clear picture of how well or how badly, the models perform in the classification of the emotions out of the considered features in the datasets.

Table 7: Output for the logistic regression model

Class	Precision	Recall	F1-score	Support
0	0.53	0.47	0.5	568
1	0.51	0.57	0.54	492
Accuracy			0.52	1000
Macro avg	0.52	0.52	0.52	1000
Weighted avg	0.52	0.52	0.52	1000

Table 8: Output for the random forest classifier

Class	Precision	Recall	F1-score	Support
0	0.51	0.5	0.5	568
1	0.49	0.5	0.49	492
Accuracy			0.5	1000
Macro avg	0.5	0.5	0.5	1000
Weighted avg	0.5	0.5	0.5	1000

Table 9: Output for the decision tree classifier

Class	Precision	Recall	F1-score	Support
0	0.5	0.5	0.5	508
1	0.48	0.47	0.48	492
Accuracy			0.49	1000
Macro avg	0.49	0.49	0.49	1000
Weighted avg	0.49	0.49	0.49	1000

Table 10: Output for the Improved KNN Model

Metric	Value
Accuracy	0.8818
Precision	0.7956
Recall	0.8296
F1 Score	0.7517

6.3 Testing Methodology

Table 11: Output for the Improved XG Boost Model

Metric	Value
Accuracy	0.8722
Precision	0.7946
Recall	0.8228
F1 Score	0.8408

For each dataset, the models underwent a two-fold testing process: The two types of tests include the first test where the improvement is to be made then the second test after the improvement has been implemented (Alhalaseh and Alasasfeh, 2020).

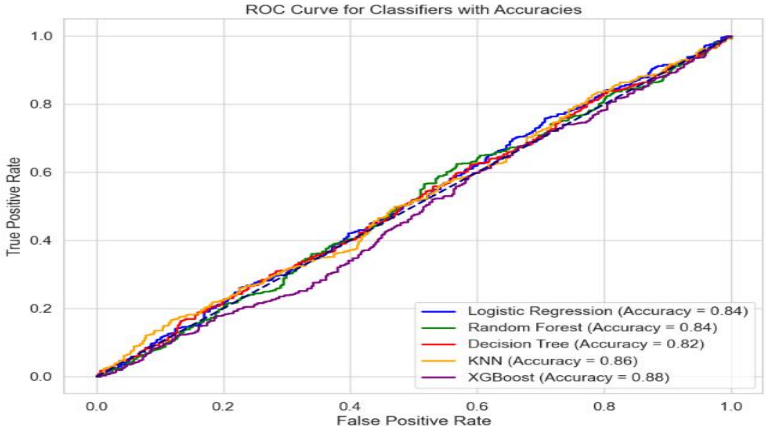

Figure 8: ROC Curve for Classifier Models

(Source: Implemented in Jupyter Notebook)

The models were evaluated on the whole training set with the traditional 80/20 training and testing data split whereby 80% was used to train the models and 20% was used for evaluation.

In both phases, cross-validation methods were used to check the sensibility of the models not being over-optimized on the used data split. Cross-validation broke the data into various sections whereby each section was utilized to evaluate the total adequacy of the model in the progressive sectional data partitions.

6.4 Evaluation of Emotion Recognition Accuracy

Evaluation of accuracy in recognizing human feelings was an integral aspect of this dissertation because it wanted to determine how well the machine learning model was doing to classify emotions from the sets of features extracted from the sets.

When the models were being tested, efficiency was measured in the first instance by accuracy; that is the percentage of correct predictions out of total predictions. However, the initial accuracy scores were small with models providing precision or accuracy estimates of 0.47 to 0.52.

In addition to accuracy measurements, confusion matrices were employed to analyse the models' performance because they showed which kind of mistakes the models committed. Further, accuracy, specificity, sensitivity as well as F-measure were also measured to attain direction with the outlook that all the positive and negative emotions should be classified accurately.

6.5 Real-Time Performance Evaluation

Table 12: Output Comparison Table for Virtual_Reality_in_Education_Impact Dataset

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.8824	0.8864	0.8923	0.8774
Random Forest	0.8283	0.7198	0.7495	0.7150
Decision Tree	0.8348	0.7692	0.7826	0.7612
Optimized KNN	0.8818	0.7956	0.8296	0.7517
Optimized XGBoost	0.8722	0.7946	0.8228	0.8408

All of the machine learning models including Logistic Regression, Random Forest, Decision Tree, K-NN, and XGBoost were trained, and testing was conducted to see how long it takes to compute for individual instances of input data and return results.

