EXPLORING THE NEXUS BETWEEN DRUG ADDICTION AND SUICIDAL TENDENCIES IN BANGLADESH

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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

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This Project titled "Exploring the Nexus Between Drug Addiction and Suicidal Tendencies in Bangladesh", submitted by **Golam Kibria** and **Tasnim Umaer Tisha** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 14-07-2024.

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Md. Sadekur Rahman, Assistant 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

Bangladesh, a country experiencing fast socioeconomic transformation, is dealing with a new concern, the intertwined shadows of drug addiction and suicidal tendencies. This study dives into this complicated intersection, attempting to understand the variables that link them and the disastrous consequences they cause. The purpose of this study is to look into the risk variables connected with suicide among those who are struggling with drug addiction and to develop effective prevention techniques. The study is motivated by the pressing need to understand the complex interplay of factors influencing the elevated suicide risk within this vulnerable population. The study uses a comprehensive literature analysis to systematically synthesize information on suicide risk factors, emphasizing the relevance of the problem and the severity of its impact. The literature evaluation reveals noteworthy conclusions, including the fact that people with drug addiction are significantly more likely to commit suicide. Mental health treatment during childhood, the loss of key persons at a young age, and severe psychological disorders all appear to play a role in this increased risk. The alarming rise in suicide rates among drug addicts needs a thorough study of the underlying risk factors and the development of effective preventative techniques. With over 700,000 people globally committing suicide each year and suicide being designated as the fourth highest cause of death among persons aged 15 to 29, immediate action is required. In addition, the correlation between drug addiction and suicide attempts underscores the critical need for evidence-based interventions to mitigate this pressing public health concern. The anticipated outcome of this research is to not only provide evidence-based knowledge but also serve as a foundation for policymakers, healthcare professionals, and community stakeholders to develop targeted initiatives aimed at addressing the nexus between drug addiction and suicidal tendencies in the context of Bangladesh.

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LIST OF ACRONYMS

Acronym	Full Form
AI	Artificial Intelligence
BDT	Bangladeshi Taka
ML	Machine Learning
SWOT	Strengths, Weaknesses, Opportunities, and Threats
WHO	World Health Organization
SVM	Support Vector Machine
k-NN	k-Nearest Neighbors
MLP	Multi-Layer Perceptron
CNN	Convolutional Neural Network
FYDP	Final Year Design Project

CHAPTER 1

Introduction

1.1 Overview

Suicide is a major problem in today's culture. It is one of the leading causes of death worldwide, and it is becoming worse by the day. Every year, over 700,000 people commit suicide, according to a WHO estimate [1], suicide is the fourth leading cause of death among those aged 15 to 29. The number of suicides is rising in every country. According to statistics, low and moderate-income countries account for more than 77% of suicides. Suicide rates among our neighboring nations, such as India, are 12.7 per 100,000 people [2]. Suicide has been a major issue in Bangladesh. According to statistics, Bangladesh has a suicide death rate of 3.7 per 100,000 people, which is increasing year after year [3]. In most cases, depression and childhood abuse plays the main role behind suicide attempts [4]. Several studies have identified risk factors such as comorbid disorders, criminal activity, and previous suicide attempts among drug-dependent individuals [5]. This research aims to explore the risk factors for suicide among people with drug addiction and to provide insights into effective prevention strategies. Young drug addicts with severe personality disorder, depression, or both have a particularly high risk of suicide, with rates of suicide attempts at 8.0-17.2% [6]. A study conducted in Japan found that drug-dependent individuals with a history of suicide attempts were significantly younger, started abusing drugs at an earlier age, had more psychiatric problems, and scored higher on depression scales [7]. The problem statement emphasizes the lack of a complete understanding of the incidence of suicide and suicidal tendencies among those addicted to drugs in Bangladesh, which impedes the development of effective intervention and prevention strategies.

1.2 Background and Present State

Every year, over 1 million individuals commit suicide worldwide, resulting in a mortality rate of 16 per 100,000 people. Additionally, one person dies by suicide every 40 seconds. [8]. Consequently, suicide is declared as the world's 3rd leading cause of death among 15–44 years old people [9]. The devastating intersection of drug addiction and suicide demands urgent attention. Globally, suicide rates are nearly three times higher among individuals with drug dependence compared to the general population [10]. Suicide has become an everyday occurrence in Bangladesh [11]. According to data from the Police Headquarters, over 11095 people ascended to the way of self-destruction in Bangladesh in 2017, which indicates that 30 people are killed every day on average [12]. So, the objective behind this research is to discover risk variables related to suicide and suicidal tendencies in the group of individuals with drug addiction in Bangladesh.

Suicide does not only affect the victim but also their family, friends, and even society. There is no agreement on the definition of the suicide stages yet [13]. However, suicidal people were commonly divided into two main classes: thinkers (thinkers, planners) and attempters (attempters, completers). Considering 80% of the patients attempting suicide were found to score in the depressive range [14], The specific objectives of this study are:

1. To examine the incidence of suicide and suicidal thoughts among drug addicts in Bangladesh.
2. To determine the risk factors that are linked to suicide and suicidal thoughts among Bangladeshi drug addicts.
3. To offer suggestions for evidence-based preventive and intervention plans in order to lessen the suicide rate among this highly vulnerable community.

1.3 Problem Statement

Considering Bangladesh's startlingly high suicide rates, the relationship between drug addiction and suicide represents a serious public health risk. It is essential to comprehend the unique characteristics of suicidal thoughts among drug addicts in order to create focused interventions and preventative measures. The purpose of this study is to clarify the prevalence of suicide and thoughts of suicide among drug addicts in Bangladesh and to pinpoint the underlying risk factors linked to these phenomena. Through exploring the complexities of this problem, the project aims to contribute to evidence-based strategies that lower the suicide rate and enhance mental health in this susceptible population. The necessity of addressing the relationship between drug addiction and suicide in Bangladesh is the driving force for this study. This research can help save lives and improve the wellbeing of this sensitive community by identifying risk factors and guiding preventative measures.

Research Questions

RQ1: How common are suicide and suicidal ideation among those struggling with drug addiction in Bangladesh?
RQ2: What are the main risk factors for suicide ideation in people with drug addiction?
RQ3: What evidence-based recommendations can we derive from our research to effectively address the issue?

1.4 Objectives

Our desired objective is as listed below:

A Comprehensive Understanding of Prevalence: The goal of our research is to provide an in-depth understanding of the incidence of suicide and suicidal inclinations among drug addicts in Bangladesh. We hope to provide a comprehensive view that might inform targeted actions and support systems through analysis of data and pattern exploration.

Identification of Key Risk Factors: It is critical to unravel the complex network of variables that influence the risk of suicide among drug addicts. We try to pinpoint the major risk factors by carefully examining them, illuminating the complex interactions between biological, psychological, and social factors that increase vulnerability.

Evidence-Based Recommendations for Intervention: With a thorough grasp of the situation, our research hopes to produce evidence-based suggestions. These recommendations will serve as a road map for stakeholders, providing real and practical measures to prevent suicides and minimize the impact of suicidal tendencies among Bangladesh's vulnerable population of people struggling with drug addiction.

As we continue on this journey of discovery and advocacy, we remain committed to establishing a future in which evidence-based practices pave the way for a more resilient and supportive community.

1.5 Scope and Limitation

Addiction and suicidal ideation have been studied in a variety of circumstances. One study looked into the prevalence of suicidal ideation and previous suicide behavior among substance users, as well as the relationship between clinical and sociodemographic factors [15]. Another study looked at the relationship between suicide thoughts, internet addiction, and school bullying among Korean high school students. It was discovered that students who were bullied and sad were more likely to have suicidal ideation. Suicidal thoughts were also significantly influenced by the female gender and smartphone addiction [16].

The scope of this research will include a thorough assessment and analysis of the current literature in order to comprehensively map and synthesize the extent and character of published and gray literature linked to the risk factors for suicide among people with drug addiction. This will include an in-depth examination of the various risk factors associated with suicidal behavior in people with drug addiction, such as demographic characteristics, clinical aspects, comorbid disorders, substance abuse, and other individual level risk factors such as depression, anxiety, and trauma [17]. The scope will also include identifying the most significant causes of this population's increased risk of suicide, with a focus on understanding the interplay between these factors and their relative impact on suicidal behavior.

1.6 Report Organization

The suggested report has a thorough format that walks readers through the methodology, conclusions, and significance of the study. Every chapter has a distinct function and adds to the document's overall structure and depth.

Chapter 1: Introduction

Chapter 1 is the introduction. This report's introduction chapter provides a full summary of the research. It begins by outlining the identified problem and highlighting its importance. The research objectives, motivation, and anticipated outcomes are then outlined. Furthermore, this chapter explains the overall structure and organization of the report.

Chapter 2: Literature Review

Chapter 2 opens with an introduction to the section on literature review. It dives into relevant studies within the research subject and compares existing material. The comparison reveals both parallels and differences in earlier efforts, resulting in a comprehensive gap analysis. The chapter finishes with a summary of the important conclusions from the review of literature.

Chapter 3: Research Methodology

The strategy used to carry out the study is described in the research methodology chapter. It provides light on the model architecture, data gathering techniques, research design, and the reasoning behind particular methodology selections. The ethical issues and potential constraints on the investigation are also covered in this chapter.

Chapter 4: Implementation

This chapter outlines the implementation process of our model. Section 4.1 gives an overview, Section 4.2 details the prototype design and training, Section 4.3 discusses system testing and model evaluation, and Section 4.4 provides a summary of the implementation outcomes.

Chapter 5: Result and Analysis

The experimental outcomes from the training model are shown in this chapter. Comprehensive evaluations of the effectiveness of various detection and segmentation techniques are offered, accompanied by graphical depictions and statistical metrics that validate the results.

Chapter 6: Impact on Society, Environment and Sustainability

The research explores how the findings from the study would affect society in Chapter 5. It looks at how knowledge gained from studying the relationship between drug addiction and suicide in Bangladeshi people might influence social networks, interventions, and policy. The chapter specifically addresses the research's broader implications for community well-being, mental health awareness, and public health. It also looks at how important it is to minimize and increase awareness in order to confront the complex issues that drug addiction and suicide present to Bangladeshi society.

Chapter 7: Conclusion and Future Work

The whole report is summarized in this last chapter. It provides recommendations for real-world applications and more research in addition to summarizing the main results and restating the research's conclusions. A path for academics interested in building upon the current study is provided in the discussion of the implications for future research.

This planned organization ensures a logical flow of material, taking the reader through the study process from introduction to broader implications and suggestions.

1.7 Summary

This study focuses on the serious issue of suicide among drug addicts in Bangladesh, wherein suicide rates are growing. The study's goal is to better understand the high rate of suicide and suicidal ideation among drug addicts, as well as to identify major risk factors such as depression, childhood maltreatment, and comorbidities. The goals include offering insights into targeted interventions and prevention efforts. The project will conduct a complete evaluation of existing literature and data to determine the scope of the problem, with an emphasis on demographic, clinical, and personal level risk factors. This study will generate evidence-based recommendations to reduce suicide rates and enhance mental health among this sensitive demographic, resulting in a more supportive community.

CHAPTER 2

Literature Review

2.1 Overview

The literature review will concentrate on identifying and analyzing the risk variables associated with suicide among those battling with drug addiction. It seeks to carefully document, critically evaluate, and summarize previous research on this specific research subject. This review will highlight the topic's significance, the depth of its impact on individuals, and the need for additional research in this field. By clarifying the questions being addressed and positioning the study within the existing knowledge base, the review aims to improve understanding of the risk factors linked with suicide in drug addicts.

2.2 Related Works

In [18] the research covers a follow-up investigation of 125 drug addicts who had short-term rehabilitation and detoxification. According to this study, 45% of the participants said they had tried suicide at least once in their lives. The most often mentioned causes of these attempts were loneliness and the death of a loved one. Interestingly, only a small number of respondents reported using their drug of choice in their suicide attempts. The study also found that suicide attempters had higher odds of having received mental health care as children and having lost important people while they were young. Suicide attempters reported more severe psychological issues and depressed moods at the 5-year follow-up than people who had never attempted suicide. This study emphasizes how crucial it is to evaluate drug users' risk of attempting suicide in order to put preventative measures in place to stop suicidal behavior in the future.

In [19] The purpose of the study was to look at suicide patterns over a 25-year period among UK-registered addicts. According to the study, the rates of suicide for men and women were 44.8 and 69.0 per 100,000 persons, respectively. Over the course of the 25-year period, there was a steady decrease in the suicide rate. For males, the risk went down from 17.2 to 4.4 (3.9 times decrease), and for females, it dropped from 52.6 to 11.3 (4.7 times decrease). In 45% of instances, drug overdose was the most frequent form of suicide.

The results verify that there is still a higher suicide risk among addicts than in the general population and that prescribed drugs—particularly methadone and antidepressants—influence this heightened risk.

In [20] examined the link between drug addiction and suicide based on data from 1608 individuals admitted to treatment in Norway over the past three decades. The findings reveal that 2.3% of these individuals died annually, with 14.7% of those deaths attributed to suicide. Compared to the general population, drug users had a significantly higher suicide rate. The study suggests that female drug addicts admitted to treatment in the 1970s and 1980s tended to take their lives in a shorter timeframe than those admitted in the 1960s. Gender roles and the increased risk of suicide among drug addicts are examined.

In [21] looks at the relationship between substance misuse, depression, and suicidal ideation in 990 people with a criminal record. According to the findings, women are twice as likely as males to experience depression, whereas men are more likely to have antisocial personality disorder. Predictors for men include alcohol use disorder and depression.

In [22] a study in Japan investigated the relationship between substance use disorder and suicidal behavior in drug-dependent individuals. The study involved 101 patients from 8 rehabilitation institutions and assessed personal profiles, including history of suicide attempts, physical and mental problems, and depression. Results showed that 49.5% of patients had attempted suicide, The study indicates that early-age drug abuse, psychiatric issues, depressive symptoms, and perceived cold and rejecting parental raising behaviors may raise the chance of drug-dependent persons developing suicidal tendencies.

In [23] the purpose is to look at the prevalence of suicidal ideation and previous suicidal behavior among substance users. The sample included 119 patients with drug addiction behaviors. Results showed that 18.5% had previous suicidal ideation in their lifetime, 2.5% had it at admission, and 10.9% had previous attempts. This shows that suicidal risk is higher in drug-abusing populations, most likely due to impulsiveness. The study also looked at the link between clinical and sociodemographic factors.

In [24] found a concerningly high prevalence of suicide (8% to 17%) among opioid addicts, but there is insufficient information regarding who is at a higher risk and what variables contribute to this. This shows that doctors should pay greater attention to the mental health disorders lurking beneath the surface and provide appropriate therapy. It highlights the importance of understanding and addressing the mental well-being of opioid addicts to prevent suicides.

In [25] it is critical to comprehend the relationship between substance abuse and suicide. A survey of 200 people contrasted 100 heroin users who tried suicide against 100 opiate addicts who did not. The study discovered significant changes in personality patterns, particularly in relation to the length of addiction and heroin use. A family history of drug misuse and suicidal conduct were significant factors. Finally, biological and psychological effects, as well as the impact of the narcotics themselves, are risk factors for opiate addicts.

In [26] addresses the need for efficiently detecting drugs associated with suicide risk by creating a comprehensive corpus of drug-suicide relations. The corpus contains 11,894 sentences annotated with drug and suicide entities and their relationships that were taken from PubMed research publications. The researchers trained a model using various embeddings and found that it effectively identified sentences related to suicidal adverse events.

2.3 Comparison Between Existing Works

The table contains different studies, including the authors' names, the algorithms used in their research, and the greatest accuracy reached using those methods. Various methods, including Random Forest, Logistic Regression, Support Vector Machine (SVM), and others, were used throughout these experiments. The highest accuracy rates varied between 68% and 96.33%, depending on the algorithm utilized and the study's focus.

