PREDICTIVE MODELING OF SMARTPHONE ADDICTION AMONG UNIVERSITY STUDENTS IN BANGLADESH: A MACHINE LEARNING APPROACH

BY

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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

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APPROVAL

This Project titled **"Predictive Modeling of Smartphone Addiction Among University Students in Bangladesh: A Machine Learning Approach"**, submitted by **Mst Allamanumani** 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 **July 14, 2024**.

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We hereby declare that this project has been done by us under the supervision of **Dr. Arif Mahmud, Associate Professor, 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.

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ABSTRACT

This study aims to develop a predictive model for smartphone addiction among university students in Bangladesh using machine learning techniques. The research encompasses data collection through a comprehensive survey, which included demographic information and responses to 25 questions designed to assess smartphone usage patterns and behaviors. A weighted composite score was calculated for each respondent to represent their level of addiction, which was then normalized for standardization. Various machine learning models were trained and evaluated, including logistic regression, decision trees, and support vector machines, among others. The logistic regression model demonstrated the highest accuracy of 97% in predicting smartphone addiction. The study also identified key factors associated with smartphone addiction, such as loneliness, depression, and poor sleep quality. Additionally, the research found that smartphone addiction had negative impacts on students' academic performance and social interactions. The findings of this study provide valuable insights for university administrators and policymakers to develop targeted interventions and support services to address the growing issue of smartphone addiction among university students in Bangladesh. The predictive model can be further refined and integrated into student well-being programs to identify and support those at high risk of addiction.

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ML	Machine Learning
SVC	Support Vector Classifier
CM	Confusion Matrix
TP	True Positive
FP	False Positive
FN	False Negative
TN	True Negative

CHAPTER 1
INTRODUCTION

1.1 Overview

In the contemporary educational milieu of Bangladesh, the ubiquitous use of smartphones among university students has given rise to concerns regarding the escalating issue of smartphone addiction. The prevalence of smartphone addiction within the context of Bangladeshi university students is a significant worry, as evidenced by various studies. For instance, investigations in South Korea found that smartphone addiction among university students was associated with adverse effects on physical health, academic performance, and social interaction (Achangwa, Ryu, Lee & Jang 2022).

In addition, Albursan, Qudah, Al-Barashdi, Bakhiet, Darandari, Al-Asqah, and Albursan (2022) found that university students across a number of nations had high rates of smartphone addiction, and that addiction was associated with depressive symptoms, loneliness, and poor sleep. Studies have demonstrated the detrimental effects of smartphone addiction on students' learning and general academic achievement (Sunday, Adesope & Maarhuis 2021). These findings underscore the significance of exploring and addressing smartphone addiction specifically among university students in Bangladesh, emphasizing the necessity for a predictive modeling approach utilizing machine learning techniques to develop effective interventions and mitigate the adverse effects associated with this phenomenon.

1.2 Background and Present State

Smartphone addiction has become a global concern, particularly among university students who are heavy users of mobile technology. The pervasive nature of smartphones has transformed the way students communicate, access information, and engage in academic and social activities. However, this convenience comes with significant downsides. Excessive smartphone use has been linked to various negative outcomes, including physical health issues, psychological problems, and impaired academic performance.

Globally, numerous studies have documented the rising trend of smartphone addiction among university students. For instance, research conducted in South Korea has highlighted how smartphone addiction adversely affects students' physical health, academic performance, and social interactions (Achangwa, Ryu, Lee & Jang, 2022). In a similar vein, Albursan et al.'s study from 2022 spanning several nations showed that university students' smartphone addiction is significantly influenced by characteristics like as sadness, loneliness, and poor sleep quality. Additionally, a study by Sunday, Adesope, and Maarhuis (2021) showed how smartphone addiction impairs academic performance and learning in students.

In the context of Bangladesh, the situation is equally concerning. With the rapid increase in smartphone penetration, particularly among the younger population, university students in Bangladesh are highly susceptible to smartphone addiction. Despite this, there is a noticeable gap in the research specifically addressing the nuances of smartphone addiction within Bangladeshi university settings. The unique socio-economic, cultural, and technological landscape of Bangladesh necessitates a focused investigation to understand the contributing factors and consequences of smartphone addiction among its university students.

A number of research have tried to predict smartphone addiction using machine learning approaches. For instance, Lee and Kim (2021) used machine learning methods to predict addiction levels with different degrees of accuracy, including decision trees, random forests, and XGBoost. Similarly, Giraldo-Jiménez et al. (2022) utilized traditional and advanced machine learning models to develop a prediction model for smartphone dependency. However, these studies often lack the cultural and contextual specificity required for effective application in Bangladesh.

In summary, while the global body of research on smartphone addiction provides valuable insights, there remains a critical need for studies that address the specific context of Bangladesh. To lessen the negative consequences of smartphone addiction among college students, it is crucial to comprehend the particular cultural, socioeconomic, and technological aspects of Bangladesh in order to create prediction models and interventions that work. By applying machine learning techniques to develop a prediction model specifically suited to the Bangladeshi environment, this study seeks to close this knowledge gap and address this pressing issue.

1.3 Problem Statement

The issue of smartphone addiction among university students is becoming more and more prevalent, and it has serious consequences for both their academic and mental well-being. Numerous physical health problems, sleep disorders, musculoskeletal and neurological disorders, and mental health problems like sadness, stress, and loneliness have all been related to the prevalence of smartphone addiction. Additionally, it has been discovered that smartphone addiction negatively affects academic performance in general and student learning in particular. The prevalence of smartphones among university students makes it imperative to create efficient interventions, such machine learning models, to anticipate and lessen the negative consequences of smartphone addiction.

1.4 Objectives

The rising concern of smartphone addiction among university students necessitates a thorough investigation into its multifaceted impacts and underlying causes. The main objective of this study is to create a predictive model that can precisely classify and identify smartphone addiction levels among university students in Bangladesh. To achieve this, the study has set forth several key objectives:

1. **Comprehensive Understanding:** The primary objective is to acquire a comprehensive understanding of smartphone addiction, elucidating its diverse impacts on the physical well-being, mental health, and academic performance of university students.

2. **Causative Factors Examination:** An examination of the factors contributing to smartphone addiction is imperative, seeking to identify the root causes that precipitate this phenomenon.

3. **Predictive Model Development:** A paramount objective is the development of a sophisticated machine learning model designed to predict and categorize levels of smartphone addiction among university students.

4. **Academic Contribution:** A fundamental objective is to contribute substantively to the academic discourse by disseminating empirical insights into smartphone addiction and proposing an innovative approach to intervention through the integration of advanced machine learning methodologies.

Through the pursuit of these objectives, this research endeavors to not only unravel the intricacies of smartphone addiction but also to proactively contribute to the development of practical and effective strategies for its mitigation within the university milieu.

1.5 Scope and Limitations

The scope of the project will focus on the following specific aspects of smartphone addiction among university students:

1. **Factors Contributing to Smartphone Addiction:** The study will investigate the relationship between smartphone addiction and psychological problems, loneliness, low self-esteem, and lack of confidence in university students pursuing bachelor, graduate, and postgraduate degrees.

2. **Smartphone Usage and Addiction Behavior:** The study will look at the connection between university students' smartphone usage habits and their addiction-related behaviours.
3. **Demographic Focus:** The study concentrates on undergraduate university students, recognizing the unique challenges and dynamics pertinent to this academic stratum.

The boundaries of the research will be defined by the specific focus on university students and the factors, usage patterns, and sociodemographic influences related to smartphone addiction. The scope of the study will be restricted to university students, and its generalizability to other populations may be limited. Furthermore, the study will take into account the data's limitations, including the cross-sectional design of the research and the particular student population in Bangladesh.

1.6 Report Organization

The research report on "Predictive Modeling of Smartphone Addiction Among University Students in Bangladesh: A Machine Learning Approach" is meticulously structured into distinct chapters to systematically present the findings and insights. This organizational framework ensures a clear and logical flow of information, facilitating comprehensive understanding.

The report begins with Chapter 1, which introduces the issue of smartphone addiction among university students in Bangladesh. An overview of the frequency and detrimental impacts of smartphone addiction on academic performance and health is given in this chapter. It articulates the motivation and objectives of the study, emphasizing the necessity of developing a predictive model. The scope, expected outcomes, and the overall structure of the research are also outlined, setting the foundation for the subsequent chapters.

Chapter 2 delves into the existing literature on smartphone addiction, highlighting the importance of understanding the context and methodologies previously employed. Through a comparative analysis, this chapter identifies the diversity in predictive modeling approaches and outlines the gaps that this study aims to address within the Bangladeshi context. This review serves as the basis for developing the conceptual framework, hypotheses, and evidence-based strategies to mitigate smartphone addiction.

Chapter 3 details the methodology and requirement analysis, along with the design specifications for the predictive model. It describes the structured approach adopted, which integrates machine learning techniques for predictive modeling. The chapter covers data collection methods, feature extraction, model selection, and performance evaluation, emphasizing the iterative refinement process to adapt to dynamic patterns of smartphone addiction. The chapter also discusses the use of a dedicated website for data collection, addressing privacy concerns, and includes project management and financial considerations.

Chapter 4 focuses on the implementation of the predictive model. The model's training, prototype design, system testing, and evaluation are all thoroughly described. This chapter describes the development process, including the selection of algorithms, training procedures, and evaluation metrics, ensuring a comprehensive understanding of the model's implementation.

Chapter 5 presents the results and analysis of the study. It showcases the experimental and simulation results, accompanied by performance and comparative analyses. The chapter discusses the predictive model's outcomes, such as accuracy, precision, recall, and F1-score, and provides a comparative analysis with existing models, highlighting the strengths and limitations of the developed model.

Chapter 6 discusses the impact of the findings on smartphone addiction intervention strategies. It looks at the prediction model's real-world applications and how they might be used to create focused therapies that lessen the harmful impacts of smartphone addiction in university students. The chapter also provides suggestions for additional study and model improvements.

Finally, Chapter 7 concludes the report by summarizing the key findings, reflecting on the research objectives, and emphasizing the significance of the study. It gives a succinct summary of the advances this research has brought to the study of machine learning and smartphone addiction. The chapter also addresses the study's shortcomings and makes recommendations for future research avenues to build on the findings and increase our knowledge of and efforts to mitigate smartphone addiction among Bangladeshi university students.

