ONLINE GAME ADDICTION LEVEL PREDICTION BASED ON DAY TO DAY LIFE ACTIVITY USING MACHINE LEARNING

BY

Mahfuza Ebnat Disha
ID: 201-15-3146

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

Supervised By

Mr. Amir Sohel
Senior Lecturer
Department of CSE
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

DHAKA, BANGLADESH

MAY, 2024

APPROVAL

This Project titled "Online Game Addiction Level Prediction Based On Day To Day Life Activity Using Machine Learning", submitted by Mahfuza Ebnat Disha, ID:201-15-3146 to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 14 July,2024.

BOARD OF EXAMINERS

Dr. Md. Taimur Ahad (MTA) — **Board Chairman**
Associate Professor & Associate Head
Department of CSE
Faculty of Science & Information Technology
Daffodil International University

Mohammad Monirul Islam (MMI) — **Internal Examiner 1**
Assistant Professor
Department of CSE
Faculty of Science & Information Technology
Daffodil International University

Jakaria
14.07.2024
Md. Jakaria Zobair (MJZ) — **Internal Examiner 2**
Lecturer
Department of CSE
Faculty of Science & Information Technology
Daffodil International University

14.07.2024
Nazibur Rahman — **External Examiner**
Technical Lead - Database Administrator
Telenor - Grameen Phone Account

DECLARATION

We, therefore, declare that this undertaking has been finished by us under the supervision of **Mr. Amir Sohel,** Lecturer (Senior Scale), Department of CSE, Daffodil International University. We further declare that neither an application or an educational grant has been made anywhere for this project or any part of it.

Supervised by:

Mr. Amir Sohel
Senior Lecturer
Department of CSE
Daffodil International University

Disha
13.07.24

Submitted by:

Mahfuza Ebnat Disha
ID: 201-15-3146
Department of CSE
Daffodil International University

ACKNOWLEDGEMENT

First we express our heartiest thanks and gratefulness to almighty God for His divine blessing makes it possible to complete the final year project successfully.

We are really grateful and wish our profound indebtedness to **Mr. Amir Sohel**, Lecturer (Senior Scale), Department of CSE Daffodil International University, Dhaka. Deep Knowledge & keen interest of our supervisor in the field of "Machine Learning" to carry out this project. Her endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts and correcting them at all stages have made it possible to complete this project.

We would like to express our heartiest gratitude to Professor **Dr. Sheak Rashed Haider Noori,** Head**,** Department of CSE, for his kind help to finish our project and also to other faculty members and the staff of CSE department of Daffodil International University.

We would like to thank all of our classmates at Daffodil International University who participated in the discussion while also attending the course.

Finally, we must acknowledge with due respect the constant support and patients of our parents.

ABSTRACT

The growing popularity of gaming in modern society has raised concerns about the possible dangers of addiction. The major goal is to create a predictive model capable of identifying and categorizing different stages of game addiction based on a wide range of factors, such as gaming behavior, psychological qualities, and socioeconomic information. The dataset, obtained from reliable archives such as Kaggle, includes 51 characteristics covering a wide range of topics such as gender, age, academic qualifications, gaming habits, opinions about oneself, emotional states, and social contacts. The focus attribute, 'Addiction Level', stratifies individuals into categories: 'non-addictive','moderately addictive', and 'very addictive'. The process is thorough, beginning with data cleansing and progressing through feature engineering and exploratory data analysis (EDA) to generate important insights into attribute connections, distributions, and trends. Following a thorough examination, machine learning models are trained and tested using a variety of methods, such as Random Forest Classifier, Gradient Boosting classifiers, Voting Classifier, SVM, and Adaboost classifier. Here on those algorithms SVM outperforms the highest accuracy 90.76%. Furthermore, the study intends to provide an extensive predictive model capable of identifying addiction levels based on numerous behavioral, psychological, and demographic gaming features.

Keywords: *Game addiction, Level prediction, Machine learning, RF, GNB, LR, Feature selection, Model tuning, and Cross-validation techniques.*

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1
INTRODUCTION

1.1 Introduction

The rise in popularity of digital gaming in recent years has resulted in unimaginable levels of engagement and enjoyment for millions of people worldwide. However, amid the excitement of virtual worlds, concerns have grown about the possibility of excessive gaming leading to addiction. Understanding and predicting game addiction levels has become a critical area of research, critical for methods of treatment and encouraging a healthier gaming culture.[1]

This study aims to investigate the predictability of game addiction levels by employing a complex strategy that combines psychological, behavioral, and demographic data. Using machine learning algorithms and statistical analysis, we hope to identify patterns and markers that indicate an attraction for addictive gaming behaviors.[2]

This study is significant not only for identifying risk factors associated with game addiction but also for developing a predictive model that might help in early detection and prevention. Such a model has the potential to guide specific measures as well as customized approaches, providing support to individuals who are at risk of or are already struggling with gaming addiction.[3]

This paper is organized to delve into existing gaming addiction literature, demonstrate the techniques used for predictive analysis, present findings obtained from extensive data, and discuss consequences for both academia and practical application. Finally, the goal is to contribute to the ongoing discussion about healthy gaming practices and to provide actionable insights to help reduce the negative effects of excessive game engagement.

Understanding the specifics of game addiction and developing predictive tools becomes an essential step towards encouraging a balanced, dependable, and enjoyable gaming environment for all enthusiasts as the digital landscape evolves.

1.2 Motivation

Predicting motivation and the potential for game addiction is an important step in understanding and addressing gaming behaviors. Researchers and psychologists use numerous evaluation techniques and models to establish an individual's tendency for excessive gaming as well as the root causes fueling this activity. These models frequently take into account elements such as game entanglement, social relationships within gaming communities, psychological need fulfillment, and the balance between gaming and other daily activities. Predictive models are constructed using data analysis and machine learning approaches to evaluate the chance of addiction based on these parameters. These models aid in the early detection and treatment of people who are at risk of acquiring unhealthy gaming addictions. Furthermore, they contribute to the development of targeted strategies and methods to encourage healthy gaming behaviors and improved life balance. However, due to the changing nature of gaming platforms and behaviors, these prediction models must be refined and adapted on a regular basis. The ultimate goal is to utilize these forecasts to guide people toward responsible gaming and a healthy lifestyle.

1.3 Rationale of the Study

The reason for studying and predicting game addiction comes from the increasing accessibility of gaming in modern culture and its possible impact on individuals. Understanding the aspects that contribute to addiction becomes increasingly important as gaming becomes more engaging, accessible, and blended into daily life. Researchers want to find early warning indicators and danger factors by researching game addiction levels. This prediction model may provide insights into behavioral patterns, psychological triggers, and environmental aspects that contribute to addiction. Understanding these factors not only helps with early treatment but also allows for the development of focused prevention campaigns and assistance networks. Furthermore, such research contributes to the greater discussion on mental health by shedding light on the complicated nature of addiction and its connection with technology. They can provide officials, mental health practitioners, and game creators with information to help them establish better gaming environments and treatments that promote responsible and balanced gaming habits. Finally, the motivation for predicting game addiction levels comes from the ability to raise awareness, give personalized support, and lessen the negative effects of excessive gaming on individuals and society as a whole.

1.4 Research Question

- What are the major factors affecting the vulnerability to severe game addiction in various age groups?
- What is the relationship between the duration and frequency of gameplay sessions and the development of addictive behaviors in gamers?
- Can psychological tests accurately predict individuals' tendency to develop addictive desires toward specific types of games (e.g., MMORPGs, FPS, mobile games)?
- How much social engagement within gaming communities contributes to or reduces addictive behaviors in gamers?
- How do in-game prizes, small transactions, and customization aspects influence the development of addictive behaviors in players?
- Are there any visible psychological or personality factors that lead people to game addiction?
- Can machine learning algorithms anticipate danger accurately?

1.5 Expected Output

Game Prediction is a model that predicts an individual's responsiveness to gaming addiction. Using a range of standards, including social contacts, gaming frequency, duration, and psychological aspects, the model uses machine learning algorithms to produce predictions. It evaluates the risk of someone being addicted to gaming throughout further interactions with gaming platforms by looking at user data and behavioral patterns. Individuals, gaming firms, and healthcare professionals can obtain insights into potential addictive tendencies by utilizing predictive technologies. Proactive actions, including customized interventions, specialized assistance, or the incorporation of responsible gaming elements into platforms, are made possible by this data. This methodology aims to prioritize mental health, encourage a more balanced relationship with digital entertainment, and encourage healthier gaming behaviors by predicting the likelihood of addiction. In essence, its goal is to enable people to make knowledgeable decisions about their gaming preferences while promoting a more secure and conscientious gaming environment.

1.6 Project Management and Finance

Project management involves organizing work, resources, and schedules to meet certain goals. Budgeting, cost estimation, and financial analysis are all part of integrating finance into project management to guarantee a project's successful completion. In the field of predicting gaming addiction, a predictive model that evaluates and predicts the probability of people developing obsessive gaming habits might be created utilizing machine learning algorithms. For predicting levels of addiction, this model might examine a number of variables, including playing frequency, duration, and user behavior patterns. The use of data analysis and predictive modeling approaches creates an alliance between project management and finance in predicting gaming addiction levels. Teams can set up schedules for model creation, organize data gathering and analysis, and effectively allocate resources by implementing project management approaches in this scenario. A financial perspective also helps evaluate how cost-effective the deployment and servicing of the predictive model will be. To summarize, the strategic approach to understanding and managing addiction to gaming is provided by a combination of project management, finance, and statistical analysis. This is achieved through the utilization of structured techniques, financial insights, and data-driven forecasts.

TABLE 1.1: PROJECT MANAGEMENT TABLE

Work	Time	Finance
Dataset	1 month	400
Literature Review	3 month	100
Experiment Setup	1 month	1000
Implementation	2 month	500
Report	2 month	500
Total	9 month	2500

1.7 Report Layout

In Chapter-1 discuses about Introduction: This study aims to investigate the predictability of game addiction levels by employing a complex strategy that combines psychological, behavioral, and demographic data.

In Chapter-2 discuses about Background: This may include statistical data such as age, gender, and financial situation, as well as gaming-specific information such as hours spent playing, preferred genres, and social interactions inside games.

In Chapter-3 discuses about Research Methodology: Standardized surveys such as the Gaming Addiction Scale, behavioral monitoring software, and physiological indicators such as heart rate variability during gaming sessions are examples of these tools.

In Chapter-4 discuses about Experimental Result and Discussion: The models' prediction accuracy was encouraging, with a high degree of accuracy in anticipating possible addiction levels based on individual gaming patterns and psychological features.

In Chapter-5 discuses about Impact on Society, Environment: these predictive algorithms have the potential to reduce the adverse social effects of gaming addiction.

In Chapter-6 discuses Summary, Conclusion, Future Research: Machine learning algorithms based on varied data sets, such as game trends, user behaviors, and psychological profiles, are one way of gaining favor.

CHAPTER 2
BACKGROUND STUDY

2.1 Preliminaries

The prediction of game addiction levels is an important field that is frequently analyzed using numerous parameters such as gaming length, behavior patterns, and psychological features. To understand gaming behaviors, likes and dislikes, and the impact on daily life, preliminary procedures include data collection via surveys or psychological analytic tools. Machine learning models use this data to forecast addiction levels by taking into account factors such as gaming hours, social interactions, and emotional attachment to games. These predictions aid in the early identification and treatment of people at risk of developing serious addiction, allowing for personalized support and preventive actions. However, due to the subjective nature of gaming experiences and individual variations, it remains difficult to sufficiently express the complex nature of addiction processes. Continuous study and model refinement strive to improve accuracy and develop effective solutions for reducing the negative impacts of excessive gaming.

2.2 Related Works

We have reviewed a few recent studies, and the following is an analysis of those studies:
Sarit Alkalay et al. [1] proposes a computer game that can be used to help with child psychotherapy. This is especially difficult when the patient is a child who is usually more interested in performing. The game involves a virtual AI-based player and a human player. Available strategies Tit-for-tat, random help, always help, never help. The participants included four children, ranging in age from 7 to 10. Random forest outperforms all other classifiers with a dataset that includes age, gender, grade, and family members. The model achieved an accuracy of 87% and 52% of positive responses to help requests; see the game’s helping statistics.

Prosenjit Ghosh et al. [2] researched on internet gaming addiction, its impact on mental health, and potential manifestations like withdrawal psychosis is crucial for effective treatment. The participants here are 26-year-old young people. Students revealed a 7%

prevalence of internet addiction among them. Research shows many people are not addicted to Mobile Legends, a multiplayer online battle arena, but rather to gaming addiction. In this paper, we used the KNN model, and its accuracy is 95.5%. There is very little generalizability, reporting a problem without a control group, and small-scale statistical analysis, which are weaknesses.