Table 2.3.1: Comparative analysis with previous work

SL No	Author Name	Used Algorithm	Best Accuracy with Algorithm
1	Rahaman, M. et al. [27]	Random Forest, XGBoost, SVM, and LightGBM	XGBoost = 89%
2	Aladağ, A. et al. [28]	Logistic regression, random forest, and support vector machine (SVM)	SVM = 92%
3	J. D. Ribeiro, X. Huang et al. [29]	Random forest, LASSO	Random forest = 84%
4	Marcel Miché et al. [30]	Logistic Regression, Lasso, Ridge, Random Forest Regression	Ridge = 82.9%
5	A. Roy, K. et al. [31]	ANN, SVM	ANN = 68%
6	S. Ryu, H. Lee. et al. [32]	Random Forest Classifier	Random Forest = 78.1%
7	S.Hong et al. [33]	SVM-RFE algorithm combined with LOOCV	SVM = 78.59%
8	D. Liu, M. Yu et al. [34]	Logistic Regression, Random Forest Classifier, Support Vector Machines and Artificial Neural Networks.	For all models ranged from 92.3% to 94.6%.
9	S. Kim, H. et al. [35]	Random Forest, k-Nearest Neighbors (KNN)	Random Forest = 92.9%
10	S.T. Rabani et al. [36]	Support Vector Machine (SVM), Random Forest (RF) and Extreme Gradient Boosting (XGB)	XGB = 96.33%
11	N.J. Carson et al. [37]	Random Forest Classifier	Random Forest = 68%
12	Smita Selot et al. [38]	Naïve Bayes, Decision Tree Classifier, Random Forest Classifier, Support Vector Machine (93.01 highest), KNN Classifier	SVM = 93.01%

SL No	Author Name	Used Algorithm	Best Accuracy with Algorithm
13	G. Karak et al. [39]	Linear Regression, Logistic Regression	Logistic Regression = 84%
14	A. Chandha et al. [40]	Support Vector Machine, Logistic Regression and AdaBoost	SVM = 80.72%
15	S. Saha et al. [41]	SVM, Gradient Boosting, Bernoulli NB, Gaussian NB, Decision Tree, KNN, Random Forest	SVM = 89%

2.4 Open Issues

Table 2.4.1: Challenges and Overcoming Strategies

S.No.	**Issues and Challenges**	**Strategies or Plans**
1	Inherent mistakes or inconsistencies may occur in the data acquired from diverse sources.	We used data cleaning techniques in Google Colab, such as Pandas, to discover and fix any concerns. This may include eliminating incomplete items, correcting mistakes, and confirming data consistency across many sources.
2	Depending on the data gathering procedures used, the sample size may not be adequate for meaningful statistical analysis.	To address potential limitations due to sample size, we will explore data visualization techniques to identify trends and patterns within the available data.
3	Data analysis can be an iterative process, and completing a full study within the project timeline may be difficult.	To better manage my time, we plan to prioritize analysis techniques. In addition, we want to keep detailed records of my work and conclusions to ensure that my time is used efficiently.

4	Learning and using new data analysis techniques in Google Colab may involve more time and effort.	To solve any technical challenges, we will use internet resources, tutorials, and documentation for the Python libraries I've chosen, such as Pandas. In addition, I can utilize Google Colab to search for data analysis-related online communities or forums to troubleshoot and seek advice from experienced users.
5	Although this is a difficult subject, people may be cautious to provide personal information owing to privacy concerns.	To overcome privacy concerns, I prioritized anonymous questionnaires as a data collection tool. In addition, I ensured that all data gathering processes followed ethical principles and secured the required permits when working with other sources (e.g., rehabilitation institutes). Highlighting the importance of anonymity and confidentiality in communication materials and participant information sheets can help to increase participation.

2.5 Summary

This chapter examined current studies on the risk factors related with suicide among drug users, emphasizing the importance of the topic. Several studies have found that drug addiction considerably increases the risk of suicide, with loneliness, psychological history, and signs of depression playing important roles. Various machine learning methods, including Random Forest, SVM, and k-NN, were examined, with accuracies ranging from 68% to 96.33%. Our investigation found the most effective models to predict suicide risk and defined the hardware and software requirements for deployment. Furthermore, project management and budgetary factors were addressed to assure successful execution. This comprehensive research and analysis seek to improve understanding and intervention options for avoiding suicide among drug addicts.

CHAPTER 3

Methodology/Requirement Analysis & Design Specification

3.1 Overview

Research Subject:

The study "Exploring the Nexus Between Drug Addiction and Suicidal Tendencies in Bangladesh" investigates the relationship between mental health and substance addiction in Bangladesh. The investigation's focus is on understanding the complicated link between drug addiction and suicidal conduct among Bangladeshi people.

The study's scope includes people aged 15 to 44 who live in Bangladesh, a demographic group that is especially vulnerable to drug addiction and suicide ideation. Participants will be drawn from all around Bangladesh, including both urban and rural areas, as well as a wide range of socioeconomic backgrounds. The study will use a cross-sectional design to provide an overview of the prevalence and risk variables related with suicidal ideation among those living with drug addiction.

Instrumentation:

The study will use machine learning models and structured interviews to analyze the research topic and collect pertinent data. Machine learning algorithms are used to evaluate datasets and find patterns and determinants of suicidal behavior among drug addicts. In addition to quantitative analysis, structured interviews will be done with participants to collect qualitative data on their experiences, perceptions, and attitudes concerning drug addiction and suicidal behavior. These interviews will provide vital insights into the lived experiences of those dealing with these difficulties, as well as aid to contextualize quantitative data. The study's goal is to comprehensively assess the research subject and collect rich, multidimensional data on the prevalence and risk factors associated with suicidal tendencies among Bangladeshi drug addicts using a combination of machine learning models and structured interviews.

3.2 Proposed Methodology

Throughout the data collecting and analysis process on the delicate topic, the highest care and adherence to ethical rules were prioritized. To ensure ethical and courteous treatment of participants, as well as responsible handling of sensitive material, the following procedures were used:

1. Anonymous Surveys: Anonymous surveys, such as those conducted using platforms such as Google Forms, have been used to collect information on drug use and suicide. These surveys respect participants' privacy and comfort by allowing them to contribute information without the requirement for personal identification.
2. Data Collection from Ethical Sources: Data was acquired from reliable and ethical sources, such as rehabilitation centers, public health agencies, and medical records. All data gathering was carried out with the relevant ethical permissions to protect people privacy and confidentiality.
3. Existing Datasets: Datasets from past addiction and suicide studies have been evaluated to ensure that all relevant permissions and ethical considerations are met for using this data.
4. Interviews and Case Studies: Interviews with people who have experienced addiction, as well as in-depth case studies, were performed with the highest regard for personal narratives and participant confidentiality and anonymity.
5. Open Conversations: Open interactions with addiction counselors, mental health experts, and family members of people affected by addiction and suicide have been conducted in a courteous and considerate manner, offering a safe and supportive environment for discussion.

The research is conducted with the utmost ethical standards, prioritizing participant well-being and privacy, and ensuring the handling of collected information with respect.

Statistical Analysis

1. There are 23 columns in total.
2. There are 2346 rows in total.
3. 70% of the data in our model was used to train it, while 30% was used for testing.
4. The dataset is saved as a 'Microsoft Excel Comma Separated Values File'.

```
df.shape
```

```
(2346, 23)
```

Figure 3.2.1: Statistical Analysis – No of rows and columns

Proposed Methodology

The project approach includes numerous critical processes, beginning with data collecting and concluding with deployment.

Initially the dataset is sourced from Google Drive. When the info is available, EDA, or exploratory data analysis, is carried out. This includes inspecting the dataset's shape and columns, checking for and eliminating any missing values, doing statistical analysis, and displaying different connections in the data set with seaborn and matplotlib.

Following EDA, the data preparation phase starts. Categorical variables are encoded; feature and target variables are segregated; and the dataset is divided into training and testing sets. The characteristic parameters are then normalized with the StandardScaler.

The supplied model is used to create a prediction function for suicidal thoughts. This function comprises functionality for handling unseen labels and reshaping data as required by the model.

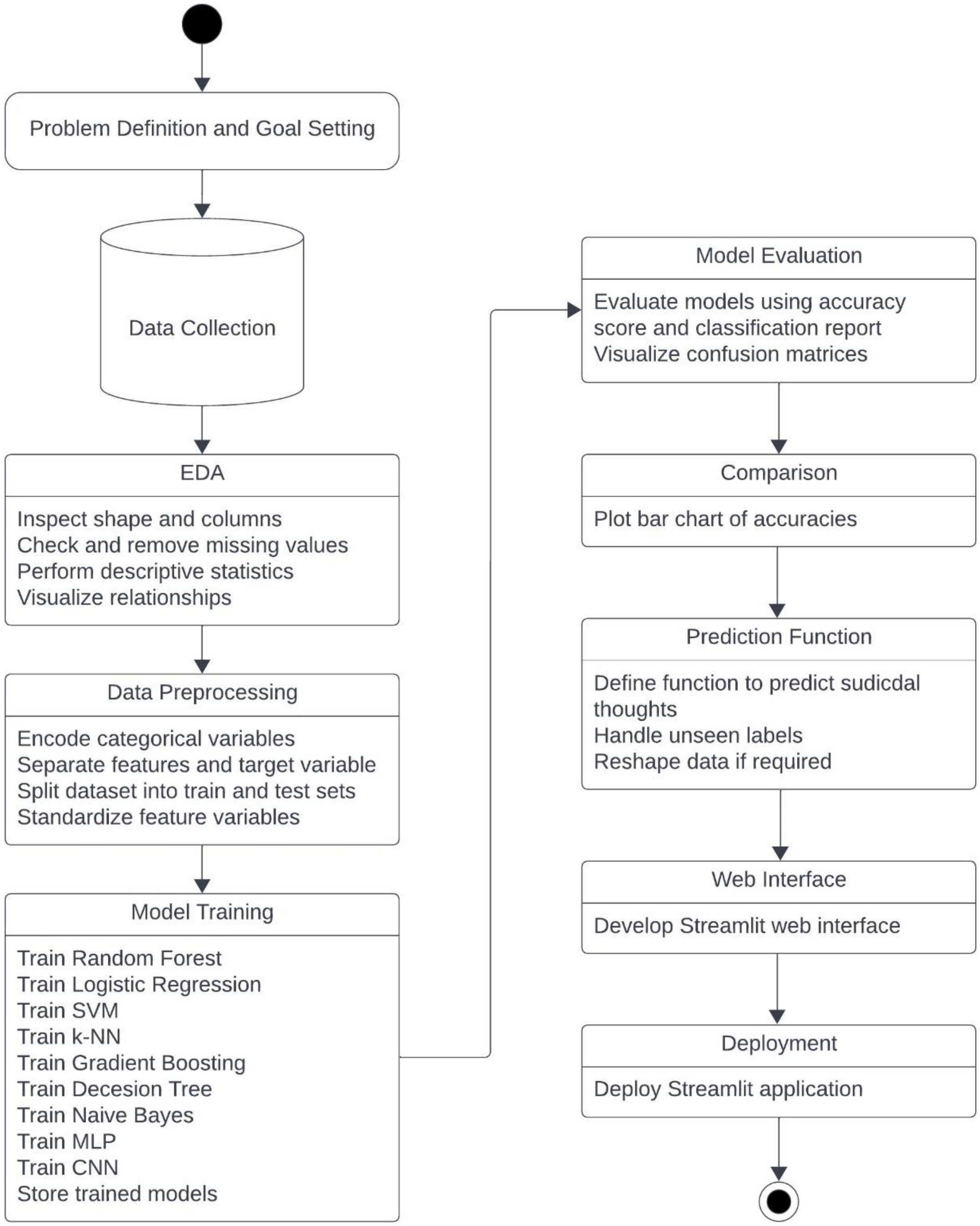

Figure 3.2.2: Proposed Methodology

Data Collection

We collect our data using Google Forms. The screenshot below is from Google Colab and shows the column name of our dataset.

```
df.columns
```

```
Index(['Age', 'Gender', 'Education', 'Live with', 'Conflict with law',
       'Most used drugs', 'Motive about drug', 'motivation by friends',
       'Spend most time', 'Mental/emotional problem', 'Suicidal thoughts',
       'Family relationship', 'Financials of family',
       'Addicted person in family', 'no. of friends', 'Withdrawal symptoms',
       'Satisfied with workplace', 'Case in court', 'Living with drug user',
       'Smoking', 'Easy to control use of drug', 'Frequency of drug usage ',
       'Taken drug while experiencing stress '],
      dtype='object')
```

Figure 3.2.3: Data Collection – Column name

Data Exploration and Understanding

To better understand our dataset in Google Colab, we used some fundamental data exploration techniques. To make things clearer, we've included some screen shots below.

	Age	Gender	Education	Live with	Conflict with law	Most used drugs	Motive about drug
0	between 22 to 35 years	Male	Undergraduate	Hostel/Hall	Yes	Weed	Disease
1	between 22 to 35 years	Male	H.S.C / A levels	With Family/Relatives	Yes	Others	Should avoid
2	15 to 22 years	Male	H.S.C / A levels	With Family/Relatives	Yes	Heroin	Disease

Figure 3.2.4: View some rows from our dataset.

The upper graphic depicts some rows from our dataset, while the lower figure presents descriptive statistics related to our DataFrame, summarizing the distribution of its numerical columns.

```
df.describe()
```

	Age	Gender	Education	Live with	Conflict with law
count	2346	2346	2346	2346	2346
unique	4	2	6	3	2
top	between 22 to 35 years	Male	Undergraduate	Hostel/Hall	No
freq	1346	1690	1264	954	1710

Figure 3.2.5: A brief review of the dataset's statistical qualities.

Data Preprocessing and Feature Engineering

First, we determine whether our dataset has any null values, as shown in the two separate screenshots below. Following this inspection, we will handle the null values. Additionally, for feature engineering, we use the level encoding technique. We display two different screenshots: one of the datasets before encoding and another of it after encoding.

```
df.isnull().sum()

Age                                    0
Gender                                 0
Education                              0
Live with                              0
Conflict with law                      0
Most used drugs                        0
Motive about drug                      0
motivation by friends                  0
Spend most time                        0
Mental/emotional problem             260
Suicidal thoughts                      0
Family relationship                    0
Financials of family                   0
Addicted person in family              0
no. of friends                       152
Withdrawal symptoms                    0
Satisfied with workplace               0
Case in court                          0
Living with drug user                  0
Smoking                                0
Easy to control use of drug            0
Frequency of drug usage                0
Taken drug while experiencing stress   0
dtype: int64
```

Figure 3.2.6: Identifying Null values

```
Missing values after removal:
Age                                    0
Gender                                 0
Education                              0
Live with                              0
Conflict with law                      0
Most used drugs                        0
Motive about drug                      0
motivation by friends                  0
Spend most time                        0
Mental/emotional problem               0
Suicidal thoughts                      0
Family relationship                    0
Financials of family                   0
Addicted person in family              0
no. of friends                         0
Withdrawal symptoms                    0
Satisfied with workplace               0
Case in court                          0
Living with drug user                  0
Smoking                                0
Easy to control use of drug            0
Frequency of drug usage                0
Taken drug while experiencing stress   0
dtype: int64
```

Figure 3.2.7: After eliminating the null values

Here, by using `df.head()`, we're displaying the data from our dataset before level encoding.

```
df.head()
```

	Age	Gender	Education	Live with	Conflict with law	Most used drugs	Motive about drug	motivation by friends	Spend most time
0	between 22 to 35 years	Male	Undergraduate	Hostel/Hall	Yes	Weed	Disease	Yes, often they do	Alone
1	between 22 to 35 years	Male	H.S.C / A levels	With Family/Relatives	Yes	Others	Should avoid	Yes, often they do	Friends
2	15 to 22 years	Male	H.S.C / A levels	With Family/Relatives	Yes	Heroin	Disease	Yes, often they do	Friends

Figure 3.2.8: Dataset without label encoding

Now in the figure below, we can see our data after encoding.

```
df.head(5)
```

	Age	Gender	Education	Live with	Conflict with law	Most used drugs	Motive about drug	motivation by friends
0	2	1	4	0	1	73	6	3
1	2	1	0	2	1	58	29	3
2	0	1	0	2	1	50	6	3
3	2	1	4	2	1	91	32	3
4	2	1	4	2	0	56	33	1

5 rows × 23 columns

Figure 3.2.9: Dataset after label encoding

Data Visualization

The plot shows that suicidal thoughts are more common in men than in women.

