DECIPHERING THE IMPACT AND EVOLUTION OF GAMING IN EVERYDAY LIFE: A MACHINE LEARNING-CENTRIC ANALYSIS

BY

Md. Tamim Hossen
ID: 202-15-14414

FINAL YEAR DESIGN PROJECT REPORT

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

Supervised By

Dr. Arif Mahmud
Associate Professor & Program Director MIS
Department of CSE
Daffodil International University

Co-Supervised By

Mr. Tanvirul islam
Lecturer
Department of CSE
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

DHAKA, BANGLADESH

July 2024

APPROVAL

This Project titled "**DECIPHERING THE IMPACT AND EVOLUTION OF GAMING IN EVERYDAY LIFE: A MACHINE LEARNING-CENTRIC ANALYSIS.**", submitted by **Md. Tamim Hossen** 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 **15-07-2024.**

BOARD OF EXAMINERS

Dr. Sheak Rashed Haider Noori
Professor & Head
Department of CSE
Faculty of Science & Information Technology
Daffodil International University

Board Chairman

Amit Chakraborty Chhoton
Assistant Professor
Department of CSE
Faculty of Science & Information Technology
Daffodil International University

Internal Examiner 1

Mr. Mohammad Jahangir Alam
Sr. Lecturer
Department of CSE
Faculty of Science & Information Technology
Daffodil International University

Internal Examiner 2

Dr. Md. Arshad Ali
Professor
Department of CSE
Hajee Mohammad Danesh Science and Technology University

External Examiner

DECLARATION

We hereby declare that this project has been done by us under the supervision of **Dr. Arif Mahmud, Associate Professor & Program Director MIS, Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

Supervised by:

Dr. Arif Mahmud
Associate Professor & Program Director MIS
Department of CSE
Daffodil International University

Co-Supervised by:

Mr. Tanvirul islam
Lecturer
Department of CSE
Daffodil International University

Submitted by:

Md. Tamim Hossen
ID: 202-15-14414
Department of CSE
Daffodil International University

ACKNOWLEDGEMENT

First, I express our heartiest thanks and gratefulness to almighty for His divine blessing making it possible for us to complete the final year project/internship successfully.

I am grateful and wish our profound indebtedness to **Dr. Arif Mahmud, Associate Professor & Program Director MIS**, Department of CSE Daffodil International University, Dhaka. Deep Knowledge & keen interest of our supervisor in the field of "*Field name*" to carry out this project. His 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.

I would like to express our heartiest gratitude to the **Head of the Department of CSE**, for his kind help in finishing our project and also to other faculty members and the staff of the Department of CSE, Daffodil International University.

I would like to thank our entire course mate in Daffodil International University, who took part in this discussion while completing the course work.

Finally, I must acknowledge with due respect the constant support and patience of our parents.

ABSTRACT

This study explores the complex interrelationships between gaming and everyday life, looking at how these interactions social dynamics, and cognitive capacities. The lines separating reality from virtual experiences have gotten increasingly hazy as gaming platforms have developed quickly with technology breakthroughs, bringing in a revolutionary era in which gaming is integrated into many facets of our everyday lives. By means of a mobile application, a heterogeneous group of participants, including gamers and non-gamers, will be presented with a sequence of tasks, encompassing puzzles and inquiries, with the aim of evaluating their reactions. The gathered data will be examined using advanced machine learning algorithms to find complex patterns and correlations, providing insight into how people's gaming habits affect their ability. Specifically, their efficiency and special awareness. Ethical considerations will continue to be crucial throughout this investigation in order to protect participant privacy and ensure data integrity. With the goal of providing deep understanding of the various ways that gaming affects daily life, this interdisciplinary approach will help shape future approaches to use gaming's potential to improve their efficiency and awareness to their surroundings and enrich daily experiences.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS

ML	Machine Learning
LR	Logistic Regression
SVM	Support Vector Machine
KNN	K-Nearest Neighbors
GB	Gradient Boosting
RF	Random Forest
DT	Decision Tree

CHAPTER 1

Introduction

1.1 Overview

In recent years, the convergence of gaming with everyday life has emerged as a prominent area of exploration, fueled by rapid advancements in gaming technologies and their integration into various aspects of daily routines. This research delves into the multifaceted relationship between gaming and everyday scenarios, aiming to uncover the diverse impacts and potential improvements from this fusion. As gaming platforms evolve, they transcend their traditional roles, expanding into realms such as education, healthcare, and business. This expansion broadens gaming's scope of influence, blurring the boundaries between virtual experiences and reality, and presenting new opportunities for innovation and optimization.

Gaming significantly impacts cognitive abilities, enhancing problem-solving skills, critical thinking, and spatial awareness. It also fosters social connections, creating communities that enhance communication and collaboration skills. These social dynamics can lead to improved teamwork and creativity in various settings. Moreover, gaming often simulates complex decision-making scenarios, allowing players to practice and refine these skills, which can be applied in professional environments where decision-making under pressure is critical.

This study employs advanced machine learning methodologies to explore the intricate connections between gaming activities and their effects on cognitive and social dynamics. By synthesizing empirical evidence, theoretical frameworks, and computational analyses, the research aims to provide a comprehensive understanding of the nuanced dynamics at play. The interdisciplinary approach bridges gaming, machine learning, and real-world applications, offering valuable insights that elucidate the current landscape. Ultimately, the goal is to inform future strategies for harnessing the potential of gaming to enrich and improve various facets of everyday life experiences, from enhancing learning outcomes in education to fostering innovation in the workplace.

Key ML algorithms that are explored in order to achieve the goal.

Overview of Key Machine Learning Techniques

1. Logistic Regression:
Logistic regression is a statistical method used for binary classification, modeling the probability of a categorical outcome using the sigmoid function. It assumes a linear relationship between the independent variables and the log-odds of the dependent variable. Widely used for its interpretability, it finds applications in fields like medicine and finance.
2. Random Forest:
An ensemble learning technique, Random Forest constructs multiple decision trees during training and combines their outputs for improved accuracy and reduced overfitting. By using methods like bootstrap aggregating and random feature selection, it enhances model robustness and versatility.
3. Gradient Boosting:
This technique builds models sequentially, with each new model correcting errors from previous ones. It uses gradient descent optimization to minimize a loss function, making it effective for both regression and classification tasks. Its focus on error reduction enhances predictive performance.
4. Support Vector Machine (SVM):
SVM is used for classification and regression, excelling in high-dimensional spaces. It finds the optimal hyperplane that separates classes, using kernel functions to handle non-linear relationships. Its ability to maximize margins between classes leads to improved generalization.
5. K-Nearest Neighbors (KNN):
A simple, yet effective, algorithm for classification and regression, KNN operates on the principle that similar data points are near each other. It bases predictions on the 'K' nearest neighbors, making it intuitive and versatile for various applications.

1.2 Background and Present State

Background:
The convergence of gaming with everyday life has been propelled by technological advancements that integrate gaming into various sectors. Historically, gaming was primarily seen as entertainment, but its potential for cognitive development and skill enhancement has gained recognition. Research has shown that gaming can improve spatial awareness, problem-solving skills, and decision-making, leading to its application in fields such as education, healthcare, and business.

Present State:
Currently, gaming is widely acknowledged for its cognitive benefits. Many games are specifically designed to enhance skills like spatial awareness and efficiency. The integration of gaming elements into educational and professional settings has led to

innovative learning and training approaches. However, research continues to explore the depth and breadth of these impacts, focusing on how different game types and durations affect specific cognitive abilities. As gaming technology continues to evolve, its role in everyday life is expanding, presenting new opportunities and challenges for further study.

1.3 Problem Statement

There has been significant work regarding the violent and other effects of gaming in a person. However, the question remains whether all the impacts are horrible or not and also can these effects somehow improve some key behaviors? If we consider two people, one is a gamer, the other one is not, through some puzzles, questions and some reaction tests, we figure out who performs better. If gaming has any impact on a person’s efficiency and effective decision making.

1.4 Objectives

The primary objective of this research is to comprehensively explore the impact of gaming on various facets of everyday life and uncover potential avenues for improvement and optimization. Leveraging advanced machine learning methodologies, the study aims to analyze complex patterns, trends, and correlations within vast datasets to elucidate the nuanced dynamics at play. Specifically, the research seeks to investigate how gaming influences cognitive abilities, problem-solving skills, social interactions, and decision-making processes across diverse scenarios. By amalgamating empirical evidence, theoretical frameworks, and computational analyses, the study endeavors to provide valuable insights that not only elucidate the current landscape but also inform future strategies for harnessing the potential of gaming to enrich and improve daily life experiences. Ultimately, the goal is to contribute to a deeper understanding of the intricate relationship between gaming and everyday life and pave the way for innovative applications and optimizations in this rapidly evolving field.

1.5 Scope and Limitations

This research project focuses on investigating the impact of gaming on various aspects of everyday life, with a specific emphasis on cognitive abilities, social dynamics, and decision-making processes. The scope encompasses both the positive and negative effects of gaming, as well as potential avenues for improvement and optimization. The research will employ advanced machine learning techniques to analyze complex data patterns and correlations, shedding light on the intricate relationship between gaming activities and their influence on daily life scenarios.

Key areas within the project scope include:

1. Focus on Efficiency and Spatial Awareness: The project specifically examines the impact of gaming on efficiency and spatial awareness, exploring how gaming activities influence these cognitive abilities.
2. Targeted Gaming Platforms: The study may involve specific types of games known for enhancing spatial skills, such as puzzle games and strategy-based games.
3. Participant Demographics: The research could focus on a diverse demographic, including different age groups and gaming experience levels, to provide comprehensive insights into how these factors affect outcomes.
4. Social Dynamics: Investigating the impact of gaming on social interactions, communication skills, teamwork, and community engagement.
5. Machine Learning Analysis: Employing machine learning algorithms to analyze large datasets collected from gaming activities and real-life scenarios, identifying patterns, trends, and correlations.
6. Empirical Evidence and Theoretical Frameworks: Synthesizing empirical research findings and theoretical frameworks to provide a comprehensive understanding of the effects of gaming on everyday life.
7. Interdisciplinary Approach: Adopting an interdisciplinary approach that integrates insights from gaming research, psychology, sociology, neuroscience, and machine learning to explore the complex dynamics at play.

Limitations:

1. Narrow Focus: By concentrating only on efficiency and spatial awareness, the study may overlook other cognitive and social benefits of gaming, such as emotional regulation or teamwork.
2. Generalizability: Results may not be applicable to all types of games or gaming platforms, limiting the broader applicability of findings across different gaming genres.
3. Short-Term Analysis: If the study is limited to short-term effects, it may not capture long-term impacts on efficiency and spatial awareness.
4. Controlled Environment: Experiments conducted in controlled environments may not accurately reflect real-world gaming experiences and their effects on cognitive abilities.
5. Subjective Measures: Assessing spatial awareness and efficiency may involve subjective measures, which can introduce bias and affect the reliability of the results.

While the project aims to provide valuable insights into the impact of gaming on everyday life, it acknowledges the inherent complexity of the topic and the need for further research to fully understand the nuances involved. As such, the scope of the project will be focused and targeted, with clear objectives and methodologies outlined to guide the research efforts effectively.

1.6 Report Organization

Report Organization:

The research report will be organized into several key sections, each addressing specific aspects of the study in a logical and structured manner. The proposed organization of the report is as follows:

1. Introduction:

- Includes overview of the research topic and its significance, research objectives and aims and Brief overview of the methodology and scope of the study.

2. Literature Review:

- Includes review of relevant literature on the impact of gaming on everyday life, examination of empirical evidence, theoretical frameworks, and previous research findings. Also, the identification of gaps, controversies, and areas for further exploration

3. Methodology:

- Description of the research design and approach, Explanation of data collection methods and techniques. Along with an overview of the analytical tools and techniques employed, including machine learning methodologies. Also, the Ethical considerations and safeguards implemented throughout the research process.

4. Implementation

This section details the practical execution of the research, including the steps taken to apply the chosen methodologies. It covers the setup of experiments or simulations, data processing, and any challenges encountered during implementation.

5. Result And Analysis

- This section presents the findings of the study, highlighting key data and trends. It includes a comprehensive analysis of the results, using statistical tools and machine learning models, to interpret the impact on efficiency and spatial awareness. Visual aids like charts and graphs may be used for clarity.

6. Impact On Society, Environment and Sustainability
- This section examines the broader implications of gaming on society, discussing both positive and negative effects. It also considers environmental factors and the sustainability of integrating gaming technologies into everyday life, assessing potential long-term impacts.

7. Conclusion And Future Work
- This final section summarizes the main findings and their significance, reflecting on the research objectives. It outlines the limitations of the study and suggests areas for further research, proposing directions for future investigations to build on the current work.