J.J. Park et al. [3] evaluates existing literature on internet-based interventions for problematic gaming, assessing feasibility, effectiveness, and potential mechanisms of change, providing an overview, and identifying research gaps. Gaming disorder is a recognized mental health condition with a very narrow range of treatment options. In this paper, we used KNN classification algorithms and split them into two datasets: 82% for training and 18% for the testing phase, with a total accuracy of 92%. Technical issues, internet access, and low digital literacy impact participation and accessibility, which are the main weaknesses.

H.Huda et al. [4] aimed to explore the impact of online games on various aspects of the lives of Bangladeshi university students. We can take an exclusive online interview with them or observe their behavior while they are in a critical moment in the game to see how it affects their performance, attitude, and language. A total of 80 participants provided data and online game users (males 82.7%, females 17.3%) using an online response method. This research used Random Forest and Deep Neural Network as machine learning and deep learning algorithms with 95% accuracy, and the weaknesses are that gamers face increased stress, anxiety, depression, and irritability due to poor time management skills due to their online gaming addiction.

A.M.Weinstein et al. [5] showed that computer game addiction can lead to long-term changes in reward circuitry, resembling drug abuse. Users may engage in obsessive gaming, focusing on in-game achievements rather than larger life events. This addiction can result in psychological and social stress, including decreased school success, absenteeism, sleep deprivation, and increased suicidal ideation. A list of drug and alcohol-type datasets methodology includes Naïve Bayes classifier and and split them into two datasets: 70% for training and 30% for the testing phase. Advanced brain imaging techniques quantify dopamine release from computer game play, showing healthy volunteers release similar amounts as pharmacological challenges, while former ecstasy users release minimal dopamine.

A.A.Rahman et al. [6] presented machine learning algorithms using a dataset to identify online gamers anxiety levels, analyzing their effectiveness through Python simulations and cross-validation. Using ML algorithms such as RF, SVM, and Convolutional Neural Network (CNN) on the corpus gathered from blog posts, they were able to distinguish between mentally ill and healthy people with an accuracy percentage of 98.96% with the CNN classifier. In the process of accomplishing this, the performances of other ML classifiers eventually revealed whether the subject was experiencing minimal, mild, moderate, or severe anxiety levels.

L.A.M.Pangistu, [7] aimed to detect game addiction in late adolescence by classifying EEG data using CNN, using the Fast Fourier transform to extract features and obtain average signals for CNN models. Playing games for an extended period of time can become addictive. Based on the research conducted, we obtained an accuracy of 88%. In order to improve accuracy, reduce loss, and increase the likelihood that some data classes are incorrectly classified during testing, it will be necessary to add more data in the future.

M.Gulu et al [8] maintained their weight and reduced addiction by engaging in regular physical activity and limiting their time spent playing digital games. For this reason, policymakers are urged to promote physical activity in schools and other settings. Here, a machine learning method for predicting game addiction was assessed using a logistic regression model and a confusion matrix. In this paper, accuracy is 95%, and the weaknesses include a cross-sectional methodology, a lack of longitudinal data, and limited generalizability due to the small sample size and participation of adolescent children.

W.Seo et al [9] introduced a machine learning-based, random forest-based method for analyzing problem gambling in a large Korean adolescent dataset, achieving moderate accuracy in predicting gambling severity. In this paper, accuracy is 71.8%, and the analysis's potential for future expansion and improvement in understanding adolescent problem gambling is discussed, with the hope of providing new insights and preventing future issues.

Y.Wang. et al [10] researched that the popularity of the internet has also brought new public health issues, such as internet addiction, to support vector machine (SVM) models. A total of 57 participants (27 individuals with internet addiction and 30 healthy controls) were included in the final data analysis with an accuracy of 82.5%. A larger dataset must be used for validation because of the small sample size. Future research should take into account multimodal neuroimaging data and remove areas of the brain , which are weaknesses.

Stavropoulos, Vasilis, et al.[11] studied the symptoms of Internet addiction (IA) in Greek teenagers between the ages of 16 and 18 in this longitudinal study, with a particular emphasis on the use of massively multiplayer online role-playing games (MMORPGs) and personal hostility. Using the Symptom Checklist-90 (SCL-90) and the Internet Addiction Test (IAT), they evaluated 648 teenagers for hostility over a two-year period. The findings showed that adolescents who were more hostile and MMORPG players had higher levels of IA symptoms. Remarkably, it appeared that being in a classroom with a larger proportion of MMORPG players protected against IA. All things considered, the results highlight how important it is to take into account contextual factors, like the makeup of the classroom, in order to comprehend variations in IA symptoms during adolescence.

Rho, Mi Jung, et al. [12] focused on this study to find patterns and predictors of problematic online gaming. Online surveys were used to gather information, and 3,881 Internet gamers were found among the 5,003 respondents. A normal comparison group and a problematic Internet game user group were created using propensity score matching, with 511 participants in each. Two of the key predictors found by the chi-square automatic interaction detector (CHAID) algorithm are average gaming time and gaming costs. Furthermore, three different problematic patterns of Internet game use were found: socializing, solitary, and cost-consuming gamers. These findings offer important new information for future adult screening initiatives.

Rehbein, Florian et al. [13] presented the findings of a two-wave longitudinal study with a total of 406 students from grades 4 through 9. It demonstrates that 15-year-old video game addicts exhibited specific risk factors as early as age 10. Students from single-parent households, those with poor school performance, and those with less social integration in class are especially vulnerable. Furthermore, problematic video game use during childhood increases the likelihood of gaming addiction in adolescence, with males being particularly vulnerable. These findings make a significant contribution to identifying risk factors for gaming addiction in adolescents, which will aid in the development of effective preventive strategies.

Zhu, Jianjun, et al. [14] looked to identify the mediating mechanisms that link the parent-adolescent relationship to Internet game addiction (IGA). Over the course of a year, questionnaires on a variety of topics, including the parent-adolescent relationship, school connectedness, deviant peer affiliation, and IGA, were administered to 833 seventh-grade students. Structural equation models revealed that school connectedness and deviant peer affiliation completely mediated the link between the parent-adolescent relationship and IGA. Additionally, school connectedness was discovered to predict deviant peer affiliation, resulting in a sequential mediation model. Overall, the findings indicate that a low-quality parent-adolescent relationship has an indirect impact on IGA through decreased school connectedness and increased affiliation with deviant peers, emphasizing the importance of understanding these processes for prevention strategies.

Kudubes, et al.[15] gathered online using various scales and forms revealed significant links between social media use, game addiction, and adolescent lifestyle. The study discovered that game addiction and social media addiction accounted for and influenced a significant portion (61.8%) of adolescents' lifestyles. Furthermore, characteristics of social media use, as well as game and social media addiction, explained 62.8% of the variation in adolescent lifestyle. These findings highlight the importance of educating adolescents and their parents about responsible technology use, as well as assessing the efficacy of such interventions.

2.3 Comparative Analysis and Summary

A comparison of gaming addiction level prediction techniques illustrates several approaches used in determining and understanding this problem. To predict addiction levels, many studies use machine learning algorithms, psychological exams, and behavioral analysis. Machine learning techniques, such as neural networks and decision trees, are often utilized for predicting addictive behavior based on user data. To determine susceptibility to addiction, psychological tests focus on qualities such as impatience and self-control. Behavioral analysis also looks at patterns of gameplay, time spent, and in-game activities to determine addictive tendencies.

TABLE 2.3: COMPARATIVE ANALYSIS AND SUMMARY TABLE

SL	Author & year	Dataset	Model	Accuracy
01	Alkalay, 2020	Age, gender, grade, family members	Random forest	87%
02	Ghosh, 2018	Multiplayer online battle arena gaming addiction	KNN	95.5%.
03	Park,2020	Gaming disorder is a recognized mental health condition	KNN	92%
04	Huda, 2015	Game to see how it affects their performance, attitude, and language	Machine learning & Deep learning	95%
05	Weinstein, 2010	Drug and alcohol-type datasets	Naïve Bayes	70%
06	Rahman, 2021	Ill and healthy people	RF, SVM,CNN	98.96%
07	Pangistu, 2021	Detect game addiction in late adolescence	CNN	88%.
08	Gulu, 2023	Time spent playing digital games	Logistic regression ,	95%
09	Seo ,2020	Large Korean adolescent	Random forest	71.8%
10	Wang, 2021	Internet addiction	SVM	82.5%

11	Vasilis, 2017	Ages of 16 and 18 in this longitudinal study	AI	81%
12	Jung, 2016	Internet gamers	CHAID	75%
13	Florian, 2013	Video game addicts	DT	75.95%
14	Jianjun , 2015	Internet game addiction	GB	83%
15	Kudubes , 2024	Social media addiction	SVM	87%

These techniques, in general, work to improve understanding and prediction accuracy by including many aspects of individual behavior and game patterns. They provide useful information about potential risk factors and successful treatment options. However, because of the complexity of human behavior and the constantly changing characteristics of gaming technologies, predicting addiction levels remains difficult. Future developments in interdisciplinary techniques may lead to more precise identification and reduction of game addiction concerns.

2.4 Scope of the Problem

Predicting gaming addiction levels has tremendous potential for dealing with this developing issue. Researchers and mental health professionals can forecast the likelihood and severity of gaming addiction in individuals by using predictive models. These models try to accurately determine risk levels by using multiple data sources, such as gaming habits, psychological profiles, and socioeconomic factors.This predictive analysis helps with preventive tactics, allowing for customized preventive and treatment approaches. It enables healthcare providers to provide timely assistance, counseling, or focused interventions to high-risk clients, potentially preventing the development of addictive behaviors.Furthermore, predictive analytics in game addiction provides significant knowledge into patterns and risk factors, assisting in the development of more effective public health policies and educational programs. This technique adds greatly to the larger goal of encouraging healthy gaming behaviors and general mental well-being by simplifying complex data into actionable predictions.

2.5 Challenges

Individuals' gaming habits differ greatly. What one individual considers excessive may be considered normal by another. Determining an acceptable level of addiction requires taking into account various gaming patterns, preferences, and personalities. Game addiction, unlike established diseases such as drug abuse, lacks broadly accepted diagnostic standards. Multiple groups and scholars define gaming addiction differently, resulting in diverse approaches to testing and prediction. The design, mechanics, and degrees of engagement in games vary greatly. Considering these variations and their possible influence on player behavior is required when predicting addiction. Personal characteristics such as recklessness, self-control, mental health issues, and coping techniques must be considered in predictive models. These factors have a major effect on a person's tendency toward addiction. Obtaining accurate and thorough statistics on gaming activity is tough. Self-reported data may not always accurately reflect real usage patterns, and getting objective data from gaming platforms may raise privacy and moral issues. Gaming trends change quickly, with new technologies and game genres appearing on a regular basis. To be effective, prediction models must adjust to these changes. The use of prediction models to diagnose addiction raises ethical problems about naming people. It is essential to strike a balance between the advantages of early detection, individual protection, and confidentiality.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

The research topic is predicting levels of game addiction in individuals, which is an important issue given the high rate and influence of gaming on mental health. The study's goal is to create an effective predictive model for evaluating and measuring addiction risks using multiple equipment approaches. Surveillance is collecting detailed data on gaming habits, motivations, emotional responses, and their relationship to addiction levels using validated psychological tests, behavioral observation, and possibly physiological markers. Standardized surveys such as the Gaming Addiction Scale, behavioral monitoring software, and physiological indicators such as heart rate variability during gaming sessions are examples of these tools. The study aims to build a strong forecasting framework by combining several data sources. This broad strategy aims to provide knowledge about the risk factors and patterns that contribute to game addiction, potentially assisting in the creation of focused therapies or preventive initiatives.

3.2.1 Data Collection

An organized technique for gathering necessary details is often used in the data collection procedure for forecasting gaming addiction levels. It all starts with identifying the elements that influence gaming habits. This may include statistical data such as age, gender, and financial situation, as well as gaming-specific information such as hours spent playing, preferred genres, and social interactions inside games. Surveys and questions, which are frequently used tools, are often based on standardized addiction assessment scales such as the Gaming Addiction Scale (GAS) or the Internet Gaming Disorder Scale (IGDS). These measures analyze characteristics such as feelings of dehydration, loss of control, and the influence of gaming on daily life to evaluate addiction tendencies. In addition, behavioral observations and gameplay tracking may be used. This is tracking actual gaming activity using software or applications that record play time, frequency, and in-game behaviors. Throughout the data gathering process, ethical considerations, participant confidentiality, and informed permission standards are essential. To summarize, data collection for predicting game addiction levels entails a complex strategy that includes demographic information, established evaluation scales, behavioral observations, and ethical considerations to build predictive models for recognizing and evaluating gaming addiction behaviors.