1.7 Summary

The introduction gives a thorough summary of the study with a particular emphasis on the growing problem of smartphone addiction among Bangladeshi university students. The prevalence of this phenomenon is underscored by evidence from global studies, with specific attention to the South Korean context. The adverse effects on physical health, academic performance, and social interaction emphasize the urgency of addressing smartphone addiction within the unique cultural and educational milieu of Bangladesh. The research's motivation and objectives are clearly outlined, emphasizing the need for a predictive modeling approach using machine learning techniques. The study's scope, anticipated outcomes, and organizational structure are carefully delineated, setting the stage for a thorough investigation into the multifaceted aspects of smartphone addiction in Bangladeshi university students.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

Reviewing existing literature on smartphone addiction holds paramount significance as it lays the groundwork for well-informed and contextually relevant research. This exploration into prior studies serves as a crucial entry point into the discourse surrounding smartphone addiction, providing key insights across various dimensions.

By delving into earlier research, the investigator gains a nuanced understanding of the contextual factors influencing smartphone addiction, including cultural, social, and psychological dimensions. The examination of methodologies employed in past studies offers valuable insights into effective approaches for studying smartphone addiction, thereby informing the design and implementation of the current study. The review enables the identification of prevalent patterns, trends, and recurrent themes within the existing body of literature, serving as a foundation for aligning the current research with established knowledge and identifying potential gaps.

Furthermore, the literature review contributes to the development of a robust conceptual framework for the present research, building on existing theoretical frameworks and conceptual models. This ensures a theoretically grounded approach to understanding and predicting smartphone addiction. A critical evaluation of findings from prior research allows for a nuanced assessment of the strengths, weaknesses, and limitations of existing studies. This critical evaluation informs the researcher's approach to addressing gaps and enhancing the methodological rigor of the current study.

Insights gleaned from the literature review contribute to the formulation of informed hypotheses, guiding the research questions and hypotheses that will be tested through the current study. Understanding the outcomes and effectiveness of interventions implemented in previous studies provides a basis for formulating evidence-based strategies to mitigate smartphone addiction among university students.

2.2 Related Works

Every aspect of society has at least one smartphone, which is used for a variety of purposes including social media, messaging, calling, surfing, and entertainment (Arora, Chakraborty, Bhatia & Puri 2023). Numerous studies have already been conducted on smartphone addiction and the health consequences that are linked to it, especially for university students. With the use of Korea Internet and Security Agency (KISA) mobile phone log data, Lee and Kim (2021) sought to investigate the ability of predicting the degree of smartphone addiction. 29,712 respondents completed the 2017-developed Smartphone Addiction Scale. were, nevertheless, examined in addition to hypothesis testing utilising machine learning methods including Xgboost, Random Forest, and Decision Tree. The accuracy percentage of the random forest model (82.59%) and the decision tree model (74.56%) was the highest and lowest respectively, out of the 27 factors used to predict smartphone addiction.

In 2020, Mazumdar, Karak, and Sharma carried out a poll using a carefully crafted questionnaire to find out how people use their smartphones. Using the K-means method, they find that men are more likely than women to use their cellphones to access books and e-books. However, women have the biggest number of phone users who use them for more than 12 hours, while males have the highest number of users who use them for less than 6 hours.

Giraldo-Jiménez, Gaviria-Chavarro, Sarria-Paja, Bermeo Varón, Villarejo-Mayor, and Rodacki (2022) provided a data-driven prediction model for smartphone reliance based on machine learning approaches using an analytical retrospective case-control approach. A variety of classification methods, including both conventional and state-of-the-art machine learning models, were employed. For smartphone dependency, random forest, logistic regression, and support vector machine-based classifiers demonstrated the best prediction accuracy, ranging from 76-77%. The stratified-k-fold cross-validation method was used to ascertain this.

Arora, Chakraborty, Bhatia, and Puri (2023) evaluated smartphone addiction using unbiased metrics of features used in real-time. With the help of specially designed Android applications, real-time smartphone usage data was gathered. Then, with an accuracy rate of more than 80%, two linear classification models logistic regression and support vector machines were used to predict smartphone addiction among university students.

Elhai, Yang, Rozgonjuk, and Montag (2020) examined a model of psychiatric variables, age, and sex as drivers of the severity of problematic smartphone use (PSU) in a sample of Chinese university students using supervised machine learning. Using numerous simulated replications on a random sample of participants, we created our statistical model of age, sex, and psychological traits in evaluating PSU severity. Then, we used a range of machine learning techniques to externally test the model on the remaining population of participants.

The research on the detrimental effects of smartphone addiction on South Korean university students has been thoroughly reviewed by Achangwa, Ryu, Lee, and Jang (2022) using factual data.They Located Eight studies looked studied the connection between smartphone addiction and the psychological and mental health of Korean university students. Smartphone addiction has been connected to physical health problems such as neurological disorders, musculoskeletal problems, and sleep disruptions. Furthermore, a negative relationship was shown between smartphone addiction and poor academic achievement, procrastination, impulsivity, self-esteem, a reduction in social interaction, loneliness, and suicide.

Albursan, Qudah, Al-Barashdi, Bakhiet, Darandari, Al-Asqah and Albursan (2022) aimed to ascertain the degree and trends of university students' smartphone addiction and academic procrastination. Using the Italian scale of smartphone addiction, they gave the test to 556 Saudi university students, both male and female. The findings showed that 62.8% of the sample procrastinated on average, 7.7% had a high level, and 37.4% of the sample was addicted to using smartphones. Furthermore, a statistically significant positive correlation was discovered between academic procrastination and smartphone addiction, and a statistically significant negative correlation was discovered between quality of life and smartphone addiction. Life quality was found to have a weak association with academic procrastination. The findings also showed that academic procrastination and quality of life could predict smartphone addiction.

In a survey conducted by Chaudhury and Tripathy (2018), over 222 university students answered questions on their demographics, internet usage habits, and smartphone addiction. Using classification models, machine learning techniques were applied to analyse the data.

2.3 Comparison between existing works

Table 2.3.1: Comparative analysis with previous work

SL No	**Author Name**	**Used Algorithm**	**Best Accuracy with Algorithm**
1.	Arora, A. et al. [6]	Support Vector Machine, Logistic Regression	Logistic Regression = 82.67%
2.	Lee, J. et al. [4]	Decision Tree, Random Forest, Xgboost	Random Forest = 82.59%
3.	Giraldo-Jiménez, C. F. et al. [5]	Random Forest, Logistic Regression, Support Vector Machine	Support Vector Machine (SVM) = 77%
4.	Mazumdar, A. et al. [8]	K-means	Not applicable
5.	Chaudhury, P. et al. [7]	Naive Bayes Classifier, Support Vector Machines (SVM), Radial Basis Function (RBF) Neural Network	Support Vector Machines (SVM) = 81%
6.	Elhai, J. D. et al. [9]	Lasso Regression, Ridge Regression, Support Vector Machine (SVM), XGBoost, Random Forest	-
7.	Aggarwal, S. et al. [10]	Decision tree, Decision tree with AdaBoost, Logistic regression, k-Nearest neighbors, Naive Bayes	Decision tree and Decision tree with AdaBoost = 75%
8.	Duan, L. et al. [11]	Logistic Regression, Decision Tree	Decision Tree = 87.3%

2.4 Open Issues

A comprehensive analysis of prediction models for smartphone addiction that are especially adapted to the Bangladeshi setting is lacking in the research currently in publication. Understanding the ways in which Bangladesh's distinct technical landscape, socioeconomic issues, and cultural quirks influence smartphone addiction among university students is severely lacking. While many studies look at the problem globally, very few particularly look at the dynamics of smartphone addiction among Bangladeshi university students.

Some research has utilized machine learning techniques to predict levels of smartphone addiction. However, there remains a need for more comprehensive and diverse predictive modeling studies. Existing studies have identified relationships between academic performance and smartphone addiction, and some have explored the gender ratio in smartphone addiction. Nevertheless, there is a lack of comparative studies that not only predict smartphone addiction but also identify those at high risk of addiction. By creating a prediction model specifically for Bangladesh and accounting for its distinct cultural, socioeconomic, and technical characteristics, this research seeks to close these gaps. By doing this, it seeks to pinpoint those who are most vulnerable and provide a more comprehensive knowledge of smartphone addiction among university students in Bangladesh.

2.5 Summary

In summary, the present study has its basis in the literature evaluation, which has shed light on a number of important features of smartphone addiction among university students. The review highlighted the pervasive use of smartphones across various facets of society and the multitude of tasks they perform, underscoring the significance of understanding the implications of excessive usage. Key findings from the existing literature include the exploration of predictive models for smartphone addiction using machine learning techniques. Algorithms including Support Vector Machine, Logistic Regression, Decision Tree, Random Forest, and Xgboost were used in studies by Arora et al. (2023), Lee and Kim (2021), Giraldo-Jiménez et al. (2022), and others to predict smartphone addiction levels with remarkable accuracy. These models contribute to the evolving landscape of smartphone addiction research, providing insights into potential intervention strategies. The literature review also shown the detrimental impacts of smartphone addiction on a range of life domains for university students, including academic performance, social interactions, mental and physical health. Varied methodologies, including surveys, questionnaires, and data-driven prediction models, have been employed to unravel the intricate relationship between smartphone usage and addiction. The comparative analysis showcased the diversity in approaches and algorithms used in previous studies, emphasizing the need for a tailored approach that considers the unique cultural and academic landscape of Bangladesh. Despite the valuable contributions of existing research, there remains a significant gap in the literature concerning predictive models specifically designed for the context of Bangladesh, considering cultural nuances, socio-economic factors, and the distinctive technological environment.