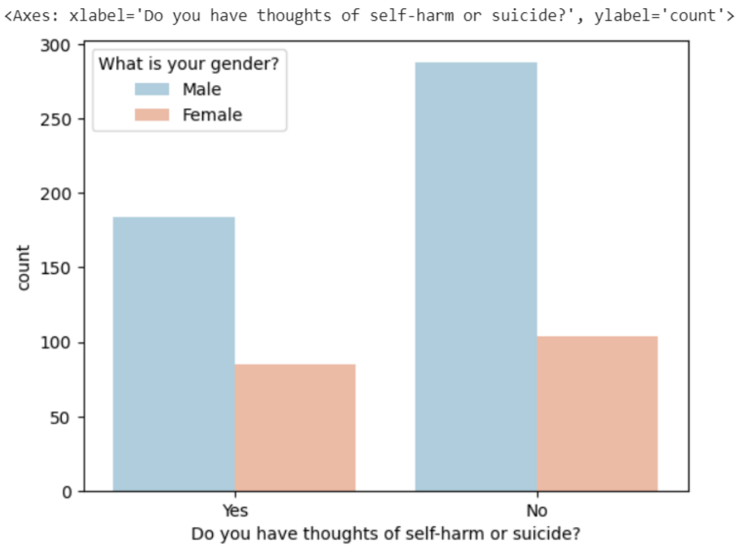

Figure 3.2.10: Identifying suicidal thoughts depending on gender

The plot below shows that regular drug use is more common in undergraduates than in others.

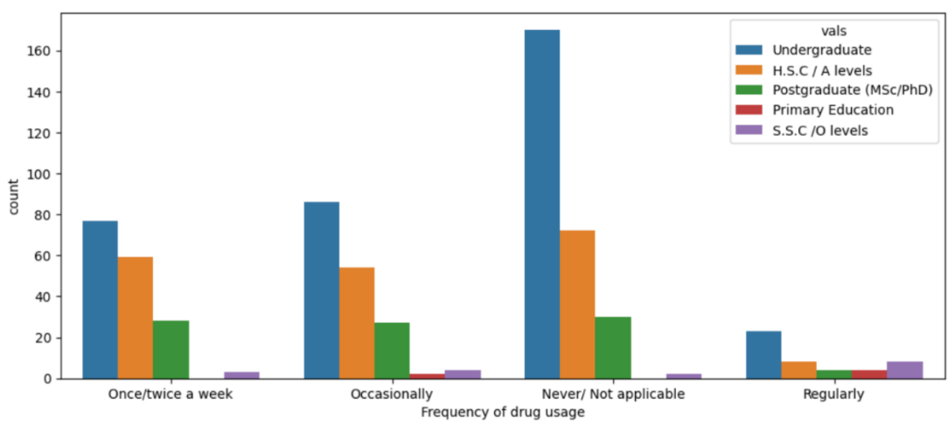

Figure 3.2.11: Identifying suicidal thoughts depending on education

The graphic below shows that men use drugs more frequently than women.

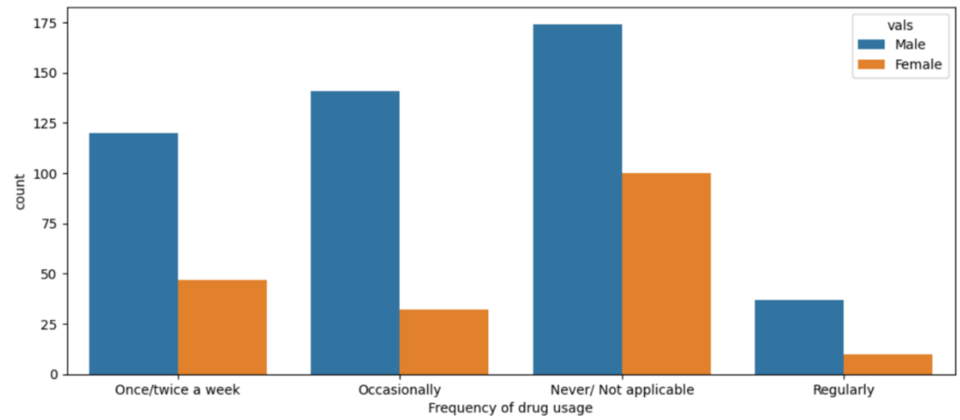

Figure 3.2.12: Finding the frequency of drug use based on the gender.

According to the plot below, regular drug use increases when a person has more than five friends.

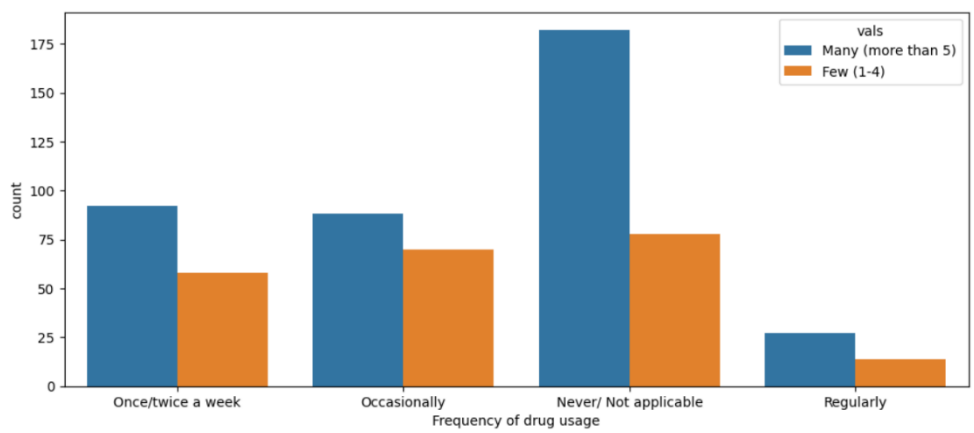

Figure 3.2.13: Finding the frequency of drug use based on the number of friends.

According to the plot below, people with average family relationships are more likely to use drugs regularly.

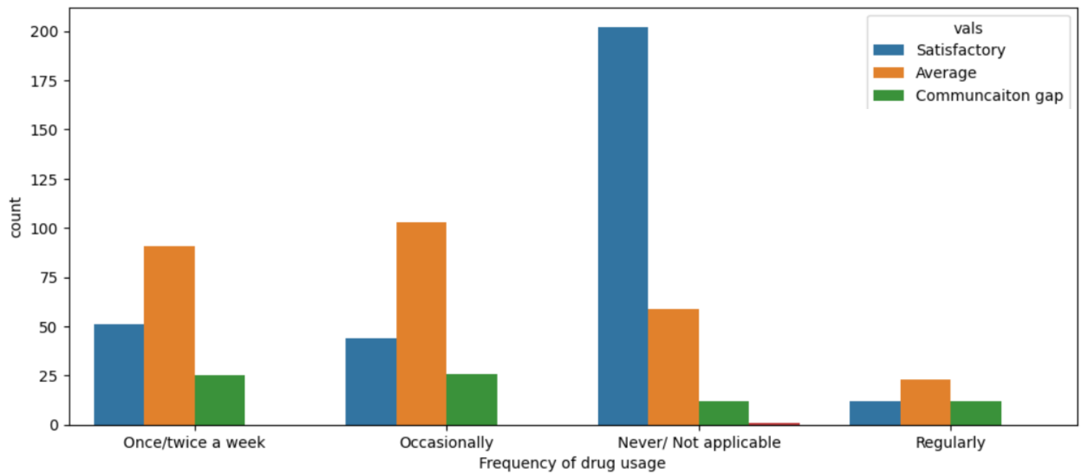

Figure 3.2.14: Finding the frequency of drug use based on the family relationship.

According to the plot below, drug use is more common among people aged 22 to 35.

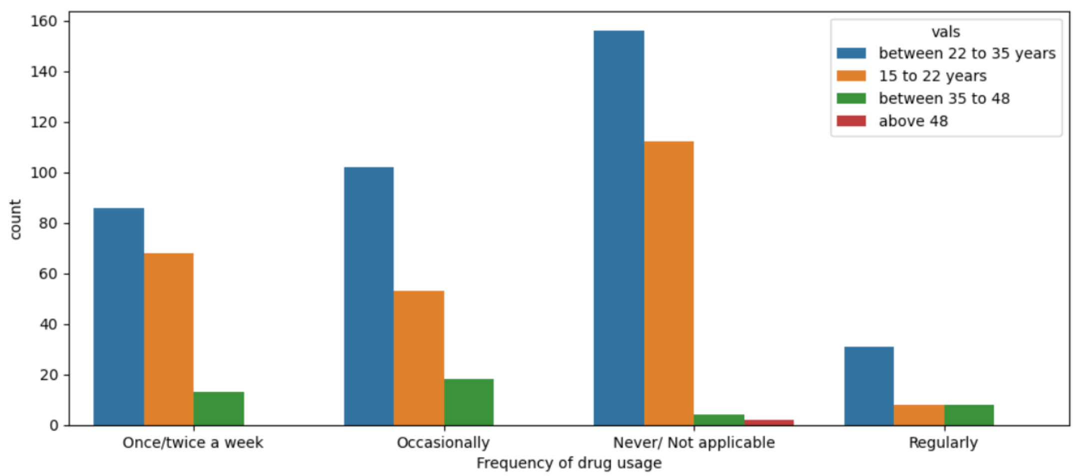

Figure 3.2.15: Finding the frequency of drug use based on the age.

According to the plot below, those in the poor/weak part of society are more likely to use drugs regularly.

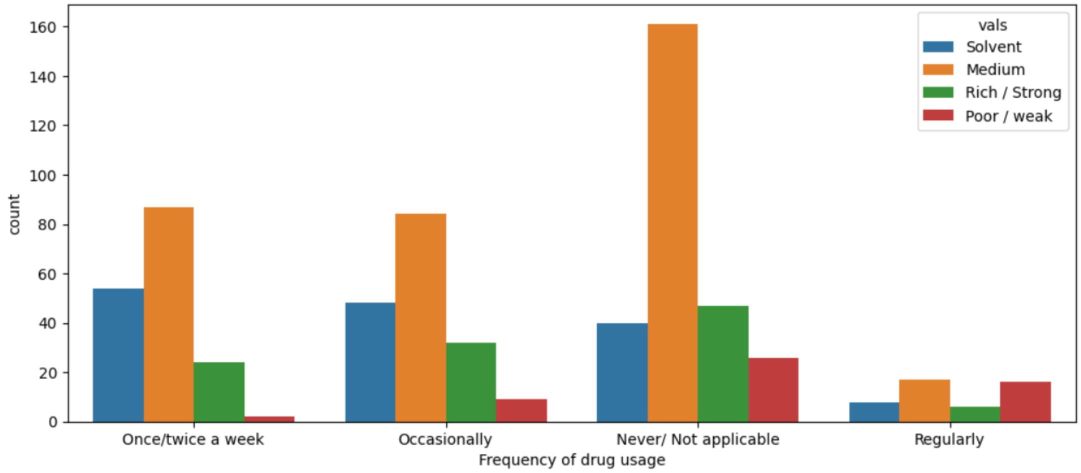

Figure 3.2.16: Finding the frequency of drug use based on the family status.

The plot below shows that persons who live with their family use drugs more frequently.

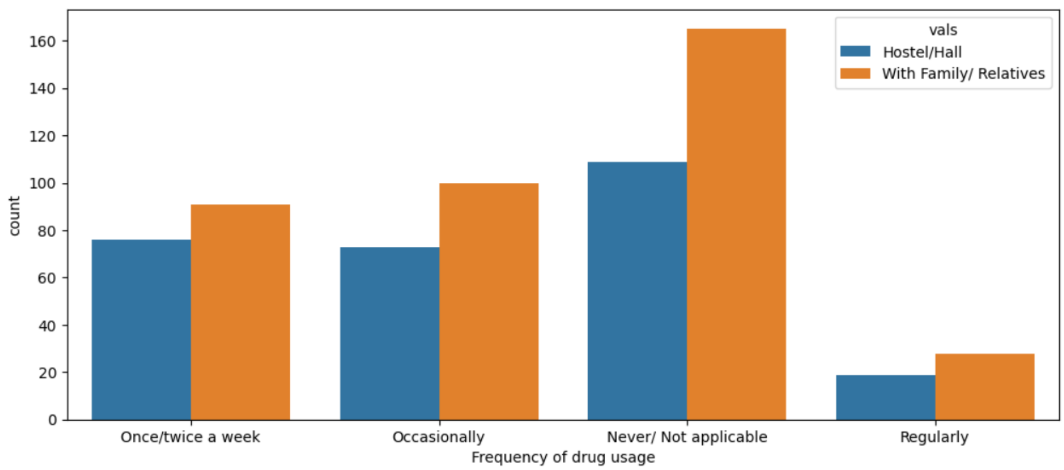

Figure 3.2.17: Finding the frequency of drug use based on household members.

According to the plot below, regular drug use is more common in those who are not now facing any legal issues.

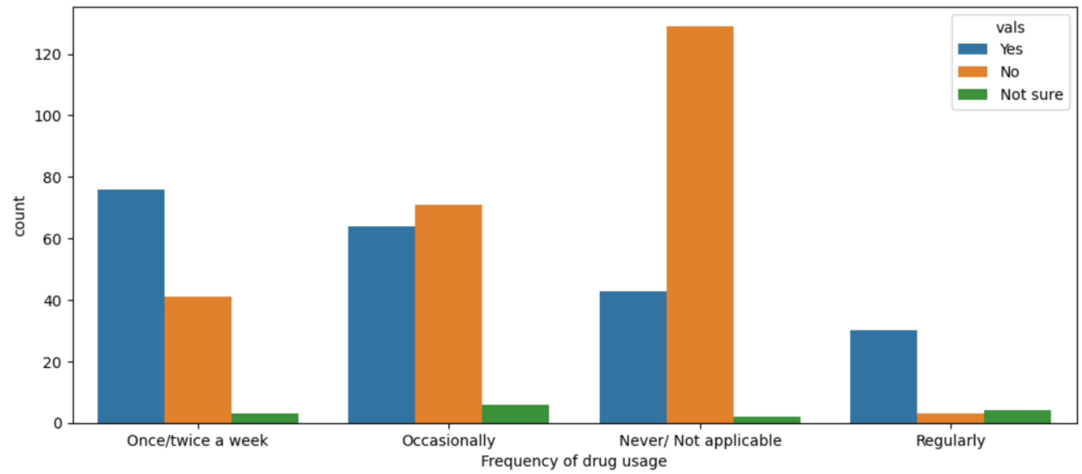

Figure 3.2.18: Estimating drug use frequency based on a court case.

According to the plot below, Male are more likely to use drugs on a regular basis if their friends are already using drugs.