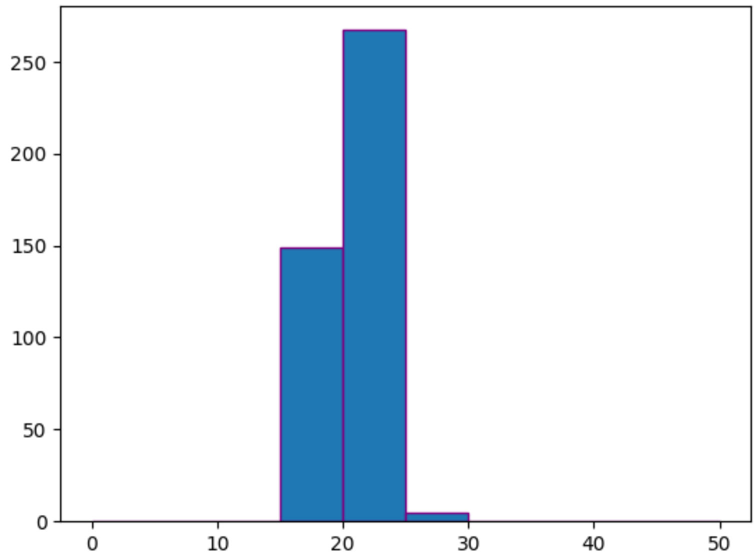

Figure 3.1: Dataset Age Group Bar Plot

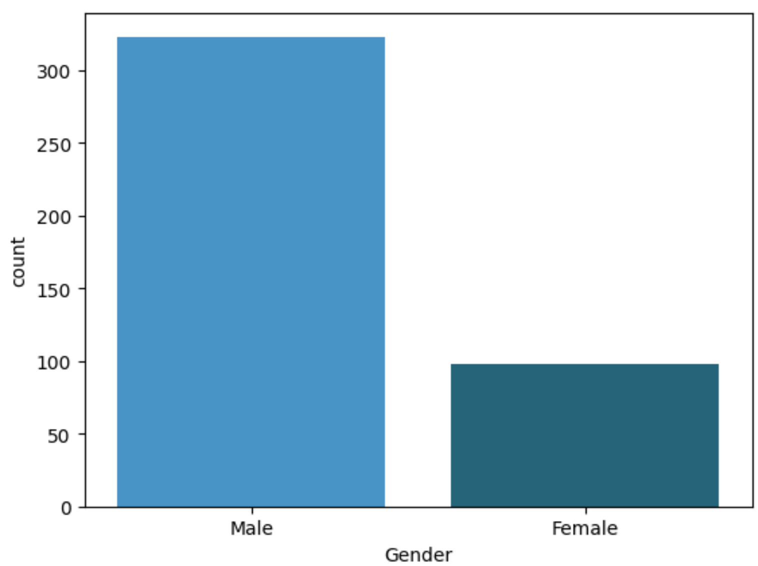

Figure 3.2: Dataset Gender Bar Plot

The above bar plot in Figure 3.2 shows the distribution of two categorical attributes, "Male" and "Female," with counts of 350 and 100, respectively. The horizontal axis usually represents the categories (in this case, "Male" and "Female"), whereas the vertical axis represents the count or frequency. The plot includes two bars: one for "Male" with a height of 350 and another for "Female" with a height of 1000. The bars visually represent the comparison between the two attributes, showing that the "Male" count is slightly higher than that of the "Female."

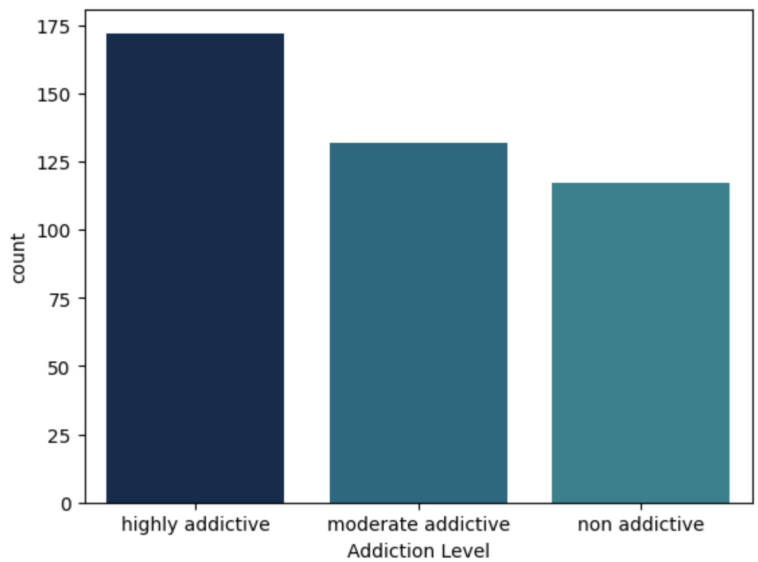

Figure 3.3: Target Attribute Plot

Figure 3.3 showing the Target attribute plot. Here there are three target attributes such as highly addictive, moderate addictive addiction level and last one is non addictive. The value of highly addictive is 160, Moderate addictive addiction level is 125 and non addictive value is 115.

3.3 Statistical Analysis

Statistical analysis, which uses data to predict patterns and behaviors, is critical in anticipating game addiction levels. Various criteria, such as gaming time, frequency, game kind, and socioeconomic status, can be analyzed using this approach to determine patterns suggestive of addictive behaviors. A model can be constructed to predict the likelihood or degree of game addiction in individuals using techniques such as regression analysis or machine learning algorithms. This model employs historical data to uncover connections and interdependence among various variables and their impact on addiction levels. It may demonstrate, for example, that longer hours of gameplay combined with specific game genres or age groups are associated with higher addiction tendencies. Furthermore, statistical analysis aids in identifying risk factors that strongly contribute to addiction preferences. It can reveal patterns that were previously undetected, enabling focused actions or preventive measures. Statistical analysis, in basic terms, acts as a strong tool for forecasting and summarizing the potential for game addiction by extracting useful insights from a variety of data, allowing proactive approaches to address and reduce addictive behaviors in gaming situations.

3.4 Proposed Methodology

The process for predicting gaming addiction levels includes numerous steps, including data collection, data labeling, enhancing images, data splitting, training the model, recognition, and output generation. The proposed methodology is outlined below:

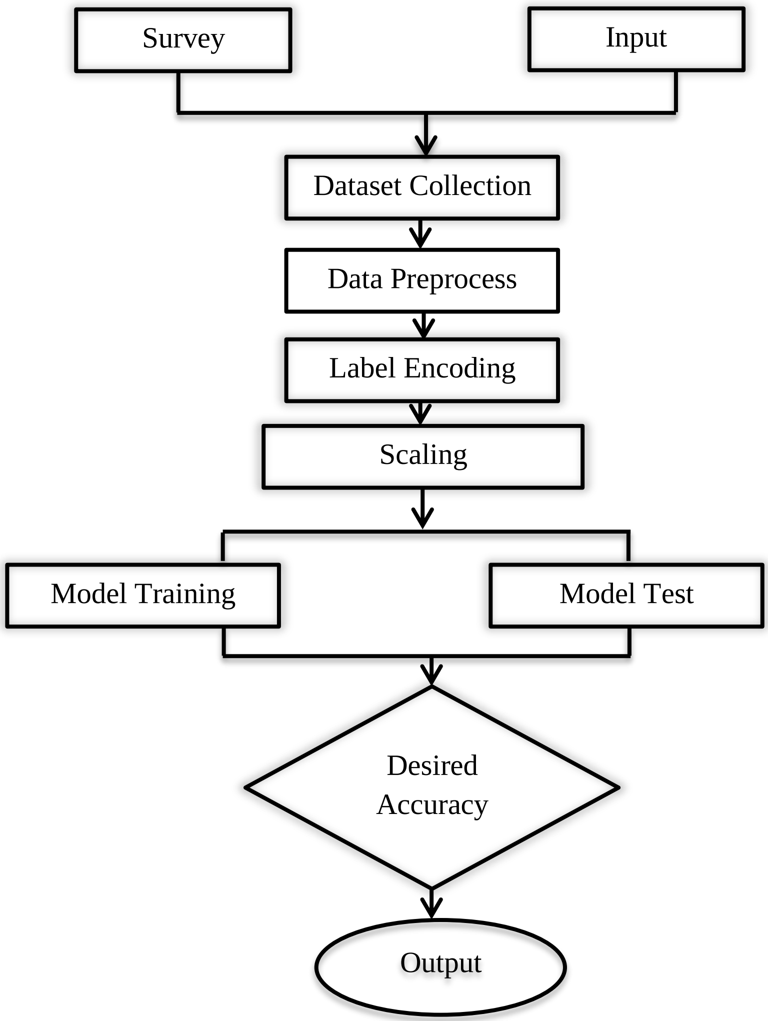

Figure 3.1: Flow Chart

Data Labeling:

Based on known addiction measures or expert ratings, categorize the obtained data into different addiction levels (e.g., low, moderate, or high). Assign labels to each data point showing the level of addiction.

Data Splitting:

Divide the dataset into training, validation, and testing sets (for example, 70-15-15 split) to train the model, tune hyperparameters, and evaluate performance.

Data Pre-Proceding:

Handling missing values, Begin by determining which attributes have missing values and estimating the total quantity of missingness in the dataset. Decide on a strategy. Determine an appropriate technique for dealing with missing values depending on the dataset and the specific characteristics at hand. This could include removal, imputation, or domain-specific approaches. Follow the recommended rules for dealing with missing values in the dataset. This could include eliminating rows or columns with missing data, replacing missing values with statistical measures (mean, median, mode), or employing more complex techniques such as predictive modeling.

Training the Model:

Select a machine learning or deep learning algorithm (e.g., neural networks, SVM, decision trees) that is appropriate for the dataset characteristics. Using the training dataset, train the model, modifying parameters to optimize performance and avoid excessive fitting. To improve model performance, consider feature selection or extraction strategies.

Table 3.1: DEMOGRAPHIC DATA

Variables	Clasification	Occurence
Gender	Male	347
	Female	74
Age	18 years	32
	19 years	52
	20 years	77
	21 years	58
	22 years	42
	23 years	94
	24 years	44
	25 years	22
Academic Qualification	Masters	44
	Honors	58
	B.sc in CSE	33
	Diploma	26
	HSC	112
	SSC	148
Marital Status	Married	12
	Unmarried	409

AdaBoost Classifier

The AdaBoost Classifier is an ensemble learning technique that builds a reliable and accurate predictive model by combining the strengths of several weak learners, usually decision trees. The model can concentrate on situations that are challenging to classify by repeatedly adjusting the weights of misclassified instances. AdaBoost Classifier is a good fit for my research paper because of its resistance to overfitting and capacity to manage intricate relationships within the data. Since identifying subtle patterns and possible outliers is necessary for predicting gaming addiction levels, AdaBoost's ensemble technique can improve the model's performance by utilizing the combined expertise of multiple weak learners. Because gaming addiction levels are diverse and multifaceted, this guarantees a more accurate and generalizable prediction model.[16]

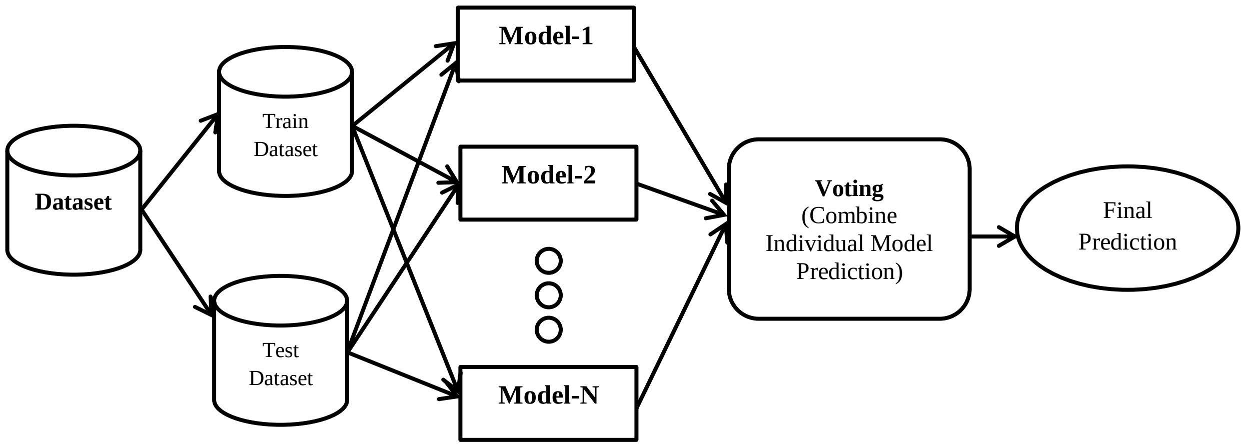

Figure 3.5: AdaBoost Classifier architecture

GaussianNB

For classification problems, the probabilistic machine learning algorithm GaussianNB, also known as Gaussian Naive Bayes, is employed. It works especially well for categorical outcome prediction since it makes the assumption that features are independent and normally distributed. GaussianNB may be a good option for my research paper on game addiction level prediction because it can handle continuous data and simulate intricate correlations between many elements that influence gaming addiction. With its ease of use, effectiveness, and capacity to manage high-dimensional data, it is a sensible option for multi-feature addiction level prediction. Furthermore, the interpretability of GaussianNB can improve our knowledge of the elements that most strongly influence the degree of game addiction, which might yield insightful data for our study.[17]