1.7 Summary

This research project explores the evolving relationship between gaming and everyday life, aiming to uncover the multifaceted effects and potential improvements arising from their integration. The study employs advanced machine learning techniques to analyze complex data patterns and correlations, shedding light on the intricate dynamics at play.

The literature review provides a comprehensive overview of existing research, highlighting both the positive and negative impacts of gaming on cognitive abilities, social interactions, and decision-making processes. Building upon this foundation, the methodology section outlines the research design, data collection methods, and analytical tools utilized in the study.

Through empirical analysis, the research aims to generate valuable insights that contribute to a deeper understanding of the transformative power of gaming. By synthesizing empirical evidence, theoretical frameworks, and computational analyses, the study seeks to inform future strategies for leveraging gaming to enrich and improve various facets of everyday life experiences.

Ultimately, the research endeavors to provide actionable recommendations for practitioners, policymakers, and researchers, paving the way for innovative applications and optimizations in this rapidly evolving field.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

The intersection of gaming and machine learning has catalyzed significant progress in diverse fields. Cutting-edge techniques such as signature table methods and alpha-beta pruning have revolutionized game-playing strategies, enabling programs to delve deeper into game trees and enhance their playing abilities. Moreover, the integration of human computation through online games with machine learning algorithms has transformed the annotation of multimedia content. For instance, platforms like Herd It utilize the collective intelligence of crowds to gather reliable music annotations, facilitating the automatic annotation of vast music datasets. This symbiotic relationship between gaming and machine learning not only showcases technological innovation but also holds promise for revolutionizing digital experiences and decision-making processes in various industries.

Additionally, machine learning has found extensive application in cybersecurity, where it aids in defending against adversarial attacks through robust learning techniques grounded in game theory principles. In the realm of sports analytics, machine learning algorithms play a pivotal role in predicting game outcomes with remarkable accuracy, thereby informing decision-making processes related to team management and recruitment. Beyond entertainment, machine learning-driven interactive gaming interfaces leverage motion-driven systems to provide players with customizable sensor-based controls, enhancing their gaming experiences. This convergence of gaming and machine learning underscores the transformative potential of these technologies in reshaping industries and driving innovation forward.

2.2 Related Works

Gaming is among the most engaging and rewarding activities in everyday life. Games and education have enjoyed a long history together. It has long been believed that the origin of games may lie in training simulations conducted by our most remote ancestors. Games are a way of knowing the world, a mediation between experience and understanding. Their existence in recorded throughout history with roots in our most fundamental practices. Games are common throughout human culture. In recent years, scientific but also public interest in using games for serious purposes increased dramatically and there is accumulating evidence that serious games successfully promote learning in various scenarios. Video games are at the center of a debate over what is helpful or harmful to children and adolescents, and there is research to substantiate both sides. It is well known that exposing an organism to an altered visual environment often results in modification of the visual system of the organism. Typical impressions regarding video games, the effects of playing video games, and of gamers themselves, are largely negative. These impressions are oversimplified at best, and simply wrong, at worst. The recent advancements in machine learning (ML) techniques have led to significant improvements in various domains, including game-playing algorithms, multimedia content annotation, cybersecurity, sports analytics, and interactive gaming interfaces. One notable advancement is the development of a new signature table technique and an improved book learning procedure, which surpasses the traditional linear polynomial method, particularly in game-playing scenarios such as checker games. By employing alpha-beta pruning and forward pruning techniques, this approach allows programs to explore deeper levels of game trees, enhancing their playing abilities while still falling short of defeating master players. Additionally, the integration of human computation through online games with ML algorithms has revolutionized the annotation of multimedia content. For instance, the Herd It music annotation game harnesses the wisdom of crowds to collect reliable music annotations, which are then used to train supervised ML systems for automatic annotation of large music datasets. This game-powered ML approach provides a scalable and reliable method for making massive amounts of multimedia data searchable. Furthermore, ML finds extensive application in cybersecurity, where it addresses the challenges posed by adversarial attacks through robust learning techniques grounded in game theory principles. These techniques enable learning systems to anticipate and defend against malicious activities effectively. In the realm of sports analytics, ML algorithms, including ensemble methods and support vector machines, are employed to predict game outcomes in the National Hockey League (NHL) with high accuracy, aiding in decision-making processes related to team management and recruitment. Moreover, ML-driven interactive gaming interfaces leverage motion-driven music systems to enhance player experiences by enabling the development of customizable sensor-based controls in video game systems. Beyond entertainment, ML algorithms are increasingly being applied in serious games, where they facilitate decision-making and learning processes, offering players immersive and realistic experiences. However, despite these advancements, challenges remain, particularly in understanding defensive deception strategies in cybersecurity and optimizing ML algorithms for predicting match winners in esports, such as the Dota 2 computer game. Overall, these diverse applications underscore the profound impact of ML on various industries and highlight the ongoing efforts to overcome existing challenges and push the boundaries of innovation in the field.

2.3 Comparison between existing works

The comparative analysis presented in Table 1 highlights the diverse range of algorithms

utilized in previous studies and their corresponding best accuracy results.

Table 2.3.1: Comparison between existing works

SL No	Author Name	Used Algorithm	Best Accuracy with Algorithm
1.	A. L. Samuel [1]	Book Learning, Linear Polynomial Evaluation, Signature Tables, Smoothing Techniques.	___________
2.	Pers et al. [2]	Random Forest	SVM= 83%
3.	Barrington et al. [3]	Decision Tree, Support Vector Machine, Random Forest, Logistic Regression	Random Forest=94.9%
4.	Gu et al. [4]	Support Vector Machine (SVM) Ensemble methods	SVM 94.05%
5.	Zhou et al. [5]	Support Vector Machine (SVM): generative adversarial networks (GANs)	_______
6.	Ninaus et al. [6]	Support Vector Machine (SVM)	SVM 64.18%
7.	M. Frutos-Pascual and B. G. Zapirain [7]	Naive Bayes Classifier Artificial Neural Networks (ANNs)	________

		support Vector Machines (SVMs)	
8.	C. G. Diaz et al.[8]	k-nearest neighbor (k-NN) Multilayer Perceptron (MLP) Neural Networks Dynamic Time Warping (DTW)	________
9.	Zhu [9]	ML-based Defensive Deception Techniques Probabilistic Models	________
10.	Semenov et al. [10]	Naive Bayes classifier, Logistic Regression, Factorization Machines, Gradient Boosting of Decision Trees	Factorization Machines 67%

2.4 Open Issues

Gaming's potential to enhance various aspects of a person's life is a subject of significant debate and research. Here's an analysis of the potential gaps in the argument that gaming can improve someone:

1. Limited Generalization: While some studies suggest that gaming can enhance cognitive functions such as problem-solving, spatial awareness, and decision-making, it's essential to recognize that these benefits may not apply universally. The effects of gaming can vary based on the individual, the type of game, the frequency of play, and other factors. Therefore, generalizing the positive impact of gaming on everyone may overlook individual differences.

2. Context Matters: The impact of gaming on individuals depends heavily on the context in which it occurs. For example, educational games designed to teach specific skills may have different effects compared to recreational games played purely for entertainment. Additionally, the social environment surrounding gaming, such as interactions with peers or family members, can influence its effects on an individual. Ignoring these contextual factors can oversimplify the relationship between gaming and personal improvement.

3. Long-term Effects: While short-term studies may demonstrate immediate cognitive benefits of gaming, there is limited research on the long-term effects. It's unclear whether the cognitive skills enhanced through gaming translate into real-world benefits over time. Longitudinal studies that track individuals' gaming habits and outcomes over extended periods are needed to better understand the lasting impact of gaming on personal development.

4. Individual Differences: People vary widely in their preferences, motivations, and responses to gaming. What may be beneficial for one person could be detrimental to another. Factors such as age, personality, underlying mental health conditions, and cultural background can influence how gaming affects an individual. Therefore, any analysis of gaming's potential to improve someone should account for these individual differences.

Addressing these gaps requires a nuanced approach that considers both the potential benefits and drawbacks of gaming, acknowledges individual differences, and recognizes the importance of context in shaping the relationship between gaming and personal development. Although Significant work has been done in order to calculate the negative effects of gaming in an individual also to check whether gaming has positive effects on a person. No significant work has been conducted on the premises that gaming may improve someone’s quality and how much they may benefit over a person that does not play games on a regular basis.

2.5 Summary

The synergy between gaming and machine learning has spurred remarkable advancements across various domains. Techniques like signature table methods and alpha-beta pruning have enhanced game-playing algorithms, while the integration of human computation with machine learning has streamlined multimedia content annotation. In cybersecurity, machine learning defends against adversarial attacks using game theory principles, while sports analytics benefits from accurate outcome predictions. Interactive gaming interfaces leverage motion-driven systems to customize player experiences. This convergence signifies not only technological progress but also the potential for transformative innovation across industries.

CHAPTER 3
METHODOLOGY

3.1 Overview

The objective of this research paper is to delve into the intricate relationship between gaming and decision-making skills in everyday life scenarios. By investigating the influence of gaming on cognitive abilities, this study aims to shed light on whether gaming has some positive effects individuals' performance in real-life situations.

3.2 Proposed Methodology

The proposed methodology involves collecting data using google forms which will have a range of questions designed to determine a person's efficiency and special awareness. Measures will be implemented to ensure data privacy and obtain informed consent from participants. The machine learning algorithms that are used on the given data are Linear Regression, SVM, Random Forest, Gradient boosting and KNN. As SVM is used for classification, regression and outliers' detection it will create the boundary between a gamer and a non-gamer.

The following figure shows the workflow diagram.

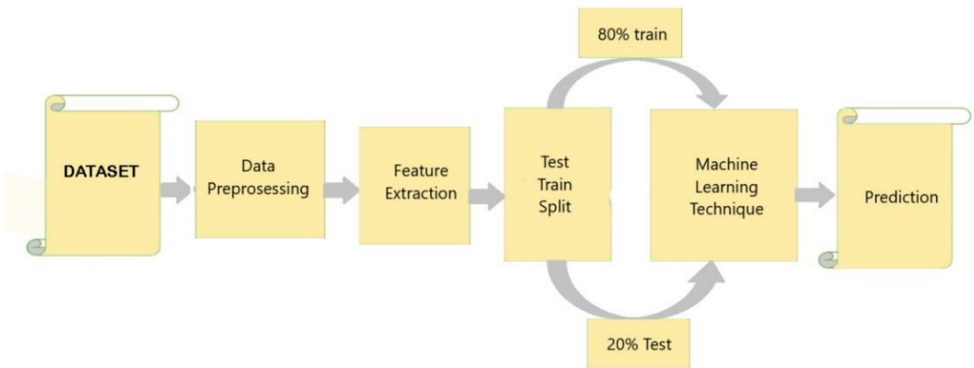


Figure 3.3.1: Workflow Diagram

3.3 Data Collection

The data for this study was collected through a survey administered to over 400 individuals in Bangladesh. The survey consisted of 29 multiple choice questions designed to assess a persons spacial awareness and their efficiency in everyday life. The questionnaire was distributed using Google Forms, ensuring ease of access and convenience for respondents.

There were 24 questions which were text based statements that people can respond and 5 were puzzle based. The specific text based questions included:

1. I prioritize tasks effectively to ensure important deadlines are met.
2. I am able to complete tasks within the allocated time frame.
3. I efficiently allocate resources (time, money, materials) to accomplish tasks
4. I am proactive in identifying and resolving inefficiencies in workflows or processes.
5. I am adaptable and can quickly adjust to changing priorities or circumstances.
6. I communicate effectively with colleagues or team members to ensure smooth workflow.
7. I use technology and tools to streamline workflows and increase productivity
8. I am skilled at breaking down complex tasks into smaller, manageable steps to facilitate completion.
9. I am able to multitask effectively without sacrificing the quality of my work.
10. I am organized and maintain a clear and efficient workspace
11. I am able to focus on tasks without getting easily distracted.
12. I am able to maintain a healthy work-life balance, ensuring that I am productive while also taking time for self-care and relaxation.
13. I have a strong sense of direction and rarely get lost in unfamiliar environments.
14. I am skilled at estimating distances between objects or locations without the use of measuring tools.
15. I find it easy to visualize objects or spaces in three dimensions (e.g., mentally rotating objects, understanding spatial relationships).
16. I am skilled at recognizing patterns and shapes in my environment.
17. I rarely bump into objects or misjudge distances when walking or moving around.
18. I enjoy activities that require spatial reasoning, such as puzzles, mazes, or building models.
19. I am comfortable using maps or navigation systems to find my way in unfamiliar places
20. I have a good sense of scale and proportion, which helps me visualize how objects or spaces relate to each other.
21. I can quickly adapt to changes in my environment and navigate efficiently in different settings.

22. I am skilled at judging heights, depths, and spatial dimensions accurately.
23. I have a good memory for landmarks and key locations in my environment.
24. I am skilled at assembling or disassembling objects, following diagrams or instructions

There were 5 options to each inquiry:

1. Strongly Disagree
2. Disagree
3. Neutral
4. Agree
5. Strongly Agree

This range of inquiries were designed to understand and assess their capabilities.