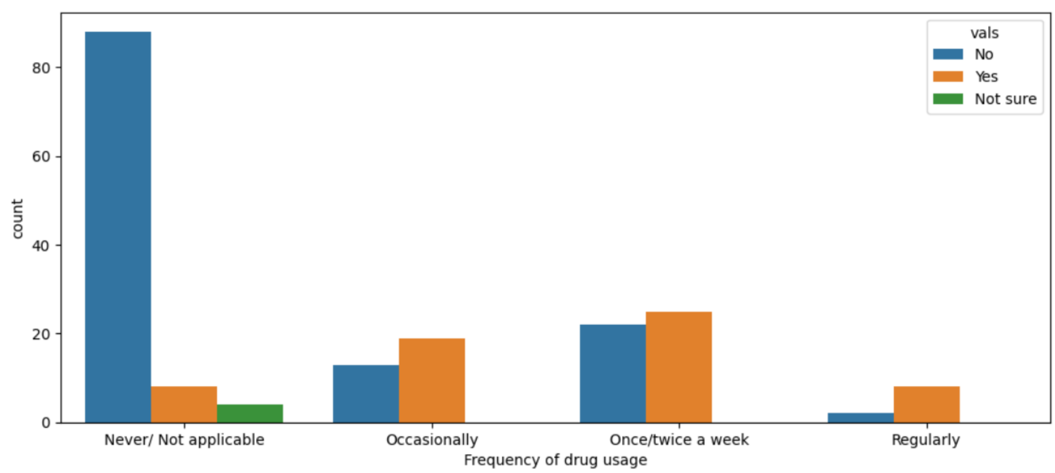

Figure 3.2.19: Estimating drug use frequency based on whether friends use drugs.

The figure below shows that regular drug use influences both males and females when they are in the company of a friend who uses it on a regular basis.

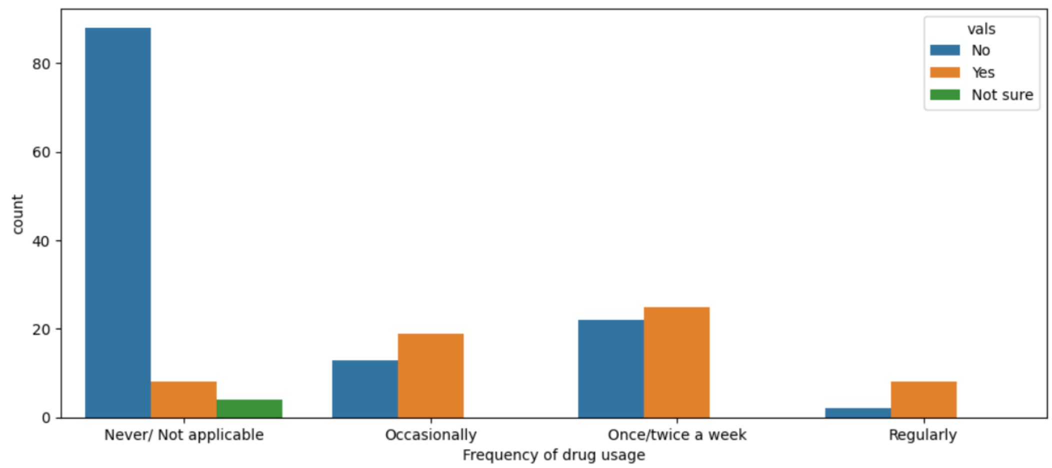

Figure 3.2.20: Estimating drug usage frequency based on how often they use drug

Suicidal ideation is lower in males who take drugs on a regular basis, according to the plot below.

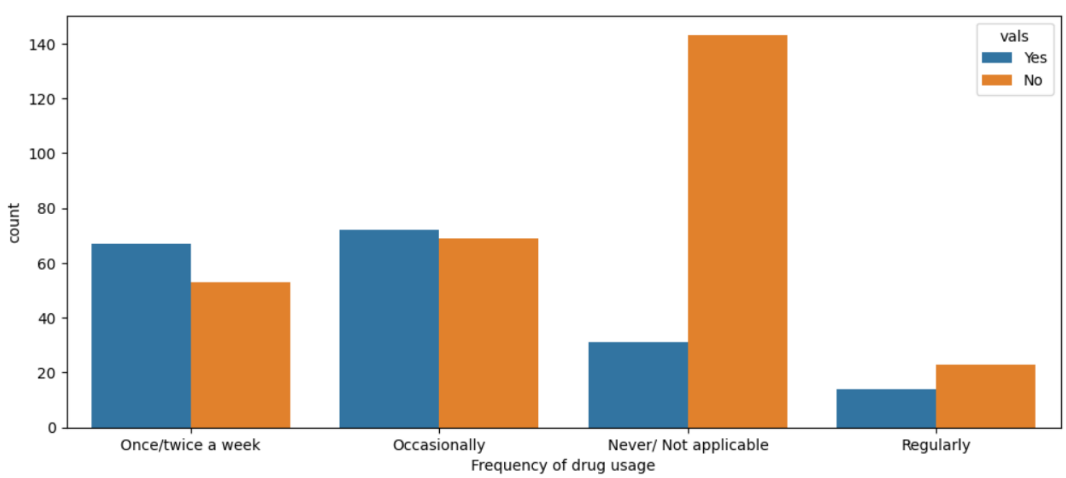

Figure 3.2.21: Estimating drug consumption frequency based on how often males use drugs

Suicidal ideation is more common in female regular drug users, according to the plot below.

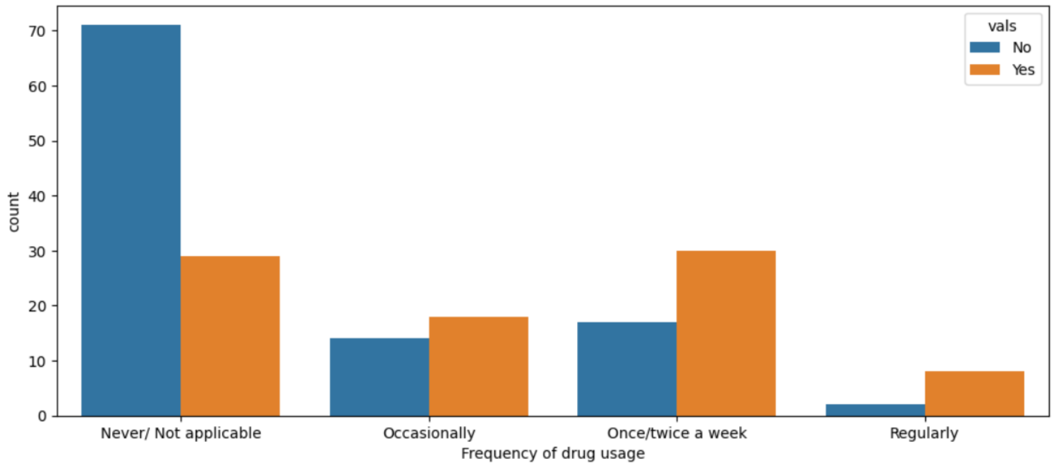

Figure 3.2.22: Estimating drug consumption frequency based on how often females use drugs

Suicidal ideation is more common among undergraduates, according to the plot below.

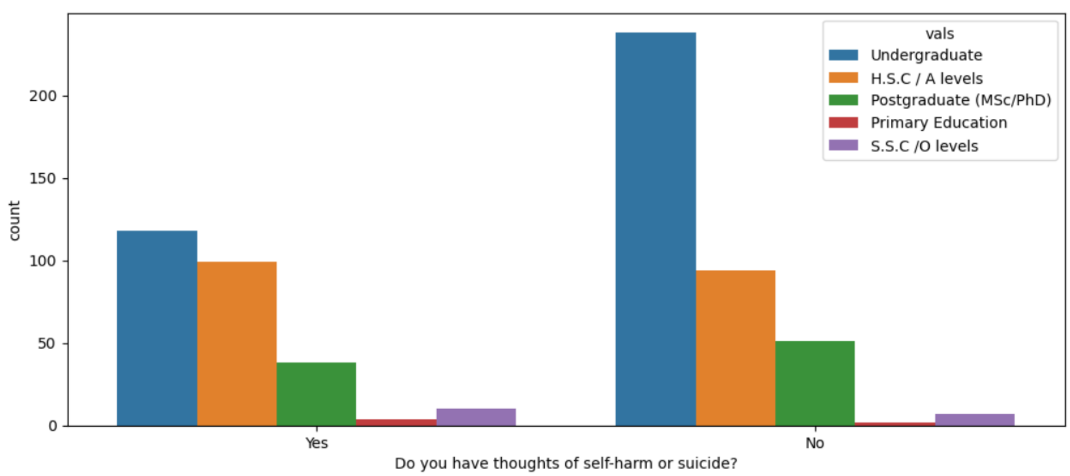

Figure 3.2.23: Estimating Suicidal Thoughts Based on Education

From the below plot, we notice that regular usage is more in persons who are regular/everyday smokers. An interesting truth from the plot is that if a person does not smoke, he or she may not get into the regular usage of drugs.

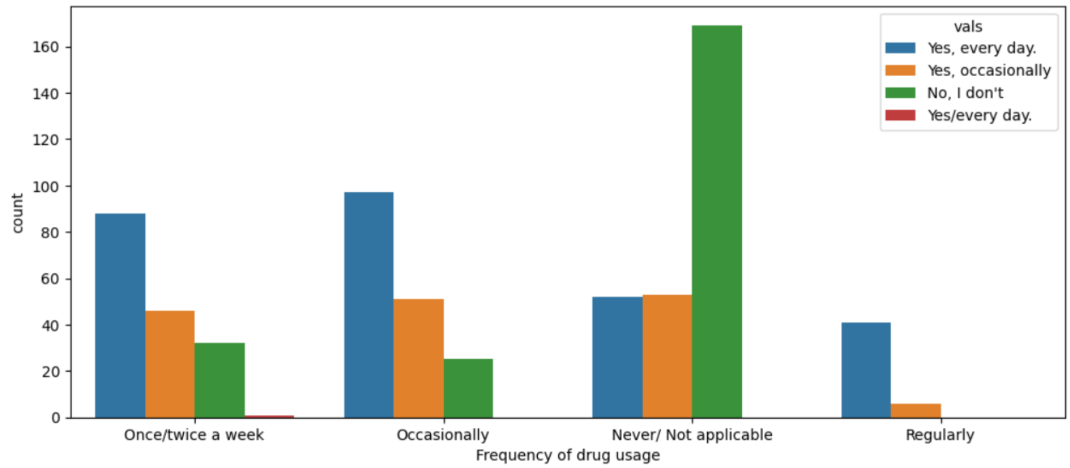

Figure 3.2.24: Frequency of drug use based on how often people smoke

The plot below shows that females who spend the majority of their time with friends use drugs on a regular basis. It is interesting to note that if they spend the majority of their time with family or relatives, they are less likely to become attached.

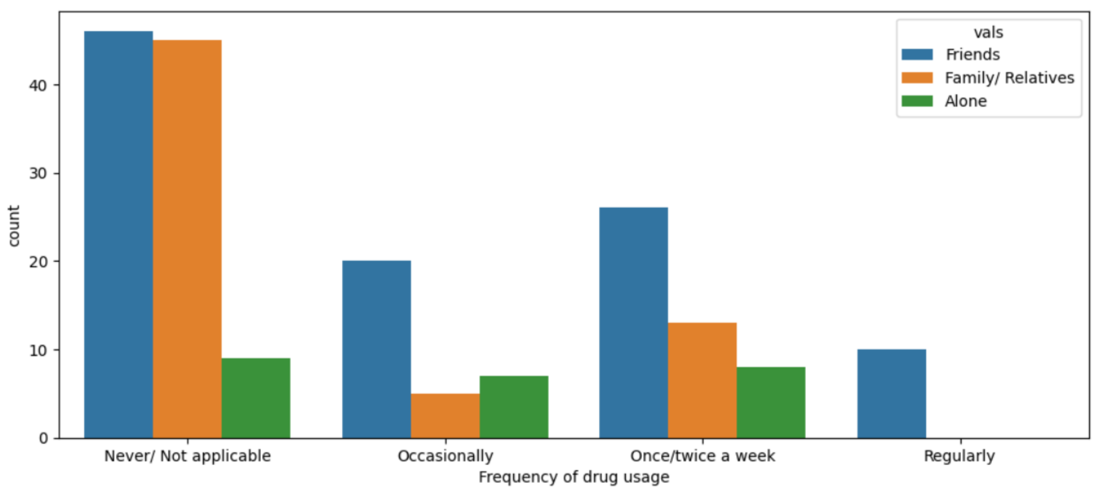

Figure 3.2.25: The frequency of drug usage among female household members.

The plot below shows that males use drugs on a regular basis and spend the majority of their time with friends. One interesting aspect to observe is that if they spend the most of their time with family or relatives, they are less likely to become addicted.

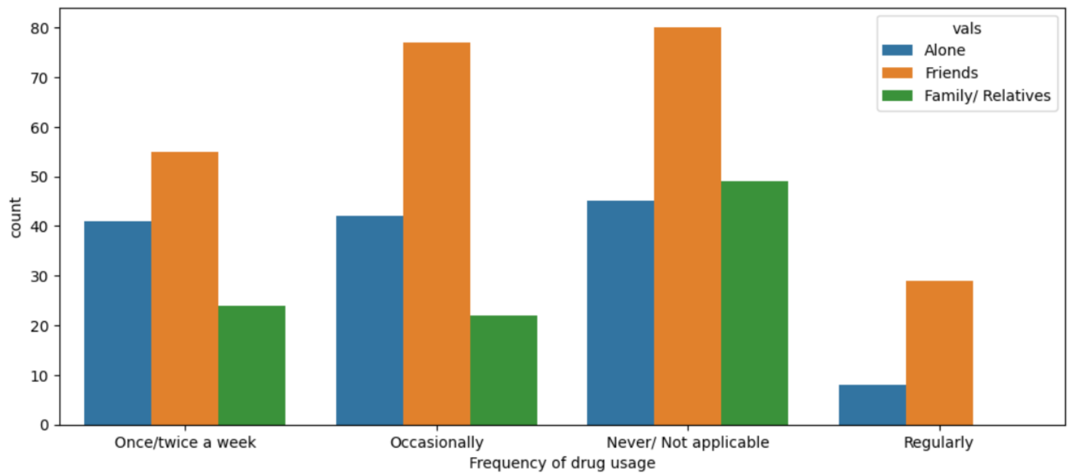

Figure 3.2.26: The frequency of drug usage among male household members.

The graphic below shows that males who use drugs on a regular basis have withdrawal symptoms.

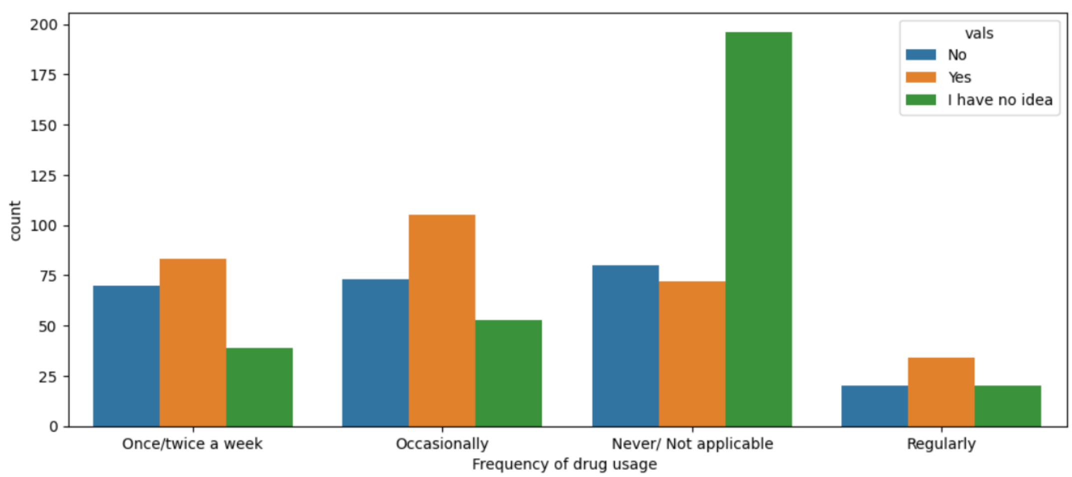

Figure 3.2.27: The relationship between drug frequency and withdrawal symptoms - Male

The plot below shows that females who use drugs on a regular basis have withdrawal symptoms.

