Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

Digital Object Identifier 10.1109/ACCESS.2017.Doi Number

Analysis on Impacts of Game Addiction Based on Machine Learning.

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ABSTRACT The usage of computers, mobile phones, and the internet has evolved into essential tools in people's daily lives thanks to the advancement of technology. Technology has improved living circumstances while also introducing new threats. There are several addiction theories in particular that have a harmful impact on human existence. The definitions of addiction now include addiction to digital games. The cognitive, psychological, and social lives of the individual are significantly impacted by game addiction. It is evident that such addictions, which are very prevalent among children and young people and are fast expanding around the world. Our research was a survey-based data analysis and prediction for measuring game addiction by user’s input. We predict three models from the survey data(Game Addiction, Physical problems, mental health). We trained our machine learning model with the survey data using Neural Network, SVM, Multi linear regression, Decision tree, random forest algorithms. Of these algorithms, the Neural Network algorithm result were highest (Game Addiction 99.89%, Physical problems 79.35%, mental health 90.22%) in accuracy. Besides we conducted T-test, P-value, Heat map and various bar charts showing relations between different features.

INDEX TERMS Neural Network, SVM, Machine Language project, Random Forest, Multi Linear Regression, Decision Tree, Hypothesis, T-test, P-value, Game Addiction, Playing Game, Mental Disorder, Physical Problem.

1. INTRODUCTION

Information and communication technology development has altered everyday routines and habits. Internet use and the virtual world have become more important in people's lives. Children who previously played traditional games with their peers in the street and parks choose playing on computers in electronic virtual settings. These preferences have led to a rise in the number of people who become hooked to video games on a daily basis. Addiction to digital games is one of the most serious issues; it was formerly only a risk for kids and teenagers, but it is now a risk for adults in their middle and older years. According to Griffiths, playing digital games too much and too frequently can result in addiction, which is the unintentional use of computers and video games that results in social or emotional issues for the user.

Video game addiction is a widely contested concept, just like other behavioral addictions. While there are some alarming impacts of video gaming, especially in younger players, there is not enough long-term study or supporting data to say with certainty that excessive video game playing is an addiction. Additionally, the relentless marketing of the video game business, whose own research, predictably, indicates no negative effects, must compete with warnings from organizations like the American Medical Association, which contends that video games may be dangerous. The Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-V), considered the "gold standard" manual for mental health issues, now lists Internet Gaming Disorder as a disease that merits more research. Therefore, suggested criteria have been published, despite the fact that it is not yet officially acknowledged as an illness. In terms of the quantity of time spent playing, the intense emotional commitment to the activity, and the patterns of social issues faced by gaming addicts, video game addictions are comparable to other addictions. We conducted this research with data for getting some results like the relation between game and mental-physical health, their behaviors and academic results. For getting relationships we implemented various Algorithms such as SVM, Neural Network, Random Forest, Decision tree and Multi linear regression. In this regard we had to collect data from university students and we processed that data for finding the relation between the features of our research for that we used Heat map, bar chart by fulfilling some conditions, T-test and P-value.

The concern of this research is verifying the effects of game addiction on different university students, as well as their physical and mental health. This study analyzed data on people with a range of mentalities, behaviors, and phycological backgrounds to examine the most prevalent causes of game addiction. In order to evaluate this study's standard and quality, it is crucial to contrast the findings with other recent works.

2. LITERATURE REVIEW

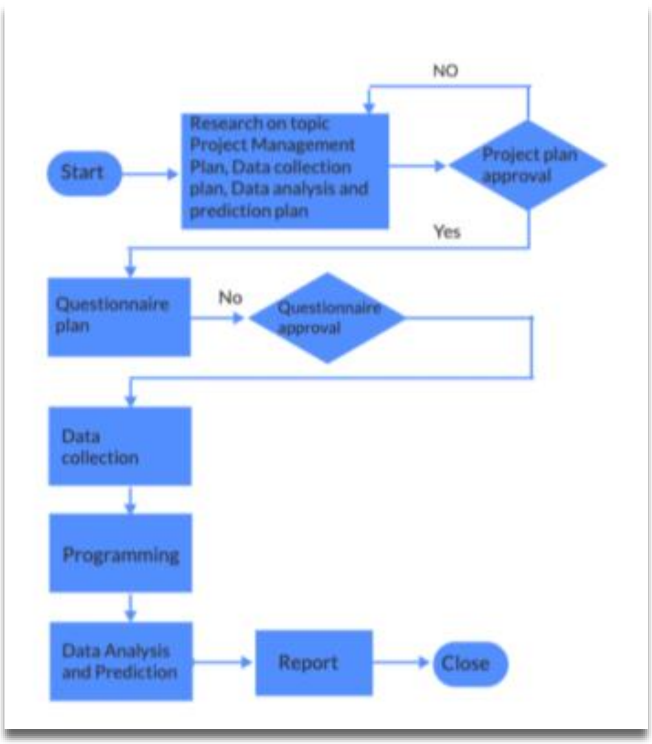
Digital game addiction has been added to the concepts of addiction. Game addiction negatively affects the cognitive, psychological, and social life of the individual. The sample of the study included 646 students studying at İnönü University in the 2018-2019 academic year [1]. Online game addiction also referred to as internet gaming disorder, is not listed in psychiatric classification systems. In Turkey neither a scale nor a study is present to evaluate online game addiction/ addicts. The authors evaluated the reliability and validity of "The Game Addictions Scale" developed by Lemmens in 2009[2]. The investigation was the first of its sort in Ghana and throughout Africa. The prevalence of video game addiction was examined, as well as some of its correlates. Both the influence of certain demographic parameters on video game addiction and certain demographic factors themselves were looked at [3]. Results of the IGDS9-SF can be obtained by summing up all responses given to all nine items. Scores range from a minimum of 9 to a maximum of 45 points, with higher scores indicative of Internet Gaming Disorder. Researchers should check if participants have endorsed at least five criteria out of the nine [4]. Excessive gaming among adolescents has various negative impacts on an individual. This paper provides evidence of five physical health impacts of DA associated with adolescents. Based on the study, it is concluded that DA among Malaysian adolescents can cause various impacts on physical health such as obesity, back pain, and neck pain [5]. Students who played video games for more than eight hours had an anxiety level of about 37%. The academic results of students addicted to gaming have been negatively affected. Ferahim Yeşilyurt, Faculty of Education, Fatih Sultan Mehmet University, Istanbul, Turkey [6]. The average daily playtime of gamers in Lebanon was 2.2 hours, but on the weekends, it doubled to over 3 hours. 9.2% of the study's sample were classed as having IGD using the IGD-20 Test. Risk of IGD increased by being younger, having lower academic achievement and having lower sleep duration [7]. Students with personal computers demonstrated noticeably greater levels of internet and computer game addiction than students without access to the internet. Male students had greater Internet and computer gaming addiction rates than female students, while there was no statistically significant difference between the two groups of students regarding grade and game type[8]. Tuncay Ayas published a research paper in 2012 entitled "The Relationship between Internet and Computer Game Addiction Level and Shyness among High School Students". The research was conducted through a general survey model. According to the research paper,the correlation between the Internet and shyness is consistent[9]. 13% teenagers displayed video game addiction tendencies in both problematic and addicted categories among them 8.23% are male and 4.77% of the participants are female. 68.4% teenagers possessed promotion focus and 31.6% were tended to have prevention focus on the basis of regulatory focus [10]. In 2011, Zhengchuan Xu, Ofir Turel & Yufei Yuan published a journal paper named "Online game addiction among adolescents:motivation and prevention factors". Data was collected by using a paper-based survey among 623 adolescents. The results highlight several functional demands that motivate online gaming and addiction [11].