3.4 Hardware/ Software Requirement

In order to accomplish the research objectives, a comprehensive analysis of requirements is conducted. As for the hardware specifications, it is required to have a PC containing minimum 8GB RAM, as for software google colab would be used for running the diagnosis or the ML algorithm and google forms will be used for collecting the data. For the analysis as to how to measure these aspects or changes in a person's behavior an outside consultation was required which shall be obtained by consulting with multiple psychology students.

3.5 Project Management and Financial Analysis

Project Management:

- **Objectives:**
  I. To understand the effects of regular gaming on a person compared to a person who does not play games regularly.
- **Timeline:**
  I. Phase 1: Planning, research, Data collection.
  II. Phase 2: Data Processing, Splitting, Selecting Algorithm to predict result, Applying algorithm, Analysis and Result.
- **Resource Planning:**
  I. **Tools:** Google form, Google colab.
  II. **Data Collection:** Data is collected from a google form that has different questions and puzzles for the purpose.

Table 3.5.1: Estimated Cost for Machine Learning based Project

SN	Components	Estimated Cost (BDT)
01.	Visiting Stakeholders	500-1000
02.	Data Collection and Processing	4000-5000
03.	Documentation and Report Writing	500-1000
Total Estimated Cost		5000-7000

3.6 Summary

In summary, this paper aims to provide valuable insights into the impact of gaming on decision-making skills in everyday life. By leveraging machine learning techniques and a structured research approach, the study seeks to advance our understanding of the relationship between gaming and cognitive abilities, informing future research, practice, and policy in this field.

CHAPTER 4
IMPLEMENTATION

4.1 Overview

The machine learning model training process was meticulously executed to develop a robust predictive model. Data was collected through carefully designed Google Forms, focusing on questions that assessed individual abilities, integrating both quantitative and qualitative data into a comprehensive dataset. Rigorous data quality checks addressed missing values, outliers, and inconsistencies, ensuring that the dataset was clean and reliable for model training. During data preprocessing, numerical features were normalized or standardized to prevent certain variables from dominating the training process, while categorical variables were encoded into suitable numerical formats.

Feature selection was conducted using correlation analysis and feature importance scores, enhancing model performance by focusing on the most impactful variables. Appropriate machine learning algorithms were chosen based on the problem's nature and specific requirements like interpretability and computational efficiency. The dataset was then split into training and test sets, allowing the model to learn patterns from the training data. Evaluation metrics, including accuracy, precision, and recall, confirmed the model's effectiveness. Iterative optimization refined feature selection, preprocessing steps, and hyperparameters, improving accuracy and generalizability. Comprehensive documentation throughout the process ensured transparency and reproducibility of results.

The model evaluation phase was critical in assessing the performance and generalizability of the trained models. A range of metrics and methods provided a comprehensive understanding of the model's performance. The confusion matrix offered detailed insights into different types of errors and model accuracy, while metrics like accuracy, precision, and recall provided straightforward assessments of overall performance. The F1-score balanced precision and recall, offering a single performance score, particularly useful when both metrics needed equal weighting.

Graphical tools like the ROC curve and precision-recall curve aided in assessing classification performance across different decision boundaries, especially in imbalanced datasets. Confidence intervals were calculated around metrics such as accuracy, precision, recall, and F1-score to understand the stability and reliability of the model's performance.

This thorough evaluation confirmed the model's accuracy, reliability, and effectiveness across various conditions and data subsets, ensuring its readiness for practical application.

4.2 Train Model

The machine learning model will be trained through the following steps:

1. Data Collection:
   - Source Gathering: Gathered data from a carefully created google form that comprises of questions that would leave a decent assessment of individuals abilities.
   - Data Integration: Integrated data includes both quantitative and qualitative information.
   - Data Quality Assurance: Performed checks to ensure data quality, addressing issues like missing values, outliers, or inconsistencies that could affect model training.
2. Data Preprocessing:
   - Cleaning: Handled missing data through imputation techniques or deletion if appropriate. Removed outliers that could skew the model's learning process.
   - Normalization/Standardization: Scaled numerical features to a standard range to prevent variables with larger ranges from dominating the model training process.
   - Encoding: Converted categorical variables into numerical representations (e.g., one-hot encoding) suitable for ML algorithms that require numerical input.
3. Feature Selection:
   - Importance Assessment: Analyzed the relevance of features through methods like correlation analysis, feature importance scores from tree-based models, or domain expertise.
4. Model Selection:
   - Algorithm Choice: Selected appropriate ML algorithms based on the nature of the problem and the characteristics of the data. As this is a classification task, the selected models are: Logistic Regression, Decision Tree, Random Forest, SVM, Gradient Boosting, KNN.
   - Consideration of Requirements: Considered factors like interpretability, scalability, and computational efficiency when choosing algorithms suitable for the research objectives and dataset size.
5. Training:
   - Dataset Splitting: Divided the dataset into training and test sets. The training set is used to train the model and the test set to evaluate final model performance.
   - Model Fitting: Trained the selected ML model on the training data, where the algorithm learns patterns and relationships between input features and target variables.

6. Evaluation:
- Performance Metrics: Assessed model performance using appropriate evaluation metrics such as accuracy, precision, recall and mean squared error (MSE), R-squared (R^2) for regression.

7. Testing:
- Generalization Testing: Evaluated the trained model on the independent test dataset not used during training or validation to assess its ability to generalize to new, unseen data.
- Performance Verification: Verified that the model performs adequately across different subsets of the data and under various conditions to confirm its reliability.

8. Optimization:
- Iterative Refinement: Iteration was performed on feature selection, preprocessing steps, model architecture, and hyperparameter tuning based on evaluation results to improve model accuracy and generalizability.
- Documentation: Maintained documentation of each step, including data preprocessing decisions, model configurations, and evaluation outcomes, to ensure transparency and reproducibility of results.

4.3 Model Evaluation

Model evaluation is a critical phase in machine learning that assesses the performance and generalizability of trained models. It involves several key steps and considerations:

Evaluation methods for classification models typically focus on assessing how well the model predicts the classes of the target variable. Here are some common evaluation metrics used in this classification task:

1. Confusion Matrix: A table that summarizes the performance of a classification model. It shows the counts of true positive, true negative, false positive, and false negative predictions.
2. Accuracy: The proportion of correctly predicted instances (both true positives and true negatives) out of the total number of instances.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}}$$

3. Precision: The proportion of correctly predicted positive instances (true positives) out of all predicted positive instances (true positives + false positives).

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}}$$

4. Recall (Sensitivity): The proportion of correctly predicted positive instances (true positives) out of all actual positive instances (true positives + false negatives).

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}}$$

5. F1-score: The harmonic mean of precision and recall. It balances both metrics and provides a single score that represents the model's performance.

$$\text{F1} - \text{score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

6. ROC Curve (Receiver Operating Characteristic Curve): A plot that illustrates the performance of a binary classifier system as its discrimination threshold is varied. It plots the true positive rate (Recall) against the false positive rate (1 - Specificity).
7. Precision-Recall Curve: A plot of precision versus recall at various thresholds. It is useful when dealing with imbalanced datasets where one class dominates the other.

4.4 Summary

The machine learning section of the paper outlines the rigorous process used to develop a predictive model. It covers data collection from Google Forms, thorough data quality checks, preprocessing steps like normalization and encoding, and strategic feature selection. The chosen algorithms were tailored to fit the problem, and the model's performance was evaluated using metrics such as accuracy, precision, and recall. Iterative optimization refined the model, with documentation ensuring transparency. This section underscores the methodical approach to building a robust and applicable predictive model.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

This section presents the experimental results of applying multiple machine learning algorithms to classify individuals based on their abilities. The study evaluates the performance of Logistic Regression, KNN, Decision Trees, Random Forest, Gradient Boosting, and SVM using metrics such as accuracy, precision, recall, and F1-score. Each algorithm's capability to classify data is analyzed, providing insights into their effectiveness in the context of the research objectives. Additionally, hypothesis testing through feature importance analysis is conducted to validate the relationship between gaming and individuals' abilities. Comparative analysis among the models further elucidates their strengths and weaknesses, aiding in the selection of the most suitable algorithm for the classification task. The findings contribute to understanding how different machine learning approaches perform in assessing and predicting individual abilities based on the dataset's characteristics.

5.2 Experimental Result

It refers to the outcomes and findings obtained from conducting experiments or tests within a research study. In the context of this machine-learning model, experimental results include data, measurements, and analyses that illustrate how well a proposed model, hypothesis, or methodology performed

5.2.1: Model performance:

The models that are used in this research are:

i. Logistic regression
ii. Random Forest
iii. Gradient Boosting
iv. SVM
v. Decision Trees
vi. KNN

Multiple factors were considered figuring out the proper algorithm that needs to be used.

Performance Metrics: To be able to determine the effectiveness of an algorithm we have chosen some performance metrics. They are

1. Accuracy
2. Precision
3. Recall
4. F1-Score

The results of performance metrics and Classification report are as follows:

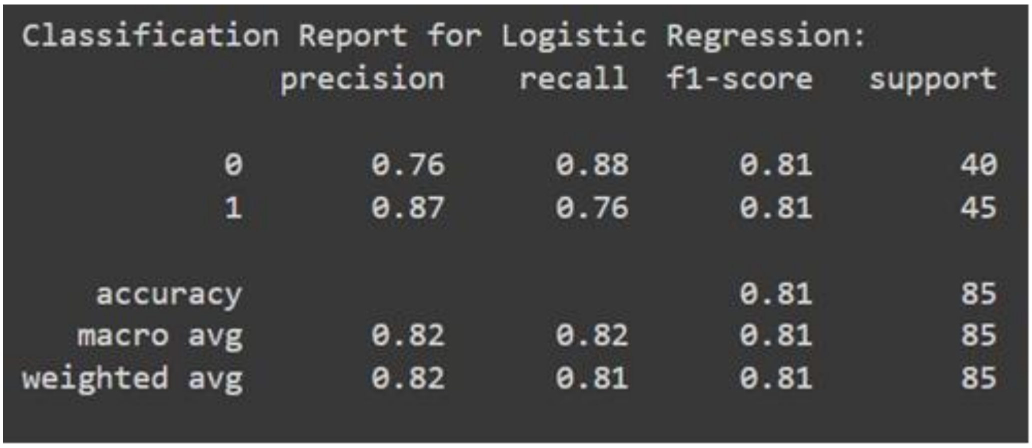
Logistic Regression:

1. Performance Metrics for LR:

Table 5.2.1.1 : Performance Metrics of Logistic Regression

Logistic regression			
Accuracy 81.17	Precision 0.87	Recall 0.75	F1-Score 0.80

2. Classification Report:



Classification Report for Logistic Regression:

	precision	recall	f1-score	support
0	0.76	0.88	0.81	40
1	0.87	0.76	0.81	45
accuracy			0.81	85
macro avg	0.82	0.82	0.81	85
weighted avg	0.82	0.81	0.81	85

Figure 5.2.1.1: Classification Report: Logistic Regression

3. Interpretation: From the table and the figures given above it can be clear that Logistic regression can properly classify the given data with 81% accuracy.

KNN:

1. Performance Metrics for KNN:

Table 5.2.1.2 : Performance Metrics of KNN

KNN			
Accuracy 84.70	Precision 0.9	Recall 0.8	F1-Score 0.84

2. Classification Report:

```
Classification Report for K-Nearest Neighbors:
              precision    recall  f1-score   support

           0       0.80      0.90      0.85        40
           1       0.90      0.80      0.85        45

    accuracy                           0.85        85
   macro avg       0.85      0.85      0.85        85
weighted avg       0.85      0.85      0.85        85
```

Figure 5.2.1.2: Classification Report: KNN

3. Interpretation: From the table and the figures given above it can be clear that KNN can properly classify the given data with 85% accuracy.

Decision Trees:

1. Performance Metrics for DT:

Table 5.2.1.3 : Performance Metrics of Decision Trees

Decision Trees			
Accuracy 89.41	Precision 0.92	Recall 0.86	F1-Score 0.89

2. Classification Report:

```
Classification Report for Decision Tree:
              precision    recall  f1-score   support

           0       0.86      0.93      0.89        40
           1       0.93      0.87      0.90        45

    accuracy                           0.89        85
   macro avg       0.89      0.90      0.89        85
weighted avg       0.90      0.89      0.89        85
```

Figure 5.2.1.3: Classification Report: Decision Trees

3. Interpretation: From the table and the figures given above it can be clear that Decision Trees can properly classify the given data with 89% accuracy. The confusion metrics denotes that number of False-Negative is 3 and number of False-Positive is 6. Meaning this also is a good classification model.