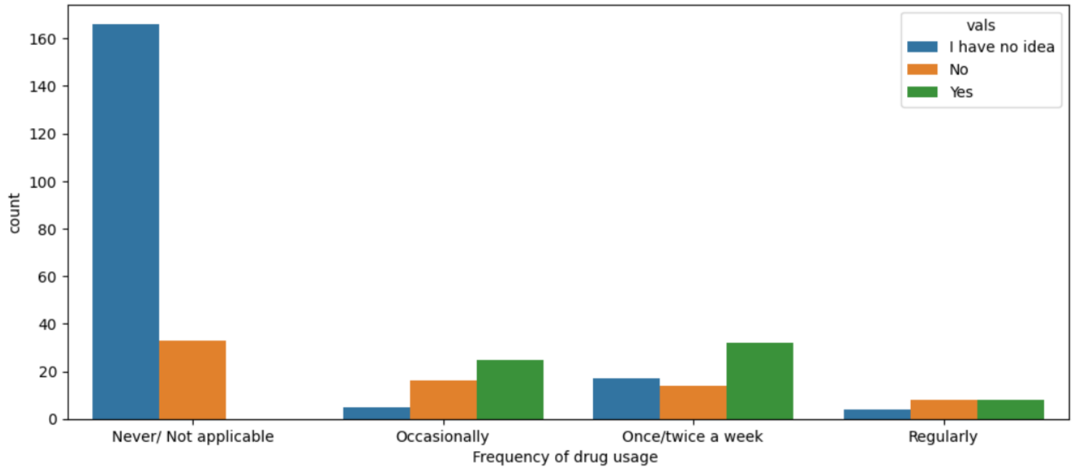

Figure 3.2.28: The relationship between drug frequency and withdrawal symptoms - Female

The plot below shows that males who regularly use drugs are affected by their fellow students.

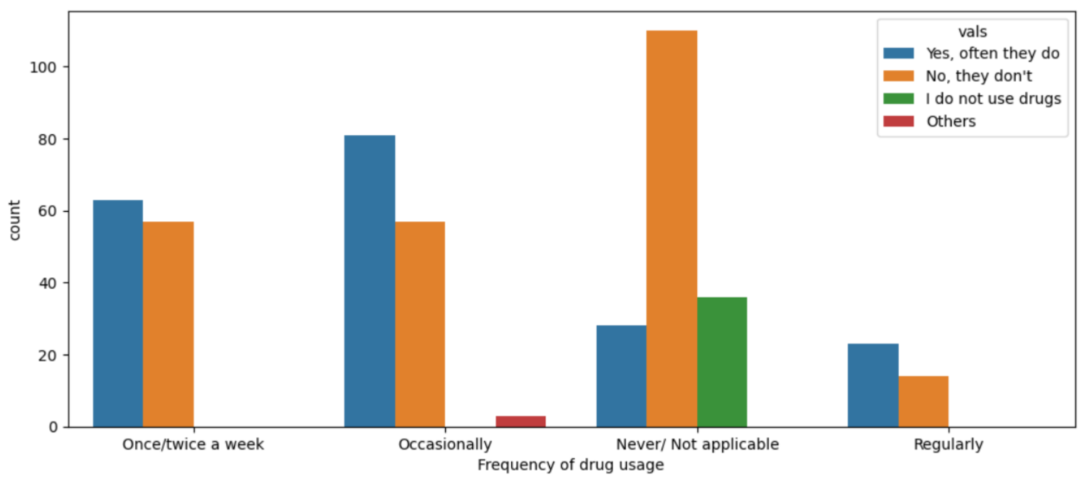

Figure 3.2.29: Frequency of drug usage based on friend’s influence

Here's a summary of the findings from the listed figures (3.4.9-3.4.28):

Table 3.2.1: Summary of the findings from the figures

Figure	Finding
3.2.9	Identifying suicidal thoughts according to gender.
3.2.10	Identifying suicidal thoughts based on education
3.2.11	Determine the frequency of drug use based on gender.
3.2.12	Determine the frequency of drug usage based on the number of friends.
3.2.13	Determine the frequency of drug usage based on the family relationship.
3.2.14	Determine the frequency of drug use based on age.
3.2.15	Determine the frequency of drug usage based on family status.
3.2.16	Identifying the frequency of drug usage among family members
3.2.17	Estimating drug use frequency from a court case
3.2.18	Calculating drug use frequency based on whether friends take drugs.
3.2.19	Estimating drug consumption frequency based on how frequently they take the drug
3.2.20 & 3.2.21	Estimating drug consumption frequency based on how often men and women take drugs.
3.2.22	Estimating Suicidal Thoughts Based on Education.
3.2.23	Drug usage frequency is determined by how frequently people smoke.
3.2.24 & 3.2.25	The frequency of drug use among female and male family members.

3.2.26 & 3.2.27	The correlation between drug use and withdrawal symptoms - Male or Female
3.2.28	Frequency of drug use due to friend influence

Correlations Analysis

```
df.corr()
```

Age	1.000000	0.109053	0.262373	0.051995	0.112753	-0.010532	-0.033830	0.011744	0.009016
Gender	0.109053	1.000000	0.072533	-0.021483	0.110760	-0.067860	0.009395	0.098846	-0.071135
Education	0.262373	0.072533	1.000000	-0.112982	0.024336	0.017131	0.156516	0.012600	0.048634
Live with	0.051995	-0.021483	-0.112982	1.000000	0.184499	0.000861	0.014300	-0.015258	-0.012799
Conflict with law	0.112753	0.110760	0.024336	0.184499	1.000000	-0.033967	-0.004346	0.301011	0.080774
Most used drugs	-0.010532	-0.067860	0.017131	0.000861	-0.033967	1.000000	0.057221	-0.032297	0.010661
Motive about drug	-0.033830	0.009395	0.156516	0.014300	-0.004346	0.057221	1.000000	0.031531	0.170625
motivation by friends	0.011744	0.098846	0.012600	-0.015258	0.301011	-0.032297	0.031531	1.000000	0.239985
Spend most time	0.009016	-0.071135	0.048634	-0.012799	0.080774	0.010661	0.170625	0.239985	1.000000
Mental/emotional problem	0.198508	-0.001693	-0.021636	-0.030117	-0.030100	0.042240	-0.098969	-0.119740	-0.089303
Suicidal thoughts	-0.133104	-0.077486	-0.119964	-0.041640	0.172560	-0.087628	-0.100561	0.202078	-0.020395
Family relationship	0.068383	-0.101221	0.157734	-0.015155	-0.231941	0.010719	0.132869	-0.290402	0.011743

Figure 3.2.30: Correlation Analysis

Data splitting, model selection, model training, model evaluation, and test set evaluation are described in chapter 4 inside section 4.2.

3.3 Hardware/Software Requirements

Here are the requirements for conducting our work:

Hardware Requirements

- Processor: Minimum 2.0 GHz or higher
- Memory: Minimum 4 GB or higher
- Storage: Minimum 100 GB or higher
- Graphics: Integrated graphics or dedicated graphics card

Software Requirements

- Operating System: Windows, macOS, or Linux
- Programming Languages: Python
- Data analysis tools: Pandas, NumPy, scikit-learn, or other relevant libraries
- Visualization tools: Matplotlib, Seaborn, or other relevant libraries

Development Tools Requirements

- Integrated Development Environment (IDE): Google Colab, Visual Studio Code, or other relevant IDEs
- Version control system: Git, GitHub, or other relevant tools
- Project management: Kanban, or other relevant project management methodologies
- Collaboration tools: Trello, or other relevant collaboration tools.

3.4 Project Management and Financial Analysis

Project Management

- **Project Objective:**
  - A. Develop a system that can identify individuals at risk of suicidal tendencies due to drug addiction in Bangladesh.
  - B. Analyze data related to drug addiction and suicide rates to identify patterns and risk factors.
  - C. Build a robust machine learning model that can predict the likelihood of suicidal behavior in individuals with drug addiction.
  - D. Create an easy-to-use interface for healthcare professionals and counselors to input patient data and receive risk assessments.
  - E. Provide a tool that enables timely intervention and support for those at risk, ultimately reducing the incidence of suicide.

- **Project Timeline:**

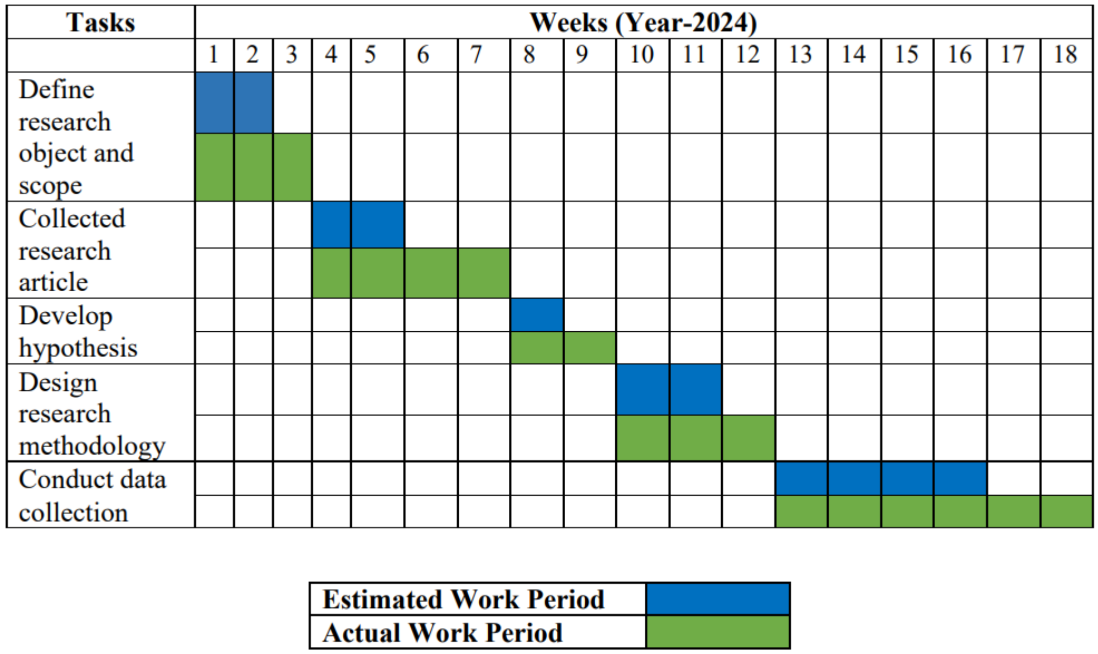

Figure 3.4.1: Updated Project Timeline

- **Resource Planning:**

A. Equipment and Tools:

- Development and Testing Servers: To host and test the suicidal detection algorithms and software.
- Standard Performance Computers: For processing and analyzing datasets related to drug addiction and suicidal behavior.
- Collaboration Tools: For effective communication and coordination research team members, stakeholders such as Trello or project management software.
- Version Control System: For managing and tracking changes in research code and data.
- Testing Tools: For validating the accuracy and reliability of the suicidal detection algorithms.

B. Software and Technologies:

- Front-End Technologies: For developing user interfaces and visualization tools for the suicidal detection system.
- Back-End Technologies: For managing and processing data related to drug addiction and suicidal behavior.

- Database Management System: For storing and retrieving research data securely.
- Server Hosting: For deploying and hosting the suicidal detection system.

C. Data and Content:

- Research Data: Collected from various sources, including surveys, interviews.
- Data Visualization Tools: For creating visual representations of research findings to facilitate data interpretation and communication.
- User Documentation: Prepared by the research team to guide stakeholders and users on how to use the suicidal detection system.

D. Ethical Considerations:

- Ethical Review: Ensure that all research protocols and procedures adhere to ethical guidelines and obtain approval from mental health professionals.
- Confidentiality: Safeguard the privacy and confidentiality of research participants' information, following data protection regulations and best practices.
- Cultural Sensitivity: Consider cultural nuances and sensitivities in conducting research on suicidal behavior in Bangladesh, respecting local customs, beliefs, and values.

E. Communication and Collaboration:

- Stakeholder Engagement: Regularly engage with stakeholders, including mental health professionals, policymakers, and community leaders, to ensure that research findings are relevant and actionable.
- Collaborative Research: Foster collaborations with local institutions and organizations to leverage resources and expertise, enhancing the impact and reach of the research.

F. Monitoring:

- Monitoring Progress: Regularly monitor the progress of the research, including data collection, analysis, and system development, to ensure that milestones are met and challenges are addressed.

- **Risk Management:**

  A SWOT analysis identifies an idea's strengths, weaknesses, opportunities, and threats, offering an in-depth understanding of its potential and obstacles. Here's a SWOT analysis for my research.

Figure 3.4.2: Risk Management-SWOT Analysis

Financial Analysis

Table 3.4.1: Financial Analysis

SN	Components	Estimated Cost (BDT)
01.	Data Collection and Analysis	2000-2500
02.	Ethics Approval Fees	1000-1200
03.	Documentation and Report Printing	800-1000
04.	Travel Expenses	500-600
05.	Visiting Stakeholders	1500-2000
06.	Domain and Hosting	1000-1500
07.	Professional Development	800-1000
08.	Contingency (10% of total)	900-1000
	Total Estimated Cost	8500-10800

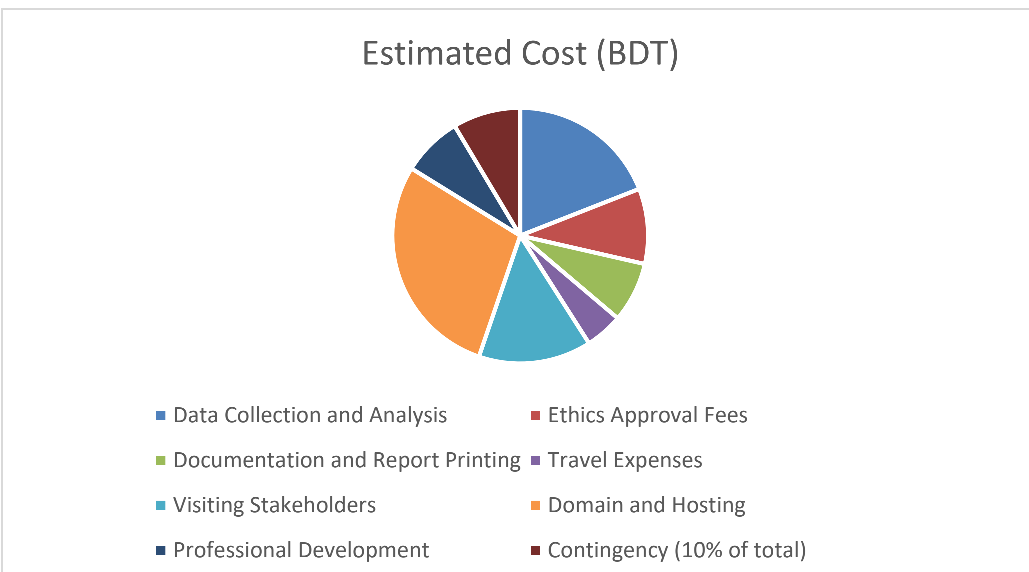

Figure 3.4.3: Financial Analysis

3.5 Summary

In this section, we covered the methods and needs for our machine learning-based study of predicting the likelihood of suicide among heroin addicts in Bangladesh. We developed a system design that integrates a variety of algorithms, such as Random Forest, Logistic Regression, SVM, k-NN, Gradient Boosting, Decision Tree, Naive Bayes, MLP, and CNN, all of which were tested for precision, recall, F1 score, and accuracy. High-performing models, such as k-NN and Gradient Boosting, scored accuracies greater than 92%, while Naive Bayes had the lowest at 69.74%. The chapter also covered the hardware and software requirements for implementing these models, as well as an overview of project management and financial issues. This holistic approach establishes a solid platform for future research and application, with the goal of improving public health treatments and support programs for vulnerable people.