Most of game addiction studies have focused on internet game addiction related to negative effects such as psychological problems and social isolation. In the association between personality traits and game addiction, we found a strong effect of neuroticism on game addiction. The more people feel loneliness the higher they are engaged in virtual space in order to fill the paucity of offline relationship [12]. Study conducted among 851 Dutch adolescents (49% female) of which 540 played games (30% female). Games with a violent descriptor and an age rating lower than 12 (e.g., Bomberman, Ratchet & Clank) were considered fantasy violence and not coded as violent games [13]. The GAS was used to evaluate two samples of Swiss men from the French (N = 3318) and German speaking regions. GAS scores were positively and modestly correlated with the MDI, the Neuroticism-Anxiety and Aggression-Hostility subscales of the ZKPQ-50-cc[14].

Online survey is the most commonly used data collection method in studies of technology addiction. Factors that predispose players to addiction include personality traits, psychopathological conditions and demographic variables. Our review examines studies that examine online gaming addiction in the context of massively multiplayer online role-playing games [15]. An eCRF has been developed for the investigators to document their study data in a database stored, maintained, and administered by the IZKS Mainz. The aim of STICA is the reintegration of the patients into a normal life, including controlled use of computer and internet [16]. A study looked into the gender-specific predictors of internet game addiction among higher-grade elementary school students in a city. 356 kids in the fifth or sixth grade of a primary school participated in the study. Internet game addiction was 10.1% (boys 17.2%, girls 2.4%), with boys more prone to addiction than girls (boys: $r=-.36$, $p<.001$, girls: $r=21$, $p=.005$) [17]. The relationships between video game use and negative consequences are debated, but fairly well established. A 10% increase in video game addiction is associated with increased risk of depression, aggression and conduct problems. Video game addiction was not associated with frequency of heavy episodic drinking [18]. The DSM-5 created a category for "substance-related and addictive disorders". Video games were also considered for inclusion, but the working group decided there wasn't enough evidence yet. Concern about video game addiction is most prominent in east Asia. Many gamer's experience artifacts from virtual worlds bleeding into the real world [19]. Linear regression model that corresponds to the practical situation is proposed in the paper, which is to set up simple linear regression model based on practical problem and to implement the following with the help of the latest and most popular Python3.6 [20]. Recent study to develop hybrid model based on convolutional neural network and long short-term memory provided a satisfactory hybrid model for seasonal stability and its prediction performance proved to be superior than multilayer perceptron and LSTM. Self-adaptive neuro-fuzzy weighted extreme learning machine to improve prediction accuracy and real-time air pollution concentration prediction has been investigated by[21].

3. METHODOLOGY

First, we research on many interested topics that can we do some research on those or anyone who has done already. Then how can we collect the data set for that project. When we all become sure about our idea, we talk with our advisor sir with our plan proposal and have to convince him about the topic and why this kind of research is needed. After the approval we started to collect our data through Google form. Then analysis them with codes and from the output we make a report on our project.

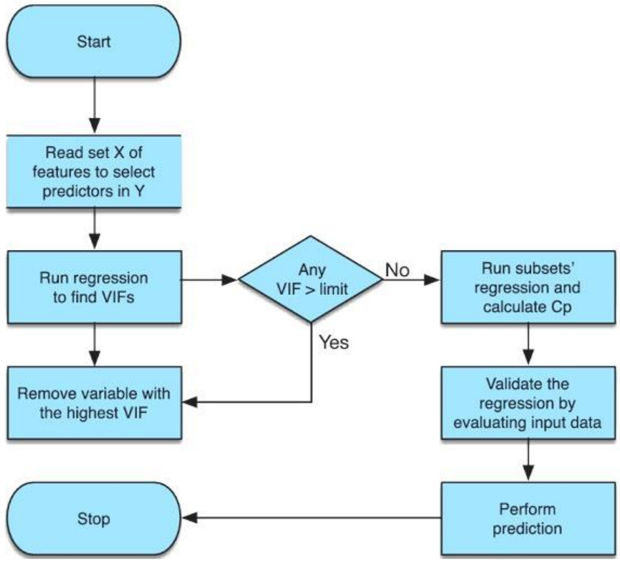


Flowchart of this project.

3.1 Models

3.1.1 Multi Linear Regression

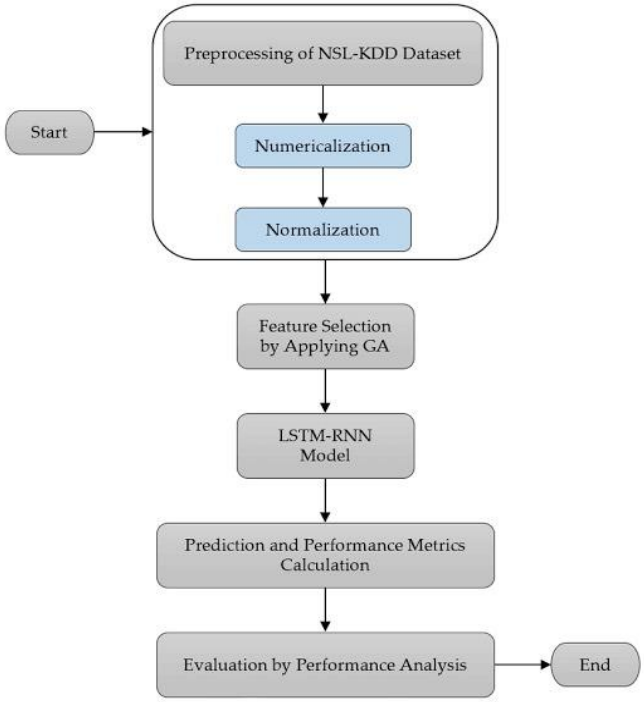
Multiple linear regression is a statistical method for predicting a variable's outcome based on the values of two or more other variables. Multiple regression is a subset of linear regression and is sometimes referred to as just that. The variables we employ to forecast the value of the dependent variable are referred to as independent or explanatory variables.



Flowchart of Multi Linear Regression

3.1.2 Neural Network:

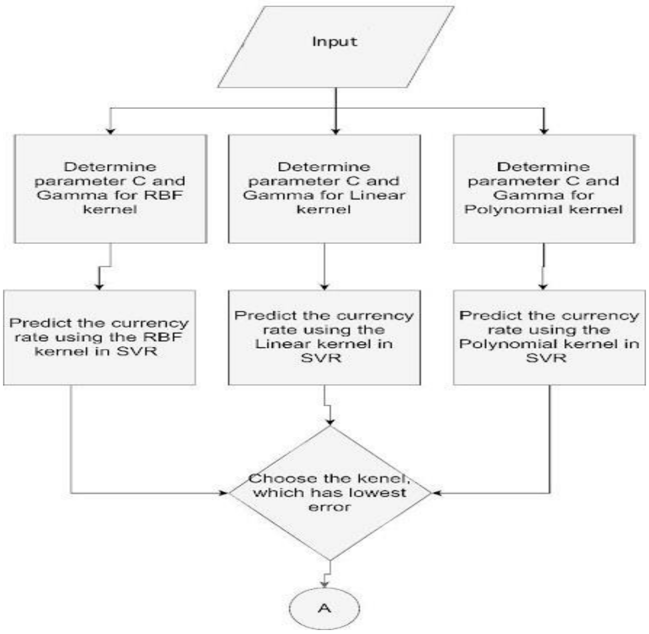
A neural network is a collection of algorithms that aims to identify underlying links in a set of data using a method that imitates how the human brain functions. The artificial intelligence-based idea of neural networks is gaining prominence in the design of trading systems and predictive analytics.