Random Forest:

1. Performance Metrics for RF:

Table 5.2.1.4 : Performance Metrics of Random Forest

Random Forest			
Accuracy 90.58	Precision 0.93	Recall 0.88	F1-Score 0.90

2. Classification Report:

```
Classification Report for Random Forest:
              precision    recall  f1-score   support

           0       0.88      0.93      0.90        40
           1       0.93      0.89      0.91        45

    accuracy                           0.91        85
   macro avg       0.91      0.91      0.91        85
weighted avg       0.91      0.91      0.91        85
```

Figure 5.2.1.4: Classification Report: Random Forest

3. Interpretation: From the table and the figures given above it can be clear that Random Forest can properly classify the given data with 91% accuracy.

Gradient Boosting:

1. Performance Metrics for GB:

Table 5.2.1.5 : Performance Metrics of Gradient Boosting

Gradient Boosting			
Accuracy 90.58	Precision 0.93	Recall 0.88	F1-Score 0.90

2. Classification Report:

```
Classification Report for Gradient Boosting:
              precision    recall  f1-score   support

           0       0.88      0.93      0.90        40
           1       0.93      0.89      0.91        45

    accuracy                           0.91        85
   macro avg       0.91      0.91      0.91        85
weighted avg       0.91      0.91      0.91        85
```

Figure 5.2.1.5: Classification Report: Gradient Boosting

3. Interpretation: From the table and the figures given above it can be clear that Gradient Boosting can properly classify the given data with 91% accuracy.

SVM:

1. Performance Metrics for SVM:

Table 5.2.1.6 : Performance Metrics of SVM

SVM			
Accuracy	Precision	Recall	F1-Score
91.76%	0.95	0.88	0.91

2. Classification Report:

```
Classification Report for Support Vector Machine:
              precision    recall  f1-score   support

           0       0.88      0.95      0.92        40
           1       0.95      0.89      0.92        45

    accuracy                           0.92        85
   macro avg       0.92      0.92      0.92        85
weighted avg       0.92      0.92      0.92        85
```

Figure 5.2.1.6: Classification Report: SVM

3. Interpretation: From the table and the figures given above it can be clear that SVM can properly classify the given data with 92% accuracy.

5.2.2: Hypothesis Testing:

The test mainly dives into whether the selected categories clearly identifies the persons abilities and to check whether their abilities are improved compared to someone who does not play games on a regular basis. For the hypothesis testing, we have performed a feature importance testing. What the feature importance testing tells us is that which feature are most important when it comes to classifying them. As the classification accuracy is high, the feature that is most important will be able to create a standard as to whether the hypothesis is true or not. Once the feature is selected we can see which group has the most amount of person with that feature, that will determine whether the hypothesis is right or wrong. If the Most important feature is mostly available in gamer that will mean the hypothesis is right.

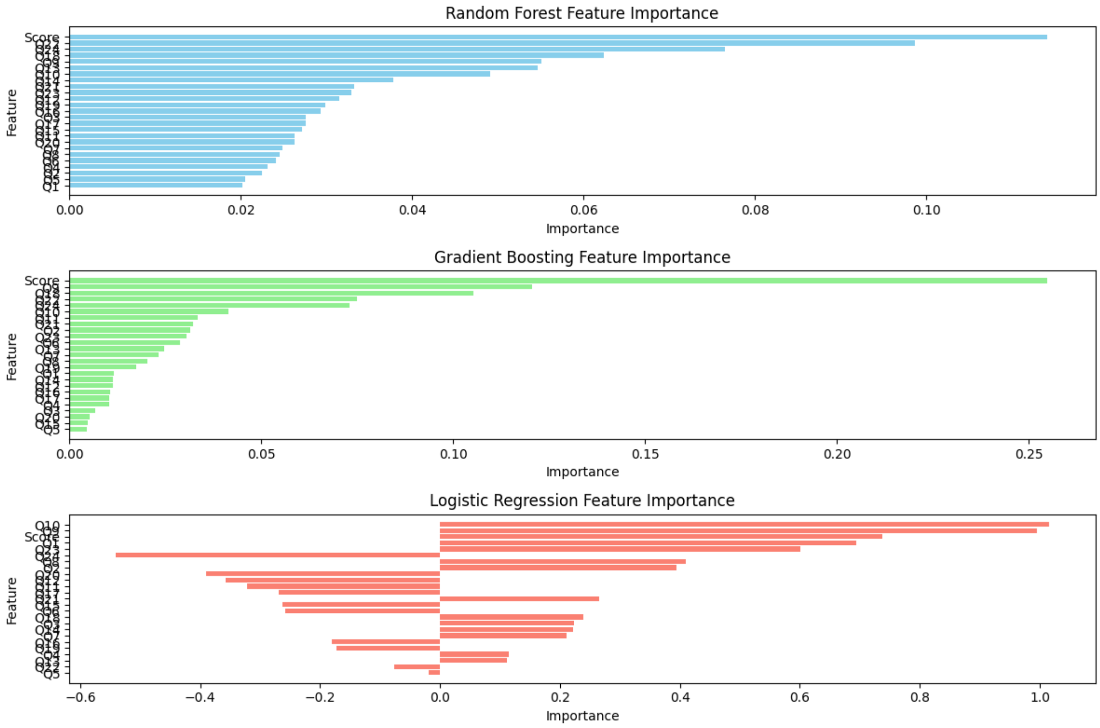


Figure 5.2.2.1 : Feature Importance

It can be determined that the most important feature here is the score. As we explore the database to figure out other possible ways to test the hypothesis, we have implemented a scoring system, along with a statistical analysis, which will further support the hypothesis. The results:

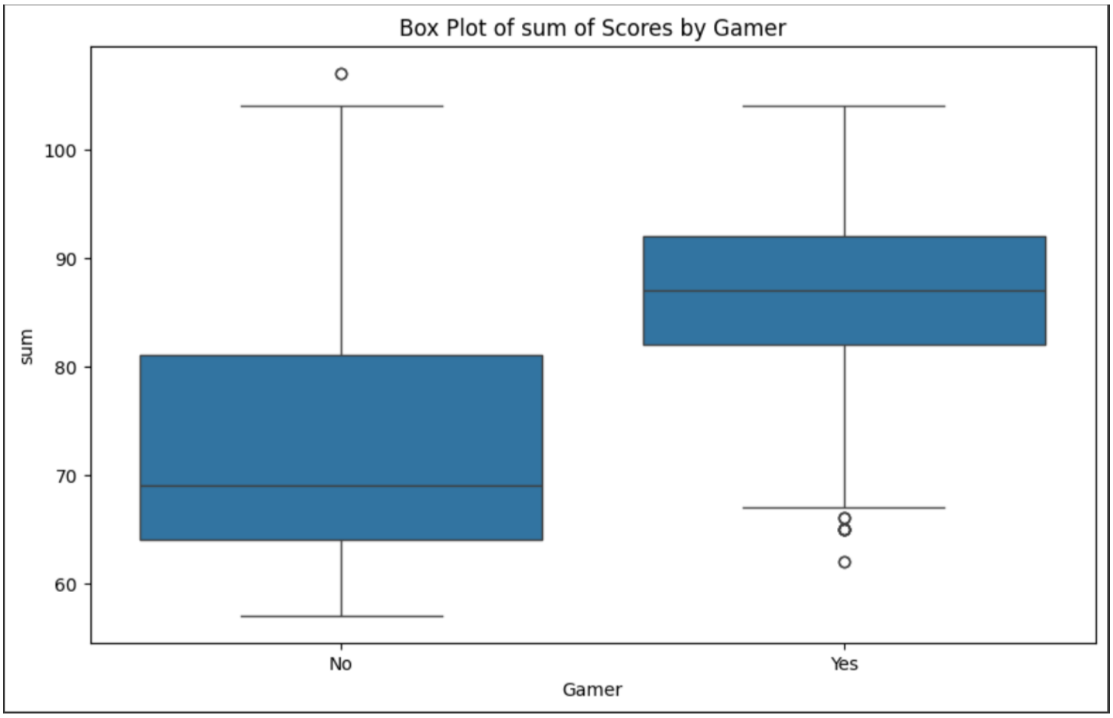


Figure 5.2.2.2 : Box plot of sum of score

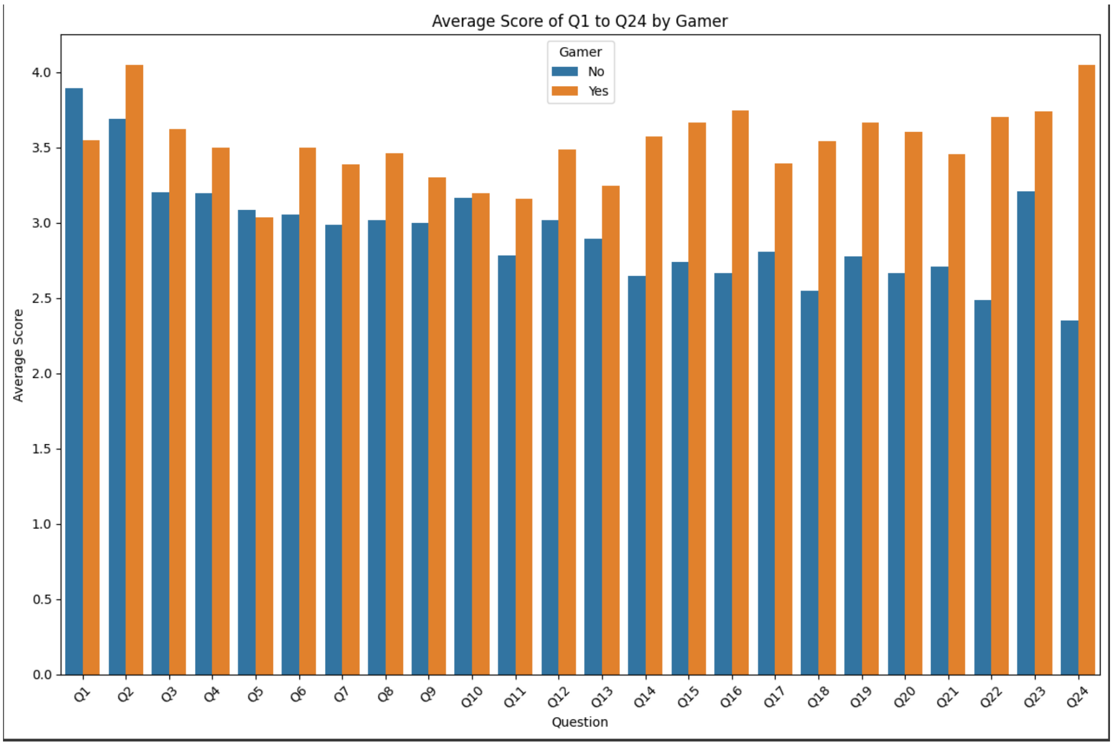


Figure 5.2.2.3 : Average score plot

The plots here analyzes that the score feature is high among the gaming class. Which proves the hypothesis.

5.3 Comparative Analysis

Comparative analysis is a method used to compare different entities, phenomena, or approaches to identify similarities, differences, strengths, and weaknesses. As there are several performance metrics here that determine the result for each algorithm. There is also other methods to compare among the selected algorithms.

1. Accuracy
2. Precision
3. Recall
4. F1-Score
5. Confusion matrix:
6. ROC Curve
7. Precision-recall curve

Accuracy: A comparison of the accuracy of different models suggest that SVM has an accuracy of 92%. With Random forest and Gradient boosting both having an accuracy of 91%. So, based on that SVM is the best model for accuracy.