CHAPTER 3

METHODOLOGY/ REQUIREMENT ANALYSIS AND DESIGN SPECIFICATION

3.1 Overview

In crafting the methodology for predictive modeling of smartphone addiction among Bangladeshi university students, this section outlines a structured and multifaceted approach. Emphasizing the integration of machine learning techniques, the methodology aims to develop a robust predictive model that can discern levels of smartphone addiction within the targeted population. Using machine learning algorithms to assess and forecast smartphone addiction is the central tenet of the methodology.By leveraging these algorithms, the research aims to uncover complex patterns and relationships within the collected data, advancing a more sophisticated knowledge of the variables driving smartphone addiction among Bangladeshi university students. The methodology involves the development of a comprehensive predictive modeling framework, including important phases such feature engineering, model selection, data preprocessing, and performance assessment. To guarantee the prediction model's precision, dependability, and interpretability, each step is meticulously crafted. Prior to model development, the collected dataset undergoes thorough preprocessing. This includes handling missing data, addressing outliers, and normalizing features to create a clean and standardized dataset. The quality of the dataset is crucial in achieving accurate predictions. A careful selection of machine learning models is undertaken, considering the unique characteristics of smartphone addiction in the Bangladeshi context. Potential algorithms include logistic regression, decision trees, ensemble methods, and other advanced techniques. The choice of models aims to strike a balance between accuracy, interpretability, and applicability to the specific demographic and cultural nuances of the study population. A thorough assessment of the predictive model's performance is conducted using recognised measures including the F1-score, accuracy, precision, and recall. This evaluation verifies the model's accuracy and dependability in classifying and forecasting various degrees of smartphone addiction among Bangladeshi university students. The approach aims to provide a high-level prediction model for smartphone addiction among university students in Bangladesh, offering significant contributions to the comprehension and alleviation of this widespread problem in the academic setting.

3.2 Proposed Methodology/ System Design

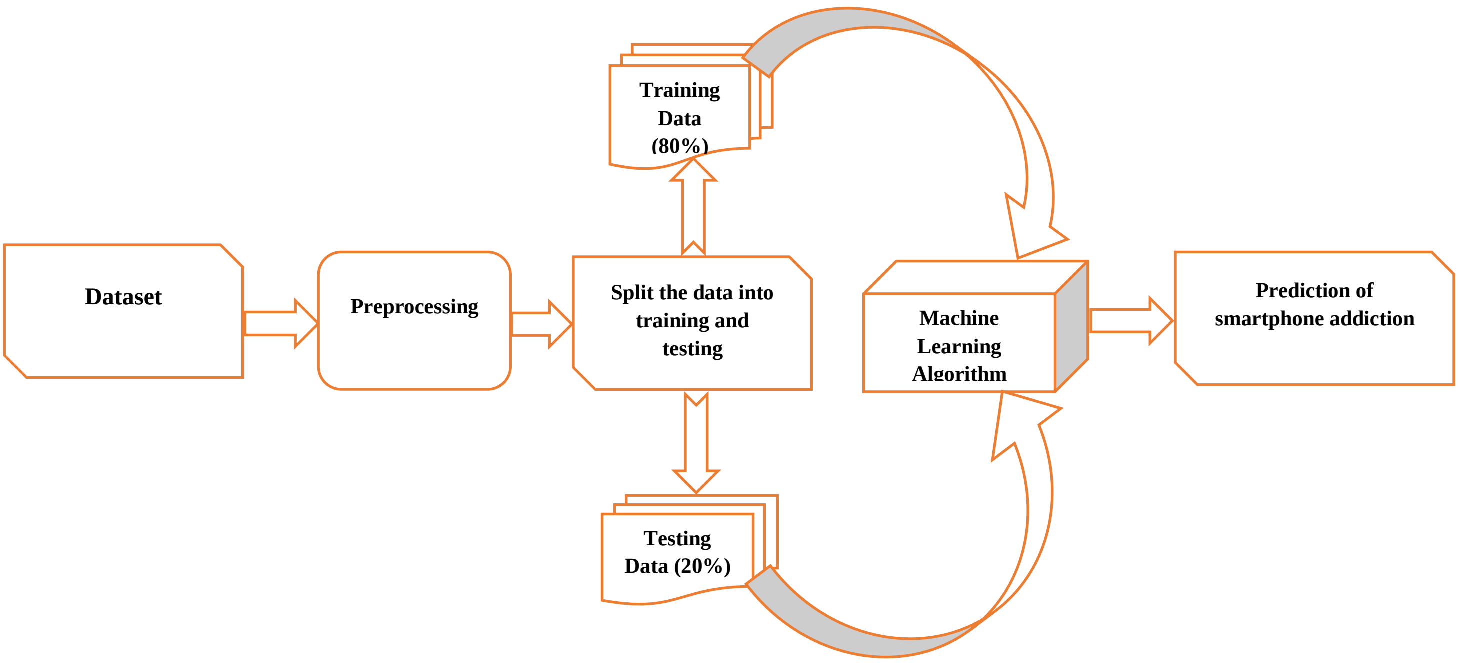

Figure 3.2.1 Work flow Diagram for Smartphone Addiction

3. 3 Data Collection

The data for this study was collected through a survey administered to over 1000 university students in Bangladesh. The 25 survey questions were intended to evaluate several facets of smartphone use and its possible effects on students' wellbeing and academic achievement. Google Forms was used to distribute the questionnaire, making it easy to access and convenient for responses. The first 20 questions were adapted from (Mazumdar Karak & Sharma 2020) paper. The questions were tailored to capture different dimensions of smartphone addiction, including frequency of usage, dependency, and its effects on daily activities and mental health. The specific questions included:

1. Do you use your phone to click pictures of class notes?
2. Do you buy books/access books from your mobile?
3. How often is your phone in your hand?
4. Does your phone's battery last a day?
5. When your phone's battery dies out, do you run for the charger?
6. Do you worry about losing your cell phone?
7. Do you take your phone to the bathroom?
8. Do you use your phone in any social gathering?
9. How often do you check your phone without any notification?
10. Do you check your phone just before going to sleep/just after waking up?
11. Do you keep your phone right next to you while sleeping?
12. Do you check emails, missed calls, texts during class time?
13. Do you find yourself relying on your phone when things get awkward?
14. Are you on your phone while watching TV or eating food?
15. Do you have a panic attack if you leave your phone elsewhere?
16. How often do you click selfies/photos?
17. You don't mind responding to messages or checking your phone while on a date?
18. Do you use your phone for playing games for a long time?
19. Do you prefer extended phone time or a vacation?
20. Do you talk over the phone in a day for a long time?
21. How often do you use your smartphone during study hours?
22. Have you experienced any academic difficulties or distractions due to smartphone usage?
23. Do you believe your smartphone usage habits have influenced your academic performance positively or negatively?

24. Have you experienced any mental health challenges that you attribute to smartphone addiction?
25. Do you feel that your smartphone usage habits affect your overall well-being and mental health?

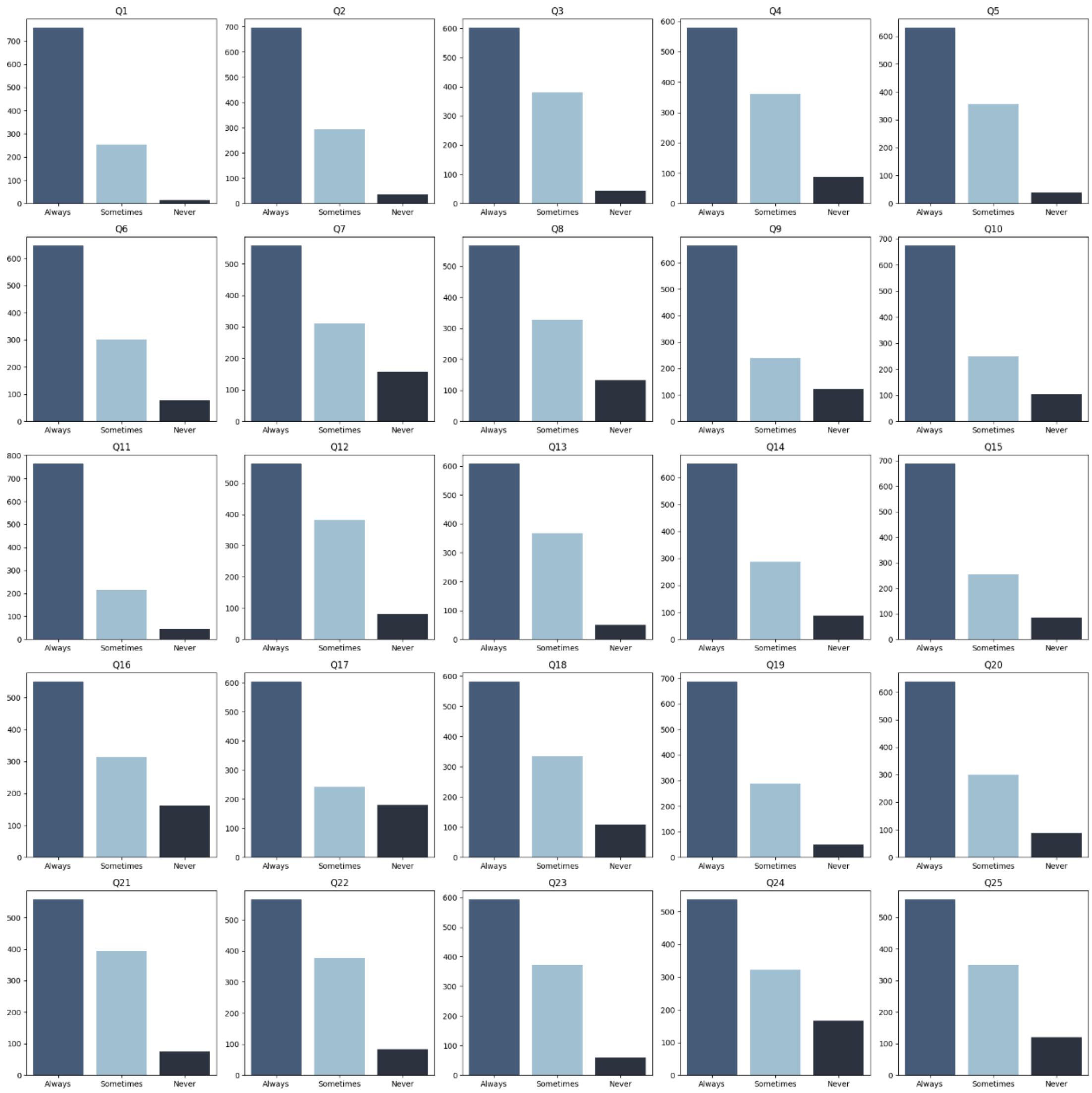

Figure 3.3.2: Visualization of survey response distribution

The answers for these questions were scaled on a three-point scale: 1 (Always), 2 (Sometimes), and 3 (Never). This scaling provided a standardized way to measure the frequency and intensity of smartphone use behaviors among the respondents. Each question aimed to gather insights into the students' habits and attitudes towards smartphone use, as well as the potential negative consequences associated with excessive usage. The collected data provided a comprehensive overview of smartphone addiction among university students, serving as the foundation for subsequent analysis and model training.