Flowchart of Neural Network

3.1.3 Support Vector Machine (SVM)

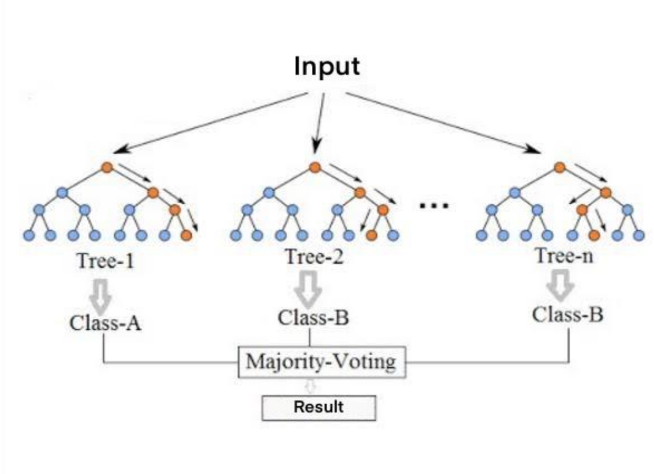
Support Vector Machine or SVM is one of the most popular Supervised Learning algorithms. The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future.



Flowchart of SVM

3.1.4 Random Forest Classifier

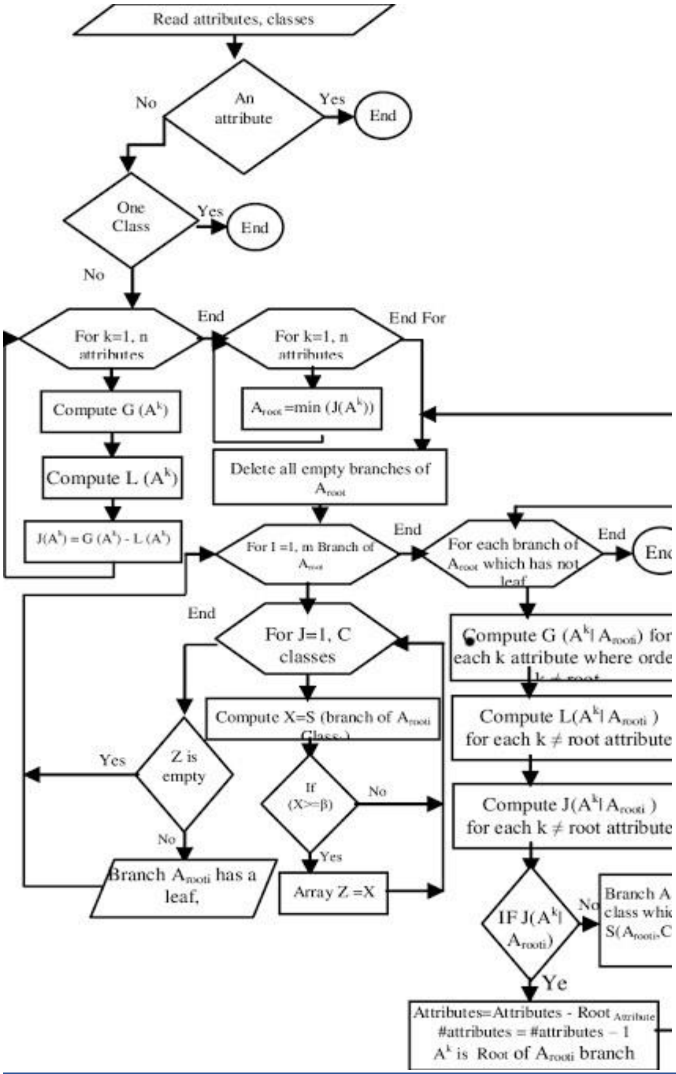
Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. The name comes from the concept of ensemble learning, which is a process of combining multiple classifiers to solve a complex problem.



Flowchart of Random Forest Classifier

3.1.5 Decision Tree

Decision Tree algorithm belongs to the family of supervised learning algorithms. The goal of using a Decision Tree is to create a training model that can use to predict the class or value of the target variable. It can be used for solving regression and classification problems too.



Flowchart of Decision Tree

3.2 Hypothesis

Two sampled T-test: To ascertain whether there is statistical support that the related population means are statistically substantially different, the Independent Samples t Test, also known as the 2-sample t-test, analyzes the means of two independent groups.

Level of significance: the level of significance at which we accept or reject the null hypothesis. Since it is impossible to accept or reject a hypothesis with 100% accuracy, we choose a level of significance that is typically 5%. This is typically indicated with the mathematical symbol alpha, which is typically 0.05 or 5%, meaning that you should have 95% confidence that your output will produce results that are similar in each sample.

Null hypothesis : The null hypothesis, or default stance, in inferential statistics states that there is no correlation between two phenomena that are being assessed or that there is no association between groups.

P-value: The probability of discovering the observed, or more extreme, outcomes when the null hypothesis (H 0) of a study question is true is known as the P value, or computed probability; the definition of "extreme" depends on how the hypothesis is being tested. When your P value falls below the selected level of significance, you reject the null hypothesis and agree that your sample contains solid evidence that the alternative hypothesis is true. It DOES NOT IMPLY a "significant" or "important".

3.3 Data Splitting

The complete dataset needed to be divided in order to make predictions. The dataset is divided into two equal halves as a result. A training one and a testing one. In this study for neural network and SVM, 80% of the data were used for testing, and the remaining 20% were used for training. In this study for Random Forest and decision tree, 70% of the data were used for testing, and the remaining 30% were used for training.

3.4 Data Encoding

The study includes a substantial amount of data encoding. The majority of the data were categorical. Thus, they were transformed into a numerical format so that machine learning methods could be applied to them to get better results.

3.5 Training And Testing for Prediction:

In this study, classifiers and regressions that were trained using training datasets for SVM, Random Forest, decision tree, multi-linear regression and LSTM 2 dense neural networks were all used. As a result, we cancelled multi linear regression and moved to neural network because the multi linear regression ultimately demonstrated 33.42% accuracy (Low Accuracy). We proceed further with the left four.

4. Data Analysis

4.1 Data Collection

To gather information from Bangladeshi university students of well-known varsities like BRAC, AIUB, Daffodil, UIU, ULAB a survey was conducted. 30 questions were included in the google form. There were many categories of questions. First 20 questions used the measure if they were addicted to the game of not. Among the first 20 questions, there were some questions to measure if they are suffering from any kind of mental disorder or not. Question number 21 to 26 were used to find out about their physical problems and the last 4 questions (27-30) were used to learn about their academic life. The answers were containing a scaling score. The total scores of the questions indicate if they are addicted or not, whether are they suffering from mental or physical problems also if they are facing any kind of academic problems in their personal life. The survey was conducted for a period of 1 month from 12th August to 10th September. A google form consisting of the questions was circulated among the students they filled the questions with multiple choice and submitted the form. Those form was taking data from the user anonymously. The data set has information from 456 respondents. The game addiction scale (GAS-21) was used to identify the addicted among the population. Internet gaming disorder scale (IGDS9-SF). Also, we measured the physical condition of the participant and try to know about their academic life to relate that does game addiction have any impacts on someone's academic life? Game addiction checklist consists of 25 questions, where a person can score themselves from 1-5 by describing how much they can relate to a certain situation. The rubric starts from 1(“Never") and ends with 5(“Very Often”), and after answering all the questions they can come to know if he/she is depressed or not. The 30 questions that consist of the questionnaire can be divided into four categories. The first category is whether that person is addicted or not which has 20 questions, if a person receives a score of greater than 59 after responding to all the questions, addiction is assumed. The second category is to measure mental disorders (Q.no. 1,5,7,8,15,16,17,19), If the score is greater than 29 after responding to all the questions, mental disorder is assumed. the third category is physical problems which have 6 questions (Q.no. 21-26), If the score is greater than 12 after responding to all the questions, the physical problem is assumed and the last category is about academic life questions, there are 4 questions about it(Q.no. 27-30).