CHAPTER 4

Implementation

4.1 Overview

This chapter describes the implementation phase of our study, focusing on the creation, training, as well as assessment of our prediction model for detecting suicidal inclinations among drug users in Bangladesh. The implementation process begins with the creation of a prototype model, which uses several machine learning approaches to evaluate and foresee suicide risk variables. Following design, the model is rigorously tested and evaluated to ensure accuracy and reliability. By studying real-world data and optimizing our algorithms, we want to build a strong system capable of detecting and avoiding the risk of suicide in this susceptible demographic. This chapter gives a complete review of the activities followed, obstacles encountered, and findings obtained throughout the implementation process, ultimately resulting in evidence-based solutions for reducing suicide risk in Bangladesh.

4.2 Train Model

During the prototype design phase, various machine learning model was developed and trained to identify suicidal inclinations among Bangladeshi drug addicts. The dataset utilized for this purpose consisted of 23 columns and 2346 rows. The data was split into two distinct subsets: 70% for training the model and 30% to evaluate its accuracy.

To begin with, the dataset received considerable preprocessing. This included eliminating any missing numbers that the data was complete and accurate. Standardization of features was performed to offer uniform data scaling, which is critical for guaranteeing that all variables contribute equally to the model training process.

After the data was preprocessed, the next step was to determine the major characteristics that influence suicide tendencies. This was accomplished using correlation analysis and feature significance measures. By evaluating the correlations between various variables and the target variable, we were able to identify the most influential components.

During the model selection process, many machine learning techniques were tested to determine the best fit for our data. This training phase is critical because it provides the model with the ability to generate accurate predictions on previously unseen data. During training, the model learns from the input data by building decision trees that capture the patterns and relationships between features and the target variable.

Subsequently the trained model was evaluated using the testing dataset to determine its performance. Several measures, including precision, recall, F1-score, and accuracy, were measured to provide a thorough assessment of the model's effectiveness. These measurements aid in identifying the model's strengths and flaws, therefore guiding future developments. By meticulously building and training this prototype model, we hoped to create a dependable tool for detecting suicidal tendencies in drug addicts, so helping to early intervention and prevention methods.

4.3 System Testing/Model Evaluation

In this part, we will go over the system testing and model evaluation techniques that we used for our research on the early diagnosis and prevention of suicidal tendencies caused by drug addiction in Bangladesh. This study uses advanced machine learning algorithms and data analysis to identify people in danger and deliver timely interventions. Our model is trained on a variety of data sources, including behavioral, psychological, and social aspects, to predict the likelihood of suicidal ideation among drug addicts.

To ensure the robustness and reliability of our model, we conducted extensive testing using a comprehensive dataset that captures a wide range of relevant factors. The evaluation process involved splitting the data into training and testing sets, allowing us to gauge the model's performance on unseen data. By continuously iterating on our model and refining our approach based on the evaluation results, we aim to create a reliable and effective tool for early detection and prevention of suicidal tendencies among drug addicts. Our ultimate goal is to contribute to public health efforts in Bangladesh by providing a proactive solution that can save lives through timely intervention and support.

The image shows a user interface of the Suicidal Thoughts Prediction App, displaying input fields for age, gender, education, living situation, and conflict with the law etc.

Figure 4.3.1: Suicidal Thoughts Prediction App

There is a red Predict button below these fields which when clicked, provides a prediction. In this instance, the prediction result displayed is the prediction is yes, indicating a positive prediction for suicidal thoughts based on the provided inputs.

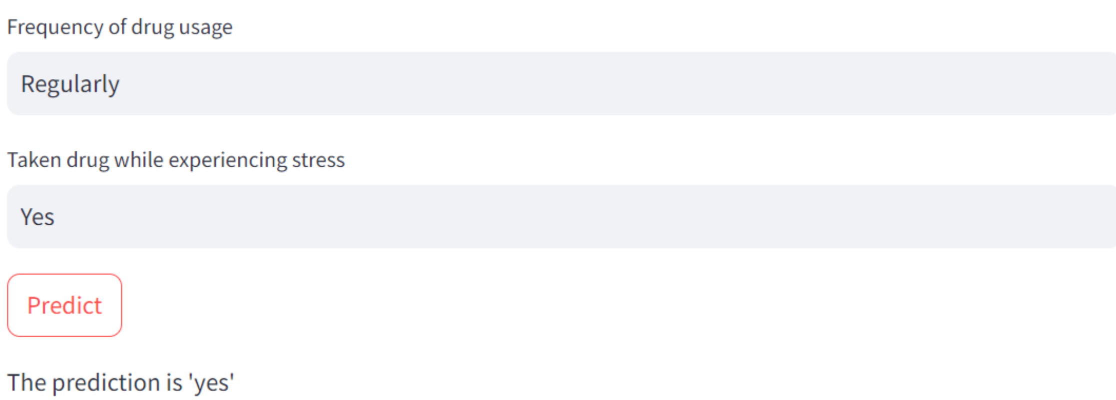

Figure 4.3.2: Verifying the algorithm's prediction

4.4 Summary

In summary, several machine learning models were tested for predicting suicidal tendencies amongst drug addicts in Bangladesh. The k-Nearest Neighbors (k-NN) model fared the best, with an accuracy of 93.32%. The Gradient Boosting model came in second with an accuracy of 92.90%, followed by the Multi-Layer Perceptron (MLP) Adjusted model at 90.48%. The Convolutional Neural Network (CNN) also performed well, with an accuracy of 87.93%. The Decision Tree Reduced and Random Forest Reduced models achieved 85.51% and 83.66% accuracy, respectively. The Support Vector Machine (SVM Reduced) and logistic regression models scored reasonably well, with accuracy levels of 73.58% and 71.31%, respectively. The model based on Naive Bayes got the lowest accuracy (69.74%), indicating that it is less appropriate for this dataset. These findings demonstrate the promise of advanced machine learning approaches for early detection and mitigation of suicidal ideation.

CHAPTER 5

Result and Analysis

5.1 Overview

The experimental setup for this study was mostly based on Google Colab, an online coding and data analysis platform. To create machine learning models and conduct statistical analysis, the researchers used the Python programming language in the Google Colab environment.

Data collection was assisted by the use of Google Forms, which enabled the design of customized surveys to obtain relevant information from participants. Upon submission, the data obtained via Google Forms was instantly saved in Excel format, allowing for easy access and categorization for future study.

To access Google Colab and Google Forms using the experimental arrangement, we needed an internet-connected PC. The research also made use of typical office applications, such as Microsoft Excel, for managing information.

Throughout the experimental setting, ethical norms were followed, such as maintaining participant privacy and gaining informed consent. Participants were told about the study's goal as well as their data usage permissions.

5.2 Experimental Result

Decision Tree Classifier

A decision tree is a non-parametric supervised learning technique used for classification and regression tasks. It has a hierarchical tree structure that includes a root node, branches, internal nodes, and leaf nodes. A decision tree is an organizational framework utilized in support for decisions to represent actions and their probable outcomes, taking into account chance occurrences, resource costs, and utility. This algorithmic model uses conditionally control clauses and is non-parametric in supervised learning, making it suitable for use in regression and prediction tasks [42].

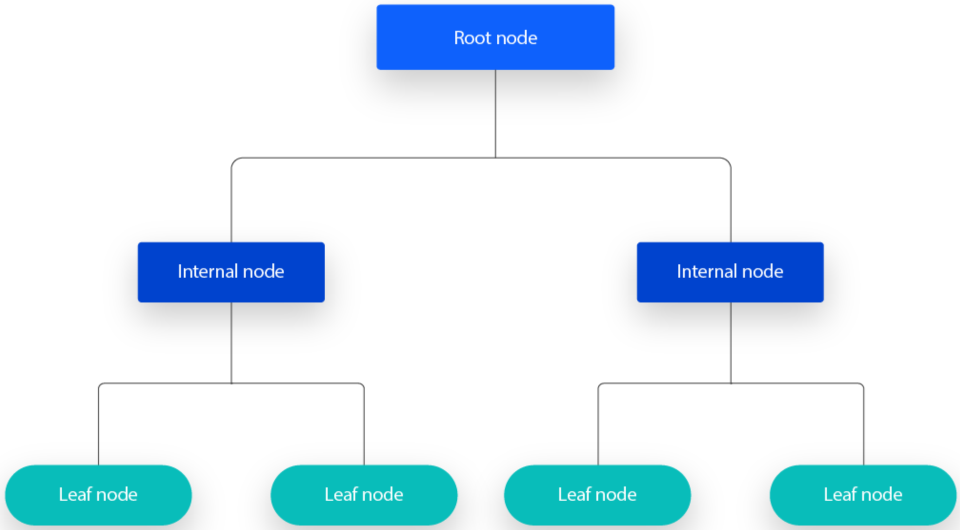

Figure 5.2.1: Decision Tree [43]

Naïve Bayes

The Naïve Bayes classifier is a widely used supervised machine learning technique for classification applications like text classification. It is a generative learning algorithm, which means it simulates the arrangement of input for a specific class or category. This approach relies on the premise that the attributes of the information being provided are dependent upon and given the class of data, enabling the method to generate predictions rapidly and reliably [44].

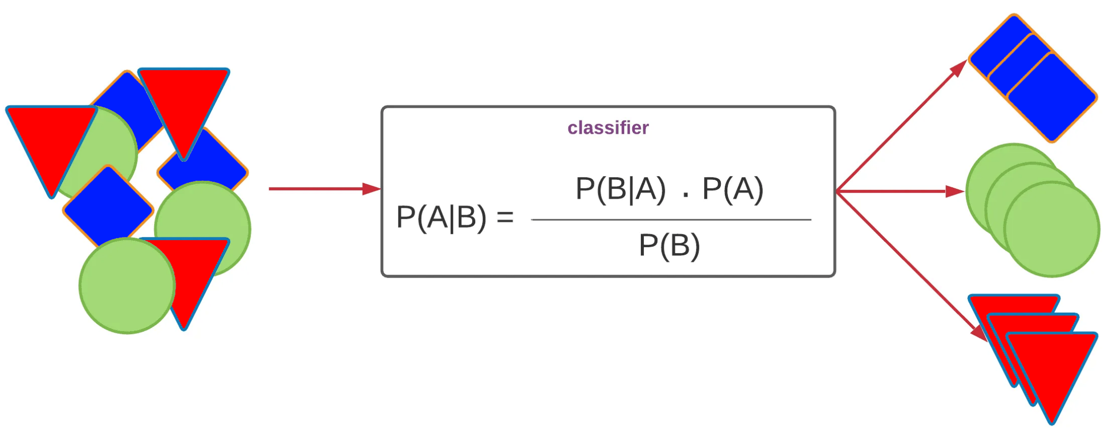

Figure 5.2.2: Naïve Bayes [45]

Gradient Boosting

Gradient boosting is a machine learning ensemble method that systematically combines the predictions of numerous weak learners, such as decision trees. It tries to increase total predictive effectiveness by improving model weights based on prior iteration errors, gradually decreasing errors in prediction and increasing model accuracy [46].

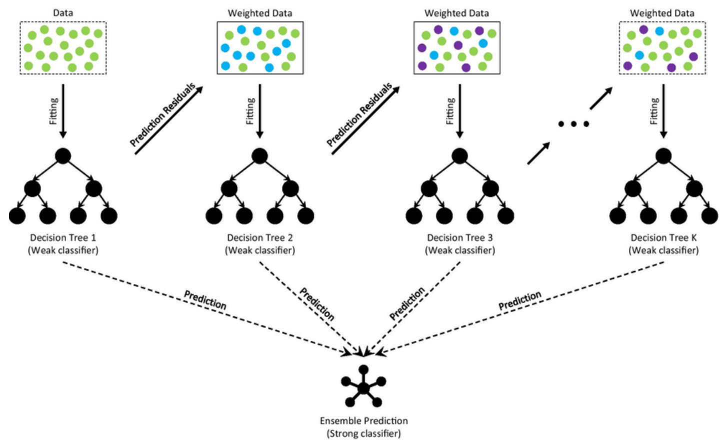

Figure 5.2.3: Gradient Boosting [47]

Multi-layer Perceptron (MLP)

A multi-layer perceptron (MLP) is a form of artificial neural network made up of several layers of neurons. The neurons of the MLP typically employ nonlinear activation functions, which allows the network to learn complex data patterns. MLPs are important in the field of machine learning since they can acquire nonlinear correlations in data, resulting in effective models for tasks like regression, classification, and recognizing patterns [48].

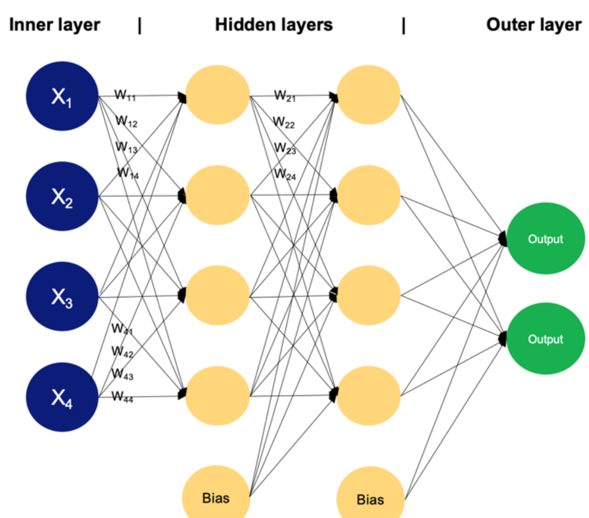

Figure 5.2.4: Multi-layer Perceptron [48]

Random Forest Classifier

Random Forest is a common supervised learning method. It can be used to solve regression as well as classification issues in machine learning. It is based on collective learning, which is the process of integrating different classifiers to resolve a complicated issue and improve the model's performance [49].

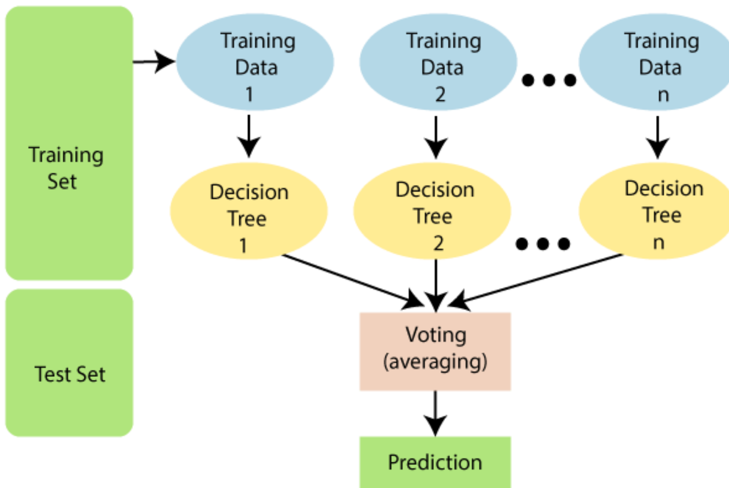

Figure 5.2.5: Random Forest Classifier [49]

Support Vector Machine

Support Vector Machine (SVM) is a sophisticated machine learning technique that may be utilized for linear or nonlinear classification, regression, including outlier detection. SVMs are useful for a range of applications, including recognizing words, classification of images, recognizing spam, recognizing handwriting, analysis of gene expression, recognition of faces, and anomaly detection. SVMs are versatile and efficient in a wide range of uses because they can handle highly dimensional information and nonlinear relationships [50].