3. 4 Hardware/ Software Requirement

Hardware Requirements:

To effectively develop and implement the predictive modeling framework for smartphone addiction among university students, the following hardware components are essential:

- High-performance laptops or desktop computers for data processing, model training, and evaluation.

- A dedicated server for hosting the data and machine learning models, equipped with a multi-core processor, sufficient RAM, and storage.

- Reliable networking hardware to ensure stable internet connectivity for data collection and collaboration.

Software Requirements:

The software stack for developing and deploying the predictive model includes the following:

1. **Operating System:** Windows 10, macOS, or a Linux distribution such as Ubuntu for the development environment.

2. **Programming Languages:** Python is primary language for data analysis, machine learning, and implementation of predictive models.

3. **Development Environments and Tools:**

    - Google Colab for writing and testing code.
    - Version Control: Git for source code management and collaboration.

4. **Machine Learning Libraries and Frameworks:**

    - Scikit-learn: For implementing various machine learning algorithms.
    - Pandas and NumPy: For data manipulation and numerical computations.
    - Matplotlib and Seaborn: For data visualization.
    - MongoDB: For handling unstructured data if needed.

5. **Data Collection:** Google From: Used to collect the data from university student and accessing datasets and competition platforms.

6. **Collaboration and Documentation:**

   - Google Drive For storing and sharing project documents and data.
   - Overleaf: For collaborative writing of research papers and documentation.

These hardware and software requirements are designed to ensure the smooth execution of the project, from data collection and preprocessing to model development, evaluation, and deployment.

3.5 Project Management and Financial Analysis

Project Management:

- **Project Objectives:**
  A. To develop and design a machine learning model that can predict smart phone addiction precise accuracy.
  B. To find factors and patterns associated with smartphone addiction among university students**.**
- **Project Timeline:**

  A. Phase 1:
  i. Project planning (1-2 weeks)
  ii. Research (2-3 weeks)
  iii. Data collection (3-4 weeks)
  iv. Data Prepressing (2 weeks)

  B. Phase 2:
  i. Machine Learning Algorithm Selection (1-2 weeks)
  ii. Training and testing the model (3-4 weeks)
  iii. Evaluating the model (2 weeks)

- **Risk Management:**

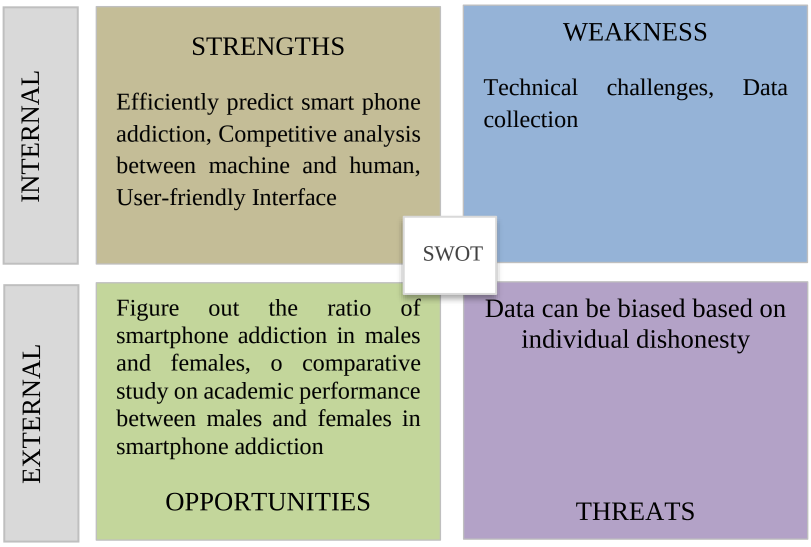

Figure 3.5.1: SWOT analysis

- **Communication Plan:**

  Stakeholder Meetings:

  Purpose: To perform a competitive analysis between male and female.

  Participants: University Student.

Financial Analysis:

Table 3.5.1 Financial Analysis

SN	Components	Estimated Cost (BDT)
01.	Software and Tools	2000-3000
03.	Data Collection and Processing	3000-4000
04.	Documentation and Report Writing	500
	Total Estimated Cost	7500

3.6 Summary

The comprehensive methodology for predicting smartphone addiction among Bangladeshi university students unfolds through a strategic integration of machine learning techniques. Central to this approach is the meticulous treatment of data, encompassing preprocessing stages that involve refining and standardizing datasets. The subsequent emphasis on feature engineering ensures the extraction of pertinent variables crucial for enhancing predictive accuracy. Model selection, a pivotal aspect, involves a judicious choice of machine learning models such as logistic regression and ensemble methods, carefully tailored to the distinctive dynamics of smartphone addiction within the Bangladeshi context. Rigorous performance evaluation, employing metrics like F1-score and precision, guarantees the reliability and efficacy of the predictive model in categorizing and forecasting smartphone addiction levels among university students. A crucial aspect of this methodology lies in its iterative refinement process, allowing for continual adjustments based on insights gained during analysis. This adaptive approach ensures the model's resilience in capturing dynamic patterns inherent in smartphone addiction, contributing to its ongoing enhancement. The overarching goal is to deliver a sophisticated predictive model that not only adds nuanced insights into smartphone addiction but also provides practical implications for effective mitigation within the academic setting. The methodology stands as a structured and dynamic framework, attuned to the specific nuances of Bangladeshi university students, aiming to contribute substantively to the understanding and proactive management of smartphone addiction in this unique demographic and cultural context.

CHAPTER 4

IMPLEMENTATION

4.1 Overview

The study aims to develop a predictive model for smartphone addiction among university students in Bangladesh. Smartphone addiction is an emerging concern, with potential negative impacts on academic performance, mental health, and overall well-being. By leveraging machine learning techniques, we seek to identify patterns and predictors of smartphone addiction, providing insights that can inform interventions and support services.

The dataset for this study was collected through a survey that included demographic information and responses to 25 questions designed to gauge smartphone usage patterns and behaviors. Each question's response is weighted based on its perceived importance in contributing to addiction, allowing for the calculation of a composite score that represents each respondent's level of addiction.

The composite score is then normalized to standardize the range of scores, and a threshold is applied to classify respondents into "addicted" and "not addicted" categories. For the purpose of predicting smartphone addiction, a number of machine learning models are trained and assessed. A thorough assessment of the models' prediction ability is provided by utilising a variety of metrics, such as accuracy, precision, recall, F1-score, and confusion matrix.

This research not only aims to identify the most accurate predictive model but also to offer a methodological framework for future studies in similar domains. Stakeholders can create focused initiatives to lessen smartphone addiction's negative effects on kids' life by knowing the variables that contribute to it.

4.2 Train Model

To train our model, we must go through several essential steps, starting from data preprocessing to model evaluation. Based on the preprocessed dataset, this section describes the training procedure and outcomes of multiple machine learning models to forecast smartphone addiction among university students.

Data Preprocessing

- **Load and Clean Data:** The dataset was loaded from an Excel file. First, irrelevant columns such as removed to focus on the essential data. Then we renamed the question column to q1 to q25 for simplicity. The "Age" column is converted to numeric values, filling missing values with the mean.
- **Encoding and Mapping:** The "Gender" column is label-encoded to convert categorical values into numeric. Responses to questions (Q1 to Q25) are mapped to numeric values: 'Always' to 1, 'Sometimes' to 2, and 'Never' to 3.
- **Weighted Composite Score:** Each question is assigned a weight based on its importance in predicting addiction. The composite score for each respondent was calculated using the weighted sum of their responses. The formula for calculating the composite score (C_i) is:

  $$C_i = \sum_{j=1}^{25} \omega_j x \, Q_{ij}$$

  where ω_j represents the normalized weight for question j, and Q_{ij} represents the response of respondent i to question j.
- **Normalized Score:** To standardize the scores, they were normalized to a range of 0 to 100 using the formula:

  $$Nmalized\ Score = (\frac{C_i - \min(\mathrm{C})}{\max(\mathrm{C}) - \min(\mathrm{C})}) \text{ x } 100$$

  where $\min(\mathrm{C})$ and $\max(\mathrm{C})$ are the maximum and minimum composite scores in the dataset, respectively.
- **Threshold Determination:** To categorize respondents into "addicted" and "not addicted," a threshold value was established. By analyzing the distribution of the normalized scores. The 70th percentile represents a score above which the top 30% of the data points lie. This means that setting the threshold at the 70th percentile allows us to classify the top 30% of students with the highest scores as "addicted". That means normalized scores above 70^{th} percentile was classified as "addicted" (Class 1), while those with scores 70^{th} or below were classified as "not addicted" (Class 0).
- **Data Splitting:** To preserve the distribution of the target variable, the dataset is stratified and divided into training (80%) and testing (20%) sets.

Model Training: The following five machine learning models were trained and assessed: K-Nearest Neighbours, Random Forest, Decision Tree, Support Vector Classifier, and Logistic Regression.

4.3 Model Evaluation:

After training various machine learning models to predict smartphone addiction, the next crucial step is evaluating their performance. This section details the evaluation metrics used, the results obtained, and a comparative analysis of the models' effectiveness.

Evaluation Metrics:

- **Accuracy:** calculates the percentage of cases that are accurately classified relative to all instances.

$$Accuracy = \frac{True\ Positives + True\ Negatives}{True\ Positives + True\ Negatives + False\ Positives + False\ Negatives}$$

- **Precision**: shows the percentage of actual positive forecasts among all positive predictions.

$$Precision = \frac{True\ Positives}{True\ Positives\ +\ False\ Positives}$$

- **Recall**: calculates the ratio of actual positives to genuine positive predictions.

$$Precision = \frac{True\ Positives}{True\ Positives\ +\ False\ Negatives}$$

- **F1-Score**: harmonic mean of memory and precision, offering a solitary measure that equalises the two.