4.2 Data description

The variables and inquiries we utilized as our predictors are all included in the table below. There are 20 predictor variables in all.

Table-1: Variables of our survey

Variable name	Type of variable	Included questions	Given options
thinkof Playing GameDay Long	Predictor	Did you think about playing a game all day long?	‘Never’, ‘Rarely’, ‘Sometimes’, ‘Often’ and ‘Very Often’
Spend Free Timeon Game	Predictor	Did you spend much free time on games?	‘Never’, ‘Rarely’, ‘Sometimes’, ‘Often’ and ‘Very Often’
Feeling of Game Addiction	Predictor	Have you felt addicted to a game?	‘Never’, ‘Rarely’, ‘Sometimes’, ‘Often’ and ‘Very Often’
Playing Longer Then Intended	Predictor	Did you play longer than intended?	‘Never’, ‘Rarely’, ‘Sometimes’, ‘Often’ and ‘Very Often’
Spend Large Timeon Game	Predictor	Did you spend increasing amounts of time on games?	‘Never’, ‘Rarely’, ‘Sometimes’, ‘Often’ and ‘Very Often’
Unable To Stop Playing	Predictor	Were you unable to stop once you started playing?	‘Never’, ‘Rarely’, ‘Sometimes’, ‘Often’ and ‘Very Often’
Gaming To Forget RealLife	Predictor	Did you play games to forget about real life?	‘Never’, ‘Rarely’, ‘Sometimes’, ‘Often’ and ‘Very Often’
Gaming To Release Stress	Predictor	Have you played games to release stress?	‘Never’, ‘Rarely’, ‘Sometimes’, ‘Often’ and ‘Very Often’
Gaming To Feel Better	Predictor	Have you played games to feel better?	‘Never’, ‘Rarely’, ‘Sometimes’, ‘Often’ and ‘Very Often’
Unable To Reduce Gaming	Predictor	Have you failed when trying to reduce game time?	‘Never’, ‘Rarely’, ‘Sometimes’, ‘Often’ and ‘Very Often’
Unsuccessful Influen Ceof Others	Predictor	Have others unsuccessfully tried to reduce your game use?	‘Never’, ‘Rarely’, ‘Sometimes’, ‘Often’ and ‘Very Often’
Angry Issue	Predictor	Have you felt bad and angry when you were unable to play?	‘Never’, ‘Rarely’, ‘Sometimes’, ‘Often’ and ‘Very Often’
Stress Issue	Predictor	Have you become stressed when unable to play?	‘Never’, ‘Rarely’, ‘Sometimes’, ‘Often’ and ‘Very Often’
Unsocial Issue	Predictor	Have you neglected others (e.g., family, friends) because you were playing games?	‘Never’, ‘Rarely’, ‘Sometimes’, ‘Often’ and ‘Very Often’
Fight Issue	Predictor	Did you have fights with others (e.g., family, friends) over your time	‘Never’, ‘Rarely’, ‘Sometimes’, ‘Often’ and ‘Very Often’

		spent on games?	
Break off Relationship	Predictor	Have you lost an important relationship because of your gaming activity?	'Never', 'Rarely', 'Sometimes', 'Often' and 'Very Often'
tendTo Deceive	Predictor	Have you deceived any of your family members or others because the amount of your gaming activity?	'Never', 'Rarely', 'Sometimes', 'Often' and 'Very Often'
Sleep Issue	Predictor	Has your time on games caused sleep deprivation?	'Never', 'Rarely', 'Sometimes', 'Often' and 'Very Often'
Tend Tolose Hobbies	Predictor	Have you lost interests in previous hobbies and other entertainment activities as a result of your engagement with the game?	'Never', 'Rarely', 'Sometimes', 'Often' and 'Very Often'
Tend To Neglect Important Activities	Predictor	Have you neglected other important activities (e.g., school, work, sports) to play games?	'Never', 'Rarely', 'Sometimes', 'Often' and 'VeryOften'.

4.3 Data Processing

We have collected information for the dataset from 458 participants. Among them, 199 were found as addicted, and 259 as not addicted. So, we can see that 43.45% of the total responders were found addicted to games. Various reasons such as neglect someone, thinking about the game day long, being angry when can't play, relief stress by playing, playing to forget about real life, etc. Their big proportion is not game addicted of 56.55%.

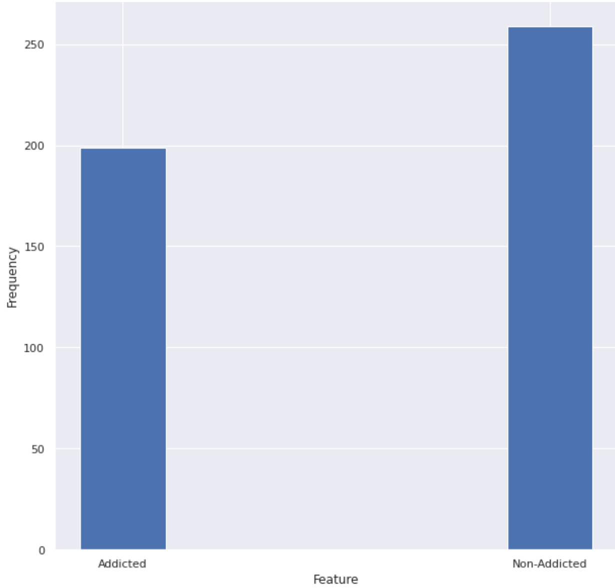


Fig 1: Total number of Addicted and non-addicted person

Among the depressed people, 42.71% have been found mental disorder and 77.39% found as they are having physical issues. Among addicted and mental disorder they feel some problems most of the time same for addicted and physical problems.

Table-2: Distribution of participants in the dataset who were non-addicted and not only addicted but also had mental disorders and physical issues.

class	number	percent
addicted	199	43.45%
Non addicted	259	56.55%
Addict + mental disorder	85	42.71%
Addict + physical problem	154	77.39

Table-3: Shows us how many of the participants those who are game addicts have mental disorders and physical problems and academic life, as well as the proportions of them who experience these issues most frequently for whatever causes.