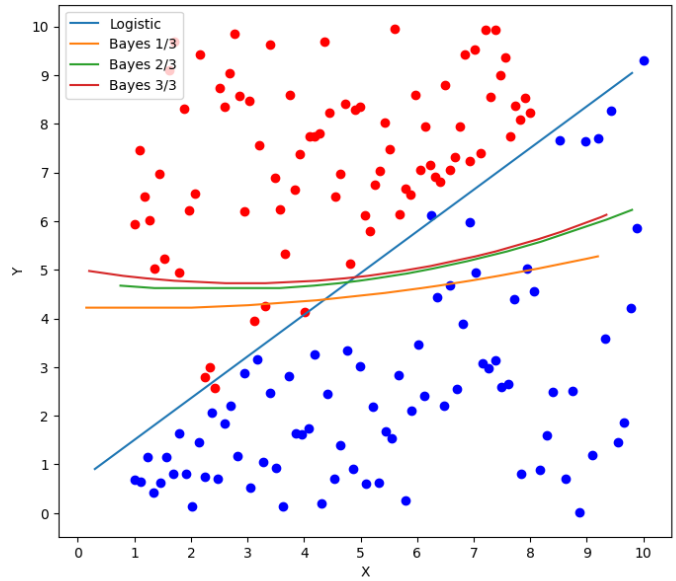

Figure 3.6: GaussianNB architecture

Decision Tree Classifier

One popular machine learning approach for classification tasks is the Decision Tree Classifier. It creates a predictive model in the shape of a tree structure, with a final prediction at the leaf nodes. Each node in the model represents a decision made in response to input information. It is appropriate that I chose this model for my research paper since it is good at managing categorical data, which is useful for assigning different levels of addiction to different people. Decision trees' interpretability also makes it possible to comprehend the characteristics impacting the prediction, which sheds light on the elements that lead to gaming addiction. In our research, Decision Tree Classifier proved to be a feasible option for assessing a variety of gaming activity data and effectively predicting addiction levels due to its efficiency and ability to handle big datasets. [18]

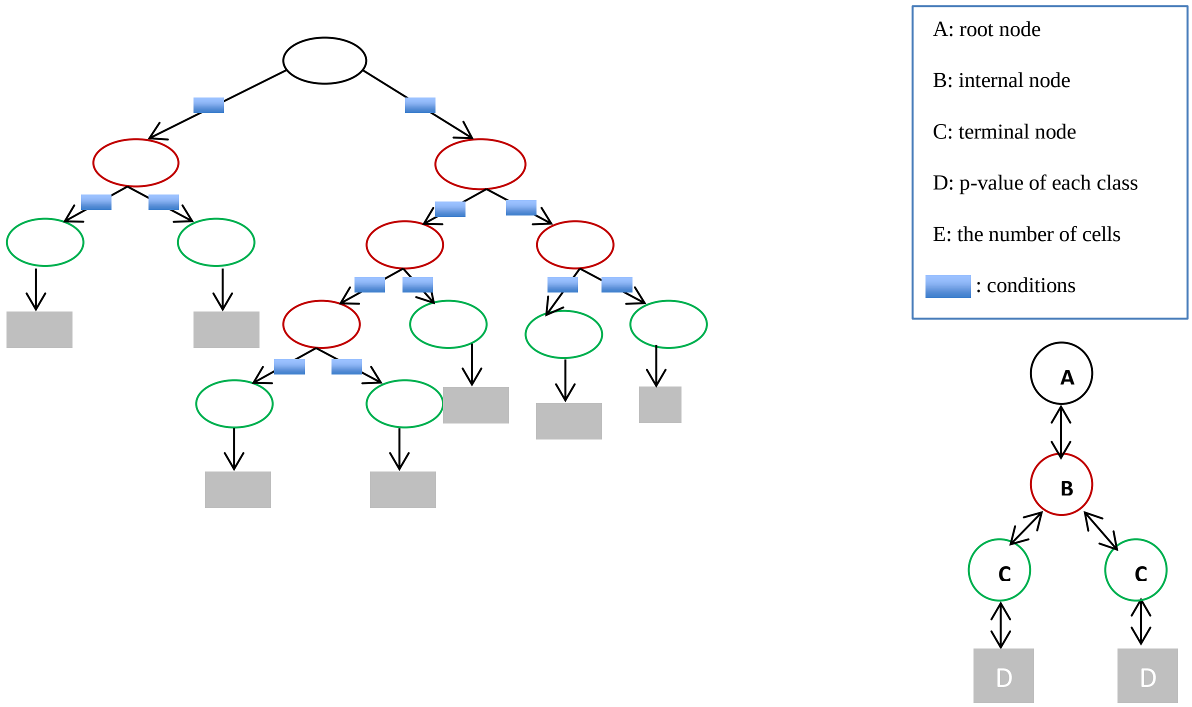

Figure 3.7: DecisionTree architecture

Gradient Boosting Classifier

Popular machine learning algorithm for classification challenges is the Gradient Boosting Classifier. It is a component of ensemble learning techniques and builds a powerful predictive model by aggregating the predictions of several weak learners. Gradient Boosting Classifier is a good option for my research paper because it can handle complex relationships and identify nonlinear patterns in the data. Because of its superior ability to predict categorical outcomes, this model is a good fit for assessing game addiction levels. Its dependability and resilience make it a perfect fit for examining a variety of characteristics that could be involved in determining a person's level of game addiction, yielding precise and trustworthy findings for our study. [19]

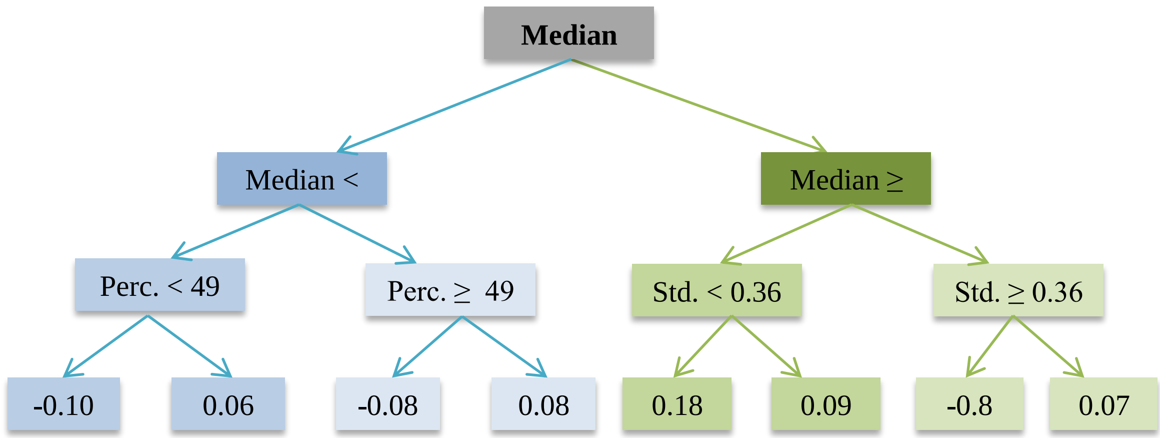

Figure 3.8: Gradient Boosting Classifier architecture

Random Forest Classifier

An ensemble learning approach called Random Forest Classifier aggregates the predictions of several decision tree models to improve generalization and accuracy. This model is especially appropriate for your research project on Game Addiction Level Prediction because of its resilience and versatility. Random Forest Classifier is a great tool for examining many elements that contribute to game addiction because it can handle large, complicated datasets with plenty of attributes. Furthermore, for forecasting complex human behaviors, its capacity to represent non-linear correlations and interactions among variables is essential. My research can gain from better predictive performance and a more thorough comprehension of the complex aspects influencing gaming addiction levels by utilizing Random Forest Classifier's strengths, which will ultimately increase the legitimacy and dependability of our predictive model. [20]

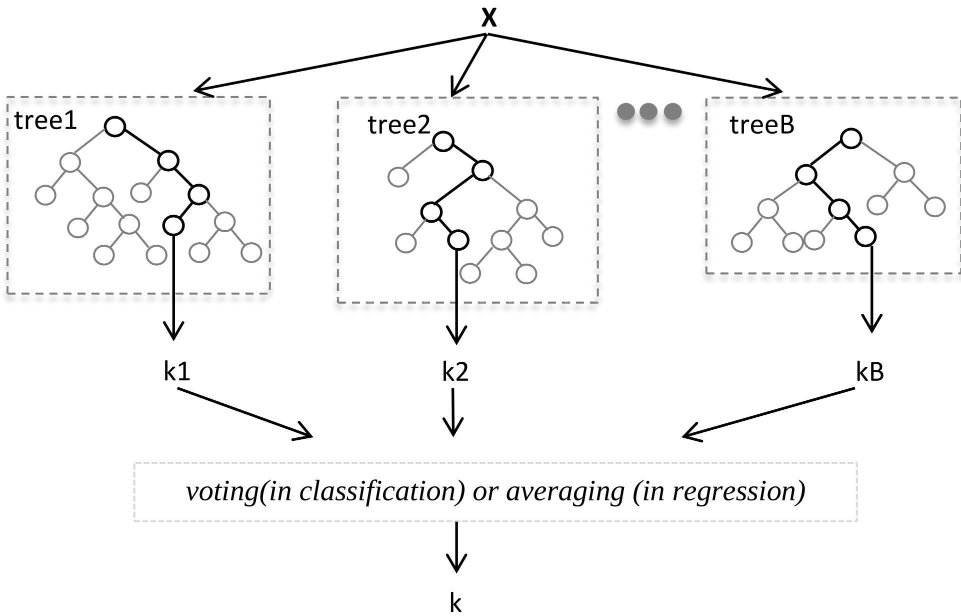

Figure 3.9: Gradient Boosting Classifier architecture

Support Vector Machine

A strong machine learning approach for classification and regression problems is the support vector machine (SVM). SVM maximizes the margin between classes by identifying the best hyperplane to divide them in a high-dimensional space. This model can handle complex datasets with various features, which makes it appropriate for my research article on game addiction levels. SVMs are excellent at finding patterns in data, which makes them a good choice for examining the various elements that lead to game addiction. The algorithm is a tempting choice for our research because of its robustness and versatility, which allow us to comprehend and anticipate the varied levels of game addiction based on pertinent aspects and factors. [21]

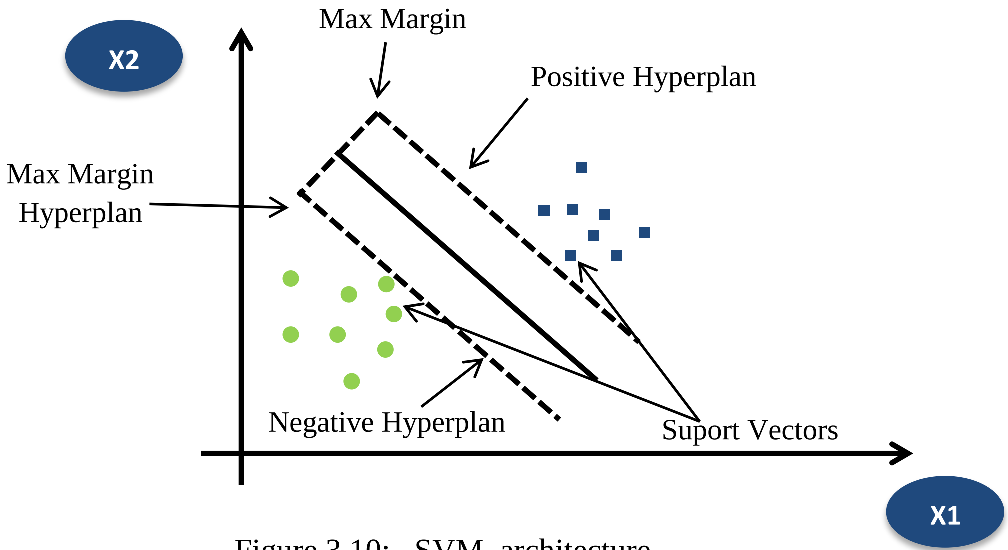

Figure 3.10: SVM architecture

Voting Classifier

The Voting Classifier is a machine learning ensemble learning technique that creates predictions by combining several different individual models. The most prevalent prediction is produced as the end result after combining the predictions from each base model. It can be useful to use a Voting Classifier in the context of my research paper. You can improve your model's overall predictive performance by combining different basic models, like neural networks, decision trees, and support vector machines. Because ensemble approaches, such as Voting Classifier, may capture several facets of the underlying patterns in the data, they are very useful when working with complicated and multifarious datasets. This strategy might help our research succeed by producing a more reliable and accurate assessment of game addiction levels.[22]