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

- **Confusion Matrix**: reveals information about the model's classification performance by providing a thorough breakdown of true positives, false positives, true negatives, and false negatives. The confusion matrix is represented as:

$$Confusion\ Matrix = \begin{bmatrix} TP & FP \\ FN & TN \end{bmatrix}$$

With the use of these assessment metrics, the models' performances are thoroughly evaluated, enabling comparison and the determination of the best model for.

4.4 Summary

In this chapter, we detailed the comprehensive process of developing and evaluating machine learning models to predict smartphone addiction among university students in Bangladesh. This process included several critical steps, starting from data preprocessing to the training and evaluation of multiple models. We began with data preprocessing, where we cleaned and prepared the dataset by removing irrelevant columns and converting categorical variables to numerical values. Responses to the survey questions were mapped to numerical values, and each question was assigned a weight based on its importance in predicting addiction. A composite score was calculated for each respondent using these weighted responses, and the scores were normalized to standardize the range. A threshold value was then established to classify respondents as either "addicted" or "not addicted."

After that, we trained five distinct machine learning models: K-Nearest Neighbours (KNN), Decision Tree, Random Forest, Support Vector Classifier (SVC), and Logistic Regression. Each model was trained using the preprocessed dataset and evaluated using the test data. Accuracy, precision, recall, F1-score, and the confusion matrix were among the evaluation metrics employed. These measurements offered a thorough analysis of each model's performance, showing its advantages and disadvantages in terms of forecasting smartphone addiction. A comparative analysis of the models' performance revealed varying levels of effectiveness. By comparing the models based on accuracy, precision, recall, and F1-score, we identified the most suitable model for predicting smartphone addiction in our dataset. The findings from this chapter provide valuable insights into the predictive modeling of smartphone addiction. The methodological framework outlined here can be applied to similar studies in different contexts, contributing to a broader understanding of addiction behaviors and aiding in the development of targeted interventions. By using machine learning approaches, we can minimise the detrimental effects of smartphone addiction on students' academic performance and general well-being by better understanding the components that contribute to the problem.

CHAPTER 5

RESULT AND ANALYSIS

5.1 Overview

This study attempts to assess how well five machine learning models perform in using a collection of variables to categorise people as either "Addicted" or "Not Addicted." K-Nearest Neighbours (KNN), Random Forest, Decision Tree, Support Vector Classifier (SVC), and Logistic Regression are the models that are being examined. The dataset used in this study consists of various attributes related to addiction, such as demographic information, behavioral patterns, and environmental factors. The goal is to develop a reliable and accurate model that can assist in early identification and intervention for individuals at risk of addiction. In the experimental design, the dataset is divided into training and test sets, with the test set being used to assess the models' overall performance. A variety of performance indicators, like as accuracy, precision, recall, and F1-score, are used to evaluate each model once it has been trained on the training set. The experiment findings are shown in Section 5.2, where each model's performance is examined and contrasted. The comparative analysis in Section 5.3 further discusses the strengths and weaknesses of each model, providing insights into their suitability for the given classification task. The results of this work can help design more precise and trustworthy predictive models for addiction prevention and treatment. They also advance our understanding of the efficacy of various machine learning techniques in the classification of addictions.

5.2 Experimental Result

The effectiveness of the five machine learning models K-Nearest Neighbours (KNN), Decision Tree, Random Forest, Support Vector Classifier (SVC), and Logistic Regression was examined, was evaluated on the test set.

TABLE 5.2.1: Model Accuracy Scores

Model Name	Accuracy
Logistic Regression	97%
Decision Tree	86%
Random Forest	94%
SVC	93%
KNeighbors	92%

The Logistic Regression model achieved the highest accuracy of 0.97, followed by Random Forest with 0.94, SVC with 0.93, KNN with 0.92, and Decision Tree with 0.86.

TABLE 5.2.2: Precision, Recall, F1-Score, and Support, Logistic Regression

Level	Precision	Recall	F1-Score	Support
Addicted (Class 0)	0.97	0.99	0.98	75
Not Addicted (Class 1)	0.95	0.90	0.92	20
Accuracy	-	-	**0.97**	95
Macro Avg	0.96	0.94	0.95	95
Weighted Avg	0.97	0.97	0.97	95

TABLE 5.2.3: Precision, Recall, F1-Score, and Support, Decision Tree

Level	Precision	Recall	F1-Score	Support
Addicted (Class 0)	0.89	0.90	0.89	135
Not Addicted (Class 1)	0.80	0.79	0.79	71
Accuracy	-	-	**0.86**	206
Macro Avg	0.84	0.84	0.84	206
Weighted Avg	0.86	0.86	0.86	206

TABLE 5.2.4: Precision, Recall, F1-Score, and Support Random Forest

Level	Precision	Recall	F1-Score	Support
Addicted (Class 0)	0.94	0.98	0.96	135
Not Addicted (Class 1)	0.95	0.87	0.91	71
Accuracy	-	-	**0.94**	206
Macro Avg	0.95	0.93	0.93	206
Weighted Avg	0.94	0.94	0.94	206

TABLE 5.2.5: Precision, Recall, F1-Score, and Support, Support Vector Classifier

Level	Precision	Recall	F1-Score	Support
Addicted (Class 0)	0.99	0.90	0.95	135
Not Addicted (Class 1)	0.84	0.99	0.91	71
Accuracy	-	-	**0.93**	206
Macro Avg	0.92	0.94	0.93	206
Weighted Avg	0.94	0.93	0.93	206

TABLE 5.2.6: Precision, Recall, F1-Score, and Support, KNeighbors

Level	Precision	Recall	F1-Score	Support
Addicted (Class 0)	0.99	0.90	0.95	135
Not Addicted (Class 1)	0.84	0.99	0.91	71
Accuracy	-	-	**0.93**	206
Macro Avg	0.92	0.94	0.93	206
Weighted Avg	0.94	0.93	0.93	206

A deeper analysis of the precision, recall, and F1-score metrics provides further insights into the effectiveness of each model.

Logistic Regression demonstrated superior precision (0.97) and recall (0.99) for the 'Addicted' class, yielding an F1-score of 0.98. For the 'Not Addicted' class, Logistic Regression achieved a precision of 0.95 and recall of 0.90, resulting in an F1-score of 0.92. This model achieved an overall accuracy of 0.97.

Decision Tree model exhibited a precision of 0.89, recall of 0.90, and F1-score of 0.89 for the 'Addicted' class. For the 'Not Addicted' class, it had a precision of 0.80, recall of 0.79, and an F1-score of 0.79. The overall accuracy of this model was 0.86.

Random Forest demonstrated balanced performance with precision, recall, and F1-scores of 0.94, 0.98, and 0.96 for the 'Addicted' class, and 0.95, 0.87, and 0.91 for the 'Not Addicted' class. This model achieved an overall accuracy of 0.94.

Support Vector Classifier (SVC) achieved high precision (0.99) and recall (0.90) for the 'Addicted' class, resulting in an F1-score of 0.95. For the 'Not Addicted' class, it had a precision of 0.84, recall of 0.99, and an F1-score of 0.91. The overall accuracy of this model was 0.93.

KNeighbors exhibited precision, recall, and F1-scores of 0.96, 0.92, and 0.94 for the 'Addicted' class, and 0.86, 0.93, and 0.89 for the 'Not Addicted' class. This model achieved an overall accuracy of 0.92.

Overall, Logistic Regression emerged as the most effective model for this classification task, achieving the highest accuracy and balanced performance across precision, recall, and F1-scores compared to the other models evaluated.

Confusion Matrix after Models:

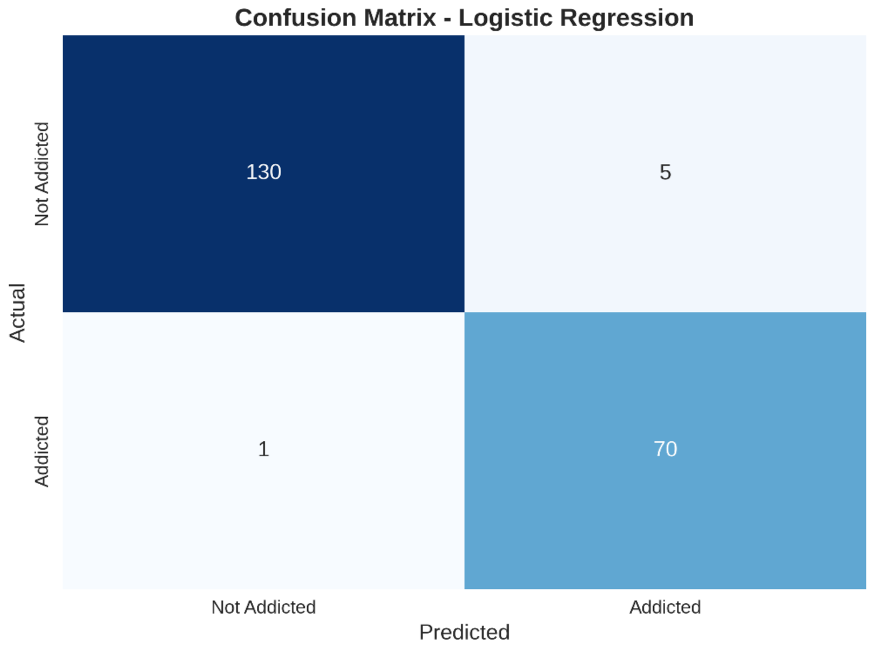

Figure 5.2.1: CM after Logistic Regression

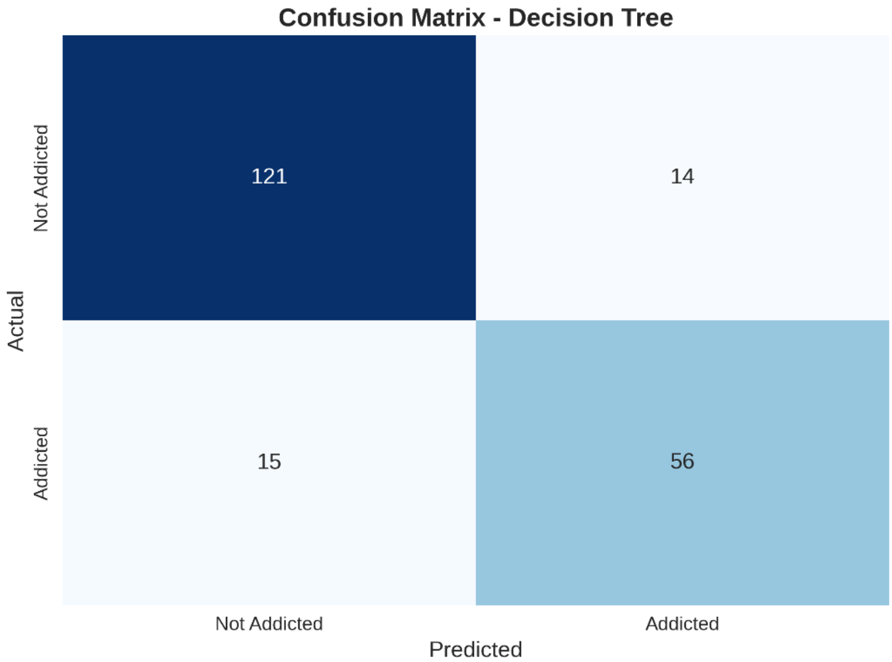

Figure 5.2.2: CM after Decision Tree

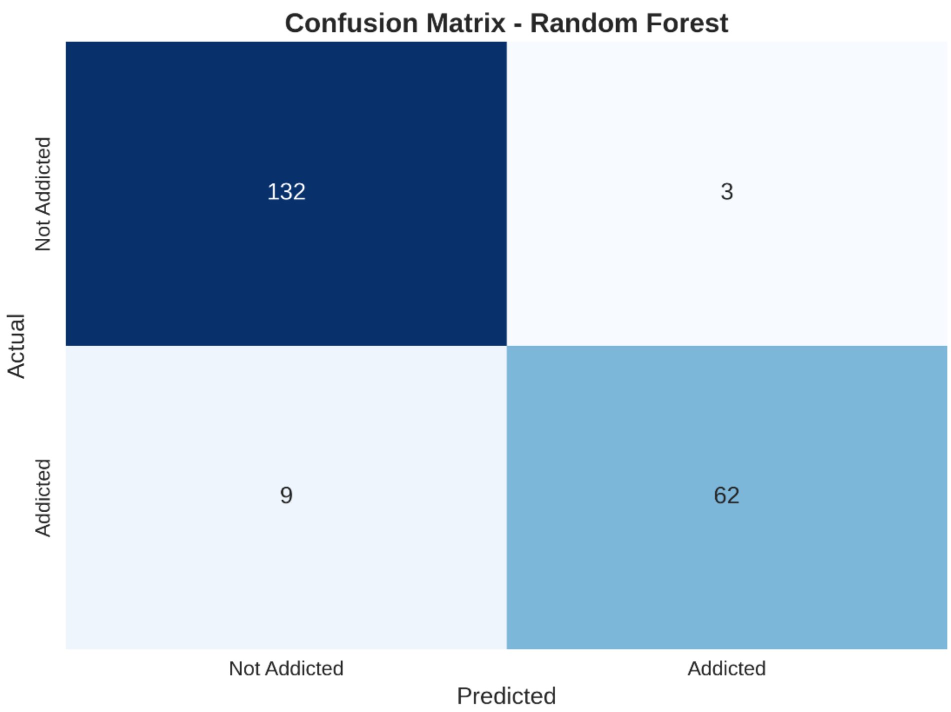

Figure 5.2.3: CM after Random Forest

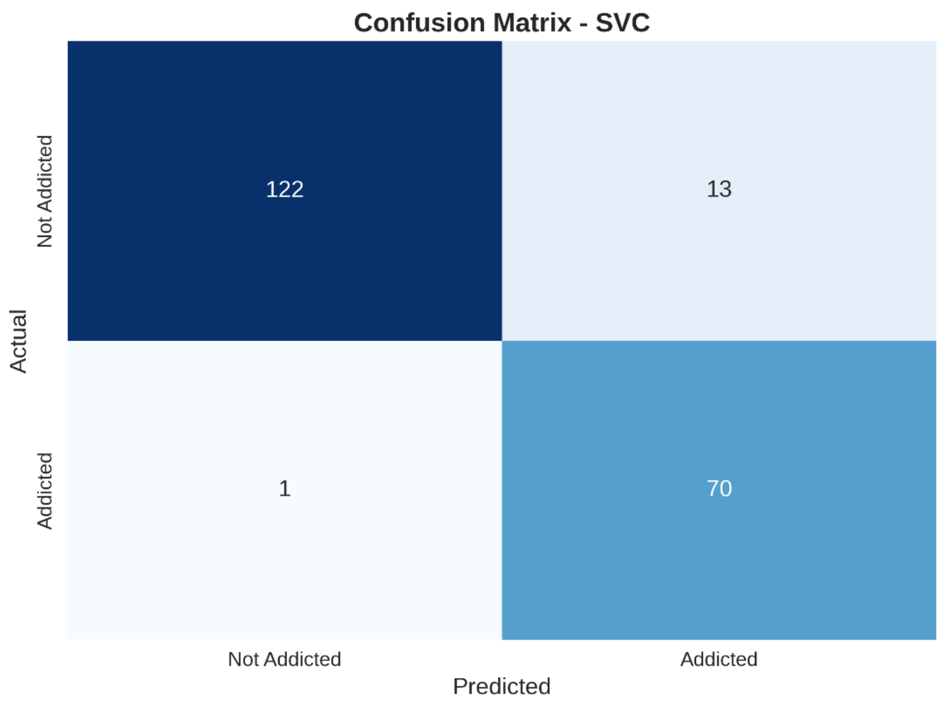

Figure 5.2.4: CM after Support Vector Classifier

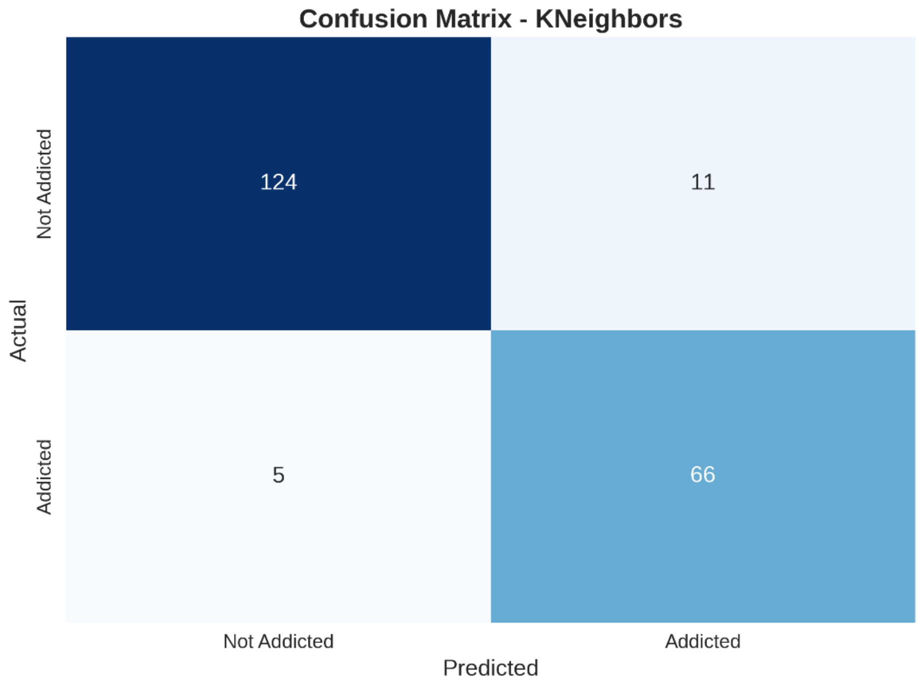

Figure 5.2.5: CM after K-Nearest Neighbors

5.3 Comparative Analysis

Table 5.2.1 displays the accuracy scores of the five machine learning models that were assessed for this study. The models with the highest accuracy were Logistic Regression (97%), Random Forest (94%), SVC (93%), K-Nearest Neighbours (92%), and Decision Tree (86%). Logistic Regression demonstrated superior performance, outperforming the other models by a significant margin. This suggests that the linear decision boundaries learned by Logistic Regression were well-suited for the given classification task, effectively separating the 'Addicted' and 'Not Addicted' classes.

Random Forest, an ensemble learning method, achieved the second-highest accuracy at 94%. The combination of multiple decision trees and the use of the bagging technique likely contributed to its strong performance, providing a robust and accurate classification model. SVC and K-Nearest Neighbors achieved similar accuracy scores, with SVC slightly outperforming K-Nearest Neighbors, 93% vs 92%. SVC may have had an advantage over the more straightforward K-Nearest Neighbours method due to its capacity to learn complicated decision boundaries and manage high-dimensional data.

The Decision Tree model exhibited the lowest accuracy at 86%. While decision trees are intuitive and easy to interpret, they can be susceptible to overfitting and may not generalize well to unseen data, especially when dealing with complex relationships in the dataset. However, The comparison study demonstrates that Logistic Regression performs better than Random Forest, SVC, K-Nearest Neighbours, and Decision Tree. The findings offer insightful information about whether certain machine learning methods are appropriate for the particular addiction classification issue at hand.