SL.	Problems	t-test	P value	Category	Percentage%
Addiction +Mental disorder	Thinking of game all daylong	-41.846619251 30569	1.290308622 4879465e-214	Never Rarely Sometimes Often Very Often	1.18 1.18 28.24 45.88 25.53

Addiction+Mental disorder	Forget about life	-40.351090500138426	3.080241619552916e-205	Never Rarely Sometimes Often Very Often	0.00 0.00 18.82 42.35 38.82
Addiction+Mental disorder	To release stress	-44.54472979611329	2.890002889112066e-231	Never Rarely Sometimes Often Very Often	1.18 0.00 16.47 34.12 48.24
Addiction+Mental disorder	Aggression	-41.072973684765486	8.896146000434733e-210	Never Rarely Sometimes Often Very Often	0.00 0.00 38.82 45.53 17.65
Addiction+Mental disorder	Unsocial	-38.107792815347764	5.465582709427789e-191	Never Rarely Sometimes Often Very Often	0.00 1.18 32.94 42.35 25.53
Addiction+Mental disorder	Breakup	-31.533207789797228	2.8501880394903764e-148	Never Rarely Sometimes Often Very Often	1.18 10.59 43.53 28.24 16.47
Addiction+Mental disorder	Sleep Issue	-38.18027555567946	1.8795369110441046e-191	Never Rarely Sometimes Often Very Often	0.00 0.00 16.47 28.24 55.29
Addiction+Physical prob	Neck and back pain	-40.523456318729366	2.5268984210041887e-206	Never Rarely Sometimes Often Very Often	0.00 3.90 33.12 41.56 21.43
Addiction+Physical prob	Orthopedic Issue	-36.94675812288953	1.5491986524624592e-183	Never Rarely Sometimes Often Very Often	0.00 5.19 50.00 31.82 12.99
Addiction+Physical prob	Eye Issue	-37.364272992126956	3.1951780086419923e-186	Never Rarely Sometimes Often Very Often	0.65 2.60 31.82 32.47 32.47
Addiction+Physical prob	Hearing Issue	-32.34532805398627	1.3377081825529703e-153	Never Rarely Sometimes Often Very Often	2.60 7.79 36.36 31.82 21.43
Addiction+Physical prob	BMI Status	-44.247421437343405	1.8962437793099884e-229	Never Rarely Sometimes Often Very Often	2.60 42.86 38.96 11.04 4.55
Addiction+Academic	Co-curricular	-43.07114184541558	3.236574964724974e-222	Never Rarely Sometimes Often Very Often	12.06 35.68 38.69 10.55 3.02
Addiction+Academic	Present in class	-40.76716055243315	7.402470195664573e-208	Never Rarely Sometimes Often Very Often	2.51 17.00 47.47 24.26 8.04
Addiction+Academic	cgpa	--	--	1.50-2.00 2.00-2.50 2.50-3.00 3.00-3.50 3.50-4.00	7.04 15.08 49.25 20.10 8.54

4.4 Data Visualization

An essential component of data analysis is data visualization. By using data visualization, we are less likely to overlook any crucial analysis details. In order to visualize data, we have created a bar plot to show the relationship between who are game addicted with having the problem of mental disorder and thinking of game all day long.

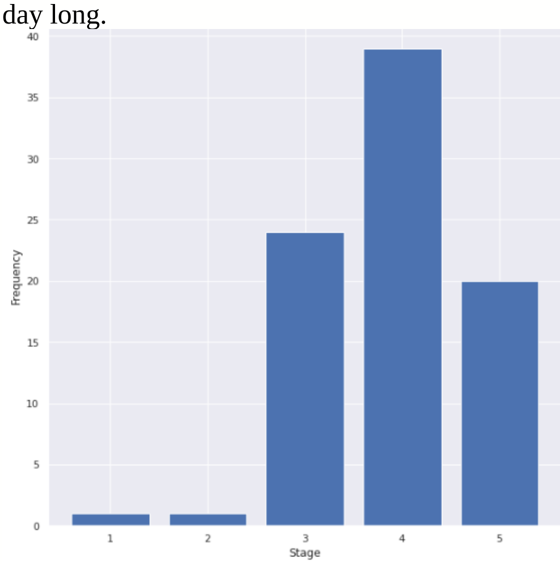


Fig 1: Total number of Addicted people with Mental Disorder (think about playing game day long).

The bar plot shown above shows that, out of all the respondents, 45.43% have the greatest rate of thinking game all day long in range of often.

Bar plot about relationship between who are game addicted with having the problem of mental disorder and play game to forget about life.

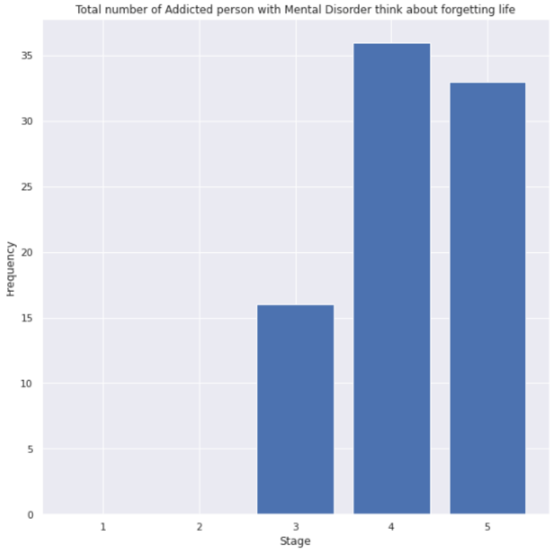


Fig 2: Total number of Addicted people with mental Disorder (think about forgetting life).

The bar plot shown above shows that, out of all the respondents, 42.35% have the greatest rate of forgetting about life in range of often.

Bar plot about relationship between who are game addicted with having the problem of mental disorder and play game to release stress.

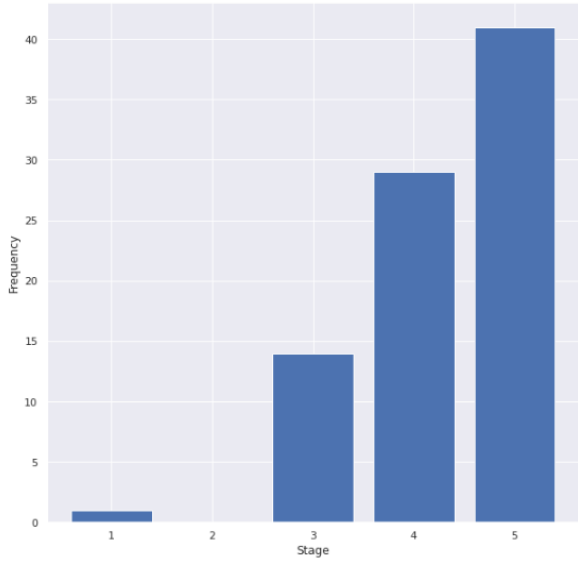


Fig 3: Total number of Addicted persons with Mental Disorder (think about gaming to release stress).

The bar plot shown above shows that, out of all the respondents, 48.24% have the greatest rate of trying to release strees in range of very often.

Bar plot about relationship between who are game addicted with having the problem of mental disorder and aggression.

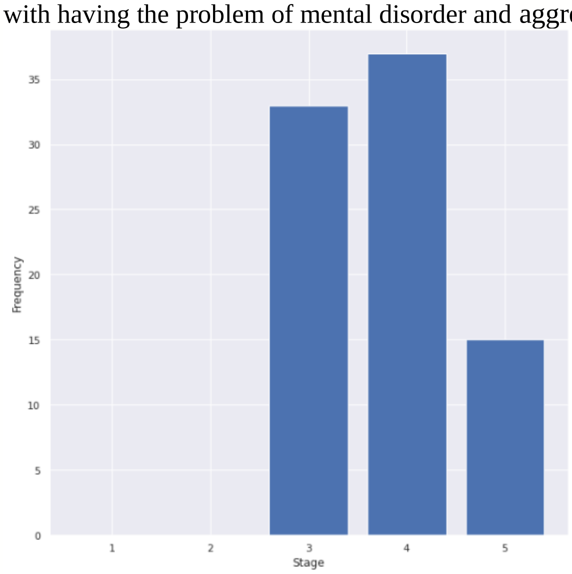


Fig 4: Total number of Addicted persons with Mental Disorder (feel angry when unable to play games).