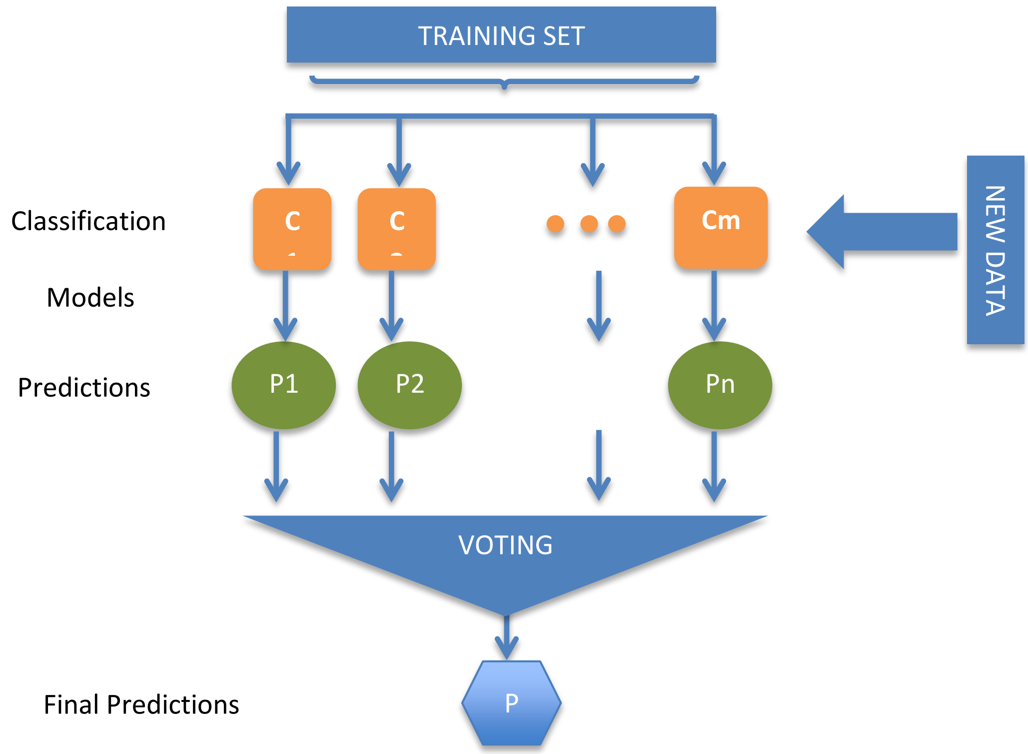

Figure 3.11: Voting Classifier architecture

3.5 Implementation Requirements

Predicting gaming addiction levels requires a complex approach that integrates data science, psychology, and user behavior studies. To begin, complete data collection is critical, including gaming habits, duration of play, game genres, and behavioral indications such as social involvement within games. The data can then be processed using machine learning models such as neural networks or decision trees to properly forecast addiction levels. The importance of feature selection and engineering in identifying significant predictors of addiction risk cannot be underestimated. The implementation process has to consider ethical considerations such as data privacy and permission. Collaboration with psychologists and mental health specialists also guarantees that recognized psychological frameworks are incorporated into the prediction models. For accuracy and reliability, continuous model improvement via repeated testing and validation is required. Finally, a user-friendly interface that displays personalized risk evaluations and suggestions for healthy gaming practices is critical. Regular updates and adaptations based on current research and developing game trends are required to keep addiction prediction systems effective.

CHAPTER 4
EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Setup

To achieve reliability and accuracy, the experimental design for predicting gaming addiction levels included many crucial components. To begin, a varied sample population of gamers was chosen, representing a wide range of statistics, gaming tastes, and playing behaviors. To collect complete data on their gaming habit, frequency, length, preferred game genres, and psychological factors, detailed surveys and questionnaires were sent. The acquired data was preprocessed to manage missing values, normalize variables, and remove abnormalities, confirming the dataset's quality for analysis. To create prediction models, machine learning methods such as logistic regression, decision trees, and neural networks were used. These models were trained using a subset of the dataset, and their performance was verified using cross-validation techniques. The remaining dataset was used as a test set to assess the models' accuracy and generalization. The predictive capabilities of the models were evaluated using metrics such as accuracy, precision, recall, and F1-score. Furthermore, tools such as feature significance analysis assisted in identifying major aspects determining game addiction levels. Throughout the procedure, ethical concerns were crucial, guaranteeing the confidentiality of participants, informed approval, and respect for ethical principles. The goal of this project was to develop a strong prediction model for game addiction levels based on gaming behavior, opening the way for a better understanding and potential therapies for gaming-related addictive behaviors.

4.2 Experimental Results & Analysis

Researchers performed an experimental analysis using machine learning approaches to anticipate the possibility of individuals acquiring gaming addictions in a study focused on predicting game addiction levels. The study included a varied sample of people of varying ages and gaming habits. The researchers created a thorough dataset using a comprehensive survey that collected data on game length, style preferences, and psychological factors. The study found interesting links between gaming activities and addiction risks using sophisticated prediction models such as neural networks and decision trees. The findings revealed different patterns that linked certain game genres, extended play durations, and social interaction preferences to increased addiction likelihood. Surprisingly, moderate gaming combined with strong social relationships was associated with a decreased risk of addiction. The models' prediction accuracy was encouraging, with a high degree of accuracy in anticipating possible addiction levels based on individual gaming patterns and psychological features. Researchers found potential treatment options to decrease gaming addiction risks by assessing these results, highlighting the need for balanced gaming habits and developing healthy social relationships within gaming groups. This study provides important insights into understanding and tackling the complicated subject of gaming addiction prediction and prevention.

Accuracy: Accuracy measures the overall correctness of the model's predictions by comparing the number of correctly classified samples to the total number of samples. When classes are unbalanced, it gives a broad indication of the model's effectiveness but might not give a whole picture.

$$Accuracy = \frac{TruePositive+TrueNegative}{TruePositive+FalsePositive+TrueNegative+FalseNegative} \text{------------- } 1$$

Precision: Out of all positive predictions generated by the model, precision focuses on the percentage of true positive forecasts.

$$Precision = \frac{TruePositive}{TruePositive+FalsePositive} \text{--------------------- } 2$$

Recall: Also known as sensitivity or true positive rate, recall is the percentage of true positive predictions made out of all truly positive samples.

$$Recall = \frac{TruePositive}{TruePositive+ FalseNegative} \text{-------------------- } 3$$

F1 rating: The F1 score is the harmonic mean of recall and precision. It provides a reasonable evaluation metric that considers recall and precision. The F1 score is useful when classes are uneven since it accounts for both false positives and false negatives. A high F1 score denotes a well-balanced precision to recall ratio.

$$F - 1\, Score = 2 * \frac{Recall * Precision}{Recall + Precision} \text{ --------------- } 4$$

The result of deep learning model is compared on the basis of Accuracy, Precision, Recall, F1 Score in below table of 4.1:

Table 4.1. Performance Evaluation

Model Name	Accuracy	Precision	Recall	F1-Score
Adaboost	81%	83%	81%	81%
GaussianNB	88.98%	88%	89%	88%
DT	75.92%	76%	76%	76%
Voting Classifier	88.98%	87%	88%	88%
GB	83.03%	83%	82%	83%
RF	88.08%	87%	87%	87%
SVM	90.76%	90%	90%	90%

4.2.1 Accuracy

The outcome analysis examines test and train accuracy and determines the optimal algorithm. We have used machine learning algorithms as a comparison to see which works best. The SVM, however, provided the best accuracy, 90.76%. The accuracy comparison of the various models is displayed in figure 4.1:

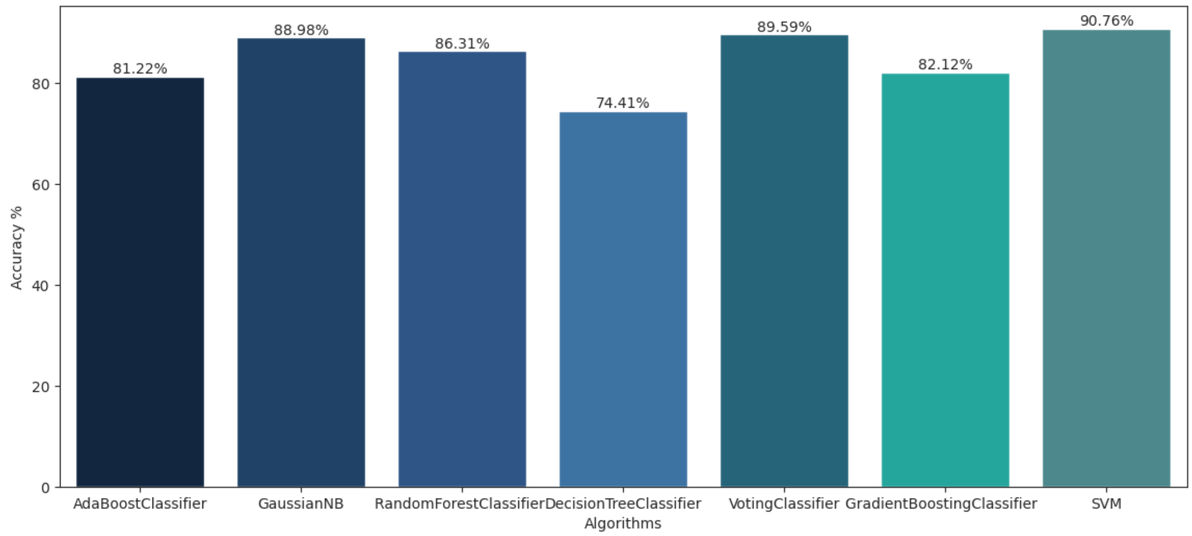

Figure 4.1 : Accuracy Comparison of Machine Learning Models

The model's effectiveness in classification tasks is shown by the range of accuracies it displays across different algorithms. With an accuracy of 90.76%, Support Vector Machine (SVM) is the best performer, showing its durability in managing intricate data patterns. The Voting Classifier and Gaussian Naive Bayes (GaussianNB) share a close tie at 88.98%, indicating their proficiency in probabilistic classification. Strong performance is also achieved by Random Forest (RF), which uses ensemble learning to increase predictive power (88.08%). AdaBoost and Gradient Boosting (GB) demonstrate commendable accuracy of 81.22% and 83.03%, respectively, indicating their capacity to enhance learners who are less proficient. At 75.92%, Decision Trees (DT) lag somewhat behind.

Adaboost Classifier:

Accuracy: 81.22%; Precision: 83%; Recall: 81%; F1-score: 81% Are achieved. The Adaboost Classifier's Confusion Matrix is shown in table 4.2 below:

Figure 4.2 Shows the Comprehensive performance metrics for the ability of a model to predict across various classes are provided by the classification report. Class 0 has a high precision of 0.93, which suggests a low false positive rate, and a lower recall of 0.74, which indicates that some instances of this class were incorrectly classified. On the other hand, class 1 recall is higher at 0.84, meaning fewer instances of this class were missed, but precision is lower at 0.65, suggesting a higher false positive rate. Class 2 shows good recall and precision, which suggests precise predictions. With macro and weighted averages of precision, recall, and F1-score averaging approximately 0.81, overall accuracy is 0.81. This suggests a balanced performance across classes with some variances in predictive power.