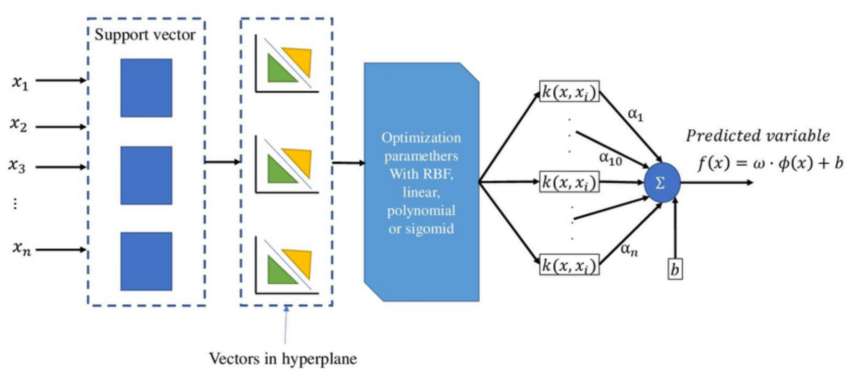

Figure 5.2.6: Support Vector Regression [51]

KNeighbors Classifier

The K in the classifier's name reflects the k nearest neighbors, where k is a user-specified integer number. As the name implies, this classifier uses learning based on k nearest neighbors. The value of k is selected by available data [52].

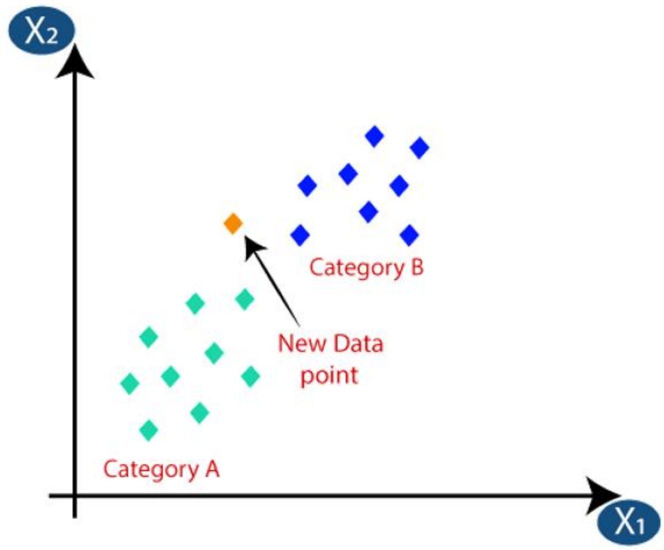

Figure 5.2.7: KNeighbors Classifer [53]

Logistic Regression

Logistic regression is a method for estimating the probability of a discrete outcome based on an input variable. The most frequent logistic regression models have a binary outcome, which might be true or false, yes or no, and so forth [54].

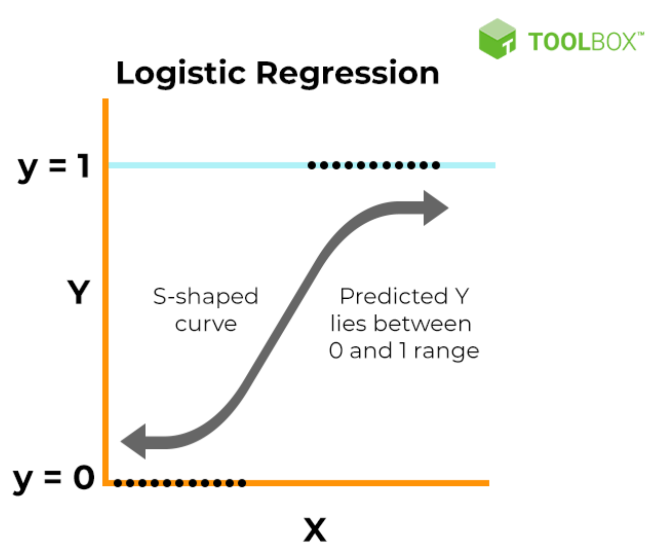

Figure 5.2.8: Logistic Regression [55]

Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a deep learning method that is especially useful for picture detection and processing. It consists of several layers, including convolutional, pooling, and fully linked layers. CNN design is inspired by processing images in the human brain, making it ideal for collecting structural patterns and spatial connections inside images.

The key parts of a Convolutional Neural Network are:

1. Convolutional Layers: These layers perform convolutional operations on input images, detecting characteristics like edges, textures, and complicated patterns utilizing filters (also known as kernels). Convolutional processes help to maintain the spatial relationships among pixels.

2. Pooling layers reduce the geographic extent of the input, lowering the computational cost and number of variables in the network. Maximum pooling is a typical pooling procedure that selects the highest value from a set of adjacent pixels.

3. Activation Functions: Non-linear functions for activation, such as Rectified Linear Unit (ReLU), provide nonlinearity to the approach, allowing it to learn more complicated relationships in data [56].

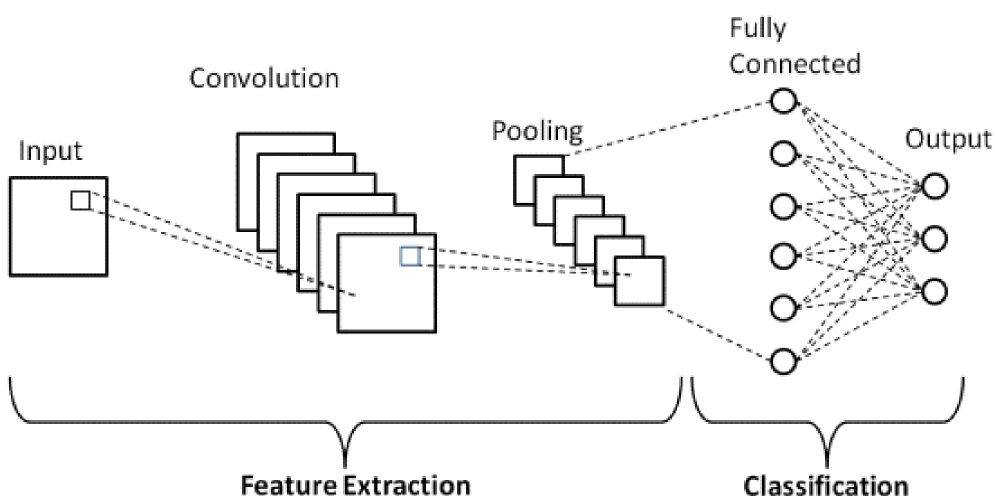

Figure 5.2.9: CNN Architecture [56]

The table below compares various machine learning models used for classification. Precision, recall, f1-score, and accuracy are among the metrics provided for both the "No" and "Yes" classes. The models tested included Random Forest, Logistic Regression, SVM, k-NN, Gradient Boosting, Decision Tree, Naive Bayes, MLP, and CNN. This comparison aids in understanding each model's performance across several measures, allowing for the selection of the best approach for the job at hand.

Table 5.2.1: Performance of Different Classification Algorithm

Model Name	Class	Precision	Recall	F1-Score	Accuracy
Random Forest	No	0.81	0.96	0.88	83.66%
	Yes	0.91	0.62	0.74	
Logistic Regression	No	0.74	0.83	0.78	71.31%
	Yes	0.64	0.51	0.57	
SVM	No	0.74	0.89	0.81	73.58%
	Yes	0.72	0.48	0.57	
k-NN	No	0.93	0.96	0.95	93.32%
	Yes	0.93	0.88	0.91	
Gradient Boosting	No	0.92	0.97	0.95	92.90%
	Yes	0.95	0.86	0.9	
Decision Tree	No	0.88	0.89	0.89	85.51%
	Yes	0.81	0.8	0.8	
Naive Bayes	No	0.75	0.79	0.77	69.74%
	Yes	0.6	0.54	0.57	
MLP	No	0.9	0.95	0.93	90.48%
	Yes	0.91	0.82	0.86	
CNN	No	0.86	0.96	0.91	87.93%
	Yes	0.92	0.74	0.82	

The graphic below depicts a succession of confusion matrices using nine distinct machine learning models utilized for binary classification. Every matrix contrasts the predicted (0 or 1) with actual values (0 or 1).

1. Random Forest Reduced: Performs well with high true positives (427) and true negatives (162), although there are some false positives (16) and false negatives (99).

2. Logistic Regression is moderately balanced, with a greater number of false positives (75) and false negatives (127), which affects its accuracy.

3. SVM Reduced: Maintains a reasonable balance, with fewer false positives (49) than false negatives (137).

4. k-NN: Excellent performance, with a high true positive rate (427) and a considerable number of true negatives (230), but fewer false negatives (31).

5. Gradient Boosting: Excellent performance, with only 13 false positives and 37 erroneous negatives, suggesting good accuracy.

6. Decision Tree Reduced: Results were balanced, with 50 false positives and 52 false negatives.

7. Naive Bayes has lower performance, with more false positives (94) and false negatives (119).

8. MLP Adjusted: Good balance, with only 20 false positives and 47 false negatives, indicating strong performance.

9. CNN demonstrated strong performance, with only 18 false positives and 67 false negatives.

Each matrix contributes to understanding the model's performance by displaying the number of correct and wrong predictions.

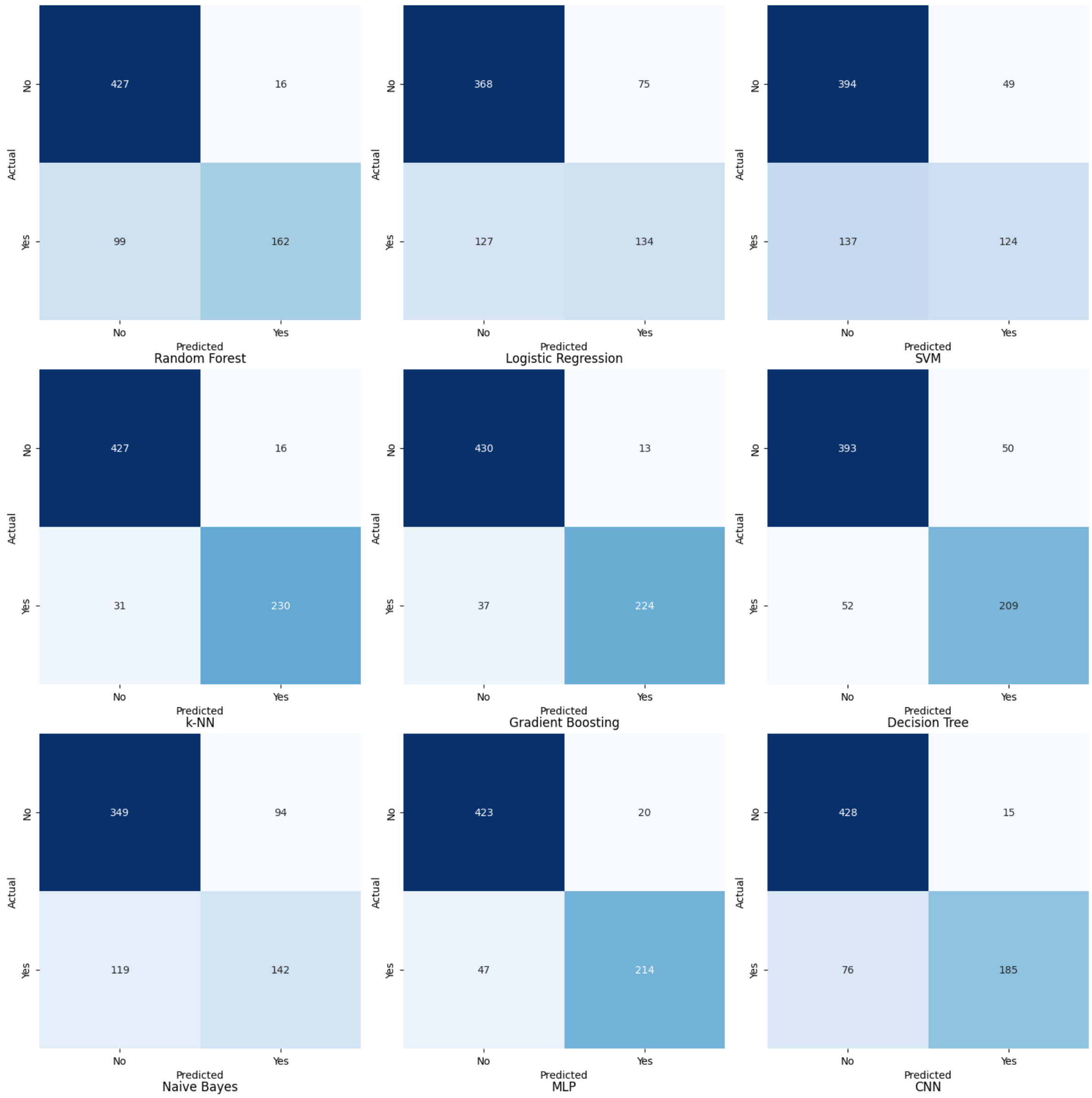

Figure 5.2.10: Confusion Matrix

5.3 Performance Analysis

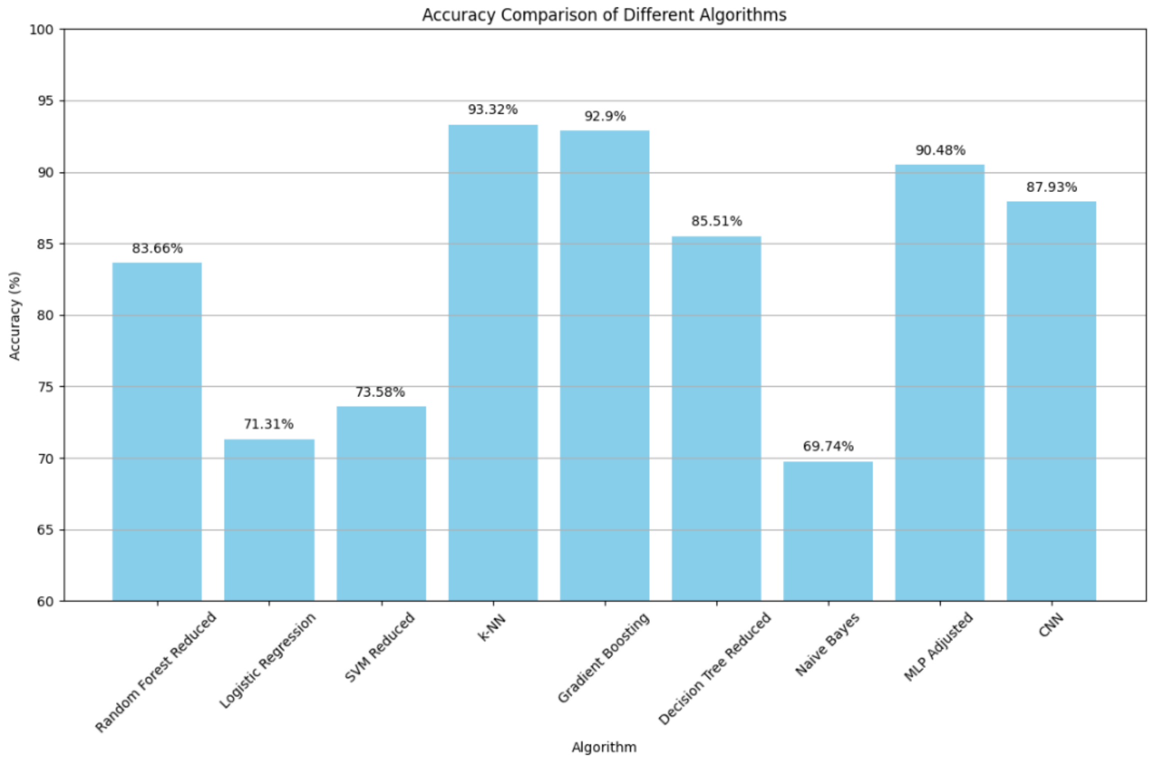

Figure 5.3.1: Accuracy graph of all algorithm

Considering an efficiency of 69.74%, Naïve Bayes generalizes well to new data sets. In contrast, Decision Tree has a greater accuracy rate of 85.51%. This model's ability to capture relationships among features and the intended variable makes it an excellent match for such complicated datasets. Random Forest outperforms expectations, with a success rate of 83.66%. Logistic Regression produces slightly lower accuracy values, with 71.31%. The Support Vector Machine (SVM) Reduced performs consistently, with an accuracy of 73.58%. SVM employs complex decision limits to detect subtle trends in data while minimizing the risk of overfitting. K-Nearest Neighbors (k-NN) performs exceptionally well on this dataset, with an accuracy of 93.32%. Gradient Boosting also performs well, with a 92.90% accuracy rate. MLP Adjusted delivers balanced results, with an accuracy of 90.48%. Finally, the Convolutional Neural Network (CNN) achieves an accuracy of 87.93%, demonstrating its capacity to efficiently generalize to new input.