The bar plot shown above shows that, out of all the respondents, 48.24% have the greatest rate of aggression in range of often.

Bar plot about relationship between who are game addicted with having the problem of mental disorder and unsocial.

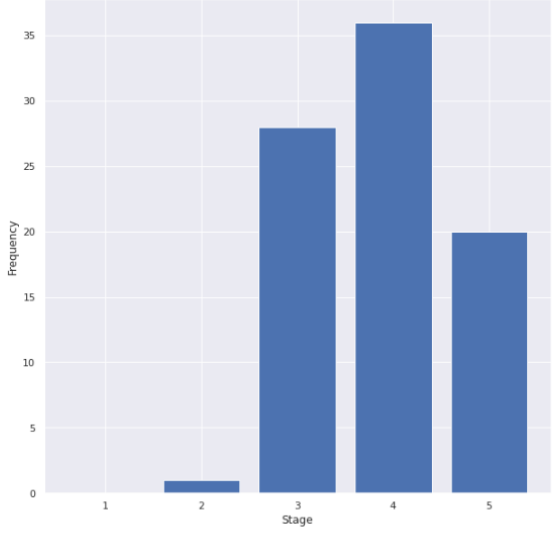


Fig 5: Total number of Addicted persons with Mental Disorder (unsocial).

The bar plot shown above shows that, out of all the respondents, 42.35% have the greatest rate of unsocial in range of often.

Bar plot about relationship between who are game addicted with having the problem of mental disorder and break up of important relationship.

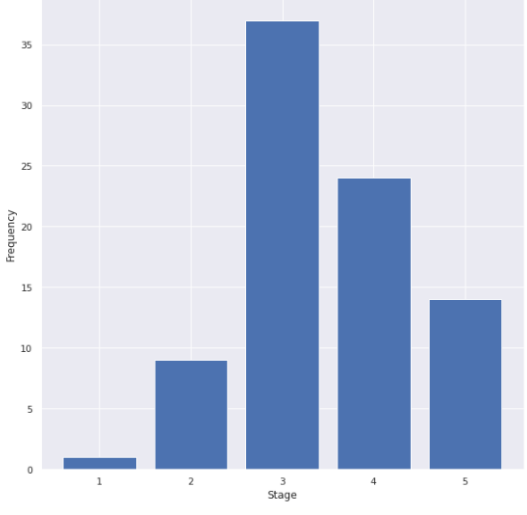


Fig 6: Total number of Addicted persons with Mental Disorder (have lost an important relationship).

The bar plot shown above shows that, out of all the respondents, 43.53% have the greatest rate of unsocial in range of sometimes.

Bar plot about relationship between who are game addicted with having the problem of mental disorder and sleep issues.

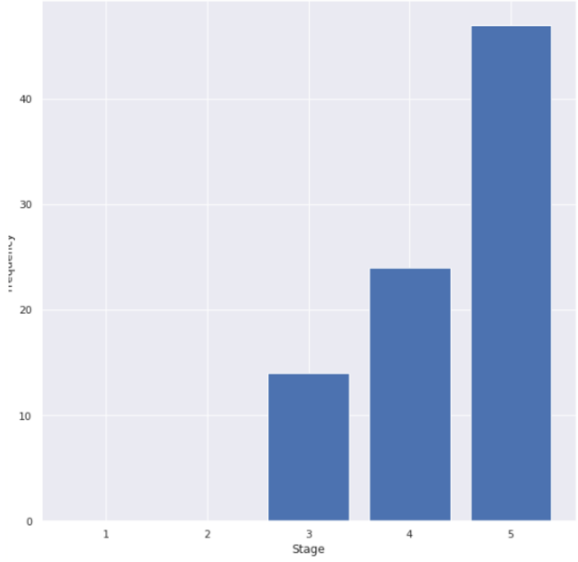


Fig 7: Total number of Addicted persons with Mental Disorder (have sleep deprivation).

The bar plot shown above shows that, out of all the respondents, 55.29% have the greatest rate of sleep issue in range of very often.

Bar plot about relationship between who are game addicted with having physical problem like neck and back pain.

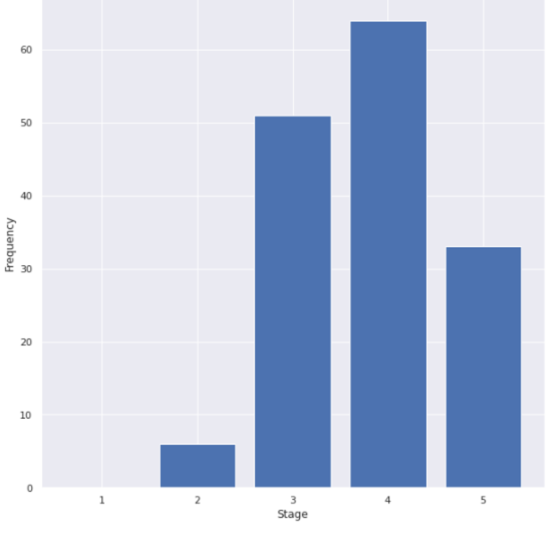


Fig 8: Total number of Addicted persons with physical problems (neck and back pain).

The bar plot shown above shows that, out of all the respondents, 41.56% have the greatest rate of neck and back pain in range of often.

Bar plot about relationship between who are game addicted with having physical problem like orthopedic.

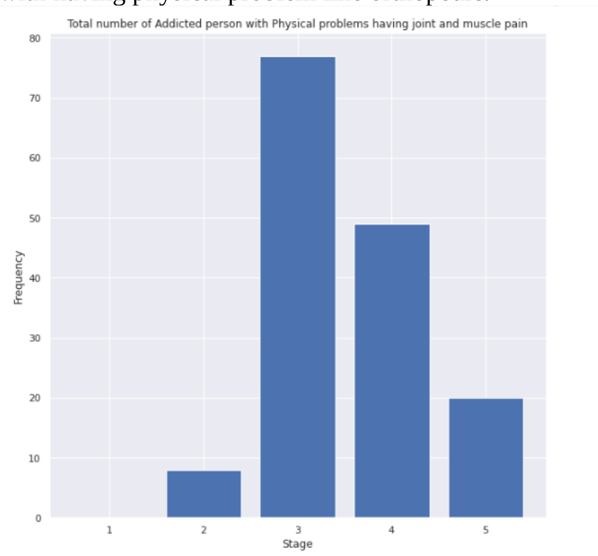


Fig 9: Total number of Addicted persons with physical problem (joint and muscle pain).

The bar plot shown above shows that, out of all the respondents, 50.00% have the greatest rate of neck and back pain in range of sometimes.

Bar plot about relationship between who are game addicted with having physical problem like eye issues.

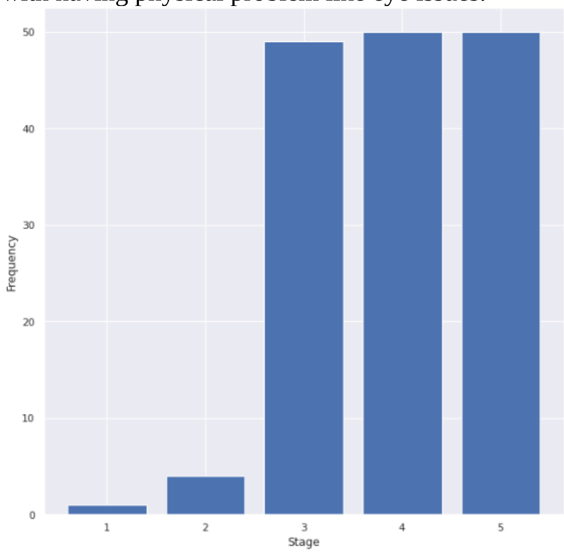


Fig 10: Total number of Addicted persons with physical problems (eyesight issue).