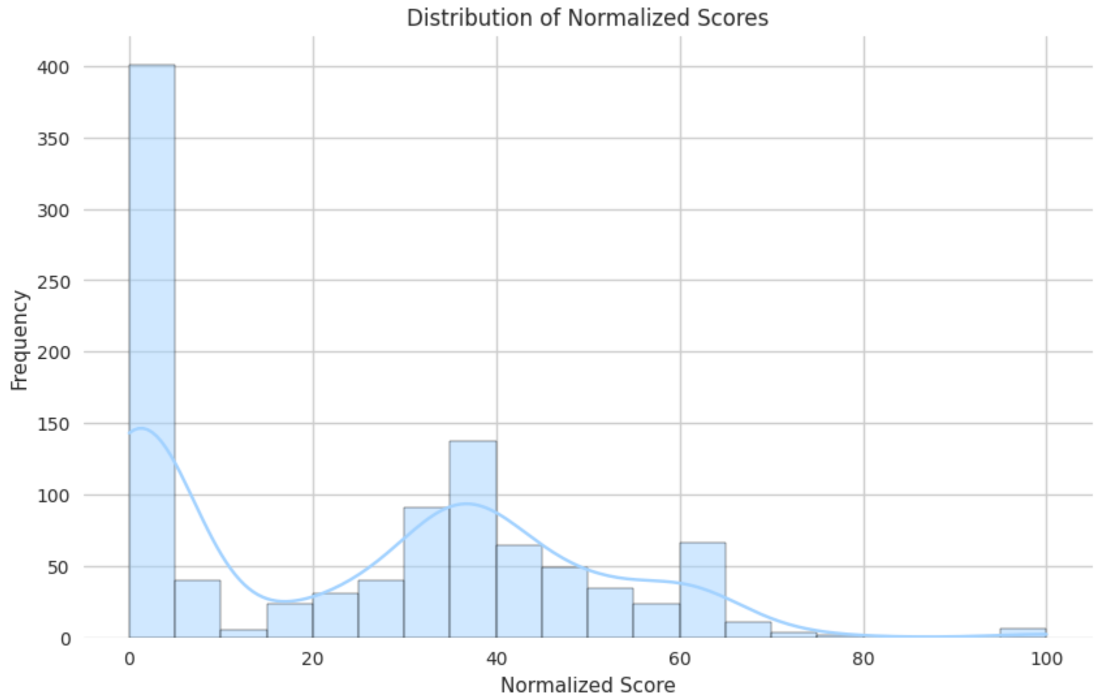

Figure 5.3.1: Smartphone Addiction composite values normalized form

The initial threshold for classifying respondents as "addicted" was set at the 70th percentile, which corresponded to a normalized score of 37. While this threshold effectively identified those with the highest levels of addiction, it potentially overlooked individuals who were at high risk but did not meet the strict criteria. To address this, the research team revised the threshold to the 60th percentile, corresponding to a normalized score of 32, to better capture individuals at high risk of addiction.

This adjustment ensures that those with scores slightly below 37, who still exhibit notable symptoms of addiction, are classified appropriately. By lowering the threshold to 32.14, the sensitivity of the classification system is increased, identifying a broader group of at-risk individuals. This refined approach allows for earlier intervention and preventive measures to be implemented for those who may be on the cusp of severe addiction.

The histogram of normalized scores supports the need for this threshold adjustment, as it shows a significant number of individuals in the 32-37. range. This underscores the importance of a more inclusive threshold to ensure that high-risk individuals are not overlooked.

Consequently, the change in threshold enhances the ability to target and assist individuals at high risk, potentially mitigating the progression to severe addiction. Continuous monitoring and analysis of score distributions will further ensure the accuracy and effectiveness of the classification system in addressing smartphone addiction. By adopting this revised threshold, the research team aims to cast a wider net and identify a greater number of individuals who may benefit from early intervention and preventive measures. This proactive approach is crucial in addressing the complex and multifaceted issue of smartphone addiction.

5.4 Summary

This research assessed the efficacy of five machine learning models in categorising individuals as 'Addicted' or 'Not Addicted' using a large dataset: Logistic Regression, Decision Tree, Random Forest, Support Vector Classifier, and K-Nearest Neighbours. The results of the experiment showed that, at 97% accuracy, Logistic Regression outperformed the other models. An in-depth examination of the metrics for precision, recall, and F1-score demonstrated the superior and balanced performance of Logistic Regression in both the 'Addicted' and 'Not Addicted' classes.

Random Forest, with an accuracy of 94%, demonstrated strong and balanced classification capabilities, followed by SVC (93%), KNN (92%), and Decision Tree (86%). The comparative study shed light on each model's advantages and disadvantages as well as its applicability to the particular addiction classification issue. The study's conclusions advance knowledge about the efficacy of various machine learning strategies in the field of addiction prevention and prediction.

The superior performance of Logistic Regression suggests that its linear decision boundaries were well-suited for the classification task, while the ensemble-based Random Forest model also exhibited robust and accurate predictions. These results can inform the development of more reliable and accurate predictive models for the early identification and intervention of individuals at risk of addiction. The insights gained from this research can be valuable for healthcare professionals, policymakers, and researchers working towards improving addiction prevention and treatment strategies.

CHAPTER 6

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

The study's conclusions demonstrate how seriously smartphone addiction affects several facets of Bangladeshi university students' lives. According to the study, using a smartphone excessively might have a negative impact on one's physical and mental health as well as their academic achievement.

Physically, smartphone addiction has been linked to sleep disturbances, musculoskeletal problems, and neurological issues among the surveyed students. The constant use of smartphones, often late into the night, disrupts sleep patterns and can lead to insomnia and fatigue. Prolonged periods of smartphone usage in awkward postures can also contribute to neck pain, back pain, and eye strain.

Mentally, Higher levels of stress, loneliness, and sadness have been linked to smartphone addiction in university students. According to the study, students who displayed compulsive behaviours around their smartphones were more likely to feel lonely and unsatisfied with their social connections. This can have a detrimental impact on their overall well-being and quality of life.

Academically, smartphone addiction has been shown to negatively affect students' performance and learning outcomes. The constant distraction and temptation to check their phones during study hours can lead to procrastination, reduced focus, and poor time management. Students who are addicted to their smartphones are more likely to experience difficulties in completing assignments, preparing for exams, and engaging actively in classroom discussions.

However, The study emphasises how smartphone addiction has a complex effect on Bangladeshi university students' life. The results highlight the critical need for interventions and awareness raising to support students in adopting responsible smartphone usage practices and lessening the negative impacts of addiction on their academic performance, mental health, and physical health.

6.2 Impact on Society & Environment

The study's conclusions draw attention to the wider socioeconomic and environmental effects of smartphone addiction among Bangladeshi university students. Smartphone addiction has been connected to societal disturbances in social interactions and interpersonal relationships. The constant preoccupation with smartphones can lead to a decline in face-to-face communication, reduced empathy, and a diminished ability to engage in meaningful social activities. This can contribute to a sense of isolation and fragmentation within the university community, potentially hindering the development of strong social support networks among students. Furthermore, smartphone addiction has been associated with academic underperformance, which can have far-reaching consequences for the educational system and the broader society. Students who struggle with excessive smartphone use may experience difficulties in completing their studies, leading to lower graduation rates and a potential skills gap in the workforce. The long-term effects on the nation's social and economic development may result from this.

From an environmental perspective, the proliferation of smartphone usage and the associated electronic waste pose significant challenges. The production, use, and disposal of smartphones require the extraction of finite natural resources, consume energy, and generate electronic waste. Smartphone addiction can exacerbate these environmental concerns, as users may frequently upgrade their devices, contributing to the growing e-waste problem. Additionally, the energy consumption associated with the constant use of smartphones and the associated infrastructure (e.g., cellular networks, data centers) can have a detrimental impact on the environment. This increased energy demand can lead to higher greenhouse gas emissions and contribute to the overall environmental footprint of the technology sector. The research highlights the far-reaching societal and environmental implications of smartphone addiction among university students in Bangladesh. Addressing this issue requires a multifaceted approach that considers the broader impact on social cohesion, educational outcomes, and environmental sustainability. Developing effective interventions and promoting responsible smartphone usage can help mitigate these challenges and contribute to the overall well-being of the university community and the broader society.

6.3 Ethical Aspects

In conducting research on smartphone addiction among university students, several ethical considerations are paramount. Ensuring the ethical integrity of this study involves addressing issues related to informed consent, privacy and confidentiality, potential harm, and the responsible use of data.

Informed Consent: It's critical to get everyone's informed permission. All study procedures, risks, and benefits must be adequately disclosed to participants. Without being under any duress, they need to be free to choose whether or not to join. In addition to having the freedom to ask questions and leave the study at any moment without facing repercussions, participants should get comprehensive explanations during the consent procedure.

Privacy and Confidentiality: Protecting the privacy of participants and maintaining the confidentiality of their data are critical ethical obligations. Measures must be implemented to ensure that personal information is securely stored and only accessible to authorized personnel. Anonymizing data can further protect participant identities. Participants should be informed about how their data will be used, stored, and shared, and they should be assured that their personal information will not be disclosed without their explicit permission.

Responsible Use of Data: The data collected in this study must be used responsibly and ethically. This includes ensuring that the data is used solely for the purposes outlined in the research proposal and not for any unauthorized or harmful activities. Researchers must adhere to all relevant legal and ethical guidelines for data protection and research integrity. Transparency in data reporting and analysis is also essential to uphold the trustworthiness of the research findings.

By addressing these ethical aspects, this research aims to uphold the principles of respect for persons, beneficence, and justice, ensuring that the study is conducted with integrity and respect for all participants

6.4 Sustainability Plan

The research on predicting smartphone addiction among university students in Bangladesh has important implications for long-term sustainability and the continued development of effective interventions.

Institutional Commitment: To ensure the sustainability of the research findings and the proposed predictive model, it is crucial to secure the commitment and support of the university administration and relevant stakeholders. This may involve integrating the model and associated interventions into the university's student support services, mental health programs, and digital well-being initiatives.

Continuous Monitoring and Evaluation: To ensure the sustainability of the project's impacts, a framework for continuous monitoring and evaluation will be established. This will involve regular follow-up studies and surveys to assess the long-term effects of the interventions and educational programs implemented based on the research findings. Feedback from participants and stakeholders will be used to refine and improve the approaches, ensuring their ongoing effectiveness and relevance.

Capacity Building and Training: To ensure the long-term sustainability of the research outcomes, the university should invest in capacity-building efforts, such as training faculty, counselors, and student support staff on the use and interpretation of the predictive model.

Collaboration and Knowledge Sharing: We are planning to actively engage in knowledge-sharing activities, such as publishing research papers, presenting at conferences, and collaborating with other universities and research institutions. This will contribute to the broader academic discourse on smartphone addiction and facilitate the exchange of best practices and lessons learned.