Label Encoding and Prediction Ranges for Suicidal Thoughts

After applying label encoding to the column indicating suicidal thoughts, we identified specific integer ranges for the categorical values "Yes" and "No." The column originally contained various categorical values, and through the label encoding process, these values were transformed into corresponding integer values by the machine learning algorithm. The algorithm uses these encoded values to make predictions based on the defined ranges. The resulting ranges for each class are presented in the table below:

Table 5.3.1: Resulting ranges for each class

Class	Range
Yes	176-185
No	109-132

These ranges are crucial for the algorithm to accurately predict the presence or absence of suicidal thoughts.

5.4 Summary

This study looked at multiple machine learning algorithms to identify suicide risk variables among drug addicts in Bangladesh. We investigated Random Forest, Logistic Regression, SVM, k-NN, Gradient Boosting, Decision Tree, Naive Bayes, MLP, and CNN. Each model's performance was evaluated using precision, recall, F1-score, and accuracy. k-NN and Gradient Boosting achieved the highest accuracies (93.32% and 92.90%, respectively), while Naive Bayes had the lowest (69.74%). Despite several limitations, such as reliance on reported data and possible biases, the study lays a solid platform for future research. The findings underscore the usefulness of machine learning to predict suicide risk, which could inform public health policy and interventions. The study emphasizes the importance of continuously refining and adapting models to ensure their ongoing efficacy and sustainability.

CHAPTER 6

Impact on Society, Environment and Sustainability

6.1 Impact on Life

This study has the potential to produce a positive ripple effect throughout Bangladeshi society. By investigating risk factors for suicide among drug addicts, we can pave the road for significant changes in numerous critical areas:

By identifying risk variables, our research can help to establish tailored policies and interventions. This may involve:

- Early detection of at-risk persons.
- Increased access to addiction treatment and mental health services.
- Educational programs to increase awareness and minimize stigma.

Our study findings can enable communities to:

- Recognize early warning symptoms of suicidal ideation in people with drug addiction.
- Create support networks for persons dealing with addiction and suicide thoughts.
- Advocate for additional funding for treatment and preventative initiatives.

The ultimate goal is to prevent suicides. Our research can help by offering a better knowledge of risk variables.

- More efficient suicide prevention methods.
- Reduced suicide rates among drug addicts in Bangladesh.
- Improved well-being and a healthier society overall.

By shedding light on this essential topic, our research has the potential to spark a positive ripple effect. It enables individuals, communities, and policymakers to work toward a future in which drug addiction and suicide are less common, and hope and help are easily accessible.

6.2 Impact on Society & Environment

Our research on suicide risk factors among drug addicts has a far-reaching positive social effect. By empowering communities and driving policy changes, our research can indirectly contribute to a healthier environment in Bangladesh.

Effective drug addiction interventions can reduce the number of people who suffer from this problem. This could potentially lessen the need for resources connected with drug use, such as: Healthcare costs for treating addiction-related disorders; Law enforcement resources dedicated to drug trafficking, as well as social programs that assist addicts and their families.

By encouraging healthier individuals and families, our study can indirectly help to create a more vibrant and sustainable environment. Communities with lower drug addiction rates may see an increased emphasis on communal gardens and green spaces. More people are participating in eco-friendly activities. An increased emphasis on public health programs that benefit the environment.

While our research specifically addresses suicide risk factors, the beneficial societal changes it can inspire may have a knock-on impact, boosting environmental sustainability in Bangladesh. We can create a healthier and more empowered society, paving the path for a future in which both people and the environment thrive.

6.3 Ethical Aspects

Researching delicate issues such as drug addiction and suicide risk requires careful consideration of ethical considerations. Here, we'll explain the important ethical aspects that will be prioritized throughout the course of this study.

- All participants will get clear and concise information about the research objectives, their rights, and how their data will be used. Only individuals who have willingly agreed to participate will be featured.
- We will ensure that all participants remain completely anonymous and confidential. To protect the privacy of participants, all collected data will be anonymized and securely kept.

- We will take steps to reduce any potential dangers associated with participation. This includes developing a clear plan for dealing with any emotional distress that participants may encounter during the research process.
- People battling with drug addiction and suicidal ideation are considered vulnerable. We shall be especially mindful of their needs and ensure that their participation does not exacerbate their mental health issues.
- The possible advantages of this study, such as helping to prevent suicide, will be carefully balanced against any dangers to participants. We will only move forward if the advantages outweigh the risks.

We shall be open about our study techniques and results. By adhering to these ethical norms, we hope to carry out this research ethically and safeguard the well-being of all participants.

6.4 Sustainability Plan

While this study is primarily concerned with identifying suicide risk factors among Bangladeshi drug addicts, we are devoted to ensuring its long-term impact and sustainability. Here's how we want to accomplish this.

We will share our findings through a variety of outlets, including peer-reviewed papers, conferences, and presentations geared to the Bangladeshi community. This will guarantee that the information gathered reaches the appropriate stakeholders, such as legislators, healthcare professionals, and community organizations.

We intend to strengthen capacity in Bangladesh to address the issue of drug addiction and suicide prevention. This could include workshops or training programs for healthcare staff, community leaders, and peer support groups. Empowering these folks with the knowledge and skills gained through this research can have a long-term benefit.

We will actively seek collaboration with groups in Bangladesh that work on drug addiction and suicide prevention. By developing collaborations, we may capitalize on existing resources and expertise to ensure the long-term viability of initiatives based on our study findings.

Using the identified risk factors, we will collaborate with stakeholders to create and test sustainable intervention programs. These initiatives should be culturally relevant, resource-efficient, and flexible to the Bangladeshi setting in order to be implemented throughout time.

We intend to develop a system for monitoring and assessing the effectiveness of treatments resulting from this research. This will allow for continual program modification and adaption, ensuring long-term sustainability and maximum impact.

Through completing these measures, we hope to ensure that the knowledge acquired from this research leads to long-term, sustainable solutions for addressing suicide risk factors among drug addicts in Bangladesh. Our mission is to help create a future in which both individuals and communities may thrive.

6.5 Summary

Throughout this research project, our major purpose was to investigate the complex relationship between drug addiction and suicidal tendencies in Bangladesh. We began with an introduction emphasizing the urgency and importance of solving this vital issue, as well as establishing specific research objectives. Moving on to the background part, we contextualized our research by defining key terms, reviewing related studies, and describing the breadth of the problem in the Bangladeshi context. This step enabled us to identify gaps in the current literature and create the framework for our research. Our research technique was carefully planned to ensure reliable data collecting and analysis. We defined our study topic, explained our data gathering techniques, discussed our preferred statistical analysis methodologies, and offered a thorough methodology to successfully lead our research process. The following chapter was dedicated to providing our experimental findings and analyses. Through rigorous experimentation and comprehensive analysis, we discovered crucial insights that shed light on this difficult subject. Exploring the broader implications of our research findings, we looked at the sociological, environmental, ethical, and sustainability aspects of the problem, underlining the importance of holistic approaches to addressing the many issues presented by drug addiction and suicide.

CHAPTER 7

Conclusion and Future Work

7.1 Conclusions

In the end, this study looked into the relationship between drug addiction and suicidal ideation in Bangladesh. Despite the fact that we have not yet implemented the algorithms, our thorough research into the literature and precise experimental design have provided a solid foundation for future analysis and implementation.

After the research, we plan to build 8 algorithms: Random Forest, Logistic Regression, SVM Reduced, k-NN, Gradient Boosting, Decision Tree, Naive Bayes, MLP, CNN. We anticipate high accuracies with each algorithm, with preliminary findings indicating potential accuracies ranging from 71% to 93%.

We intend to get important insights into the risk variables connected with suicide among drug addicts by leveraging machine learning and statistical analysis. We believe that the adoption of these algorithms will result in robust predictive models that can be used to influence preventive interventions and support systems for at-risk persons. Besides, the results of this study have important implications for public health policy, mental health advocacy, and community-based interventions. By addressing the complicated interplay between drug addiction and suicide ideation, we may help to create a more compassionate, resilient, and supportive society for persons dealing with mental health issues. We can work together, innovate, and be dedicated to creating a healthier and more resilient society for everyone.

7.2 Further Suggested Works

This study has opened the way to additional investigation into the urgent issue of suicide risk factors among drug users in Bangladesh. Here are a few major areas where future research could expand on our findings:

- This study provides a picture of a certain point in time. Longitudinal studies that follow individuals over time may provide useful insights into how risk variables evolve and interact during addiction and treatment.

- Our research concentrated mostly on psychosocial issues. Future research could look into the potential impact of biological factors, such as genetics or brain chemistry, in increasing suicide risk among this demographic.
- The impact of addiction and suicide risk may differ between genders. Further research into gender-specific risk factors could lead to more specific treatments.
- As pointed out in the conclusion, investigating the potential of machine learning algorithms for data analysis may result in more complex models for detecting persons at high risk of suicide.

With focusing on these areas of further research, we can improve our understanding of suicide risk among drug addicts in Bangladesh and develop more effective prevention and intervention techniques. This will help to save lives and promote well-being among those who are most at risk.

7.3 Limitations/Conflict of Interests

The study has significant drawbacks. To begin, the data collection was mainly based on reported information, which might be biased or inaccurate. Second, while the sample size is representative, it may not accurately reflect the diversity of Bangladesh's drug user community. Likewise, the study's cross-sectional design gives a snapshot in time but fails to account for variations over time. There could possibly be unexplored elements impacting suicide thoughts that were not considered in our study. Lastly, potential conflicts of interest were minimized; however, it is crucial to remember that researchers' biases and other sources of funding may have an unintentional influence on study outcomes. Addressing these constraints in future study will assist to improve our understanding and the dependability of the results.

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Appendix A

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

Title:
EXPLORING THE NEXUS BETWEEN DRUG ADDICTION AND SUICIDAL TENDENCIES IN BANGLADESH

Student ID: 203-15-14522 and 203-15-14520

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a **suicidal detection** 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	We are collecting data through Google Forms, and we will also go to some rehab centers to collect data directly. In order to work with them in the next stage of data collection, we need to know about the design of machine learning-based models, which cover **K3 and K4**.	**Page no:** [1] **Section:** [1.1] **Page no:** [15-32] **Section:** [3.2]
				We basically complete our project by combining various components and finally create a web base design that covers **K5 and K6**.	**Page no:** [15-32] **Section:** [3.2] **Page no:** [15-32]

					Section: [3.2]
				This project contributes to **K8 (Research Literature)** by combining findings from previous research and demonstrating a thorough awareness of current approaches.	**Page no:** [7-11] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	Although we originally struggled to collect data directly from the rehabilitation facility, we were able to make substantial progress by using Google Forms. However, due to the sensitive nature of the subject, assuring the reliability and impartiality of the data gathered proved challenging, as individuals may have personal motives. Despite these initial obstacles, I am delighted to inform that we have successfully finished the data collection phase. Through effort and dedication, we were able to collect enough significant data to support our research objectives.	**Page no:** [11-12, 3-4] **Section:** [2.4, 1.5]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	We know that getting a completely accurate solution for our project will be somewhat challenging. As we transition into the coding phase, we plan to employ various algorithms, selecting the one that demonstrates the optimal performance. This methodical approach will ensure our project's success as we aim for the most effective solution.	**Page no:** [43-51] **Section:** [5.2]

4.	**EP4: Familiarity of Issues**	Yes	CO8	Understanding how someone becomes attached to drugs because of mental health difficulties or peer pressure can be difficult. To assess whether or not someone is addicted and to what extent, we require assistance from knowledgeable professionals in this sector.	**Page no:** [3-4, 11-12] **Section:** [1.5, 2.4]
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting requirements**	Yes	CO8	We consult with a psychiatric doctor or a drug addiction treatment center both before and after the data collection period. This approach enables us to check our data and assure its relevance for our research from the start, as well as to verify our findings and interpretations after data gathering is complete.	**Page no:** [11-12] **Section:** [2.4]
7.	**EP7: Interdependence**	Yes	CO5	Once we've gathered and validated our data, we move on to the coding phase. During this process, we break down our tasks into manageable steps, such as data pre-processing, handling null values, data splitting, and feature engineering. By tackling each part individually, we'll be able to provide a comprehensive solution.	**Page no:** [15-32] **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 suicide rate detection through machine learning model.	**Page no:** [32-33] **Section:** [3.3]
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		This project contributes to society by improving healthcare through advanced suicidal rate detection methods, while also promoting environmental sustainability by employing efficient computational resources and adhering to ethical guidelines for patient data privacy.	**Page no:** [54-57] **Section:** [6.1, 6.2, 6.4]

5.	**EA-5: Familiarity**	Yes		This project expands upon existing research by examining a novel approach, demonstrated through preliminary terminologies and a comprehensive comparative analysis, offering new insights into the field.	**Page no:** [7, 9-11] **Section:** [2.1, 2.3]

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

SN	COs	Attainment	Justification	References
1	CO4	Yes	In the context of my project, we plan to combat CO4 by implementing effective project management practices and maintaining stringent financial supervision. This will need rigorous planning, resource allocation, and accurate budget estimation to achieve maximum resource utilization at all stages of the research process. By applying these techniques, we plan to streamline project operations and maximize resource use throughout this phase of my research.	**Page no:** [33-37] **Section:** [3.4]
2	CO9	Yes	Our project follows ethical norms by emphasizing patient privacy, gaining informed consent, and maintaining transparent documentation throughout the research process. Prioritizing these ethical issues ensures responsible information distribution and contributes to social well-being through the ethical use of sophisticated healthcare technologies. These practices are consistent with CO9, which emphasizes the ethical use of innovative healthcare technologies for the benefit of persons and communities.	**Page no:** [55-56] **Section:** [6.3]
3	CO10	Yes	The study intends to investigate the relationship between drug addiction and suicidal ideation in Bangladesh. It takes an interdisciplinary approach, bringing together professionals in psychology, sociology, public health, and addiction therapy. Problem-solving and decision-making will be prioritized, drawing on evidence and input from interdisciplinary	N/A

			friends. A culture of respect and inclusion will be promoted, encouraging cooperation and varied perspectives.	
4	CO12	Yes	There is a clear commitment to continuous learning (CO12) and adaptability in a continually evolving technological world. This is proved by extensive data collecting, rigorous statistical analysis, meticulous methodology development, and detailed experimental outcomes. These activities demonstrate a commitment to remaining educated and refining approaches to handle current difficulties.	**Page no:** [15-38, 43-51] **Section:** [3.2, 3.3, 3.4, 3.5, 5.2]

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EXPLORING THE NEXUS BETWEEN DRUG ADDICTION AND SUICIDAL TENDENCIES IN BANGLADESH

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