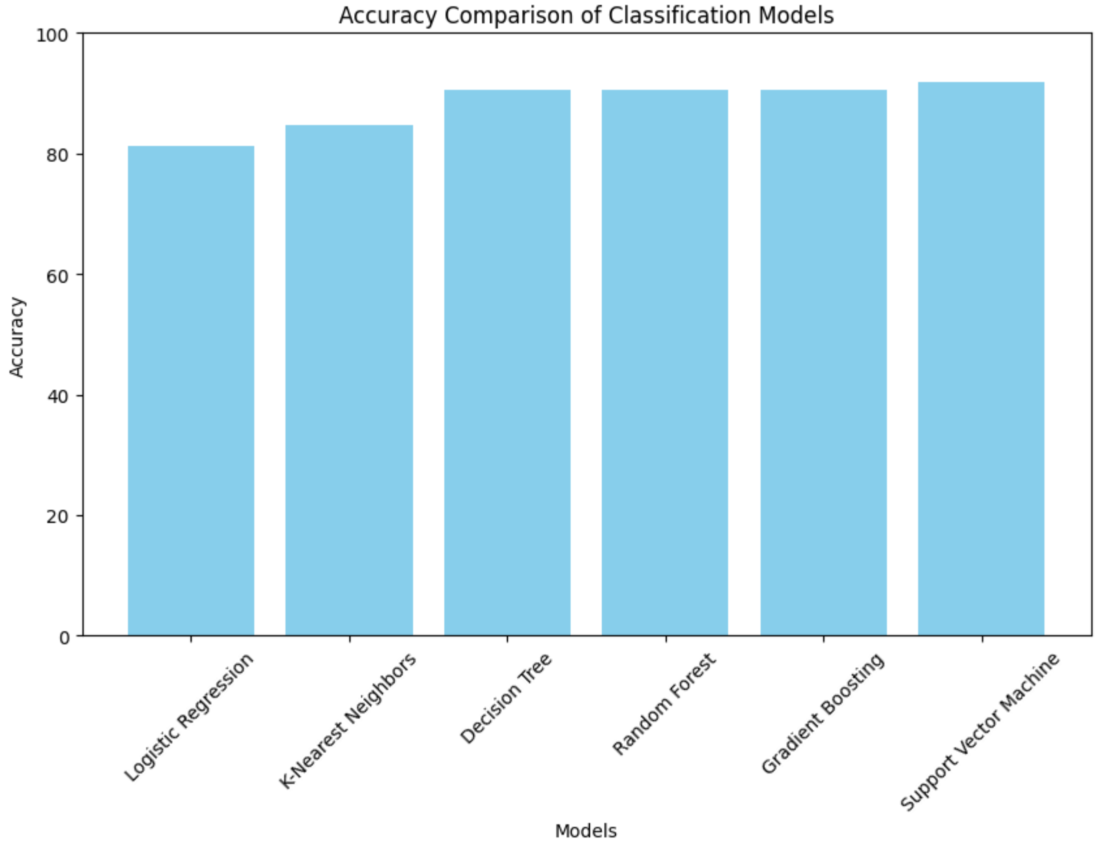


Figure 5.3.1 : Accuracy Comparison

Precision: A comparison of the precision of different models suggest that SVM has an precision of 0.95. With Random forest and Gradient boosting both having an precision of 0.93. So, based on that SVM is the best model for precision.

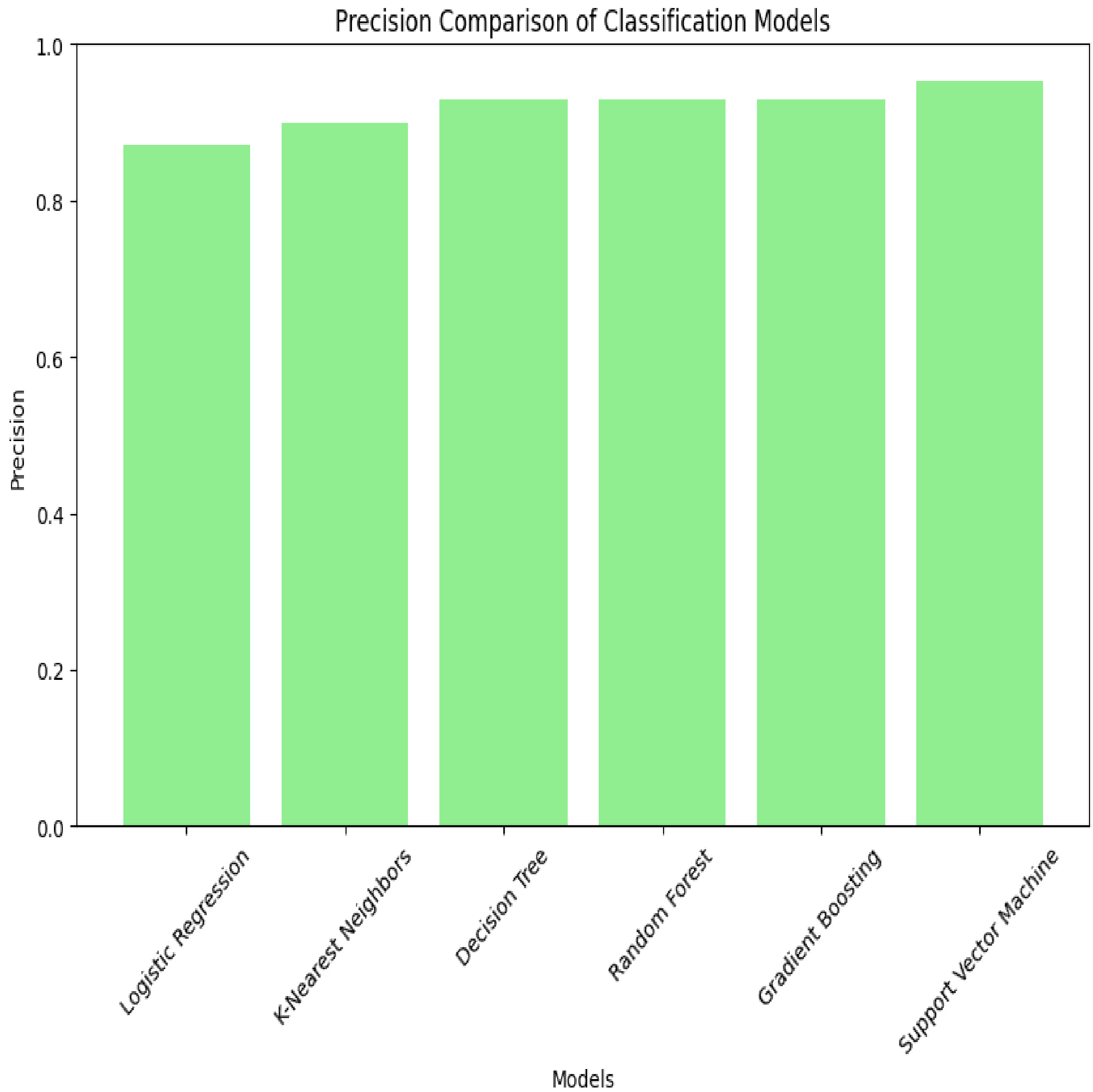


Figure 5.3.2 : Precision Comparison

Recall : A comparison of the recall of different models suggest that SVM, Random forest and Gradient boosting all having an recall of 0.88. So, based on that any of the models can be selected for this metric.

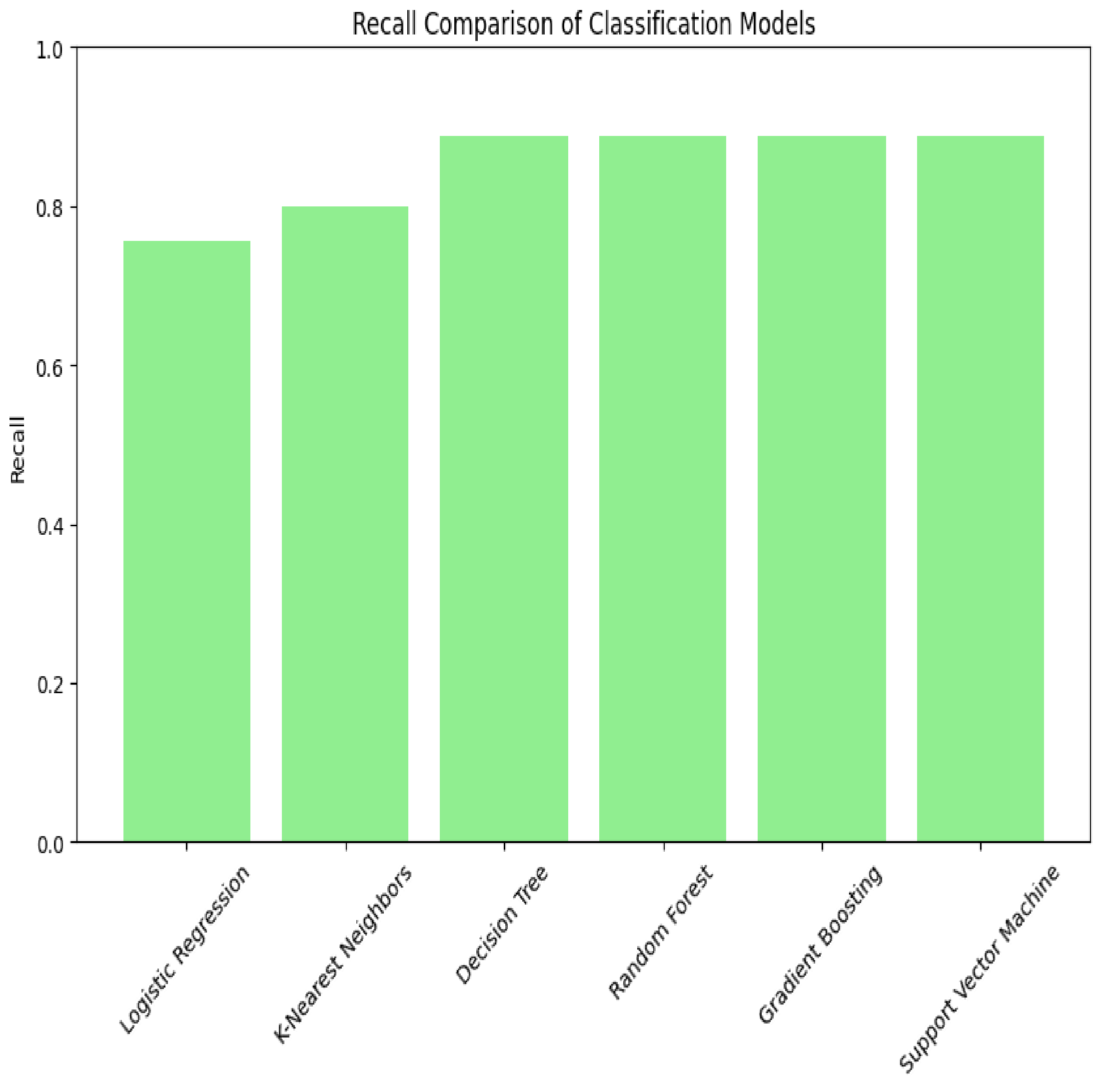


Figure 5.3.3 : Recall Comparison

F1-Score : A comparison of the F1-Score of different models suggest that SVM has an F1-Score of 0.91. With Random Forest and Gradient boosting both having an F1-Score of 0.90. So, based on that SVM is the best model for F1-Score.

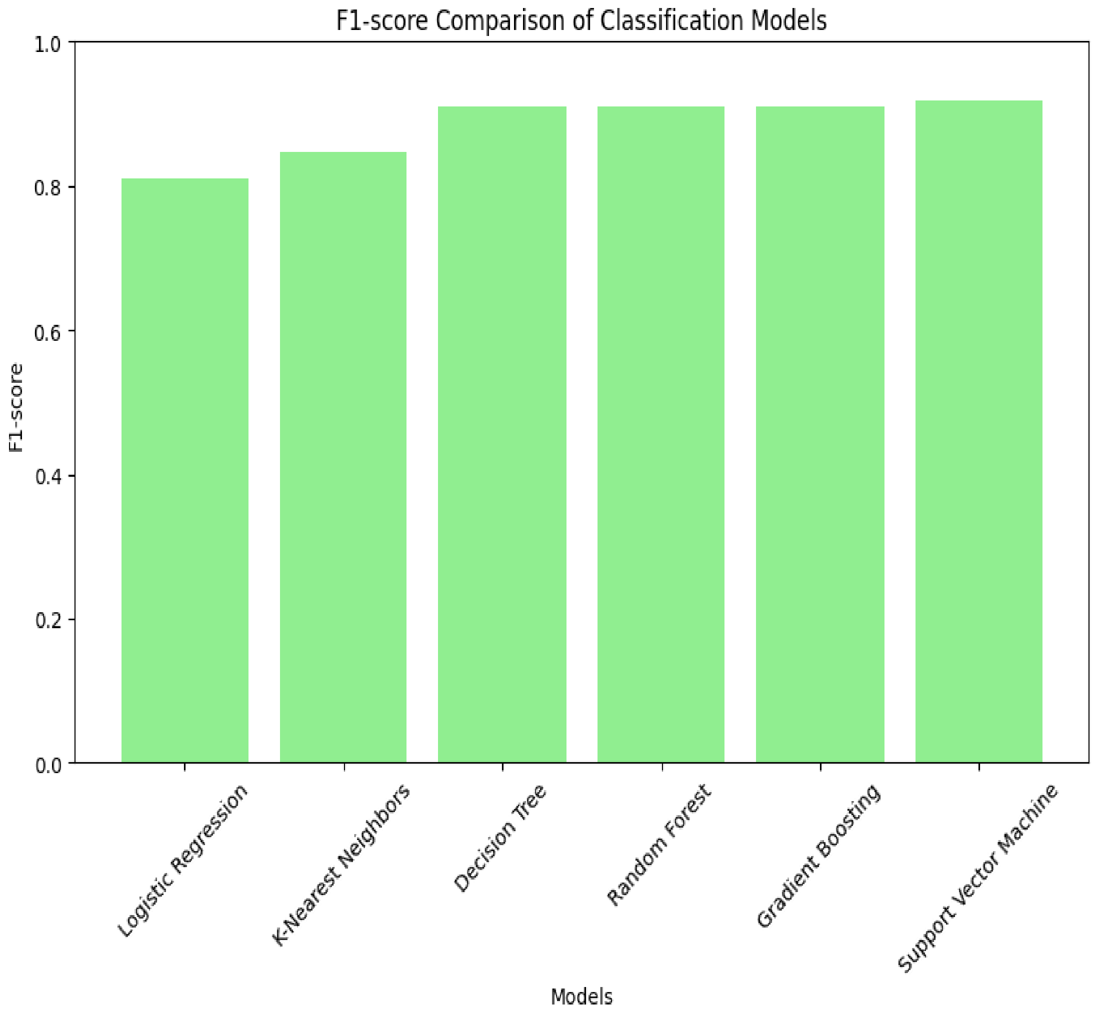


Figure 5.3.4 : F1-Score Comparison

Confusion Matrix:

In a confusion matrix, the lower the number of false-positive and false-negative, the better the model is performing.