The bar plot shown above shows that, maximum people are having eye issues as it is a common issue now a day. There are the rages of sometimes is 31.82%, often is 32.47%, very often is 32.47%.

Bar plot about relationship between who are game addicted with having physical problem like hearing problem.

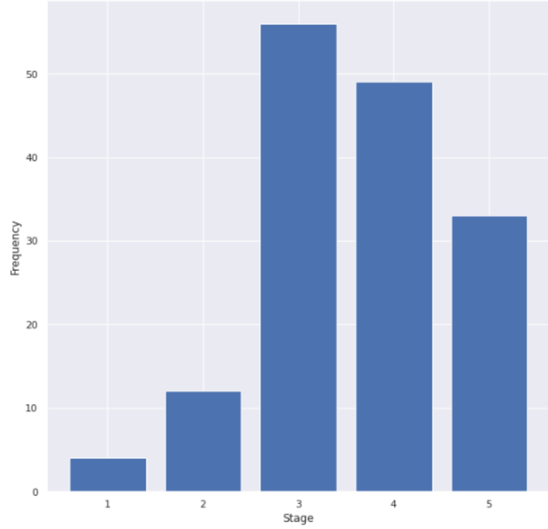


Fig 11: Total number of Addicted persons with physical problems (hearing issue).

The bar plot shown above shows that, out of all the respondents, 36.36% have the greatest rate of hearing issues in range of sometimes.

Bar plot about relationship between who are game addicted with having physical problem and their BMI status.

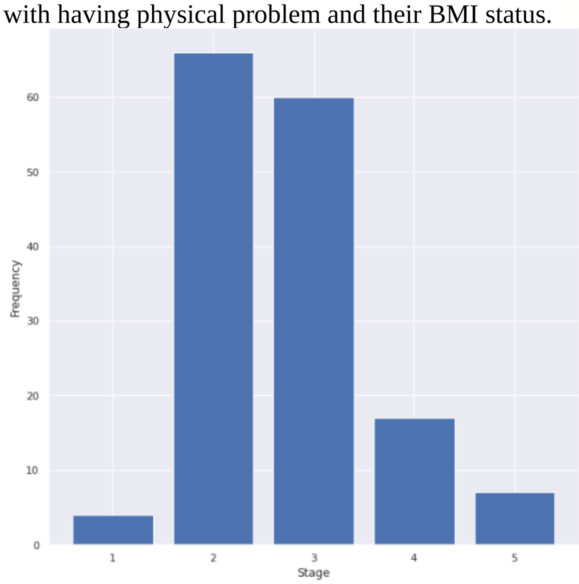


Fig 12: Total number of Addicted persons with physical problems.

Maximum has the BMI,42.86% below than normal BMI.

Bar plot about relationship between who are game addicted, their academic life (engagement with co-curricular).

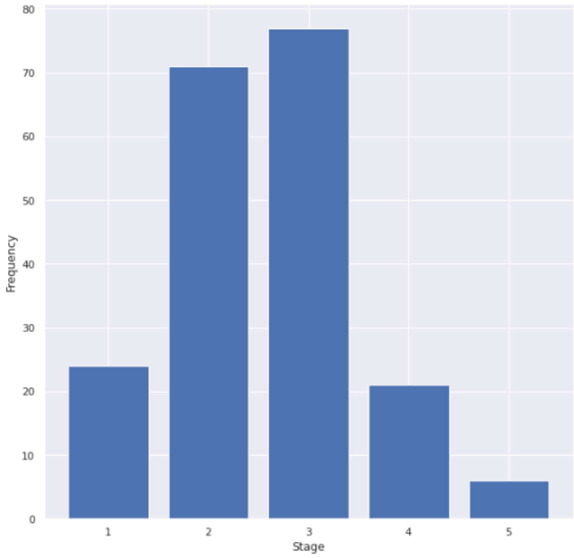


Fig 13: Addicted person who attend co cocurricular activities

The bar plot shown above shows that, out of all the respondents, 38.69% have the greatest rate of engagement with co-curricular in range of sometimes.

Bar plot about relationship between who are game addicted, their academic life (present in class).

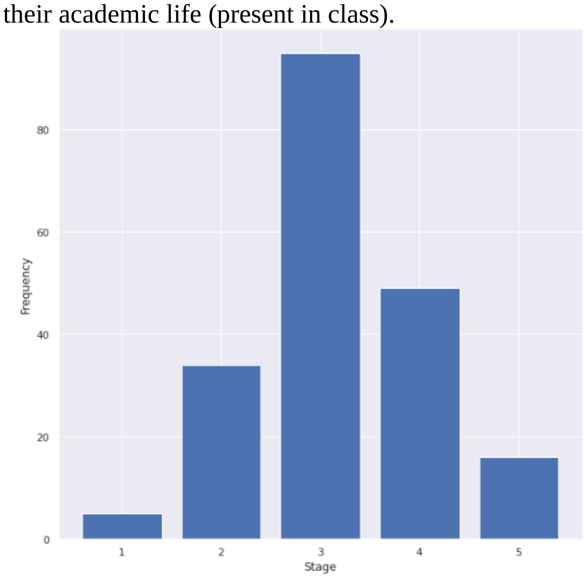


Fig 14: Addicted persons attendance in class.

The bar plot shown above shows that, out of all the respondents, 47.47% have the greatest rate attendance in class in range of sometimes.

Bar plot about relationship between who are game addicted, their academic life (CGPA).

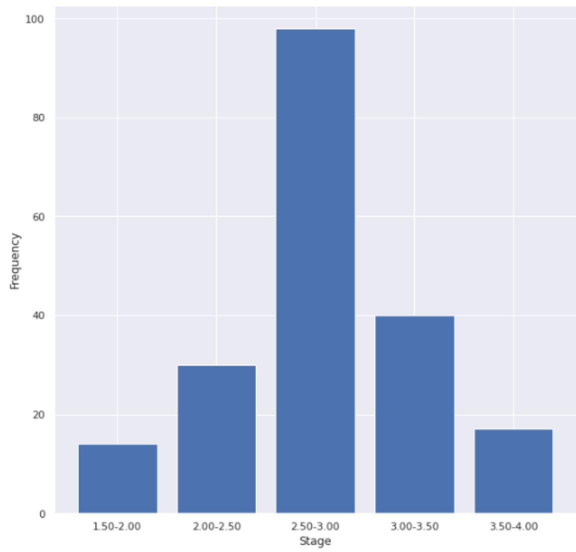


Fig 13: CGPA

The bar plot shown above shows that, out of all the respondents, 49.25% have the maximum rate CGPA in range of sometimes.

5. Result from machine learning algorithms

The result has been analyzed in different ways and discussed in below subsections.

5.1 Model Evaluation using Matrices

The used models are evaluated by the Precision, Recall, F1 score, and Confusion Metrics.

1) Precision:

The percentage of accurately anticipated positive observations to all predicted positive observations is known as precision.

Precision= True positive/True negative

The precision of a good classifier should be one. In other words, only when the numerator and denominator are equal.