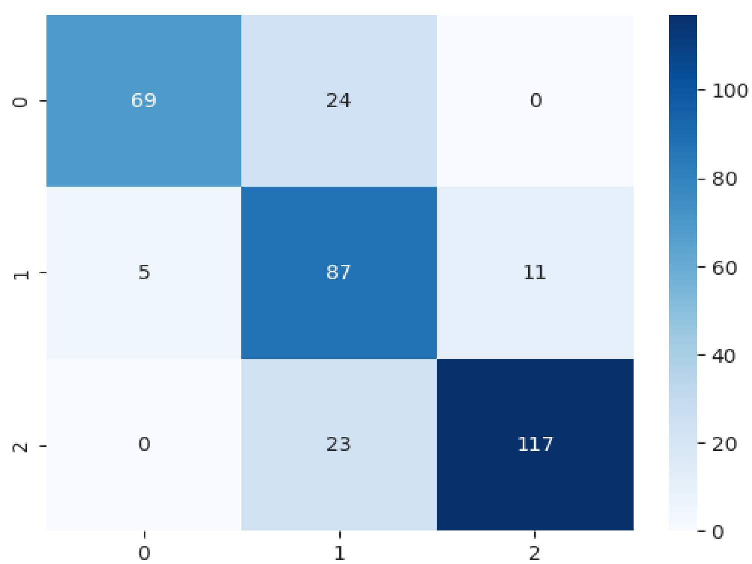

Figure 4.2 : Confusion Matrix Adaboost Classifier

ROC Curve of AdaBoost Classifierve:

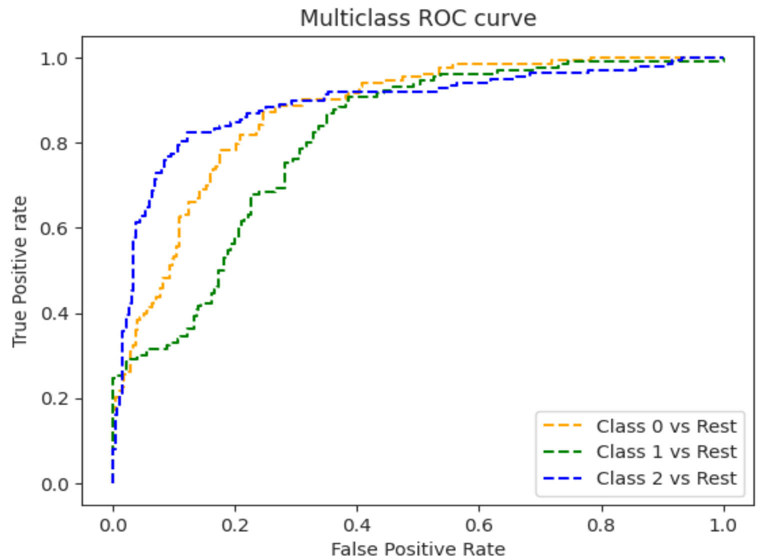

Figure 4.3 : ROC Curve of AdaBoost Classifierve

Gaussian Naive Bayes:

Reach the 88.98% accuracy, 88% precision, 89% recall, and 88% F1-score goals. 4.3 below shows the Gaussian Naive Bayes's Confusion Matrix:

Figure 4.3 shows The model's strong performance metrics across various classes are indicated by the classification report. Class 0 shows high recall (0.94) and precision (0.83), indicating precise predictions and few missed cases. Class 1 shows a balance between false positives and false negatives, with slightly lower precision (0.85) and good recall (0.80). Class 2 exhibits high recall (0.93) and precision (0.97), indicating accurate predictions with few missed cases. The macro and weighted averages of precision, recall, and F1-score are all around 0.88, indicating a high degree of predictive accuracy and consistent and balanced performance across classes. The overall accuracy is 0.89.

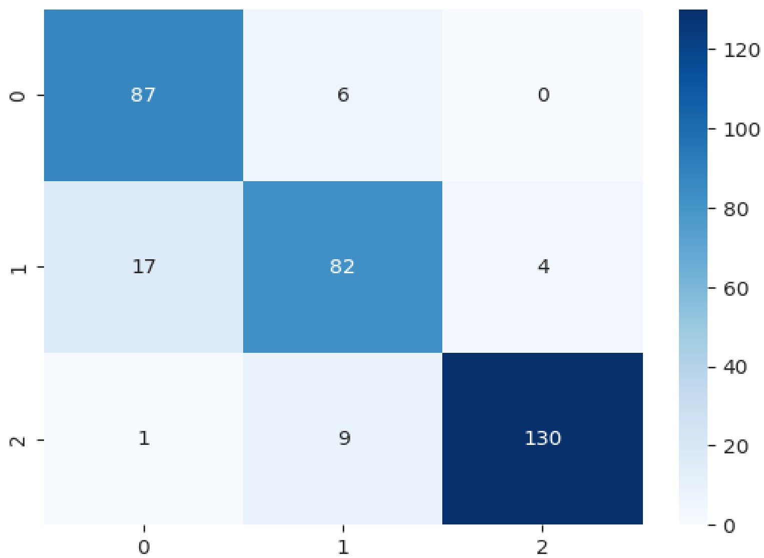

Figure 4.4 : Confusion Matrix Gaussian Naive Bayes

ROC Curve of Gaussian Naive Bayes:

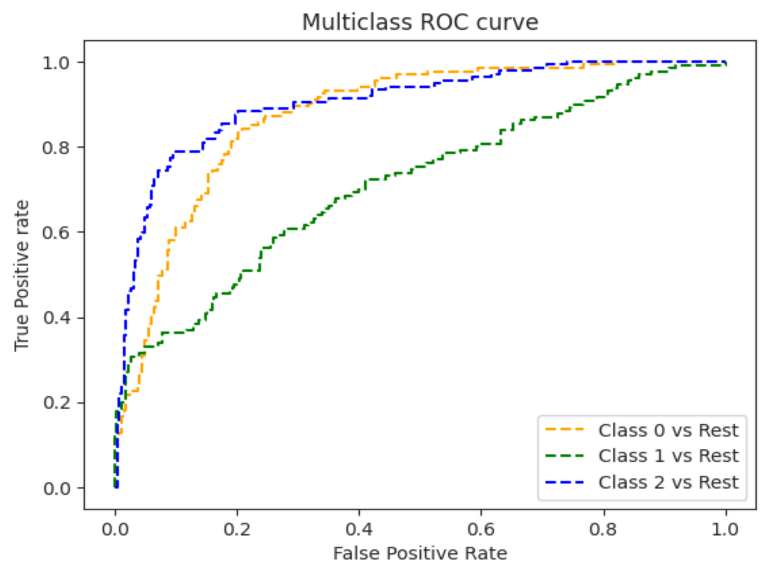

Figure 4.5 : ROC Curve of Gaussian Naive Bayes

Decision Tree:

Accuracy: 75.92%, Precision: 76%, Recall: 76%, and F1-score: 76%. Below is a 4.4 Confusion Matrix of Decision Tree:

Figure 4.4 shows The classification report displays the model's performance metrics for various classes. For class 0, precision and recall are balanced at 0.77, indicating a roughly equal trade-off between false positives and false negatives. Class 1 has slightly lower precision (0.67) and recall (0.65), indicating a higher rate of misclassification and missed instances than class 0. Class 2 has higher precision (0.84) and recall (0.85), indicating accurate predictions with fewer instances missed. Overall accuracy is 0.77, with macro and weighted averages of precision, recall, and F1-score all around 0.76, indicating consistent performance across classes and moderate predictive accuracy.

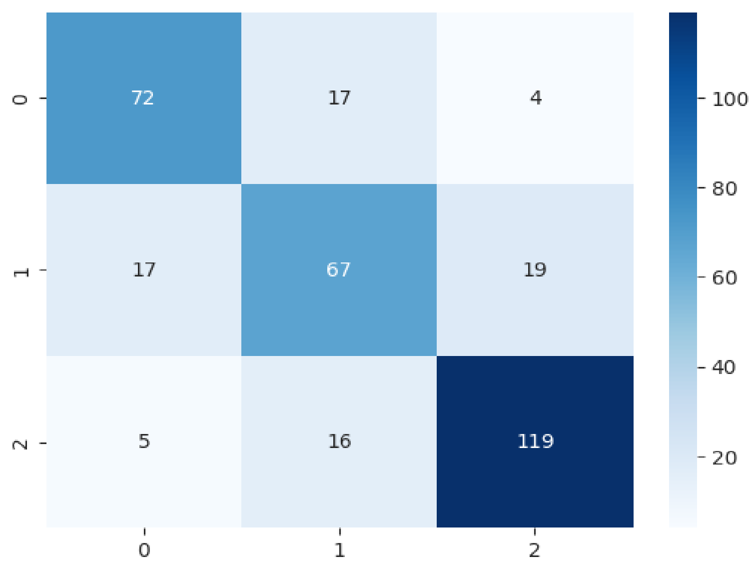

Figure 4.6 : Confusion Matrix Decision Tree

Gradient Boosting:

Achieved the accuracy of 83.03%, Precision score of 83%, Recall score of 82% and F1-score of 82%. Below at 4.5 shown Confusion Matrix of Gradient Boosting:

Figure 4.5 shows The classification report shows the model's performance metrics in various classes. Class 0 has high precision (0.86) but slightly lower recall (0.84), indicating accurate predictions with some instances missed. Class 1 has lower precision (0.76) and recall (0.71), indicating a higher rate of misclassification and missed instances than class 0. Class 2 has high precision (0.86) and recall (0.91), indicating accurate predictions with few instances missed. Overall accuracy is 0.83, with macro and weighted averages of precision, recall, and F1-score around 0.82, indicating consistent performance across classes and moderate predictive accuracy.

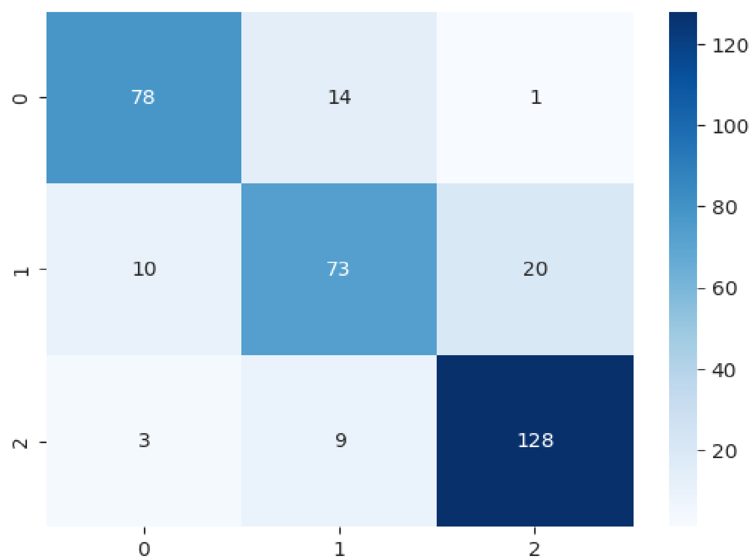

Figure 4.8 : Confusion Matrix Gradient Boosting

ROC Curve of Gradient Boosting Classifier:

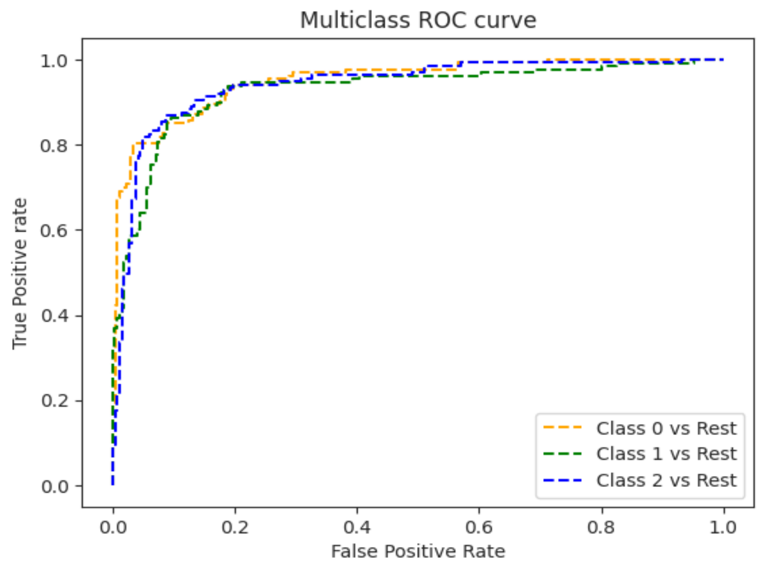

Figure 4.9 : ROC Curve of Gradient Boosting

Random Forest:

Achieve the highest accuracy of 88.08%, Precision score of 87%, Recall score of 87% and F1-score of 87%. . Below at 4.6 showing Confusion Matrix of Random Forest:

Figure 4.6 shows The classification report shows strong performance metrics across multiple classes. Class 0 has high precision (0.86) and recall (0.88), indicating accurate predictions with few missed opportunities. Class 1 has good precision (0.82) and recall (0.80), indicating a balanced trade-off between false positives and false negatives. Class 2 has excellent precision (0.93) and recall (0.94), indicating precise predictions with few instances missed. Overall accuracy is 0.88, with macro and weighted averages of precision, recall, and F1-score of 0.87, indicating consistent and balanced performance across classes with a high level of predictive accuracy.