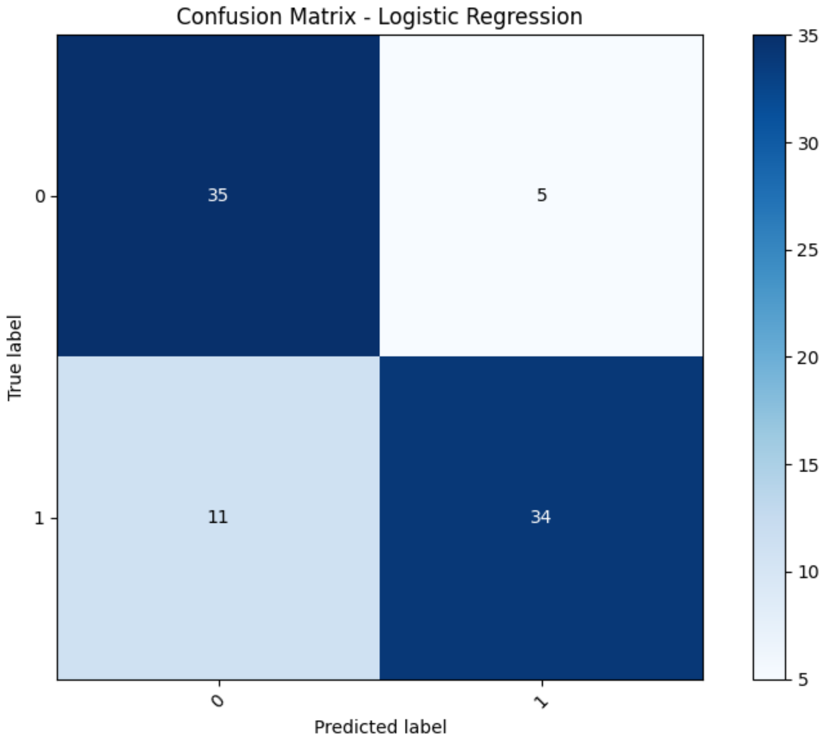


Figure 5.3.5 : Confusion Matrix: Logistic Regression

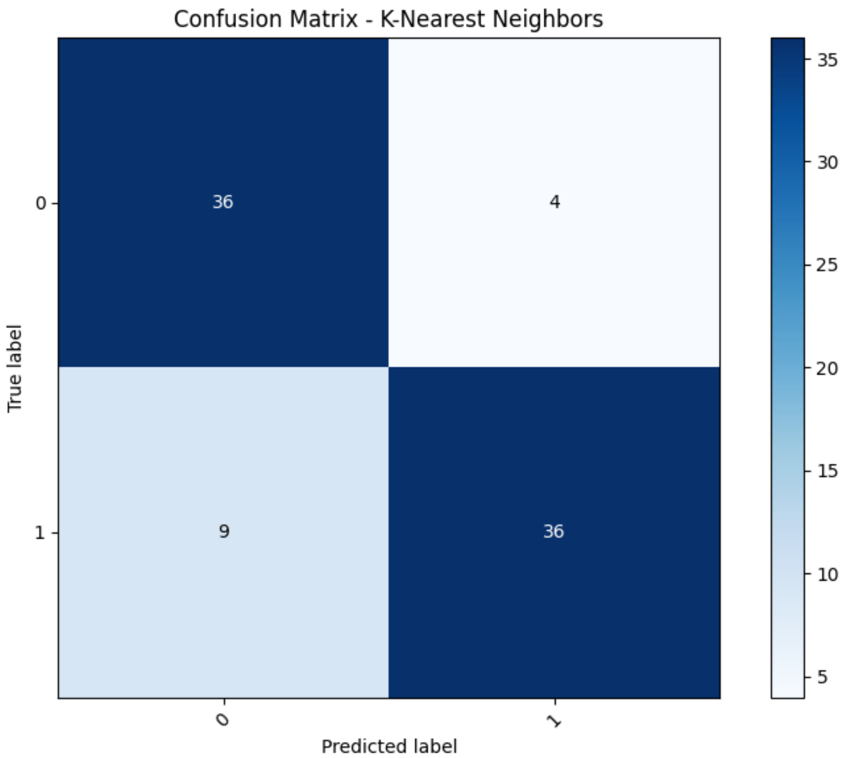


Figure 5.3.6 : Confusion Matrix: KNN

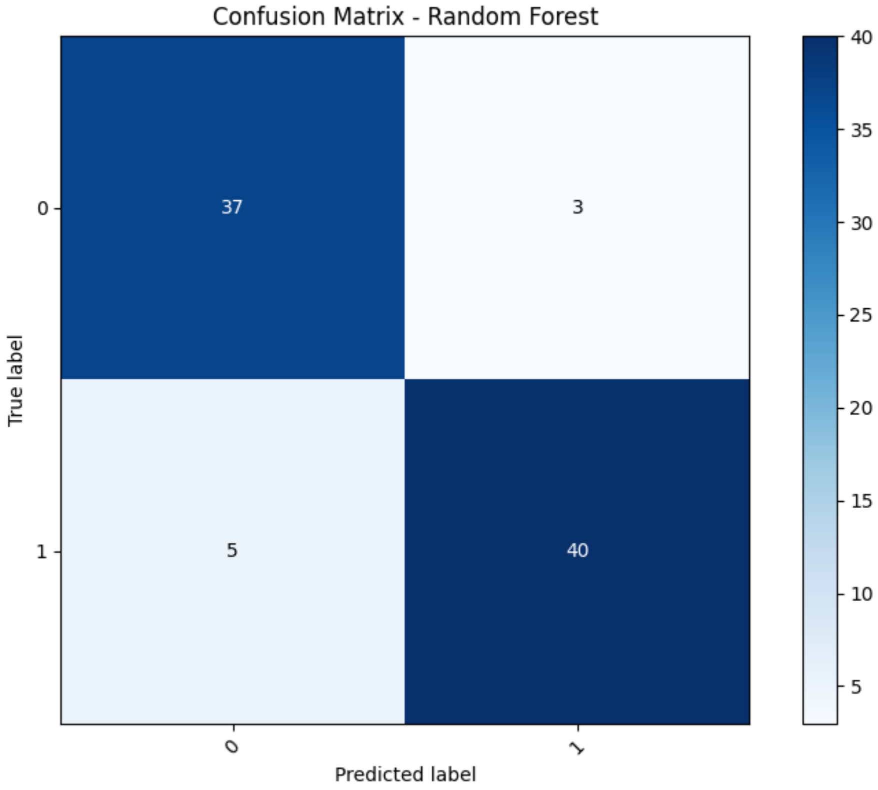


Figure 5.3.7 : Confusion Matrix: Random Forest

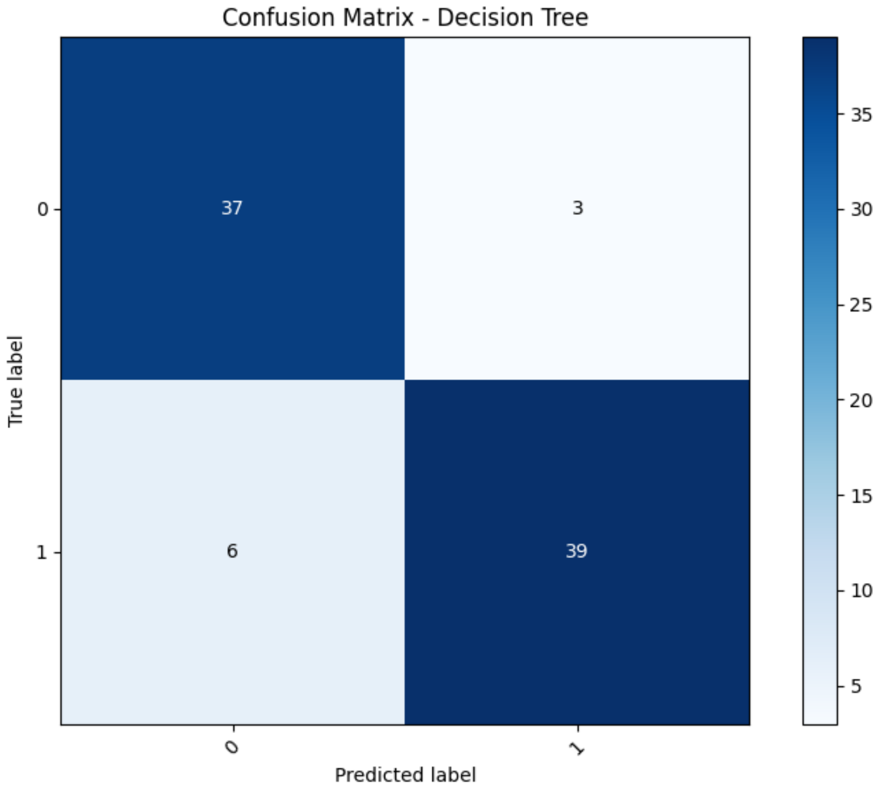


Figure 5.3.8 : Confusion Matrix: Decision Tree

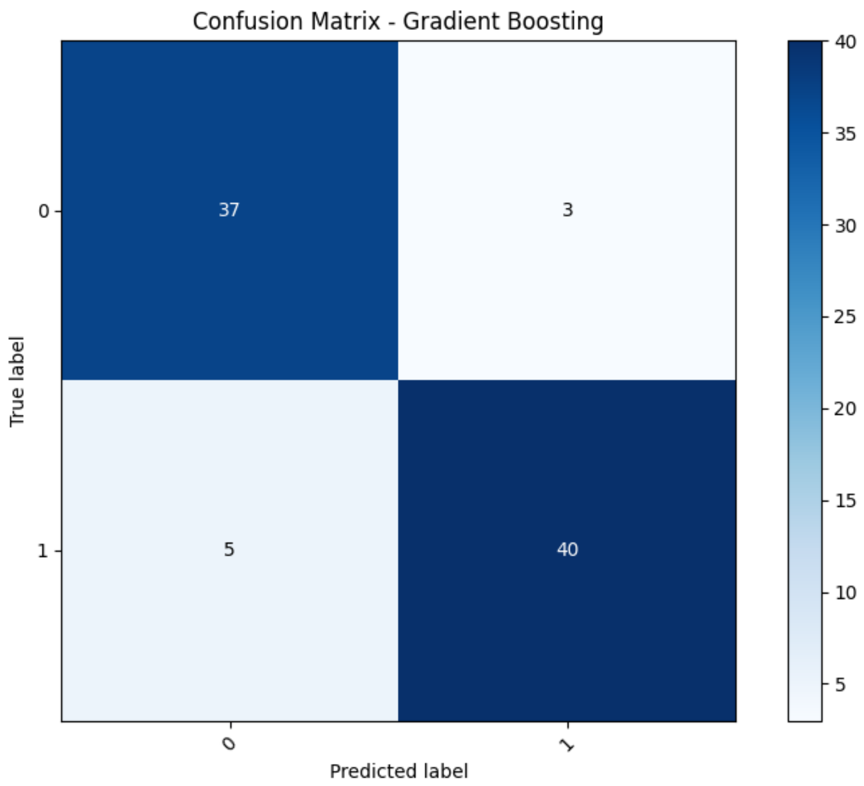


Figure 5.3.9 : Confusion Matrix: GB

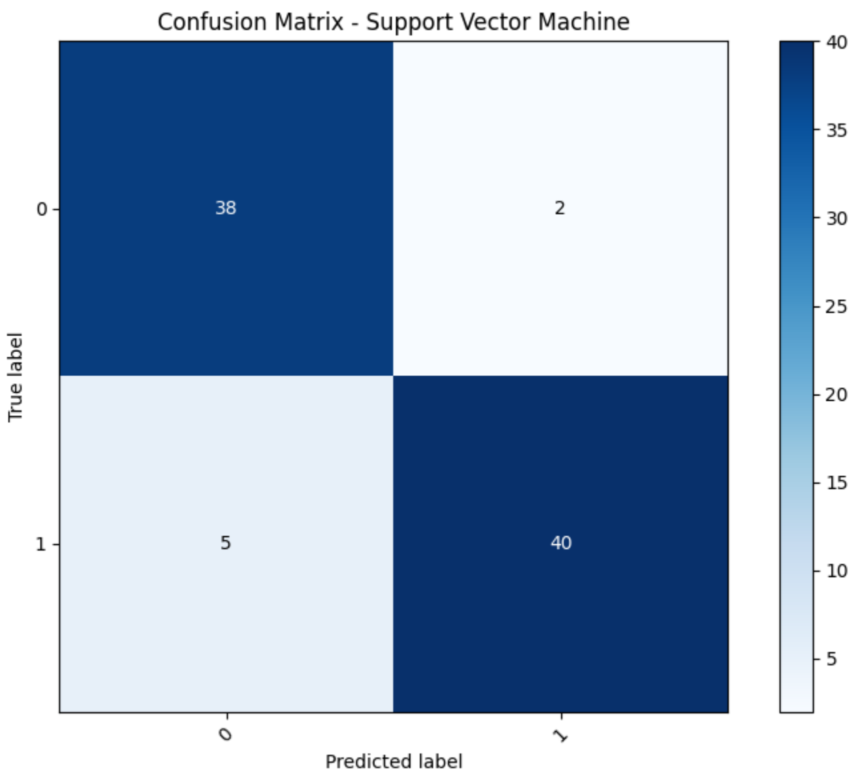


Figure 5.3.10 : Confusion Matrix: SVM

Comparing between different models we can see that SVM has the lowest number of False-positive and False-negative.