TruePositive=TruePositive+FalsePositive

And the accuracy rises to 1. This suggests that the rate of false positives is also zero. The value of the denominator rises relative to the numerator when False Positive increases and accuracy decreases.

2) Recall:

The proportion of accurately anticipated positive observations to all actual observations in the class is known as recall.

Recall = True Positive/Total Actual Positive

By classifying them as Actual Positives, recall calculates the number of True Positives that our model actually captures. Recall will be the model metric used to select the best model when False Negative has a high cost, using a similar idea.

3) F1 Score:

Recall and Precision are averaged to produce the F1 Score. Therefore, both false positives and false negatives are considered while calculating this score. Even though it is less evident, F1 is typically more trustworthy than accuracy, especially when the class distribution is unequal. When the costs of false positives and false negatives are comparable, accuracy performs well. It is best to assess both Precision and Recall if the costs of false positives and false negatives differ significantly.

4) Classification Reports:

The Precision, Recall, F1-score, and Support, as well as the measured Accuracy, Macro Average, and Weighted Average for all the Model Evaluation Metrics, are all included in the classification report. For each of the used models, the reports are provided below.

5) Confusion Matrix:

The confusion matrix is a measure of the effectiveness of machine learning for classification. It provides details on the types of errors produced as well as classification faults made by the classifiers. The matrix compares actual goal values with expected values from the machine learning model. This gives us a thorough view of the accuracy of the classification model.

Neural Network

Table 1: Physical Problem

SL.	Precision	Recall	F1-Score	Support
0	0.74	0.93	0.82	45
1	0.91	0.68	0.78	47
Accuracy			0.80	92
Macro avg	0.83	0.81	0.80	92
Weighted avg	0.83	0.80	0.80	92

Table 2: Mental Disorder

SL.	Precision	Recall	F1-Score	Support
0	0.96	0.97	0.96	69
1	0.91	0.87	0.89	23
Accuracy			0.95	92
Macro avg	0.93	0.92	0.93	92
Weighted avg	0.95	0.95	0.95	92

Table 3: Addiction indicator

SL.	Precision	Recall	F1-Score	Support
0	1.00	1.00	1.00	48
1	1.00	1.00	1.00	44
Accuracy			1.00	92
Macro avg	1.00	1.00	1.00	92
Weighted avg	1.00	1.00	1.00	92

SVM

Table 1: Physical Problem

SL.	Precision	Recall	F1-Score	Support
0	0.81	0.87	0.84	45
1	0.86	0.81	0.84	47
Accuracy			0.84	92
Macro avg	0.84	0.84	0.84	92
Weighted avg	0.84	0.84	0.84	92

Table 2: Mental Disorder

SL.	Precision	Recall	F1-Score	Support
0	1.00	0.70	0.82	69
1	0.52	1.00	0.69	23
Accuracy			0.77	92
Macro avg	0.76	0.85	0.75	92
Weighted avg	0.88	0.77	0.79	92

Table 3: Addiction indicator

SL.	Precision	Recall	F1-Score	Support
0	1.00	1.00	1.00	48
1	1.00	1.00	1.00	44
Accuracy			1.00	92
Macro avg	1.00	1.00	1.00	92
Weighted avg	1.00	1.00	1.00	92

Random Forest

Table 1: Physical Problem

SL.	Precision	Recall	F1-Score	Support
0	0.78	0.88	0.83	78
1	0.82	0.67	0.73	60
Accuracy			0.79	138
Macro avg	0.80	0.78	0.78	138
Weighted avg	0.79	0.79	0.79	138

Table 2: Mental Disorder

SL.	Precision	Recall	F1-Score	Support
0	0.98	0.97	0.97	116
1	0.83	0.91	0.87	22
Accuracy			0.96	138
Macro avg	0.91	0.94	0.92	138
Weighted avg	0.96	0.96	0.96	138

Table 3: Addiction indicator

SL.	Precision	Recall	F1-Score	Support
0	0.88	0.99	0.93	76
1	0.98	0.84	0.90	62
Accuracy			0.92	138
Macro avg	0.93	0.91	0.92	138
Weighted avg	0.93	0.92	0.92	138

Decision Tree

Table 1: Physical Problem

SL.	Precision	Recall	F1-Score	Support
0	0.82	0.86	0.84	71
1	0.84	0.81	0.82	67
Accuracy			0.83	138
Macro avg	0.83	0.83	0.83	138
Weighted avg	0.83	0.83	0.83	138

Table 2: Mental Disorder

SL.	Precision	Recall	F1-Score	Support
0	1.00	0.72	0.84	103
1	0.55	1.00	0.71	35
Accuracy			0.79	138
Macro avg	0.77	0.86	0.77	138
Weighted avg	0.89	0.79	0.80	138

Table 3: Addiction indicator

SL.	Precision	Recall	F1-Score	Support
0	0.99	1.00	0.99	73
1	1.00	0.98	0.99	65
Accuracy			0.99	138
Macro avg	0.99	0.99	0.99	138
Weighted avg	0.99	0.99	0.99	138

5.2 Accuracy of the models

Five types of classifiers and regression methods are used in this study. The performance of these classifiers and regressions was observed. The outcomes from the classifiers and regressions were checked and finally. The Support Vector Machine and the neural network algorithm is finalized to predict the stage of depression more accurately. According to our analysis, Multi Linear regression had the most accuracy among all five methods that we have used and the number of accuracies was so low so we removed that model. Random forest and decision tree has the same level of accuracy, so we need to keep them in focus.

Model Used	P.P(%)	M.D. (%)	A.Ind. (%)
SVM	80.43	94.57	98.91
NN	79.35	90.22	99.89
RFC	79.71	94.93	90.58
DT	73.19	91.30	94.20

Support Vector Machine – SVM
Neural Network- NN
Random Forest Classifiers- RFC
Decision Tree- DT
Physical Problems- P.P
Mental Disorder- M.D
Addiction Indicator- A.Ind.
Multi Linear regression was removed from the table because of its low accuracy (33.42%) and further we stopped working on that.

6. Comparison With existing works

The majority of past research has focused on predicting impacts of game addiction. In this research we wanted to see the impact of game addiction on various university students, their physical health condition and mental condition. This study used the most common reasons for addiction on games and some other background information in persons of various mentality, habits, and phycological backgrounds. It is vital to compare the results of this study to other current works to assess its standard and quality. Moreover, we used 5 models to analysis and predict the answers.

7. Conclusion

The aim of this study is to find out the impacts of digital game addiction levels by using demographic variables. To conduct this research we have taken a dataset of 458 participants and then we figured out how many people have game addiction. To determine if a person is addicted to gaming or not, a questionnaire consisting of 30 questions was circulated among various ages of people. We have considered GAS-21 (Game Addiction Scale 21) to diagnose addiction levels among individuals. Then we have considered IGDS9-SF(Internet Gaming Disorder Scale–Short-Form) to investigate if a game addict person has any kind of mental disorder. We have also tried to predict the impacts on academic performances and physical problems among the game addict students. To predict the prevalence of game addiction among a participant, LSTM and Multiple Linear Regression models have been used. The accuracy of the model for physical problems is 80.83% and for mental disorders 92.93%. Addiction indicator accuracy is 100% because input and output are the same(measured by own questions). Such addictions resemble modern illnesses. As a result, people experience higher levels of stress and anxiety, negative relationships with those around them, excessive irritability, uncontrollable aggressive thoughts, and other issues that have a negative impact on their quality of life. Such studies are thought to be crucial for ensuring that parents, educators, and authorities are aware of these risks and can effectively develop programs to address them.

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