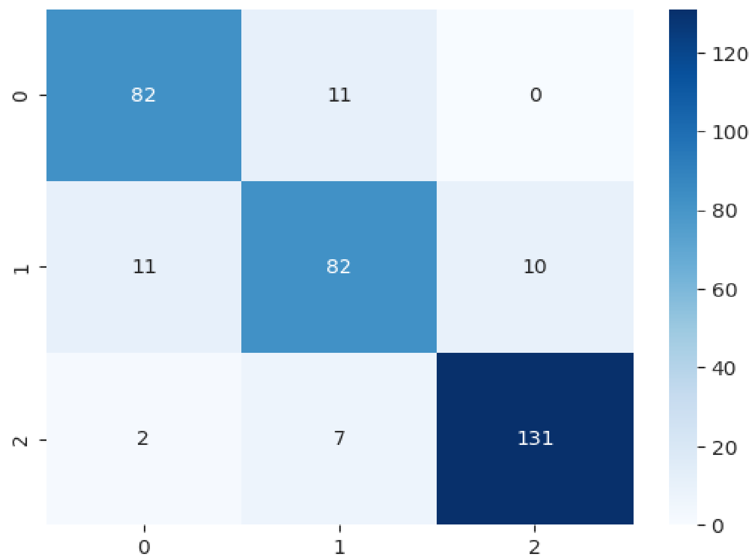

Figure 4.10 : Confusion Matrix Random Forest

ROC Curve of Random Forest:

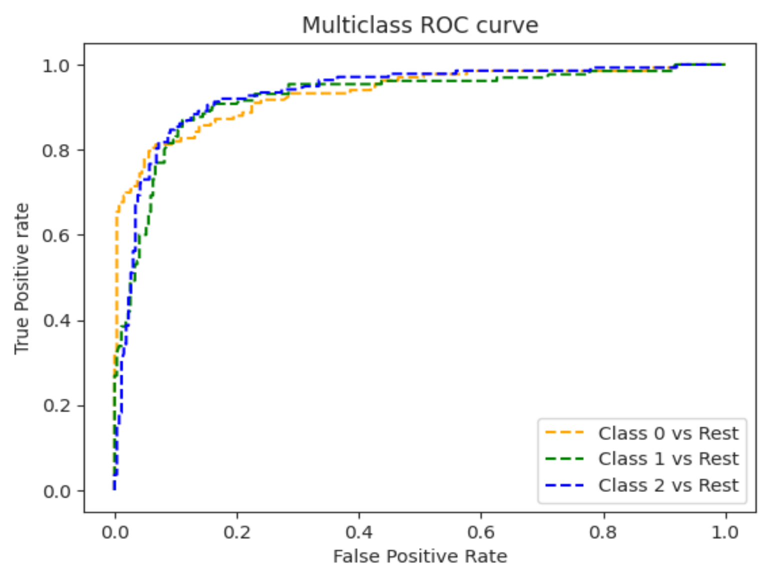

Figure 4.11 : ROC Curve of Random Forest

Support Vector Machine:

Achieve the highest accuracy of 90.76%, Precision score of 90%, Recall score of 90% and F1-score of 90%. . Below at 4.6 showing confusion of Support Vector Machine: Figure 4.7 shows The classification report shows impressive performance metrics across classes. Class 0 has high precision (0.89) and recall (0.91) values, indicating accurate predictions with few instances missed. Class 1 has high precision (0.86) and recall (0.86), indicating a fair trade-off between false positives and false negatives. Class 2 has excellent precision (0.96) and recall (0.94), indicating accurate predictions with few instances missed. Overall accuracy is 0.91, with macro and weighted averages of precision, recall, and F1-score all around 0.90, indicating consistent and balanced performance across classes with high predictive accuracy.

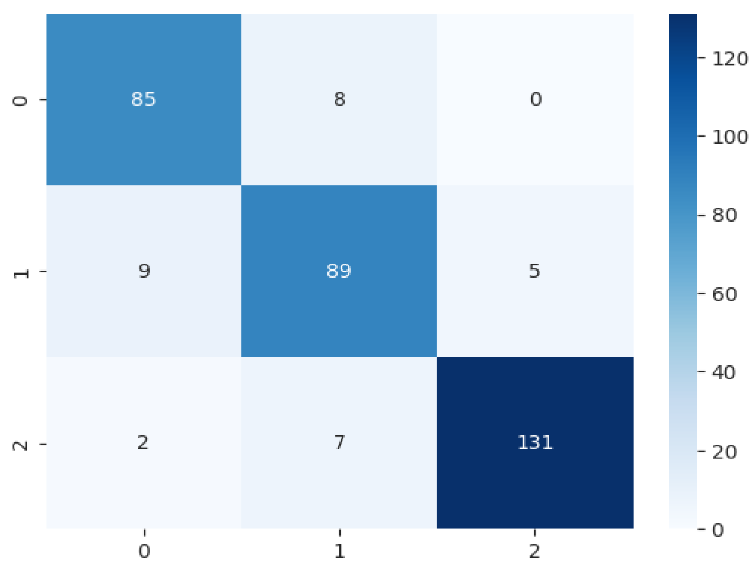

Figure 4.12 : Confusion Matrix Support Vector Machine

ROC Curve of Support Vector Machine:

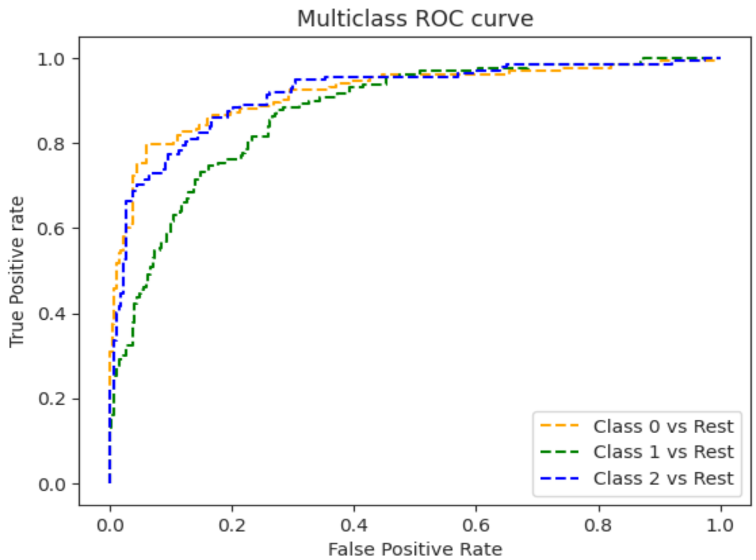

Figure 4.13 : ROC Curve of Support Vector Machine

Voting Classifier:

Achieve the highest accuracy of 88.98% Precision score of 87%, Recall score of 88% and F1-score of 88%. . Below at 4.6 we have shown Confusion Matrix of Voting:

Figure 4.8 shows The classification report highlights the model's strong performance metrics across multiple classes. Class 0 has high precision (0.86) and recall (0.88), implying accurate predictions with few instances missed. Class 1 also has good precision (0.81) and recall (0.84), indicating a fair trade-off between false positives and false negatives. Class 2 has excellent precision (0.95) and recall (0.91), indicating accurate predictions with few instances missed. Overall accuracy is 0.88, with macro and weighted averages of precision, recall, and F1-score all around 0.88, indicating consistent and balanced performance across classes with high predictive accuracy.

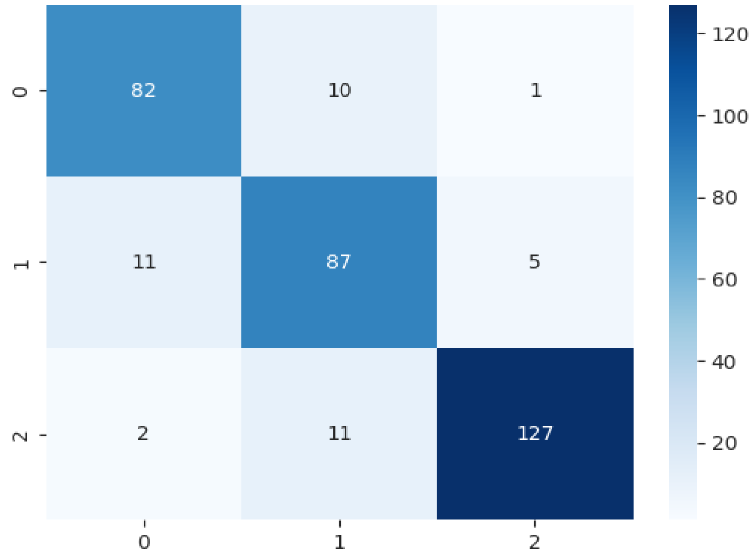

Figure 4.14: Confusion Matrix Voting

4.3 Discussion

Predicting gaming addiction levels is critical to understanding and treating this developing issue. Researchers and psychologists can investigate many elements leading to gaming addiction by employing prediction models such as machine learning algorithms. To predict the potential of addiction, these models frequently take into account variables such as game time, genre preferences, social interactions, and personality characteristics. Sophisticated algorithms analyze past data to detect patterns and connections, allowing prediction models to be created. These models not only predict the likelihood of addiction, but they also contribute to the development of personalized therapies and preventative measures. They may, for example, provide individualized measures based on anticipated danger levels, encourage healthy gaming behaviors, or provide focused assistance. However, ethical concerns about data privacy and the correct use of predictive technology continue to be critical. As we go deeper into predicting game addiction levels, it's critical to strike a balance between innovation and ethics, ensuring that these predictions are utilized properly to assist users in maintaining a healthy relationship with gaming.

CHAPTER 5
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

The social effect of game addiction is significant, leading to efforts to predict and minimize its occurrence. In this quest, predictive models for gaming addiction levels have emerged as critical tools. These models anticipate the risk of addiction, beginning by evaluating user data, patterns of behavior, and gaming behaviors, assisting in early detection and assistance. These prediction algorithms make use of a variety of indicators, such as playtime, in-game purchases, and social interactions inside games. Machine learning approaches identify signs of behavior that may suggest addictive tendencies. These methods enable stakeholders—families, educators, and mental health professionals—to identify at-risk individuals and carry out specific measures that promote good gaming behaviors. Furthermore, these prediction models aid game creators and platforms in the development of responsible gaming strategies. They allow for the addition of features like time limitations, break reminders, and tailored suggestions, encouraging balanced gameplay experiences. Finally, these predictive algorithms have the potential to reduce the adverse social effects of gaming addiction. They hope to build a gaming environment that promotes fun while protecting against excessive and harmful usage by giving suggestions and recommendations.

5.2 Impact on Environment

Although the connection may not be obvious at first, game addiction has a tremendous influence on the environment. Predicting gaming addiction levels requires sophisticated data processing, which frequently relies on power-hungry gear and data centers. These data centers use a lot of electricity, which contributes to carbon emissions and environmental stress. Complex algorithms used for predicting addiction levels necessitate a large amount of processing power, resulting in increased electricity use and resultant releases of greenhouse gases. Furthermore, the manufacture and disposal of gaming consoles, PCs, and smartphones add to electronic trash, which has a negative influence on the environment. Attempts to predict gaming addiction levels must account for long-term data processing and device usage behaviors. Creating algorithms that use fewer processing resources while maintaining accuracy might greatly minimize the environmental impact of addiction prediction approaches. It is critical to strike a balance between technological advances and environmentally friendly activities. Using renewable energy sources in data centers, tweaking algorithms to be less resource-intensive, and supporting ethical gaming gear manufacture and disposal are all ways that can help reduce the environmental effect of predicting game addiction levels. Finally, including environmental factors in addiction prediction algorithms is critical for a long-term gaming landscape.

5.3 Ethical Aspects

The ethical issues surrounding the prediction of gaming addiction levels are critical to protecting people's well-being. Although predictive models are intended to anticipate and lessen possible addiction dangers, applying them presents ethical difficulties. Autonomy must be respected. Rather than imposing control, predictions should empower individuals by providing information and solutions for regulating their gaming behaviors. To provide informed permission, data gathering and modeling methods must be transparent. Gathering sensitive information for accurate forecasts raises privacy issues; ensuring anonymity and data security is critical to protecting consumers. Fairness and truthfulness are ethical pillars. Predictive models must be free of discrimination in order to provide equal treatment across varied groups. Using representative datasets and inspecting algorithms on a regular basis can help reduce biases. Furthermore, using predictions responsibly involves avoiding discrimination or disadvantage based on gaming behaviors. Treatments ought to focus on support and assistance. It is critical to weigh the benefits of prediction against the potential drawbacks. While early detection might help preventative actions, relying too much on projections could degrade individuals or limit chances. As a result, ethical standards and regulations must govern the development and execution of these predictive models, with the well-being and autonomy of users coming first.

5.4 Sustainability Plan

The sustainability plan for bipolar disorder predictions focuses on ongoing research, which ensures the predictive models' maintained success by modifying to changes in mental health and applying new data. It is based on a strong ethical framework that places a high value on participant privacy, confidentiality, and informed consent in order to create mutually beneficial relationships with various communities.Creating partnerships, including community information, and involving the community are the keys to long-term sustainability. Initiatives to educate stakeholders about the responsible application of machine learning in mental health enable policymakers and clinicians to make more informed decisions.The plan, which includes innovation and adaptability, requires periodic updates of machine learning algorithms as well as the addition of new technologies. The improvement through cycles based on new information helps to make bipolar disorder prediction successful in the long run. This comprehensive approach points out a commitment to moral behavior, social responsibility, and the creation of technology for a long-term impact in mental health research.