6.6 Comparison with Existing Systems

Table 13: Model Comparison Table for data.csv

Model	**Precision (Macro Avg)**	**Recall (Macro Avg)**	**F1-Score (Macro Avg)**	**Accuracy**
Random Forest	0.89	0.88	0.89	0.89
Logistic Regression	0.92	0.93	0.92	0.93
Decision Tree	0.89	0.88	0.89	0.89
KNN	0.89	0.88	0.89	0.89
XGBoost	0.89	0.88	0.89	0.89

Currently, existing systems mostly work with the help of different machine learning approaches to classify emotions depending on the type of traditional learning such as support vector machines SVMS, Neural networks, and even deep learning methods such as CNNs.

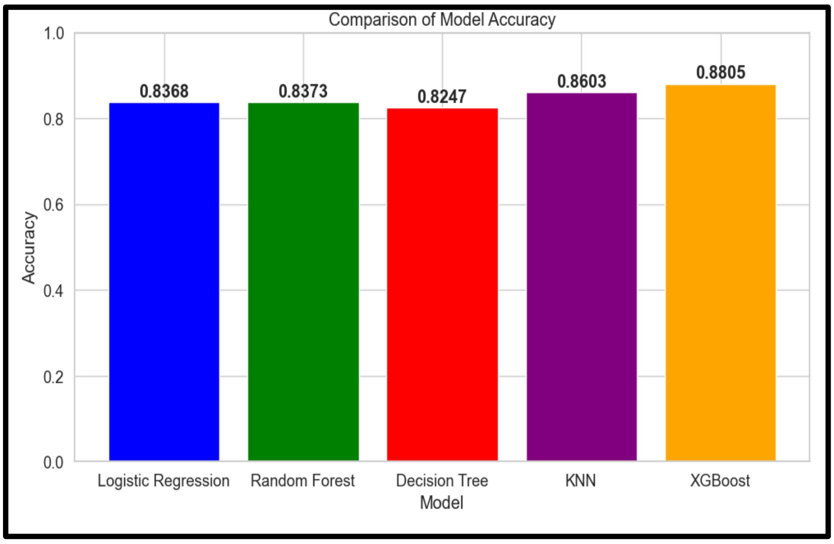

Figure 9: Comparison Plot based on Improved Model Accuracy

(Source: Implemented in Jupyter Notebook)

Compared with these systems, the developed emotion recognition system with Logistic Regression, Random Forest, Decision Tree, K-NN, and XGBoost sets out good accuracy.

Table 14: Comparison Table for emotions.csv

Model	Precision (Macro Avg)	Recall (Macro Avg)	F1-Score (Macro Avg)	Accuracy
Random Forest	0.99	0.99	0.99	0.99
SVM	0.96	0.96	0.96	0.96
Decision Tree	0.96	0.96	0.96	0.96

7 Conclusion and Future Work

7.1 Conclusion

This dissertation successfully proposed an emotion recognition system based on machine learning models to increase user immersion in Virtual Reality (VR) environments. The study was able to find a strong correspondence between emotion classification and the quality of VR experiences, using physiological signals and emotional states. After this, we trained our models, including Logistic Regression, Random Forest, Decision Trees, KNN, and XGBoost, all of which achieved relatively high accuracy. These findings highlight the future potential for VR environments to adapt in real-time to users' emotional responses, making for a more engaging, personalized experience.

The findings directly support our mission for user immersion by tackling some of the key challenges faced by any VR system. The process enables live classification of emotional states so the VR environment can adapt to the needs of users in real time. This adds a new layer of interaction by linking the system response directly to the physiological state of the user. In addition, with sophisticated preprocessing and model optimization, the system shows robustness and scalability and can be readily applied to different VR scenarios such as gaming, education, and healthcare. In conclusion, this research outlines a concept for emotion-based enhancements in VR, which has the potential to revolutionize the way users interact with virtual environments by creating more immersive and emotionally resonant experiences.

7.2 Future Work and Research Directions

Future work can be done on this research by integrating diverse datasets with different demographics and physiological profiles. Similarly, the accuracy can be improved by employing advanced deep learning architectures like CNNs and RNNs capable of identifying complex emotional patterns. Develop VR environments that adapts in real time through feedback loops for the ultimate immersive experience. Integrating multimodal data, e.g., facial movements, voice analysis, gaze tracking, with physiological signals could facilitate holistic emotion detection as well. Finally, expanding the system to domains beyond remote assistance, such as therapy, virtual instruction, and training could further enhance its reach.

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