ROC :

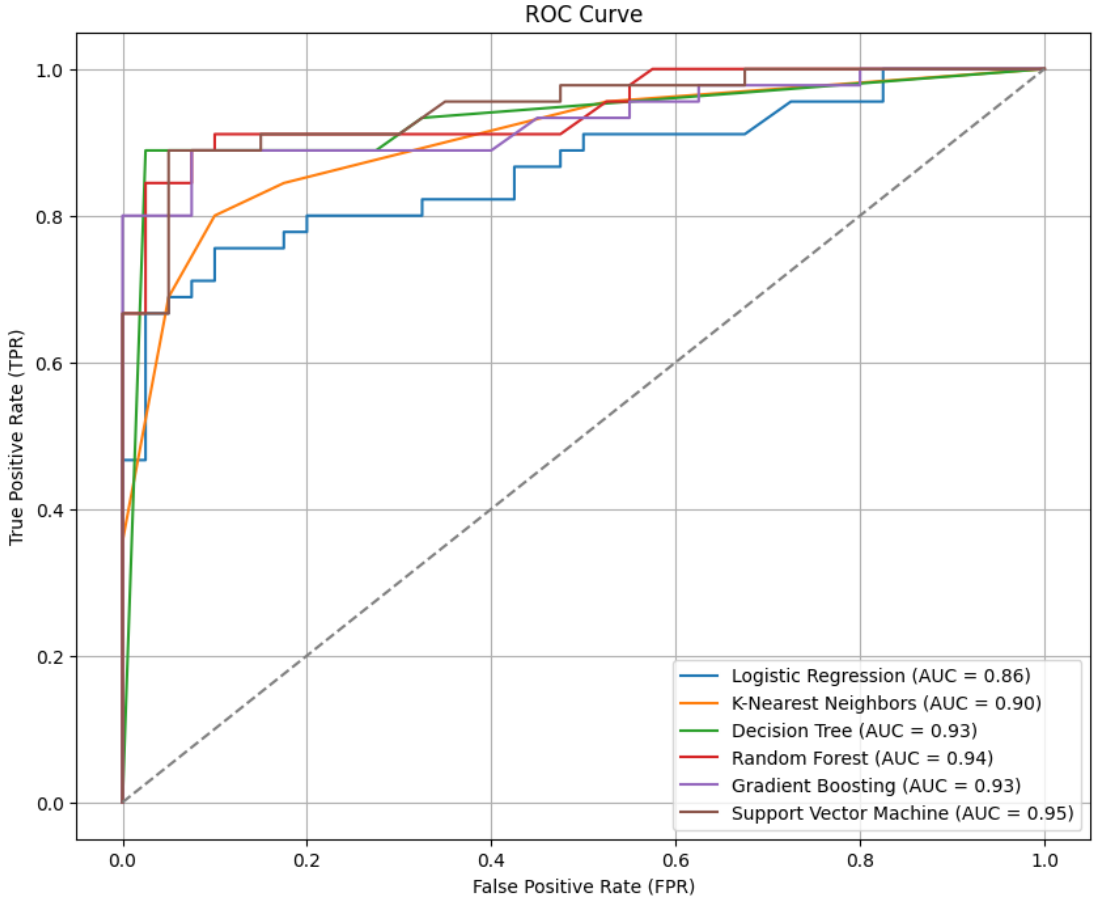


Figure 5.3.11: ROC Comparison

According to the ROC AUC score SVM has the highest score just a bit more that Random Forest.

```
Logistic Regression: ROC AUC = 0.86
K-Nearest Neighbors: ROC AUC = 0.90
Decision Tree: ROC AUC = 0.90
Random Forest: ROC AUC = 0.94
Gradient Boosting: ROC AUC = 0.93
Support Vector Machine: ROC AUC = 0.95
```

Figure 5.3.12 : ROC AUC score

Precision-recall curve:

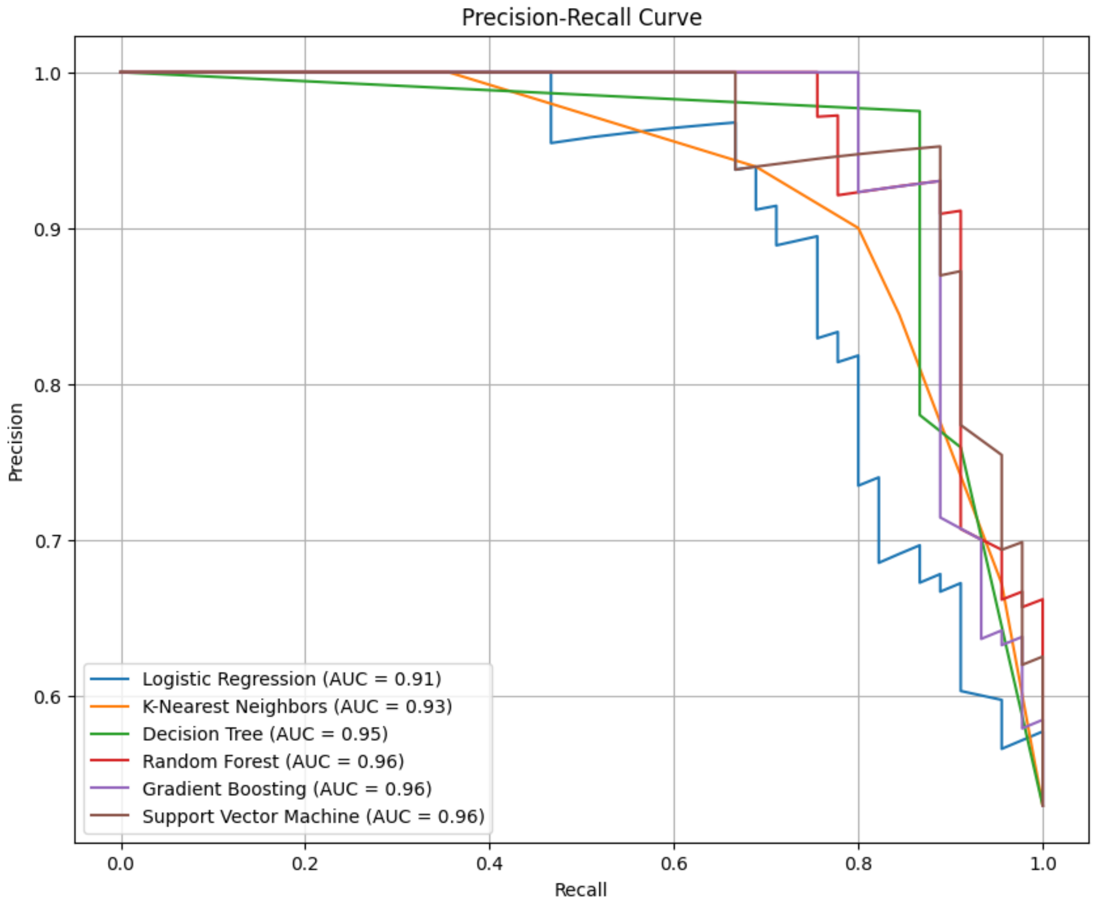


Figure 5.3.13: Precision-recall curve

Here SVM, GB and Random Forest have the highest AUC of 0.96. So all performed similarly. All modes can be called similarly effective in this case.

5.4 Summary

The experimental results section provides a detailed examination of the performance of six machine learning algorithms—Logistic Regression, KNN, Decision Trees, Random Forest, Gradient Boosting, and SVM—in classifying individuals based on their abilities. Each algorithm was evaluated using key performance metrics including accuracy, precision, recall, and F1-score.

Logistic Regression demonstrated an accuracy of 81.17% with a precision of 0.87 and recall of 0.75, indicating its effectiveness in classification. KNN achieved higher performance metrics with an accuracy of 84.70%, precision of 0.90, and recall of 0.80. Decision Trees showed robust performance with an accuracy of 89.41%, precision of 0.92, and recall of 0.86, highlighting its suitability for this task.

Random Forest and Gradient Boosting both performed similarly well, each achieving an accuracy of 90.58% with precision and recall scores of 0.93 and 0.88, respectively. SVM emerged as the top performer with an accuracy of 91.76%, precision of 0.95, and recall of 0.88, underscoring its superior ability to classify individuals based on their abilities.

Additionally, hypothesis testing through feature importance analysis revealed insights into the significance of gaming habits in determining individual abilities. Comparative analysis across the models further emphasized SVM's dominance across various performance metrics, making it the preferred choice for accurate classification in this study.

CHAPTER 6
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

This research could significantly impact everyday life by enhancing cognitive abilities such as spatial awareness and efficiency, promoting the use of games as cognitive development tools in educational and professional settings. It may lead to innovative teaching methods that incorporate gaming, improving engagement and learning outcomes. In the workplace, the findings could influence training programs, using gaming elements to enhance decision-making and problem-solving skills. Additionally, understanding gaming's social dynamics could foster better communication and teamwork. The research might also explore therapeutic uses in healthcare, contributing to mental health treatments and rehabilitation. Furthermore, policymakers could use the findings to develop balanced guidelines on gaming use, maximizing benefits while addressing potential drawbacks.

6.2 Impact on Society & Environment

This research could enhance society by improving cognitive skills and educational outcomes through the integration of gaming into learning environments. It may foster better social interactions, communication, and teamwork, benefiting both educational and professional settings. By understanding the social dynamics influenced by gaming, communities can leverage these insights to create more inclusive and engaging spaces that promote collaboration and personal development.

From an environmental perspective, the research could explore sustainable practices within the gaming industry, potentially leading to innovations that reduce the carbon footprint of gaming technologies. This could encourage the development and adoption of eco-friendly gaming solutions. Additionally, the findings might inform policymakers in creating guidelines that promote responsible gaming habits, aligning with broader sustainability goals and fostering an awareness of environmental impacts.

6.3 Ethical Aspects

The ethical aspects of this research include:

1. Data Privacy: Ensuring participants' personal information and gaming data are securely protected and anonymized.
2. Informed Consent: Clearly communicating the study's purpose, procedures, and potential impacts to participants, and obtaining their consent before involvement.
3. Bias and Fairness: Avoiding biases in data collection and analysis, ensuring that the research is inclusive and representative of diverse populations.

4. Impact on Mental Health: Monitoring and mitigating any potential negative effects of gaming on participants' mental well-being.
5. Sustainability: Considering the environmental impact of gaming technologies and promoting sustainable practices.
6. Responsible Reporting: Accurately presenting findings without exaggeration, ensuring the results are used ethically in policy and practice.

6.4 Sustainability Plan

Sustainability Plan for the Research

1. Resource Management:
   - Utilized digital tools and platforms to minimize paper use and reduce the carbon footprint associated with physical materials.
   - Use of energy-efficient devices and equipment during data collection and analysis.
2. Data Collection:
   - Designed experiments and simulations to require minimal computational resources, reducing energy consumption.
   - Used virtual meetings and remote collaboration tools to decrease travel-related emissions.
3. Ethical Considerations:
   - Ensured that all aspects of the research, including participant recruitment and data collection, adhere to ethical guidelines that promote environmental consciousness.

4. Waste Reduction:
   - Implemented recycling and proper disposal practices for any physical materials used during the research process.
   - Encouraged electronic submissions and digital documentation to minimize waste.