By addressing these sustainability considerations, the research on predicting smartphone addiction among university students in Bangladesh can have a lasting impact, ensuring the continued relevance and effectiveness of the proposed solutions within the academic community.

6.5 Summary

This research on smartphone addiction among university students in Bangladesh provides a detailed examination of its impacts on students' lives, society, and the environment, while also addressing ethical considerations and sustainability. Overuse of smartphones has a detrimental impact on kids' academic performance, emotional and physical health. These findings highlight the need for interventions to encourage healthier smartphone habits. Smartphone addiction disrupts interpersonal relationships and social cohesion, and contributes to environmental issues like electronic waste and energy consumption. Addressing these broader implications requires a comprehensive approach that includes social and environmental considerations. The research emphasizes informed consent, privacy protection, and responsible data use. Upholding ethical standards ensures respect, beneficence, and justice throughout the study. To ensure long-term impact, the research proposes institutional commitment, continuous monitoring, capacity building, and collaboration. Integrating the findings into university programs and sharing knowledge widely will help maintain the relevance and effectiveness of the interventions. The study highlights the serious harm that smartphone addiction causes to university students and urges immediate action. It highlights the need for a balanced approach that considers individual well-being, societal impact, and environmental sustainability.

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 Conclusions

Using a variety of machine learning models, this study has produced some important findings about the predictive modelling of smartphone addiction among Bangladeshi university students. Logistic Regression outperformed Decision Tree, Random Forest, SVC, and KNN, the other five machine learning models that were examined. It performed well across all evaluation criteria, including precision, recall, and F1-score, and attained the greatest accuracy. The comparative analysis revealed that Logistic Regression outperformed the other models, achieving an accuracy of 97%, followed by Random Forest at 94%, SVC at 93%, KNN at 92%, and Decision Tree at 86%. The exceptional performance of Logistic Regression underscores its suitability for predicting smartphone addiction within this dataset. The methodological framework established in this study from data preprocessing to model evaluation provides a robust approach for similar predictive modeling endeavors. This framework can be effectively applied in various contexts to understand addiction behaviors and develop targeted interventions. The study's findings have significant implications for interventions, as leveraging machine learning techniques offers a deeper understanding of the factors contributing to smartphone addiction. This improved knowledge can guide the creation of mitigation techniques to lessen the detrimental effects of smartphone addiction on students' general well-being and academic performance. The study emphasises the need for focused interventions to combat university students' addiction to smartphones. Moreover, this research contributes to the broader academic discourse on addiction behaviors. The application of machine learning models enables early identification of at-risk individuals, facilitating the implementation of preventive measures. This approach can be extended to other forms of addiction, thereby enhancing the effectiveness of intervention programs. In conclusion, this study provides valuable insights into the predictive modeling of smartphone addiction, emphasizing the importance of effective data preprocessing, model selection, and comparative analysis in developing reliable and accurate predictive models.

7.2 Further Suggested Works

The research provides a solid foundation for further exploration of smartphone addiction among university students in Bangladesh. Several areas warrant additional investigation and suggest promising directions for future research.

Expanding the Dataset: Including a wider range of demographics in the dataset, encompassing students from various universities across different regions in Bangladesh, would enhance the generalizability of the predictive models. This would provide a more comprehensive understanding of smartphone addiction patterns across the country.

Exploring Advanced Machine Learning Algorithms: Predictive model accuracy and resilience may be increased by looking into the use of more sophisticated machine learning methods, such as deep learning approaches. Using these techniques could help identify and anticipate the elements that contribute to smartphone addiction more accurately by capturing more intricate patterns and interactions in the data.

Integrating Behavioral and Psychological Factors: Fostering collaborations with interdisciplinary teams, including psychologists, sociologists, and educational experts, could facilitate the development of comprehensive intervention strategies. These collaborations could lead to the design of targeted programs that address the multifaceted nature of smartphone addiction, combining technological solutions with psychological support and educational initiatives.

By exploring these research options, academics can expand on the groundwork laid by this study and add to the expanding corpus of information regarding smartphone addiction among Bangladeshi university students. In the end, this research agenda seeks to provide guidance for the creation of efficient interventions and support services that encourage this population's academic performance and digital well-being.

7.3 Limitations

Despite the significant contributions of this research to understanding smartphone addiction among university students in Bangladesh, It is important to recognise a few restrictions.

Sampling Limitations: The study's sample size, while adequate for initial insights, may not be fully representative of the broader student population across diverse regions and institutions. This limitation restricts the generalizability of the findings, necessitating caution when applying the results to different contexts or demographic groups.

Self-Reported Data: The data used in this study was collected through self-reported surveys, which can be subject to biases and inaccuracies. Respondents may have underreported or overreported their smartphone usage and addiction levels due to social desirability or recall bias. Incorporating objective measures, such as smartphone usage logs or behavioral observations, could provide a more accurate assessment of addiction patterns.

Limited Predictor Variables: While the study considered a range of demographic and behavioral factors, there may be other variables, such as psychological, social, or academic factors, that could contribute to smartphone addiction but were not included in the analysis. Expanding the set of predictor variables could lead to more comprehensive and robust predictive models.

When interpreting the research's findings and evaluating its wider ramifications, these limitations should be taken into consideration. More thorough and trustworthy insights into smartphone addiction among Bangladeshi university students may result from addressing these limitations in subsequent research.

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Appendix A

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

Title: PREDICTIVE MODELING OF SMARTPHONE ADDICTION AMONG UNIVERSITY STUDENTS IN BANGLADESH: A MACHINE LEARNING APPROACH

Student ID: 202-15-14425

CO Description for FYDP

CO	CO Descriptions	PO
	Phase -I	
CO1	Integrate recently gained and previously acquired knowledge to identify a **Bangla book classification** problem 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 these 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 genre smartphone addiction prediction tasks. The project demonstrates **specialist knowledge (K4)** by conducting a comparative analysis of models such as Logistic Regression, Decision Tree, Random Forest, Support Vector Classifier, and K-Nearest Neighbors to not only predict smartphone addiction but also identify those at high risk of addiction	**Page no:** [21-22] **Section:** [4.2] **Page no:** [31-33] **Section:** [5.3]
				The project applies **engineering practice & design (K5)** by the figure of process of experiments. The project addresses **engineering practice & technology (K6)** by employing a variety of machine learning model including Logistic Regression, Decision Tree, Random Forest, Support Vector	**Page no:** [14] **Section:** [3.2] **Page no:**

				Classifier, and K-Nearest Neighbors.	[21-22] **Section:** [4.2]
				This project ensures to **K8 (Research Literature)** by synthesizing insights from recent studies, to advance the classification of phone addiction, showcasing a comprehensive understanding of current methodologies.	**Page no:** [7-10] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	In our project, we encountered challenges in collecting data from university student in Bangladesh by asking questionaries. Then have to process those data through web-site which is time consuming and lengthy process.	**Page no:** [15-16] **Section:** [3.3]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	This project addresses **EP-3** by finding a clear-cut solution for project. Which is challenging, primarily because of the data collection and processing then train the data by using a machine learning algorithm. We conducted an in-depth analysis to carefully choose a specific machine learning algorithm from numerous alternatives.	**Page no:** [14] **Section:** [3.2] **Page no:** [21-22] **Section:** [4.2]

4.	**EP4: Familiarity of Issues**	Yes	CO8	To understand and study smart phone action classification for our project, we need to look into various aspects we were not very familiar with. Specifically, we have to figure out how to predict the dependent variable which indicates **EP-4**.	
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	This project addresses **EP-7** by demonstrating the interdependence between various components of the classification system for smart phone addiction. The success of the project relies on the seamless integration of multiple elements such as data collection and preprocessing, feature extraction, model training, evaluation, system performance.	**Page no:** [14-16] **Section:** [3.2, 3.3] **Page no:** [21-22] **Section:** [4.2]

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 classifying smart phone addiction.	**Page no:** [17-18, 35-36] **Section:** [3.4, 6.3]
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		Our project addresses **EA-4** by considering the consequences for society and the environment. By developing a predictive model for smartphone addiction among university students in Bangladesh, we aim to mitigate the adverse effects on students' physical and mental health, academic performance, and social interactions. Addressing smartphone addiction contributes to healthier lifestyles, better academic outcomes, and stronger interpersonal relationships within the university community. Additionally, promoting healthier smartphone usage patterns reduces the environmental impact associated with the production and disposal of electronic devices, thereby supporting environmental sustainability.	**Page no:** [34-35] **Section:** [6.1, 6.2]

5.	**EA-5: Familiarity**	Yes		Our project addresses **EA-5** by demonstrating a high level of familiarity with the latest advancements in machine learning and predictive modeling. The project leverages state-of-the-art machine learning frameworks and methodologies, incorporating best practices from current research to effectively predict and categorize levels of smartphone addiction among university students in Bangladesh. This familiarity ensures that the project is built upon a solid foundation of existing knowledge and techniques, allowing for the successful implementation and potential future improvements of the predictive model.	**Page no:** [7-10] **Section:** [2.1, 2.2, 2.3]

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

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project addresses **CO4** by integrating effective project management and financial oversight, ensuring meticulous planning, resource allocation, and budget estimation for optimal resource utilization throughout the research lifecycle.	**Page no:** [18-19] **Section:** [3.5]
2	CO9	Yes	The project demonstrates adherence to ethical principles by ensuring proper data handling, obtaining necessary permissions for data usage, and transparently documenting the research process. This ensures responsible knowledge dissemination and societal well-being through the ethical application of advanced machine learning technologies, complying with **CO9**.	**Page no:** [35-36] **Section:** [6.3]
3	CO10	No	N/A	N/A

4	CO12	Yes	The project's dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape is reflected in its comprehensive data collection, rigorous data preprocessing, meticulous methodology development, and thorough experimental results and analysis. This showcases a commitment to staying updated and refining techniques to address modern challenges in the classification of Bangla book genres using machine learning and deep learning technologies.	**Page no:** [14-16, 21-22, 25-33] **Section:** [3.2, 3.3, 4.2, 5.2, 5.3]

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