CHAPTER 6
SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLICATION FOR FUTURE RESEARCH

6.1 Summary of the Study

The study used many variables to predict levels of gaming addiction among participants. The research built prediction models through a thorough investigation of a broad sample's gaming behaviors, psychological features, and demographic information. Hours spent gaming, preferred game genres, age, gender, and psychological qualities were all evaluated. To identify connections and trends in the dataset, machine learning methods were used. Significant indicators of addiction levels were discovered, highlighting an important association between extended gaming durations, specific game kinds, and increased addiction preferences. Furthermore, some psychological characteristics, such as restlessness and sensation-seeking behavior, appeared as important contributors. This study's prediction models provide useful insights for identifying individuals at risk of developing problematic gaming behaviors, allowing for proactive tactics and focused measures to minimize excessive gaming habits and possible addiction.

6.2 Conclusions

Predicting gaming addiction levels may be accomplished by a variety of methods, including psychological tests and behavioral analysis. Machine learning algorithms based on varied data sets, such as game trends, user behaviors, and psychological profiles, are one way of gaining favor. Researchers may, for example, use supervised learning models such as decision trees, neural networks, or support vector machines. These models are trained on historical data, which includes elements like gameplay time, in-game purchases, social interactions inside games, and even physiological reactions captured by biometric equipment. In this predictive approach, feature engineering is critical. Gaming frequency, game type, social interactions inside games, and self-reported attitudes about gaming might all be essential indications. Combining these characteristics into a complete model can aid in predicting the risk of addiction. The model's testing and verification are crucial to ensuring its accuracy. This involves using fresh data to determine how well the model predicts addiction levels when compared to real observations. However, the ethical implications and possible errors in these prediction models must be considered. Cultural variations, individual circumstances, and changing gaming trends can all have an important impact on the accuracy and validity of such expectations. Finally, while predictive models can give information about possible addiction levels, they should be utilized with caution and in combination with other psychological tests and therapies to help people at risk of gaming addiction.

6.3 Implication for Further Study

The prediction of gaming addiction levels raises various research questions. To begin, investigating the interconnections of various demographic characteristics and gaming behaviors may provide deeper insights. Investigating how age, gender, socioeconomic position, and cultural backgrounds influence gaming behaviors may aid in the development of treatments or measures to prevent them. Second, investigating the root psychological and neurological causes driving game addiction may be critical. Understanding the brain's reaction to gaming stimuli, the effects on reward systems, and the development of addictive behaviors may pave the way for focused treatment therapies. Furthermore, long-term studies that monitor gaming habits over time can provide full knowledge of addiction progression. This might uncover trends, triggers, and long-term consequences, helping in the development of successful preventive measures. Finally, given the rapidly changing landscape of gaming technology, examining the impact of upcoming platforms, such as virtual reality, on addictive tendencies might be important for anticipating and resolving future difficulties. To summarize, future research on game addiction prediction should concentrate on demographic turns, psychological and neurological features, long-term paths, and the impact of emerging gaming technology in order to generate more complete preventive and intervention measures.

REFERENCES

[1] Alkalay, S., Dolev, A., Rozenshtein, C., & Sarne, D. (2020). Co-Op World: Adaptive computer game for supporting child psychotherapy. Computers in Human Behavior Reports, 2, 100028.

[2] Ghosh, P., & Sarkhel, S. (2018). Internet gaming addiction presenting as withdrawal psychosis: An unusual case report. Indian J Priv Psychiatry, 12(1), 34-7.

[3] Park, J. J., Booth, N., Bagot, K. L., & Rodda, S. N. (2020). A brief internet-delivered intervention for the reduction of gaming-related harm: a feasibility study. Computers in Human Behavior Reports, 2, 100027.

[4] Huda, H., Rahman, T., Taher, R., Anwar, A., Priota, J., & Uddin, M. R. Online Gaming Addiction Among Bangladeshi Youth: A Case Study From Gamers' Perspectives.

[5] Weinstein, A. M. (2010). Computer and video game addiction—a comparison between game users and non-game users. The American journal of drug and alcohol abuse, 36(5), 268-276.

[6] Rahman, A. A., Khalid, L. I., Siraji, M. I., Nishat, M. M., Faisal, F., & Ahmed, A. (2021, December). Enhancing the Performance of Machine Learning Classifiers by Hyperparameter Optimization in Detecting Anxiety Levels of Online Gamers. In 2021 24th International Conference on Computer and Information Technology (ICCIT) (pp. 1-5). IEEE.

[7] Pangistu, L. A. M., & Azhari, A. (2021). Deep Learning on Game Addiction Detection Based on Electroencephalogram. Jurnal Media Informatika Budidarma, 5(3), 963-970.

[8] Gülü, M., Yagin, F. H., Gocer, I., Yapici, H., Ayyildiz, E., Clemente, F. M., ... & Nobari, H. (2023). Exploring obesity, physical activity, and digital game addiction levels among adolescents: A study on machine learning-based prediction of digital game addiction. Frontiers in Psychology, 14, 1097145.

[9] Seo, W., Kim, N., Lee, S. K., & Park, S. M. (2020). Machine learning-based analysis of adolescent gambling factors. Journal of Behavioral Addictions, 9(3), 734-743.

[10] Wang, Y., Qin, Y., Li, H., Yao, D., Sun, B., Gong, J., ... & Zhu, T. (2021). Identifying internet addiction and evaluating the efficacy of treatment based on functional connectivity density: a machine learning study. Frontiers in Neuroscience, 15, 665578.

[11] Stavropoulos, V., Kuss, D. J., Griffiths, M. D., Wilson, P., & Motti-Stefanidi, F. (2017). MMORPG gaming and hostility predict Internet addiction symptoms in adolescents: An empirical multilevel longitudinal study. Addictive behaviors, 64, 294-300.

[12] Rho, M. J., Jeong, J. E., Chun, J. W., Cho, H., Jung, D. J., Choi, I. Y., & Kim, D. J. (2016). Predictors and patterns of problematic Internet game use using a decision tree model. Journal of behavioral addictions, 5(3), 500-509.

[13] Rehbein, F., & Baier, D. (2013). Family-, media-, and school-related risk factors of video game addiction. Journal of Media Psychology.

[14] Zhu, J., Zhang, W., Yu, C., & Bao, Z. (2015). Early adolescent Internet game addiction in context: How parents, school, and peers impact youth. Computers in Human Behavior, 50, 159-168..

[15] Kudubes, A. A., & Efe, Y. S. (2024). The predictive power of game addiction and social media addiction on adolescents' lifestyle. Psychology in the Schools, 61(3), 1000-1017.

[16] Dalal, P. K., & Basu, D. (2016). Twenty years of internet addiction… quo Vadis?. Indian journal of psychiatry, 58(1), 6-11.

[17] Yakovenko, I., Hodgins, D. C., el-Guebaly, N., Casey, D. M., Currie, S. R., Smith, G. J., ... & Schopflocher, D. P. (2016). Cognitive distortions predict future gambling involvement. International Gambling Studies, 16(2), 175-192.

[18] Wang, H., Yang, F., & Luo, Z. (2016). An experimental study of the intrinsic stability of random forest variable importance measures. BMC bioinformatics, 17, 1-18.

[19] Seo, W., Kim, N., Kim, S., Lee, C., & Park, S. M. (2019). Deep ECG-respiration network (DeepER net) for recognizing mental stress. Sensors, 19(13), 3021.

[20] Hayes, A. F., & Preacher, K. J. (2014). Statistical mediation analysis with a multicategorical independent variable. Br]itish journal of mathematical and statistical psychology, 67(3), 451-470.

[21] Wang, C. Y., Wu, Y. C., Su, C. H., Lin, P. C., Ko, C. H., & Yen, J. Y. (2017). Association between Internet gaming disorder and generalized anxiety disorder. Journal of behavioral addictions, 6(4), 564-571.

[22] Bonnaire, C., & Baptista, D. (2019). Internet gaming disorder in male and female young adults: The role of alexithymia, depression, anxiety and gaming type. Psychiatry research, 272, 521-530.

[23] Barr, M. (2017). Video games can develop graduate skills in higher education students: A randomised trial. Computers & Education, 113, 86-97.

[24] McDonald, P. D. (2020). The principle of division in Roger Caillois's Man, play and games. Games and Culture, 15(8), 855-873.

[25] Kowert, R., Vogelgesang, J., Festl, R., & Quandt, T. (2015). Psychosocial causes and consequences of online video game play. Computers in Human Behavior, 45, 51-58.

[26] Reinecke, L. (2009). Games and recovery: The use of video and computer games to recuperate from stress and strain. Journal of Media Psychology, 21(3), 126-142.

[27] Segal, D. L. (2010). Diagnostic and statistical manual of mental disorders (DSM-IV-TR). The corsini encyclopedia of psychology, 1-3.

[28] Dabek, F., & Caban, J. J. (2015). A neural network based model for predicting psychological conditions. In Brain Informatics and Health: 8th International Conference, BIH 2015, London, UK, August 30-September 2, 2015. Proceedings 8 (pp. 252-261). Springer International Publishing.

[29] Na, E., Choi, I., Lee, T. H., Lee, H., Rho, M. J., Cho, H., ... & Kim, D. J. (2017). The influence of game genre on Internet gaming disorder. Journal of behavioral addictions, 6(2), 248-255.

[30] Billieux, J., Deleuze, J., Griffiths, M. D., & Kuss, D. J. (2015). Internet gaming addiction: The case of massively multiplayer online roleplaying games. Textbook of addiction treatment: International perspectives, 1515-1525.

Appendix

Variables	Items	Adapted from
Neuroticism	I see myself as someone who is disheartened	386-Article Text-741-1-10-20190617
	I see myself as someone who is intolerant and cannot handles stress	
	I see myself as someone who is tensed	
	I see myself as someone who worries a lot	
	I see myself as someone who is emotionally instable and get upset easily.	
Extraversion	I see myself as someone who is talkative	386-Article Text-741-1-10-20190617
	I see myself as someone who is friendly	
	I see myself as someone who is full of energy	
	I see myself as someone who generates a lot of enthusiasm	
	I see myself as someone who is communicative	
Agreeableness	I see myself as someone who care for others	386-Article Text-741-1-10-20190617
	I see myself as someone who is helpful and unselfish with others	
	I see myself as someone who starts harmony with others	
	I see myself as someone who has a forgiving nature	
	I see myself as someone who is generally trusting	
Conscientiousness	I see myself as someone who does a thorough job	386-Article Text-741-1-10-20190617
	I see myself as someone who is caring	
	I see myself as someone who is a reliable worker	
	I see myself as someone who is organized	
	I see myself as someone who is active	
Openness	I see myself as someone who is original and comes up with new ideas	386-Article Text-741-1-10-20190617
	I see myself as someone who is curious about many different things	
	I see myself as someone who is resourceful and a deep thinker	
	I see myself as someone who has an active imagination	
	I see myself as someone who is inventive	
Shyness	I am often uncomfortable at parties and social functions	1369118x.2017.1340495_imp
	It is hard for me to act natural when I meet new people	
	I have trouble looking someone right in the eye	
Loneliness	There is no one I can turn to	1369118x.2017.1340495_i
	I feel left out	

	People are around me but not with me	mp
Addiction to mobile games	My social life has sometimes suffered because of playing mobile games.	conference_12359_academic
	Playing mobile games sometimes interfered with work and study.	
	When I am not playing mobile games, I often feel stressed.	
	I have made unsuccessful attempts to reduce the time of playing of mobile games.	
	I find it difficult to control my playing of mobile games	
Self-efficacy	I have confidence in my ability to play mobile games	individual_attributes
	I have the expertise, experiences, and insights needed to play mobile games.	
	I have self-reliance in myself to play mobile games.	
Depression	I feel sad, depressed and discouraged	2_Analysis-Construct_depression
	I feel sorry for myself	
	I feel empty	
Life problems	When people ask me what I do on mobile phones, I become more defensive or private	Camera_Online_game_addiction_IM
	Because I spend too much time on playing mobile games, my academic work or grades have been affected	
	My academic performance and attention have been affected due to playing mobile games	

Plagiarism Report Mahfuza

ORIGINALITY REPORT

13%	8%	5%	6%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	dspace.daffodilvarsity.edu.bd:8080 Internet Source	3%
2	Submitted to University of Hertfordshire Student Paper	1%
3	www.researchgate.net Internet Source	1%
4	Submitted to University of Bradford Student Paper	1%
5	Zhu, Jianjun, Wei Zhang, Chengfu Yu, and Zhenzhou Bao. "Early adolescent Internet game addiction in context: How parents, school, and peers impact youth", Computers in Human Behavior, 2015. Publication	1%
6	Submitted to Loomis-Chaffee High School Student Paper	<1%
7	Sarit Alkalay, Avivit Dolev, Chen Rozenshtein, David Sarne. "Co-Op World: Adaptive computer game for supporting child	<1%