6.5 Summary

The research investigates the impact of gaming on cognitive abilities, focusing on enhancing spatial awareness and efficiency. It aims to integrate gaming into educational and professional settings, leading to innovative teaching methods and improved engagement. In the workplace, findings could influence training programs, using gaming to enhance decision-making and problem-solving skills. Additionally, the study explores gaming's social dynamics, fostering better communication and teamwork, and contributing to therapeutic uses in healthcare.

Societally, the research could enhance cognitive skills, social interactions, and educational outcomes, creating more inclusive environments that promote collaboration. Environmentally, it examines sustainable practices in the gaming industry, potentially reducing the carbon footprint and encouraging eco-friendly solutions. Policymakers might use these insights to develop guidelines promoting responsible gaming and aligning with sustainability goals.

Ethical considerations include ensuring data privacy, obtaining informed consent, avoiding biases, and monitoring mental health impacts. The sustainability plan focuses on resource management, reducing waste, and promoting digital tools to minimize environmental impact. The study emphasizes ethical reporting and the broader implications of gaming on society and the environment.

CHAPTER 7
CONCLUSION AND FUTURE WORK

7.1 Conclusions

This study use cutting-edge machine learning techniques to investigate the relationship between personal abilities and gaming behaviors. It explores the ways in which gaming might affect and forecast a range of human capacities, including decision-making, social dynamics, and cognitive processes. The study employs a thorough methodology that combines data gathering, preprocessing, model training, and assessment to provide new perspectives on how gaming affects daily life.

Methods of Research:

Data Integration and Collection: A structured Google Form was used to collect a wide range of quantitative and qualitative data about players' gaming habits and abilities.

Preprocessing and Feature Selection: To get the dataset ready for analysis, thorough preprocessing included variable cleaning, normalization, and encoding. Techniques for feature selection were used to determine which features had the greatest bearing on the study's conclusions.

Model Selection and Instruction: Based on how well they performed on classification tasks, six machine learning models—KNN, Gradient Boosting, Random Forest, Decision Trees, and SVM—were chosen. To predict and categorize individual talents, a training dataset was used to train and optimize each model.

Assessment and Comparative Analysis: The efficacy of the models was assessed using performance indicators such as accuracy, precision, recall, and F1-score. SVM was shown to be the most precise and accurate classifier after a comparative examination of the models, and it was especially good at managing the dataset's complexity.

Key Findings:

Model Performance: With an accuracy of 91.76%, precision of 0.95, and recall of 0.88, SVM outperformed the other models in terms of classification accuracy.

Impact of Gaming: Effects of Video Games By using feature importance analysis for hypothesis testing, it was confirmed that gamers have different cognitive and social capacities from non-gamers, highlighting the important role that gaming habits have in predicting individual talents.

Comparative Perspectives: SVM's advantage in correctly identifying people based on their gaming-related qualities was highlighted by a comparative analysis across models, offering strong support for its efficacy in predictive modeling.

7.2 Further Suggested Works

This research contributes to understanding how gaming behaviors can serve as predictors of cognitive and social abilities. In the future, leveraging the insights and findings from this research could lead to the development of a web application aimed at assisting people based on their gaming habits and individual abilities. Such an application could provide personalized assessments, recommendations, or interventions tailored to enhance cognitive skills, social interactions, or decision-making processes. By integrating machine learning models like SVM for accurate predictions, the app could offer users actionable insights into their strengths and areas for improvement, ultimately supporting personal development and well-being in various contexts.

7.3 Limitations

Some potential limitations of the research:

1. **Sample Bias:** The study's data collection may suffer from sample bias if the respondents are predominantly from a specific demographic or gaming background, limiting the generalizability of findings to broader populations.
2. **Data Quality:** Despite efforts in data cleaning and preprocessing, the quality of data obtained from self-reported surveys or forms may vary, leading to inaccuracies or biases in the analysis.
3. **Feature Selection:** The methodology used for feature selection could influence the model's performance and interpretability. Alternative approaches or additional features not considered in this study might yield different insights.
4. **Model Selection:** While several machine learning algorithms were tested, the choice of models could impact the study outcomes. Different algorithms might produce varying results depending on their assumptions and parameter settings.
5. **Interpretation of Causality:** Correlation between gaming habits and individual abilities does not necessarily imply causation. Other factors or confounding variables not accounted for in the study could influence the observed relationships.
6. **Temporal Factors:** The study's cross-sectional design may overlook changes in gaming habits or abilities over time. Longitudinal studies could provide deeper insights into the dynamics and development of these relationships.

7. **Ethical Considerations:** The ethical implications of using personal data, particularly in sensitive areas like gaming habits and cognitive abilities, need careful consideration to ensure privacy and mitigate potential biases.
8. **Validation and Reproducibility:** While the models showed promising results within the study's context, validation on independent datasets or replication of findings by other researchers is crucial for confirming the robustness and reliability of the results.

References:

[1] A. L. Samuel. “Some studies in machine learning using the Game of Checkers. II—Recent progress” (1967, November 1). IBM Journals & Magazine | IEEE Xplore.

[2] Pers, T. H., Albrechtsen, A., Holst, C., Sørensen, T. I. A., & Gerds, T. A. (2009). The Validation and Assessment of Machine Learning: A Game of Prediction from High-Dimensional Data. PLOS ONE, 4(8), e6287.

[3] Barrington, L., Turnbull, D., & Lanckriet, G. R. G. (2012). Game-powered machine learning. Proceedings of the National Academy of Sciences of the United States of America.

[4] Gu, W., Foster, K., Shang, J., & Wei, L. (2019). A game-predicting expert system using big data and machine learning. Expert Systems With Applications, 130, 293–305.

[5] Zhou, Y., Kantarcıoğlu, M., & Xi, B. (2018). A survey of game theoretic approach for adversarial machine learning. WIREs Data Mining and Knowledge Discovery, 9(3).

[6] Ninaus, M., Greipl, S., Kiili, K., Lindstedt, A., Huber, S., Klein, E., Karnath, H., & Moeller, K. (2019b). Increased emotional engagement in game-based learning – A machine learning approach on facial emotion detection data. Computers & Education, 142, 103641.

[7] M. Frutos-Pascual and B. G. Zapirain, "Review of the Use of AI Techniques in Serious Games: Decision Making and Machine Learning," in IEEE Transactions on Computational Intelligence and AI in Game.

[8] C. G. Diaz, P. Perry and R. Fiebrink, "Interactive Machine Learning for More Expressive Game Interactions," 2019 IEEE Conference on Games (CoG), London, UK, 2019, pp. 1-2, doi: 10.1109/CIG.2019.8848007.

[9] Zhu, M. (2021, January 21). Game-Theoretic and Machine Learning-based Approaches for Defensive Deception: a survey. arXiv.org.

[10] Semenov, A. M., Romov, P., Korolev, S., Yashkov, D., & Neklyudov, K. (2017b). Performance of Machine Learning Algorithms in Predicting Game Outcome from Drafts in Dota 2. In Communications in computer and information science (pp. 26–37).

[11] Granic, I., Lobel, A., & Engels, R. C. M. E. (2014). The benefits of playing video games. American Psychologist, 69(1), 66–78.

[12] Rieber, L. P., & Noah, D. (1997, April). Effect of gaming and visual metaphors on reflective cognition within computer-based simulations. In Proceedings of AERA Annual Meeting.

[13] Groos, K. (1901). The play of man. New York: Appleton.

[14] Roberts, J. M., Arth, M. J., & Bush, R. R. (1959). Games in culture. American Anthropologist, 61, 597-605.

[15] Gentile, D. A. (2011). The multiple dimensions of video game effects. Child Development Perspectives, 5(2), 75–81.

[16] Green, C. S., & Bavelier, D. (2003). Action video game modifies visual selective attention. Nature, 423(6939), 534–537.

[17] Passmore, Holli-Anne & Holder, Mark. (2014). Gaming for good: Video games and enhancing prosocial behavior.

Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title:

DECIPHERING THE IMPACT AND EVOLUTION OF GAMING IN EVERYDAY LIFE: A MACHINE LEARNING-CENTRIC ANALYSIS

Student ID: 202-15-14414

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a problem related to the "**Impact of gaming in everyday life"** for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish this goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**

CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**
CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This project demonstrates **fundamental engineering (K3)** principles by employing machine-learning algorithms to differentiate between gamers and non-gamers. The project demonstrates **specialist knowledge (K4)** by conducting a comparative analysis of different models such as Logistic Regression, SVM, KNN, Random Forest, Decision Tree and Gradient Boosting to classify not only different groups but also to figure out whether the gameplay enhances their capabilities.	**Page no:** [15-16] **Section:** [4.2] **Page no:** [25-33] **Section:** [5.4]
				The project applies **engineering practice & design (K5)** by the figure of process of experiments. The project addresses **engineering practice & technology (K6)** by employing different Machine learning models to achieve a proper classification.	**Page no:** [11] **Section:** [3.2] **Page no:** [15-16]

					Section: [4.2]
				This project ensures to **K8 (Research Literature)** by taking points on similar papers and synthesizing that information to further understand the requirement and procedure.	**Page no:** [6-9] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	As the Data has been collected from various sources and through means of no direct contact, the data validation was difficult and the data collection process was time consuming.	**Page no:** [12-13] **Section:** [3.3]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	As the data was collected using a google form, proper data collection, management and training model was done with analysis of what would be the best practice.	**Page no:** [12-13] **Section:** [3.3] **Page no:** [16-17] **Section:** [4.2]

4.	**EP4: Familiarity of Issues**	Yes	CO8	Although game development is a part of computer science but the mental effect of gaming was a territory that had to be explored and knowledge was gathered. which indicates **EP-4**.	**Page no:** [16-17] **Section:** [4.2]
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting requirements**	Yes	CO8	Stakeholders were visited who provided insights as to how these human capabilities can be determined.	**Page no:** [13-14] **Section:** [3.5]
7.	**EP7: Interdependence**	Yes	CO5	This project's comprehensive approach addresses high-level problems by integrating various components across data collection, data processing and proposed methodology, ensuring a holistic solution to complex challenges in calculating efficiency in life and spatial awareness, which ensures **EP-7**.	**Page no:** [11-13] **Section:** [3.2, 3.3, 3.4]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	Our project utilizes diverse resources such as high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical considerations to ensure systematic research and contribute to advancements in detection of improved efficiency and spatial awareness in gamers compared to non-gamers through Machine learning.	**Page no:** [13] **Section:** [3.4]
2.	**EA2: Level of interaction**	No		N/A	N/A
3.	**EA3: Innovation**	No		N/A	N/A

4.	**EA4: Consequences for society and the environment**	Yes		The research explores using gaming to enhance cognitive skills and social interactions in education while promoting sustainable practices in the gaming industry.	**Page no:** [36] **Section:** [6.1, 6.2]
5.	**EA-5: Familiarity**	Yes		This project addresses EA-5 expands upon existing research by examining machine-learning approaches to differentiate between gamers and non-gamers. The project leverages state of the art machine learning methodologies, which incorporates the best practices from current research to efficiently classify the difference between gamers and non-gamers spatial awareness and efficiency. This similarity ensures that the project is built upon a solid foundation of existing knowledge.	**Page no:** [6-9] **Section:** [2.2, 2.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	In order to mitigate CO4, this project combines efficient project management with financial control. Careful planning, resource distribution, and budget estimation are guaranteed to	**Page no:** [13-14] **Section:** [3.5]

			provide the best possible resource utilization throughout the duration of the study project.	
2	CO9	Yes	By putting patient privacy first, getting informed consent, and openly recording the research process, the project demonstrates adherence to ethical principles. It also ensures responsible knowledge dissemination and societal well-being through the moral application of technologies that abide by CO9.	**Page no:** [36-37] **Section:** [6.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's thorough data collection, rigorous statistical analysis, careful methodology development, and thorough experimental results and analysis all demonstrate a dedication to continuous learning (CO12) and adaptation within the dynamic technological landscape. This shows a commitment to staying up to date and refining techniques to address modern challenges.	**Page no:** [11-13, 19-34] **Section:** [3.2, 3.3, 3.4, 5.2, 5.3]

GAMING IN EVERYDAY LIFE

ORIGINALITY REPORT

21%	17%	11%	17%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to Daffodil International University Student Paper	2%
2	dspace.daffodilvarsity.edu.bd:8080 Internet Source	2%
3	fastercapital.com Internet Source	1%
4	Lloyd P. Rieber, David Noah. "Games, simulations, and visual metaphors in education: antagonism between enjoyment and learning", Educational Media International, 2008 Publication	1%
5	Abdelaziz Testas. "Distributed Machine Learning with PySpark", Springer Science and Business Media LLC, 2023 Publication	1%
6	Submitted to George Bush High School Student Paper	<1%
7	Submitted to Liverpool John Moores University	<1%